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Estimating and understanding smallholder crop production variability from pixel to village levels thanks to satellite observation in Mali

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*What you see depends on how you view the world.
To most people, this is just dirt.
To a farmer, it is potential.*

—Doe Zantamanta - Happiness in your life

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List of Acronyms

AGB	Above Ground Biomass
AMEDD	Association Malienne d'Eveil au Développement Durable
ASAP	Anomaly Hot Spots of Agricultural Production
AVHRR	Advanced Very High Resolution Radiometer
BNDA	Banque National de Développement Agricole
CCI	Climate Change Initiative
CCS	Cotton Cereal System
CE	Commission Error
CEC	Cation Exchange Capacity
CMDT	Compagnie Malienne de Développement de fibre Textile
DAP	Di-Ammonium Phosphate
DEM	Digital Elevation Model
DG	Digital Globe
EO	Earth Observation
ESA	European Space Agency
EWS	Early Warning Systems
FAO	Food and Agriculture Organization
FEWS NET	Famine Early Warning Systems NETwork
GC	Ground Cover
GCP	Ground Control Point
GEE	Google Earth Engine
GEO1	GeoEye 1
GEOGLAM	GEO Global Agricultural Monitoring
GI	Gini Index
GIEWS	Global Information and Early Warning System
GLAM	Global Agriculture Monitoring
HR	High Resolution
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
IT	Information Technology
ITCZ	Intertropical Convergence Zone
JECAM	Joint Experiment for Crop Assessment and Monitoring
JRC	Joint Research Center
HRE	High Resource Endowment
LAI	Leaf Area Index
LRE	Low Resource Endowment
MACCS	Multi-sensor Atmospheric Correction and Cloud Screening
MARS	Monitoring Agriculture through Remote Sensing
MRE	Medium Resource Endowment
MNLA	Mouvement National de Libéralisation de l'Azawad
MODIS	MODerate resolution Imaging Spectroradiometer
MR	Medium Resolution
NIR	Near-Infrared
NDVI	Normalized Difference Vegetation Index
NGO	Non-Governmental Organization

OE	Omission Error
OMS	Organisation Mondiale de la Santé
PO	Producers Organization
PU	Production Unit
QB02	QuickBird 2
RE	Red Edge
RE	Resource Endowment
RF	Random Forest
RMSE	Root Mean Square Error
SRTM	Shuttle Radar Topography Mission
SDG	Sustainable Development Goal
SSA	Sub-Saharan Africa
STARS	Spurring Transformation in Agriculture through Remote Sensing
SVM	Support Vector Machine
SWIR	ShortWave Infrared
TOA	Top Of Atmosphere
TS	Time Series
UAV	Unmanned Aerial Vehicle
UCL	Université catholique de Louvain
UN	United Nations
USGS	United States Geological Survey
VAM	Vulnerability Analysis and Mapping
VHR	Very High Resolution
VI	Vegetation Index/Indices
WFP	World Food Program
WHC	Water Holding Capacity
WV2	WorldView 2

List of Symbols

F -score	F-score
K	Potassium
N	Nitrogen
OA	Overall Accuracy
PA	Producers' Accuracy
ρ	Reflectance
UA	Users' Accuracy
p	Proportion
p	p-value
P	Phosphorus
P	Probability
r	Resolution
p_o	Original proportion
R^2	Determination coefficient

Introduction

Importance of smallholder farming in Africa

In 2016 there were 570 million farms in the world, most of them being small and family farms (Lowder *et al.*, 2016). Globally small and medium farms produce between 51% and 77% of most commodities consumed by humans (Herrero *et al.*, 2017). Nevertheless, strong differences exist between regions. In North and South America, Australia and New Zealand, large farms (more than 50 ha) produce between 75% and 100% of cereals, livestock, and fruits. In Europe, North Africa and Central America, medium size farms (20-50 ha) are the ones that produce most of the commodities. In Southeast Asia, South Asia and sub-Saharan Africa (SSA), small farms (< 20 ha) contribute to more than 75% of most commodities (Herrero *et al.*, 2017). A large part of the food consumed in Africa and Asia is produced by smallholders (Bosc *et al.*, 2013). Smallholder rainfed agricultural systems host more than 50% of the rural population in developing countries and yet produce 90% of the food (Morton, 2007). While smallholder farming systems differ widely according to countries and agro-ecological zones, they often share common features such as limited resource endowment, labor scarcity, low productivity of labor, high productivity of capital and high-risk management in economic decisions (Cousins, 2010; Dixon *et al.*, 2004).

Adamopoulos and Restuccia (2014) showed that, in the richest countries, medium size farms and large farms occupy 70% of the cropland while in the poorest countries, 70% of the cropland is occupied by farms smaller than 5 ha. In 2016, Africa had 51 million farms, among which 80% were smaller than 2 ha in size (Lowder *et al.*, 2016). Besides, Eastwood *et al.* (2010) showed that from 1970 to 1990 the number of farms decreased in Europe and North America and at the same time, the size of farms increased. On the contrary, the number of farms increased for the same period in Asia and Africa with a drop in farm size. It is likely that the average surface area per farm will continue to fall in Africa and will start rising in Asia from 2010 onward (Masters *et al.*, 2013). In fact, in SSA, most agricultural interventions planned in the 1970's and 1980's with the goal to move to large-scale agriculture failed leading to persistent smallholder farming systems (Lowder *et al.*, 2016). Large population growth still occurs in Africa and will continue to occur in the coming years (Gerland *et al.*, 2014). The world population is expected to increase with a probability of 80% to a

range of 9.6-12.3 billion in 2100 with much of the increase expected in Africa (Gerland *et al.*, 2014). This is partially related to higher fertility rates and a slowdown in the fertility decline. As a large part of the African population increase will occur in rural areas, the importance of smallholder farmers will increase in the near future (AGRA, 2016)*.

Transformation of the African agricultural systems

According to United Nations (UN)[†] urban population growth rates from 2000 to 2015 reached 4.0% in SSA, 2.5% in Asia and 1.4% in Latin America and the Caribbean. In West Africa, the share of urban population in food market reaches between 60 and 70% (Badiane and Makombe, 2015). This drops to 48% in East and Southern Africa due to lower urban population (23%). Let's note a singularity of Africa compared to Asia: most persons moving to urban areas did not move into manufacturing and rather work in the services sector, that literally exploded (Rodrik, 2016). This phenomenon was called "*urbanization without industrialization*". Next to the importance of cities in the food market, urban and rural populations diversify more and more their diets. Reardon *et al.* (2015) showed that 60 to 65% of the urban diet is composed of non-staples products such as vegetables, meat, fish, fruits, dairy and oils in West, East and Southern Africa. Rural and urban households consume in large part local products while imports cover only 10 to 20% of the total consumption (AGRA, 2017). Even rural population buys food. A recent study highlighted that rural families buy 44% (in value terms) of the food that they consume in East and Southern Africa (Dolislager, 2017). Besides, the purchased-as-processed food is now largely expanding in both rural and urban areas. This results in the fact that today, an African family has to produce food for its own needs plus one other rural family and one or two urban families due to three main reasons: high food market share of the urban population, high consumption of local products and participation of the rural population in the market (AGRA, 2017).

Food security concept

Global food production is sufficient today to feed the world population. The minimum dietary energy requirement (MDER) of 1,850 kcal/person/day estimated from Food and Agriculture Organization (FAO), is lower than the per capita food availability that reached 2,900 kcal/person/day in 2013. This is true even though around a third of the food produced is wasted, another third is used to feed animals and a significant part of cropland is also exploited for biofuel production (Godfray *et al.*, 2010; Gustavsson *et al.*, 2011; Parfitt *et al.*, 2010; Tscharntke *et al.*, 2012). Although there is enough food for the world population, 18.9% of Africans were chronically undernourished in 2016 (FAO, 2016).

*AGRA relates to Alliance for a Green Revolution in Africa

[†]<https://esa.un.org/undp/wup/>

The food security concept was defined during the World Food Summit in 1996 as "*the physical and economic access for all people and at all times, to sufficient safe and nutritious food to meet their dietary needs and food preferences for a healthy and active life*" (FAO, 1996). This concept includes four dimensions: (i) the food availability related to the food production and distribution, (ii) the food accessibility driven by food allocation, food preference and food affordability, (iii) the food utilization including nutritional value, social value and food safety, and (iv) the food stability of the other dimensions in time (Pinstrup-Andersen, 2009).

The Economist journal built a Global Food Security Index (GFSI) providing information on root causes of food insecurity by analyzing three core variables of food security. It aims to partially answer the question: How food-secure is a country? for 113 countries, selected to be as representative as possible of the diversity, the economic importance and the population size (The Economist, 2017). Table 1 shows that countries like Mali – which will be the country studied in the thesis – have very little affordability but also limited availability and quality and safety. As food is unequally shared amongst world population (Alexandratos *et al.*, 2012), improving access to food and promoting extra-agricultural activities is important to increase food security (Frelat *et al.*, 2016).

Table 1: The Global Food security index for 10 countries derived from The Economist (2017). This index examines three food security core variables: affordability, availability and quality and safety in 113 countries.

Global ranking	Country	Overall score	Affordability	Availability	Quality & Safety
1st	Ireland	85.6	84.4	86.5	85.8
2nd	US	84.6	85.9	82.7	86.6
8th	France	82.3	80.1	81.9	88.7
17th	Belgium	79.8	80.7	77.9	82.9
38th	Brazil	67.7	69.2	63.6	75.3
44th	South Africa	64	62.7	66.8	59.7
82nd	Senegal	44.2	31.6	57.0	40.8
90th	Benin	39.6	30.0	47.8	41.4
91st	Mali	39.4	24.0	51.6	44.2
113th	Burundi	25.1	13.5	32.7	33.4

While the portion of the world population living in poverty was 10.9% in 2013, this number reached 42.3% in SSA for the same year (WorldBank, 2018, using the \$1.9 earnings a day as international extreme poverty line). The number of undernourished and poor people in Africa directly corroborates concerns exposed by the three first Sustainable Development Goals (SDGs), adopted by world leaders in September 2015 during a historic UN summit: (i) no poverty, (ii) zero hunger, and (iii) good health and well-being. According to their large number, smallholder farmers are key to rural development and food production in Africa. However, they are facing barriers to fulfill the SDGs.

Challenges of smallholder farming in SSA

The human population is increasing faster in Africa than in other parts of the world (United Nations, 2015). Africa's population will more than double in the next 35 years (Cleland, 2013). As in many regions of SSA the population is increasing and no more land is suitable for agricultural expansion, the farm size is decreasing (Harris *et al.*, 2014). Faced with land scarcity and the challenge to produce sufficient food, farmers can respond in three main ways: (i) agriculture intensification, (ii) extra-agricultural activities development, and (iii) human fertility rate reduction (Headey and Jayne, 2014). According to the heterogeneity of farmer conditions and motivations (Dufumier, 2005), a combination of these solutions will be needed to fulfill the SDGs. National policy interventions can promote one of these strategies as in Malawi for agricultural productivity (Dorward and Chirwa, 2011), in Uganda for non-agricultural wage jobs (Fox and Sohnesen, 2012) and in Rwanda for contraceptive services (Bongaarts, 2011). While we agree that these three aspects are key challenges today, this thesis mainly focuses on the agriculture intensification approach.

The agriculture intensification: concept and definition

During the Green Revolution, the worldwide crop production strongly increased solving part of the food security issues but affecting the environment strongly (Conway, 1997; Tilman *et al.*, 2001). Since the 2000's, the damages caused to the environment by this agriculture intensification have been considered as a major force driving the environment beyond the planet boundaries (Foley *et al.*, 2011). In SSA, it is no more possible to continue with the "*agriculture as usual*" without risking a sharp decline in soil natural fertility (Mueller *et al.*, 2012; van Ittersum *et al.*, 2016; van Noordwijk *et al.*, 1997). As a consequence, intensification of farming systems that is both sustainable and productive is required. These systems should be less dependent on manufactured inputs based on fossil fuel and chemicals and should preserve the environment (Therond *et al.*, 2017). Three main terms are used to characterize the transition towards sustainable agriculture: "*ecological intensification*", "*sustainable intensification*" and "*agro-ecological intensification*". Nonetheless, these concepts overlap in their respective definitions and practices. In the context of this thesis we will use the sustainable intensification concept as it is generally loosely defined allowing lots of models to be labeled under it (Tittonell, 2014).

While various definitions of sustainable intensification exist, they share three main principles: (i) an increase in food, feed or fiber production per unit of land, (ii) the preservation of important ecosystem services, and (iii) the resilience to shocks and stresses, including climate change (Pretty *et al.*, 2011). Different traits of sustainable intensification will be studied along the thesis. Sustainable intensification requires amongst others sustainable soil and land management, and no or efficient use of external agro-inputs to limit negative externalities to the environment (see Chapter 4). In this thesis, we agree with Vanlauwe *et al.* (2014a) that "*sustainable intensification can only be achieved*

when the diversity in agro-ecological conditions, farm household endowment, farming systems, and socio-economic conditions within the landscape is taken into account" (see Chapter 6). An other study demonstrates that the potential of soil conservation technologies, in general, is site-specific and directly depends on the local biophysical and socio-economic environments (Giller *et al.*, 2009).

Key challenges for agriculture intensification in Africa

The key challenges faced by farmers in Western and Eastern Africa for agriculture production are: the water stress, the land erosion and soil degradation, the decline in soil fertility, the low fertilization options, the low mechanization and the high climate variability (see Chapter 3, section 3.5.3.) (Förch *et al.*, 2013; Karlson and Ostwald, 2015; Potts *et al.*, 2013). Soil degradation refers to the loss of biological and economic productivity of land and its ability to provide quantitative and qualitative goods or services (Blaikie and Brookfield, 2015). Poor soil fertility and land degradation are major limitations to food security in SSA, putting many smallholder farmers in a vulnerable position (Sanchez, 2002; Tittonell *et al.*, 2012). Rainfall variability impacts crop production and food security in SSA farming systems, which are almost exclusively rainfed (see Chapter 2). This effect is expected to increase with climate change in a way that is uncertain and complex (Cooper *et al.*, 2008).

In view of the challenges faced by smallholder farmers in SSA to guarantee good crop production, agriculture monitoring systems and Early Warning Systems (EWS) are important. Their goal is to track the current evolution of the growing season by monitoring crop conditions and tracking factors impairing crop productivity.

Early warning systems and agriculture monitoring systems in SSA

The severe famines of the 1970's and 1980's in SSA spurred the development of EWS and agriculture monitoring systems all over Africa. Buchanan-Smith *et al.* (1995) defined the early warning system as "*a system of data collection to monitor people's access to food, in order to provide timely notice when a food crisis threatens and thus to elicit appropriate response.*" These EWS showed their effectiveness to deliver near real-time information to help governments and relief agencies respond to humanitarian crises in Africa (Tefft *et al.*, 2006). Lots of EWS exist in Africa and only the most famous ones are presented here. The Inter-State Committee for Drought Control in the Sahel (CILSS) is an integrated mechanism operational in SSA to manage and prevent food security crises *. The Global Information and Early Warning System (GIEWS) was built up by FAO in 1975 and continuously delivers key indicators to assess food security globally †. The Famine Early Warning System Network (FEWS NET) created

*<http://www.cilss.int/>

†<http://www.fao.org/giews/>

by USAID following the 1984-1985 drought and famine in East and West Africa, provides early warning and analysis of food insecurity. It provides objective information for more than 36 of the world's most food-insecure countries [§]. The Seasonal Monitor is a core function of the World Food Program (WFP) work for food security analysis. They examine, amongst other things, real-time series (TS) data streams and seasonal forecasts to assess the progress of the growing season and to highlight potential developments that may be of humanitarian concerns. Next to food production variability, EWS also analyse the fluctuation of market prices affecting food security. In SSA, the food market functioning is threatened by different barriers that prevent smallholder farmers from accessing the markets and productive assets, including transaction and transportation costs (Jacques *et al.*, 2018).

While EWS are designed for curative approaches and are relevant for food crisis detection, agriculture monitoring systems deliver information on crop status to improve crop production and market price fluctuation forecasts and to better understand risks in food supply (Justice and Becker-Reshef, 2007). They are also used for the development of agricultural support interventions which aim to prevent the occurrence of food crisis. Fritz *et al.* (2018) proposed a comparison of the eight most famous agriculture monitoring systems including Monitoring of Agriculture with Remote Sensing (MARS) [¶], GEO Global Agriculture Monitoring (GEOGLAM) (Whitcraft *et al.*, 2015a) and CropWatch (Bingfang and Qiangzi, 2004). This paper described the gaps in data that are critical for agriculture monitoring, including cropland maps, crop calendars, and meteorological data. It also concluded that the new sources of data provided by remote sensing and mobile phones and a better data sharing will help will help to improve agricultural monitoring in the near future.

Despite these operational systems, food security concerns are not entirely solved as demonstrated by recent local food crises in different countries of the region, *e.g.*, Ethiopia in 1999-2000, Malawi in 2001-2002, Niger in 2005 (Devereux, 2009; Genesio *et al.*, 2011). This is related to the outstanding challenges to monitor agricultural conditions in SSA including: (i) the difficulty to get ground crop production data, (ii) the difficulty to assess the quality of the ground data, (iii) the translation of large-scale information to local scale food insecurity detection, (iv) the monitoring of minor crops contributing to the family basket and food security. The Cairo plan in April 2000 identified the strengthening of these systems as one of the priority areas for cooperation between African Union and European Union in order to improve food security in Africa.

While smallholder farming is spread over entire Africa, the current EWS and agriculture monitoring systems do not suit smallholder farming applications. These systems often provide too coarse information for smallholder farming monitoring and tend to neglect local specificities of cropping systems and farm-

[§]<http://www.fews.net>

[¶]<https://ec.europa.eu/jrc/en/scientific-tool/mars-bulletins-food-security>

ers' socio-economic conditions (see Chapter 2). Besides, large improvements of the systems methodologies are still expected as the methods did not significantly evolve for decades. Recent advances in remote sensing accessibility and technology offer possibilities to improve these systems and make them useful for smallholder farmers.

Remote sensing applied to smallholder agriculture monitoring in Africa

Remote sensing applications for smallholder agriculture traditionally face considerable challenges because of small field size, mixed cropping, heterogeneity in management practices, landscape fragmentation, and widespread presence of trees within the fields (Delrue *et al.*, 2013; Vancutsem *et al.*, 2012). However, with recent improvements in sensor technologies, such as the European Space Agency (ESA) Sentinel constellation, almost all spatial and temporal resolution constraints have been lifted. Thus, it becomes possible today to monitor crop production at levels of granularity increasingly compatible with smallholder farming (Atzberger, 2013). This opens the way for the development of practical applications for agriculture monitoring, allowing the exploitation, rather than the mitigation, of spatial heterogeneity, and the demonstration that increased productivity and enhanced livelihoods are not necessarily antithetical with complex cropping systems, and may actually thrive on the latter.

Cropland and crop type mapping

One of the first applications of remote sensing is the cropland classification to estimate cultivated area based on EO images and to constraint crop monitoring systems to cropland regions (see Chapter 1). This approach is interesting as it offers wall-to-wall and up-to-date information on the cropland distribution. Many global land cover products delivered at different resolutions ranging from 30 m to 10 km contain cropland classes. Nevertheless, several studies have highlighted discrepancies in the extent and spatial distribution of cropland within these products (Fritz *et al.*, 2010; Waldner *et al.*, 2015d; Wu *et al.*, 2008) with global cropland extent fluctuating between 1.11 and 3.62 billion hectares depending on the products (Biradar *et al.*, 2009a). These discrepancies are even higher in Africa (Fritz *et al.*, 2013) especially because of the agricultural landscape fragmentation, the spatial heterogeneity of the cropland, the diversity of the cropping systems and the mosaic of cropland, fallow and natural grassland (Delrue *et al.*, 2013; Vancutsem *et al.*, 2012). Some of the global products containing cropland classes are presented here with their main issues to classify cropland in Africa. Medium resolution (MR) Landsat-based (30 m) cropland maps, such as the Cropland-Use Intensity (CUI) are accurate, but their methodology prevents regular updates (Chen *et al.*, 2015; Fritz *et al.*, 2010). Low resolution (LR) land cover maps, such as the Moderate Resolution Imaging Spectroradiometer (MODIS) product (Friedl *et al.*, 2002) and the ESA Climate Change Initiative (CCI) Land cover (Defourny, 2014), offer current

cropland information. However, these global land cover maps do not focus on agriculture and tend to neglect regional specificities of West Africa. Specific cropland maps do exist, such as the Global Map of Rainfed Cropland (GMRCA) and the Global Irrigated Area Map (GIAM), but their resolution of 10 km is not suitable for regional applications (Biradar *et al.*, 2009a; Prasad *et al.*, 2009) and are too coarse for monitoring and planning purposes. Please refer to Appendix A for information on spatial resolution.

At local scale, some studies achieved accurate land cover and crop types classifications (see Chapter 5) of smallholder farming systems using high resolution (HR) imagery (Sweeney *et al.*, 2015), very high resolution (VHR) imagery (Debats *et al.*, 2016) or a combination thereof (Lebourgeois *et al.*, 2017). While some authors deemed VHR compulsory for such purposes (Lebourgeois *et al.*, 2017; McCarty *et al.*, 2017), others found HR to be sufficient (Pervez *et al.*, 2014). Settling this question is probably context-specific. Results from Leroux *et al.* (2017) in West Africa and from Duveiller and Defourny (2010) suggested that a 10 m spatial resolution may suffice for land cover classification in most of the regions.

Yield estimation

Quantitative estimates of smallholder yields from EO also offer potential for improved scalability and objectivity, compared to estimates generated from ground measurements or farmer surveys, which are local and subject to farmers' perceptions (see Chapter 5). Two popular approaches used to estimate crop yield from EO include (i) empirical models based on linear regressions between yield measurements and spectral VIs, and (ii) crop growth models involving the use of weather, soil, plant, management and satellite data. In theory, the agility of crop models featuring a finer-scale representation of plant, soil and management processes confers them a higher accuracy for potential yield estimation. However in practice, they are constrained by data availability (Burke and Lobell, 2017; Morel *et al.*, 2014) and lack of granularity, and are biased towards temperate, high-yielding cultivars (Gaiser *et al.*, 2010; Srivastava *et al.*, 2016). On the other hand, EO yield estimators evaluate actual yields and can be applied at granular scales increasingly congruent with the reality of smallholder agricultural systems. A set of recent studies (Burke and Lobell, 2017; Jain *et al.*, 2016; Lobell *et al.*, 2015; Morel *et al.*, 2014) focused on yield estimation from EO. As satellite imagery cost in heterogeneous landscapes is not a concern anymore, Chivasa *et al.* (2017) highlighted that remote sensing might be relevant for estimating maize yield in heterogeneous African agricultural landscapes. This approach requires to adequately pick HR multispectral sensors, accurate classification methods and robust field data. A third hybrid approach based on the assimilation of EO derived biophysical variables into a crop growth model have been designed for long (Delécolle *et al.*, 1992) and implemented by few (de Wit *et al.*, 2012; Hoefsloot *et al.*, 2012) because of the challenging matching between models and EO-derived variables.

The concept of yield gap

While enhancements in remote sensing offer possibilities to deliver relevant information to smallholder farmers, the yield gap concept is useful to study the crop production variability (see Chapter 6). Since a few years, various studies used the yield gap concept (the difference between potential yield and actual yield) as an indicator of yield growth potential in a given region (Hall *et al.*, 2013; Licker *et al.*, 2010; Lobell *et al.*, 2009; Pasuquin *et al.*, 2014). The potential yield corresponds to the yield of a specific cultivar, achievable when water and nutrients are unlimited and biotic stresses controlled, within a defined region (Evans, 1993). Most studies used field measurements and crop models to estimate yield gaps (Affholder *et al.*, 2013; van Ittersum *et al.*, 2013). The Global Yield Gap Atlas (van Ittersum *et al.*, 2013) has built a standardized methodology to estimate yield gaps all over the world with a crop growth model used over homogeneous climatic areas. Nevertheless, this elegant approach oversimplifies the well-known interactions between climate, soil, agricultural practices and human rationale taking place at the local scale. Lobell (2013) mentioned the vast potential of remote sensing tools to measure and understand the magnitude of crop yield gaps at different scales and at almost any time. These approaches will only be valid if the yield gap estimations take the local context into account, including agro-climatic conditions and cropping system specificities.

To conclude, EO offers potential to improve scalability and objectivity of agricultural statistics (*e.g.*, cultivated area, yield forecasting, crop production estimation) in smallholder farming systems, compared to estimates generated from survey data. Remote sensing can also be used to deliver relevant information for EWS and agriculture monitoring systems. Next to the importance of remote sensing for smallholder agriculture monitoring, remote sensing can also be useful for ex-ante programming of interventions in agricultural systems. Indeed, numerous development agencies active in SSA are looking for advice on how best to assist smallholder farmers in agricultural development. Nevertheless, they are often not in a position to get relevant information on realistic and practical options for farmers (Giller *et al.*, 2009). Remote sensing could be used to deliver guidance to design appropriate agricultural support interventions adapted to the farmer's needs and to the diversity of farmers.

Scope and objectives

The evolution of African smallholder farming systems has been induced by socio-economic drivers, by local innovations as well as by agricultural development interventions. These interventions (*e.g.*, fertilizer or seed supply, microcredit, diversification, off-farm activities) were often based on the assumption that they were applicable in the same way to most farmers in a given village or even in a given region. They aim to improve farmers' food security and decrease their vulnerability in a context of environmental, demographic and economic pressures. The technological packages regularly proposed to African farmers which often consist of improved seeds, mineral fertilizer, and equipment, are productivity-oriented and ignore the local agro-ecological heterogeneity and the diversity of socio-economic conditions. Recognizing the diversity of farmers' trajectories is a recent priority for agricultural development stakeholders. Therefore, it is essential to develop methods to document the different cropping systems and their respective heterogeneity observed at village or landscape level in order to (i) better design and target the interventions to specific farmer's needs, (ii) establish the baseline corresponding to the ex-ante situation and anticipate the potential impact of interventions, and (iii) assess a posteriori the intervention efficiency.

Today operational agriculture monitoring systems face many challenges to deliver accurate and up-to-date information relevant for smallholder farming systems while the observing capability has drastically increased. The long-term continuity, open and free access policy of European Copernicus satellite observation opened a new era of high revisit time and high spatial resolution global imagery. This unprecedented observing systems capability introduces a paradigm shift for agriculture monitoring in Africa in particular. Complex smallholder farming systems, where heterogeneous fields often do not exceed one ha, could now be regularly monitored with an appropriate spatial resolution at low cost for the imagery and from field to regional scale. From a research perspective, the first challenge is to fully exploit these very recent enhancements of EO capability. The second is to socialize the new big data flow by integrating, *inter alia*, socio-economic information in a relevant way for crop monitoring in smallholder farming systems.

The opportunity to capture the cropping heterogeneity in smallholder farming systems drives the motivation of this thesis. Its overarching objective is formulated as follows:

to develop an overall methodology for estimating and understanding the variability of crop production down to village, farm and field levels in African smallholder farming systems. □

This overall objective is pursued by attempting to answer the three following research questions.

1. How to improve current agriculture monitoring systems by making them more relevant for smallholder farmers with Earth Observation?

Today, operational agriculture monitoring systems and EWS make use of Earth Observation to inform on growing conditions which helps to guide food and agricultural supports and prevent food crises. Nevertheless, they are most of the time based on low spatial resolution time series and not up-to-date cropland masks. We wanted to test whether these current systems can capitalize on different types of optical observing capabilities compatible with smallholder farming systems: (i) to find a method for mapping in an automated way annual cropland, and (ii) to depict the inter-annual variability of growing conditions from national down to commune level with more appropriate spatial resolution. These two goals investigated for a study case in West Africa will question current operational early warning and agriculture monitoring systems relying on 1 km - 250 m spatial resolution data. ■

2. How to use decametric and temporally-dense Earth Observation images to estimate local crop production and the heterogeneity of complex smallholder farming systems?

Accurate estimations of local crop production are crucial in smallholder farming systems to improve agricultural statistics, better target the agricultural support, and a posteriori assess the impact of agricultural interventions. While crop production is crucial for smallholder farming systems monitoring, its estimation is seldom available at the local scale and often relies on ground surveys that lack reliability and spatial representativeness. In this thesis, we wanted to take advantage of the recent decametric observing system – Sentinel-2 mission – to investigate the crop production heterogeneity building on precise crop type mapping and local yield estimation. This requires to develop methods at field and village levels to (i) map accurately the crop types from Sentinel-2 time series and ground data, (ii) estimate yield from remotely-sensed estimators, and (iii) estimate yield gaps which are very useful as an indicator of yield growth potential in a given region. These methods are developed for a case study at the commune level. ■

3. How to combine socio-economic and geospatial data to identify key drivers of crop production variability in order to support sustainable farmer strategies of intensification?

As African population is expected to increase in the coming years with most of its population directly depending on agriculture to meet its basic needs, sustainable agriculture intensification is required. In that context, identifying the key drivers of crop production variability is needed to target agricultural support to the farmer's needs better. We defined a method to identify the driving forces of crop production variability by combining data sources from various disciplines in a systemic multi-disciplinary framework. The motivation

is thus twofold: (i) to evaluate the impact of fertilization treatments on crop growth and its detectability by Earth Observation, and (ii) to determine how farmer rationale and socio-economic conditions of farmers affect crop production variability. While most of the yield gap approaches oversimplify the local complex interactions between climate, soil, agricultural practices and human rationale, our overall ambition is to study yield gap variability considering the whole diversity of farming systems and farmer rationales. ■

These three questions are tested at different scales with a focus on Mali's cotton belt thanks to the great opportunity of building on a test site of the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT). The experience of their staff, the strong collaboration between UCL and ICRISAT, the local expertise (including a collaboration with a local NGO: Association Maliene d'Eveil au Développement Durable (AMEDD)), and above all the convergence of international projects led by ICRISAT have been instrumental in the data collection for this thesis.

Mali's cotton belt experiences fast population growth and increasing land shortage (Soumaré, 2008) which are widespread challenges across SSA. While the region has shown favorable agricultural intensification pathways with cotton production from 1960 to 2000, the agricultural production has stagnated since the cotton crisis (2004) (Benjaminsen *et al.*, 2010; Falconnier *et al.*, 2016). In response to that the Malian government pledged to, amongst others, increase agricultural productivity (de la Croix *et al.*, 2011). To complete this challenge, it is required to take into account the heterogeneity of farms in the region as they are expected to respond in different ways to changes in socio-economic conditions (Falconnier *et al.*, 2015, 2018).

Outline of the thesis

The overall structure of the research is illustrated in Figure 1 linking each chapter's contribution to one of the three research questions with sub-research questions. Each chapter refers to a specific scale (from regional to field levels) as illustrated at the bottom of the Figure 1. The respective objectives of each chapter are shortly described here below. The core of the thesis (Chapters 1 to 6) contains four chapters based on scientific papers and two chapters not to be published (Chapters 2 and 3). The four scientific papers are at different levels of progress with Chapters 1, 4 and 5 already published, and Chapter 6 just submitted. Each chapter starts by giving the highlights and then follows a classical scientific paper structure.

Chapter 1 develops a methodology to map, in an automated way, annual cropland in the Sahelian and Sudanian agrosystems taking advantage of the 100 m spatial resolution of PROBA-V. Accurate and up-to-date information on cropland extent lacks in these regions while it is crucial for EWS. The cropland map produced is used in Chapter 2 to delineate cultivated area.

Chapter 2 develops a methodology to capture the inter-annual variability of growing conditions over four successive years (2014-2017) and from national down to the commune levels benefiting from enhancement in sensor technologies (spatial resolution). This chapter questions the current operational agriculture monitoring systems using large spatial resolution and not up-to-date cropland maps.

Chapter 3 describes the diversity of farming systems and farmer strategies in the cotton belt of southern Mali thanks to open-ended interviews conducted with 50 farmers in the commune of Koningue. In this chapter, we propose a description of farming systems according to those concerned^{||}. It is a key chapter to invite the potential reader to "*dive-in*" the local context in which take place Chapters 4, 5 and 6.

Chapter 4 measures the sensitivity of the NDVI recorded by satellite (VHR images) to on-farm soil fertility treatments applied to the five main crop types in Mali's cotton belt. The mineral fertilization effects are explored with respect to within-field variation, between field variation and field position in the catena. This chapter contributes to the understanding of crop production variability along with Chapter 6.

Chapter 5 proposes a methodology to estimate crop production at village level using HR Sentinel-2 TS and ground data in the Koningue commune. The agricultural production assessment requires both accurate EO mapping of dominant crops and correct yield estimate per crop type. The best remotely-sensed yield estimator is used in Chapter 6 to estimate yield gaps.

Chapter 6 proposes an innovative method to enrich the yield gaps comprehension by integrating socio-economic conditions and farmer rationale (*inter alia*, resource allocation). The yield gaps are estimated from remotely-sensed yield estimator (Chapter 5). Both natural and human factors affecting yield gaps are studied.

^{||} In French: "*à dire d'acteurs*"

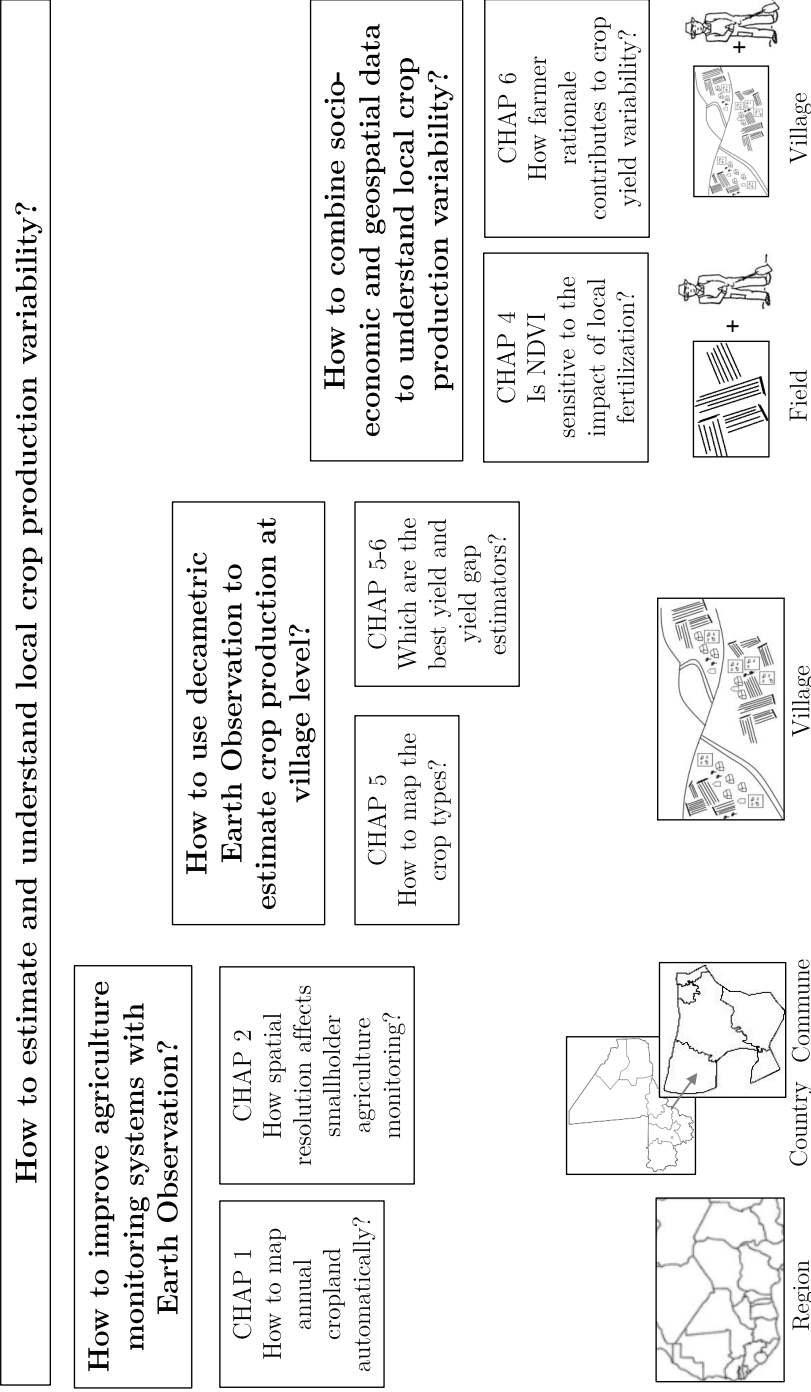


Figure 1: Building blocks covering the scientific hypotheses of the thesis.

Multi-scale study areas nested in Mali

Six different scales are investigated in this thesis: the Sudano-Sahelian region, the administrative regions of Mali (Sikasso, Ségou, Mopti, and Gao), the circle of Koutiala, the Koningue commune, the villages of the Koningue commune, and the field level (Figure 2). Chapter 1 covers the Sudano-Sahelian region considered as the area between 17°W - 23°E and 9°N - 18°N , in West Africa (Figure 2a). This region has a strong north-south gradient linked to the movements of the Intertropical Convergence Zone (ITCZ). The climate is tropical with two distinct dry and rainy seasons. In the Sahelian region (isohyets from 250 to 500 mm) the growing period is short (60–90 days) and starts with the onset of precipitations between May and June (Akponikpe *et al.*, 2011a; Sivakumar, 1990). In the Sudanian region (isohyets from 500 to 1,000 mm) the growing period is longer (more than 150 days) and spans from May to November (Jagtap, 1995). A clear gradient is observed from the Sahel southwards with progressively longer growing periods towards the south (Vrieling *et al.*, 2013).

The Republic of Mali is a country in West Africa with no access to coast (Figure 2b). Mali is the eighth largest country in Africa with an area over 1,240,000 km² and a population reaching 18 million in 2017. More than 90% of the Malian population lives in the southern part (one-third of the country area with the higher amount of rainfall) while less than 10% lives in the northern part (two-thirds of the country area, much drier). Since Mali independence in 1960, Tuareg breeders revolt against the Malian government about territory borders. In 2010, instability in northern Mali increased and rebellion against the Malian government was led by the National Movement for the liberation of Azawad (MNLA). In March 2012, a military coup occurred and led to a declaration of independence of the Azawad (north part of Mali) by armed groups. The international community responded to that by the deployment of the UN Multidimensional Integrated Stabilization Mission in Mali (MINUSMA).

In June 2015, peace negotiations led to agreements between the government and the rebel coalitions. Nevertheless, its implementation is challenging and security is still critical especially in the north (Sangaré *et al.*, 2016). Political instability directly affects the Malian population and prevents us from completing field surveys on an annual basis. In 2015, the Republic of Mali ranked 176th out of 188 countries in the UN Human Development Index. Agriculture is crucial for Mali economy, cotton being the main crop export. Gold, livestock, and agriculture account for 80% of the Malian exports. More than 80% of Malians work in agriculture and 15% in the service sector.

Chapter 2 makes the transition between the national scale (Mali) and the commune level. It analyses the administrative regions of Mali (Figure 2b), the Koutiala circle (Figure 2c) and the Koningue commune (Figure 2d) regarding crop growing conditions variability. Mali has three levels of administrative divisions: region, circle, and commune. Each of them is analyzed in Chapter 2.

The Sikasso region is one of the most productive regions of Mali regarding agriculture, especially for cereals and cotton. It is characterized by relatively high population density (36 inhabitants/km²)**. The Koutiala circle includes the Koutiala city with more than 140,000 residents (third city of Mali). The agricultural region surrounding Koutiala is characterized by high density of fields, strong fertility transfers, and average annual rainfall of 850 mm.

Chapters 3, 4, 5 and 6 take place in the Koningue commune and its villages (Figures 2d and 2e). This commune was identified as a good study site to develop a methodology to estimate and understand the local crop production variability, as it is part of the ICRISAT test sites. Besides, it is included in a region featuring high spatial variability in crop production and high challenges for agriculture monitoring. The Koningue commune includes five villages: Dougan, Sukumba, Nguessou1, Nguessou2, and Banesso. It is located in the Koutiala circle within the oldest cotton production basin of Mali.

**<http://www.instat-mali.org/nada/index.php/catalog/8>, consulted the 23th April 2018, Recensement Général de la Population et de l'Habitat 2009.

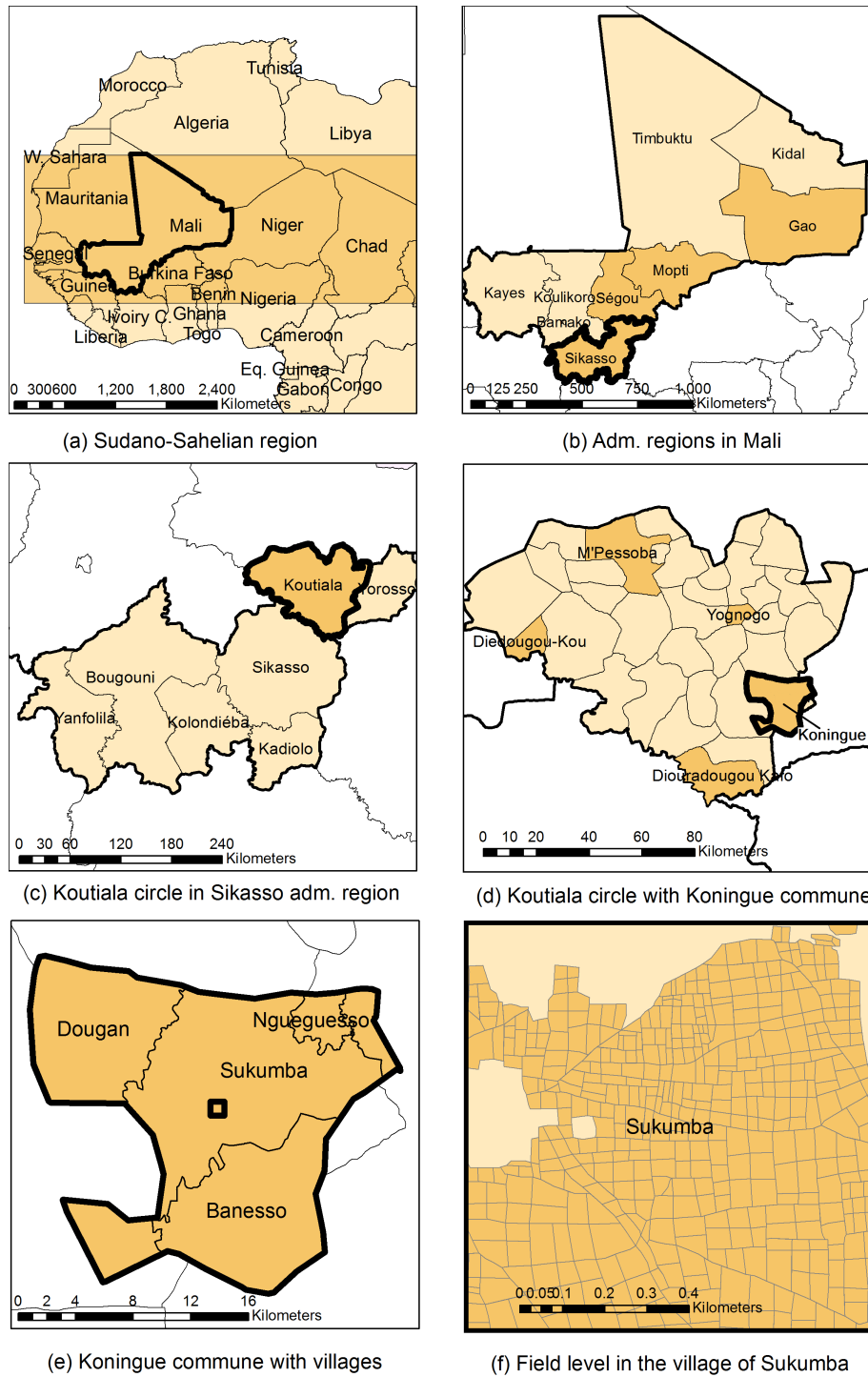


Figure 2: Study areas location for the multiple scales addressed in the thesis. The study areas are drawn in orange and the changes of scale are indicated by the bold lines.

Chapter 1

Cropland mapping over Sahelian and Sudanian agrosystems: A knowledge-based approach using PROBA-V TS *

Highlights

- A knowledge-based supervised classification of annual cropland built on PROBA-V time series reaches 84% of overall accuracy.
 - The fully automated method opens possibilities to easily get wall-to-wall and up-to-date data.
 - The good accuracy is linked to the 100 m spatial resolution, the methodology and the quality of the labeling layer (GlobeLand 30).
 - Misclassifications are explained by low data availability during the cropping season and landscape fragmentation.
 - Further improvements are expected with better cloud screening and higher spatial resolution.
-

Abstract. EWS for food security require accurate and up-to-date information on the location of major crops in order to prevent hazards. A recent systematic analysis of existing cropland maps identified priority areas for cropland mapping and highlighted a major need for the Sahelian and Sudanian agrosystems. This chapter proposes a knowledge-based approach to map cropland in the Sahelian and Sudanian agrosystems that benefits from the 100 m spatial resolution of the recent PROBA-V sensor. The methodology uses five temporal features

*Adapted from Lambert, M.-J., Waldner, F., and Defourny, P. (2016). Cropland mapping over Sahelian and Sudanian agrosystems: A knowledge-based approach using PROBA-V time series at 100 m. *Remote Sensing*, 8(3), 232.

characterizing crop development throughout the vegetative season to optimize cropland discrimination. A feature importance analysis validates the efficiency of using a diversity of temporal features. The fully-automated method offers the first cropland map at 100 m using the PROBA-V sensor with an overall accuracy of 84% and a F-score for the cropland class of 74%. The improvements observed compared to existing cropland products are related to the hectometric resolution, to the methodology and to the quality of the labeling layer from which reliable training samples were automatically extracted. Classification errors are mainly explained by data availability and landscape fragmentation. Further improvements are expected with the upcoming enhanced cloud screening of the PROBA-V sensor.

1.1 Introduction

In West Africa, about 70% of the population depends on cropping systems to meet their basic needs (CORAF/WECARD, 2007). Rainfed and small-holder agriculture are the two major components of the food production system (Brevault *et al.*, 2014; Jalloh *et al.*, 2012; Lahmar *et al.*, 2012). Nevertheless, inter-annual crop production variability, mainly due to the variability of the rainfall distribution and poor soil fertility, has led to chronic food insecurity (Akponikpe *et al.*, 2011a). Recurrent severe regional droughts occurred in 1972–1973 and 1983–1984 and led to famines that affected millions of people (Dardel *et al.*, 2014). Even though no regional drought has occurred since 1984, localized famines recently hit some Sahelian countries (Genesio *et al.*, 2011). In addition to natural variability, socio-economic and political factors, such as population growth, social conflict, and low economic development, put pressure on cropping systems (Karlson and Ostwald, 2015; Potts *et al.*, 2013). It is of primary importance to monitor land use change (Bailis *et al.*, 2005; Manning *et al.*, 2009; Mertz *et al.*, 2012) and to develop an in-depth understanding of the detailed spatial patterns and the temporal dynamics of cropland (Liu *et al.*, 2005). EWS *e.g.*, FEWS-NET and GIEWS, for food security require accurate and up-to-date spatial information about the cropland to monitor food production (Genesio *et al.*, 2011). Nevertheless, mapping cropland remains challenging in this region, especially because of the agricultural landscape fragmentation, the spatial heterogeneity of the cropland, the diversity of the cropping systems and the mosaic of cropland, fallow and natural grassland (Delrue *et al.*, 2013; Vancutsem *et al.*, 2012).

Many global land cover products delivered at different resolutions ranging from 30 m to 10 km contain cropland classes. HR Landsat-based (30 m) cropland maps, such as Cropland-Use Intensity (CUI), Africover and GlobeLand 30, are consistent, but the methodology prevents regular updates (Chen *et al.*, 2015; Fritz *et al.*, 2010). MR land cover maps, such as MODIS product, ESA CCI Land cover, GlobCover, Global Land Cover 2000 (GLC 2000), Global Land Cover by National Mapping Organizations (GLCnmo), Global Food Security Analysis-support Data (GFSAD), International Institute for Applied Systems

Analysis (IIASA) cropland, EcoClimap II and GLC-Share (Friedl *et al.*, 2002; Defourny, 2014; Teluguntla *et al.*, 2015; Bartholomé and Belward, 2005; Ryutaro *et al.*, 2014; Vancutsem *et al.*, 2012; Bontemps *et al.*, 2011; Tchuente *et al.*, 2010; Latham *et al.*, 2014), offer current cropland information. Yet, most of these global land cover maps do not focus on agriculture and tend to neglect the regional specificities of West Africa. Specific cropland maps do exist, such as the global map of rainfed cropland (GMRCA) and the global irrigated area map (GIAM), but their resolutions of 10 km are not suitable for regional applications (Biradar *et al.*, 2009a; Prasad *et al.*, 2009) and are too coarse for monitoring and planning purposes.

Several studies have highlighted discrepancies in the extent and the spatial distribution of cropland within global products (Fritz *et al.*, 2010; Waldner *et al.*, 2015d; Wu *et al.*, 2008). For Africa, the MODIS product contains 30% more crop area than the GlobCover product (Fritz *et al.*, 2013). The global cropland extent fluctuates between 1.11 and 3.62 billion hectares according to different global products (Biradar *et al.*, 2009a). The complexity of the Sahelian and Sudanian agrosystems increases the inconsistencies between global croplands (Figure 1.1).

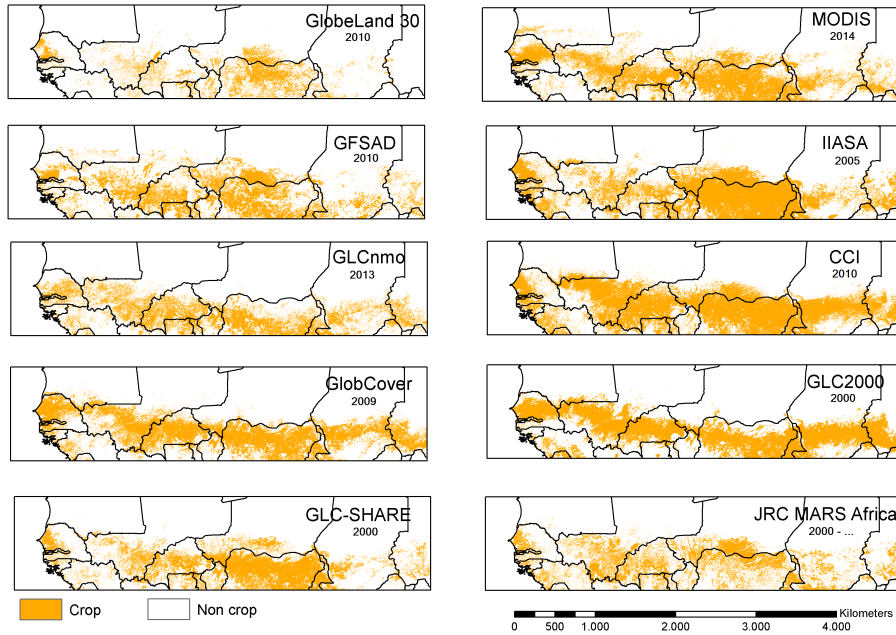


Figure 1.1: Cropland over Sahelian and Sudanian agrosystems on ten global products showing the high variability of cropland extent detection.

Some of the differences are explained by the spatial resolution, the year of production, as well as differences in the thematic legend classes and the cropland definition (Table 1.1).

Table 1.1: Diversity of agriculture-related classes for the 10 previous global land cover maps. GlobeLand 30 is based on Landsat images (30 m); GlobCover and CCI are based on MERIS images (300 m); MODIS and GLCnmo are based on MODIS images (500 m); GLC 2000 is based on SPOT-Vegetation images (1 km); the JRC MARS map hybrid product at 250 m; and IIASA cropland, GLC Share, and Global GFSAD hybrid products at 1 km.

Product	Cropland
GlobeLand30	Cultivated land
GFSAD	Cropland, irrigation major
	Cropland, irrigation minor
	Cropland, rainfed
	Cropland rainfed minor fragments
	Cropland rainfed very minor fragments
GLCnmo	Cropland: herbaceous crop
	Cropland/other vegetation mosaic
	Paddy field: graminoid crops/non graminoid crop
GlobCover	Rainfed cropland
	Mosaic cropland (50%–70%)/vegetation (20%–50%)
	Mosaic vegetation (50%–70%)/cropland (20%–50%)
	Cultivated and managed areas
	Post-flooding or irrigated croplands
GLC Share	Cropland
MODIS	Cropland
	Mosaic cropland/natural vegetation
IIASA	>25% of probability of crop
CCI	Cropland rainfed
	Cropland irrigated or post flooding
	Mosaic cropland (>50%)/natural vegetation
	Mosaic natural vegetation (>50%) / cropland
GLC2000	Cultivated and managed areas
	Mosaic cropland/shrubland or grass cover
	Mosaic cropland/tree cover/natural vegetation
JRC MARS	GlobCover

In this comparison, the mosaic classes of cropland and natural vegetation are considered as cropland. The GlobeLand 30 cropland class considers land used for agriculture, horticulture and gardens, including paddy fields, irrigated and dry farmland, vegetation and fruit gardens (Chen *et al.*, 2015), while MODIS cropland is defined by land covered with temporary crops followed by harvest and a bare soil period (Pittman *et al.*, 2010). Bontemps *et al.* (2012) highlighted high year-to-year instabilities in labels, especially between cropland and natural vegetation for GlobCover and MODIS products.

Many classification algorithms have been developed to discriminate land cover from satellite data. Parametric classifiers, such as the maximum likelihood classifier, and non-parametric classifiers, such as the neural network classifier, decision tree classifiers, and machine learning algorithms, are among the most popular (Hansen *et al.*, 1996; Swain and Davis, 1978). Due to their discriminating power, many types of neural networks have been developed (Lippmann,

1987). Decision tree classifiers transform very complex classification problems into more straightforward decision-making processes (Landgrebe, 1991). The use of machine learning algorithms is becoming increasingly important, yielding high accuracies for land cover classification and often outperforming other algorithms (Huang *et al.*, 2002; Mountrakis *et al.*, 2011; Pal and Mather, 2004; Paneque-Gálvez *et al.*, 2013; Szuster *et al.*, 2011).

Taking advantage of the spatial resolution of PROBA-V, this research aims at developing a new method to map cropland in the Sahelian and Sudanian agrosystems where global products remain inconsistent and cropland mapping challenging (Waldner *et al.*, 2015d). The fully-automated methodology limits the use of field data and could produce regional cropland on a regular basis for crop monitoring. The relative importance of spectral-temporal features used in the method is studied. Then, the resulting 2014 Sudano-Sahelian Cropland map is validated with photo interpretation on VHR imagery and compared to other global products. The spatial distribution of errors is assessed, and potential explanatory variables are studied. Finally, an error analysis focuses on challenging areas where most discrepancies between global products occurred.

1.2 Materials

1.2.1 Study site

This research focuses on the Sahelian and Sudanian agrosystems in West Africa with the area of interest ranging from 17°W–23°E to 9°N–18°N, comprising a region more than 4,300 km long and 1,000 km wide (Figure 1.2). This region is known for a strong north-south gradient linked with the movements of the ITCZ. Climatic conditions range from arid and desert regions in the north to sub-humid areas in the south through semi-arid areas. The study area is characterized by two clearly distinct seasons: a rainy season and a dry season. A flat topography with low plateaus and valleys characterizes the landscape.

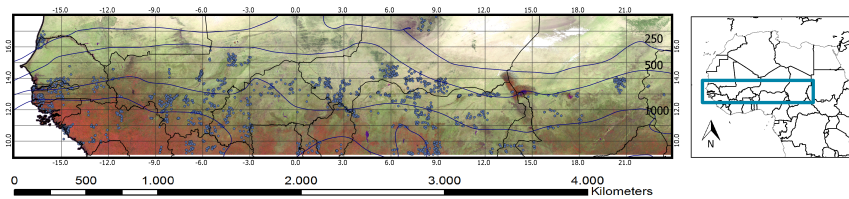


Figure 1.2: Study site with the validation sample (blue points) and regional grid (in grey) with isohyets of 250 mm, 500 mm and 1000 mm. The background image corresponds to the surface reflectances in infrared, mid-infrared and red bands for the dates corresponding to the maximum of red reflectance (maximum red feature).

In the Sahelian region, sowing occurs at the beginning of the rainy season. The growing period is short (60–90 days). The start and the length of the

growing period are positively correlated with the onset of precipitation, which is more variable than the ending date of the rainy season (Akponikpe *et al.*, 2011a; Sivakumar, 1990). In the Sudanian region, the length of the rainy season equals the length of the dry season, resulting in growing period of more than 150 days between May and November (Jagtap, 1995) (Figure 1.3). A clear gradient is observed from the Sahel southwards with progressively longer growing periods towards the south (Vrieling *et al.*, 2013). The fields are usually very small and of various shapes, with many fields with an area less than 1 ha.

A similar gradient as for SOS is visible from the Sahel southwards with increasingly longer growing periods towards the south.

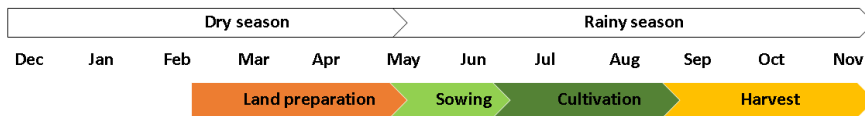


Figure 1.3: Calendar of seasons and agricultural management. The study region contains two clearly distinct seasons with crop cultivation during the rainy season and land preparation at the end of the dry season.

1.2.2 Data

PROBA-V (description of all sensors used in Appendix A) is the successor satellite of SPOT-Vegetation and was launched in May 2013 in order to fill the gap between SPOT-Vegetation and Sentinel-3. While it was not in the initial specification of the mission, this sensor currently offers global coverage every five days at a 100 m spatial resolution in four wavebands, blue, red, near-infrared (NIR) and shortwave infrared (SWIR), thanks to its central camera. PROBA-V 100 m surface reflectance has been composited on a weekly basis using a mean composite approach. The TS of eleven months (48 composites) from 19 March 2014 to 12 February 2015 was prepared and includes the growing season. The data availability mainly depends on cloud/shadow contamination and the non-five-day global coverage at 100 m in the lower latitudes due to the 517 km swath (Dierckx *et al.*, 2014). False cloud detections are systematically observed over some high brightness areas, such as desert (Figure 1.4). However, these areas do not contain crops and will not degrade the classification results. In the study area, 37 out of the 48 seven-day composites were on average usable (77%), making it possible to understand the temporal behavior of the main crop types. However, clouds are more frequent in lower latitudes and during the vegetation growth season. These factors could limit classification quality in those regions (Figure 1.5).

A labeling layer map was built from GlobeLand 30 (Chen *et al.*, 2015) with the specific contribution of ESA CCI Land Cover (Defourny, 2014) for the irrigated cropland. The labeling layer is the reference map from which the training dataset is extracted for the supervised cropland classification.

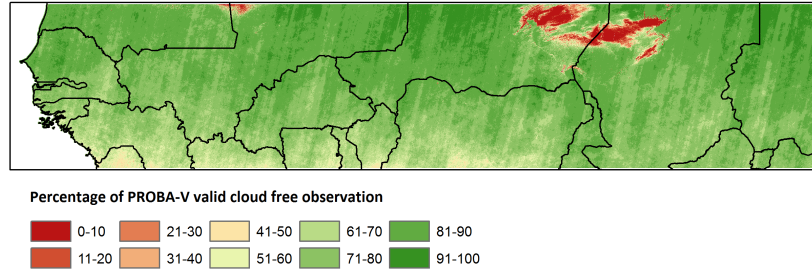


Figure 1.4: Percentage of PROBA-V valid cloud-free observation for the study area during the whole time series. False detection of clouds is systematically observed over the desert area. The valid cloud-free observation percentage decreases with latitude.

GlobeLand 30 offers a global land cover of 10 classes at 30 m based on Landsat images for 2010. The accuracy of this global dataset was first computed with an independent validation dataset of Zhao *et al.* (2014) and results in an OA of 88%. GlobeLand 30 was then validated with a set of 7 HR images. A Pareto boundary analysis showed the performance of the 30 m spatial resolution and the better balance between Omission Error (OE) and Commission Error (CE) for GlobeLand 30. The area under the Pareto boundary defines the performance of the spatial resolution, as the smaller the area, the more performant the resolution (for more details, see (Boschetti *et al.*, 2004)). This area is two-fold smaller for GlobeLand 30 than for the Joint Research Center (JRC) product and three-fold smaller than for the MODIS and the CCI products.

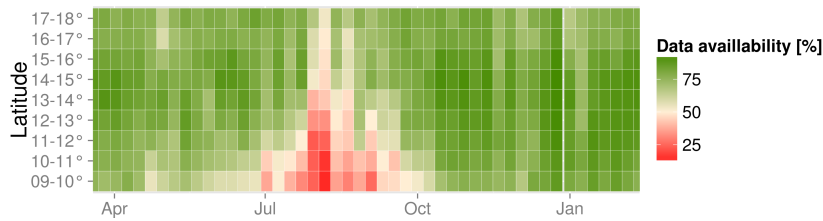


Figure 1.5: Percentage of data available for each degree of latitude ranging from 9° to 18°. Low data availability is observed in low latitudes and during vegetation growth (from July to October).

The CCI Land Cover project delivers three global land cover products, the most recent relating to 2008–2012 period. In the study area, agriculture is mainly rainfed, while irrigation occurs at specific locations, *e.g.*, the Niger basin. The semi-arid conditions lead to a strong spectral contrast between rainfed cropland and irrigated cropland. Therefore, a separate class for irrigated cropland has been created with all single pixels belonging to the crop class in GlobeLand 30 and irrigated crop in the ESA CCI Land Cover Map. The final labeling layer contains eleven classes: the ten of GlobeLand 30 plus the irrigated crop class from the CCI Land Cover.

1.3 Methodology

The challenge of cropland mapping in West Africa is dealing with the very strong latitudinal gradient in terms of seasonal dynamics, as well as land cover. A knowledge-based approach identifies relevant temporal features throughout the growing period to optimize cropland capture. A support vector machine (SVM) classifier was selected for its good performances compared to other classification algorithms' classifiers (Mountrakis *et al.*, 2011; Pal and Mather, 2004). First, the 2014 Sudano-Sahelian Cropland map was compared to existing global products to study discrepancies. Then, classification errors were related to potential explanatory variables, such as location, valid cloud-free observation, and landscape characteristics. Finally, classification errors were also studied in regions where global products disagreed on cropland. The method developed is fully automated, *i.e.*, meaning no human action during the whole processing from images to cropland map.

1.3.1 Cropland classification

The development of cropland mapping in Sahelian and Sudanian regions proceeds in a three-step method: (i) extraction of the temporal features from filtered PROBA-V TS; (ii) efficient local training based on trimmed data; and (iii) classification using SVM (Figure 1.6).

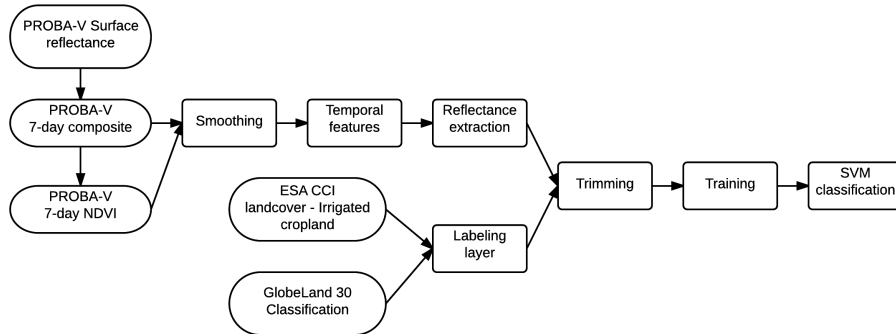


Figure 1.6: Three-step methodology for cropland classification: (i) extraction of the temporal features; (ii) local training based on trimmed data; (iii) classification using SVM.

Extracting temporal features from PROBA-V

A knowledge-based approach permits a better classification of cropland based on relevant temporal and spectral features. The features were surface reflectance composited at specific events of the growing season when crops are expected to behave differently than other land covers do. Among the cropland discrimination studies (Akbari *et al.*, 2006; Matton *et al.*, 2015; Waldner *et al.*, 2015e,a), five temporal features were selected: the maximum of the red band (max red),

the minimum and maximum of Normalized Difference Vegetation Index (NDVI) and the increasing and decreasing slopes of the NDVI profile (Figure 1.7a). The NDVI is computed following Equation (1.1):

$$NDVI = \frac{\rho_{NIR} - \rho_{Red}}{\rho_{NIR} + \rho_{Red}} \quad (1.1)$$

Soil preparation practices, such as tillage and sowing, clear the land surface contrasting with naturally-vegetated areas and resulting in higher reflectance in the red band. This timing corresponds to the maximum of red reflectance. During the rainy season, the vegetation development and the growth rate are expected to be superior in cropland than in non-cropland areas. This was captured by the NDVI maximum and minimum and the increasing slope of the NDVI. At the end of the season, crops are harvested, leading to a sharp decrease in vegetation, which is captured by the decreasing slope of NDVI. These features are specific to the vegetation cycle and do not relate to a specific time, thus making it possible to take into account the high latitudinal gradient and the diversity of agricultural practices (crop type, management). PROBA-V reflectances were smoothed with a Whittaker temporal filter to fill the gaps and remove the residual noise (Eilers, 2003). Some studies confirmed the adequacy of this smoother for TS filtering (Atkinson *et al.*, 2012; Atzberger and Eilers, 2011). These smoothed reflectance values were extracted at a specific stage of temporal features for each pixel of the study area. The max red feature, for instance, was derived from the reflectances (4 bands) of the date at which the red reflectance reached a maximum for each pixel. Hence, neighboring pixels can belong to different dates, but correspond to the same phenological event. This led to twenty inputs for classification (five temporal features and four spectral bands) called spectral-temporal features (Figure 1.7).

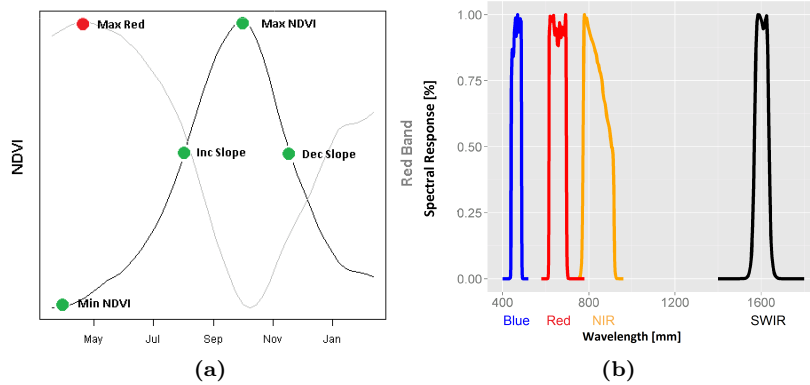


Figure 1.7: (a) Representation of the five temporal features (minimum NDVI, maximum NDVI, increasing slope, decreasing slope and maximum red); (b) Spectral response of the four bands (blue, red, NIR, SWIR) of the PROBA-Vegetation instrument.

Trimming and local training

Due to the ability of SVM to handle small training sets (Foody and Mathur, 2004), a trimming procedure was performed to remove misleading data due to the absence of an error-free and up-to-date labeling layer and recent land cover change. The trimming used spectral values of all classes to identify mislabeled pixels in a specific class. This was done by clustering so as to select pixels with the highest probability of belonging to a specific cluster. A random sample was used to select pixels from two sets of pixels: (i) pixels of class i , (ii) pixels from all classes except i . The clustering classification identified clusters of class i that belonged to a different class. Following the clustering, the probability of each cluster to be of class i was assessed. The probability of each cluster to be of class i corresponds to the purity of the cluster, *i.e.*, the number of pixels of class i divided by the total number of pixels for a given cluster. Samples of group i belonging to the cluster with higher than a 75% probability of being classified as i were selected as the training dataset for this specific class i . This approach was repeated for each class. The class proportion in the training set was maintained similar to that initially found in the labeling layer. Additional cleaning was applied to discard pixels belonging to a class that deviated strongly from the distribution (95% of the confidence interval) of that class in at least one of the four bands of the five features.

SVM classification

The trimmed data training set was used to calibrate the SVM classifier (for more details, see Wang (2005)). SVM searches the optimal separating hyperplane in a multidimensional space that maximizes the margin between the defined hyperplane and the data. The one-against-one method was used to perform multiclass-classification with i classes on the SVM. Therefore, $i(i-1)/2$ binary classifiers were trained, and the final class was obtained through a voting procedure. The SVM classifier identifies the hyperplane using support vectors and margins. The cost-support vector classification was trained with a Gaussian radial basis kernel function to ensure a high level of automation. The γ parameter of the SVM was set at ten to optimize performance and computation time (Huang *et al.*, 2002; Vapnik and Vapnik, 1998).

1.3.2 Handling the spatial gradient and the landscape diversity

The combination trimming-training-classification was applied on a moving window of $1 \times 3^\circ$ to handle the latitudinal gradient. Indeed, the vegetation dynamic in cropland and natural vegetation can fluctuate strongly with latitudes (see Chapter 2, section 2.5.2.) (Bégué *et al.*, 2011; Bégué *et al.*, 2014; Hiernaux *et al.*, 2009; Renier *et al.*, 2015). To limit the boundary effect between grid cells, the training was performed on a larger grid cell. A buffer of 1° in longitudinal direction and of 0.3° in latitudinal direction was chosen as a compromise between processing time, high latitudinal gradient and recovery rate (40%). To mosaic smoothly the moving window results, five staggered

cropland classifications were compiled by majority voting to obtain regional consistent cropland.

1.3.3 Relative importance of spectral-temporal features

A preliminary analysis of the respective spectral-temporal features' contribution was completed to identify the subset of the twenty spectral-temporal features that maximizes the classification accuracy. Twenty spectral-temporal features could increase both noise and processing time. A random forest (RF) algorithm was run to calculate the spectral-temporal feature importance by turning off one feature (while others remained constant) and computing the resulting loss in accuracy through the mean decrease in the Gini Index (GI) (Breiman, 2001). This analysis carried out for four classes of crop proportions calculated on quantiles: very low crop proportion ($<1.4\%$), low crop proportion ($1.4\%–4.4\%$), medium crop proportion ($4.4\%–17.8\%$) and high crop proportion ($17.8\%–72.2\%$) (Figure 1.8). The distribution of crops varies across a latitudinal gradient with a higher proportion of crops between 10° and 13° of latitude.

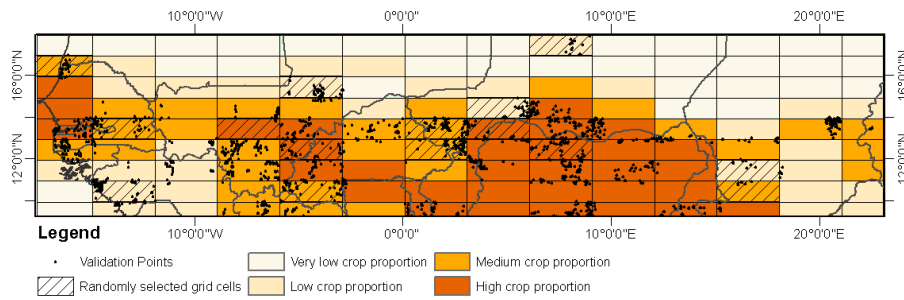


Figure 1.8: Crop proportion of each grid cell and randomly-sampled grid cells for SVM classification with the best selected features. A higher crop proportion is observed in lower latitudes.

The feature importance analysis was computed for each grid cell within a crop proportion class. Then, a random sample of five grid cells per crop proportion class was used to perform the classification with the best selected features (Figure 1.8). The best features were selected according to a decision rule; the mean decrease in GI must exceed the mean of the mean GI decrease for a given grid cell. The accuracy of SVM classification with the best selected features was compared to SVM classification with all features using a Student test computed on the F-score.

1.3.4 Validation

A two-stage sampling was designed to collect the validation sample. The first sampling units were 40 grid cells within the 126 grid cells of the study area. The second sampling unit was a stratified random sampling, as recommended by Wagner and Stehman (2015), within the selected grid cells. The strata corresponded to the eleven land cover classes of the labeling layer. The sample

size allocated to each stratum was twenty pixels. All of the random 100 m by 100 m pixels automatically generated were visually assessed with 2014 images in Google Earth. Each random pixel was labeled by visual interpretation in one of the two classes: crop and non-crop, depending on whether more than 50% of the pixel was covered by the specific class. The availability of 2014 images was the main limiting factor in building this dataset. A set of 2,315 points with 1,616 non-crop and 699 crop validation samples had finally been collected. In total, 30% of the validation points belong to the crop class. This proportion (30%) matches the magnitude of the crop proportion in this region observed on the global product (crop proportion ranging from 13% to 42%).

Typically, the accuracy of a map is assessed by measuring the degree of agreement between the classification output and the validation dataset. A confusion matrix was used to derive the metrics of classification accuracy (Foody, 2005). Liu *et al.* (2007) recommended amongst fourteen category-level and twenty map-level accuracy measures the Users' Accuracy (UA), Producer's Accuracy (PA) and Overall Accuracy (OA) as primary accuracy indices. The OA was computed as the ratio of the sum of all correctly-classified pixels on the sum of all validation pixels. The F-score was calculated as a combination of PA and UA for a specific land cover class. The UA for a specific class is the ratio between correctly-classified pixels and all pixels classified as the specific class. The PA for the specific class is the fraction of correctly-classified pixels and all ground truth-specific class pixels. Because of this research focus on cropland, the F-score was only computed for crop class and is called the F-score in the following sections (Equation (1.2)).

$$\text{F-score} = \frac{2 \times \text{PA} \times \text{UA}}{\text{PA} + \text{UA}} \quad (1.2)$$

1.3.5 Error analysis

The accuracy assessment described in Section 1.3.4 provides a global performance evaluation, although it is well established that classification accuracy varies across space and that errors are not equally distributed spatially (Foody, 2002; Leroux *et al.*, 2014; Renier *et al.*, 2015; Waldner *et al.*, 2015b). Eight potential explanatory variables were proposed to explain the classification accuracy computed by OA and the F-score: latitude and longitude of the grid cell center, availability of cloud-free data and five landscape metrics indices. Within the five landscape metrics, some are specific to crops, such as crop proportion, Matheron index, and crop fragmentation, while others are related to the overall landscape, such as fragmentation and entropy. These landscape features were measured on the labeling layer in order to explain the spatial distribution of errors. The correlation and the importance rank computed with the RF algorithm were calculated for all of the potential explanatory variables.

The perimeter area ratio for all classes of land cover is used as a proxy of landscape fragmentation (Equation (1.3)):

$$\text{Perimeter Area Ratio} = \frac{\sum_{i=1}^n \text{Perimeter}_i}{\sum_{i=1}^n \text{Area}_i} \quad (1.3)$$

where i represents a specific class of land cover and n the total number of land cover classes.

The Shannon entropy index measures the diversity of the landscape due to the number of land cover classes and the proportions of those classes (Equation (1.4)) (Turner *et al.*, 1989). In general, this index increases when the number of classes is higher and when the proportions of all existing classes are equal.

$$\text{Shannon Entropy Index} = \sum_{i=1}^n P_i \times \ln(P_i) \quad (1.4)$$

where P_i is the proportion of a class i .

The Matheron index (Equation (1.5)) measures the ratio between the total outer perimeter of crop cells edges (sum for all patches) and the product between the area of crop and the total area (Mayaux and Lambin, 1995):

$$\text{Matheron Index} = \frac{\text{Crop Perimeter}}{\sqrt{\text{Crop Area}} \times \sqrt{\text{Total Area}}} \quad (1.5)$$

1.4 Results

1.4.1 Spectral-temporal feature importance

First, the diversity of the features seems to complement them according to the cropland proportion. The maximum in red reflectance and the minimum NDVI seem the two most discriminant features in higher crop proportion regions (Figure 1.9). These features refer to the start of the growing period when differences between cropland and natural vegetation are high due to land preparation. In fact, high crop proportion areas correspond to regions with higher amounts of rainfall, which makes natural vegetation greener at the beginning of the season when crops are considered as bare soils due to land preparation. All temporal metrics seem important in one or another crop proportion class without a specific distinction for any one of them. The mean decrease in GI was computed for the 20 spectral-temporal features for each of the four crop proportion classes. When a given spectral-temporal feature is left out, the higher mean decrease in GI compared to the GI obtaining using all 20 features leads to the higher importance of this spectral-temporal feature. Regardless of the crop proportion classes, as expected, the blue band contributes the least in cropland discrimination due to the impacts of aerosols and atmospheric scattering (Jia *et al.*, 2014) (Figure 1.9). The SWIR band is of higher importance than the NIR band, while the red and the SWIR bands are the two most important bands for the classification.

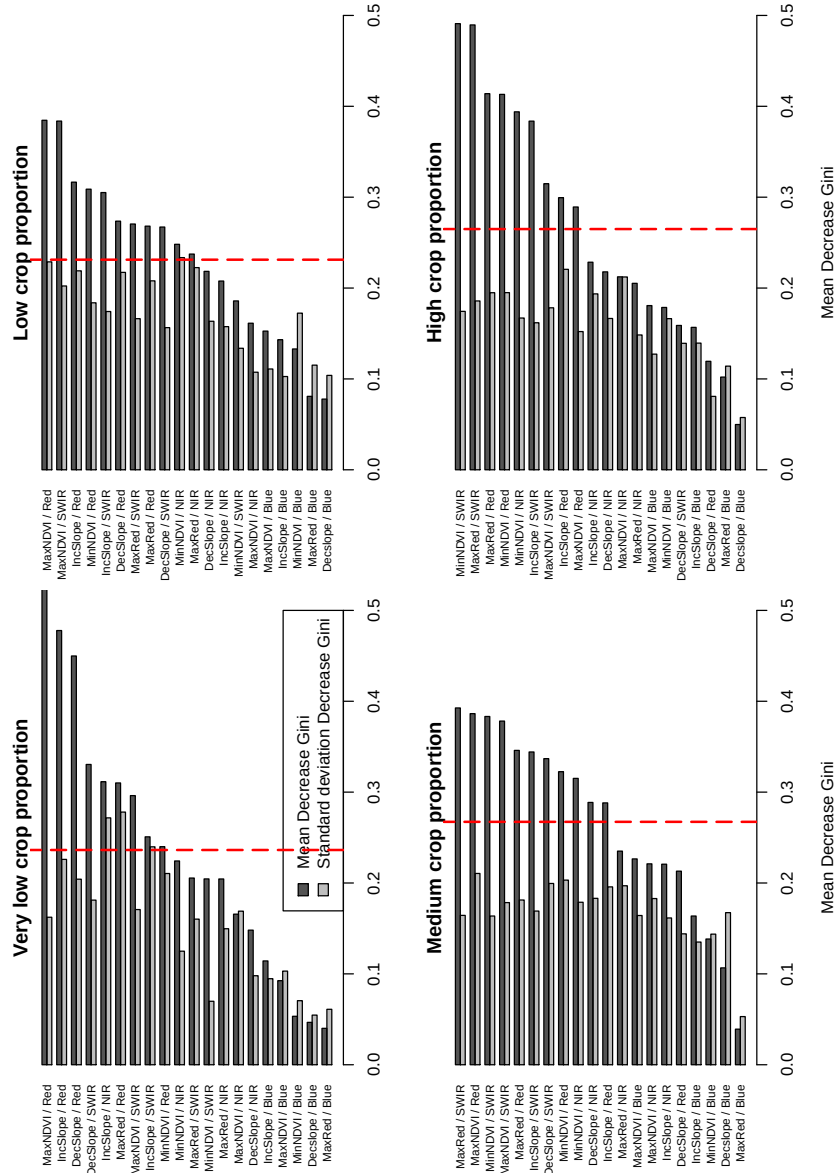


Figure 1.9: Respective contribution of each spectral-temporal feature for crop discrimination for the different cropland density classes. The dotted vertical line corresponds to the decision rule for selecting the best features.

Following the feature importance analysis, the best features were selected (SVM select) to compare classification accuracy with regards to the classification using all of the features (SVM all). Due to the absence of validation points in the very low crop proportion area, only three crop proportion classes were considered, and five grid cells were randomly selected in each crop proportion stratum. OA and F-score were computed for the two classifications: SVM select and SVM, both by crop proportion classes. SVM select classification slightly outperforms SVM for low and medium crop proportion strata, while SVM excels in the high crop proportion landscape (Figure 1.10).

Standard deviations are rather larger for SVM select than for SVM. The two classifications were compared using a Student test on the F-score. The assumptions of the test were verified: the normality of the variable and the equality of the variances of both samples were confirmed by a Shapiro-Wilk test (p -value = 0.735) and a Fisher test (p -value = 0.872), respectively. The two F-score values are considered equal (p -value = 0.873), which avoids rejecting the null hypothesis of the equality of samples. Based on these results and to make the method as generic as possible for all agricultural landscapes, the SVM classification was applied at the regional scale using all twenty spectral-temporal features.

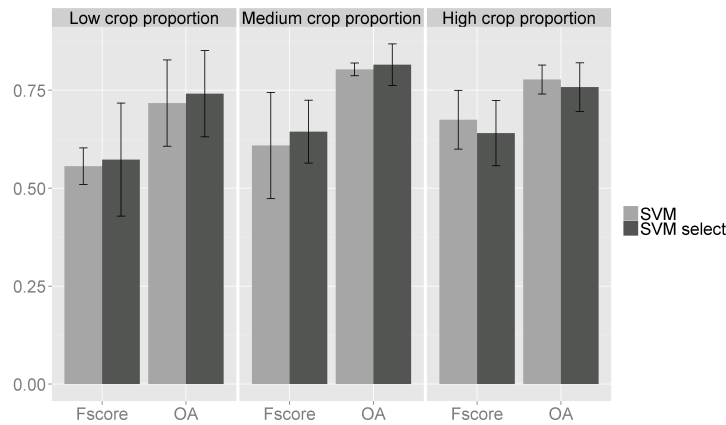


Figure 1.10: Comparison of the accuracy for SVM classification with all features (SVM) and selected features (SVM select). The whiskers represent the standard deviation of the five selected grid cells for each crop proportion class.

1.4.2 Qualitative analysis of 2014 Sudano-Sahelian cropland map

The visual comparison of the 2014 Sudano-Sahelian Cropland map and the labeling layer, mostly derived from GlobeLand 30, highlights the actual contribution of the PROBA-V classification. The images used for this analysis are a combination of Digital Globe (DG) images acquired during 2014, Spot 5 and RapidEye imagery for the years 2012 and 2013. Images 1 and 2 are respectively

a WorldView 2 of 26 June 2014 and a GeoEye of 14 June 2014. Images 3–7 are Spot 5 of the 2013 season, while Image 8 is a RapidEye image acquired on 29 January 2012 (Figure 1.11).

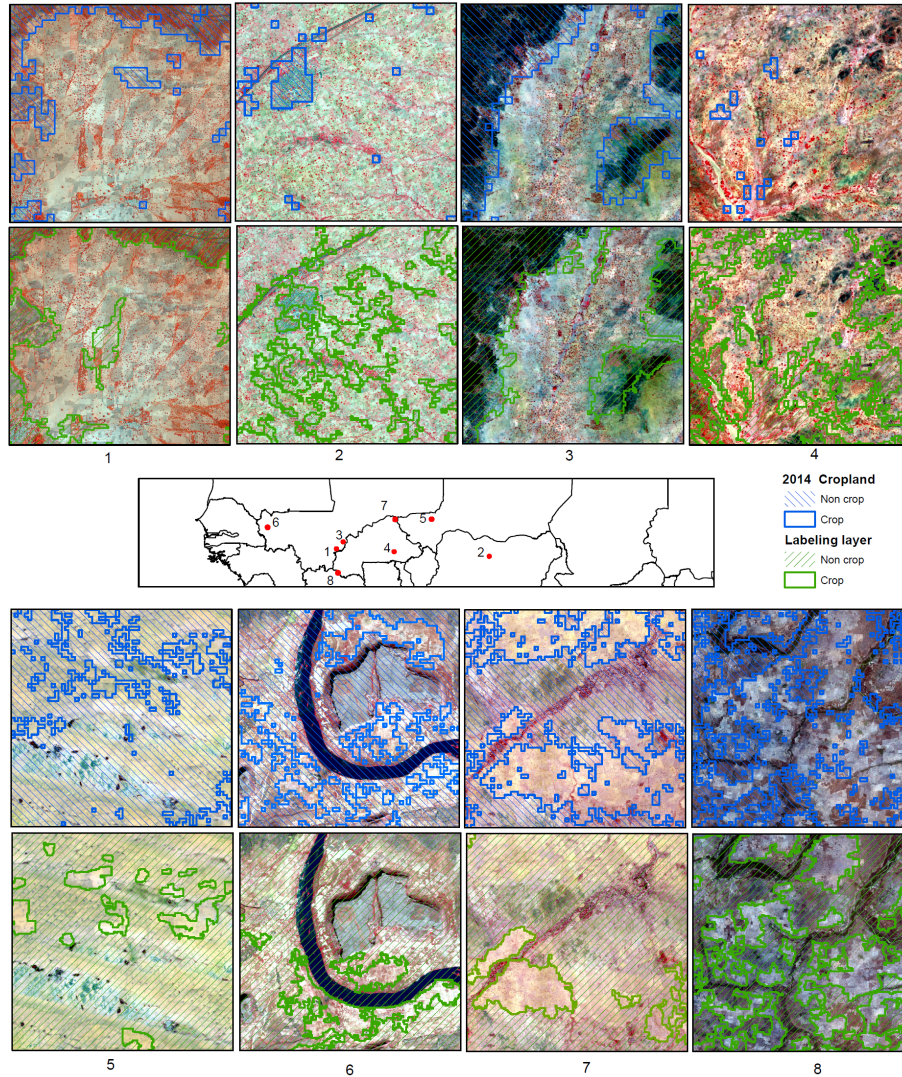


Figure 1.11: Some examples of cropland in the 2014 Sudano-Sahelian Cropland map (at 100 m) and the labeling layer (at 30 m). Background images are: (1) WorldView 2 of 26 June 2014; (2) GeoEye of 14 June 2014; (3–7) Spot 5 of the 2013 season; and (8) RapidEye of 29 January 2012.

Cropland boundaries are more precise in the labeling layer, probably due to higher spatial resolution, while the non-cultivated lithosols are better delineated by the 2014 Sudano-Sahelian Cropland map (Image 1, in Figure 1.11).

Roads are better defined by the labeling layer, which, however, includes more noise and incorrect non-crop area. The village patches are larger in the 2014 Sudano-Sahelian Cropland map, but unlike the labeling layer, it does display the full extent of the village (Image 2 in Figure 1.11). The contrasted landscape shown in image 3 with cultivated valleys and rocky plateaus yields an accurate classification in both cases. The labeling layer with the higher spatial resolution even captures the forest in the very bottom of the valley as non-crop (Image 3 in Figure 1.11). In a more complicated landscape, the 2014 Sudano-Sahelian Cropland map failed to discriminate bare soil areas (in pink in Image 4) and dark surfaces (in black), while some of the cropland is mapped as non-crop in the labeling layer (Image 4 in Figure 1.11).

In arid areas, errors observed in both datasets are probably due to the labeling layer, which drives the classification training. Crops in these arid areas are very sparse, and discrimination between bare soil and crop is challenging (Image 5, in Figure 1.11). This is confirmed by Image 7 in the north of Burkina Faso, where crops alternate with bare soil. The labeling layer missed considerable cropland areas, while these are correctly mapped by the 2014 Sudano-Sahelian Cropland map. Hence, in this area, spectral-temporal features allow the better capture of crop areas thanks to the temporal dimension of the PROBA-V TS (Image 7, in Figure 1.11). In irrigated regions, the labeling layer failed to capture all cropland areas. The 2014 Sudano-Sahelian Cropland map captures more crops, but also more noise (Image 6, in Figure 1.11). Finally, Image 8 sums up what is often found in these illustrations. The 2014 Sudano-Sahelian Cropland map seems to better capture all of the cropland areas, but has more difficulty in drawing exact boundaries and in capturing small landscape features, such as forest in the bottom valley. Conversely, the labeling layer is sometimes too restrictive and misses some of the cropland (Image 8, Figure 1.11). Difficulties in differentiating between cropland and fallows, and misclassification of shrubland, bare soil and desert area as cropland remain in the final product.

Supervised classification with visual determination of the area of interest was performed on each site. Wall to wall validation between HR images and GlobeLand 30 or 2014 Sudano-Sahelian Cropland map was assessed (Figure 1.12). The theoretical Pareto boundaries are represented by continuous lines while the computed omission error (OE) and commission error (CE) of the two products of interest (GlobeLand 30 and 2014 cropland) are represented by dots.

Proximity between the commission-omission point of the 2014 Sudano-Sahelian Cropland map and the Pareto boundary implies a high performance of the algorithm classification. To better quantify the visual interpretation of the 2014 Sudano-Sahelian Cropland map and the labeling layer, quantitative analysis of the accuracy of the 2014 Sudano-Sahelian Cropland map was assessed. The produced cropland was also compared to other existing global products.

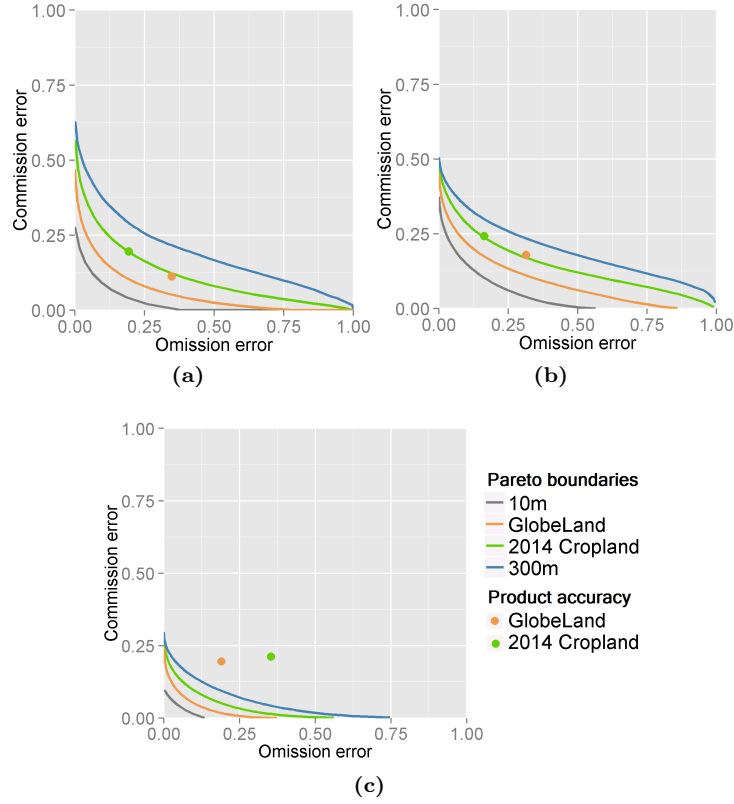


Figure 1.12: Three examples of Pareto boundary, commission and omission errors for GlobeLand 30 and 2014 Sudano-Sahelian Cropland map. Pareto boundaries were also computed for a 10 m product and a 300 m product. (a) Site in center Mali ; (b) Site in Sikasso region (Mali south-east); (c) Site in southern Mali.

1.4.3 Accuracy of the cropland map and comparison with existing global products

The OA computed from the 2,315 validation points reaches 84% and the F-score for crop class 74%. The confusion matrix shows better PA and UA for the non-crop class: 89% compared to 74% for crop classes. UA and PA are identical for both classes (Table 1.2). The same validation dataset was applied on the crop/non-crop maps derived from the 10 previous global products. The cropland fluctuation between 2010 and 2014 is expected to be less important than the map errors, allowing the comparison of these products. All products were resampled to the 100 m resolution using the majority method. High variability of accuracies was observed regardless of the production year of the map (Figure 1.13).

Table 1.2: Confusion matrix for the regional cropland map using the 2315 validation points. Overall accuracy (OA), producer’s accuracy (PA) and user’s accuracy (UA) are computed in percent.

	Non Crop	Crop	UA [%]
Non crop	1431	180	89
Crop	185	519	74
PA [%]	89	74	OA[%] = 84

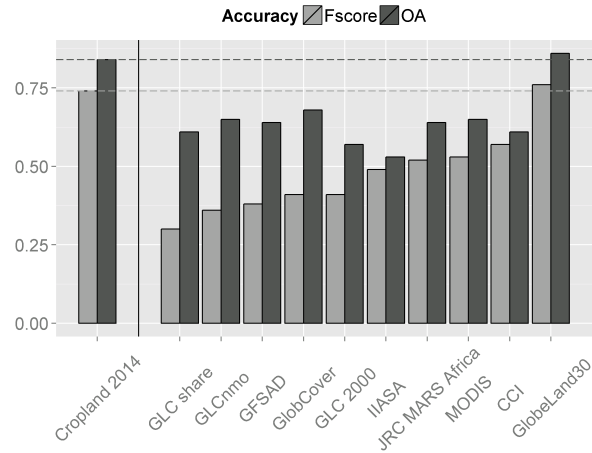


Figure 1.13: Comparison of the 2014 Sudano-Sahelian Cropland map with the ten previous global products showing high variability in the accuracy indices and better performance for the 2014 Sudano-Sahelian Cropland map and GlobeLand 30 used as the labeling layer.

The 2014 Sudano-Sahelian Cropland map and the GlobeLand 30 product almost reach the same performance levels (OA: 84% *vs.* 86%; and F-score: 74% *vs.* 75%, respectively). Other products studied show substantially lower accuracy indices. This confirms the adequacy of the labeling layer and the efficiency of the methodology in exploiting recent annual remote sensing datasets. Similarities of the accuracy indices of GlobeLand 30 and our cropland product must be balanced against disagreement between those products (Figure 1.14). Eighty-five percent of pixels are labeled identically by GlobeLand 30 and the 2014 Sudano-Sahelian Cropland map, while 41% of pixels classified as crops in one or another are mapped as crops in both products. As expected, because of the higher OA and F-score of GlobeLand 30 for the entire validation dataset (Figure 1.13), the OA in the conflict region (414 validation pixels) reaches 54% for GlobeLand 30 and 46% for the 2014 Sudano-Sahelian Cropland map.

However, one might argue that these measures are excessively harsh, as the size of the validation pixels for the >100 m products is smaller than the

products' pixel sizes. They might be revised when considering a validation pixel size that matches the products. Nonetheless, the variation in OA when validating a product at 300 m in place of one at 100 m with the 100 squared meter validation pixels is only of 2%. This number rises to 6% when a 1 km product is used, which still cannot explain the total discrepancies between global land cover products. It was computed by aggregating the labeling layer at 100 m, 300 m, and 1 km, defining the label of each pixel as crop or non-crop when more than 50% is covered by the specific class and, finally, computing accuracy.

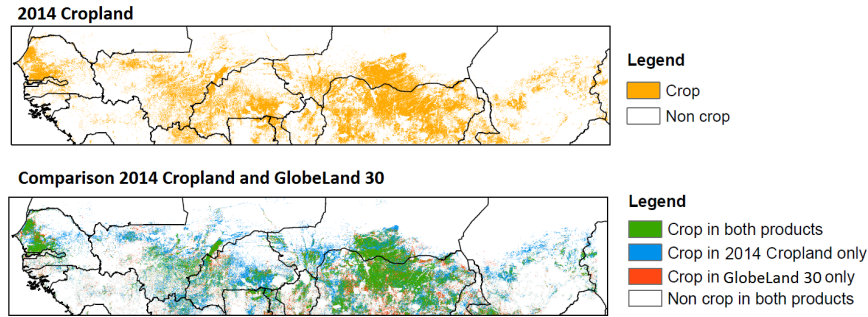


Figure 1.14: The 2014 Sudano-Sahelian Cropland map derived from PROBA-V at 100 m and the comparison with GlobeLand 30 derived from Landsat imagery acquired around 2010.

1.4.4 Spatial distribution of errors

Grid cells including more than twenty validation points, *i.e.*, 38 grid cells, were selected to estimate locally the OA and the F-score. The eight possible explanatory variables were also computed for each grid cell. In total, 41% of the variance of the OA is explained by the eight potential explanatory indices for only 21% of the F-score (Table 1.3, Figure 1.15). OA and F-score are strongly linked to fragmentation; the lower the fragmentation, the more accurate the classification. Entropy is negatively correlated with both F-score and OA. This means that the lower the number of classes and the higher the proportion of the classes, then the higher is the accuracy. As expected, the accuracy is highest when few classes are present with small fragmentation and a high proportion in each class. Spatial heterogeneity is confirmed as an important factor in driving land cover map accuracy (Latifovic and Olthof, 2004; Smith *et al.*, 2003).

Looking at the spatial distribution of latitude impacts both the F-score and the OA: it increases the accuracy in northern regions where fewer clouds are present. Longitude is correlated with OA, so that accuracy rises when going west. The effect of longitude on crop F-score is null (Table 1.3). This might be due to the fact that the western side of the study area features lower crop proportion which eases the classification and increases the OA. Conversely, crop proportion increases when going east making the classification more challenging, and explaining a decrease in OA. Hence, misclassification issues in less vegetated

areas, such as desert or bare soil, could lead to lower accuracy indices. Specific cropland characteristics do not affect the F-score more than OA in terms of correlation, which was unexpected. Nevertheless, the importance rank computed by RF highlighted the relevance of crop-specific indices for cropland classification (Table 1.3). The Matheron index and crop proportion are negatively related to accuracy because a higher fragmentation and a higher number of crop patches make classification difficult due to the number of mixed pixels at the edges (Leroux *et al.*, 2014). Data availability affects OA and F-score. The encountered errors were partially explained by the high fragmentation of the landscape, and the low latitude linked with lower data availability. Very few validation points were available in high latitudes due to the absence of HR imagery in these regions.

Table 1.3: Correlation and importance rank for Overall accuracy (OA) and F-score computed on eight potential explanatory variables.

	OA		F-score	
	Correlation	Ranking	Correlation	Ranking
Location				
Latitude	0.44	2	0.33	3
Longitude	-0.28	5	-0.09	7
Time-series				
Data availability	0.25	3	0.22	1
Landscape characteristics				
Fragmentation	-0.39	1	-0.2	6
Entropy	-0.13	6	-0.1	8
Matheron Index	-0.29	4	-0.05	5
Crop proportion	-0.05	8	0.09	2
Crop fragmentation	-0.24	7	0.01	4
Total variance explained [%]	41.24		21.05	

The regression ($R^2 = 0.412$) was then applied to the entire study area to predict the OA (Figure 1.16). According to the model, a degradation of OA is observed in the southeast of the study region.

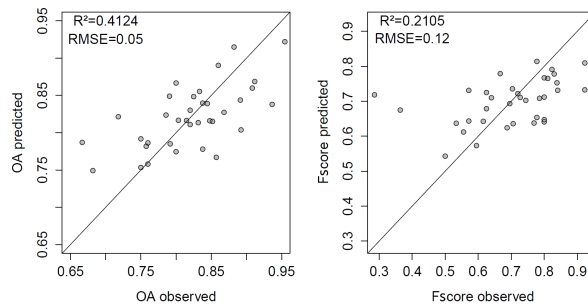


Figure 1.15: OA and F-score predicted by the multiple regression compared to the OA and F-score observed.

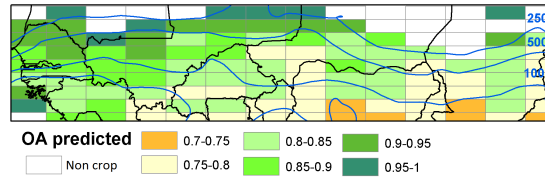


Figure 1.16: Prediction of OA over the study area based on a multiple regression using eight explanatory variables related to spatial localization, data availability and landscape characteristics.

1.4.5 OA and F-score in the disagreement region of global products

To further identify the accuracy of the products, it is of paramount interest to focus the analysis on challenging areas where most discrepancies between maps are observed. A global agreement map built from the global products (see Table 1.1) ranges from zero, where all products agree on the non-crop class, to ten, where all products agree on the crop class. A value of five represents the highest disagreement between products as five products classified the pixel as crop and five classified the pixel as non-crop. OA and F-score were computed for each of the eleven classes of agreement using the validation points belonging to that class. The OAs of all global products, except GlobeLand 30 and the 2014 Sudano-Sahelian Cropland map, have similar behavior (Figure 1.17). The highest accuracy of the majority of products is met in regions labeled as non-crop by all products, and accuracy then drops until values around 0.45, when most products disagree. Finally, OA increases to yield an accuracy of 80% when all products agree on crop class. GlobeLand 30 and the cropland map produced in this study have a nearly identical profile, which could be summarized as a slight decrease in accuracy when agreement on crop arises. F-score increases when agreement on crop occurs. GlobeLand 30 and the 2014 Sudano-Sahelian Cropland map behave very differently to others. The F-score of the new product and GlobeLand 30 starts with a higher value in regions where many products agree on non-crop. This means that these two products correctly label crops in regions where almost all global products mislabeled crop as non-crop.

1.4.6 Fragmentation of the landscape

The proportion error defined by Moody and Woodcock (1995) represents the proportion by which individual classes are over- or under-estimated at a lower resolution than the initial one (Equation (1.6)):

$$E_r = (p_r - p_0)/p_0 \quad (1.6)$$

where p_0 is the original proportion of the crop class at 30 m and p_r is the estimated crop proportion at resolution r (90 m or 300 m in this study). The 90 m cropland map is obtained by aggregating the 30 m for three pixels and the 300 m for 10 pixels. The label of this obtained pixel is crop when more than

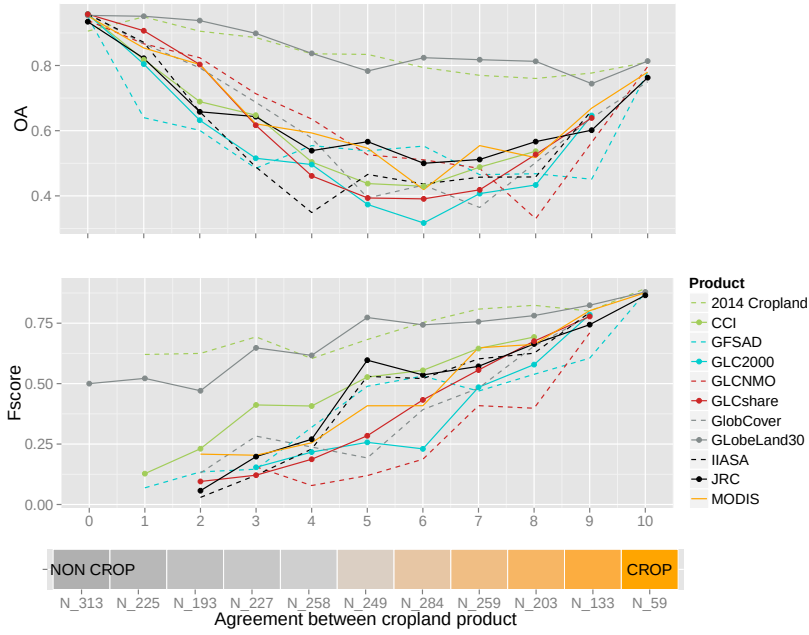


Figure 1.17: Evolution of OA and F-score with agreement computed on ten global products. The X axis corresponds to the agreement between global products with 0 = all products classify pixels as non-crop and 10 = all products classify pixels as crop; N corresponds to the number of validation points corresponding to a given class of agreement.

50% of the area is classified as crop. The 90 m products are considered to be very close to the 100 m resolution, as available for the PROBA-V sensor. In low and medium crop proportion classes, the underestimation of crops is of 5% for the 90 m products and more than 25% for the 300 m products (Table 1.4). The advantage of 100 m in a highly fragmented landscape is useful and can fill the gap between HR and MR.

Table 1.4: Proportion error for two cases (initial resolution = 30 m; and lower resolution = 90 m or 300 m) within the four crop proportion classes.

Crop Proportion	Very Low	Low	Medium	High
Proportion error (30 m–90 m) (%)	NA	–5.2	–5.2	–0.6
Proportion error (30 m–300 m) (%)	NA	–29.8	–27.0	–5.7

1.5 Discussion

The proposed classification method of PROBA-V 100 m TS yields an OA of 84% similar to that of GlobeLand 30 from which training data were derived.

Both products overpass all other global products in terms of accuracy. The accuracy of GlobeLand 30 ought to be linked to its 30 m spatial resolution and a highly interactive verification procedure (Chen *et al.*, 2015). GlobeLand 30 is produced with a POK-based (pixel object knowledge) methodology, a pixel and object-based method with knowledge. The knowledge-based interactive verification procedure of GlobeLand 30 was developed through a web service and relies on intensive manual corrections. The fully-automated method presented aims at overcoming this limitation by enabling the production of cropland maps on an annual basis. Three main factors can explain the accuracy of the 2014 Sudano-Sahelian Cropland map: the 100 m spatial resolution of the TS, the methodology itself and the quality of the labeling layer. The hectometric spatial resolution makes it possible to resolve fine landscape patterns, especially in these regions where field size often does not exceed 1 ha. Similarly, a recent study has highlighted significant better performance using 100 m PROBA-V data than 300 m data for crop type classification (Roumenina *et al.*, 2015).

Misclassifications are mainly explained by low data availability due to high cloud cover during vegetation growth (25% of OA explained by data availability) and by landscape fragmentation (39% of OA explained by fragmentation). Remaining errors in the training dataset are minimized by the stringent trimming procedure limits, from which 30% of the best points were retained. Highly fragmented landscape is better captured by HR images as demonstrated with Pareto boundaries. The Sentinel-2, 5-day coverage at 10 m in 13 spectral bands, will probably offer a good combination of spatial-spectral and temporal resolution. Landsat 8, 16-day coverage at 30 m in 11 spectral bands, offers a spatial resolution able to catch the landscape fragmentation of the study region. Nevertheless, the temporal coverage might be too small to catch vegetation behavior during the vegetation growth. Discrepancies between the GlobeLand 30 product and the 2014 Sudano-Sahelian Cropland map can partly be linked to the time production of the map, the spatial resolution, the input data and the interactive verification for GlobeLand 30.

Spectral-temporal features were used to fully exploit the PROBA-V TS. Nevertheless, the remaining noise in the PROBA-V surface reflectance image could partly explain some misclassification. The noise might be related to undetected clouds and shadows. PROBA-V cloud screening uses both blue and SWIR bands. Due to the time lag between bands (12 s between NIR and SWIR), two separate masks are built and then merged (Sterckx *et al.*, 2014). Threshold rules are applied on the SWIR (blue) band to detect cloud with an additional check on the blue (SWIR) band. These threshold values are static and applied globally, leading to misclassifications of bright surfaces as clouds (Dierckx *et al.*, 2014). Furthermore, borders of large clouds are poorly detected, and the remaining haze effect affects the reflectances. Some cases of cloud omission, others of cloud commission, are also present. In addition, part of the noise is related to the spectral-temporal features themselves. Spectral-temporal features are based on extreme values and are thus more sensitive to noise, as noise itself is characterized by extreme values (Waldner *et al.*, 2015b). Region-

dependent and dynamic cloud screening are currently being invested by the PROBA-Vegetation team and could significantly improve the cloud mask (Erwin *et al.*, 7/10/2014). This could improve feature extraction and thus classification by significantly decreasing noise in the TS. If no significant improvements are made to the cloud product delivered, we believe that a stronger temporal filter should be applied prior to performing the Whittaker filter in order to identify undetected clouds.

1.6 Conclusions

This fully-automated method has delivered the first cropland at 100 m for the Sahelian and Sudanian region using the PROBA-V sensor. The product reaches an OA of 84% and an F-score of 74% for the crop class. These accuracy indices are significantly larger than major global products (except GlobeLand 30 which was used as labeling layer) as a result of the 100 m spatial resolution, the crop-specific knowledge-based methodology and the adequate choice of the labeling layer. The diversity of the spectral-temporal features chosen to take advantage of the entire PROBA-V TS and its full spectrum seems to adequately complement each other for cropland discrimination in heterogeneous crop proportion landscapes. Misclassifications observed in the 2014 Sudano-Sahelian Cropland map are partially explained by undetected clouds, haze and shadows, data availability and fragmentation of the landscape.

Further improvements are expected with the upcoming enhanced cloud screening. The recent launch of the European Sentinel-2 sensor offers new possibilities for monitoring land and vegetation with its spatial resolution of 10 m and its 13 spectral bands. The methodology is scale-independent and could be applied on Sentinel-2 TS to better capture the landscape specificities in the Sudano-Sahelian regions. Annual cropland maps could be updated on a regular basis using this fully automated method in order to monitor cultivated area extension and abandonment over a large area.

Chapter 2

Inter-annual crop growth variability at different scales in Sahelian and Sudanian agrosystems

Highlights

- Current operational monitoring systems as WFP Seasonal Monitor and GLAM can hardly detect local inter-annual variability of crop growing conditions.
 - Landsat 8 NDVI TS masked with a Sudano-Sahelian cropland map easily depict local spatial and temporal variability of crop growing conditions.
 - Improving operational monitoring systems is required to better inform decision-makers of agricultural conditions and impediments to worldwide food security.
-

Abstract. Monitoring spatial and temporal changes in crop vegetation cover is key to improve operational agriculture monitoring systems, and food security. Enhancements in sensors capabilities and computing capacities offer new possibilities to study crop spatio-temporal vegetation variability from country to commune scale. Taking advantage of the Landsat 8 archive (30 m spatial resolution), NDVI TS are computed inside the cropland area for four years (2014-2017) at different scales of interest. At the national scale of Mali, sharp contrasts in NDVI TS are observed between Gao administrative region in the north (Sahelian climate) and Sikasso in the south (Sudanian climate). At the local scale, the communes of the Koutiala circle feature strong spatial differences in vegetation growth according to the year. The start of the season can be delayed by more than a month between two communes of the same circle, which directly affects crop production and food security. At the Koutiala circle level, high inter-annual crop vegetation growth can be isolated and correlated to rainfall distribution. The large MODIS NDVI TS often used for agriculture monitoring is not sufficient neither to capture crop

inter-annual variability at circle level nor to work at the commune level. Thus, we recommend to use finer spatial resolution compatible with commune scale to improve the agriculture monitoring systems.

2.1 Introduction

Long-term TS obtained from EO are very useful to understand the inter-annual variability of vegetation growing conditions. Vegetation cover, greening, and browning of Sahel have been at the center of debate since the 1990's. Following the very dry period of the 1970's, an extreme drought occurred in the 1983-1985 period in West Africa causing low vegetation cover until approximately 1993. Between 1994 and 2003 vegetation recovered due to wetter conditions and changes in land use and management (Bégué *et al.*, 2011; Heumann *et al.*, 2007). This period triggered all the studies about "*Regreening Sahel*" (Brandt *et al.*, 2014; Dardel *et al.*, 2014; de Jong *et al.*, 2011; Eklundh, 2003; Herrmann *et al.*, 2005; Loew *et al.*, 2013). As early as in the 1980's, the NOAA satellites have been providing long NDVI TS (from 1981 until now) thanks to Advanced Very High Resolution Radiometer (AVHRR). The GIMMS NDVI product developed by Tucker *et al.* (2005) is available at 8 km resolution every 15 days since 1981. These long-term TS are the most used for studying vegetation variability in Sahel (Table 2.1). These studies relied on VI (mostly NDVI) to investigate temporal variations in terms of phenology, productivity, and resilience. Some confirmed the quality of AVHRR data based on higher spatial resolution* imagery such as MODIS or SPOT-Vegetation (Dardel *et al.*, 2014; Williams *et al.*, 2008). The methods to estimate vegetation variability differ from simple average method, anomalies study (Anyamba and Tucker, 2005) to trends analysis (Colditz *et al.*, 2000; Dardel *et al.*, 2014; de Jong *et al.*, 2011; Eklundh, 2003; Fensholt *et al.*, 2009; Herrmann *et al.*, 2005; Olsson *et al.*, 2005). These researchers confirmed positive trends in vegetation greening in the Sahel since 1994.

The AVHRR sensor was not designed for vegetation monitoring (NIR band overlaps a wavelength interval with high water vapor absorption) which results in noisy NDVI TS. Besides, NDVI values are impacted by the evolution of overpass time due to the drift of NOAA orbit (Fensholt *et al.*, 2009). Finally, the 8 km spatial resolution seems too large to understand local vegetation variability in complex landscapes of West Africa. Recent studies used other satellite imagery to overcome these problems. Brandt *et al.* (2014) studied vegetation trends at high spatial resolution focusing on trees. Using MODIS at 1 km resolution, Zhang *et al.* (2005) analyzed phenological changes according to latitude over a 3-year period around Africa. Verheggen and Defourny (2012) measured and analyzed the seasonal dynamic and inter-annual variability of the vegetation on a global scale with SPOT-Vegetation data. Butt *et al.* (2011) investigated the length of growing period (LGP), the start of season (SOS) and the end of season (EOS) to study livestock movements and he showed a strong variation of phenological events with latitude.

*See Appendix A for the conventions on spatial resolutions.

Table 2.1: Recent studies about dynamics of vegetation in Sahel and Africa.

Index	Proxy	Product	Sp res	Temp res	Period	Place	Authors
Vegetation Cover - Greening / browning							
NDVI	Herbaceous vegetation	GIMMS-3g	1/12°	15 days	1981-2011	Sahel	Dardel <i>et al.</i> (2014)
		LTDR	0.05°	Daily	1981-1999		Dardel <i>et al.</i> (2014)
		GIMMS	8 km	15 days	1981-2006		Dardel <i>et al.</i> (2014)
		MOD13C2	0.05°	Monthly	2000-today		Dardel <i>et al.</i> (2014)
NDVI	Vegetation	GIMMS	8 km	15 days	1981-2006	World	de Jong <i>et al.</i> (2011)
NDVI	Vegetation	GIMMS	8 km	15 days	1982-2006	Mali	Bégué <i>et al.</i> (2011)
NDVI	Vegetation	GIMMS	8 km	15 days	2000-2007	Sahel	Fensholt <i>et al.</i> (2009)
NDVI	Gross photosynthesis	GIMMS	8 km	15 days	1982-2003	Africa	Williams <i>et al.</i> (2008)
		MOD13A2	1 km	16 days	2000-2007		Williams <i>et al.</i> (2008)
		SPOT VGT10	1 km	Daily	200-2007		Williams <i>et al.</i> (2008)
NDVI	Vegetation	GIMMS	8 km	15 days	1982-2003	Sahel	Herrmann <i>et al.</i> (2005)
NDVI	Vegetation	PAL	8 km	10 days	1982-1999	Sahel	Olsson <i>et al.</i> (2005)
NDVI	Precipitation	GIMMS	8 km	15 days	1981-2003	Sahel	Anyamba and Tucker (2005)
NDVI	Vegetation	PAL	8 km	10 days	1982-2000	Sahel	Eklundh (2003)
NDVI	Woodland	MCD43A4	500 m	8 days	1982-2006	SSA	Brandt <i>et al.</i> (2014)
NDVI	Cropland	MOD13Q1	500 m	16 days	2000-2015	Sahel	Leroux <i>et al.</i> (2017)
Productivity							
NDVI	Productivity	GIMMS	8 km	15 days	1982-2007	Sahel	Fensholt and Rasmussen (2011)
fAPAR	Productivity	SeaWiFS	1.1 km	Monthly	1998-2003	Africa	Weber <i>et al.</i> (2009)
NDVI	Productivity	GIMMS	8 km	15 days	1981-1999	Senegal	Brown (2006)
STI	Dry biomass	MODISS	500 m	Daily	2004-2011	Sahel	Jacques <i>et al.</i> (2014)
Phenology							
NDVI	Phenology	GIMMS	8 km	15 days	1981-2006	World	de Jong <i>et al.</i> (2011)
NDVI	LGP, EGS	GIMMS	8 km	15 days	1982-2005	Sahel	Heumann <i>et al.</i> (2007)
EVI	Phenology	MCD43B4	1 km	16 days	2000-2003	Africa	Zhang <i>et al.</i> (2005)
EVI	SOS	MCD12Q2	500 m	Yearly	2001-2009	Mali	Bégué <i>et al.</i> (2011)
NDVI	SOS, EOS	GIMMS	8 km	Daily	1981-2008	Africa	Brown <i>et al.</i> (2010)
NDVI	Phenology	SPOT Vegetation	1 km	Daily	1999-2010	Global	Verheggen and Defourny (2012)
Resilience							
NDVI	Resilience	GIMMS	8 km	15 days	1982-2006	S. Africa	Harris <i>et al.</i> (2014)

Bégué *et al.* (2014) studied SOS changes between rangeland and cropland using 500 m MODIS. Marhino *et al.* (2014) improved the actual determination of sowing date based on meteorological data at 8 km spatial resolution. Rishmawi *et al.* (2016) analyzed the influence of various climate variables on vegetation trends in SSA over the 1982–2006 period with AVHRR. Two recent studies form the current state-of-the-art of the vegetation cover trends analysis in the Sahel respectively for cropland (Leroux *et al.*, 2017), and woodland (Brandt *et al.*, 2016). Leroux *et al.* (2017) used MODIS TS to identify local and regional drivers of vegetation cover changes by going deeper than just analyzing rainfall and vegetation relation (*e.g.*, distance to roads, distance to villages, ...).

In parallel to scientific studies, global and regional agriculture monitoring systems have been in place for decades and provide up-to-date information about food production to various stakeholders and decision-makers to support worldwide food security. These systems use five types of information: meteorological data, crop models, optical remote sensing, analyst inputs and auxiliary data (Fritz *et al.*, 2018). In this chapter, we will focus on the use of meteorological data and remote sensing information to monitor crop growing conditions. To do that, the systems face challenges in SSA including (i) the spatial resolution of satellite imagery not compatible with smallholder farming landscapes, (ii) the poor quality of global cropland map (see Chapter 1, section 1.1.), and (iii) the disaggregation of regional crisis for local food security assessment. Operational agriculture monitoring systems track the evolution of the growing season with MODIS TS at large spatial resolution (500 m to 5.6 km), which is not detailed enough for African smallholder farming systems. While some operational agriculture monitoring systems analyze crop vegetation variability across all land cover classes, a few of them restrict the analysis to cropland. To do that, MARS uses the GLC2000 product (1 km spatial resolution, production year: 2000) (Bartholomé and Belward, 2005), WFP Seasonal Monitor uses the FAO GLC-Share product ($\approx$ 1 km spatial resolution, multiple production years) (Latham *et al.*, 2014), and GLAM uses various cropland maps at about 1 km spatial resolution. The recent global EWS Anomaly Hot Spots of Agricultural Production (ASAP) (Rembold *et al.*, 2018) detects anomaly hot spots of agricultural production for food security based amongst others on NDVI at 1 km spatial resolution and landcover map of Vancutsem *et al.* (2012). These cropland maps are not up-to-date and not detailed enough for smallholder agricultural monitoring. Waldner and Defourny (2017) showed that fragmented landscapes characteristics of the study region require higher resolution images to meet accuracy requirement of the cropland map. In Chapter 1, a methodology to map annual cropland was developed and could partly solve this issue.

Food security assessments and recommendations are often provided at regional level preventing local food security analyses. At best, the WFP Seasonal Monitor examines satellite TS (MODIS) and seasonal forecasts to assess growing season status and to highlight potential developments that may be of humanitarian concern at the second administrative level of Mali (circle scale). Recent improvements in sensors technology and accessibility offer new perspectives for

crop growing conditions analysis. Landsat and Sentinel datasets offer TS at medium and high spatial resolution (30 m for Landsat and 10 m for Sentinel) which should be sufficient to study local vegetation variability.

Taking advantage of the Landsat 8 30 m TS and the computing capacity of the Google Earth Engine (GEE) platform, this study aims to assess the inter-annual and spatial crop vegetation variability from national to local scale. The spatial variability is studied: (i) at national level (Mali) where we demonstrate the relevance of NDVI TS to highlight the strong agro-climatic north-south gradient characterizing the Sudano-Sahelian region, and (ii) at local scale where multi-annual NDVI TS are analyzed for different communes of a single circle to investigate the feasibility of detecting local crop conditions. The inter-annual growing conditions variability is studied at the circle scale with NDVI TS and climatic data. Then, the inter-annual growing conditions variability detected by Landsat 8 is compared with the one of an operational monitoring system. The analysis performed questions the current operational crop monitoring systems.

2.2 Study site

The spatial variability of NDVI is studied (i) at Mali scale with four contrasted administrative regions: Gao, Mopti, Ségou and Sikasso (Figure 2.1a, in orange), and (ii) at the Koutiala circle scale with five different communes (Figure 2.1c, in beige for the circle and orange for the five communes). The temporal variability of NDVI is examined for the Koutiala circle (Figure 2.1b, in orange). The methodology allows to downscale from national to local level (*i.e.*, commune). The analysis could not be performed over the whole Sudano-Sahelian region due to colossal computing time.

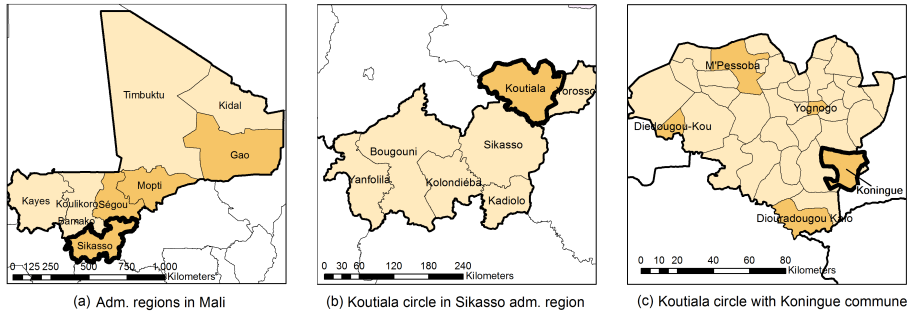


Figure 2.1: Distribution of the administrative regions of Mali (a) and the circles of Sikasso (b). The areas studied (four administrative regions, Koutiala circle and five communes) are presented in orange.

2.3 Data

2.3.1 Satellite imagery

Landsat is the world's longest collection of MR satellite imagery; it has acquired more or less systematically images every 16 days for more than four decades. Landsat 8 carries on two push-broom instruments conferring it amongst others new spectral bands (deep blue visible and infrared) and finer bands (Roy *et al.*, 2014). As a result of these improvements, the data quality and radiometric quantization of Landsat 8 has increased (more information on <https://landsat.usgs.gov/landsat-8>). Landsat 8 Top Of Atmosphere (TOA) data are available from April 2013 and acquired every 16 days. Roy *et al.* (2016) and Xu and Guo (2014) showed that differences exist between Landsat 7 NDVI and Landsat 8 NDVI, especially in low vegetation cover regions where Landsat 8 NDVI shows higher NDVI values than Landsat 7. Given these statements, only Landsat 8 TS are used and results are presented for 4 years (2014 to 2017) which correspond to the years studied in the thesis. Longer NDVI TS would obviously be better for crop vegetation inter-annual variability. Nevertheless, rigorous fusion between Landsat 7 and Landsat 8 data is a topic beyond the scope of this thesis. Besides, Sentinel data are only available since 2015 and do not yet offer sufficient historical data to study vegetation trends.

As the objective of the chapter is to compare the performance of Landsat 8 TS with the NDVI TS already used operationally for inter-annual crop conditions variability analysis, we downloaded the NDVI TS of two agriculture monitoring systems. First, the WFP Seasonal Monitor food security analysis platform uses NDVI data from the MODIS platforms Terra and Aqua, providing global coverage since 2000 (Terra) and mid-2002 (Aqua) at about 5.6 km spatial resolution and 16-day product frequency with revisit twice daily.[†] The products codes are MOD13C1 (Terra) and MYD13C1 (Aqua).

While some EWS used similar MODIS TS than WFP Seasonal Monitor at around 5.6 km spatial resolution, others use finer MODIS TS as FEWSNET and GLAM (250-500 m). To illustrate that, MODIS NDVI TS are downloaded from the GIMMS GLAM system providing near real-time Terra and Aqua MODIS 8-day composited, global NDVI datasets at around 500 m spatial resolution. These datasets are derived from the Collection 6 MOD09 and MYD09 surface reflectance products. The GIMMS MODIS GLAM System is developed for the GLAM project aiming to provide objective, timely and regular assessment of agricultural production outlook that might affect food security.[‡] These services and data provided are NASA/GIMMS and USDA/FAS contributions towards GEOGLAM.

[†]<http://reverb.earthdata.nasa.gov>

[‡]<https://landsweb.nascom.nasa.gov/>

2.3.2 Ancillary data

Rainfall estimates are critical for all agricultural monitoring systems (Fritz *et al.*, 2018). While rain gauges provide the most accurate rainfall data, the spatial network of stations is too sparse, especially in food insecure areas (Maidment *et al.*, 2017). According to Maidment *et al.* (2014) and given the objectives of this study, we select the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS). This data is also used by the WFP Seasonal Monitor §. CHIRPS offers data since 1981 based on the combination of 0.05° satellite imagery (≈ 5.6 km) and *in situ* station data. The CHIRPS relies on two global geosynchronous thermal infrared archives: the globally gridded satellite archive from 1981 to 2008 and produced by NOAA's National Climate Data Center (Knapp *et al.*, 2011), and the NOAA Climate Prediction Center dataset from 2000 to present (Janowiak *et al.*, 2001). At the global scale, CHIRPS data were developed to fill the gap of low latency and extended rainfall data (Funk *et al.*, 2015). Most of previous datasets featured either long period with very long latency (*e.g.*, Global Precipitation Climatology Centre (GPCC)) (Becker *et al.*, 2013; Willmott and Matsuura, 1995) or low latency but small period of time (Joyce *et al.*, 2004).

The CHIRPS dataset was thus selected as a good candidate by offering long record period (1981-present), sufficient spatial resolution (0.05°) and low-latency (2 days), allowing to place recent extremes in a historical context. Besides, this product was validated based on the GPCC and independent station datasets (Funk *et al.*, 2015). In this research, meteorological data are used from January 1981 to end 2017 for the Koutiala circle and are available every 10 days.

Global cropland maps were identified critical to agriculture monitoring systems as they are used to restrict the inter-annual variability analysis to the cultivated area (Fritz *et al.*, 2018). In this chapter, three sources of cropland maps are used: (i) the FAO GLC-Share used by the WFP Seasonal Monitor at 1 km spatial resolution (Latham *et al.*, 2014), (ii) the IIASA cropland map for 2005 used by the GLAM also at 1 km spatial resolution (Fritz *et al.*, 2015), and (iii) the 100 m Sudano Sahelian cropland map built in Chapter 1. In Chapter 1, we showed that the Sudano Sahelian cropland map, with an OA of 84% and a F-score of 74% for the cropland class, outperformed most of the global products in that region including GLC-Share and IIASA cropland maps.

2.4 Methodology

Assessing the inter-annual diversity of crop growing conditions from national to local scale relies on a full archive of Landsat 8 30 m spatial resolution images and on the computing capacity of GEE. The first step of the methodology is the construction of the NDVI TS from Landsat 8 surface reflectances. Then, the spatial variability is studied at national and local scales. At the national

§<http://dataviz.vam.wfp.org/seasonalexplorer/>

scale, NDVI TS of four administrative regions of Mali illustrate the north-south agro-climatic gradient. The spatial variability of crop growing conditions is studied at the Koutiala circle scale where NDVI TS of various communes are compared. Finally, the temporal variability of crop growth is studied in the Koutiala circle and analyzed along with rainfall data. It is compared with temporal variability detected by current agriculture monitoring systems.

2.4.1 Landsat 8 NDVI TS

Landsat 8 TS are accessed directly online on the GEE platform[¶] to limit the data volume handling. Landsat 8 cropland NDVI TS of a specific area are built by following five steps: (i) mosaicking and clipping the Landsat 8 images to the area of interest, (ii) screening out the clouds using the rudimentary cloud scoring algorithm of GEE^{||}, (iii) masking the non-cropland area with the Sudano-Sahelian cropland map (Chapter 1), (iv) computing NDVI from NIR and red Landsat 8 surface reflectances, and (v) averaging NDVI values for the study area. As meteorological data are available every 10 days, NDVI mosaics are temporally resampled by interpolating the 16-day Landsat 8 product to a 10-day time step using:

- A cubic spline applied to fill temporal gaps (1-day frequency);
- A polynomial filtering method of Savitzky and Golay to smooth the data and reduce the noise (Savitzky and Golay, 1964) (1-day frequency);
- A NDVI 10-day composite by averaging all 1-day smoothed NDVI inside the corresponding study area (regions, circle or communes) for a 10-day time step.

The average 10-day NDVI composites are computed for the different scales studied and for the 2014-2017 period.

2.4.2 Spatial variability of crop growth conditions: NDVI

National scale

At the country scale, Landsat 8 NDVI TS (2014-2017) are averaged over the cropland of four contrasted administrative regions: Sikasso, Ségou, Mopti, and Gao (Figure 2.1). The four administrative regions are spread along a gradient starting with Gao in the north, Mopti, Ségou, and Sikasso in the south with agro-ecological zones ranging from desert to wet Sudanian region.

Local scale

While most of the crop monitoring systems deliver food security recommendations at circle or region levels, we explore the possibilities to deliver finer information. Landsat 8 NDVI TS are computed for five communes (Daouradougou,

[¶]<https://earthengine.google.com/platform/>

^{||}<https://developers.google.com/earth-engine/landsat-simple-cloud-score>

Diedougou, Koningue, M’Pessoba and Yognogo) of the Koutiala circle and compared with Koutiala NDVI TS to assess the gain of working at a finer scale (Figure 2.1). These communes are chosen arbitrarily to be spatially distributed.

2.4.3 Temporal variability of crop growth conditions

Characteristics of the Koutiala circle level

Long-term TS of CHIRPS rainfall data (1981-2017) are used to define the inter-annual rainfall variability in the Koutiala circle. The annual total precipitation is computed for each year between 1981 and 2017 and compared to the average of annual total precipitation over this time period. Landsat 8 NDVI TS are jointly analyzed with rainfall TS for four years (2014-2017) to characterize the inter-annual vegetation growth dynamics in the Koutiala circle.

Comparison with operational crop monitoring systems

The inter-annual crop growth variability detected by Landsat 8 NDVI TS masked with the Sudano-Sahelian cropland map built in Chapter 1 is compared with what is currently done in crop monitoring systems through two examples: the WFP Seasonal Monitor and the GLAM system. The WFP Seasonal Monitor uses MODIS NDVI TS at 5.6 km spatial resolution with FAO GLC-Share 1 km cropland mask and GLAM uses MODIS NDVI TS at 500 m resolution with 1 km IIASA cropland mask (2005). This comparison aims to point out the room for improvement in operational agriculture monitoring systems.

2.5 Results

2.5.1 Landsat 8 NDVI TS

Gap-filled smoothed 10-day NDVI composites have been built from raw Landsat 8 NDVI TS (Figure 2.2 for the Sikasso administrative region).

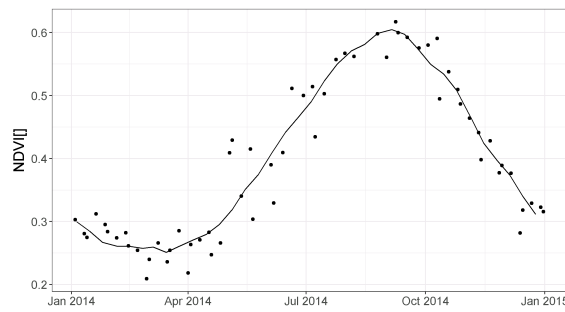


Figure 2.2: Profile of Landsat 8 NDVI values (points) for the Sikasso administrative region in 2014 and the related smoothed 10-day NDVI composite (line).

2.5.2 Spatial variability of crop growth conditions: NDVI

National scale

Spatial variability in crop vegetation is strong in Mali as different bioclimatic zones exist and have various vegetation growth potentials. Landsat 8 NDVI TS highlight the clear agro-climatic vegetation gradient with the high vegetation cover of the cultivated area in Sikasso administrative region contrasting with the low cropland vegetation cover in Gao (Figure 2.3). Mopti and Ségou administrative regions feature crop vegetation growths in-between. The LGP is also much longer in Sikasso than in Mopti, Ségou, and Gao.

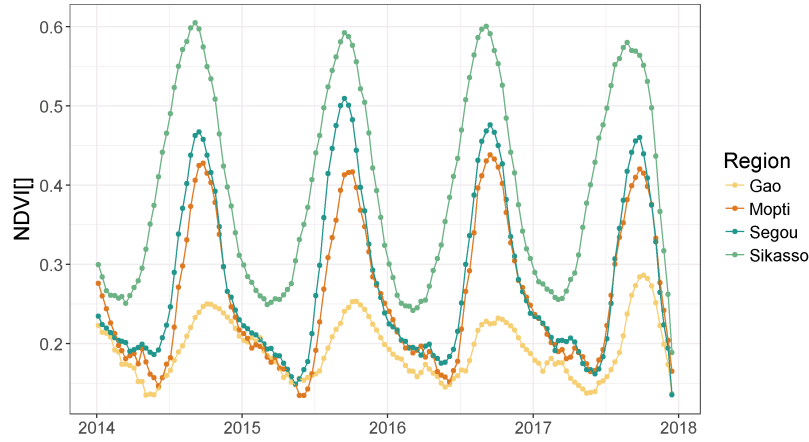


Figure 2.3: Landsat 8 NDVI time series from 2014 to 2017 averaged over cropland for four contrasted administrative regions of Mali: Gao, Mopti, Ségou, and Sikasso.

Local scale

Strong contrasts are observed between the NDVI TS of the five different communes of the Koutiala circle along the four studied years (2014-2017) (Figure 2.4). Differences in vegetation growing conditions especially occurred at the beginning of the growing season where the SOS is delayed by more than a month between Diedougou commune and M’Pessoba commune. This directly impacts the crop growth, the crop production and the duration of the lean season affecting food security at the local scale. The maximum NDVI reached respectively by the different communes in 2015 and 2017 also strongly differ: this is correlated to the crop biomass and thus to the crop production. The annual crop NDVI profiles derived from Landsat 8 at commune level (containing between 32,000 and 380,000 crop Landsat 8 pixels) are still quite usable in spite of some noise compared to those at circle level. The noise is expected to increase at even more local levels than commune which prevents the use of Landsat 8 with its 16-day revisit cycle at village or field levels.

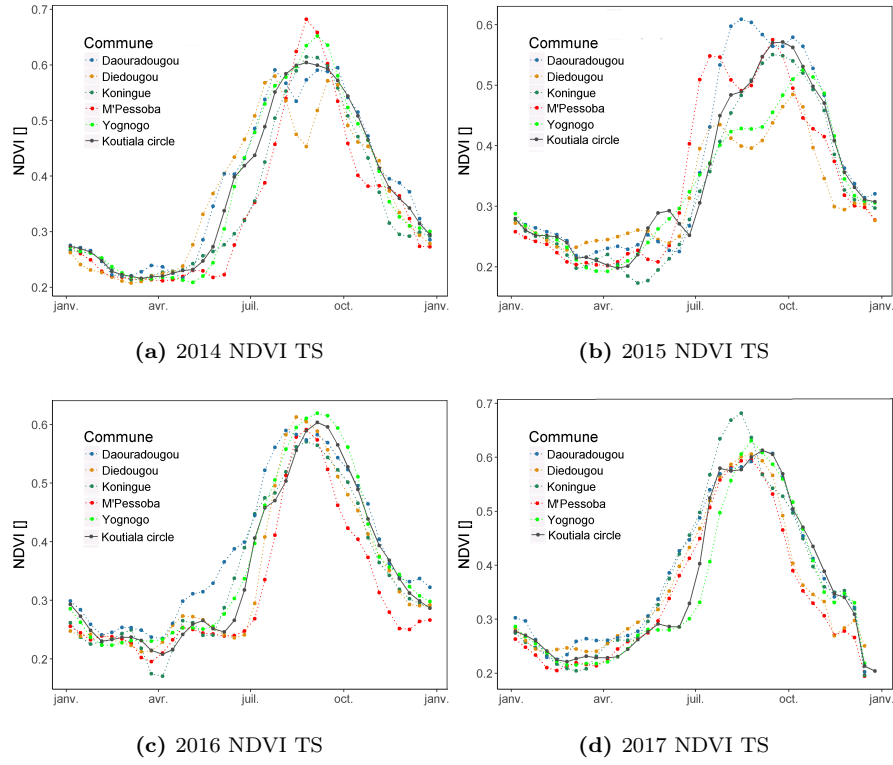


Figure 2.4: NDVI TS for the 5 studied communes of the Koutiala circle and for the whole Koutiala circle (in solid gray line).

2.5.3 Temporal variability of crop growth conditions

Characteristics of the Koutiala circle level

The annual rainfall for the Koutiala circle highlights higher annual rainfall for the 2014-2016 period than the climatological average (835 mm) (Figure 2.5).

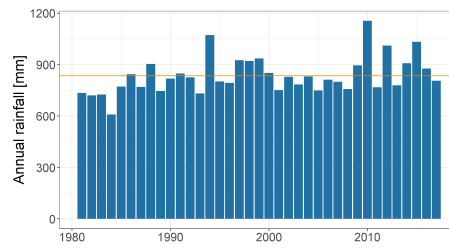


Figure 2.5: Annual rainfall in the Koutiala circle from 1981 to 2017 with climatological average rainfall computed on 37 years time series (in orange).

The 2014 and 2016 seasons reached around 900 mm of precipitation while this amount even goes to 1,032 mm for the 2015 season. The 2017 season was a bit drier than the average (806 mm). Nonetheless, the total amount of rainfall is not sufficient to characterize a growing season as the temporal rainfall distribution impacts the plant growth. 2014, 2015, 2016 and 2017 NDVI and rainfall TS are compared to the average computed for the 2014-2017 period (Figure 2.6).

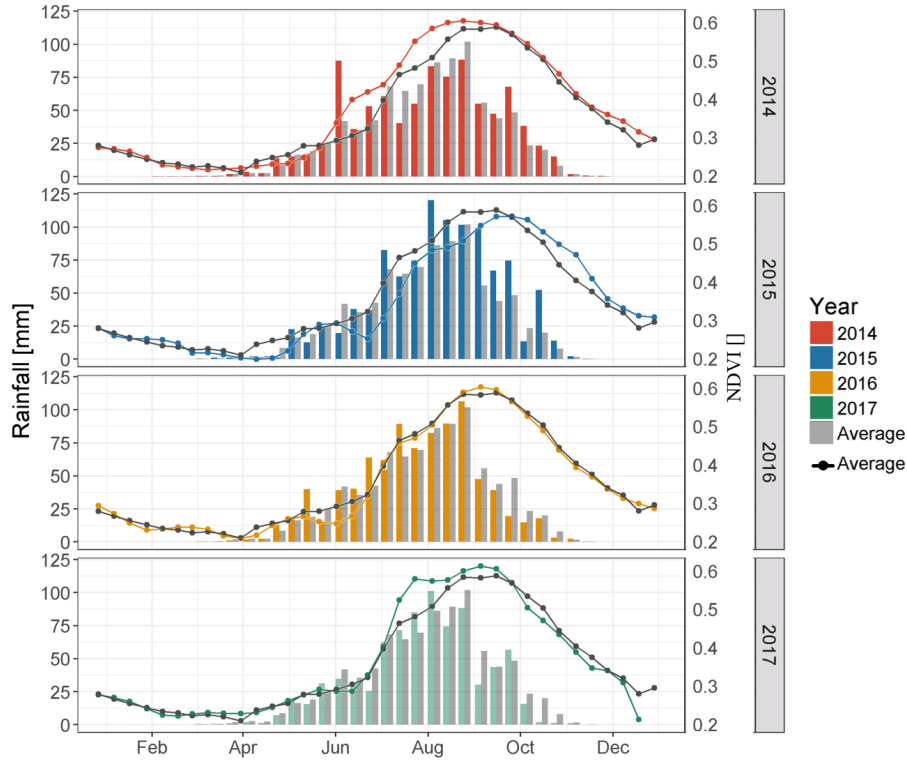


Figure 2.6: Rainfall and Landsat 8 NDVI for each year of the 2014-2017 period compared with average rainfall and NDVI for the same period (Koutiala circle).

In 2014 higher precipitations than average occurred at the beginning of the season resulting in advance of plant emergence and vegetation growth. Vegetation peak was reached a bit earlier than the average and with higher vegetation cover. In 2015 despite the total amount of rainfall which was much higher than average, a precipitation delay at the beginning of the season was observed. The vegetation peak was reached later than usual and with lower maximum NDVI value. This shows that any water stress at the beginning of the season directly affects the vegetation cover for the whole growing season. Besides, an excess of water during vegetation growth could also increase the leaching of fertilizers. In 2016 as in 2014 high precipitations at the beginning of the season yielded to small advances in the emergence and higher peak NDVI.

Nevertheless, this effect is less marked than in 2014. In 2017 the rainfall was rather abundant in the first half of the season leading to good crop growth until the vegetation peak. Then, rainfall decreased which directly impacted the crop production. This regional analysis highlights strong contrasts of crop vegetation between years, mainly driven by rainfall distribution.

Comparison with operational crop monitoring systems

The inter-annual variability in crop growth conditions of the Koutiala circle for 2014-2017 detected by cropland Landsat 8 NDVI TS are compared with operational monitoring systems: WFP Seasonal Monitor and GLAM (Figure 2.7).

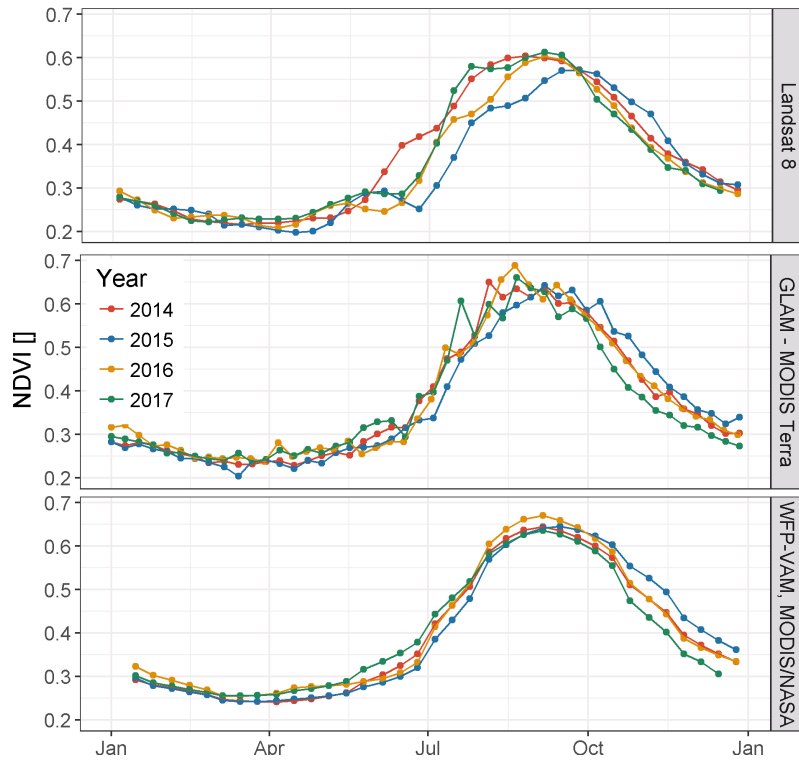


Figure 2.7: Three NDVI TS for the Koutiala circle along the four studied years and derived from (i) Landsat 8 imagery at 30 m spatial resolution, (ii) GLAM MODIS Terra imagery at 500 m spatial resolution and (iii) WFP Seasonal Monitor MODIS imagery at 5.6 km spatial resolution.

The GLAM - MODIS (Terra) NDVI TS are noisier than the Landsat 8 TS as no smoothing was applied. The Landsat 8 TS bring out the huge SOS gap between 2014 and 2015 which is hardly depicted by GLAM and WFP Seasonal Monitor. It also shows differences in the reaching of peak NDVI and in the

value of peak NDVI. The GLAM and WFP Seasonal Monitor have difficulty in accurately detecting the inter-annual crop growth variability. This can be related to: (i) too large spatial resolution of NDVI TS, (ii) too large spatial resolution (1 km) of the cropland map used, and (iii) not up-to-date cropland map. The objective of this chapter was not to quantify the different sources of improvements but rather to show that significant enhancements can be made by using Landsat 8 TS and an up-to-date cropland map.

2.6 Discussion

While in the past NOAA TS (8 km spatial resolution) were used to document the inter-annual variability of crop conditions, today operational monitoring systems rely most of the time on MODIS TS (500 m to 5.6 km spatial resolution) and a global cropland map at around 1 km spatial resolution. These systems aim to deliver relevant information on crop status (i) to track the progress of the crop growing season, (ii) to make inter-annual comparisons of seasonal dynamics, and (iii) to inform decision-makers and stakeholders of crop conditions and impediments to food-security.

The results of the present study highlighted the benefits of the spatial resolution of Landsat 8 (30 m) and PROBA-V derived cropland map (100 m) to downscale the spatial variability analysis to the commune scale. While the study highlights high spatial variability between different communes of a single circle, some operational monitoring systems, as WFP Seasonal Monitor provide information only at the circle level. The average circle size in Mali is 25,331 km² (8,740 km² for the Koutiala circle) which limits the detection of local food insecurity. Besides, Mali is part of the Sudano-Sahelian region featuring high local spatial variability in soil and rainfall (Graef and Haigis, 2001). The spatial resolutions of Landsat 8 and PROBA-V are more compatible with (i) the small average field size (1-2 ha), (ii) the high landscape fragmentation (Chapter 1, section 1.4.7) (Waldner and Defourny, 2017), (iii) the diversity of cropping systems and (iv) the mosaic of cropland, fallow and natural grassland (Delrue *et al.*, 2013; Vancutsem *et al.*, 2012).

In this research we showed that current crop monitoring systems (WFP Seasonal Monitor and GLAM) are too limited to detect inter-annual crop growth variability in the Koutiala circle compared to Landsat 8 NDVI TS masked with a Sudano-Sahelian cropland map. This is partly explained by the spatial resolution of both NDVI TS and the cropland map, the not up-to-date cropland product and the low accuracy of global cropland maps. In Chapter 1 we showed that the F-score of GLC-Share and IIASA cropland maps were respectively 29% and 52% for 2014 which is much lower than the 2014 Sudano-Sahelian cropland map reaching a F-score of 74%. As already mentioned in Chapter 1, the global cropland products tend to neglect regional specificities (Fritz *et al.*, 2011).

To go down to village or field spatial and temporal variability analyses, Landsat 8 30 m spatial resolution TS would not be sufficient. Indeed, both rainfall and growing season are fully synchronized with cloud coverage, making it challenging to assess the crop development with Landsat as it provides too few cloud-free observations over a season for a given pixel location. Sentinel-2 offers a 5-day revisit cycle with a 10 m spatial resolution that could allow overcoming this challenge, once the time series will be long enough to study crop vegetation variability.

2.7 Conclusions

Current agriculture monitoring systems deliver information which is most of the time not detailed enough to deliver local insights about agriculture monitoring and to adequately isolate the inter-annual crop dynamics. In this chapter, we aimed to assess the spatial and temporal crop conditions variability down to commune levels by benefiting from Landsat 8 TS and the computing capacity of the GEE platform. At the national scale, NDVI TS highlight the strong north-south gradient characteristic of the whole Sudano-Sahelian region. The co-existence of very heterogeneous bio-climatic zones featuring various vegetation growth potentials supports the relevance to downscale the analysis of crop vegetation variability. High variability in NDVI TS of five communes in the Koutiala circle was observed and revealed the local spatial variability characteristics of the Sudano-Sahelian region. At the circle scale, strong inter-annual variability in crop vegetation cover was observed for the 2014-2017 period and is mostly explained by rainfall distribution. This variability was hardly depicted by large MODIS NDVI TS used in operational agriculture monitoring systems as WFP Seasonal Monitor and GLAM.

As it was recognized by Justice and Becker-Reshef (2007), national and regional monitoring systems cannot effectively monitor agriculture at all scales. Nevertheless, availability of information at commune level allows developing different strategies and decision-making processes either to supply local markets, to support local initiatives (*e.g.*, collective gardens), to manage storage capacity, to promote diversification or even to design mutual local insurance mechanisms. Besides, the monitoring of local crop conditions also offer possibilities for aggregating at a larger scale (including regional and national scales) with a better representation of local diversity. In fact, some EWS providing information at aggregated scale (*e.g.*, region or circle) tempt to erase local positive or negative anomalies by providing an aggregated result. This can result in a no food crisis diagnostic while interventions are required in some specific regions.

Despite the important benefits of Landsat 8 imagery, the medium and high resolution data (10-100 m) has not yet been broadly adopted in the context of crop condition monitoring due to (i) lack of cloud-free data at this spatial resolution (Whitcraft *et al.*, 2015b), and (ii) impediments in operational adoption including lack of technological expertise and difficulty to access, store and pro-

cess high data volumes. While Landsat 8 and Sentinel-2 imageries address issues regarding spatial resolution data availability, efforts are required amongst others to (i) develop human and institutional capacity to use increasingly available EO data, (ii) document and disseminate more automated methods developed in the research sector, and (iii) improve the accessibility of in-situ data such as crop types and agricultural practices (Fritz *et al.*, 2018). Overall, greater coordination and sharing of information is also required.

Chapter 3

Diversity of smallholder farming systems and agricultural practices in Mali's cotton belt

Highlights

- Open ended interviews were conducted to characterize farming systems diversity in the Koningue commune of Mali's cotton belt.
 - Cotton cultivation has strongly shaped the farming systems in the Koningue commune.
 - Major variability in farming systems comes from the household size, the agricultural practices, the income strategy and the soil types.
 - Farmers face different challenges for agricultural production as lack of means and fertilizers, climate variability, soil poverty, land scarcity and pests and diseases.
-

Abstract.

In Mali's cotton belt, cotton crop is cultivated for years and has strongly shaped the farming systems. While cotton farmers produce a high quantity of both cotton and cereals (millet, maize, and sorghum) benefiting from the abundance of rainfalls and relatively high soil fertility compared to Malian standards, they are the poorest and the most malnourished farmers of the whole southern Mali. A detailed portrayal of farming systems diversity and farmer constraints is required to "*dive-in*" the local context (Koningue commune) and build the methodology of Chapters 4, 5, and 6. This chapter analyzes the information collected through 50 farmer interviews to characterize farming systems diversity, farmer constraints and yield variability. Important variability in farming systems is observed and related to household sizes, income strategies, and soil types. Farmers face challenges such as lack of means, lack of fertilizers, land scarcity, crop pests and diseases, and climate variability that affect the crop production.

3.1 Introduction

Cotton growing, spinning and weaving were important activities in African farming systems well before colonization (Bassett, 2002). Commercial cotton production started in the 20th century with the colonial presence. In 1896, cotton production was used to pay the taxes. A first company, the *Compagnie Française pour le Développement des fibres Textiles* (CFDT) was created in 1949 to manage the cotton production. In 1974, after Mali independence (1960), the *Compagnie Malienne pour le Développement du Textile* (CMDT) replaced the CFDT and managed the whole cotton sector. In parallel to these governmental companies, local cooperatives of producers named Producers Organization (PO) were created in the 1970's to act as intermediaries between the cotton producers and the CMDT (López Ridaura, 2005).

The CMDT undertakes several missions: (i) give agricultural advice to cotton farmers; (ii) supply the fertilizers, seeds and phyto treatment credits for cotton; (iii) manage the harvest, commercialization, and ginning of cottonseed; (iv) sell and export cotton lint for Malian textile industry; (v) sell cottonseed on the global market. The CMDT acts in areas located south of the Niger river and east of Mali over a total area of more than 130,000 km² including 6,345 villages and hamlets. In Mali, the cotton sector owns 17 ginning factories, three industrial units of lint transformation and a few industrial units for cottonseed transformation in oil, soap, and food cattle*. The farmers have not much control in front of the CMDT which fixes the quantity of fertilizers according to the farmer resources and previous cotton productions.

Mali's cotton belt is one of the most productive regions of Mali regarding agriculture, especially cereals and cotton production thanks to the abundance of rainfalls and relatively high soil fertility (compared to Malian standards) (Delarue *et al.*, 2009). Nevertheless, two paradoxes prevail in the region. First, cotton farmers are the poorest in the region – in comparison with non-cotton farmers of the same area – while they produce cash crops in large quantities (Delarue *et al.*, 2009; Mesplé-Somps *et al.*, 2008a). Cotton production followed a high increase from the 1960's to the end of the 1980's and cotton was, at that time, considered as a success story (Baquedano *et al.*, 2010). Nevertheless, at the end of the 1990's, cotton production started to decrease to reach by 2008 an average yield similar to the one produced in the 1970's (Baquedano *et al.*, 2010). The decline in cotton production is attributed to various factors including poor soil fertility management, fertilizers shifting from cotton to maize (Laris *et al.*, 2015) and extensification in more marginal zones (Benjaminsen *et al.*, 2010). In parallel, the world cotton price started to fall (in 1998) and turned the CMDT into financial crisis. In 2000-2001, the announcement of a weaker cotton price drove more than 50% of farmers to drop cotton cultivation which amplifies the financial and economic crisis (Delarue *et al.*, 2009). Despite some attempts of the Malian government supported by international agencies to restore the economy, the situation is still unstable today. The combination of low cotton

*<http://www.ipc-mali.org/index.php/cmdt>

production, dependence on fluctuating world prices and financial crisis are reasons to explain the poverty of cotton farmers. This leads to a small decreasing interest of cotton crop in favor of other cash crops such as peanut, banana or mango (Dufumier, 2005; Mesplé-Soms *et al.*, 2008a; Nubukpo and Keita, 2005).

Second, the prevalence of malnutrition in cotton households is much higher than in the rest of the population (Dury and Bocoum, 2012). The levels of growth delay and underweight are above the Organisation Mondiale de la Santé (OMS) recommendation. This is partly explained by a bad food basket composition and an inadequate wage allocation mainly controlled by men (Kelly *et al.*, 2004; Oumar *et al.*, 2013). Most of the income is allocated to production costs (*e.g.*, fertilizers, taxes, equipment) while a limited part is assigned to food and health (Dury and Bocoum, 2012).

This chapter aims to help the reader to "*dive-in*" the local context of Mali's cotton belt and more specifically of the Koningue commune. The comprehension of farmers realities in this context is required to build the methodologies of Chapters 4, 5, and 6 about crop production estimation and understanding. This description cannot be assessed with Earth Observation and requires socio-economic data. The present chapter proposes a perception-based[†] farming systems description in the cotton belt based on farmers interviews carried out with 50 farmers at the end of the 2016 growing season (October and November). The major topics addressed and analyzed are the main characteristics of farming systems, the constraints for agricultural production and the explanatory factors of yield heterogeneity. The Koningue commune was selected as a case study in Mali's cotton belt due to the opportunity of building on a test site of ICRISAT.

3.2 Study site

The study area (353 km²) is defined by the geographical footprint of the 43 POs registered in the five villages of the Koningue commune (Koutiala district, south-eastern Mali): Dougan, Sukumba, Nguéguesso 1, Nguéguesso 2 and Banesso (Figure 3.1, more information on the study area limits in Appendix B). The site is located in the older cotton production basin of Mali, characterized by relatively high population density (36 inhabitants/km² in Sikasso region[‡]), land saturation, fragmentation, and degradation. CMDT extension services provide access to subsidized inputs, an outlet for the sale of cotton production, and agronomic advice that covers the entire production system including other main crops like maize, millet, peanut, and sorghum. The combination of these factors results in a relatively advanced state of agricultural intensification, yet with vast landscape and community scale heterogeneity in production levels. Average annual rainfall reaches 835 mm with high inter-annual and intra-seasonal

[†]In French: "*à dire d'acteurs*"

[‡]<http://www.instat-mali.org/nada/index.php/catalog/8>, consulted the 23th April 2018, Recensement Général de la Population et de l'Habitat 2009.

variability. Precipitations are very dominantly convective, inducing high spatial heterogeneity at the local scale (Breusers, 2004).

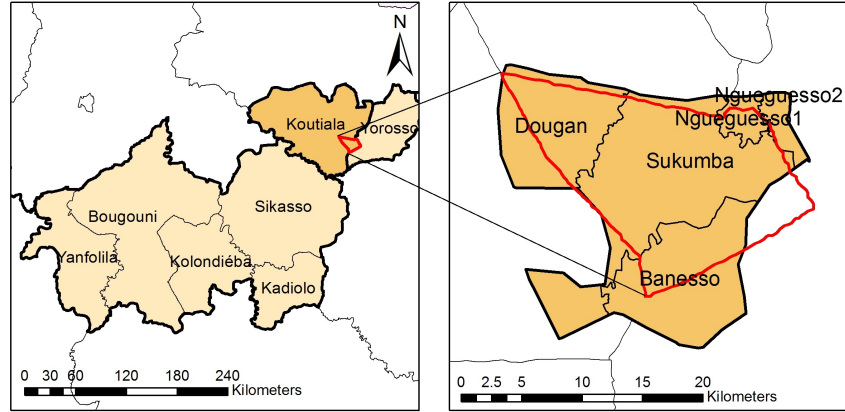


Figure 3.1: The study area (in orange on the right image) almost coincides with the administrative boundaries of the Koningue commune (in red contour) located in the Koutiala circle. The study area includes five villages. More information on the study area delimitation can be found in Appendix B.

Soil properties follow the catena, with high plateaus presenting moderately deep, argillic soils (Plintic Haplustults), midslopes featuring moderately deep to shallow, gravelly and lateritic soils (Cuirustalfs, Mollic Cuirorthents, Lithic Haplustalfs), and deep, well drained and moderately fine textured soils in the lowlands (Plintic/ Ultic Haplustalfs, Oxic Haplustults) (Blaes *et al.*, 2016; Diallo and Keita, 1995b). Local farmers distinguish five soil types (Figure 3.2): (i) "*fara dugu kolo*", rocky soils located on plateaus and slopes; (ii) "*bele dugu kolo*", red gravelly soils located on plateaus; (iii) "*cencen dugu kolo*", sandy soils located on slopes and lowlands; (iv) "*bogo dugu kolo*", loamy soils located in lowlands; and, (v) "*mana dugu kolo*", lowlands clayey soils.

Cotton (*Gossypium sp.*), maize (*Zea mays L. ssp.*), sorghum (*Sorghum bicolor (L.) Moench*) and pearl millet (*Pennisetum glaucum (L.) R. Br.*) are the main crops in the region. The growing season starts with the first rains around May and crops are harvested from early September (maize) to end of November (millet) (Figure 3.3). Maize, sorghum, millet, and peanut are cultivated mainly for household consumption. Since a few years, different studies highlighted the "*maizification*" of the area (Falconnier, 2009; Laris *et al.*, 2015). The maize crop has a few advantages compared to the other grain crops: higher yields, easier to sell, and faster maturation allowing early harvest during the lean season. However, it requires more fertilizer, is more susceptible to drought than sorghum and millet, and provides less nutritional value compared to millet.

The people living in the study area are the Minyankas. They occupy territory in southern Mali in the region of Ségou and Sikasso. They form a homogeneous

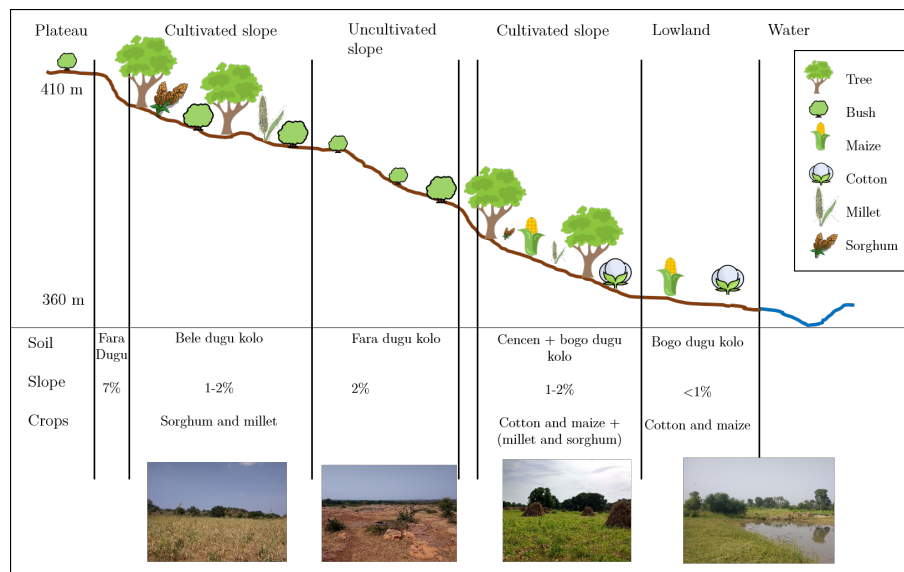


Figure 3.2: Typical toposequence observed in the study region realized on the field with professor Kalifa Traoré.

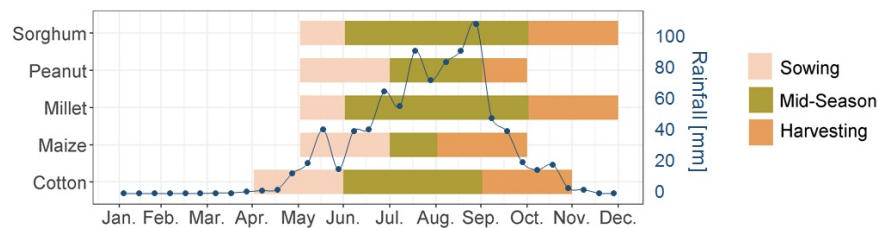


Figure 3.3: Crop calendar of dominant crops in the cotton belt region with decadal rainfall for the 2016 year. Rainfall data were downloaded from the food security analysis of WFP (Available at: <http://dataviz.vam.wfp.org/>).

ethnic group but interact strongly with other groups such as Senufo, Bobo, and Bambara at the borders of their territory (Jonckers and Colleyn, 1974). The language of Minyanka is the Mamara, and most of Minyankas are farmers. The origin of this ethnicity goes back to the Keita's allied families at the time of the empire of Mali (XIII century). There is no evidence of human presence before the Minyanka in that region of Mali; Minyankas are considered as native. During the pre-colonial period, the Minyanka's land was included in different kingdoms according to conflicts: Ségou's, Sikasso's and Kéné Dougou's kingdoms. In 1890, the arrival of the French marks the beginning of revolts in the north of the Minyanka area and led to the fall of the Kéné Dougou empire in 1898. Since then, the colonial period featured lots of incidents due to different power

conceptions between French settlers and local Minyanka (Jonckers and Colleyn, 1974). Today the politico-economic situation in the study area is relatively stable in comparison with the conflicts occurring in northern Mali (see general introduction).

3.3 Data

Different datasets were provided by the ICRISAT, a partner in the 2014-2017 STARS project (Spurring Transformation for Agriculture through Remote Sensing)[§] active in our study area. These included 2014 and 2015 seasonal TS of VHR DG imagery used in STARS to exhaustively delineate 31,248 agricultural parcels. A digital dataset on vernacular soil types and agricultural households characteristics was collected in 2015 from farmer interviews (6,700+ georeferenced samples). The household characterization dataset includes amongst others, information about the name of the household chief, his phone number, the geographic coordinates of each parcel and, the crop type. These two datasets are used to a priori sample the farmers to interview.

3.4 Methodology

To assess the diversity of the smallholder farming systems and agricultural practices in the study area, we rely on semi-structured farmer interviews, and we propose a perception-based description. An ex-ante farmers sampling based on farms typology allows selecting a priori farmers representative of the diversity of farming systems. 50 interviews were conducted and the four addressed topics are summarized and illustrated by farmer's words and histograms: (i) the main characteristics of the farming system; (ii) the stakeholders and the decision levels; (iii) the farmer constraints and (iv) the yield heterogeneity.

3.4.1 Ex-ante sampling

The selection of farmers for the interviews has to be as representative as possible of the agricultural systems diversity. An ex-ante sampling is done to sample 30 farmers. This stratified random sampling is based on the household characterization dataset. A few steps are required to clean the dataset: (i) standardization of the variables (*e.g.*, first and last name, crop types); (ii) removal of the duplicates; (iii) spatial merging of the farmer geo-referenced fields and cadastral parcels to compute field area; (iv) selection of the observations with a unique first name, last name and phone number.

The clean dataset only includes 90 farmers with a unique phone number, name, and cadastral parcels. Farmers are grouped in three clusters according to the cultivating areas: small, medium and high cultivated area farms. Out of the 90 farmers in the clean database, 30 are randomly selected amongst the clusters

[§]<http://www.stars-project.org/en/>

while conserving the proportion of each cluster in the database. The ex-ante sampling is completed with 20 additional farmers identified on the ground by local expertise and observation. This additional sample is useful to interview farmers diverging from the standard practices. In total 50 farmer interviews were conducted and numbered from 1 to 50.

3.4.2 Semi-structured interviews

The farmer interviews were semi-structured and particular attention was paid to respect the main advice of Olivier de Sardan (1995). Efforts were made to bring the interview as close as possible to a discussion. An interview guide (Appendix D) was used as a reminder throughout the interviews (checklist). The triangulation was applied to cross-check the information obtained (Olivier de Sardan, 1995). We tried to insist on the differences in agricultural practices to learn more with each farmer. Each interview lasted about one hour and was ended by a visit to the farmer fields. Confrontation of farmer's words and field observations decreases misunderstanding errors. As suggested in Olivier de Sardan (1995), the saturation was reached at the end of the field campaign meaning that no more information was obtained from new interviews.

As farmers of Sukumba community speak Mamara, an interpreter was essential to allow the discussion. The interpreter (Birama Sissoko[¶]) is a geographer with expertise in interviews in rural areas and specific knowledge of the Sukumba village. A training was realized with the interpreter and two test interviews were conducted: the first one with a field officer playing the game of a farmer in order to (i) correct the way of asking questions, and (ii) learn the local rules. Secondly, a test was done in real conditions with a farmer to fine-tune the last details. I also learned local vocabulary to understand and interact with the farmer on some topics directly.

Most of the interviews were carried out near the farmer hamlet in a quiet and shady place. Each time, we were sitting down in a triangular form between the farmer, the interpreter and the student (Figure 3.4). The introduction and the objectives explanation were crucial and determined most of the quality of the interview. As we were arriving by foot or with a moto to the hamlets, we limited the distance between the farmer and the interviewer. We insisted on the fact that the interview was independent of any organization. All the interviews were recorded to keep track of the information and to ease the interaction with the farmer by limiting the time spent taking notes. Photos were also made to print in minds some details of the farmer household, practices and environment. To complete the information obtained from the interviews with the 50 farmers, a 3-hour session of open discussion on stakeholders and decision levels was conducted after the surveys. This interview was realized with three farmers of different ages (19, 35, 58) to confront their visions and to catch the best representation of the stakeholders and decision levels in their agricultural systems.

[¶]Field operator at the NGO AMEDD.

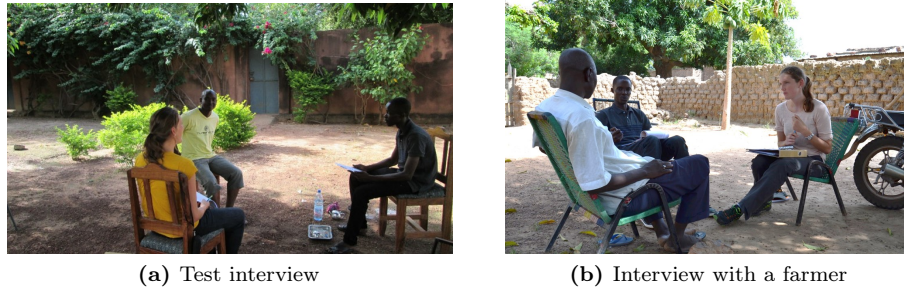


Figure 3.4: Pictures of (a) the test interview and (b) an interview with farmer.

3.4.3 Data collection and analysis

Due to time constraints, records of the interviews are not fully transcribed as it is sometimes done in social science. However, records are used when the notes are incomplete or unclear. Figure 3.5 summarizes the subjects addressed during the interviews. A database is built with all the data collected for each farmer and used to compute simple statistics about farming systems to contextualize the study area in which the next chapters of the thesis take place. The first part of the analysis describes the main characteristics of the agricultural systems including the household, the cultivated crops, the main agricultural practices, the source of income and the extra-agricultural activities qualitatively. For this part, a summary of all the farmers' interviews is made with farmer's words illustrating each new concept.

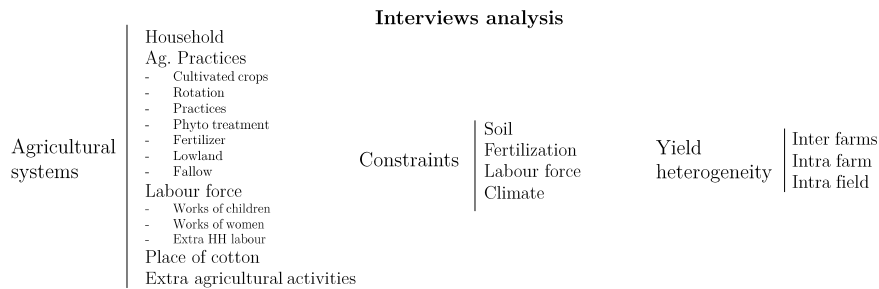


Figure 3.5: Thematics tackled in the semi-structured farmers' interviews.

The second analysis focuses on the stakeholders and the decision levels. Information obtained across all farmers' interviews and the specific 3-hour session is used to draw a summary and a graph of all decision levels. This organization is similar to the one encountered in most of the Minyanka villages of the cotton belt region. The third analysis describes the constraints for agricultural production that were identified by farmers during the interviews.

Pie charts are used to detail the importance of each constraint. Details are given for the more important constraints, and farmer's words illustrate each of the conclusions. Finally, as Chapters 4 and 6 focus on yield variability, we contextualize farmer points of view on yield heterogeneity at three scales: (i) intra-field (within a single field), (ii) intra-farm (all fields of a single farm), and (iii) inter-farms heterogeneity (fields of different farms).

3.5 Results and discussion

3.5.1 Main characteristics of the agricultural systems

Generally, farmers in the Sukumba community grow cotton for income generation and access to fertilizer. They cultivate cereals (maize, millet, and sorghum) for self-consumption, and raise livestock for traction power, manure, and as a saving account. The main characteristics of the agricultural systems encountered in this village are presented here below.

The household The average age of the interviewed farmers is 52 years. 72% of farmers did not go to school while 10% did their primary school, 12% the literacy program, 4% the secondary school and 2% reached the bachelor degree. The average size of the household is 24 persons, most of them being children.

The cultivated crops in Sukumba The four main crops are cotton, millet, maize, and sorghum but farmers also grow minor crops (Figure 3.6).

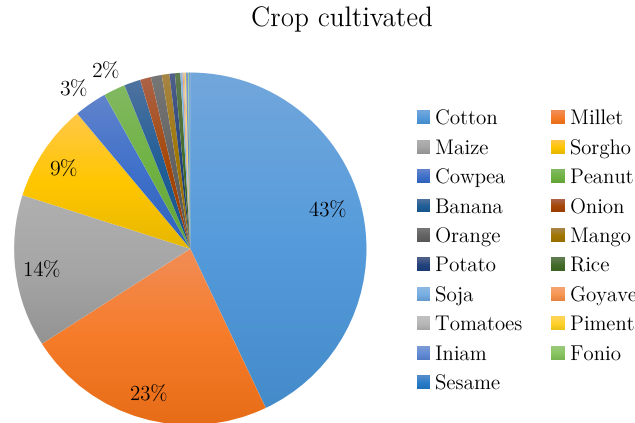


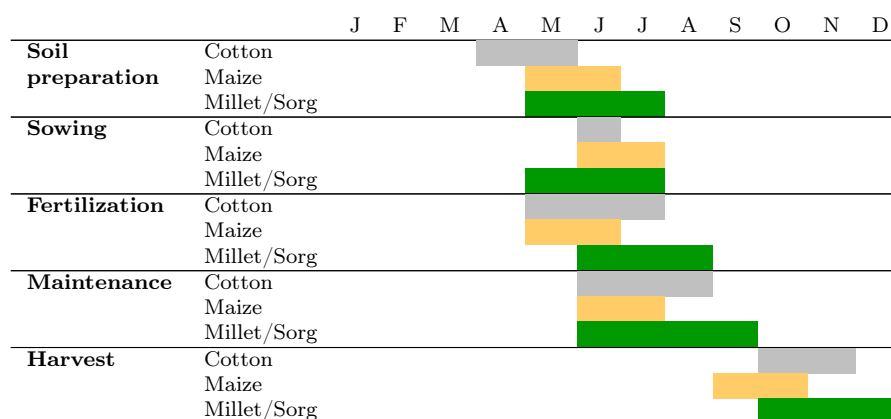
Figure 3.6: Proportion of the cultivated area per crop type for the 50 farmers.

While minor crops are often cultivated in small parcels in the lowlands, they contribute directly to the food basket diversity and to the household income as part of the production is sold.

Rotation All farmers cultivate crops in rotation. The three main rotations are (i) cotton (year 1: Y1) followed by cereals (Y2) (done by 62% of farmers); (ii) cotton (Y1) followed by maize (Y2) and then other cereals (Y3) (done by 19% of farmers); and (iii) cereals (Y1) followed by cereals (Y2) (done by 16% of farmers). The advantage of the two first rotations is that cereals benefit from fertilizers provided for the cotton crop (see Chapter 6, sections 6.4.2 and 6.4.3.). As the fertility carryover effect decreases from one year to another, maize is often cultivated directly after cotton. Other rotations exist as cotton - cotton, maize - cereal but are sparse.

Main agricultural practices The main agricultural practices follow the technical itinerary described in the box below. Because of a lack of equipment and lack of labor force, farmers cannot always strictly follow those practices. In the Sukumba community, most farmers cultivate the fields with animal traction and specific tools (*e.g.*, multicultor, plow). Nevertheless, a few farmers are forced to do all the works manually due to a lack of livestock. For details on the technical itinerary, please refer to Table 3.1.

Table 3.1: Technical itinerary for the four dominant crops: cotton, maize, millet and sorghum in Mali's cotton belt based on the Banque Nationale de Développement Agricole (BNDA). The soil preparation includes the field cleaning, the spreading of organic manure and the plowing. The maintenance consists of thinning, weeding, herbicide applications, phytosanitary treatments applications, and the ridging.



Technical itinerary for crop production in Mali's cotton belt

Cotton crop The CMDT furnishes the seeds of cotton. The soil preparation includes the field cleaning, the spreading of organic manure and the plowing. June is the optimal time to sow cotton especially from the first to the 20th. A delay in the sowing reverberates directly on the cotton yield. The cotton crop is strongly affected by adventices which favor parasites. The maintenance of cotton is done early in the growing season: (i) herbicide application the day or within 48 hours after sowing, (ii) thinning two or three weeks after sowing, (iii) weeding, and (iv) phytosanitary treatments applications. The number of weedings varies depending on the number of weeds. However, the first weeding is systematically done 15 days after sowing (sometimes coupled with cotton complex spreading) and the second 30 days after sowing. The ridging is achieved 30 to 40 days after sowing. To protect the cotton from bacteria and insects four phytosanitary treatments are done on average for each hectare. The first application is made when the first flower buds appear (30-35 days after sowing). The following applications are completed 14 days apart. The cotton complex (quantity recommended = 150 kg/ha) is applied at sowing or 15 days after it. The urea is brought to the field per 50 kg/ha dose once the flowers appear. Sometimes, the fertilizers dedicated to cotton are used for maize field resulting in a "*shifting practice*" (Laris *et al.*, 2015). The cotton is harvested at least three times from September to December. The cottonseed is weighted and collected by the CMDT in November and December.

Maize crop The maize cultivation starts by deep plowing and sowing at the beginning of the wet season. Two or three weedings are done during the vegetation growth. The hoeing is useful to conserve the soil humidity. When herbicides are available, they are applied in the fields. A thinning is done when the plant has 15 - 20 cm in height and the ridging is done when the plant measures 0.5 - 1 m. If organic manure is brought into the field, it is at the time of plowing. The quantity of organic manure fluctuates from 3 to 10 t/ha. The recommendations for mineral fertilizers applications are 150 kg/ha of urea and 100 kg/ha of DAP. Small applications of fertilizers are made several times during the growing season. The harvest starts early in September.

Sorghum and millet crops Farmers produce sorghum and millet seeds and treat them with fungicide and insecticide. The optimal period to sow millet and sorghum is from the 15th of May to the 15th of July, after a rainfall of 20 mm. The light plowing is done before sowing. The first weeding and the thinning are done 15 days after sowing. To maintain the field as clean as possible, two weedings are required along the growing season. Mineral fertilizers are seldom applied on millet and sorghum fields. The harvest is done from October to early December.

Fertilization Almost all the cotton producers interviewed use mineral fertilizer, supplied by the CMDT, on cotton and maize and follow the CMDT recommendations. Only 20% of farmers buy additional mineral fertilizer. Less than half of the farmers apply mineral fertilizer on millet and sorghum (53% for millet and 44% for sorghum). The banana producers use considerable amounts of mineral fertilizer for the banana plantation.

The organic manure is used primarily on cotton and maize fields (see Chapter 6, section 6.4.2.). As cotton is the first crop in the rotation, other crops benefit from the fertility carryover effect. The organic manure is produced from household compost pit, field compost pit, compost heap, and animals penning. The composition of pit and heap varies according to the farmers and can contain: cereal and cotton stems, weeds, fallen leaves, mud of the lowlands and animals feces.

Phyto treatments The insecticide and herbicide are supplied by the CMDT and applied, by men (dangerous and expensive product) essentially on cotton. Very few farmers use these products on other crops than cotton.

Gardening in the lowlands Just over half of the farmers (56%) cultivate small parcels in the lowlands for gardening (one parcel is approximately 0.25 ha) (Figure 3.7). The parcels are irrigated by hand and used mainly to grow shallots, tomatoes, potatoes, and banana. The production starts after cotton and cereals, around October. Vegetable production is an important source of income during the dry season.



Figure 3.7: Picture of the lowland in the Koningue commune.

Fallows 30% of farmers are likely to realize fallows in one of the following cases: (i) the soil is too weak; (ii) they lack labor force; (iii) they lack equipment; or (iv) they lack fertilizer. While fallows were historically spread within the

agricultural landscapes in SSA, cultivating crops continuously is more and more extended with fallows covering marginal areas (Gigou *et al.*, 2006).

Income and the place of cotton Farmers in the Sukumba village grow cotton for income generation. More than half of the farmers have an income strategy based on cotton only. Alternatively, half of the farmers diversify their income strategy. Seven farmers combine cotton and gardening incomes, three get their wage from banana, three other from peanut, five from cotton and cereals sales and finally five from extra-agricultural activity (Figure 3.8).

Almost half of the farmer (46%) indicate that they cultivate cotton to access fertilizers that benefit to cereals. Some farmer's words illustrate those concepts.

"When someone gets married, or someone gets cured, it is thanks to cotton. Besides, cotton offers benefits to cereals following in the rotation." ID 27

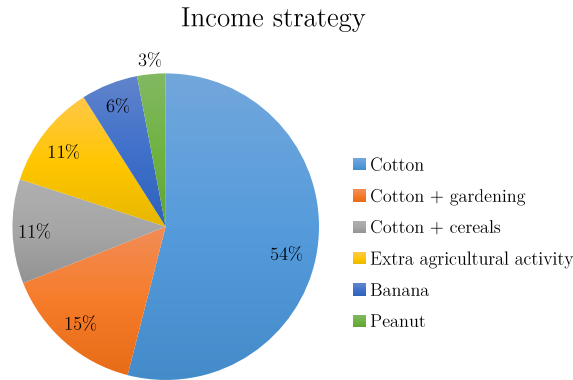


Figure 3.8: Repartition of the income strategies in the Sukumba village based on farmers' interviews.

"The cotton is very useful for the wedding and emergency needs. Shallots and potatoes are important to provide income at another time of the year." ID 19

"The cotton is not enough to provide income. I cannot buy any farm equipment. My only source of income, I get it from digging wells." ID 49

"The cotton does not contribute to income, but it is used to obtain a sufficient yield in other crops with fertilizer. My mechanic job is the activity that contributes the most to the household income and not the cotton." ID 11

"All I have, I owe it to the banana. I do not have enough land to cultivate cotton, and it is difficult to cultivate cotton and banana at the same time. I do prefer banana because if there is water, the production is good." ID 35

The difficulties to get large income from cotton is also related to low cotton production and dependence on fluctuating world prices. The recommendations and prices of seeds and fertilizers have been collected (Table 3.2).

Table 3.2: Prices of seeds, fertilizers and cereals in the Koutiala circle for the five main crop types (peanut, maize, millet, sorghum, and cotton).

			Pea.	Ma.	Mi.	So.	Co.
Quantity of seeds (kg / ha)			60-100	15-25	5-20	5-20	30
Price of seeds (FCFA/kg)			650	100-150	175-200	150-175	1070
Quantity of fertilizer (Number of bags of 50 kg/ha)	Urea		1	3	1	1	1
	NKP		0	0	1	1	0
	DAP		1	2	1	1	3
Price of fertilizer (50 kg in FCFA)	Urea	Subv	11655	11655	11655	11655	11655
		N. subv	18500	18500	18500	18500	18500
	NKP	Subv	11655	11655	11655	11655	11655
		N. subv	19500	19500	19500	19500	19500
	DAP	Subv	11655	11655	11655	11655	11655
		N. subv	25000	25000	25000	25000	25000
Tractor renting /day (FCFA)			25000	25000	25000	25000	25000
Household cereal consumption				+++++	+++	++++	
Crop price (FCFA/kg)			300-475	90-125	125-150	100-125	250

Extra-agricultural activities and exodus 40% of the interviewed farmers have a household member doing an extra-agricultural activity (*e.g.*, teacher, mechanic, dispenser, tailor) which contributes to the household income. In most of the interviewed farmers' families, some of the household's members leave the village for jobs or studies but do not help the family significantly.

"The young ladies stay at the beginning of the growing season, and then they go in the town to earn money." ID 38

3.5.2 Stakeholders and decision levels

In the Minyanka community, five stakeholders levels are generally observed (Figure 3.9). At the community level, the management of pastures and the access to water are regulated. Shepherds are grazing with animals from different farmers. It is also at the community level that some groups of women, named "*tontine*", offer services to farmers.

The household level includes all members of the household chief's family. The size of a household is highly variable and depends on the family separation degree. The household chief is the oldest person. The household might include various sub-households corresponding to a man, his wife(s) and their children. The household level contains all activities done by the household members while the production unit (PU) level includes all the activities linked to agricultural production. The PU chief can differ from the household chief for health reasons or old-age. Some household members do extra-agricultural activities outside the PU level (including jobs, milk seller, wood, and picking producers).

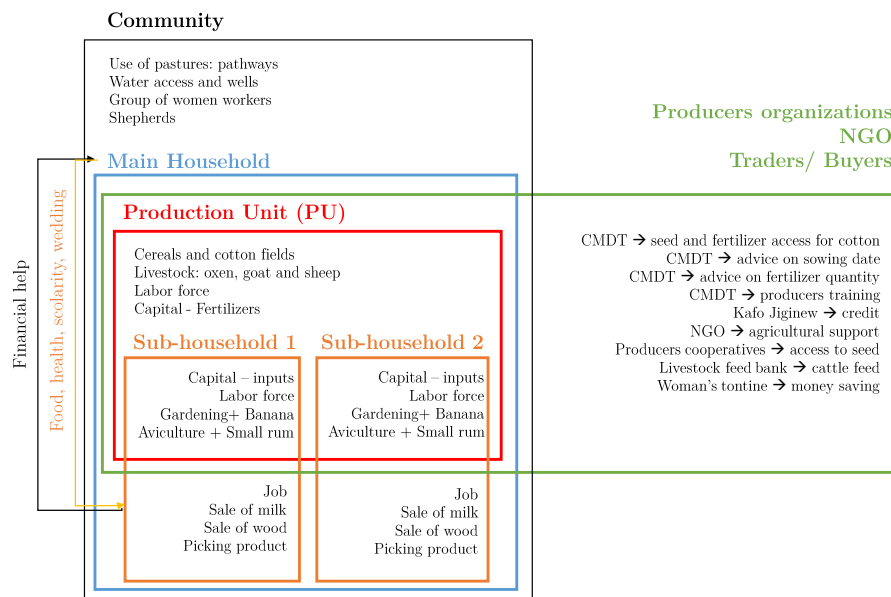


Figure 3.9: Stakeholders and decision levels for the Minyanka community based on interviews in the Sukumba village.

The PU (farm) level concerns all activities linked to the agricultural production including cereals, cotton, gardening, and livestock. Most of the time, the cereals and cotton fields are managed by the PU chief and cultivated by all members of the household, no matter the sub-household. Most of the livestock is controlled by the PU chief who designates a shepherd inside the household members. The sub-households complete specific production activities for themselves, such as gardening, aviculture, small ruminants husbandry. External organizations (PO, NGO, traders, buyers) play a key role at the PU level. The CMDT directly impacts the PU by giving access to seed and fertilizer for cotton and maize. CMDT also advices on sowing and fertilization and organizes producers training (either for agricultural practices or alphabetization). The Kafo Jiginew bank saving offers credit to the farmer through PO. The PO has to vouch for the farmer. Other organizations such as producers cooperatives (for shea butter or potato or shallot), women's "tontine", and livestock feed bank also play an important role at the PU level (Figure 3.9).

Distribution of the agricultural works The primary activity of men is agriculture. In some cases, men also complete extra-agricultural activities. Men give part of the cereals production to women for food preparation and contribute to school fees, health fees, and wedding fees. On the other side, women manage the homestead, cook, and look after the children. They contribute to agricultural

works mainly for harvest and sowing but also for thinning and organic manure spreading. When possible, women cultivate vegetables and spices in little fields (<0.15 ha) next to the house to diversify as much as possible their food basket. They also trade various products such as wood, picking products, food, traditional beer to get some money to buy food, clothes or cooking equipment. Children often contribute to agricultural works during their free time. The pupils work in the fields during holidays and after school. They often graze with the livestock or help in the plowing by holding the rope of the oxen.

The extra household labor force 66% of farmers hire extra people to work in their fields for the harvest, the organic manure and fertilizers spreading, the banana plantation, and looking after the livestock.

3.5.3 Constraints for agricultural production

During the interviews, we asked each farmer to identify its main constraints (1 or 2 maximum). Then we developed each constraint to get some details. In total, the 50 farmers mentioned 34 times the lack of man as a constraint, 21 times the fertilizers, 13 times the climate, four times the soil, four times the land scarcity, three times family conflict and three times striga. The repartition of the main constraints is presented on Figure 3.10. Only a few farmers mentioned the soil as the main problem, but once we speak about the soil, they inform to have difficulties such as low fertility, erosion, acidity, soil depth and soil depletion (subplot on Figure 3.10). Some farmer verbatims are presented here below for the different constraints.

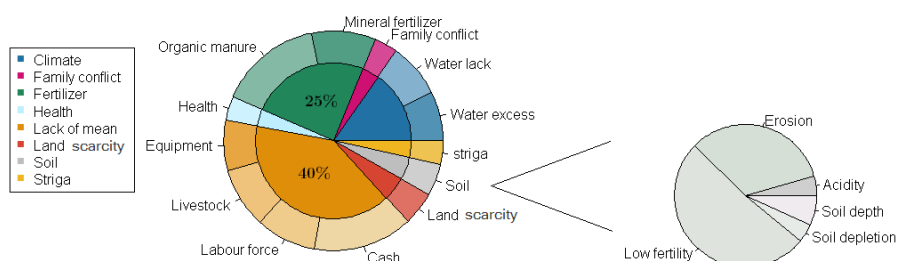


Figure 3.10: Main constraints according to farmers in the Sukumba community identified with semi-structured interviews. The inner pie chart represents the main constraints while the outer pie chart provides details about the constraints.

"The main constraint is the equipment. I'm forced to plow with donkey because I lack plowing oxen. I also lack labor force." ID 3

"For me, the main constraint is the organic manure. Even if it rains a lot, if you have no organic manure, the production will be low. I would love to buy some, but I do not find any." ID 7

"Due to my labor force and my equipment, I can easily cultivate all my fields. My only problem is the rain." ID 18

"The workers need to have the same willingness and the same goals to be able to progress together." ID 47

Lack of means

The lack of money affects lots of farmers that would like to buy equipment, livestock and also employ extra labor forces. The lack of labor force strongly affects the timing of the agricultural works. Some farmers face a reduction of herd size due to debts reimbursements to the PO relative to low cotton production unable to reimburse the CMDT credits. The PO guarantees a bridge credit giving to the farmer more time to refund the debt. Nevertheless, this is not always sufficient, and some farmers are constrained to sell part of their herd.

The lack of equipment, especially tractors, is mentioned by some farmers. A tractor costs approximately 15 million FCFA. The first tractor was bought in 1976 in the Koningue commune, and today four households are equipped with a tractor in Koningue.

"We lack plowing oxen which makes difficult to start field works on time." ID 20

"I do not have enough money. I would like to have the equipment to be able to do all the agricultural works and stop digging wells. But for now, I do not have the choice; I'm doing so to survive." ID 49

Lack of fertilizer

Mineral fertilizer 74% of farmers think that the quantity of mineral fertilizer is not sufficient. Nevertheless they cannot have access to more fertilizer for the following reasons: (i) difficulties in fertilizer supply at the PO due to CMDT restrictions, (ii) lack of money, (iii) fear of falling into debt, (iv) fear of soil behavior if too much mineral fertilizer is applied without enough organic manure.

If more mineral fertilizers were available, they would first apply it on cotton fields to avoid debt and earn money. Then, they would put it in maize fields as maize requires high fertilizers amount and finally in sorghum and millet fields (see Chapter 4).

"Mineral fertilizers are not sufficient because I cannot put it on all my crops while they all need some." ID 2

"Mineral fertilizers are not sufficient. I take what they give to me, and sometimes I buy some outside the PO, but this year it was not possible." ID 18

The cropland scarcity, the suppression of fallows and the cultivation of marginal lands due to demographic pressures directly result in low soil fertility in southern Mali (even if it is still high when compared to Malian standards). Mineral fertilizers have to be combined with organic manure that improves water retention and gives potassium inputs (Crétenet *et al.*, 1994). In Mali, natural soil fertility features phosphorus deficiency, yet mineral fertilizers easily compensate for this. However, the cotton crop is very sensitive to the amount of K, and the K requirements are not satisfied by the mineral fertilizers. In fact, in the first years of cultivation (5 to 10 years after clearing), the yield is mainly determined by water availability and mineral fertilizer (Nitrogen essentially). After 10-15 years cultivating a field, a potassium-deficiency appears if the field is not enriched with organic manure and this results in yield losses (Crétenet *et al.*, 1994). Bationo *et al.* (1998) mentioned that mineral fertilizers have to be combined with a return of crop residues and manure to reach productive and sustainable systems.

Organic manure All farmers lack organic manure (see Chapter 6, section 6.4.3.). The small quantities they can get are applied to cotton, maize or banana fields. Most of the farmers would buy organic manure if possible. Farmers are aware of the long-lasting effect of organic manure in comparison to mineral fertilizer. If more organic manure was available, they would apply it in cotton fields to avoid debt, increase the income and marry the children. Besides, as cotton is the first crop in the rotation, organic manure residual effects will benefit to cereals. Some farmers prefer to apply organic manure on maize fields for food security and to limit the lean season.

"The organic manure is never sufficient. There is not enough waste to produce organic manure. You cannot buy some in Sukumba. In Koutiala, it is possible to buy some but it is costly to bring it to the village. You need a contact at the CMDT to do that and make it profitable." ID 6

"The problem is that the organic manure is not rich enough because it does not last enough time in the pit. So I have to increase the quantity due to the low quality. If I put small amount of organic manure, I don't get anything." ID 42

Cultivated soil characteristics

The farmers cultivate four types of soil: sandy, gravelly, loamy and clayey soils. Most of the farmers agree that soils are less fertile than before due to an extended period of cultivation. The difficulties encountered vary according to the soil. Sandy soils are weak, and water run-off removes the fertilizers. Gravelly soils are poor, moderately deep and dry which is enforced with low rainfall. Clayey soils suffer from water accumulation. Loamy soils are the more favorable for agriculture purposes. Farmers often cultivate more than two types of soil and face different challenges. To limit the erosion impact, different strategies are used by farmers: ridge tillage, canals to direct water, and construc-

tion at the border of the fields (with cereal stems and stones) to limit water flow.

Ridge tillage farming is used to increase the water infiltration and to stop soil erosion. This increases the Carbon sequestration, crop growth and crop biomass (up to 50% of increase for millet, sorghum, and maize in the driest years) (Gigou *et al.*, 1997; Traoré *et al.*, 2002). The contour ridges are permanent and covered with perennial vegetation. They cover approximately 2 to 4% of the field.

"The sandy soil is poor and requires a huge amount of organic manure. One year you bring organic manure, but the year after, you should again bring some because everything is already gone." ID 22.

"On the loamy soils, the production you obtain within 1 hectare corresponds to the production of 2 hectares here in the poor and eroded sandy soils." ID 25

"On gravelly soils, you have problems if the precipitations are spare. They are also very difficult to work in." ID 32

"On the clayey soils, the water stagnates and causes damage. On the sandy soil, if the rainfalls are abundant, the seeds do not grow fast. On the gravelly soil, if the rainfalls are too sparse, it is too dry." ID 42

The soil potential corresponds to the relative strength for crop production of each soil for all farmer's fields. The soil potential of the different types was described by farmers, during the interviews, as followed:

$$\begin{array}{ll}
 \textit{Gravelly} < \textit{Sandy} < \textit{Clayey} < \textit{Loamy} & 55\% \text{ of farmers} \\
 \textit{Sandy} < \textit{Gravelly} < \textit{Clayey} < \textit{Loamy} & 33\% \text{ of farmers} \\
 \textit{Gravelly} = \textit{Sandy} < \textit{Clayey} < \textit{Loamy} & 12\% \text{ of farmers}
 \end{array} \tag{3.1}$$

There is only disagreement in the potential of sandy and gravelly soils.

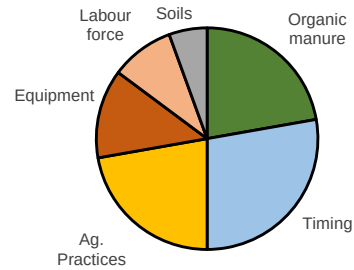
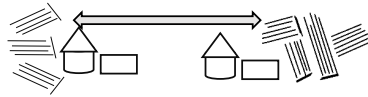
3.5.4 Yield heterogeneity explanatory factors

To get in the context of next chapters, the yield heterogeneity is discussed with farmers at three levels: (i) the inter-farms yield heterogeneity, (ii) the intra-farm yield heterogeneity and (iii) the intra-field heterogeneity. For each level, farmers are asked to mention the main factor (1 or 2 factors accepted maximum). At the farm level, the farmers were asked to compare their fields with their neighbors. The main factors explaining the inter-farms yield heterogeneity (as identified by the surveys), are the agricultural practices, the timing of these practices and the quantity and quality of the organic manure (Figure 3.11).

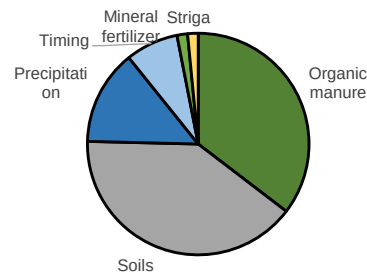
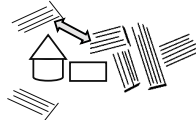
"The soil is the same as the neighbors, but the field works vary greatly. Some farmers are richer and can plow with the tractor." ID 3

"The agricultural practices are somehow similar but what does change is the timing of sowing and other works." ID 11

Inter-farms yield heterogeneity



Intra-farm yield heterogeneity



Intra-field yield heterogeneity

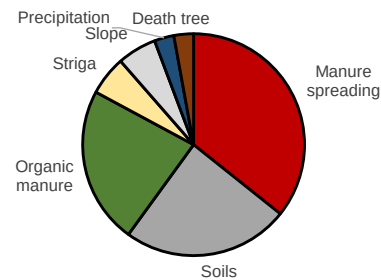
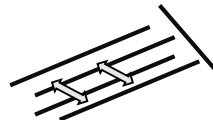


Figure 3.11: Main explanatory factors of yield heterogeneity mentioned by farmers at three scales: inter-farms heterogeneity, intra-farm heterogeneity and intra-field heterogeneity from top to bottom.

The intra-farm heterogeneity is mainly explained by soil types and organic manure (Figure 3.11). Farmers often cultivate in different places, one to five kilometers away. This leads to strong contrasts in the cultivated soils. Limited organic manure is only applied in a few fields increasing the intra-farm heterogeneity. The precipitation and the timing of field works also influence the yield.

"The gravelly soil will never give the same yield than the clayey soil. Besides, the organic manure plays a key role for the yield." ID 9

"In the lowland, the sowing was done first and the soils are better, so the yield is high. On the plateaus, the sowing was done late, and the soil is poor, so the yield is low." ID 31

"You cannot compare the hamlet with the village because the soils are very different. In the village, it is much better than here. Here, you only see the effect of the organic manure." ID 50

Intra-field heterogeneity is mainly caused by the spreading of the manure. The organic manure spreading is most of the time done by piles. Each pile is then widespread but more fertilizer remains at the exact location of the pile. The quantity and the quality of the organic manure are amplified by local soil patterns (Figure 3.11). The quality of the organic manure directly depends on the production. Dead trees also influence the organic content of the soil and increase the yield.

"We cannot put the same quantity of organic manure everywhere because there is not enough. When we start to spread manure, we think that we will spread the entire field but the more we go on, the more the quantity decreases." ID 6

"The organic manure is not spread with the same quantity all over the field. As an example, children do the spreading, so we can not control everything." ID 31

"There is a portion of the field where I put goat feces, and it always yields to higher production." ID 32

"The striga complicates the growth of the millet plants in the Sougounlasso field." ID 34

3.6 Conclusions

Mali's cotton belt is one of the more prosperous regions of southern Mali with a high level of cotton and cereals productions. Nevertheless, cotton farmers are amongst the poorest and most malnourished farmers of the whole of southern Mali. Thanks to farmer interviews conducted in the Koningue commune, we identified the main farmer constraints, the cause of production variability and the farming systems characteristics. The cotton sector is managed and controlled by the CMDT and farmers are victims of fluctuating world price and access to credits defined by CMDT. Besides, farmers faced constraints such as lack of means (including money, equipment and labor force), lack of fertilizer and climate variability that directly affect cotton production and hence income generation.

The malnutrition of cotton farmers is mainly related to a low-diversified food basket. The income generated by cotton production goes directly into the men's hands and very few are given to women while they are in charge of the household food supply.

Crop productions variability is an indicator of potential agricultural productivity improvements in a specific region. According to the farmer interviews, the inter-farms yield heterogeneity is mainly related to agricultural practices, organic manure and timing of field works. The intra-farm yield heterogeneity is related mostly to organic manure application and soil. Understanding the local context of farmers with a perception-based farming system description is an essential step to build to methodologies of next chapters taking place in the same region.

Chapter 4

Quantifying fertilizer application response variability with VHR satellite NDVI time series in a rainfed smallholder cropping system of Mali *

Highlights

- NDVI is directly related to crop height and ground coverage that are dependent on fertilization.
 - Within a single field, on average 50% of NDVI variance is due to fertilizer for half of the studied fields.
 - Field management and catena position affect stronger crop NDVI response than fertilizer applications.
 - Working in similar plant growth conditions is crucial in complex smallholder cropping system when studying the spatial and temporal response of vegetation.
-

*Adapted from Blaes, X. Chome, G. Lambert, M.-J. Traore, P.C.S. Schut, A.G.T. and Defourny, P. (2016). Quantifying Fertilizer Application Response Variability with VHR Satellite NDVI Time Series in a Rainfed Smallholder Cropping System of Mali. *Remote Sensing*, 8, 531. The author contributions is as followed: Xavier Blaes and Guillaume Chomé designed the field campaign protocol and coordinate the field data collection. Xavier Blaes, Guillaume Chomé, and Marie-Julie Lambert designed and carried out the data analysis, the methodology development and the interpretation of results under the supervision of Pierre Defourny. Marie-Julie Lambert was in charge of the satellite image preprocessing, Guillaume Chomé performed the statistical variance decomposition and Xavier Blaes coordinated UAV images processing. Pierre Sibiry Traoré and Antonius G. T. Schut directly contributed to the data interpretation. All the authors participated in the writing.

Abstract. Soil fertility in smallholder farming areas is known to vary strongly on multiple scales. This study measures the sensitivity of the recorded satellite signal to on-farm soil fertility treatments applied to five crop types, and quantifies this fertilization effect with respect to within-field variation, between field variation and field position in the catena. Plant growth was assessed in 5–6 plots per field in 48 fields located in the Sudano-Sahelian agro-ecological zone of southeastern Mali. A unique series of Very High Resolution satellite and Unmanned Aerial Vehicle (UAV) images were used to calculate the NDVI. In this experiment, for half of the fields at least 50% of the NDVI variance within a field was due to fertilization. Moreover, the sensitivity of NDVI to fertilizer application was crop-dependent and varied through the season, with optima at the end of August for peanut and cotton and early October for sorghum and maize. The influence of fertilizer on NDVI was comparatively small at the landscape scale (up to 35% of total variation), relative to the influence of other components of variation such as field management and catena position. The NDVI response could only partially be benchmarked against a fertilization reference within the field. We conclude that comparisons of the spatial and temporal responses of NDVI, with respect to fertilization and crop management, requires a stratification of soil catena-related crop growth conditions at the landscape scale.

4.1 Introduction

The demographic explosion of SSA presents significant challenges for food production, which cannot be achieved without agricultural intensification (Godfray and Garnett, 2014). Smallholder systems are characterized by enormous yield gaps (van Ittersum *et al.*, 2013) which may be reduced through integrated soil fertility management, improved crop-livestock integration, multi-purpose crops, and other sustainable intensification practices (Panel, 2013). These options will, however, be implemented in an evolving socio-economic and climatic context where multiple drivers of change may increase exposure to risk, alter patterns of vulnerability, and open opportunities for agricultural development, especially through changes in urban demand, market access, Information Technology (IT) penetration, and social differentiation (Padgham *et al.*, 2015). The huge variability in farming and cropping practices (Giller *et al.*, 2011) and returns on investments already observed today (Bielders and Gérard, 2015) is therefore likely to exacerbate in the future. Higher dependency on information may entail additional risk for smallholders and other agricultural stakeholders, notably in the presence of information asymmetries (Jacques *et al.*, 2018).

Monitoring changes in productivity across scales is a daunting challenge indeed in heterogeneous smallholder systems, for example in Mali’s cotton belt. In this area, with an increasing land shortage and reduced options for fallows (Soumaré, 2008), farmers rotate crops and apply manure, crop residues, household waste and compost to manage soil fertility in increasingly fragmented fields (currently 1.4 ha on average). Inorganic NPK fertilizer is commonly applied to cotton and maize in moderate quantities, but overall low organic

matter content and nutrient deficiencies prevail. Catenary variation in soil properties is well known to farmers (Gobin *et al.*, 2000), and hence determines in part land management practices and observed spatial cropping patterns across the landscape. Field position on the topo-sequence influences soil fertility management (Gandah *et al.*, 2003), crop types and rotations (Stoop, 1987), agro-biodiversity management (Bazile *et al.*, 2008) and agro-forestry practices (Traoré *et al.*, 2004). However, this seemingly clear-cut relationship of soil characteristics with landscape position is obscured by farm management, the complex superposition of farm-centered management rings (Prudencio, 1993), by unequal farmer endowment and resource use (Ramisch, 2005), and by several other abiotic and biotic factors of random variability (Wilding *et al.*, 1983).

Fortunately, modern information technologies including remote sensing can help to monitor crop performance at levels of granularity increasingly compatible with smallholder farming (Atzberger, 2013). This may open practical support applications for precision agriculture, allowing the exploitation, rather than the mitigation, of spatial heterogeneity, and the demonstration that increased productivity and enhanced livelihoods are not necessarily antithetical with complex cropping systems, and may actually thrive on the latter. This study focuses on the analysis of remote sensing's potential to retrieve crop status information at sub-field scales in heterogeneous smallholder rainfed production systems. The objective of the chapter is to measure the sensitivity of the NDVI signal to on-farm fertility treatments applied to five locally important crops: cotton, pearl millet, sorghum, maize, and peanut. These five crops represent over 84% of the harvested area in Mali's old cotton belt (You *et al.*, 2014). NDVI sensitivity to fertilizer applications was first analyzed at the field scale. For each crop, the amplitude and period of strongest plant response to fertilization are discussed. The spatial variance components were quantified with respect to the effects of fertilization and to within and between field variability associated with management, soil characteristics and catena position in the landscape.

4.2 Data acquisition and processing

As part of the STARS project, an intensive coordinated ground and remote sensing campaign ran during the 2014 and 2015 growing seasons in the Koutiala District (Mali) and the Bebeji Local Government Area (Nigeria). The aim was to assess the performance of remote sensing imagery for crop monitoring in smallholder farming systems. Remote sensing data acquisitions and analyses involved both VHR satellite and UAV imagery. A set of variables was concurrently collected *in situ*, following a standardized protocol for both sites, and synchronous with bi-weekly UAV and (cloud cover permitting) satellite data acquisitions. This chapter reports on data collected in the Koutiala district (Mali) in 2014.

4.2.1 Study site

The study area is situated within the terroir of the Sukumba community (commune of Koningue, Koutiala District, Sikasso Region) in the southeastern part of Mali located in the Soudano-Sahelian region (Figure 4.1) where rainfed cropping is the standard practice. Forty-eight farmer fields were selected to host fertility treatments, sampling a topo-sequence from alluvial lowlands (altitude of 350 m above sea level) to the top of the plateau, with slopes characterized by breaks with locally steep inclines (total elevation difference of about 50 m). To get more information on the study site, please refers to Chapter 3.

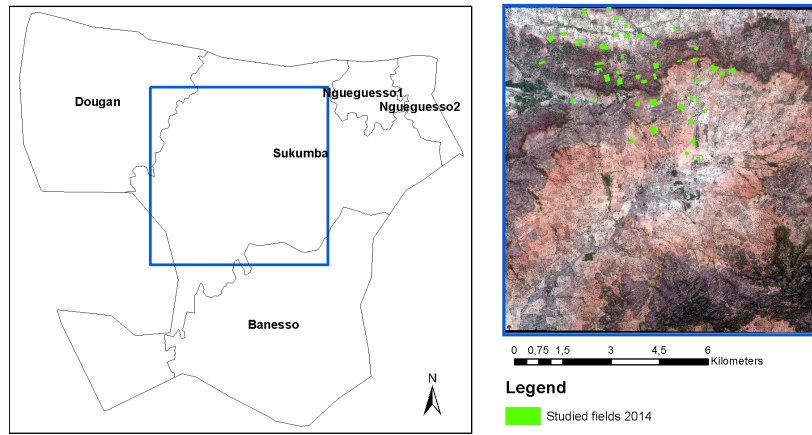


Figure 4.1: Sukumba site, near Koutiala in southeastern Mali. The 10 km $\times$ 10 km blue box locates the VHR imagery acquisition. The *in situ* bi-weekly monitored fields represented by green boundaries are spread along a catena transect from plateau (north) to lowland (south). Background imagery is a GeoEye RGB color composite from 24 June 2014.

4.2.2 VHR Satellite Series

A dataset of 15 images was acquired by the DG satellite constellation during the 2014 growing season over a 10 km $\times$ 10 km area centered on the Sukumba village (Table 4.1). The spatial resolution of these images varies from 0.5 m to 0.61 m for the panchromatic band and from 2 m to 2.44 m for the multispectral bands. This constitutes an unprecedented dataset for Sudano-Sahelian smallholder agriculture.

In order to ensure accurate imagery geo-location in a landscape characterized by relatively few artificial human-made structures, a set of 65 Ground Control Points (GCP) was used. Some GCPs were located on rock outcrops but most GCPs were concrete structures with a standard cross shape (width: 120 cm; thickness: 20 cm). All the GCPs were painted white around mid-August of 2014. They are easily identified on satellite images while they were initially

Table 4.1: Available Digital Globe images series acquired over the Sukumba site, Mali in 2014 including GeoEye 1 (GE01), WorldView 2 (WV02) and QuickBird 2 (QB02). The right column (Correction Method) refers to the specific type of processing applied to the images as described below.

Acquisition Date	Satellite	Product Level	Product Type	DEM Correction
1 May 2014	GE01	LV2A	Standard	Coarse DEM
22 May 2014	WV02	LV3D	Orthorectified	Fine DEM
30 May 2014	WV02	LV3D	Orthorectified	Fine DEM
18 June 2014	QB02	LV2A	Ortho ready	Base Elevation
24 June 2014	GE01	LV3D	Orthorectified	Fine DEM
26 June 2014	WV02	LV2A	Ortho ready	Base Elevation
8 July 2014	GE01	LV2A	Standard	Coarse DEM
11 July 2014	QB02	LV2A	Ortho ready	Base Elevation
29 July 2014	WV02	LV2A	Ortho ready	Base Elevation
7 August 2014	GE01	LV3D	Orthorectified	Fine DEM
26 August 2014	GE01	LV2A	Standard	Coarse DEM
4 October 2014	QB02	LV2A	Standard	Coarse DEM
18 October 2014	WV02	LV2A	Ortho ready	Base Elevation
1 November 2014	WV02	LV2A	Ortho ready	Base Elevation
14 November 2014	WV02	LV2A	Ortho ready	Base Elevation

designed for the georeferencing of images acquired by a UAV operating only in the northern part of the 10 km $\times$ 10 km study area. Additional GCPs corresponding to a fence or hedge corners were identified in the southern part of the study area. The geographic coordinates of GCPs were recorded with a differential GPS system with centimeter accuracy.

The complete set of GCPs covering the entire study area is only visible on images acquired after mid-August. Moreover, various processing levels have been applied by DG on the TS; some were orthorectified (the so-called Standard and Orthorectified product types), while others were not (Ortho ready product type). Therefore, combining these two constraints, four dedicated geometric correction approaches were used to ensure that the TS were geometrically consistent. The four correction methods as reported in Table 4.1 are:

- 1. Ortho ready DG-products with no digital elevation model (DEM) correction by DG (base elevation) were orthorectified using Shuttle Radar Topography Mission (SRTM) 30 m DEM and GCPs when available, *i.e.*, after 26 August 2014. Out of the total set of 65 GCPs, a subset of 38 GCPs was used to correct the 18 October 2014 image. Orthorectification resulted in a geometric accuracy of 0.84 m (RMSE), assessed on remaining GCPs not used for orthorectification. This image was thereafter taken as a master image to geometrically correct the other images in the absence of GCPs (methods 2 and 4 in Table 4.1). The same set of GCPs was used to orthorectify the three last ortho ready standard images of the series using the same method.
- 2. Ortho ready DG-products acquired before 26 August were first orthorectified with the SRTM 30 m DEM without any GCP, and were subsequently co-registered to the master image (*i.e.*, 18 October 2014 image orthorectified with the first method as describe here above) thanks to

an automatic image-to-image registration algorithm providing 25 tie-points well distributed over the image.

- 3. Products orthorectified by DG are of two types: standard product orthorectified using a coarse DEM (SRTM 90 m) and orthorectified product pre-processed by DG with fine DEM (SRTM 30 m). Both product types were simply georeferenced with the set of 38 GCPs for dates after 26 August 2014.
- 4. Products orthorectified by DG (both standard product and orthorectified product types) acquired before 26 August 2014 were georeferenced using the master image by automatic image-to-image registration (as mentioned above for case 2).

Orthorectified image digital numbers were then converted to TOA reflectance (Podger, 2011; Updike, 2011). Clouds and cloud shadows were detected using an unsupervised classification and then the areas were masked out. All the processing methods resampled the images at a 2 m pixel size using the nearest neighbor algorithm. GCPs were visualized first on panchromatic images (to increase the precision) and then applied to the multi-spectral images.

4.2.3 *In situ* data collection

Soil fertility Trials

Cropping systems in the Koutiala district are based on cotton, maize, sorghum, and millet rotations. The five main crop types that were covered by the field campaign also included peanuts. Under rainfed conditions, the growing season ranges from late May to November. A set of 48 farmer fields was selected to monitor plant growth and development during the 2014 growing season. To cover the wide range of within-season variation that may be encountered in these heterogeneous environments, suitable fields (farming management units) were identified through a participatory selection process along the catena to adequately sample gradients in soil physical and chemical properties. Within each farmer field monitored, fertility treatment plots were included to ensure a full range of variability that may be present in the local landscape. A standardized protocol (Blaes *et al.*, 2015) with recommended fertilizer type and quantity for each crop type was used (Table 4.2). Urea was applied at earing, and other fertilizers at sowing. The fertility experiment layout is schematized in Figure 4.2. Within each field, five (cotton, maize, and peanut) or six (millet and sorghum) plots of 15 m x 15 m were picketed (Figure 4.2: solid outline boxes). One plot, and the remainder of each field was managed as per farmer practice (Figure 4.2: dashed outline box). Plant growth, development, biomass and grain yields were measured in all plots. Each participating farm could contribute only one field. Small field sizes did not allow for replicates within a single field, but instead, treatments were replicated (10 cotton, 10 maize, 10 millet, 9 peanut and 9 sorghum fields) across the landscape.

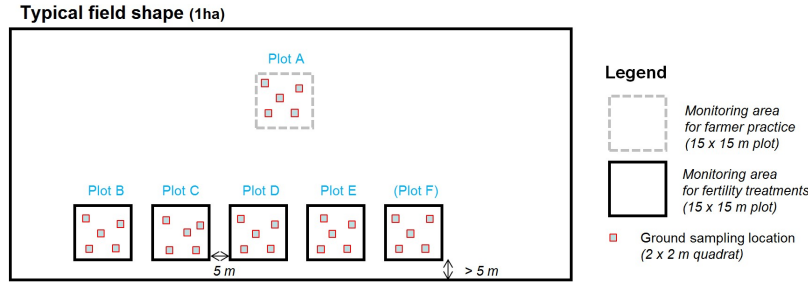


Figure 4.2: Schematic layout of the experiment in a hypothetical field of 1 ha.

Table 4.2: Fertility levels (kg/ha) for each plots of each crop type (five plots (B-F) for millet and sorghum field; four plots (B-E) for maize, peanuts, and cotton). DAP stands for Di-Ammonium Phosphate with 18% N, 46% P₂O₅ and 0% K₂O; “15-15-15”, locally called “complexe céréales” is also a NPK fertilizer with 15% N, 15% P₂O₅ and 15% K₂O; “Cotton complex”, locally called “complexe coton” is a NPKSB fertilizer with 14% N, 18% P₂O₅, 18% K₂O, 6% S, and 1% BO₃; Profeba is a compound organic fertilizer, locally called “sabunyumman” (Samake, 2015b) containing cattle manure, poultry manure and 14% N, 5% P, and 1% K in addition to various other micronutrients; Urea contains 46% N.

Millet/Sorg	DAP	15-15-15	Urea	Kg N/ha	Kg P/ha	Kg K/ha
B				0.0	0.0	0.0
C			50	23.0	0.0	0.0
D	75		50	36.5	15.1	0.0
E	150		50	50.0	30.1	0.0
F		150	50	45.5	9.8	18.7
Maize	DAP	15-15-15	Urea			
B		100	150	84.0	6.5	12.5
C	100		150	87.0	20.1	0.0
D		200	300	168.0	13.1	24.9
E	200		300	174.0	40.1	0.0
Peanut	DAP					
B				0.0	0.0	0.0
C	50			9.0	10.0	0.0
D	100			18.0	20.1	0.0
E	150			27.0	30.1	0.0
Cotton	Co Complex	Profeba	Urea			
B				0.0	0.0	0.0
C	150		50	44.0	11.8	22.4
D	200		100	74.0	15.7	29.9
E	200	10.0	100	109.6	43.1	6.0

Crop development

Within each plot, five 2 m × 2 m quadrats were used for bi-weekly ground-based monitoring of plant development and growth, synchronous with UAV image acquisitions. There are therefore, 25 quadrats (5 quadrats for each of the 5 plots) per field for cotton, maize, and peanut; and 30 quadrats (6 plots × 5 quadrats) for millet and sorghum. The 4 corners of each plot were semi-permanently picketed and their position recorded with a differential GPS with centimeter accuracy in order to measure the exact same location at each field visit. At each bi-weekly field visit, non-destructive measurements of crop status, BBCH phe-

nological development stage (Meier, 2001), weed prevalence rate, plant height, and ground cover (GC) fraction were assessed for each $2\text{ m} \times 2\text{ m}$ quadrat following standardized protocols (Blaes *et al.*, 2015) and recorded in dedicated data entry forms on smartphones.

The GC fraction of the soil background by green plant material was estimated using vertical photographs. These were taken with a 35 mm lens camera mounted on an L-shaped, 3 m telescopic pole, from nadir view above the canopy. Images were processed using the CAN-EYE freeware (Weiss, 2011) to determine GC fraction by a human interactive process classifying pixels into bare ground and green vegetation classes.

Farming practices

Information concerning crop type and variety, soil texture, and agronomic practices (soil preparation, sowing, weeding, fertilization, harvesting, etc.) was recorded for each of the 48 fields. After harvest, farmers also provided the fresh weights of total aboveground biomass and reproductive parts (quantified, for example, in number of carts or bags) for the entire field.

4.2.4 UAV data acquisition and processing

A SenseFly eBee with Canon S110NIR camera (R, G, NIR bands) was used to acquire image mosaics every two weeks (synchronously with field measurements) (Weiss, 2011). Flight plans were optimized to cover the 48 fields located in the northern part of the study area (Figure 4.1) in 7 flights, with each flight surveying a cluster of fields. Image acquisition settings ensured a 70% lateral and 75% longitudinal overlap and a target pixel resolution of approximately $10\text{ cm} \times 10\text{ cm}$ on the ground.

All the pictures of a given flight were acquired with the same camera settings optimized shortly before takeoff. The shutter speed was set to maximum, *i.e.*, $1/2,000$; and the sensitivity (ISO) and focal length settings were adjusted in order to slightly under-expose the picture (avoiding any saturation in the images). The Canon camera records images in a raw format (.CR2). They are first converted to TIF format using eMotion software. Then, AgiSOFT Photoscan Pro was used to generate a Digital Surface Model (DSM) and an orthomosaic. For accurate image geolocation, the set of 50 GCPs distributed throughout the entire area of the 7 clusters was used. These GCPs were manually geo-located for each image to ensure an accurate point cloud for DSM generation and geometric correction as required for image mosaicking.

4.3 Methods

In order to assess the sensitivity of the NDVI response to the fertilization, the methodology included four main steps. Firstly, the seasonal temporal NDVI profiles are presented for each crop type and fertilization levels. Secondly, for

each crop type and acquisition date, the potential to detect the fertilization treatments at the field scale was analyzed. Thirdly, the relationships between NDVI and plant growth (*e.g.*, GC fraction and height) were assessed. Finally, per crop type effects of fertilization treatments were compared to variation within and between fields in relation to catena position, farming practices, and the soil type.

4.3.1 Seasonal NDVI profiles under different fertilizer applications

We first graphically assess the overall impact of fertilization by extracting the NDVI response from plots observed in the VHR satellite images. The mean and standard deviation were computed per crop type for each fertilizer application (plot B to F) and from emergence to senescence. We discuss the fertilization effect with regard to landscape-scale variability.

4.3.2 Detection of fertilizer application responses at the field scale

In order to quantify the fertilization effect with regard to the total NDVI variability within one field, the variance components are estimated using an ANOVA variance decomposition method. The variance is decomposed for each field at each date (from crop emergence to harvest) using as inputs all individual pixels falling within the limit of the monitored fertilization treatment plots B–E (B–F for millet and sorghum: Figure 4.2). For this method the determination coefficients (R^2) estimates the part of variance explained by the fertilization treatment (B–E or B–F) with respect to the total variance, and thus measures the ability to discriminate fertilization treatments using NDVI. A high R^2 shows that at least one fertilization treatment affects the NDVI response. The R^2 distribution among fields of a given crop type informs about the possibilities to assess fertility levels in relation to a reference plot within the same field. A higher median R^2 indicates better discrimination of fertilization levels using NDVI for a given crop type at a given date. The R^2 distribution spread measures the consistency of the fertilizer application response between the different fields of a given crop type. R^2 values were marked as outliers when more than 1.5 times the interquartile range below quartile 1 or above quartile 3.

The normality of the residuals distribution has been verified. To validate the independency hypothesis, the spatial correlation is assessed using variograms of a UAV orthoimage acquired on 10 September 2014. Variograms were developed using the “gstat” add-on package available in the R software. Additionally, given the difficulties to compute quantitative fertilizers amount due to the combination of different fertilizers, we identify the dose increment leading to the strongest response through a 2-by-2 comparison of NDVI means for each available dose increment. This was done for the (crop-specific) date of maximum fertilizer response. The date with the highest proportion of fields with a significant (t-test

at $p = 0.05$) response to fertilization increments was defined as the date with the strongest effect of fertilizer application on crop NDVI response.

4.3.3 Relationships between plant growth indicators and NDVI

Linear relationships between NDVI, GC, and plant height were established for each crop type separately using least-squares. Each observation for GC and plant height was a mean per plot. The NDVI was determined as the mean of all pixels within a plot. The 26 August 2014 image was selected as it corresponds to the period of maximum green biomass and for this date, *in situ* data were also available. The image of 10 October 2014 was probably a better choice, as GC was larger in that period for cotton, sorghum, and millet but field data were not collected for these crops at this image acquisition date.

4.3.4 Detection of crop fertilization treatments at landscape Level

The NDVI response of a given crop type at a given date may also differ due to landscape position determining soil physical and chemical properties, agronomic management (including fertilizer application, sowing, weeding and harvesting dates) and thus plant growing conditions. Accounting for systematic variation in any of these factors can improve discrimination between fertilizer application amounts and other management practices. A hierarchical linear model was set up for each crop type to decompose the total NDVI variance to estimate the contribution of three components of variation: plot (induced by fertility treatment), field (mostly induced by other management factors) and landscape (mostly induced by environmental factors, including soil and elevation). The hierarchical model was selected, as fields are subordinate to strata while fertilizer application treatments were replicated in these fields. The average NDVI per plot was the dependent variable in the model. Therefore, a generalized linear model was fitted to the data, including all plots with treatments B–E (B–F for millet and sorghum), within the design matrix the categorical variables plot, stratum, and fields. Fields factor was nested within the stratum. The GLM procedure in S.A.S. software (version 9.3) was used to fit the model with the statement “MODEL = plot, stratum, field (stratum)”.

The levels of the stratum effect were defined using expert knowledge on catena position (plateau, midslope, and lowlands), soil texture and drainage class. We expect that within a landscape stratum, soil types are reasonably similar and that farming practices are somewhat similar. The fields were selected in the landscape and fertility plots were repeated in each field. All three factors were included as fixed terms in the model. The larger the fraction of variance explained at the plot scale, the better fertilization application differences could be discriminated with NDVI for the considered crop type. If the strata effect explains an important part of the variance along with the plot effect, the NDVI

of all the fields have to be compared within a given stratum (and not between strata) to discriminate fertilization application difference.

4.4 Results and discussion

4.4.1 Seasonal NDVI profiles under different fertilization levels

Figure 4.3 shows the impact of fertilizer application treatments on NDVI for the five crops using six VHR images well distributed along the season. Millet NDVI is fastest to rise reflecting the vigorous establishment of the species.

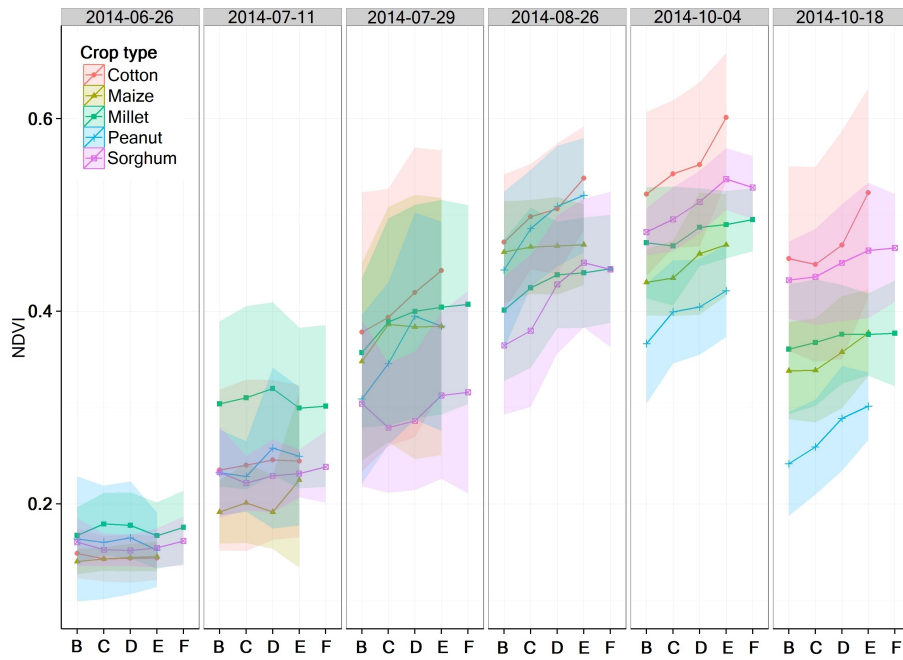


Figure 4.3: Mean and standard deviation (colored shading) of NDVI recorded in plots B–F, reflecting different fertilizer application treatments, for different dates.

By late August differences between crops tend to reduce reflecting general canopy closure. Sorghum is the latest crop to establish with a delayed NDVI response. Sorghum showed a stronger NDVI increase with fertilizer applications than the other crops, clearly visible in late August. Millet displays an overall weak or no NDVI response to fertilizer application. Maize NDVI response to fertilizer is surprisingly weak throughout, indicated that GC was not strongly affected by the additional fertilizer applications. The highest apparent response to fertilizer application in early October is misleading and reflects differences in maize senescence. A fertilization effect is also observed for both cotton and

peanut with the largest mean differences between plots on 4 October 2014 for cotton and 28 August 2014 for peanut.

However, standard deviations calculated for a given crop type and fertilization level reveal large differences between fields. The impact of fertilization on the NDVI, as observed for the five crops from about the end of August until the beginning of October, seems of comparable magnitude when compared to the background landscape-scale variability, as expressed by the large standard deviation. Detection of fertilization levels at landscape level will thus be impossible without taking into account other factors affecting NDVI.

4.4.2 Detection of fertilizer applications at the field scale

Farmer fields in Sukumba are heterogeneous and display a large NDVI variability, both between and within-fields regardless of the typically small field sizes (1.4 ha on average). The effect of fertilizer can be observed visually in the field and on both UAV and satellite images from about the end of August (Figure 4.4) until the beginning of October. The disposition of plots within the fields was done to ease the fertilization by the farmer with a systematic increase in the fertilization doses. Nevertheless, this disposition could interfere with geomorphological gradient inherent to the field. This may lead to false positive results in the few cases where the geomorphological gradient is very high.

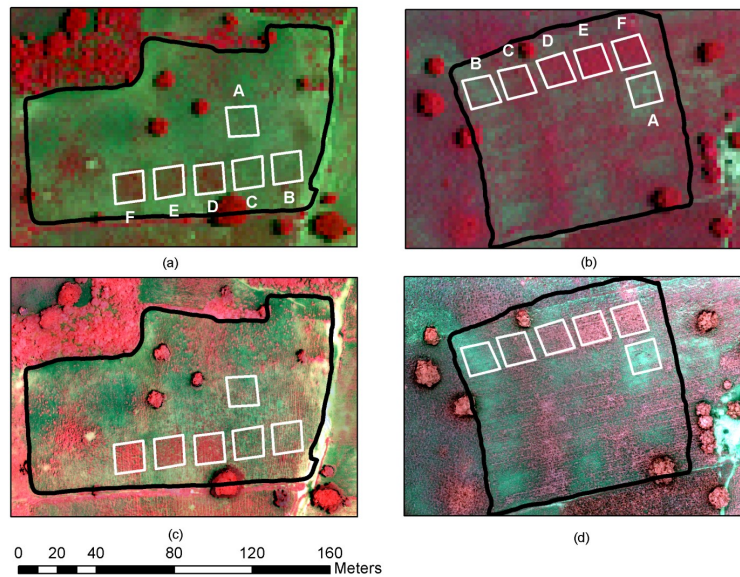


Figure 4.4: False color composites (NIR band seen in red color, red band in green and green band in blue) showing the plot effect on canopy development: late August GeoEye image at 2 m resolution (a,b); late August UAV image at 0.1 m resolution (c,d); a millet field with a sandy soil (a–c); and a sorghum field with a sandy-c.

In situ observations highlighted important height and plant color differences between the most fertilized plots and the farmer's practices (plots A). Figure 4.5 shows significant differences in the evolution of plant height and GC fraction between different plots of a millet and sorghum field (both crop types usually not fertilized by farmers). Both satellite and UAV detect gradual increase in NIR reflectance with fertilizer rates (Figure 4.4). However, the very large variability within and between the fields clearly shows that other environmental factors, such as residual soil fertility, the presence of trees, decomposing tree root systems, anthills, termite mounds, etc. affecting plant emergence and subsequent plant growth, are important as well.

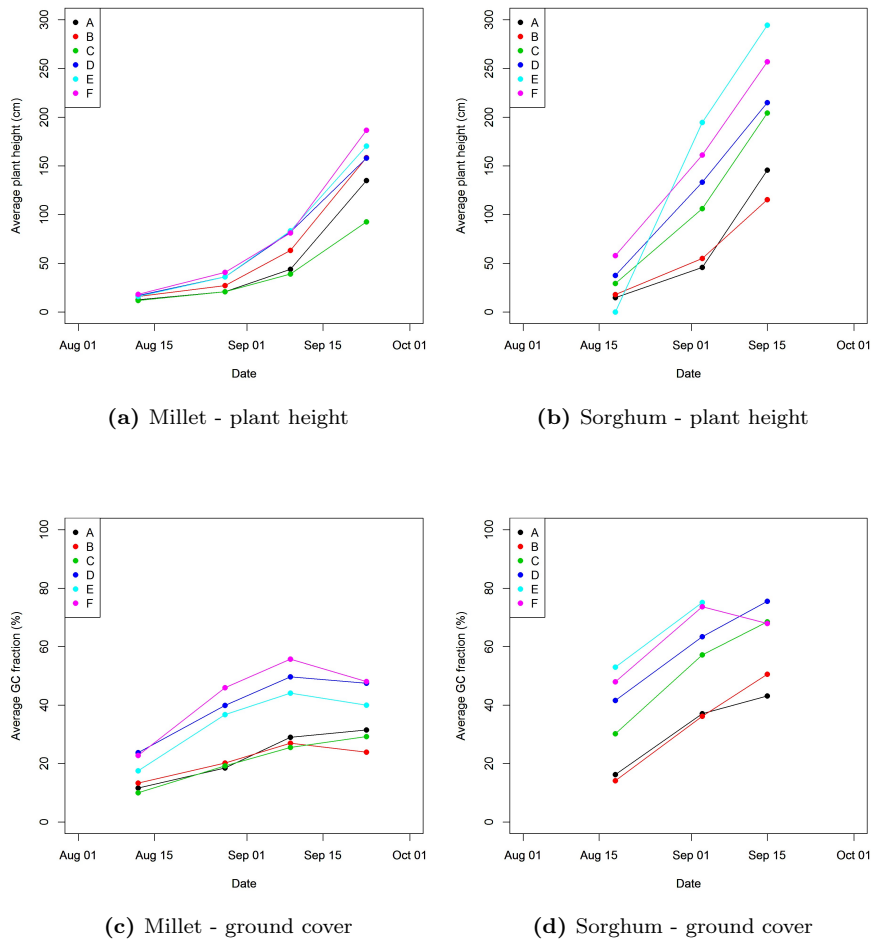


Figure 4.5: Evolution of crop height (a,b) and ground coverage (GC) fraction (c,d) for fertilizer application treatments A–F for the Millet (a–c) and Sorghum (b–d) fields also shown in Figure 4.4.

The regression model used to quantify the fertilization effect on the NDVI provides three major learnings (Figure 4.6). Firstly, the best period to observe a NDVI response to fertilization is crop specific: end of August for peanut, millet and sorghum fields and the beginning of October for cotton. Maize also appears to respond more strongly in October, but that may be due to differential patterns of senescence. Most likely, this pattern may reflect variations in soil water holding capacity (WHC) rather than a fertilizer response. Secondly, the 9–10 fields of each crop have very different responses to fertilization leading to a wide range of R^2 values. This suggests that the feasibility to detect differences in soil fertility at the landscape scale will be impeded by a very large between field variance. This is a function of different management practices (such as sowing dates, occurrence of pests and diseases) and biophysical conditions. Among these, crop type differences in the evolution of the sensitivity of NDVI to fertilization are also important. The last learning is that the response to fertilizer application on maize fields was weaker than the other crops, and is most likely the consequence of the fertilization under farmer's practices, which was not well controlled at the time of trial establishment, reducing crop response to additional fertilizer inputs. Some cotton and maize fields had already been fertilized by farmers at the time of plot establishment. The fertilization quantities prescribed by the protocol have thus been adapted, but some over fertilization should have occurred in plot B for these two crops. This could also contribute to the high value of R^2 prior the fertilization treatment, in mid-July. These high R^2 values could also indicate high intra-field heterogeneity with at least one of the fertilization plots that strongly differ from the others.

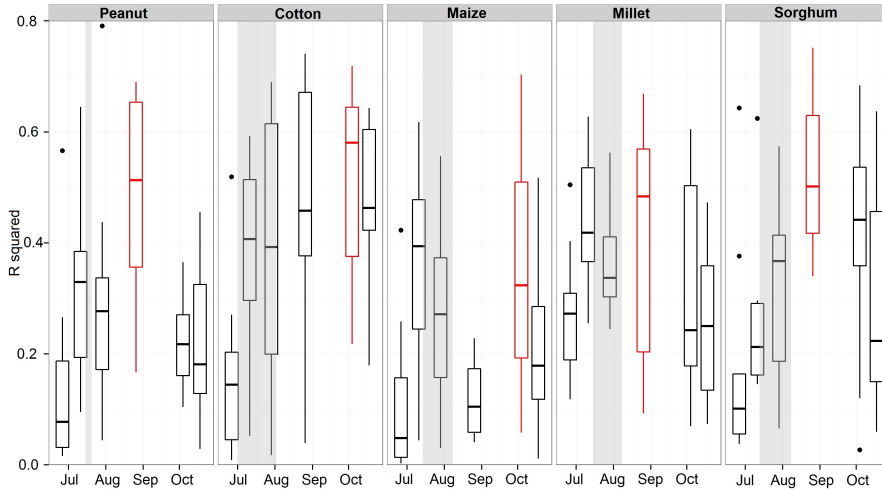


Figure 4.6: R^2 boxplot from the model describing the effect of the different fertilization levels on NDVI. The grey vertical strips indicate the fertilizers application window for each crop. The red boxplots correspond to the date where crop reaction to fertilization treatments is strongest. The black dots represent extreme R^2 values that were identified as outliers.

When NDVI response to fertilization is strongest, the regression model explained at least 50% of the variance between plots within a given field for about half of the fields, except for maize. Many factors can explain the remaining part of the within-field variation. For example, African smallholders actively maintain economically and culturally valuable tree species inside their field crops (especially rain-fed). Treatment plots were not very close to trees, however they remain exposed to competition for water and nutrients. They also largely benefit from tree and leaf litter nutrient deposit, although this varies with catena position (Traoré *et al.*, 2004). Tree cutting leads to multi-annual, residual fertility hotspots as tree root systems decompose resulting in spectacular islands of dense crop canopy. Positive feedback loops locally amplify initial differences in nutrient inputs and organic matter contents by processes that further limit plant growth and input of organic matter into the soil, such as soil crusting and soil erosion (Titttonell *et al.*, 2013).

The model used to quantify the effect of the fertilization on the NDVI relies on the assumption of independence of the observed areas (*i.e.*, the DG pixels). Figure 4.7 shows semi-variograms based on the 10 September 2014 image when fields are at their maximum GC and thus feature lowest spatial autocorrelation during the growing season.

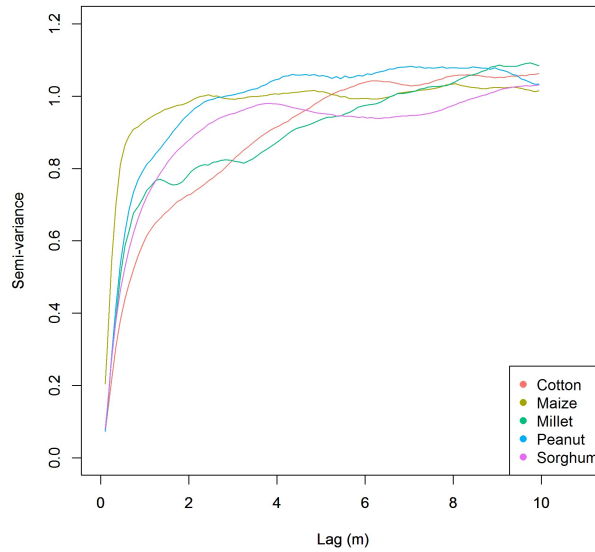


Figure 4.7: Crop-specific semi variograms fitted on NDVI values extracted from the 10 September 2014 UAV imagery with about 10 cm resolution.

Pixel values are only strongly correlated on short distances as indicated by the low nugget values and steep rise of semi-variance. Image values are more

or less uncorrelated beyond 2 m for peanut, maize and sorghum fields. The influence of spatial correlation is present at larger distances for cotton and millet, but 75% of the variance is still captured within 2 m. Without accounting for the point spread function of the various instruments, the satellite multispectral pixels can be considered as mostly independent as they sample the ground at a 2 m resolution.

The overall NDVI response to fertilizer application does not mean that all differences in application amounts can be quantified accurately. It only shows that at least one of the treatments affected the NDVI response. The NDVI difference between treatment pairs was significant in most cases (for at least 70% of the fields, as seen in Figure 4.8) for the most discriminating images as indicated by the red boxplots in Figure 4.6. More specifically, treatments in C and D plots were discriminated in all for peanut, cotton and sorghum fields. The maize crop again shows a larger similarity in NDVI response between the treatments, leading to a lower proportion of plots with a significant difference. In contrast to the other crops, in millet fields, the NDVI discriminated plots D and E (*i.e.*, doubling the DAP dose) best. For this crop, a higher fertilizer dose was required for a significant response of the canopy reflectance. However, in poor soil fertility environment, the largest difference in NDVI was expected for plots B and C, but the strongest response in Millet was surprisingly observed for plots D–E, while other crops C–D for other crops). This likely indicates a very strong response variability within-fields.

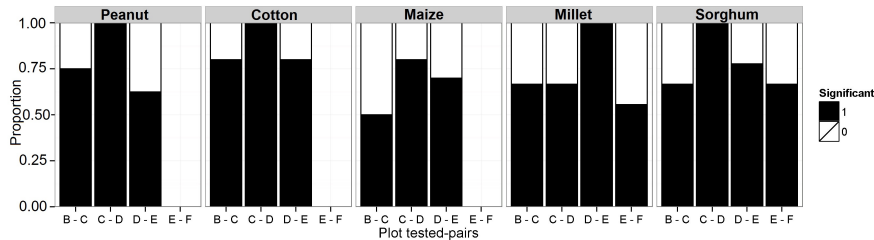


Figure 4.8: The proportion of the fields with a significant difference in mean NDVI between the fertility treatment pairs at the time of the largest observed fertilization responses: 26 August 2014 (peanut, millet, and sorghum) and 4 October 2014 (maize and cotton).

4.4.3 Relationships between plant growth indicators and NDVI

Fertilization affects NDVI because plant growth strongly responds to fertilizer under nutrient limiting conditions. Figures 4.9 and 4.10 show the relationships between NDVI and GC fraction or plant height, respectively. At the plot scale, NDVI was moderately to strongly correlated to GC fraction and plant height for cotton, millet, sorghum, and peanut.

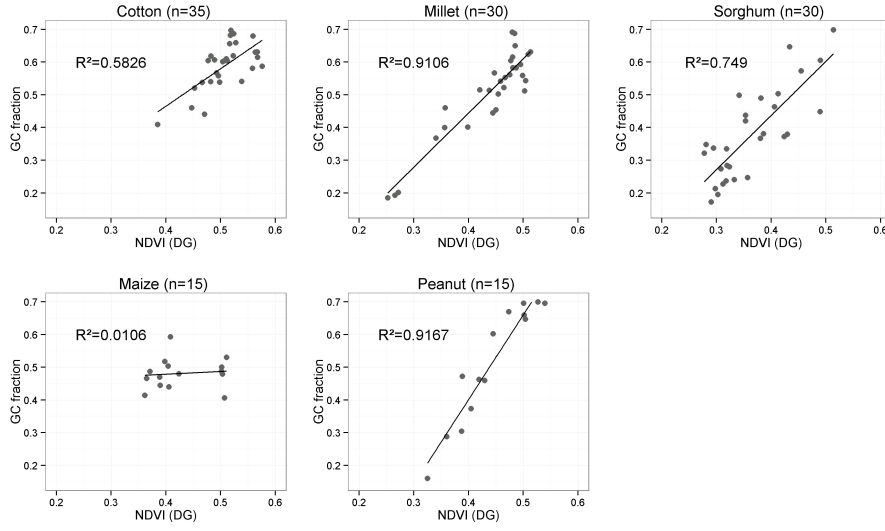


Figure 4.9: Relationships between plot mean NDVI extracted from the DG image acquired on 26 August 2014 and the green ground coverage (GC) as measured in the field around this date (± 3 days) for the five crop types.

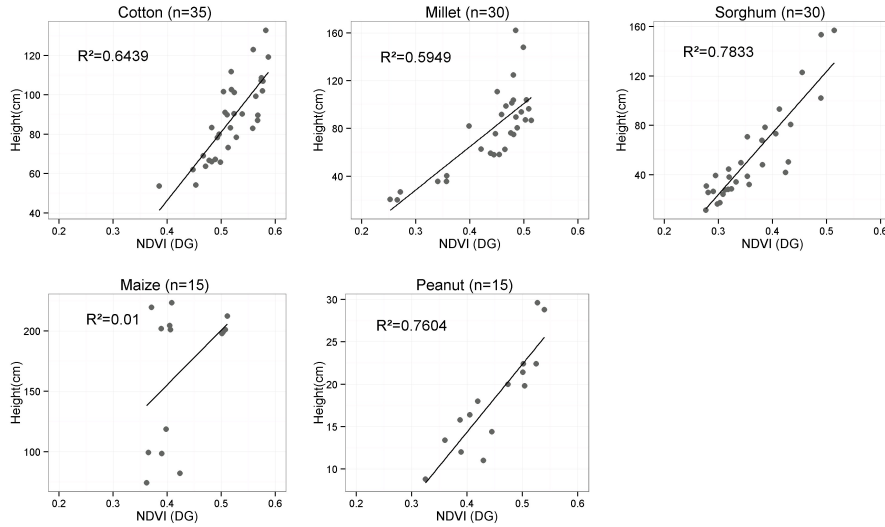


Figure 4.10: Relationships between plot mean NDVI extracted from the DG image of 26 August 2014 and mean plant height within plots as measured in the field around this date (± 3 days) for the five crop types.

A strong linear relationship was expected for peanuts between NDVI and GC fraction because of its plant canopy structure. Peanut growth leads to a

small plant height increase but a strong ground coverage increase that directly impacts NDVI by masking the background soil surface. For maize, plant height did not respond strongly to fertilization. The range in GC fraction was very small for maize fields on 26 August 2014. In general, GC fraction is fairly low, even at more advanced growing stages due to large distances between rows and relatively low nutrient application levels.

4.4.4 Detection of crops fertilization treatment at landscape level

The differences between the treatments in NDVI responses are significant when comparing plot-pairs of a given field and also when averaging over all fields. However, there is a large variation in response to fertilization treatment between individual fields. The hierarchical linear model explains 75% to 95% of the total observed variance (Figure 4.11) when introducing the stratum and field effects. A large part of the explained variation in NDVI can be attributed to the differences between strata and between fields within a stratum due to interactions of soil type and field management. The fraction of variance explained by stratum and field factors was largest in the period between sowing (occurring within the period highlighted by green color in Figure 4.11) and peak greenness (late August). NDVI differences due to different sowing dates were strongest at early growth stages but partly disappear during the growing season as the canopy closes.

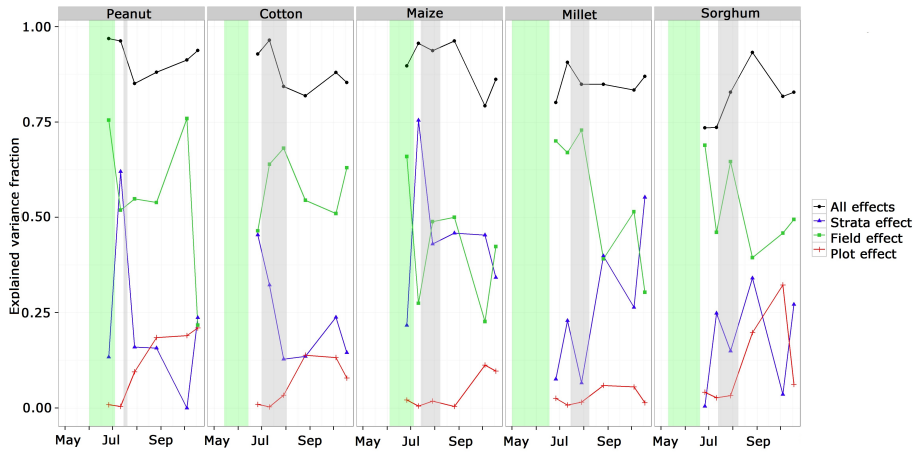


Figure 4.11: Proportion of the total NDVI variance explained by the three components of spatial variation (stratum, field, and plot) for five crops. The sowing and fertilization application windows are shown for each crop as green and grey shade, respectively.

The differences between fields within strata largely dominate the variance explanation for most of the crops. Between field variability is well known in these heterogeneous environments and, the so-called outfields further away from

the homestead usually have much lower yields and lower soil fertility than fields near the homestead (Tittonell *et al.*, 2013) due to more organic nutrient inputs. Low fertility affects not only macronutrients such as N, P or K, but also micronutrients. Therefore, fertilizer response will be better on soils with higher organic matter content (Tittonell and Giller, 2013). Soil organic matter content is often positively related with soil properties as cation exchange capacity (CEC), rainfall infiltration or soil structure (Vanlauwe and Giller, 2006). Environmental conditions including soil type, fertility, and water availability fluctuate within landscapes and even within-fields (Tittonell *et al.*, 2008). Another significant factor of inter-field variability is labor constraints, relatively more acute during the peak demand at sowing and stemming from variable farm endowment levels, often correlated with farm sizes.

Within a stratum, relatively similar plant growth patterns were observed. Moreover, strata differ in their sensitivity to climate extremes, notably meteorological drought, due to distinct slope, potential rooting depth, texture, WHC, runoff and drainage characteristics and, as a result differences in the amount of soil water that is available to plants. In case of early season dry spells or “false starts”, less favorable strata will observe more plant establishment failures leading to replanting and a delayed, more heterogeneous greening up of patches in this part of the landscape. This tends to maximize differences between strata early in the season (July) before all canopies are more fully developed including the re-planted patches (Samake, 2015a).

The fraction of variation due to field and stratum, ranging from 1% to 35% of the total variance observed. Its contribution to the explanatory power of the model was largest in early October for maize and sorghum fields and around the end of August for cotton and peanut fields (the high values observed for peanut in October were misleading as they correspond to fields already harvested). Sorghum responded strongly to fertilizer in its vegetative growth. As previously observed, Millet shows a weak response to fertilization treatment. This is partly related to more millet cultivation in the most constraining areas, reducing the fertilization effect in plots and increasing the contribution of the field effect. In addition, the fraction of variance explained by fertilization treatments would have been higher if farmers would not have fertilized some cotton and maize fields before the protocol had been put in place. Although total fertilizer application levels were adjusted proportionally to correct for that pre-existing situation, the effects of application on the control plots could not be corrected for.

4.5 Conclusions

Monitoring crop growth in spatially heterogeneous landscapes with trees in every field is very well possible with a TS of VHR imagery. Large differences in temporal signatures between fields of a given crop type were observed. On average, crops clearly responded to fertilization, in terms of both crop height

and ground coverage impacting the NDVI that is measured by a satellite sensor. NDVI differences between fertilizer treatments within individual fields were not consistent due to large within-field and within plot variation, especially for treatments with a low fertilizer application (B and C). The influence of fertilizer applications on crop NDVI response was proportionally small (lower than 35% of total variation) when compared to the influence of field management and catena position. Large differences in soil fertility and soil-related constraints, interacting with plant density and field management, such as replanting at sub-field scale, mean that many factors influence crop growth and thus the NDVI response within a field. As a consequence, a measured NDVI response can only partially be benchmarked against a fertilization reference within the field. Indeed, the variance decomposition model applied at field level showed that 50% of the NDVI variance within a field is due to the fertilizer application for only half of the fields at times when the observed NDVI response was strongest. Moreover, the period with the largest contrasts between treatments was crop specific: at the end of August for peanut and cotton and at early October for sorghum and maize. Standard precision agriculture methods based on comparisons of the response of a VI within one field (van Evert *et al.*, 2012) are therefore not very useful. Accounting for other sources of variability in these heterogeneous landscapes is needed before such an approach can be applied.

However, at the plot scale, strong relationships between NDVI and plant growth parameters including plant height and ground coverage were observed. This implies that NDVI imagery directly reflects differences in plant growth due to the inherent patterns of soil fertility and management. In the landscapes of southern Mali, differences in soils within the typical catena are large (Traoré *et al.*, 2004) and were strongly reflected in the responses of the five studied crops. We conclude that comparisons of spatial and temporal responses of VI for a particular crop type can only be done when plant growth conditions are similar, *i.e.*, within strata related to soil catena position in the landscape.

Chapter 5

Estimating smallholder crops production at village level from Sentinel-2 time series in Mali's cotton belt *

Highlights

- Crop production assessed with a maximum model uncertainty of 0.33% at village level.
 - Crop type map from Sentinel-2 achieves 80% OA.
 - Maximum LAI is the best yield estimator (amongst various vegetation indices).
 - Red edge and NIR bands are the more important features for crop type classification.
 - Peak vegetation dates are the most interesting period for crop type mapping and yield estimation.
-

Abstract. In Mali's cotton belt, spatial variability in management practices, soil fertility, and rainfall strongly impact crop productivity and the livelihoods of smallholder farmers. To identify crop growth conditions and hence improve food security, accurate assessment of local crop production is key. However, production estimates in heterogeneous smallholder farming systems often rely on labor-intensive surveys that are not easily scalable, nor exhaustive. Recent advances in high resolution Earth Observation (EO) open up new possibilities to work in heterogeneous smallholder systems. This chapter develops a method to estimate individual crop production at farm-to-community scales using high resolution Sentinel-2 time series and ground data in the commune of Koningue,

*Adapted from Lambert, M.-J., Traoré P.C.S., Blaes, X. Baret, P. and Defourny, P. (2018). Estimating smallholder crops production at village level from Sentinel-2 time series in Mali's cotton belt. *Remote Sensing of Environment*, 216, 647-657.

Mali. Our estimation of agricultural production relies on (i) a supervised, pixel-based crop type classification inside an existing cropland mask, (ii) a comparison of yield estimators based on spectral indices and derived leaf area index (LAI), and (iii) a Monte Carlo approach combining the resulting unbiased crop area estimate and the uncertainty on the associated yield estimate. Results show that crop types can be mapped from Sentinel-2 data with 80% overall accuracy (OA), with best performances observed for cotton (F-score 94%), maize (88%) and millet (83%), while peanut (71%) and sorghum (46%) achieve less. Incorporation of parcel limits extracted from very high resolution imagery is shown to increase OA to 85%. Obtained through inverse radiative transfer modeling, Sen2-Agri estimates of LAI achieve better prediction of final grain yield than various vegetation indices (VI), reaching R^2 of 0.68, 0.62, 0.8 and 0.48 for cotton, maize, millet, and sorghum respectively. The uncertainty of Monte Carlo production estimates does not exceed 0.3% of the total production for each crop type.

5.1 Introduction

In Mali's cotton belt, smallholder farming systems face soil fertility challenges, demographic, and environmental pressures that affect farmers' livelihoods and food security (see Chapter 3) (Karlson and Ostwald, 2015; Potts *et al.*, 2013). Crop production fluctuates strongly in time and space and leads to chronic food insecurity (Akponikpe *et al.*, 2011a). Smallholder rainfed agricultural systems host more than 50% of the rural population in developing countries and yet produce 90% of the food (Morton, 2007). While smallholder farming systems differ widely between countries and agro-ecological zones, they often share common features such as limited resource endowment, labor scarcity, low productivity of labor, high productivity of capital and risk management in economic decisions (Cousins, 2010; Dixon *et al.*, 2004). In developing countries, food security assessments often rely on EWS based on NDVI anomalies. Such systems offer food security alerts at medium spatial resolution that are not detailed enough to detect the emergence of local food insecurity conditions and often leverage remote sensing only in a qualitative sense (Baruth *et al.*, 2008). Meanwhile, the generation of agricultural statistics (area, yield, and production) relies almost exclusively on labor-intensive field surveys that are both constrained regarding representativeness and reliability. Recent instances of EWS failing to identify the emergence of localized famines in Ethiopia (1999-2000), Malawi (2001-2002) and Niger (2005) (Devereux, 2009; Genesio *et al.*, 2011), highlight the outstanding challenges faced by EWS in assessing local food insecurity, including data accuracy, timeliness, and disaggregation (see Chapter 2). For example, the 1999-2000 Ethiopian famine was concentrated in the lowland pastoralist areas, while EWS mainly focused on the crop-producing highlands (Maxwell, 2002).

Recent improvements in the spatial, spectral and temporal resolutions of EO satellites hold significant potential for improved food security assessments. Remote sensing applications traditionally face considerable challenges in small-

holder agriculture because of small field size, heterogeneity in management practices, the resulting landscape fragmentation, and the widespread presence of trees within the fields (Delrue *et al.*, 2013; Vancutsem *et al.*, 2012). Some studies achieved accurate land cover classifications of smallholder farming systems using HR imagery (Sweeney *et al.*, 2015), VHR imagery (Debats *et al.*, 2016) or a combination thereof (Lebourgeois *et al.*, 2017). While some authors deemed VHR compulsory for such purposes (Lebourgeois *et al.*, 2017; McCarty *et al.*, 2017), others found HR to be sufficient (Pervez *et al.*, 2014) (for details on the spatial resolution, please refer to Appendix A). Settling this question is probably context-specific. Results from Leroux *et al.* (2014) in a similar and nearby agro-ecology suggest that a 10 m spatial resolution may suffice for land cover classification in the Malian cotton belt.

Quantitative estimates of smallholder yields from EO also offer potential to improve scalability and objectivity, compared to estimates generated from survey data. Two popular approaches used to estimate crop yield from EO include (i) empirical models based on regressions between yield measurements and spectral VIs and, (ii) crop growth models involving the use of weather, soil, plant, management and satellite data. In theory, the agility of crop models featuring a finer-scale representation of plant, soil and management processes confers them a higher accuracy for yield estimation. In practice, however, they are constrained by data availability (Burke and Lobell, 2017; Morel *et al.*, 2014) and lack of granularity, and are biased towards temperate, high-yielding cultivars (Gaiser *et al.*, 2010; Srivastava *et al.*, 2016). EO-derived yield predictors, on the other hand, evaluate actual precursors of yield and can be applied at granular scales increasingly congruent with the reality of smallholder agricultural systems. A set of recent studies (Azzari *et al.*, 2017; Burke and Lobell, 2017; Han *et al.*, 2017; Jain *et al.*, 2016; Jin *et al.*, 2017; Schut *et al.*, 2018) focused on yield estimation from EO. Chivasa *et al.* (2017) suggested that the decreasing cost of EO data opens opportunities for maize yield estimation in heterogeneous African agricultural landscapes, but that reliable field data and accurate classification methods remain key. Jin *et al.* (2017) compared an empirically calibrated model using yield measurements and an uncalibrated model based on pseudo training data generated from a crop model. At an aggregated administrative scale (*e.g.*, district and division), the calibrated and uncalibrated models reach similar performances with R^2 ranging from 0.3 to 0.6 in both cases. Achieving robust smallholder landscape yield predictions is important in SSA, notably where subsistence agriculture still determines food security, and for profitable farmer participation in more contract-oriented agricultural areas. These yield predictions should also be robust at an individual crop level, to adequately represent the diversity of food and income sources, and for economic efficiency should attempt to leverage as much value as possible from open-source, free data.

This research aims to propose a method to estimate crops production at the local scale, and uncertainty thereof, in complex and heterogeneous smallholder farming systems. It involves the field-level mapping of crop type using supervised pixel-based classification, the identification of a best crop-specific yield estimator

from a temporally reduced set of vegetation status proxies (VI and LAI), and a stochastic combination of these two results and their respective uncertainties. The approach, based on Sentinel-2 EO data, is tested in 2016 in a rural commune of the Koutiala district in Mali's cotton belt.

5.2 Study site

The study area (353 km²) is defined by the geographical footprint of the 43 POs registered in the five villages of the Koningue commune (Koutiala district, south-eastern Mali): Dougan, Sukumba, Nguessou 1, Nguessou 2 and Banesso (Figure 5.1 and Appendix B for details on study area limitation). The vernacular soil map (more information in Appendix C) and the limits of the cropland map are presented in Figure 5.1. The study site was fully described in Chapter 3 and will not be detailed here.

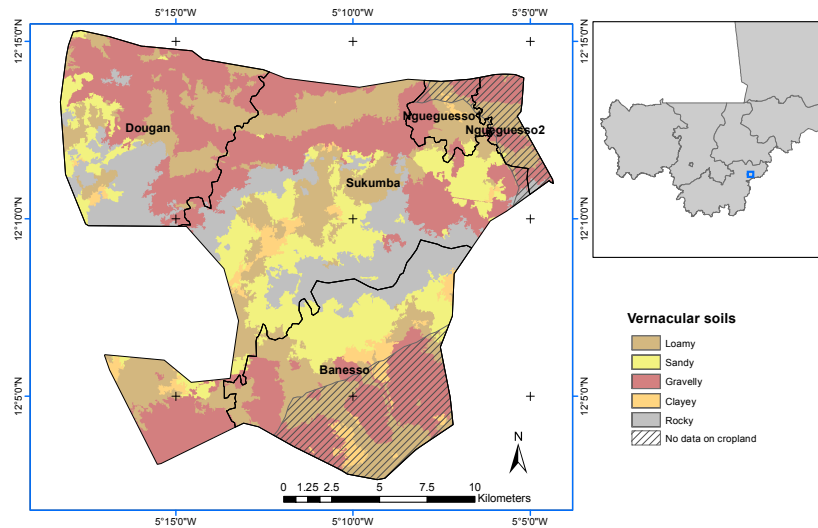


Figure 5.1: The Koningue commune with the five village areas. The vernacular soil map is shown as background and produced combining geolocalized vernacular soils information and EO data providing soil brightness and elevation. Parcel boundaries are available on the entire study area except for the southern part of the Banesso and Nguessou 2 communities (stripped black lines).

5.3 Data

5.3.1 Satellite imagery

Sentinel-2A TS for the 2016 season (temporal resolution of 10 days) were processed to level L2A following ESA Sentinel-2 for Agriculture (Sen2-Agri) protocols* (Bontemps *et al.*, 2015a) . The Multisensor Atmospheric Correction

*<http://www.esa-sen2agri.org/>

and Cloud-Screening (MACCS) algorithm uses the multi-temporal dimension of the Sentinel-2 TS to detect clouds and shadows, correct atmospheric perturbations and retrieve aerosol optical thickness (Hagolle *et al.*, 2015, 2010). From the 12 Sentinel-2A images acquired during the 2016 growing season, six were discarded due to cloud cover exceeding 50%. The remaining six images (27-07, 26-08, 05-09, 05-10, 25-10, 14-11) were used for crop type mapping and yield estimation. Within these images, local outstanding gaps (maximum size: 1.5 km²) due to the cloud and shadow filtering were filled in by linear temporal interpolation. Additionally, a cloud-free WorldView3 image at 1.24 m multispectral resolution was acquired on 9 October 2016.

5.3.2 Secondary data

Secondary thematic data layers were provided by ICRISAT, a partner in the 2014-2017 STARS project active in our study area. These included 2014 and 2015 seasonal TS of VHR DG imagery, used in STARS to, *inter alia*, (i) exhaustively delineate 31,248 agricultural parcels and generate annual cropland masks; (ii) derive a landscape-level tree mask from soil-specific NDVI thresholding of a 2014 early-season WorldView 2 image (Blaes *et al.*, 2016); and (iii) a concomitant digital dataset on vernacular soil types collected from farmer interviews (>6,700 georeferenced samples).

We used these secondary datasets to, respectively (i) update parcels databases and resulting cropland maps for 2016, by photointerpretation of the additional DigitalGlobe coverage acquired on 9 October 2016, and setting the 2016 cropland extent to a total 156 km² over the study area; and (ii) generate a vernacular soil map from the combination of STARS farmer interview data, object-based segmentation of a Sentinel-2 derived soil brightness image, and SRTM 30 m digital elevation (for details on the vernacular soil map construction, please refer to Appendix C).

5.3.3 *In situ* data

A set of 821 crop type georeferenced points were collected on the ground in October and November 2016, and included six classes: cotton, maize, millet, sorghum, peanut, and other (*e.g.*, soybean). Encompassing field boundaries were digitized on the VHR WorldView3 image of the 9th October 2016 for each of the geo-referenced points. Among the 821 resulting polygons, cotton came out as the dominant crop. It is followed by millet, maize, and sorghum covering 23.7%, 20.2% and 10.1% respectively. Peanut and other crops are minor contributors, occupying less than 3% of the sampled area.

We measured total aboveground biomass (AGB) and grain yield on a subset of 105 fields for the four dominant crop types (26 cotton, 27 millet, 27 sorghum and 25 maize), with 3 measurement replications per field. Field selection followed a stratified sampling approach based on catena position (plateau, slope, and valley) and household endowment level (low, medium, high), derived from

local expert knowledge. There were three fields per crop species in each of the nine strata. The slightly smaller sample of maize and cotton fields was due to unexpected early harvest by a couple of farmers. On each field, the operator physically verified the field perimeter with the farmer, recording the boundaries with a Trimble Juno 5 GPS. Within each field, three quadrats of 4 m² were randomly selected for destructive sampling, subject to a separation distance of 20 m from the nearest tree crown or field boundary (to avoid edge effects). Grain yield was estimated based on a threshing ratio (the weight of grain over the weight of ear/panicle) of 0.6, 0.75 and 0.85 for maize, millet and sorghum respectively (Ajeigbe, 2017 and Gangashetty, 2017, *pers. comm.*). Cottonseed weight was determined directly, so no conversion ratio was applied.

5.4 Methodology

The overall approach involves three steps: (i) mapping crop type within the existing cropland mask, and estimating unbiased crop area, (ii) predicting the yield of individual crops, and (iii) estimating production, crop-wise with associated uncertainties accounting for both crop map and yield model errors.

5.4.1 Crop type classification and crop area estimation

We used a pixel-based, supervised RF classification to discriminate main crop types within the cropland area. The reference 821 ground dataset (totaling 131,424 pixels) was split into spatially uncorrelated training (2/3) and validation (1/3) subsets following a stratified random sampling (strata being crop types). For the training sample, a 10 m internal buffer was applied on VHR-extracted field boundaries to reduce the number of mixels (that constraint was not applied to the validation sample to avoid accuracy overestimation).

The RF classifier used all Sentinel-2 bands resampled to 10 m except the blue, which was discarded due to the impact of aerosols and atmospheric scattering (Jia *et al.*, 2014). The RF classifier was chosen based on its lack of over-fitting, its parsimony for user-defined parameters, the features importance analysis, its low sensitivity to the number of inputs, its minimization of correlations between classifiers, its light computational requirements, and its robustness to noise and overtraining (Hastie *et al.*, 2009; Rodriguez-Galiano *et al.*, 2012). The number of trees was set to 500 following Rodriguez-Galiano *et al.* (2012).

To assess the most relevant combination of band and date (a.k.a "*feature*") for crop type discrimination, we computed the mean decrease in GI for each feature. In order to calculate feature importance, the RF algorithm turns off one of the features while maintaining the others constant and assesses the decrease in accuracy with the GI. The feature has the highest importance when the mean decrease in GI is the largest (Breiman, 2001). A majority voting was applied on the resulting pixel classification using the VHR-derived cropland vector layer and the SpatialEco R package, and we computed OA at both pixel and parcel

levels; UA, PA, and F-score for each crop type were computed at parcel level only.

To generate an unbiased area estimate per crop, we used a direct calibration estimator of the area, relying on ground truth to remove the bias of the classified map following Gallego (2004). In the confusion matrix, the conditional probability $P(j|i)$ is the probability to be j (ground truth) when classified as i , with j and $i \in (\text{cotton}, \text{maize}, \text{millet}, \text{sorghum})$. The unbiased area is determined by the Equation (5.1).

$$A_j = \sum_{i=1}^4 (A_i * P(j|i)) \quad (5.1)$$

Where A_j is the unbiased area of crop j , A_i is the area of pixels classified as i assuming that each pixel covers an area of 100 m², and $P(j|i)$ is the conditional probability to be j when knowing i .

Additionally, as farmers actively preserve numerous trees inside crop fields for their commercial and soil fertility maintenance values (Traoré *et al.*, 2002; Traoré, 2003) including notably shea (*Vitellaria paradoxa*) and néré (*Parkia biglobosa*), we investigated the effect of tree exclusion on crop classification accuracies, considering the low rates of changes of tree cover associated with active farmer preservation and slow growth rates. The 2014 pre-existing STARS 2 m tree mask was resampled to 10 m resolution, with resulting pixels considered as being trees if tree coverage therein exceeded 20% (to limit the effects of tree shadows and imperfect co-registration between images). Photo-interpretation of the WorldView 3 image of 9 October 2016 validated this coarser tree mask against 150 randomly selected pixels classified as tree (100) or non-tree (50). The overall accuracies and their respective standard deviations were computed to compare the performance of crop type classifications with and without trees (Rossiter, 2004). Finally, the resulting crop type map was used to explore the relationship between soil type and crop type.

5.4.2 Yield estimation

Table 5.1 references the various spectral VIs and LAI used in this study as predictors of final grain yield, separately for each crop. These include canopy chlorophyll metrics, which were shown to be more sensitive to high green LAI values than NDVI (Viña *et al.*, 2011), alongside STI and NDTI, which are related to dry biomass (Jacques *et al.*, 2014; Renier *et al.*, 2015). The LAI is defined by Chen and Black (1992) as one half the total leaf area per unit horizontal ground surface area. The LAI comes from the ESA Sen2-Agri system (Bontemps *et al.*, 2015a) where it is estimated using an artificial neural network inversion of the PROSAIL radiative transfer model based on Sentinel-2 data (Bontemps *et al.*, 2015a). Theoretically, using a full VI seasonal integral (rather than a subset thereof) should deliver higher prediction skill for crop yield, as the end result of a highly non-linear plant development and growth process. In practice, the downgraded overpass frequency imposed by Sentinel-2's incomplete deployment in 2016 limited the number of available tiles to 6.

Table 5.1: Vegetation indices selected for crop yield estimation.

VI	Formulation
Green VI	
NDVI Rouse Jr. <i>et al.</i> (1974)	$NDVI = \frac{\rho_{Nir} - \rho_{Red}}{\rho_{Nir} + \rho_{Red}}$
Green NDVI Gitelson <i>et al.</i> (1996)	$gNDVI = \frac{\rho_{Nir} - \rho_{Green}}{\rho_{Nir} + \rho_{Green}}$
Red-edge NDVI Gitelson and Merzlyak (1994)	$NDVIRE = \frac{\rho_{Nir} - \rho_{Red-Edge}}{\rho_{Nir} + \rho_{Red-Edge}}$
Chlorophylls indices	
Green Chlorophyll Index Gitelson <i>et al.</i> (2003)	$CI_{Green} = \frac{\rho_{Nir}}{\rho_{Green}} - 1$
Red-edge Chlorophyll Index Gitelson <i>et al.</i> (2003)	$CI_{Red-edge} = \frac{\rho_{Red-edge}}{\rho_{Green}} - 1$
Modified Chlorophyll Absorption Ratio Index Haboudane <i>et al.</i> (2004)	$MCARI2 = \frac{1.5[2.5*(\rho_{Nir} - \rho_{red}) - 1.3(\rho_{Nir} - \rho_{Green})]}{\sqrt{(2\rho_{Nir} + 1)^2 - (6\rho_{Nir} - 5\sqrt{\rho_{red}}) - 0.5}}$
Triangular Vegetation Index Broge and Leblanc (2001)	$TVI = 0.5 [120(\rho_{Red} - \rho_{Green}) - 200(\rho_{red} - \rho_{Green})]$
Modified Triangular Vegetation Index Haboudane <i>et al.</i> (2004)	$MTVI2 = \frac{1.5[1.2*(\rho_{Nir} - \rho_{Green}) - 2.5(\rho_{red} - \rho_{Green})]}{\sqrt{(2\rho_{Nir} + 1)^2 - (6\rho_{Nir} - 5\sqrt{\rho_{red}}) - 0.5}}$
Dry biomass indices	
Soil Tillage Index Van Deventer <i>et al.</i> (1997)	$STI = \frac{\rho_{Swir1}}{\rho_{Swir2}}$
Normalized Difference Tillage Index Van Deventer <i>et al.</i> (1997)	$NDTI = \frac{\rho_{Swir1} - \rho_{Swir2}}{\rho_{Swir1} + \rho_{Swir2}}$
LAI	
Weiss and Baret (1999)	Implemented in the ESA Sen2-Agri System

In the absence of detailed management information for each individual field used for yield model calibration, and given the large intra-specific variability in crop phenologies, we limited ourselves to peak VI (and LAI) as the sole predictor against which yield measurements are regressed. The potential of this approach has already been demonstrated elsewhere (Azzari *et al.*, 2017; Becker-Reshef *et al.*, 2010b; Jain *et al.*, 2016). For each species, yield regression models were calibrated using the most homogeneous half of the fields monitored, defined as fields located on dominant soils (sandy, loamy, and clayey) and within which heterogeneity in measured yield is lower than the 66th percentile. As for crop type classification, a 10 m internal buffer and a tree mask were applied - before VI and LAI extraction - to all studied fields in order to rely on a "pure" predictor. Due to fieldwork constraints (peanut harvest completed at the time of field campaign), only the four dominant crop types (cotton, maize, millet, and sorghum) are involved in yield estimation. The determination coefficient (R^2) computed for each linear regression serves as a performance indicator. The

yield regression models are validated using the complete dataset by computing root mean square error (RMSE), variance and standard deviation (S_j).

5.4.3 Production estimation

Uncertainties inherent to the crop type classification and to the yield estimation are combined for unbiased production estimates using a Monte Carlo approach with 100 realizations, as follows. For each pixel classified as crop type i , each realization draws a random crop type j constrained by $P(j|i)$ as derived from the confusion matrix, then applies the corresponding stochastic yield model with a Gaussian, zero-mean error term ϵ_j (Equation (5.2)).

$$\hat{y}_j = \alpha_j * LAI_{peak} + \beta_j + \epsilon_j \quad \text{with } \epsilon_j \approx \mathcal{N}(0, S_j) \quad (5.2)$$

With α_j , β_j the coefficients of the yield linear regressions for each crop type j ; ϵ_j the error on those regressions and $\hat{y}_j$ one potential realization of yield for a pixel of crop type j . The estimated yields are truncated at 0 and 10 t/ha which represents extreme theoretical values for yield in these regions. The production estimate then corresponds to the averaging across all 100 realizations of crop yields multiplied by corresponding crop area. The standard deviation of the 100 simulations of production estimates is computed and expressed the model uncertainty for crop production estimates.

5.5 Results and discussion

5.5.1 Crop type classification

Accuracy of the crop type map and the resulting crop type area

The OA of the pixel-based crop type map reaches 80.16 based on the validation dataset (± 0.27)%. After parcel filtering, it increases to 85.5 (± 0.23)% (Table 5.2). The cotton crop, covering more than 40% of the cropland, is the most reliably mapped (F-score: 93.86%), followed by maize (F-score: 87.52%) and millet (F-score: 82.5%).

Table 5.2: Confusion matrix for the crop type map after object filtering. Map categories are the rows while the reference categories are the columns (n = 22,591).

	Cotton	Maize	Millet	Sorghum	Peanut	Other	UA [%]
Cotton	9416	356	126	196	56	18	92.6
Maize	3	3986	88	255	64	138	87.91
Millet	444	196	5005	1095	13	23	73.86
Sorghum	32	37	141	740	0	0	77.89
Peanut	0	0	0	0	163	0	100
Other	0	0	0	0	0	0	/
PA [%]	95.16	87.13	93.38	32.37	55.07	0	OA=85.48

The cotton vegetative cover differs significantly from other crops making the discrimination easier. Sorghum is the least well classified with F-score

of only 45.7%. Strong misclassifications occur between sorghum and millet, which was expected due to the reasonably large calendar overlap. Pooling millet and sorghum into a single target class increases the OA to 91%. High weed infestation levels in peanut are often associated with prominent intra-field heterogeneity, leading to high OE (PA=55.07%). Conversely, no CE is observed because well-weeded peanut fields have a distinct spectral and temporal signature (Table 5.2). The confusion between millet and cotton is also noteworthy (444 misclassified cotton pixels).

Generally, our findings are congruent with the expression of differential phenotypic traits (plant phenology, canopy architecture) and management practices (sowing date, density, weeding) between dominant crops. Maize, a common stop-gap crop, is typically senescent well ahead of other species making classification easier. The thickness of cotton and millet canopies tend to homogenize crop response at the field scale, in contrast to other species. Peanut features the broadest range of weed infestation and thus reveals stark differences in household labor constraints later in the season. Sorghum, a typical frontier crop planted on more marginal soils with the least fertilizer input of all, expresses highest within-field heterogeneity among the dominant crops.

Figure 5.2 presents the resulting crop type map.

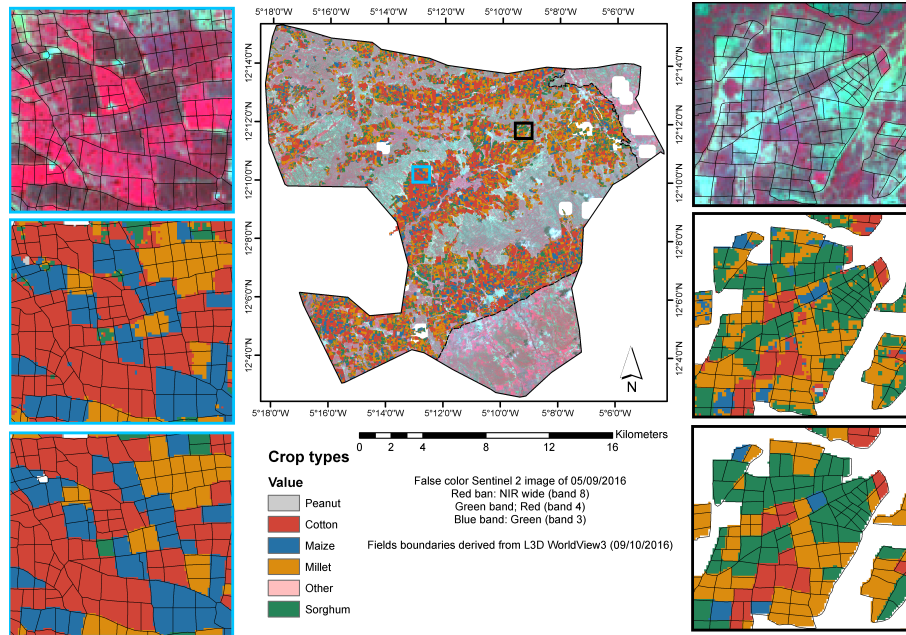


Figure 5.2: Crop type map over the study area produced with Random Forest classification based on Sentinel-2 time series. Zooms-ins are done on two different areas of the image and show, from top to bottom, the false color Sentinel-2 (9th September 2016), and the crop type classification before and after object filtering.

From top to bottom, the false color Sentinel-2, the crop type classification and the crop type classification after object filtering are shown in zooms for two different sites. The crop map produced corroborates the explicit environmental determinism guiding spatial crop allocation in rainfed systems (Figure 5.3). On each farm, cash crop (cotton) and highly-fertilized crops (cotton, maize) are preferably cultivated on more finely textured soils with highest WHC, and highest fertility. Millet, which is a more valuable and valued commodity than sorghum for both self-consumption and (in the foreseeable future) sales, is typically also inserted on the same parcels in rotation, benefiting from fertility carry-over effects. Sorghum, a robust and phenologically plastic crop is more frequently targeted to more marginal environments (such as rocky soil), although it is also often substituted for millet in rotations after cotton and maize.

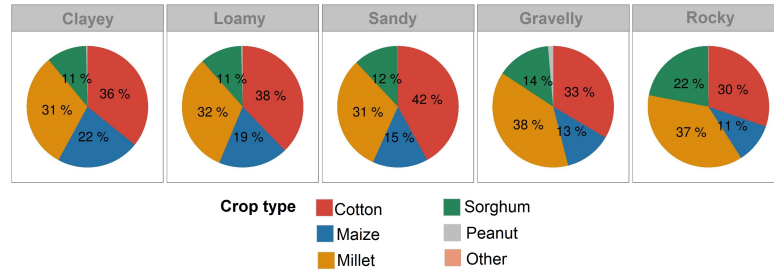


Figure 5.3: Distribution of the crops according to the vernacular soil map.

The unbiased crop type area is computed for each village within the Koningue commune (Figure 5.4). Maize and cotton crops reflect only small area differences between the pixel counting area estimate and the unbiased area estimate, as their classification accuracy is high, in contrast with the often-confused millet and sorghum crops.

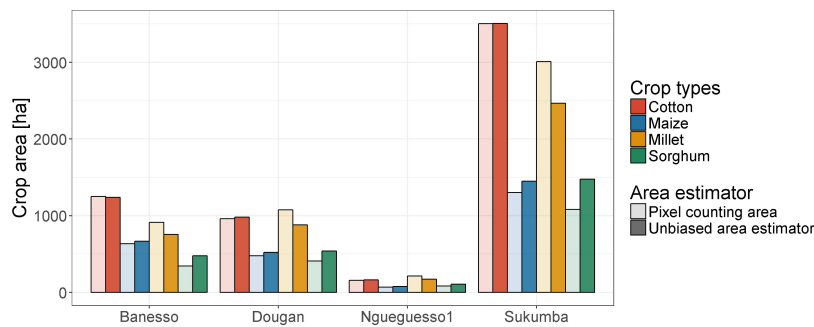


Figure 5.4: Crop area estimate for each village with the pixel counting approach and the unbiased area estimator.

Reflecting population and cultivated area sizes, Sukumba features the largest crop area for any species (total cultivated area: 8,899 ha), and Nguessou1 the smallest (entire cultivated area: 523 ha). While at comparable total cultivated areas, Banesso (3,146 ha) and Dougan (2,925 ha) respectively feature more cotton and maize, and more millet and sorghum reflecting the higher proportion of high (low) WHC soils in Banesso lowlands (Dougan highlands).

Bands and dates importance for crop type discrimination

According to the GI and as illustrated in Figure 5.5, red-edge and NIR reflectances for late-season acquisitions (Sept. 5, Oct. 5) contribute most to the crop type classification accuracy in the study area.

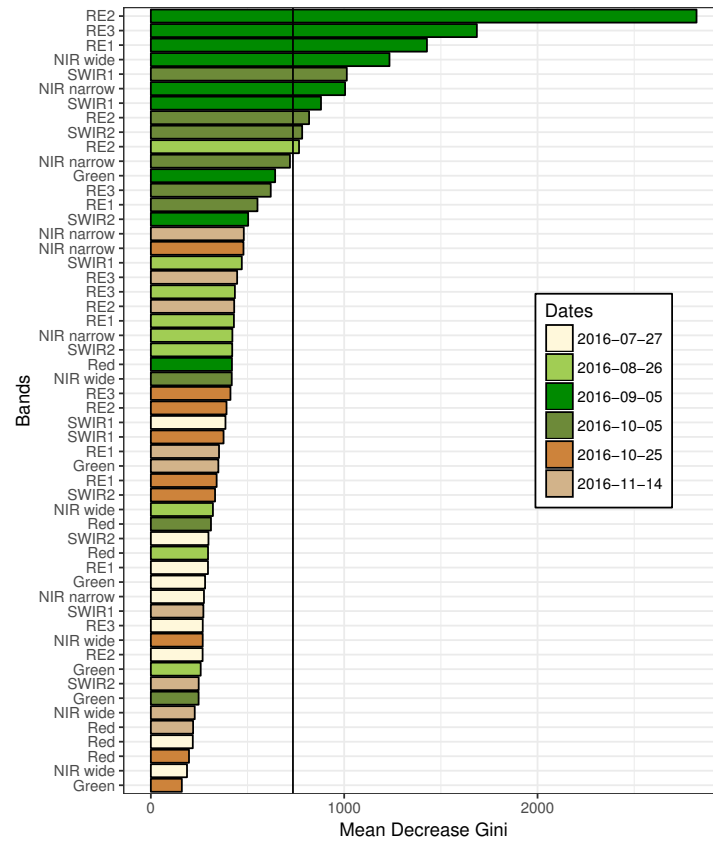


Figure 5.5: Features (band x date) importance for crop type classification. The vertical line corresponds to the mean decrease in GI across features considered. The following acronyms are used for the Sentinel-2 bands: three bands in the red edge (RE1, RE2, RE3), two bands in the NIR (NIR wide and NIR narrow) and two bands in the shortwave infrared (SWIR1, SWIR2). For more information on the bands' description, please refer to Clevers and Gitelson (2013).

Unfortunately, the first available low cloud-coverage image was acquired at the end of July 2016, excluding the start of the season from the analysis. The usefulness of red-edge and NIR bands corroborates earlier conclusions by Immitzer *et al.* (2016). The importance of the end-of-season dates might explain part of the confusion between millet and cotton because this period emphasizes similarities between the two species (canopy thickness, spherical to planophile leaf angle distribution functions) at the expense of differences. Given the limited number of cloud-free acquisitions during the 2016 cropping season and the inter-annual variability in weather and farmers responsive management, drawing a definitive conclusion on the best week for crop type mapping is probably too ambitious. However, targeting the peak LAI period in September is a pragmatic option in this production system.

Impact of in-field trees on crop type classification

The Sentinel-2 tree mask resampled from VHR tree mask (Figure 5.6) shows high performance with OA of 94.67% and F-score for tree and non-tree of 95.58% and 92.3%, respectively.

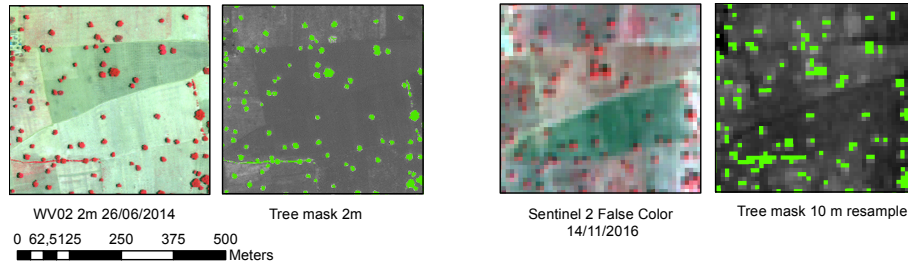


Figure 5.6: Tree mask based on VHR image at the beginning of the growing season (26/06/2014) and resampled to 10 m to match Sentinel-2 resolution. Both satellite images are presented in false colors.

Removal of the trees footprint from the classification inputs leads to a small decay in OA (from 80.16% to 79.99%), which remains within the map's standard deviation ($\pm 0.27\%$). We consequently suggest that trees removal is not required for crop type mapping at 10 m spatial resolution in the study area. This finding is consistent with the fact that the preeminence of end-of-season dates in the classification approach reduces the spectral differences between the tree and crop pixels as crops are at their maximum of vegetation growth. Besides, while it systematically varies along the catena and as a function of distance to main settlements, residual tree density remains independent of the crop type in a production system very dominantly based on inter-annual crop rotations.

5.5.2 Yield estimation

Figure 5.7 reports the strength of crop-specific linear regressions between field measurements of grain yield and total AGB. Very high R^2 s are observed for

maize and millet (0.85 and 0.84 respectively). The high values observed for AGB can be related to the small size of the plot and to bias in the sampling.

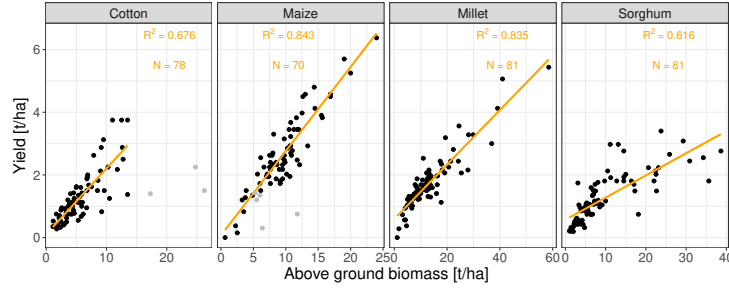


Figure 5.7: Linear regression between yield and total above ground biomass as measured *in situ* on 4 m² plots for each crop type. The outliers are colored in gray and removed from regressions.

Cotton being an indeterminate crop displayed a weaker AGB-yield relationship ($R^2=0.68$), as only one destructive sampling of cotton bolls was possible which may have under-sampled the amount of reproductive material generated. Contributing factors to low R^2 for sorghum (0.62) could include the typically wider range of soil types (notably marginal soils), and low fertilization rates. The best yield estimator differs for each crop type (Figure 5.8). Nevertheless, on the average across crop types, LAI outperforms VIs for yield estimation (average $R^2 = 0.64$ in comparison with peak NDVI reaching an average R^2 of 0.44). The superior performance of LAI can be explained in part by its higher sensitivity in conditions of higher vegetation biomass (when most VIs saturate).

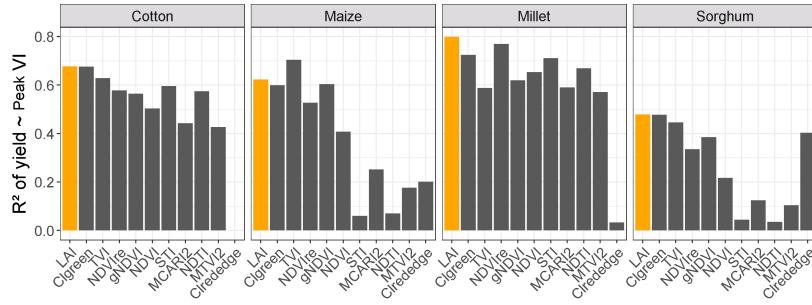


Figure 5.8: R^2 of the linear regressions between yield and peak VI's.

For yield estimation, highest R^2 is reached for millet followed by cotton and maize. Sorghum shows lower R^2 which can be linked to lower AGB - yield relationship ($R^2=0.616$) (Figure 5.7). In fact, as sorghum is often cultivated on shallow soils, low water availability can affect plant maintenance and grain filling in various proportions. Further, sorghum is often strongly photoperiod sensitive, with amounts of AGB generated function of its very variable sowing

date, which typically spans up to 6 weeks in a single landscape. A highly photoperiodic sorghum planted early would not only feature a depressed harvest index due to its lengthened vegetative phase, it could also further depress grain yield due to competing for allocation of residual soil water for biomass maintenance during the grain filling stage. Finally, significant agro-biodiversity is actively maintained by farmers, expressing mostly in sorghum with easily 3-4 contrasting genotypes being employed by farmers in response to various stressors and tactical opportunities. All these factors contribute to decouple sorghum grain yield from AGB, affecting, in turn, the correlation of yield and satellite-derived LAI.

Crop-specific yield linear regressions were calibrated on a homogeneous subset of the field data to limit the impact of the ground measurements heterogeneity and errors. Linear regressions between peak LAI and *in situ* yield averaged at parcel level for each crop type are shown in Figure 5.9. Depending on the crop, these explained between 48 to 80% of yield variability over the calibration fields. RMSE varied from 0.5 to 1 t/ha for the different crops, in a context of wide yield ranges from 1 to 6 t/ha (Table 5.3). As the peak LAI is reached around the end of August and harvest starts – for most studied crops – at the end of September, the peak LAI provides yield estimation at least one month ahead harvest.

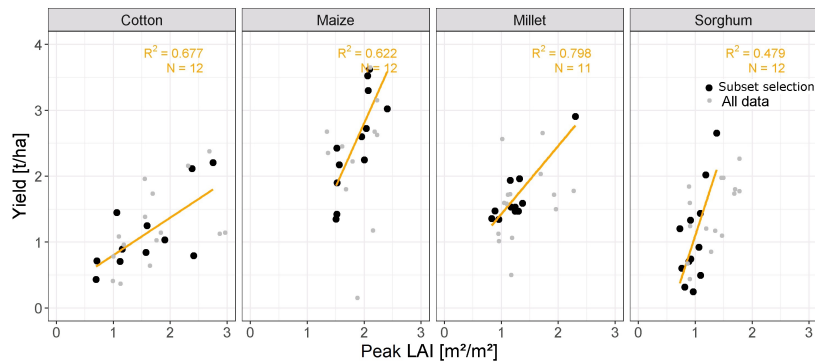


Figure 5.9: Linear regressions between peak LAI and yield for each crop type. These regressions are calibrated on a subset (black dots) composed of the more homogeneous fields.

Table 5.3: Linear regression for yield estimation and its validation.

	Equation	RMSE
Cotton	$Yield [t/ha] = -0.03 + 0.77 * peak LAI$	0.5
Maize	$Yield [t/ha] = -1.04 + 1.93 * peak LAI$	0.97
Millet	$Yield [t/ha] = 0.39 + 1.03 * peak LAI$	0.62
Sorghum	$Yield [t/ha] = -1.56 + 2.66 * peak LAI$	0.73

5.5.3 Agricultural production estimate

The Monte Carlo combination of crop type and yield estimates provides aggregate figures of crop-specific production by village (Figure 5.10). Given the considerable differences in cultivated area, the crop production levels differ strongly across villages. The highest inter-village variation in yield is observed for maize. Nguessou 1 displays the highest maize and cotton yields. Potential explanations may include the widely documented trend towards "*maizification*" of cereal cultivation in Mali's cotton belt, combined with a higher response of maize to fertilization, higher vulnerability to low soil fertility, and substantial fertility carry-over in the locally dominant cotton-maize-(another crop) triannual rotation scheme.

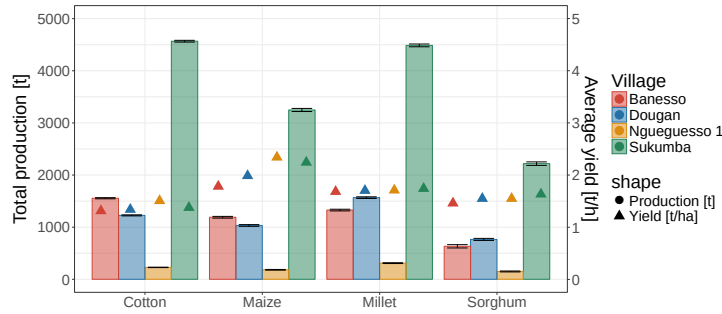


Figure 5.10: Total production (bar plot) and average yield (point plot) for each crop type and each village. Error bars represent 5 times the standard deviation on production estimate with the Monte Carlo approach.

Aggregation of production values estimated through the Monte Carlo approach results in low uncertainty of model estimate for all crop types and villages (Table 5.4). Higher uncertainties are met in Nguessou1 due to the smaller cultivated area, which increases error when aggregating at the village level. Due to their lower F-score in the classification, sorghum features higher production uncertainties. The actual error of the production estimate could only be assessed by comparison with accurate official agricultural statistics available only at a higher level of aggregation (*i.e.*, Mali's circle).

Table 5.4: Standard deviation and uncertainty (%) of crop production estimate model by the Monte Carlo approach for each crop type and village, in tons.

Standard deviation [t] Uncertainty [%]	Banesso	Dougan	Nguessou1	Sukumba
Cotton	2.19 (0.03%)	1.97 (0.04%)	0.76 (0.08%)	3.42 (0.019%)
Maize	3.32 (0.07%)	3.31 (0.08%)	1.35 (0.18%)	5.94 (0.05%)
Millet	3.24 (0.06%)	3.14 (0.05%)	1.54 (0.12%)	5.32 (0.03%)
Sorghum	3.66 (0.14%)	3.92 (0.13%)	1.79 (0.3%)	6.72 (0.08%)

5.6 Conclusions

This chapter proposes an integrated approach to estimate, using Sentinel-2 data, crop-specific production at a community level based on the combination of crop type classification, unbiased area estimate and remotely sensed yield predictors in a stochastic framework. Production estimates generated demonstrate a robust skill, featuring no more than 0.3% of model uncertainty on total production for one community and one crop type.

The recent Sentinel-2 mission opens up new prospects for food security and agricultural performance monitoring in smallholder farming systems. Subject to the availability of a field dataset (crop type polygons to train the classification), high resolution imagery (as Sentinel-2) appears sufficient to accurately classify crop type in the relatively "simple" smallholder farming systems of Mali's cotton belt (OA= 80%). The use of 2 m VHR images for object filtering improved OA by 5%. Those results were obtained inside a cropland mask derived from VHR imagery. Nevertheless, we believe that accurate cropland mask could be obtained directly from Sentinel-2 data as demonstrated using the Sen2-Agri system.

Remote sensing estimates of peak LAI outperformed all spectral VIs tested for yield estimation. The particular value of a single peak LAI predictor is that it offers yield estimation one month ahead of harvest. While the doubling of acquisition frequency brought about by the launch of Sentinel-2B in 2017 may result in an LAI time integral outperforming peak LAI for yield estimation, possible accuracy and/or lead time improvements will need to be evaluated against increased computing costs. While the growing period (especially the start of the season) coincides with high and persistent cloud coverage, preliminary evidence indicates that Sentinel-2B effectively increases the likelihood of a successful <20% cloud cover image acquisition in the Sudano-Sahelian region. Although this evidence remains anecdotal so far, a peak biomass approach such as the one proposed here may offer a sufficiently robust and scalable option for early and granular estimates of crop production.

While estimates of aggregate production are expected to improve our ability to monitor community-level food security accurately, the clear resolution of intra-landscape variability in production levels may even, more importantly, lead to better targeting of agricultural development interventions, addressing the actual bottlenecks of smallholder productivity improvement such as fertilization gaps (Schut *et al.*, 2018). Indeed, agricultural development interventions such as fertilizer or seed supply, microcredit, market access, livestock support, diversification and off-farm activities often follow one-size-fits-all approaches which are unlikely to address the diverse socio-economic and biophysical production conditions in heterogeneous smallholder systems. Efficient, granular baseline mapping of smallholder production levels offers the perspective of a truly transformative environment for the agricultural intensification required to meet food security and enhanced livelihood targets.

Chapter 6

Enriching yield gap's understanding by integrating farmer rationale in Mali's cotton belt *

Highlights

- Mapping of locally attainable yield gap from remote sensing and geospatial data at village, farm and field levels.
 - Key drivers of yield gaps are resource endowment, crops succession, and organic manure.
 - Despite yield gap approach assuming that farmer maximize their production, we showed that they manage the risk when allocating resources.
 - Risk management depends on farmer resource endowment.
-

Abstract. In Mali's cotton belt, important yield gaps (differences between potential and actual yields) are related to low soil fertility, climate variability, pests, diseases and lack of market access. However, a better understanding of yield gaps is key to target agricultural interventions supporting farmers to increase their food security and decrease their vulnerability. Most of the yield gap approaches oversimplify the complex interactions between climate, soil, agricultural practices and human rationale taking place at a very local scale (*e.g.*, the farm level). Using high spatial and temporal resolution imagery and accurate geospatial data, we estimate relative yield gaps for dominant crops (cotton, millet, maize, sorghum) of 42 farmers (327 fields) in a commune of Mali's cotton belt. The objective is to develop a method to study how farmer rationale and farmer management affect yield gaps. A hierarchical model is computed to explain yield gaps according to various human factors intervening at field

*Adapted from Lambert, M.-J., (Traoré, P.S.), Defourny, P. and Baret, P. (2018). Enriching yield gap's understanding by integrating farmer rationale in Mali's cotton belt. Submitted.

and farm scales. Defined by resource endowments and farmer strategies, the socio-economic condition of farmers significantly influences yield gaps of the most fertilized crops: cotton and maize ($p \leq 0.01$). Crop successions also have a significant effect on yield gaps, with lower yield gaps for fields cultivated after cotton or maize, thanks to a fertility carryover effect. Organic manure also significantly decreases yield gaps for cotton fields. Given that organic resources are scarce with only 24% of the main crops area manured, farmers need to prioritize their resource allocations. All farmers preferentially allocate organic manure on fields which do not benefit from fertility carryover (*i.e.*, fields following millet and sorghum in the succession). By integrating farmers' socio-economic conditions, we show that low resource endowment (LRE) farmers allocate, in proportion, more organic manure on high-potential fields to guarantee sufficient production level (low risk-taking on short-term). On the opposite medium and high resource endowment (M/HRE) farmers allocate, in proportion, more organic manure on low-potential fields to recover the soil fertility (long-term soil fertility management). This study demonstrates the contribution of remote sensing to estimate attainable yield gaps at field level and the importance to integrate socio-economic conditions and farmer rationale (*inter alia* resource allocation) to understand yield variability better. This approach is very promising to design, target and evaluate interventions as it provides a methodology to establish the baseline and to assess a posteriori the intervention efficiency.

6.1 Introduction

Despite a very slow increase in both cultivated land and labor productivity in SSA, most of the rural population still depends on agriculture to meet its basic needs (Tittonell and Giller, 2013). Smallholder farming systems face soil fertility challenges and environmental and demographic pressure. Crop production strongly fluctuates in time and space and affects food security. In SSA, yield gaps are also related to the lack of access to agricultural inputs, scarcity of labor force (due to low mechanization), pests and diseases, increasing fragmentation of farms and lack of capital (Hillocks, 2014). A better understanding of yield gaps could help to better target agricultural development interventions, inform policymakers and prioritize research objectives. Targeting is key, as demonstrated in (Saqalli *et al.*, 2011), because the farmers will respond differently to development interventions, depending on their respective socio-economic situation and farm biophysical conditions (Pala *et al.*, 1999).

For a few years, various studies have used the yield gap concept (the difference between potential or attainable yield and actual yield) as an indicator of yield growth potential in a given region (Hall *et al.*, 2013; Licker *et al.*, 2010; Lobell *et al.*, 2009; Pasuquin *et al.*, 2014). The potential yield corresponds to the yield of a specific cultivar, achievable within a defined region when water and nutrients are unlimited and biotic stresses are controlled (Evans, 1993). The attainable yield was originally defined by de Wit (1992) as the yield attainable under water and nutrient-limited conditions. The global yield gap atlas (van

Ittersum *et al.*, 2013) has designed a standardized method to estimate yield gaps all over the world with a crop growth model used over similar climatic areas. Nevertheless, this elegant approach simplifies the well-known interactions between climate, soil, agricultural practices and human rationale taking place at a local scale. The concept of yield gap computed from potential and actual yields is meaningful in highly productive agrosystems when actual yields are close to potential yields. In SSA, actual yields fluctuate at around 20% of potential yield (Titttonell and Giller, 2013). Thus, Titttonell and Giller (2013) defined a locally attainable yield as an adaptation of attainable yield which fits into the African context. This locally attainable yield is the maximum yield achievable by resource endowed farmers in the most productive field of their farm. In short to mid-term perspective, only the locally attainable yield makes sense in SSA smallholder farming systems (Titttonell and Giller, 2013).

While most studies used field measurements and crop models to estimate yield gaps (Affholder *et al.*, 2013; van Ittersum *et al.*, 2013), Lobell (2013) mentioned the vast potential of remote sensing to measure and understand the magnitude of crop yield gaps at different scales. With recent improvements in observation technologies and the associated policy access, such as the Sentinel constellation, significant spatial and temporal granularity constraints have been lifted. At best, it is now possible to monitor fields with crop growth information derived every five days from a 10 m spatial resolution imagery increasingly compatible with smallholder farming systems (see Chapter 5). While lots of studies aim to use remote sensing to estimate yield, produce yield maps and study yield variability (Azzari *et al.*, 2017; Burke and Lobell, 2017; Jin *et al.*, 2017), only a few used it to estimate yield gaps directly (Zhao *et al.*, 2015).

While the assessment of yield gaps intermingles various disciplines as agronomy, soil science, climatology and social science, the approaches studying yield gap often proceed from a pure agronomic point of view (van Ittersum and Rabbinge, 1997). Most of the studies identifying the driving factors for yield gaps focus on more efficient crop management and inputs' use. These approaches are mainly assessed at field scale and extended at regional or even global scale (Mueller *et al.*, 2012; van Bussel *et al.*, 2015a). Besides, most of the studies on yield gaps deal with a single crop or mix all crops which restrict the analysis to just one component of a complex livelihood strategy for farming households (Hillocks, 2014). In fact, as crop management takes place at farm level, yield gaps have to be analyzed with a broader understanding of the farming systems including socio-economic constraints, labor force availability, farmers' aspirations and strategies. van Noordwijk and Brussaard (2014) highlighted that focusing only on yield gap can yield to negative impacts on other components of the farming system (*e.g.*, livestock). Guilpart *et al.* (2017) proposed a novel approach to assess cropping system yield gaps by taking into account the spatial and temporal settlement of crops, such as inter-cropping, cropping intensity or succession per unit of land. Henderson *et al.* (2016) proposed a system-wide yield gap by estimating both crops and livestock yield gaps. Recent publications (Silva *et al.*, 2017; van Dijk *et al.*, 2017) drawn attention on the various

interpretations of yield gaps made by economists and agronomists. Berre *et al.* (2017) showed that the biophysically-determined attainable yield gaps vary in Malawi according to the socio-economic context of farming systems and the individual livelihood strategies of farmers. Falconnier *et al.* (2018) highlighted the importance to consider the heterogeneity of farms when aiming to increase agricultural productivity because farmers are expected to respond in different ways to changes in socio-economic conditions. Assessing and understanding yield gaps at both farm and field levels by combining natural and human factors seems relevant to target agricultural interventions to the farmer's needs.

This research aims to develop a method to study how farmer rationale and farmer management affect yield gaps in smallholder farming systems of Mali's cotton belt. Thanks to Earth Observation advances, a novel approach is proposed to retrieve relative yield gaps without tedious *in situ* yield measurements. Yield gaps variability is expected to be related to natural and human factors. To focus on the human factors impact, estimated yield gaps are corrected for natural factors variability. The human factors articulate farm level (resource endowment level, farmer strategy) and field level (agricultural practices) and are derived from socio-economic and satellite remote sensing data. A hierarchical model is built to explore the effect of human factors on yield gaps.

6.2 Material

6.2.1 Study site

The study area (353 km²) is defined by the geographical footprint of the 43 POs registered in the five villages of the Koningue commune (Koutiala district, south-eastern Mali) (Figure 6.1).

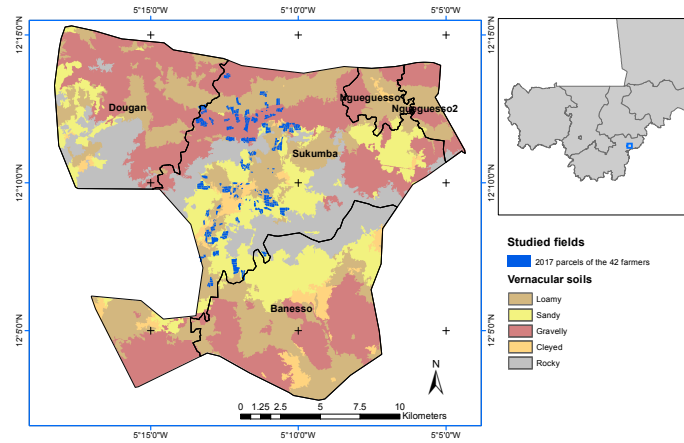


Figure 6.1: The Koningue area with its villages. Soil map is shown as background.

The site is located in the older densely populated part of the cotton production basin of Mali. The cotton belt was chosen as a study site for two main reasons: (i) the cotton belt is characterized by high spatial variability, (ii) the cotton crop is installed since more than 40 years and benefited from large homogeneous agriculture interventions managed by the CMDT (*e.g.*, access to agricultural inputs as seeds and fertilizers). This region expected to tend to a homogeneous farming system after 40 years of agronomic support, still exhibit a large crop variability which could be farmer induced. Smallholder rainfed agriculture is dominant with annual rainfall exceeding 850 mm. The impact of weather conditions is assumed homogeneous over this small study area or at least its spatial variability is considered randomly distributed with regard to our studied fields. The main crops are cotton (cash crop), maize, sorghum and pearl millet (subsistence crops). Fields averaged 1.6 ha in size and typically feature both low fertilization rates and low yields. The growing season settles on the rainy season onset and takes place from May to end of November. For a complete description of the study site, please refer to Chapter 3.

6.2.2 Satellite images

Two VHR images - Pléiade (for 2017 season), WorldView 2 (for 2016 season) (Figure 6.2) - are used to delineate farmer parcels. A Pléiade image of the entire study area, acquired on the 6th of November 2017 provides multispectral observation at 2 m spatial resolution (panchromatic image at 50 cm). This orthorectified cloud-free image was pansharpened using the Bayesian data fusion method (Fasbender *et al.*, 2008) implemented in Orfeo Toolbox (panchromatic band weight of 0.95). The resulting 50 cm multispectral color composite allows to see details such as trees, edges, and pathways which was instrumental in recognizing and digitizing farmer fields. A WorldView 2 image was acquired over the study area providing orthorectified cloud-free multispectral imagery at 1.6 m spatial resolution on the 9th October 2016.

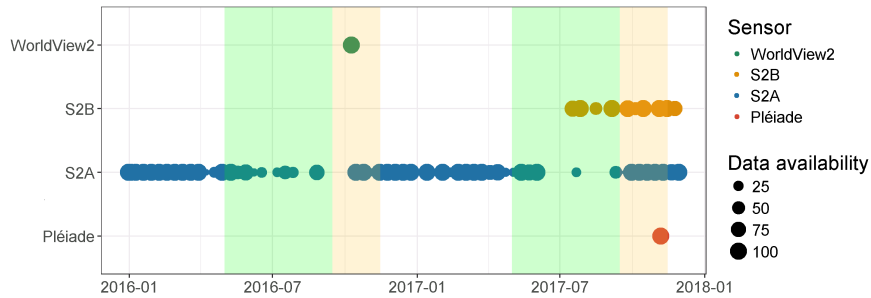


Figure 6.2: Satellite data availability for both 2016 and 2017 years and the four sensors with valid cloud-free data availability ranging from 0 when cloud cover is total to 100 when there is no cloud at all. The green color in the background indicates the growing vegetation period while the orange shows the vegetation senescence.

Sentinel-2 HR TS images are used to estimate yield gaps for the 2017 season. While Sentinel-2A was the only satellite in orbit in 2016, both Sentinel-2A and Sentinel-2B were available from July 2017, reducing the revisit time to five days. Sentinel-2 provides multispectral surface reflectance from 10 to 20 m spatial resolution after atmospheric correction and cloud masking using the ESA Sen2-Agri system. For detailed information on the data, please refer to Defourny *et al.* (2018). Despite the observation frequency, cloud coverage during the growing season limits the data availability (Figure 6.2).

6.2.3 *In situ* data collection

The study focuses on 42 farmers of the Sukumba village during 2016 and 2017 seasons. In 2016, 105 fields (25 of cotton, 26 of maize, 27 of sorghum, and 27 of millet) of the 42 farmers were sampled to collect yield and biomass measurements. The sampling strategy is fully described in Chapter 5 (Section 5.3.3.). Closed-ended interviews were conducted by field operators to collect agricultural practices on the 105 studied fields as well as the main socio-economic characteristics of each of the 42 farmers including household size, level of equipment, total cultivated area, herd size, etc.

In 2017, a one-month field campaign was conducted to get complementary information about the same 42 selected farmers. Open-ended interviews were realized to collect a complete dataset of cadastral parcels for 2016 and 2017 for the 42 farmers together with additional details about yield variability, agricultural practices, strategies, constraints, visions, and motivations. Cadastral parcels were collected with the help of VHR images. Most of the time, it was possible to recognize and draw with the farmer all his fields on the image. Nevertheless, when this task was difficult, fields were visited to collect GPS coordinates. In total, 327 parcels of 42 farmers were studied in 2017, which covers more than 530 ha, represents 3.6% of the cropland extent in the Sukumba village and includes 144 cotton fields, 63 maize fields, 77 millet fields and 43 sorghum fields. In 2016, 324 parcels were identified with one of these crop types for the same farmers and over the same area. The proportion of crops in the field dataset is similar for both years and is as follows: 50% cotton, 29% millet, 15% maize and 6% sorghum. Cotton, maize, millet, and sorghum are the dominant crops and cover approximately 80% of the harvested area in Mali's cotton belt (You *et al.*, 2014). The three main successions are realized by farmers: (i) cotton followed by cereals, (ii) cotton followed by maize and then other cereals, and (iii) cereals followed by cereals. Farmers also cultivate minor crops such as peanut, cowpea, sesame, tomato, rice, and shallots. These minor crops are not considered in this study. From now on, when we refer to farmer fields, they correspond to farmer fields with one of the main crops (cotton, millet, maize, and sorghum).

6.2.4 Ancillary data

A substantial georeferenced points database of vernacular soils (6,783 geolocated points) was built for the entire study area in 2015 thanks to farmer

interviews (P.C. Sibiry Traoré, 2015). This dataset has been used to generate a vernacular soil map based on a segmentation of soil brightness derived from Sentinel-2 and elevation data at 30 m derived from SRTM (more information in Appendix C). The vernacular soil map was already presented in the study region description (Figure 6.1). It represents farmers' opinion regarding the soil quality. The soil type is correlated with the cultivated crop type. Cotton and maize require more fertile soils and are cultivated in decreasing priority on loamy, sandy and clayey soils. On the opposite, millet and sorghum are less demanding in nutrients and more resistant to drought. As a result, they are more abundant on gravelly and rocky soils, particularly sorghum.

A 2 m tree mask was produced for the study area for 2014 (more information in Chapter 5 (Section 5.4.1)). No significant change of the tree distribution in the fields is expected between 2014 and 2017.

6.3 Overall methodology

The overall methodology is based on two main research questions (Figure 6.3): (i) how to retrieve yield gaps from satellite remote sensing and geospatial data, and (ii) what are the relevant human factors to understand the observed yield gaps better.

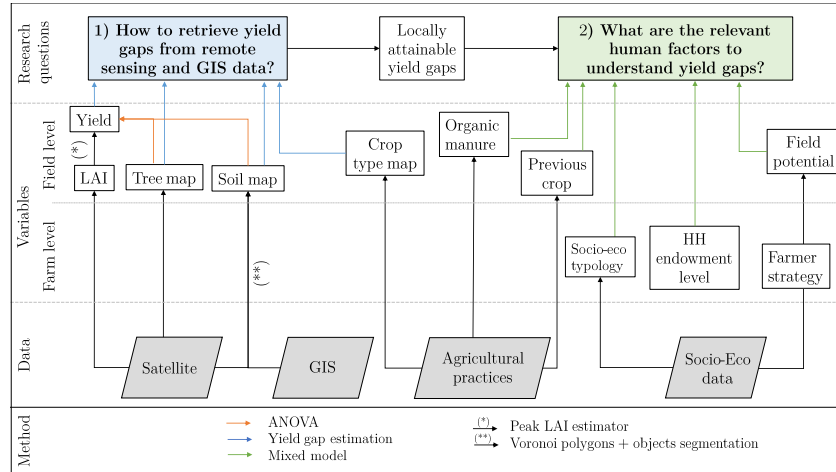


Figure 6.3: The overall approach to contextualize the yield gap regarding natural and human factors, leading to the locally attainable yield gap.

First, the yield is estimated based on remote sensing data and the influence of natural factors on yield is assessed. The estimated yield is used to estimate locally attainable yield gaps. Then, different human factors derived from sociological data and agricultural practices are used to test their influence on yield gaps (Figure 6.3). This is done to enrich the understanding of yield gaps with regard to human behaviors. As human factors play at both field and farm levels, a hierarchical model is used to solve the second research question.

6.3.1 Yield gap estimation

The peak LAI (maximum LAI observed along the growing season) is used to estimate yield as it has shown good results in the study area (Lambert *et al.*, 2018). The LAI is defined as one half the total leaf area per unit of horizontal ground surface Chen and Black (1992). LAI is retrieved from Sentinel-2 reflectances using an artificial neural network to inverse a radiative transfer model called PROSAIL. The methodology has been implemented in the ESA Sen2-Agri system (Bontemps *et al.*, 2015a) based on the method developed by Weiss and Baret (1999). The peak LAI is the maximum LAI value observed along the growing season. The peak LAI is computed at the pixel level with one peak LAI date for each pixel. As in the 2017 growing season 24 Sentinel-2 images are available, the peak LAI is computed as the maximum LAI for each pixel within these 24 images (from April to November).

As proposed by Tittonell and Giller (2013) and applied in Guilpart *et al.* (2017), Bhattarai *et al.* (2017) and Fermont *et al.* (2009), the locally attainable yield (Yl) is defined by the water and nutrient-limited yields achieved in the most productive fields of farmers in a community. In this paper, the Yl is computed as the 90th percentile of the estimated yield (peak LAI) to be consistent with the recommendations of Tittonell and Giller (2013) for smallholder farming systems. As we want to focus this research on human factors, the yield gap estimation is corrected by removing the natural factors. Indeed we expect a very significant correlation between these natural factors and yield. As we assumed homogeneous meteorological conditions over the study area, natural factors are restricted to soil type and tree presence. The effect of natural factors on yield estimation is assessed with an ANOVA (p-values). As a result, the yield gap is computed directly with peak LAI according to both crop type and soil type with the removal of all tree pixels. The geospatial data (*e.g.*, soil map) allows to go one step further to include local soil quality in the yield gap computation and thus improve the locally attainable yield gap. The yield gap is calculated as a percentage of locally attainable yield following Equation (6.1).

$$YG_{s,c} = \left(\frac{Yl_{s,c} - Peak\ LAI_{s,c}}{Yl_{s,c}} \right) * 100 \quad \text{with } Yl_{s,c} = quant90(Peak\ LAI_{s,c}) \quad (6.1)$$

Where $c \in (\text{cotton}, \text{maize}, \text{millet}, \text{sorghum})$ and $s \in (\text{clayey}, \text{gravelly}, \text{loamy}, \text{rocky}, \text{sandy})$.

Yl is the locally attainable yield defined as the maximum yield (90th percentile) achieved by farmers in their most productive field; YG is the yield gap defined as the difference between Yl and actual yield and expressed as the percentage of locally attainable yield. All yields are expressed in LAI unit. A 0% value means no yield gap as the actual yield equals the attainable yield. On the opposite, a 100% value means an enormous yield gap as the actual yield is null.

6.3.2 Relevance of human factors to understand yield gaps

Construction of human factors

Socio-economic data collected during the interviews are used to build a socio-economic typology of farms and to describe farmer strategies (defined as the main long-term objectives of the farmer, which drive farm management). Other variables such as previous crop (defined as the crop cultivated the year before for a given pixel), organic manure (defined as the occurrence of manure application in the field) and field potential are directly usable. The field potential, called "*la force du champ*" in French, is a variable used by farmers to describe their fields. It acknowledges the potential of the field in relative terms with regard to the crop production. This potential is dependent on natural (soil type, slope, rainfall distribution) and human factors (historic management influenced by workload, resources allocation, parcel fertilization history and farmers' knowledge). Field potential takes a range of values from High when the field is defined by the farmer as one of the most productive of his fields (high-potential fields) to Very low when the field is one of the least productive of his fields (very-low-potential fields). Various fields of a single farmer can have the same field potential if they present similar production potential. Let's note that the field potential is not always easily transposable from farmer to farmer as it corresponds to a relative assessment at farm level (Kambiré *et al.*, 2017). This will be taken into account by a hierarchical model development.

Based on other studies that built farm typology in Mali's cotton belt (Dufumier, 2005; Falconnier, 2009), six main variables are retained to assess household resource endowment: the total cultivated area, the number of workers in the household, the total number of people in the household, the herd size expressed in tropical livestock unit (TLU), the number of oxen and the nature and size of the equipment - plows, weeders and sewing machines - expressed in total number of equipment. The data is normalized and cluster analysis is completed following the methodology of Falconnier (2009). The ascending hierarchical classification (AHC) is used to do the cluster analysis. The Ward Euclidian distance automatically selects three clusters by minimizing the increase in total within-cluster variance after merging (Ward Jr, 1963).

Definition of the hypothesis

The tested hypothesis can be formulated as follows: farmers differentiate their resource allocation according to the crop succession, the field potential, and their socio-economic conditions.

The agro-climatic conditions are also expected to affect the household resource allocation but this is not investigated in this study as yield gaps have been corrected for natural factors. Figure 6.4 illustrates an application of the hypothesis for the organic manure allocation in two farm types: one with low resource endowment (LRE) and one with high resource endowment (HRE). The analysis allows testing whether the household resource endowment influences

the allocation of manure in a way that can be equal or unequal with respect to the field potential.

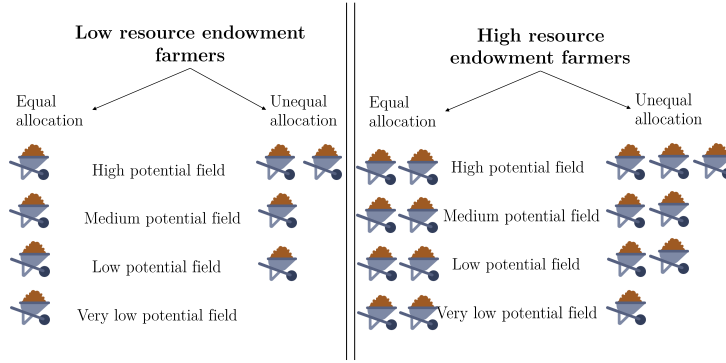


Figure 6.4: Illustration of the hypothesis for organic manure allocation, for two different household resource endowments.

To test such a hypothesis, a hierarchical linear model articulating two levels - farm and field - is used. Hierarchical models are statistical models using variables that vary at more than one level. They are relevant in this study as the explanatory variables are defined at different levels (pixel, field or farm). The model was implemented in R with the form:

$$YG = Pot + RE + OM + Pr. crop + Strategy + (1|Field) + (1|Farmer) \quad (6.2)$$

Pot represents the field potential, *RE* the resource endowments, *OM* the organic manure, and *Pr. crop* the previous crop. The hierarchy of the dataset is fully described in Figure 6.5. In total, the complete dataset includes 53,064 pixels, 327 fields and 42 farmers for the 2017 season. As the yield gap is computed at the pixel level, all variables are assigned at the pixel level (arrows in Figure 6.5).

In a first step, an empty mixed model at two levels is built for each crop type separately, with the two levels (farm and field) and no explanatory variable. It gives the decomposition of the variance according to field and farm levels only. Then, a hierarchical model with the five candidate explanatory variables is computed for each crop type. All variables are considered in a single model to recognize interdependence between variables. The hypothesis of normality and heteroscedasticity are verified by looking at the residuals. The p-value of each variable is computed thanks to a Chi-squared test (Chambers, 1992).

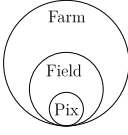
	Pixel	Field	Farm	Yield GAP
	1	a	A	10.1
	2	a	A	5
	..	..	..	..
	20	b	A	80
	21	b	A	81.2
	...	..	..	...
	200	a	B	25.2
	201	a	B	20
	...	...	...	...
TOT number	53,064	327	42	53,064
VARIABLES				
YG explanatory variables			YG correction	
Soil				X
Crop type				X
Tree				X
Previous Crop	X			
Organic manure	◀.....	X		
Field potential	◀.....	X		
HH endowment	◀.....		X	
Strategy	◀.....		X	

Figure 6.5: Dataset description with the yield gap computed according to crop type, soil and tree presence. The locally attainable yield gap is explained by field potential, organic manure, previous crop, resource endowment, and strategy. All variables are assigned at the pixel level (arrows).

6.4 Results

6.4.1 Estimation of yield gaps

The distributions of the peak LAI for each crop in 2017 are shown in Figure 6.6.

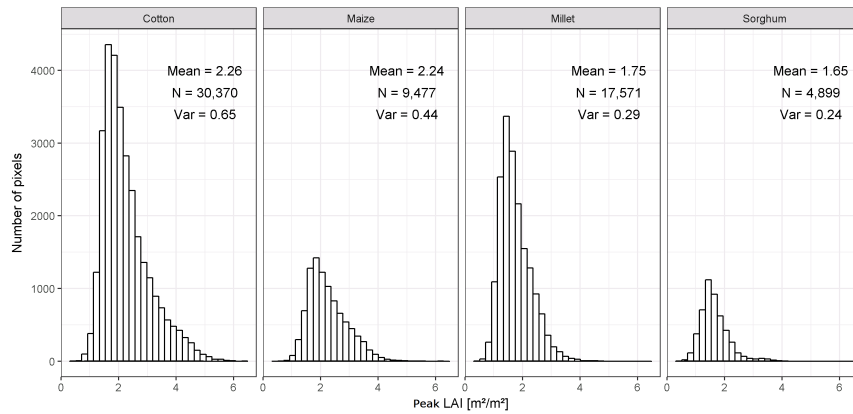


Figure 6.6: Distributions of the peak LAI for the 2017 season per crop types.

This proxy of yield respects the hypothesis of a normal distribution for all crop types according to the Shapiro test (Shapiro and Wilk, 1965). The soil has a very significant effect on estimated yield for all crops with highest p-value for sorghum (Table 6.1, Figure 6.7). The tree presence affects the peak LAI (yield estimator) significantly for all crops, but the effect is stronger for millet and sorghum. These two crops are less fertilized than cotton and maize and show lower vegetation cover, leading to higher vegetation contrasts between the canopies and cultivated plants. These results confirm our hypothesis to remove tree pixels for the yield gap computation and to compute yield gaps per soil type. The locally attainable yield gap is computed for each pixel per soil type and represents the percentage of attainable yield. From now, when we talk about yield gap, we refer to this locally attainable yield gaps.

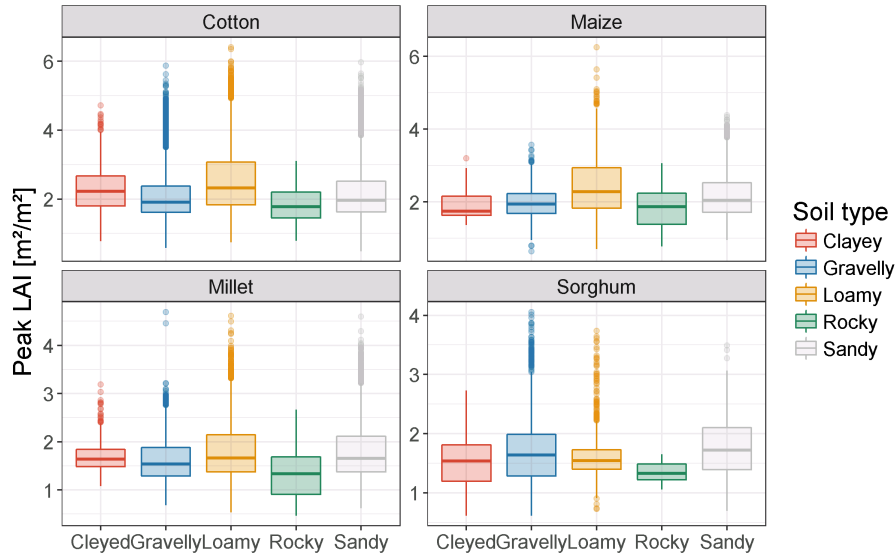


Figure 6.7: Distributions of the peak LAI per soil and crop types.

Table 6.1: P-values for soil type and tree presence as explanatory variables of yield estimator (peak LAI). Results are crop specific for trees and soils. Significance code (***) means the p-value < 0.0001.

	Cotton	Maize	Millet	Sorghum
Soil type	$< 2 * 10^{-16}$ (***)	$< 2 * 10^{-16}$ (***)	$< 2 * 10^{-16}$ (***)	$1.35 * 10^{-9}$ (***)
Tree pres.	$1.36 * 10^{-4}$ (***)	$7.88 * 10^{-5}$ (***)	$6.92 * 10^{-15}$ (***)	$4.44 * 10^{-12}$ (***)

The average yield gaps are 35% for cotton, 31% for millet, 27% for sorghum and 29% for maize. The distribution of yield gaps for the driving forces studied in this thesis are shown in Appendix E.

6.4.2 Relevance of human factors to understand yield gaps

Household resource endowment and farmer strategies

Three very different levels of resource endowment are clearly defined, distributing all the interviewed farmers of the same village in three groups of comparable sizes: low resource endowment (LRE, $n=15$), medium resource endowment (MRE, $n=13$) and high resource endowment (HRE, $n=14$) households (Figure 6.8). The LRE farms feature low cultivated area (lower than 6 ha for the majority of the farms), low equipment level, and small size of herd (TLU and oxen). The HRE farms feature large household size with more than 34 persons for most farms. The MRE farms feature a medium cultivated area size, household, and herd (Figure 6.8).

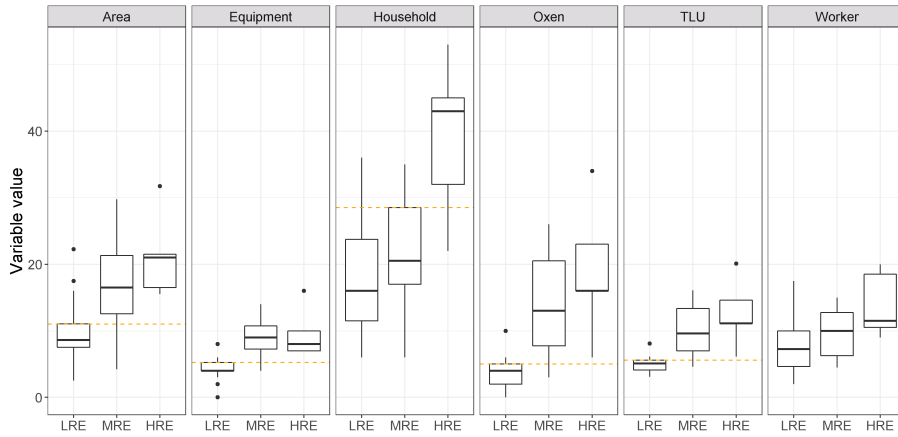


Figure 6.8: Distribution of the socio-economic variables for the three farm types: low resource endowment (LRE), medium resource endowment (MRE) and high resource endowment (HRE). Each box is delimited by the quartile 25, the median (in the middle) and the quartile 75 with whiskers showing 1.5 times the inter-quartile range and points presenting the outliers. Horizontal lines are drawn to highlight the clearest differences between clusters. TLU corresponds to the tropical livestock unit.

All farmers but three cultivate cotton in the Koningue commune. Most farmers cultivate small parcels (generally ≤ 0.25 ha) in the lowlands with shallots, potatoes, tomatoes, and peppers. If family members are abroad, they often do not contribute significantly to the family income. Many farmers carry out small extra-agricultural activities benefiting to the day to day expenses (see Chapter 3, section 3.5.1). By analyzing the farmers' interviews, farmers can be grouped into five long-term strategy classes that are related to farmer endowment levels (Figure 6.9):

- Agriculture cotton cereal system (CCS) strategy: these farmers rely mainly on agriculture. They cultivate cotton for income generation and millet

and maize for household consumption. They also cultivate shallow soils in lowlands and do not perform any extra-agricultural activities.

- Agriculture (CCS) and gardening strategy: these farmers cultivate cotton and cereals but also a large area (≥ 0.25 ha) of lowlands for gardening (shallot and potato essentially). The gardening products are sold on local and regional markets and contribute to the household income.
- Agriculture (CCS) and extra-agricultural activities (diversification): these farmers cultivate cotton to get access to fertilizers, grow cereals for self-consumption and do extra-agricultural activities (*e.g.*, shopkeeper, traditional therapist, builder, tailor, teacher, musician) for income generation.
- Agriculture (CCS) and banana: these farmers have access to large areas in lowlands which allow them to cultivate banana on large parcels (1-3 ha). Most of the time they get high income from the banana.
- Agriculture (CCS), banana and gardening: these farmers cultivate limited areas but diversify their agricultural activities with gardening and banana products. They often get extra income from these activities and invest them in cereals and cotton cultivation (*e.g.*, fertilizer, herbicide, livestock).

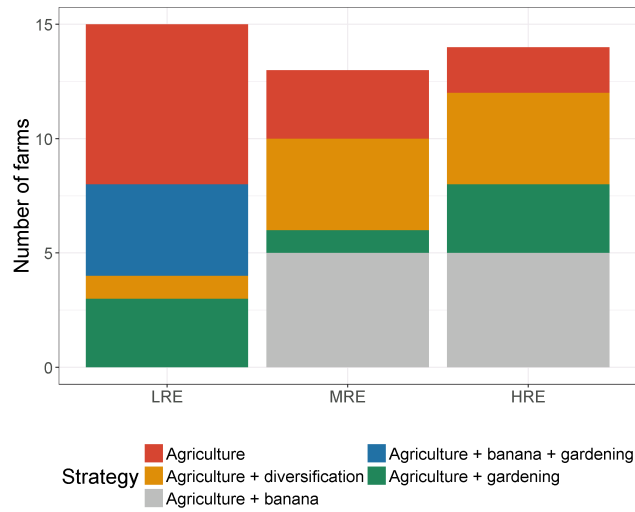


Figure 6.9: Strategy distribution of the 42 farms according to resource endowment level. LRE, MRE, and HRE stand for low, medium and high resource endowments, respectively.

While most of the LRE households have a strategy focused on CCS agriculture, MRE and HRE households feature similar characteristics with extra CCS activities (banana, extra-agricultural activities) increasing the household income. Gardening activities are encountered across all resource endowment levels. Four farmers with LRE based their strategy on CSS agriculture, gardening and banana, trying to limit risk by diversifying their activities.

A hierarchical model for articulating field and farm levels

A hierarchical empty model reveals that the combination of farm and field levels explains more than 50% of yield gap variability for all crop types. The farm level explains more than 25% of the yield gap variability for both maize and sorghum, which already illustrates some impact of human factors (Figure 6.10).

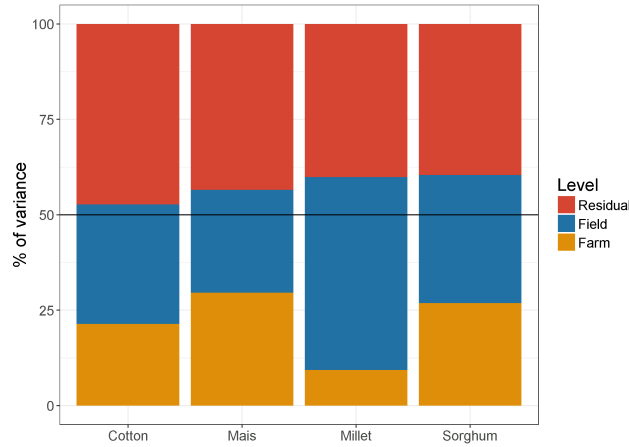


Figure 6.10: The yield gap variance percentage computed on an empty mixed model at two levels: field and farm.

The inter-farms variability is lower for cotton (21%) and millet (9%). The inter-fields variability is the highest for millet where it reaches 50%. It is followed by sorghum, cotton, and maize with an inter-fields variability of 33%, 31%, and 27%, respectively. The residual variability includes the intra-field variability and part of the unexplained variability. The high importance of field and farm levels confirms the relevance of hierarchical models to explain yield gaps.

Hierarchical model assumptions, definitions and results

At the farm level, a first analysis show (i) similar yield gap distributions for MRE and HRE farmers, (ii) low correlation between farmer strategies and yield gaps, and (iii) strong correlation between farmer strategy and household resource endowments. According to that and to ease the interpretation, MRE and HRE farmers are grouped in a single category and strategies are not included in the hierarchical model. The resulting simplified hierarchical model has the form:

$$YG = Potential + OM + RE + Prev. crop + (1|Field) + (1|Farmer) \quad (6.3)$$

Where *Potential* stands for field potential and $\in$ (High, Medium, Low, Very low), *OM* stands for organic manure application and $\in$ [Yes, No], *RE* stands for resource endowments and $\in$ (LRE, MRE/HRE), and finally *Previous crop* $\in$ (Cotton, Maize, Millet, Sorghum).

The results of the hierarchical model at field and farm levels are presented in Table 6.2 and in Appendix E. At the farm level, the household resource endowment is correlated to yield gap with a statistically significant effect for both cotton and maize. This effect is not significant for millet and sorghum (Table 6.2, Appendix E). A higher resource endowment significantly decreases the yield gaps for cotton and maize only. These crops need more agricultural inputs (*e.g.*, fertilizer, herbicide) than millet and sorghum. On the opposite, millet and sorghum are lowly fertilized and require limited external inputs. The spatial distribution of yield gaps for the 42 farmers in the whole study area is presented in Figure 6.11.

Table 6.2: P-values of the hierarchical model with the potential explanatory variables of yield gaps. Significance codes are (***) for $p < 0.0001$, (**) for $p < 0.001$, and (.) for $p < 0.1$. RE stands for resource endowments.

Yield gap:	Cotton	Maize	Millet	Sorghum
Farm level				
Resource Endowment	0.0075 (**)	0.0043 (**)	0.398	0.224
Field level				
Previous crop	$< 2 * 10^{-16}$ (***)	/	$< 2 * 10^{-16}$ (***)	/
Organic manure	$4.2 * 10^{-4}$ (***)	0.218	0.443	/
Field potential	0.019 (.)	0.404	0.028 (.)	0.267

At the field level, the previous crop strongly influences yield gaps for cotton and millet (Table 6.2, Appendix E). As cotton and maize are highly fertilized, the following crops benefit from a fertility carryover effect, decreasing the yield gap significantly. On the opposite, millet and sorghum are poorly fertilized. As a result, no fertility carryover exists, which increases the yield gap significantly. The effect of the previous crop could not be assessed for maize and sorghum as they are almost always cultivated after cotton. Indeed, all the combinations of crop successions are not equally distributed in the study area and most maize and sorghum fields are cultivated after cotton (*i.e.*, 92% of maize fields (in proportion area in our dataset) are cultivated after cotton).

Organic manure application yields to a significant decrease in yield gap for the cotton crop but not for the other crop types (Appendix E). This is related to agricultural practices as, in our dataset, 37.5% of the cotton area was manured in contrast with 10.7% of maize area, 2.9% of millet area and no proportion of sorghum area.

The field potential is correlated to yield gap with a significant effect for cotton and millet (Table 6.2, Appendix E). Let's note that as yield gaps were computed per soil types, the field potential refers mainly to human factors and rainfall distribution variability. Low correlation is observed for maize because maize is most of the time cultivated on high potential fields.

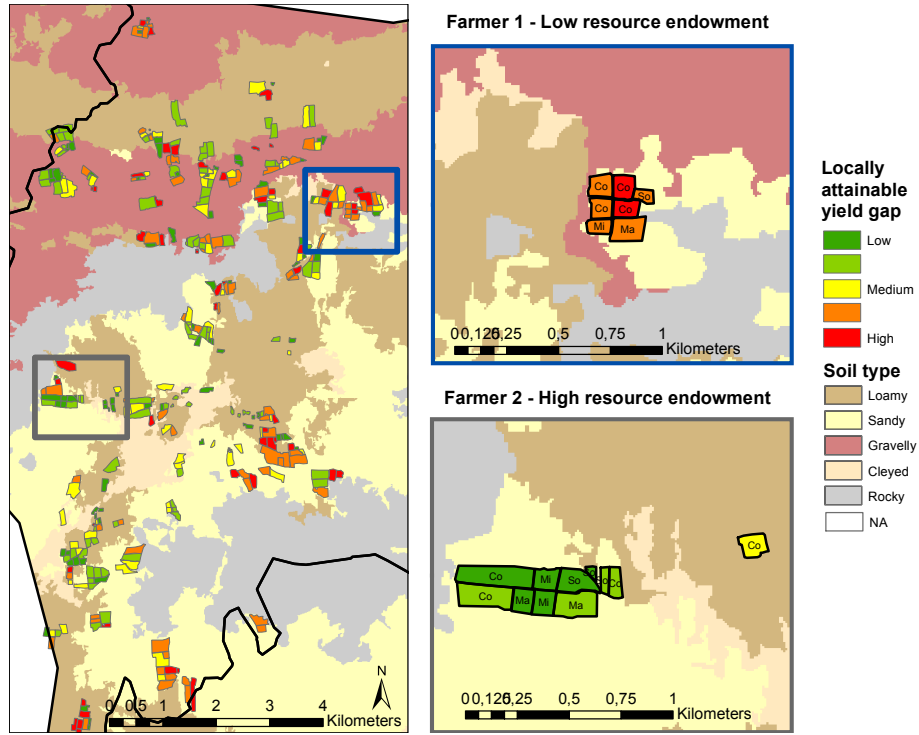


Figure 6.11: Average locally attainable yield gap per field for the 42 farmers (left) and zooms for two farmers with distinct resource endowments (right). The crop types are written within the fields with: Co for cotton, Ma for maize, Mi for millet and So for sorghum.

6.4.3 Test of the hypothesis

Farmers differentiate their resource allocation according to the crop rotation

In the study area, resources are limited as on average only 24% of the fields receive organic manure (see Chapter 3, section 3.5.3.). This proportion would be lower if all minor crops were included. The low availability of manure forces farmers to allocate resources regarding, *inter alia*, their endowment level, and their rationale. As the previous crop is key to explain cotton yield gap with a sharp contrast between fertilized crops (maize and cotton) and non-fertilized crops (millet and sorghum), we explore previous crop effect on organic manure for cotton. Two subsets of the dataset are built: (i) all cotton fields cultivated after low-fertilized crops (millet and sorghum), and (ii) all cotton fields cultivated after high-fertilized crops (maize and cotton). The organic manure has a substantial effect on cotton yield gap when the previous crops are millet or sorghum ($p = 4.24 \times 10^{-6}$) and not at all when previous crops are cotton or maize ($p = 0.11$).

The organic manure allocation is obviously related to crop succession but also to farmer socio-economic conditions characterized by resource endowments. LRE farmers cultivate on low average area per farm (6.12 ha) and apply manure on 33.8% of their cultivated area (Figure 6.12). M/HRE farmers cultivate on average larger areas (15.12 ha) but apply manure only on 22.7% of their cultivated area.

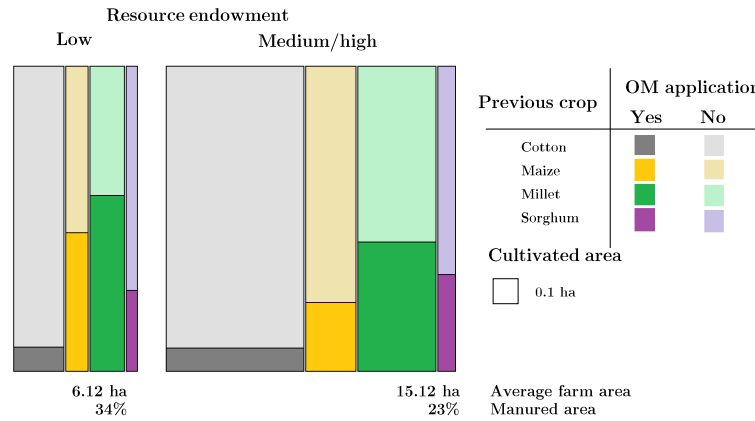


Figure 6.12: Distribution of the acreage according to the previous crop and the organic manure application within two averaged farms of two distinct resource endowment (low and medium/high). The rectangular surfaces drawn are proportional to the cultivated acreage.

This results in 58.3% of the fields cultivated after millet or sorghum that are manured in LRE farms (light green and light purple divided by all green and purple for LRE farmers in Figure 6.12). This number falls to 42% in the M/HRE farms (same ratio for M/HRE farmers in Figure 6.12). While the total proportion of field manured varies according to resource endowment, the manure allocation according to previous crops are similar in both resources endowment, with on average 62% of the organic manure applied on fields previously cultivated with millet and sorghum for both LRE and M/HRE farmers (ratio between light green plus light purple and light yellow plus light gray for both LRE and M/HRE, Figure 6.12).

Farmers differentiate their resource allocation according to the field potential

In a similar approach, the organic manure allocation can also be studied in relation with field potential and resource endowment. A first observation indicates that M/HRE farmers do not declare any of their fields having very low potential while this is the case for LRE (Figure 6.13). The LRE farmers allocate the organic manure unequally according to field potential (Figure 6.13). In fact, LRE farmers allocate organic manure preferentially on their best fields (high

potential fields for LRE farmers) while low and very low-potential fields receive less or no manure.

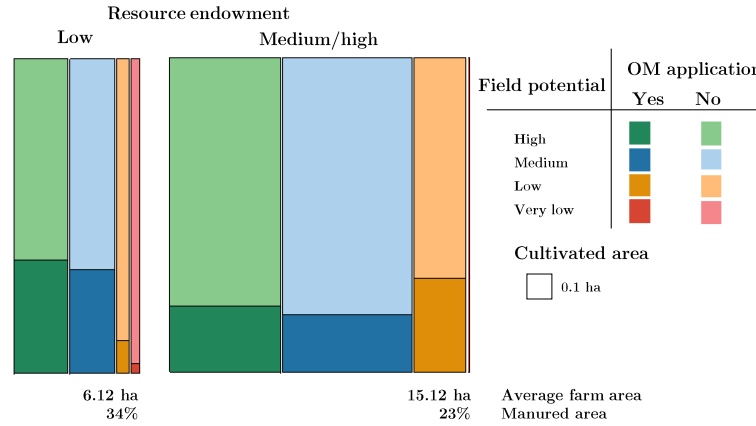


Figure 6.13: Distribution of the acreage according to the field potential and the organic manure application within two averaged farms of two distinct resource endowment (low and medium/high). The rectangular surfaces drawn are proportional to the cultivated acreage.

The M/HRE farmers allocate the organic manure more evenly on all their fields whatever the field potential. The biggest difference between resource endowment levels is observed for low-potential fields (orange in Figure 6.13). LRE farmers tend not to manure these fields while M/HRE farmers manure them in high proportion.

6.5 Discussion

6.5.1 Remotely sensed estimation of yield gaps

In Mali's cotton belt, thanks to the availability of HR satellite data during the vegetation growth, it is possible to estimate relative yield gaps from remote sensing and without *in situ* yield measurement, using peak LAI as a proxy of yield (see Chapter 5, section 5.5.2.). While operational agriculture monitoring systems often rely on costly and time-consuming ground yield measurements that lack representativity and reliability in most of the cases (see Chapter 2), this method provides the yield gap information for each pixel thanks to global imagery available free of charge, and with limited computing resources. The yield gap estimation offers relative yield gaps (percentage) and not actual yield gaps (in tons/ha for example). Nevertheless, relative yield gaps are relevant to assess the main sources of local yield gap variability.

6.5.2 Importance of human factors for yield gap explanation

While most researches on yield gap limit their analysis to natural factors and agricultural practices, this research aims to enrich the understanding of yield gaps by integrating human rationale. A study demonstrated that previous crop with the fertility carryover, soil type and inter-annual weather variability are the main factors explaining yield variability in the study region (Falconnier *et al.*, 2016). In this paper, we tested the hypothesis that decisions of farmers are influenced by their socio-economic conditions and that farmers differentiate their resource allocation according to crop succession and field potential. Figure 6.14 sums up the methodology used, with the most important relations represented by bold dark arrows. The farmer socio-economic conditions are linked to resource endowments and strategies. These resource endowments are derived from a typology and have similarities with the one of Dembele *et al.* (2017) and Falconnier (2009). The five long-term farmer strategies are strongly correlated with household resource endowments. Farmers who cultivate banana and a large area of lowlands or have an extra-agricultural activity are amongst the richer and have higher resource endowments.

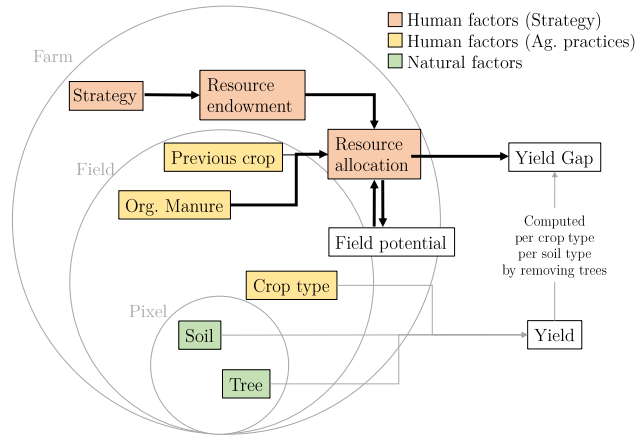


Figure 6.14: Summary of the sources of yield and yield gap variability studied in this paper at farm, field and pixel levels. Bold dark arrows represent the most important relations identified in this research.

6.5.3 Resource endowment drives resource allocation

In the study region, farmers allocate various types of resource including mineral fertilizer, labor force, organic manure, and pesticide. As cotton and maize are the most demanding crops, farmers allocate resources to these crops in priority, as illustrated by higher household resource endowments that significantly decrease yield gaps for cotton ($p = 0.0075$) and maize ($p = 0.0043$). The MRE/HRE farmers have easier access to fertilizers, seeds, and phytotreatments and have

higher equipment level and more labor force which directly benefit to cotton and maize crops. In the study area, the CMDT controls the whole cotton sector and gives access to fertilizers for cotton but also for maize according to their farmer typology and to previous cotton production. Farmers are grouped by types by the CMDT, mainly according to their equipment. Besides, CMDT permits higher input credits for the cotton producers highly equipped who reached high cotton production in the last years. LRE farms have on average higher yield gaps for cotton and maize due to lower capacity to mobilize external inputs.

6.5.4 Organic manure allocation is related to crop rotation

A few studies have already highlighted the importance of crop succession in West Africa and the fertility carryover effect of cotton and maize for crops following in the succession (see Chapter 3, section 3.5.3.) (Bagayoko *et al.*, 2000; Koulibaly *et al.*, 2009). In this study, we confirmed that the previous crop significantly impacts yield gaps for cotton and millet ($p < 2 * 10^{-16}$), with significantly lower yield gaps for fields cultivated after cotton and maize. These results are confirmed, in our study area, by Falconnier *et al.* (2016) who showed with farm trials during three years (2012-2014), a better fertility status at the beginning of the season in fields previously cultivated with cotton or maize compared with those previously cultivated with millet and sorghum.

Organic manure is scarce in the study region with only 24% of the cultivated area manured. As explained by Djouara *et al.* (2006), we recognized that cotton is the most manured crop in Mali's cotton belt, which explains the significant effect of organic manure on cotton yield gaps ($p = 4.2 * 10^{-4}$). In this context of scarcity, farmers first allocate their organic manure according to crop successions. The beneficial effect of organic manure is stronger when the previous crops are millet or sorghum as no mineral fertilizer was used as input.

When integrating socio-economic conditions, we showed that (i) on average LRE farmers manure a higher proportion of their cultivated area (33.8% corresponding on average to 2.06 ha manured of the 6.12 ha cultivated) in comparison with M/HRE (22.7% corresponding on average to 3.43 ha of the 15.12 ha cultivated); (ii) the farmers resource endowment do not affect the manure allocation with respect to crop succession as both LRE and M/HRE farmers allocate manure preferentially on fields previously cultivated with millet and sorghum. Two possible and complementary explanations of higher proportion of manured fields for LRE farmers than for M/HRE farmers are: (i) it is very difficult to buy organic manure in the Koningue commune, even when you have the resources (M/HRE), and (ii) LRE farmers manure their fields with lower manure quantity and quality.

6.5.5 Organic manure application is related to field potential

Farmers also allocate organic manure according to the field potential and resource endowment. The LRE farmers allocate unequally organic manure in relation with the field potential (Figure 6.13). They allocate most of their organic manure to high-potential fields and very few to low-potential fields. This practice is not in accordance with best practices as organic manure is expected to have higher impact on low-fertilized fields (Tovihoudji *et al.*, 2017). On the contrary, the M/HRE farmers allocate equally organic manure across field potential levels. The major difference is observed for low-potential fields that LRE do almost not fertilize while M/HRE fertilize them in high proportion. Four hypotheses are made regarding these observations: (i) LRE farmers want to guarantee an efficient use of organic manure and do not want to lose organic manure in low-potential fields that could yield to low production; (ii) M/HRE are able to guarantee crop production to satisfy the household food security and can take the risk to allocate a portion of their organic manure to low-potential fields; (iii) M/HRE allocate equally organic manure to deal with spatial heterogeneity; and (iv) the application of organic manure in low-potential fields could restore soil fertility and increase the long-term field production. These hypotheses are also related to farmer strategies. As most of LRE farmers have a strategy focused only on CSS agriculture, they manage the risk in a different way than M/HRE farmers who base their strategy also on extra activities (gardening, banana or jobs). One remaining question is: how will the organic manure allocation change if resources are less limited and if organic manure can be applied to 50% of the fields?

6.5.6 The importance of organic manure

The cotton crop is very sensitive to the amount of potassium (K) in the soil. Research trials conducted across the cotton growing area of southern Mali for about 20 years established clear relations between the exchangeable K and cotton yield (Crétenet *et al.*, 1994). In the study region, the common mineral fertilizer containing between 15 and 18% of K_2O are not sufficient to meet the K requirements of cotton plants (Samake, 2015b). Part of the exchangeable soil K is used to balance this K lack but as fields have often been cultivated for more than 10 years, the soil presents deficit K balance. Organic manure is highly beneficial to cotton fields as it improves WHC and is a source of K. Thus, it is highly recommended to apply both mineral and organic manure in cotton fields to maintain soil fertility as much as possible (Bationo *et al.*, 1998; Crétenet *et al.*, 1994).

For all crop types, an integrated soil fertility management at the cropping system level with an appropriate combination of fertilizers (organic and mineral) is needed (Minot, 2009; Vanlauwe *et al.*, 2014b, 2010). In fact, mineral fertilizers alone are not sufficient to recover soil fertility and can even be detrimental in the medium term if they are not used in an integrated soil fertility management system. This effect was mentioned by farmers during interviews. This study

focuses only on organic manure and not on mineral fertilizer due to 40 years of CMDT recommendations which standardize the mineral fertilizers applications.

6.6 Conclusions

Thanks to the combination of EO and geospatial data, we propose a new method to retrieve attainable yield gaps based on peak LAI. This methodology is unique as it avoids using complex crop growth models at the field level or time-consuming *insitu* yield measurements. It offers possibilities to compute yield gaps automatically and could be applied at a larger scale depending on the availability of cloud-free data and the characterization of meteorological conditions. The developed methodology could also be very useful for numerous development agencies looking for relevant information to better assist smallholder farmers in agricultural development (Giller *et al.*, 2009). In fact, the method can deliver guidance to design appropriate agricultural support interventions adapted to the farmer's needs and to the diversity of farmers. It could also help to establish the baseline prior to agricultural support interventions in order to better evaluate the intervention relevance by quantifying the impact on targeted fields or farmers.

In West Africa, a better understanding of yield gaps is key to increase agricultural productivity and thus improve food security. The technological package most often proposed to the African farmers may poorly suit the agro-ecological and pedo-climatic context (micro-heterogeneity), as well as to the socio-economic conditions of farmers (Niyonkuru, 2018). To reduce farmer vulnerability, it seems not relevant to compute the yield gap based on the average yield at the village scale as farmers feature differentiated practices and realities. In this study, the millet and sorghum yield gaps directly inform on food security while cotton yield gap mainly reveals the disparity in agricultural production means resulting from the strong impact of the CMDT in the study area. In the current CMDT fertilizers distribution, a mechanism of vicious circle maintains the status-quo and avoid to close the cotton yield gaps.

While the standard yield gap approaches assume that farmers use their resources to maximize crop production and benefits, we showed that LRE households allocate their resource to manage the short-term risk. In that sense, they will prefer to allocate organic manure to their best fields to ensure a certain level of production. On the opposite, M/HRE farmers manure all fields with similar organic manure quantities to manage the soil fertility in the long-term. In the study region, high yield gaps in high potential fields of LRE farmers could indicate the need for new practices. In that sense, peer-to-peer vulgarization with farmer fields schools could be developed. Finally, the study suggests that the cognitive allocation dimension has to be studied in parallel to the resources dimension. This should contribute to the adoption of proposed agricultural practices by taking into account the farmer's needs according to its rationale and its socio-economic profile.

Conclusions and perspectives

Synthesis

Agriculture monitoring in smallholder farming systems is crucial to improve food security, decrease farmer vulnerability and hence reduce rural poverty. This requires, amongst others, accurate estimation of cultivated area, crop yield, crop production, and a better understanding of crop production variability to better prevent food crisis, and above all improve the agriculture support by African states, international agencies, and NGO's. The operational agriculture monitoring systems in Africa are most of the time derived from labor-intensive ground surveys (*e.g.*, area and yield measurements in fields or yield estimation by farmers or experts) lacking representativeness and reliability and from low resolution satellites not appropriate to smallholder farming patterns.

Numerous development agencies active in SSA are looking for information on how best to assist smallholder farmers in agricultural development. The available information is not sufficient to target development interventions, and this often ends up with generic technological packages proposed to farmers that have been found unavailing (Niyonkuru, 2018).

Recent advances in EO data access and quality open up new prospects to improve agriculture monitoring and to deliver in a timely manner critical information on smallholder farming systems variability and functioning. Nevertheless, EO monitoring of smallholder farming systems in SSA faced significant challenges due to small field size, heterogeneity in management practices, landscape fragmentation, and widespread presence of trees within the fields.

The overall objective of the thesis was to develop a methodology for estimating and understanding the variability of crop production down to the village, farm and field levels in African smallholder farming systems thanks to remote sensing and socio-economic data. Table 2 sums up the work done to reach this objective. It highlights the achievements and findings and summarizes the characteristics of data and main disciplines used in each chapter. This synthesis includes a few sections describing the accomplishments and their limits with respect to the specific research questions presented in the introduction of the thesis. Finally, the upscaling of this approach using the proposed methodologies and the perspectives for further improvements are discussed.

Table 2: Thesis achievements and main findings by chapter along with details on the data used.

	Chapter					
	1	2	3	4	5	6
Achievements	Annual cropland mapping in Sahelian and Sudanian agrosystems	Assessment of growing conditions variability	Assessment of farming systems diversity and farmer strategies	Assessment of sensitivity of NDVI response to fertilization trials	Crop production estimation from HR TS (crop type mapping and yield estimation)	Identification of the key variables of yield gaps variability
Main findings	Fully automated knowledge-based method reaches 84% of OA for cropland mapping	Feasibility of monitoring inter-annual variability between communes	High diversity in farming systems and constraints	High sensitivity of NDVI to fertility treatment for within-field variability, not for between fields variability	Crop type map from Sentinel-2 reaches 80% OA; peak LAI is the best yield estimator	Yield gaps variability correlated with previous crop, socio-economic conditions and resource allocation
Disciplines	Remote sensing science	Remote sensing science	Social science	Remote sensing science	Remote sensing science	Remote sensing and social sciences
RS data	PROBA-V (5-day)	Landsat 8 (16-day)	/	Digital Globe TS	Sentinel-2A TS (10-day) / Pléiade, Digital Globe	Sentinel-2A-B TS (5-day)
Secondary data	Existing land cover map (GlobeLand30), validation dataset	Meteorological data	Semi-structured interviews	Field boundary, fertilization trials, field biophysical variables	Yield measurement, crop type per field, vernacular soil map, tree map	Field boundary dataset, vernacular soil map, farmer household characteristics
Spatial resolution	100 m	30 m	/	≤ 2 m	10 m and ≤ 2 m	10 m
Extent	West Africa	National, circles and communes	Koningue commune (356 km ²)	Sukumba village (100 km ²)	Koningue commune (356 km ²)	Koningue commune (356 km ²)

Question 1: How to improve current agriculture monitoring systems by making them more relevant for smallholder farmers with Earth Observation?

Agriculture monitoring systems and EWS often used coarse spatial resolution TS and not up-to-date cropland masks which affect the quality of the information derived and thus limit their utility for agricultural support and food crisis prevention. To improve current agriculture monitoring systems for smallholder farmers, we (i) developed a method to map the annual cropland from PROBA-V TS automatically, and (ii) compared different NDVI TS to identify the best spatial resolution for crop conditions monitoring.

While cropland maps are crucial to restrict EWS and agriculture monitoring systems analysis to the cultivated area, a recent systematic review of existing cropland maps concluded to a significant need for cropland mapping in the Sahelian and Sudanian agrosystems (Waldner *et al.*, 2015c). In these regions, most of the existing global land cover maps differ sharply in terms of cropland extent (Chapter 1, section 1.1). To solve this issue, we proposed a knowledge-based approach to map the annual cropland in the Sudano-Sahelian region by benefiting from the hectometric (100 m) spatial resolution of the PROBA-V TS (Chapter 1). Our fully-automated method provided a cropland map with 84% of OA and 74% of F-score for the crop class which is significantly higher than most of the existing global cropland maps. While the specific trimming of an existing land cover map (GlobeLand 30) limits the need for field data to train the classification, ground truth is still required to validate the map. The quality of the Sudano Sahelian cropland map results from the crop-specific knowledge-based methodology, an accurate labeling layer and the PROBA-V spatial resolution of 100 m. The developed method opens the possibility to easily access up-to-date information on cropland over vast regions of smallholder farming systems. This method can also be used with other satellite images such as Sentinel-2 which was not available at the time of Chapter 1 but offers a higher spatial resolution (10 m).

As the first objective of this question was completed by improving the cropland mapping, we can now explore how the spatial resolution affects the crop conditions monitoring. Current global and regional monitoring systems often use coarse MODIS NDVI TS (from 500 m to 5.6 km) that fail to detect inter-annual crop conditions variability (as demonstrated in Chapter 2). We used 30 m Landsat 8 data to monitor inter-annual crop growth conditions variability as it was the only EO imagery option with a spatial resolution relevant for smallholder farming systems. Indeed Sentinel-2 - launched in 2015 - does not encompass long enough TS for multi-annual variability analysis. In Chapter 2, Landsat 8 NDVI TS for 2014-2017 - masked with the Sudano-Sahelian cropland map (Chapter 1) - captured the strong inter-annual crop variability at circle

level which was hardly depicted by current operational agriculture monitoring systems. We also showed high variability of crop growing conditions in various communes of the same circle which questions again the performance of operational monitoring systems that often deliver information at circle or region levels, which is relevant in complex farming systems.

To conclude, medium resolution TS (as PROBA-V 100 m and Landsat 30 m) are used to map the cropland and to assess inter-annual crop growing conditions variability. The medium resolution offers advantages to catch local crop conditions compared to low spatial resolution such as MODIS. While today Sentinel-2 does not encompass long enough TS, its high resolution (10 m) could definitively benefit to EWS and agriculture monitoring systems by better matching smallholder cropland patterns and landscape fragmentation.

Question 2: How to use decametric and temporally-dense Earth Observation images to estimate local crop production and the heterogeneity of complex smallholder farming systems?

Today, most of the crop production estimates in African smallholder farming systems are built on field surveys that often lack spatial representativity and suffer from farmer subjectivities. However, crop production estimates are essential for agricultural statistics, for better targeting of agricultural support and for assessing a posteriori the interventions impact. Benefiting from the decametric Sentinel-2 TS, we estimated crop production at the village level for the four main crop types (model uncertainty of 0.3%) in Chapter 5. This was achieved by the combination of a crop type classification and a yield estimation thanks to a stochastic approach. We developed a method to classify crop types based on Sentinel-2 data and a robust field dataset. Results showed an OA of 85% for the crop type map. Crop type classification results can be used for agriculture statistics but are also required to estimate yield. These good results could be explained by a robust field dataset (crop type polygons to train the classification), cloud-free Sentinel-2 images at the peak of the vegetation (considered as the most crucial period for accurate crop type classification in our case) and adequate 10 m spatial resolution. Some difficulties were encountered to discriminate between millet and sorghum and to map peanut. We showed that filtering the per pixel crop type classification with VHR objects (cadastral parcels) increased the OA by 5%. Metric resolution images were compulsory to derive a farmer cadastral dataset and a tree map. VHR allows seeing details such as trees, paths, huts and granaries which facilitates, amongst others, fields digitalization and trees detection in smallholder farming systems.

Based on the crop type map, we derived the cultivated area per crop type at the village level, which varied according to the population size and the soil type distribution. Estimating cultivated area for each crop type is less time

consuming, more traceable and may be as accurate as the ground survey carried out for agricultural statistics. Besides, it allows producing crop type map at a granular scale, which is very useful to depict local crop growth conditions. This is most of the time not the case for survey-based agricultural statistics which provide information after the harvest at second administrative levels (district), but never at the commune level and the village level.

Yield estimation is the second component required for crop production estimation. As ground yield measurements and yield estimation from surveys lack representativeness and sometimes reliability, we used a remotely-sensed yield estimator. Obtained through inverse radiative transfer modeling, LAI retrieved with the ESA Sen2-Agri system achieved better prediction of final grain yield than various VI, reaching a coefficient of determination of 0.8, 0.68, 0.62, and 0.48 for millet, cotton, maize, and sorghum, respectively. These results were obtained with the temporal metric of peak LAI computed along the growing season which offers the advantage of delivering yield forecast one month ahead of harvest. We believe that the doubling of acquisition frequency brought about by the launch of Sentinel-2B in 2017 may result in a LAI time integral outperforming peak LAI for yield estimation. This will be even easier if new satellites with high spatial resolution (*i.e.*, 10 m) and daily acquisition are launched in space.

The principal limit of empirical yield estimation based on peak LAI is that it requires ground yield measurements which are time-consuming and costly. In Chapter 6, we proposed a method to estimate locally attainable yield gaps based on peak LAI without any *in situ* yield measurement. The yield gap estimation was expressed in relative terms (percentage), not in absolute terms (tons/ha for example). These locally attainable yield gaps were relevant to understand the driving forces of crop yield gap variability in a specific time and space (*e.g.*, a particular year at commune level). However, locally attainable yield gaps cannot directly be used to compare successive years nor to compare different regions to each other. This method has to be combined with inter-annual conditions variability and upscaling methods requiring further research.

We also showed that while the presence of trees within-fields did not affect crop type classification for the 2016 season in the study area, their presence strongly affected yield estimation and were removed for yield and locally attainable yield gap estimations. Thus, tree masks are required when estimating crop production variability in Mali's cotton belt.

To conclude this second question, high resolution images (Sentinel-2) are relevant for most applications assessing smallholder farming systems variability (*i.e.*, crop type mapping and yield estimation). Nevertheless, VHR images are required for specific applications and the access to VHR images is a plus as it allows to delineate easily fields' boundaries and trees. For field delineation purposes, a VHR image at the peak of the season enables seeing most of the field boundaries. For trees detection, a VHR image at the beginning of the season

allows increasing the contrast between bare soils and trees. The combination of different spatial resolutions is thus required to obtain relevant information when studying crop production variability within the smallholder farming systems as the drivers of this variability articulate at different levels.

Question 3: How to combine socio-economic and geospatial data to identify key drivers of crop production variability in order to support sustainable farmer strategies of intensification?

In the context of African population growth and land saturation, an increase in agricultural productivity is required to fulfill the two first SDGs: no poverty and no hunger. This intensification has to be sustainable to preserve the ecosystem services and to be resilient to shocks, stresses, and climate change. The yield gap concept (as described in Chapter 6) is more and more used to assess the potential of yield increase in a given region. To increase the agricultural productivity, it is necessary to identify the driving forces of yield gaps. While most studies focus only on crop management efficiency as determining factors of yield gaps, Vanlauwe *et al.* (2014a) insisted on the importance to consider the diversity in farmer resource endowments, farming systems, and socio-economic conditions.

This thesis identified critical drivers of crop production variability (*i.e.*, yield gap) by combining multiple sources of information. In Chapter 4, we showed the important impact of mineral fertilization on within-field variability and its limited impact on between fields variability with a VHR TS of DG images and fertilization trials conducted in 50 fields. At the field scale, for half of these fields, at least 50% of the NDVI variance within a field was explained by fertilization. Nevertheless, the influence of fertilizer on NDVI was comparatively small at the landscape scale (up to 35% of total variation), relative to the influence of other components such as field management and catena position. We concluded that studying the spatial and temporal responses of NDVI and more generally VI requires a stratification of soil catena-related crop growth conditions at the landscape scale. In line with this, we built a vernacular soil map for the study area (Appendix C). A strong relation between the cultivated crop type and the soil type was demonstrated in Chapter 5 with more demanding crops on more fertile soils. Besides, a solid relationship between the estimated yield and the soil type was observed in Chapter 6 with a p-value lower than 2×10^{-16} for cotton, maize, and millet and equal to 1.35×10^{-9} for sorghum. Highest yields were observed on most fertile soils with highest water holding capacity (loamy soils).

In Chapter 6, we assessed the importance of human drivers and agricultural practices on yield variability both at field and farm levels. The socio-economic conditions of farmers significantly influenced the yield gaps of cotton and maize which are the most demanding crops. Crop rotations also had a significant

effect on yield gaps, with a considerable decrease of yield gaps when crops are cultivated after cotton or maize thanks to a fertility carryover effect. Organic manure was applied preferentially on cotton and significantly decreased yield gaps for these fields. Besides, farmers allocate preferentially organic manure on fields which do not benefit from fertility carryover (*i.e.*, fields cultivated after millet and sorghum). In the study area, resources are scarce, and farmers need to prioritize when allocating resources. While standard yield gap approaches assume that farmers allocate their resource to maximize the yield, we showed that they allocate their resource to manage the risk. We concluded that LRE farmers allocate, in proportion, more organic manure on high-potential fields to reach a certain production level. They minimize the short-term risk of producing enough food and cotton. On the other side, M/HRE farmers allocate organic manure almost equally on all fields whatever their potential to recover the soil fertility in a long-term perspective and to deal with spatial variability. In that respect, they prefer to manage the soil fertility in the long-term rather than maximizing their yield in the short-term. The risk-taking is also related to farmer strategies as most LRE farmers have an activity system based on agriculture, only strengthening the importance of agriculture risk management, while others have off-farm activities or gardening production.

To reduce farmer vulnerability, most of the yield gap approaches compute the yield gap based on the average of the village or commune levels, which seems not relevant as soils and farmers feature different practices and realities. In the Sikasso region, paradoxes exist as the cotton farmers are the poorest and the most malnourished farmers in the region while they produce high quantity of cotton and cereals. This is related amongst others to the fluctuating cotton price, the CMDT financial crisis and the low-diversified food basket. Besides, most of the cotton-derived wage does not contribute to the household food supply. Thus focusing the yield gaps analysis on millet, sorghum and other minor crops is relevant to increase food security and decrease farmer vulnerability.

This chapter demonstrated the importance to integrate socio-economic conditions and farmer rationale (*inter alia* resource allocation) in the understanding of crop production variability and thus in the design of agriculture support initiatives. Whereas most of the studies on agriculture monitoring focus on a single crop, we focused our research on all main crop types (cotton, millet, maize, sorghum), which is more relevant to assess the complex livelihood strategy of farming households. Nevertheless, Waha *et al.* (2018) highlighted the importance of crop diversification (including minor crops) for food security and food diversity as it defines the food basket composition. We showed in Chapter 3 that 56% of farmers cultivate small parcels in the lowlands for gardening, which can contribute actively to the household income (see Chapter 6). Up to now, remote sensing applications in crop diversification with a focus on minor crops are seldom. The possibility to apply similar methodologies as the one developed in this thesis for monitoring minor crops should be studied, and researches in that direction should be encouraged.

To conclude the third research question, the combination of socio-economic, geospatial and remote sensing data was found very necessary to assess the driving forces of locally attainable yield gaps in smallholder farming systems. Most of the methods developed in this thesis are related to local scale (the Koningue commune). However, opportunities exist to upscale these methods to a larger size while respecting some conditions.

Towards upscaling the overall approach

Upscaling crop type mapping

The crop type mapping applied at the local scale in Chapter 5 paved the way to upscale the methodology and data exploitation at a larger scale. We have tested such an upscaling in southern Mali for a study site of more than 135,500 km² using the ESA Sen2-Agri system for the 2017 growing season in order to map cropland and crop type. The ESA Sen2-Agri system offers an operational standalone processing system to produce cropland and crop type maps at large scale (regional or national). The cropland map obtained using *in situ* data reaches 98% of OA and 89% of F-score for cropland class. The crop type map is currently limited to 63% of OA in the northern strata and 54.6% in the southern strata (Figure 3 and detailed results in Appendix F).

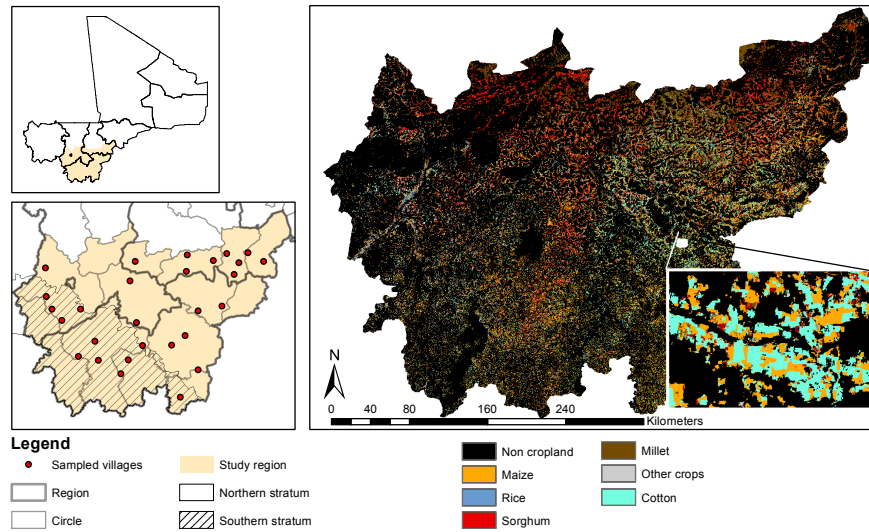


Figure 3: Crop type map for southern Mali computed with the ESA Sen2-Agri system. The points indicate the villages where crop type polygons were collected.

The cropland map accuracy is higher than what was obtained with 100 m PROBA-V TS (Chapter 1) thanks to the higher adequacy of the 10 m spatial resolution in smallholder complex farming systems, enabled by the Sentinel-2 satellite launched in 2015. For crop type classification, the accuracies are lower

than what was obtained at the local scale in Chapter 5 because new challenges arise at the regional scale. At this scale, we have to deal with (i) high variability in landscapes and agro-ecological conditions, and (ii) poor representativeness of field samples. While the sampling density was about 2 fields per squared kilometer at local scale in Chapter 5, it decreases to 0.05 field/km² at large scale in this experiment. This lower density sampling can explain the lower accuracy. Nevertheless, some crop types are well-classified as cotton (F-score=0.7) and maize (F-score=0.65). Besides, other crops which are often confused as millet and sorghum could be grouped together. The upscaling of crop type classification in these smallholder complex landscapes should for now be restricted to the major crops and to groups of similar crops, *e.g.*, dry cereals including millet and sorghum.

Besides, a landscape stratification is often required to split the entire area into different relatively homogeneous regions regarding crop growth conditions. Previous studies already highlighted that image classifications of heterogeneous areas yield to an important confusion between land cover types (Husak *et al.*, 2008). To reduce this confusion, the territory can be stratified in homogeneous regions with LR satellite (Mora and Iverson, 1997) or MR satellite (Vintrou *et al.*, 2012). Nevertheless, no robust nor operational methodology exists to obtain landscape stratification for different purposes (including crop classification, yield estimation, and crop variability analysis).

Upscaling yield gap rather than yield estimate

Yield estimation based on peak LAI showed accurate results at the local scale (Chapter 5). Nevertheless, upscaling the empirical regressions between ground yield measurements and peak LAI to estimate yield at the regional scale is not valid. Due to high heterogeneity in agro-ecological and climatic conditions, we expect empirical regressions to change in time and space. When switching from local to regional scale (as southern Mali), the water input plays a key role in explaining yield variability, especially water excess at the beginning of the crop cycle and water shortage at the end of the period (90 to 130 days after sowing) (Crétenet *et al.*, 1994). Unlike the yield estimation, the yield gap computation of Chapter 6 offers an easily scalable approach as locally attainable yield gap is computed in a relative way and does not require yield *in situ* measurements. Nonetheless this method requires again a specific landscape stratification to determine the area inside which estimated yields could be compared between each other. A soil stratification was also needed for automated locally attainable yield gap estimation, and detailed soil maps are not often available. We successfully experimented with the possibility to automatically derive simple soil stratification from different EO images (Appendix C). The robustness of such an approach for large areas should be further investigated.

Perspectives

Detecting field boundaries automatically

Field boundaries are very useful in smallholder heterogeneous farming systems in particular for two purposes: (i) improve crop type pixel-based classification with a majority filter, and (ii) assess yield variability at field and farm levels. Accessing accurate and up-to-date field boundaries is still a substantial challenge today, even more in developing countries. In Mali, we do believe that getting field boundaries data from farmers or state will not be possible in the foreseeable future due to local management of land rights and continuous change of field boundaries. In response to that challenge, few studies already proposed methods to extract field boundaries from raster data analysis (Yan and Roy, 2014) or object segmentation (Su *et al.*, 2015). Besides other studies proposed innovative approaches to update the field boundaries on a regular basis (Butenuth and Heipke, 2005; Matikainen *et al.*, 2012; Oesterle and Hahn, 2004). Most of these studies already have difficulty to produce accurate field boundaries datasets while they focus on regions where the field size is much larger than in SSA. Thus, future works to extract this important data for agricultural monitoring should be encouraged.

Dealing with cloud cover affecting optical data availability

Important cloud coverage is often seen as an issue for agricultural monitoring from optical remote sensed data. Whitcraft *et al.* (2015b) showed that early and mid-agricultural growing season features both frequent and pervasive cloud extent while these periods are critical for crop type mapping and yield forecasting. As an example, the methodology of Chapter 1 for cropland classification can suffer from weak knowledge-based spectral-temporal features if too few images are available. Indeed, we showed in Chapter 1 that the accuracy of the cropland map is strongly related to satellite data availability (low cloud cover). Even if we demonstrated the importance of peak vegetation period for both crop type classification and yield estimation (Chapter 5) (period that should be less affected by cloud cover), we believe that increasing the observation frequency (*e.g.*, from 5-day to 1-day revisit time with 10 m spatial resolution) will be beneficial for agricultural monitoring. To do that, two main alternatives have to be explored: (i) multi-sensor TS, and (ii) a combination of radar data and optical data. The use of images from multi-sensors is quite complicated (Vermote *et al.*, 2016) but some operational systems, such as the ESA Sen2-Agri system, already combine successfully different sources of data (*i.e.*, Sentinel-2 and Landsat 8) (Bontemps *et al.*, 2015b).

On the other hand, synergies with radar data offering all weather and day and night capabilities, are worth exploring and investigating. Today, combining radar and optical capabilities for agricultural support in Africa is seldom, and additional researches are needed. This challenge is also directly related to the

field boundaries challenge as the object approach is most of the time privileged in radar applications (Lobo *et al.*, 1996).

Food security in West Africa, the smaller picture

In 2003, African heads of state and governments signed the Maputo Declaration where they pledged to allocate at least 10 percent of their national budget to the agricultural sector. In 2013, only 13 countries out of 53 respected their commitments (Benin and Yu, 2012). Mali was part of these 13 countries. A group of agriculture experts affirms that countries which have invested in farming already observed significant growth of their agricultural sector coupled with a decrease in malnutrition and poverty levels (AGRA, 2017). Agriculture is a major income source for most African peasants. Next to the involvements of African states, international agricultural agencies are also looking for ways to help African farmers through POs. These organisms often propose "*ready to use*" recipes for farmers, composed of technological packages, including most of the time seeds, fertilizer, and equipment.

Nevertheless, these approaches do not suit the diversity of farmers' socio-economic and agro-climatic conditions as they often oversimplify the complex interactions between climate, soil, agricultural practices and human strategies taking place at a very local scale. While relevant information about smallholder farming systems could help to better target agricultural support, this kind of information is missing. Besides, operational monitoring systems are constrained by the data representativeness and comprehensiveness and often offer information not detailed enough for local vulnerability baseline assessment.

As demonstrated in this thesis, remote sensing technology could help to improve agriculture monitoring systems and to deliver local information about the farming system functioning and diversity. EO data combined with field data, farmer interviews, and the overall approach proposed in the thesis allows limiting the time-consuming field campaigns to specific targets and upscaling the few ground information available to relevant scale for decision-making (such as crop type polygons collection to produce crop type map). Overall, understanding challenges and issues at a local scale and according to agro-climatic and socio-economic conditions of farmers is crucial to design effective agricultural support initiatives. In that sense, we do believe in bottom-up agriculture support approaches and objectives-oriented project planning, where agriculture interventions are built with farmers based on an analysis of their main concerns.

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List of Publications

Peer-reviewed publications

Lambert, M.-J., Waldner, F., and Defourny, P. (2016). Cropland mapping over Sahelian and Sudanian agrosystems: A knowledge-based approach using PROBA-V time series at 100 m. *Remote Sensing*, 8(3), 232.

Lambert, M.-J., Traoré, P.S., Blaes, X. Baret, P. and Defourny, P. (2018). Estimating smallholder crops production at village level from Sentinel-2 time series in Mali's cotton belt. *Remote Sensing of Environment*, 216, 647-657.

Lambert, M.-J., Traoré, P.S., Defourny, P. and Baret, P. (2018). Enriching yield gap's understanding by integrating farmer rationale in Mali's cotton belt. Submitted.

Blaes, X., Chomé, G., **Lambert, M.-J.**, Traoré, P.S., Schut, A.G.T., and Defourny, P. (2016). Quantifying Fertilizer Application Response Variability with VHR Satellite NDVI Time Series in a Rainfed Smallholder Cropping System of Mali. *Remote Sensing*, 8, 531.

Waldner, F., **Lambert, M.-J.**, Li, W., Weiss, M., Demarez, V., Morin, D., Marais-Sicre, C., Hagolle, O., Baret, F., and Defourny, P. (2015). Land cover and crop type classification along the season based on biophysical variables retrieved from multi-sensor high-resolution time series. *Remote Sensing*, 7(8), 10400-10424.

Bellemans, N., **Lambert, M.-J.**, Traoré, S., Traoré, P.S. and Defourny, P. (2018). Crop classification in Mali to support agricultural statistics. In preparation.

Non peer-reviewed publications

Lambert, M.-J., Blaes, X., Traoré, P. S., and Defourny, P. (2017, June). Estimate yield at parcel level from S2 time serie in sub-Saharan smallholder farming systems. In *Analysis of Multitemporal Remote Sensing Images (MultiTemp)*,

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Blaes, X., **Lambert, M.-J.**, Chomé, G., Traoré, P. S., de By, R. A., and Defourny, P. (2016, May). Yield mapping for different crops in Sudano-Sahelian smallholder farming systems: results based on metric Worldview and decametric SPOT-5 Take5 time series. In *ESA Living Planet: Proceedings of ESA Living planet symposium 2016*, 9-13 May 2106, Prague, Czech Republic. ESA.

Traoré, P.S., Blaes X., Chomé, G., **Lambert, M.-J.**, Schut, A.G.T., Ajeigbe, H.A. and Defourny P. 2016. VHR imagery to quantify crop response to fertilizer and develop business services for smallholders. Permanent link to cite or share this item: <http://hdl.handle.net/10568/77340>

Lambert, M.-J., Waldner, F., and Defourny, P. (2015, July). Mapping annual cropland with PROBA-V 100 m over Sahelian and Sudanian agrosystems. Poster at MultiTemp in Annecy, France.

Lambert, M.-J., Waldner, F., and Defourny, P. (2015, June). Mapping annual cropland with PROBA-V 100 m over Sahelian and Sudanian agrosystems. Poster at Sentinel-3 for science workshop, in Venize, Italy.

Appendices

A. EO sensor characteristics

Table A1 sums up the main characteristics of the sensors used in the thesis. Specific explanations about the spatial resolution, the temporal resolution, and the spectral resolution can be found below.

Table A1: Main characteristics of sensors used in the thesis

Satellite	Spatial res.	Temporal res.	N° of bands	Available since
PROBA-V	100 m	5-day	4	2014
DigitalGlobe*	≤ 2.5 m	On demand	8	2001
Landsat 8	30 m	16-day	11	2013
MODIS	± 500 m	1-day	5	2000
Sentinel-2	10 m	5-day	4	2015
Sentinel-2	20 m	5-day	6	2015
Sentinel-2	60 m	5-day	3	2015
Pléiade	<2 m	On demand	8	2011
Spot-V	<10 m	2-3 days	4	2002
RapidEye	<5 m	1-5.5 days	5	2008

*Different sensors from the DigitalGlobe constellation are used including GeoEye 1, WorldView 2, WorldView 3 and QuickBird 2.

Spatial resolution

The spatial resolution corresponds to the smallest area on the globe in which a specific sensor can record spectral information. The spacing between the ground projection of two pixels is referred to as pixel size. For example, the pixel size of WorldView image is 2 m x 2 m, Sentinel-2 is 10 m x 10 m, PROBA-V is 100 m x 100 m and MODIS is around 500 m x 500 m. However, a distinction must be made between the physical sampling of the observations by the instrument and the spacing of the grid in which the data is provided (for more information, please refer to Duveiller *et al.* (2011) and Forster and Best (1994) and Radoux *et al.* (2016)). The quantity of details visible on an EO imagery directly depends on the spatial resolution (Figure A1). The conventions define large resolution image when pixel width is larger than 300 m, medium resolution (MR) image when pixel width is lower than 300 m and larger than 20 m, HR when pixel width is lower than 20 m and larger than 2 m and VHR when pixel width is lower than 2 m.

Temporal resolution

The temporal resolution is the ability to collect imagery of the same region of the globe at different periods in time. Each sensor is characterized by a revisit time defining the temporal resolution. As examples, PROBA-V has a revisit time of one day and Sentinel-2A of 10 days. Time is important to separate

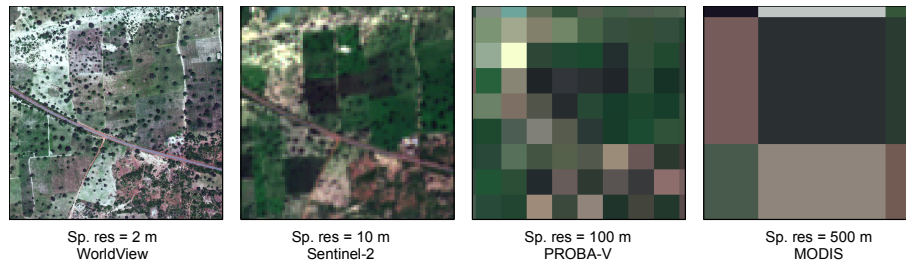


Figure A1: Earth Observation images illustrated with four pixel's sizes of the same area at 2 m, 10 m, 100 m and 500 m.

land cover classes or crop classes because the spectral signature varies along the season in a different way for each class. As an example, crops are characterized by leaf pigments absorbing solar radiation and internal cell structure that is specific to each species and depends on the development stage and thus the time period.

Spectral resolution

The spectral resolution of a sensor is a measure of its ability to resolve features in the electromagnetic spectrum. It refers to the number of bands (region of the electromagnetic spectrum) in which a sensor captures information. The higher the number of bands, the higher the spectral resolution.

B. Study area delimitation

The local study area of this thesis corresponds to the geographical footprint of the 43 POs registered in the five villages of the Koningue commune. While the five villages are part of the Koningue commune, their limits are not fully included in the administrative boundaries of the Koningue commune. Some farmers are part of a Koningue's PO while their hamlets and fields are located outside the administrative limits of the Koningue commune. Besides, no administrative boundaries exist at the village level. Taking advantage of a georeferenced dataset of household characteristics, we (i) delineate the study area according to the farmer's PO, and (ii) draw the limit of the villages inside the study area. This dataset was collected in 2015 by the STARS project and offers more than 6,700 georeferenced points with amongst others, information on the farmer name, its PO, and its village. Each PO is linked with one of the five villages of the commune. In total, the Koningue commune includes 5 villages: Banesso, Dougan, N'Gueguesso 1, N'Gueguesso 2 and Sukumba with respectively 11, 6, 1, 2 and 23 POs.

After cleaning of the 6,783 georeferenced village points (157 points were removed due to the absence of PO information), Voronoi polygons are built for each point. The Voronoi polygons assign every location in the study area to the closest georeferenced village point. All Voronoi cells of the same village are grouped together and island polygons – a polygon of a village surrounded on all sides by polygons of other villages – are modified to correspond to the adequate village. In parallel, we circumscribe the borders of the region of interest with a concave envelope. Finally, this concave envelope masks the modified Voronoi polygons (Figure A2).

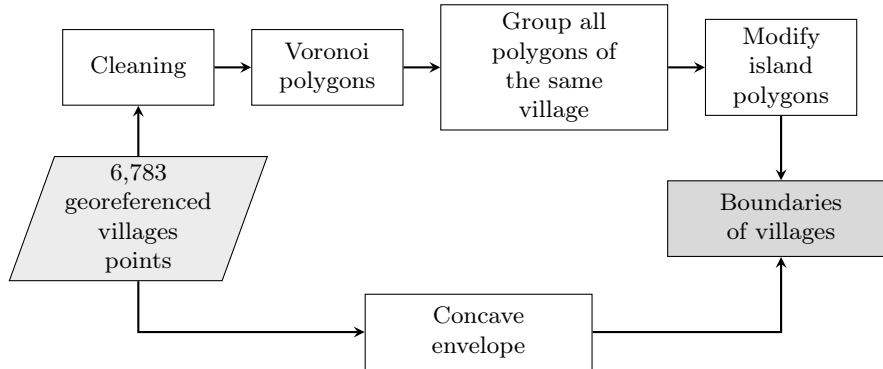


Figure A2: Methods to delineate villages boundaries.

The final village boundaries are presented in Figure A3 where the study area is in dark orange and the administrative boundaries of the Koningue commune in red. This study area is used in Chapters 3 to 6.

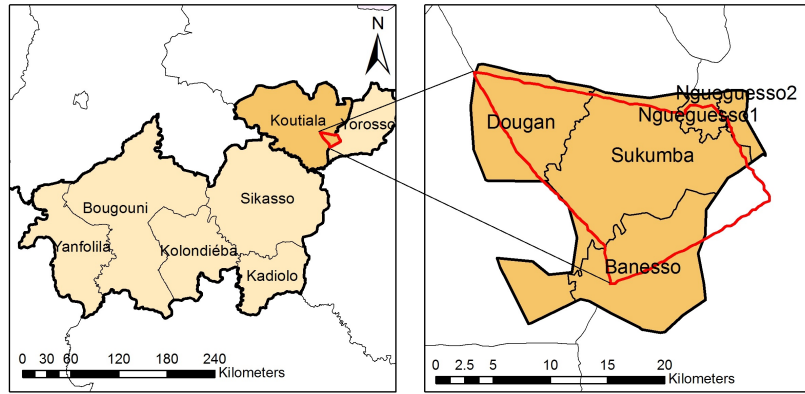


Figure A3: The Koningue commune with its five villages. The red boundaries are the administrative boundaries while the gray boundaries are the manual delimitation of commune and villages based on farmers reality.

C. Vernacular soil map

A vernacular soil map is built for the local study region thanks to a georeferenced dataset of household characteristics including 6,783 geolocalized information about the vernacular soil. This dataset was collected in 2015 by the STARS project. The vernacular soil is the local name of the soil and is related to farmer's knowledge of the soil. Kambiré *et al.* (2017) showed reasonable agreement between local and analytical fertility indicators even though farmer's perceptions are often more affected by the consequences of soil fertility than on its actual status. In this research, we assume that vernacular soil map reflects the main soil properties. As very few points were recorded in rocky areas, 281 points are manually added by photo-interpreting a VHR imagery (WorldView 2, 26 June 2014). The average density of surveyed points is 20 points per square kilometer. Voronoi polygons are built and assign every location in the study area to the closest point in the database (Figure A4). The theoretical limits of Voronoi polygons are improved by taking into account physical reality thanks to a remotely-sensed segmentation based on soil brightness and elevation. The soil brightness image is computed through the Soil Brightness Index (Bannari *et al.*, 1995) on a Sentinel-2 image at the beginning of the cultural season (28 April 2016) when bare soils show their real colors. The elevation information is derived from 30 m SRTM data. The segmentation was processed with eCognition software (multi-resolution segmentation parameters: scale = 250, compactness=0.9, shape=0.3) and 2,139 objects were obtained. A majority voting is finally applied on the rasterized Voronoi polygons and inside the 2,139 objects (Figure A4). The vernacular soil map is clipped to the study.

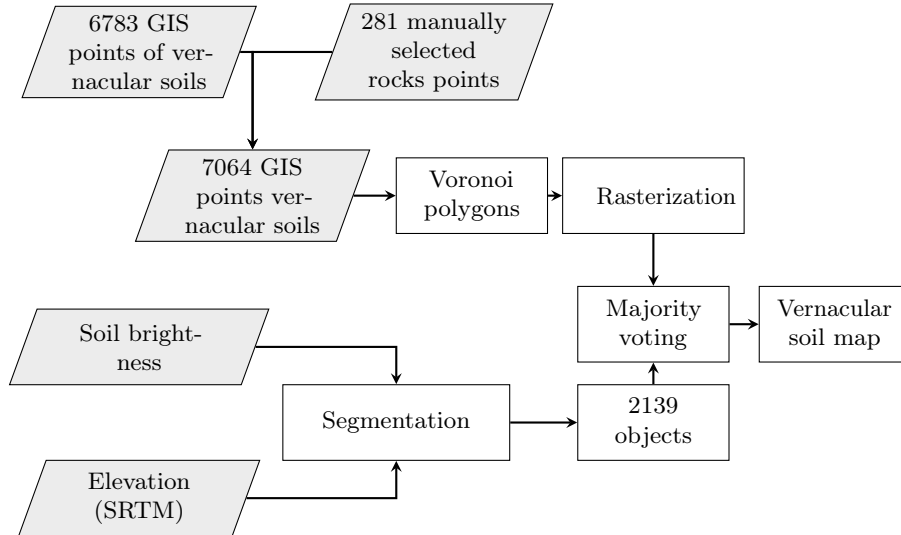


Figure A4: Methodology to build the vernacular soil map based on GIS points and remote sensing information(soil brightness and elevation).

The construction of the vernacular soil map requires a robust ground survey that is costly and time-consuming. Thus, we perform an automated soil stratification based only on remotes sensing data. We use the 2,139 objects built from the segmentation of soil brightness and elevation and apply a simple clustering algorithm. Thanks to that, we easily group the objects into two class: low fertility soils and high fertility soils. If we assume that sandy, loamy and clayey soils are high fertility soils and that gravelly and rocky soils are low fertility soils, the automated soil stratification reaches 96% of OA. The main issues of this methodology are that we can not distinguish more than two strata of soils with an automated method (Figure A5).

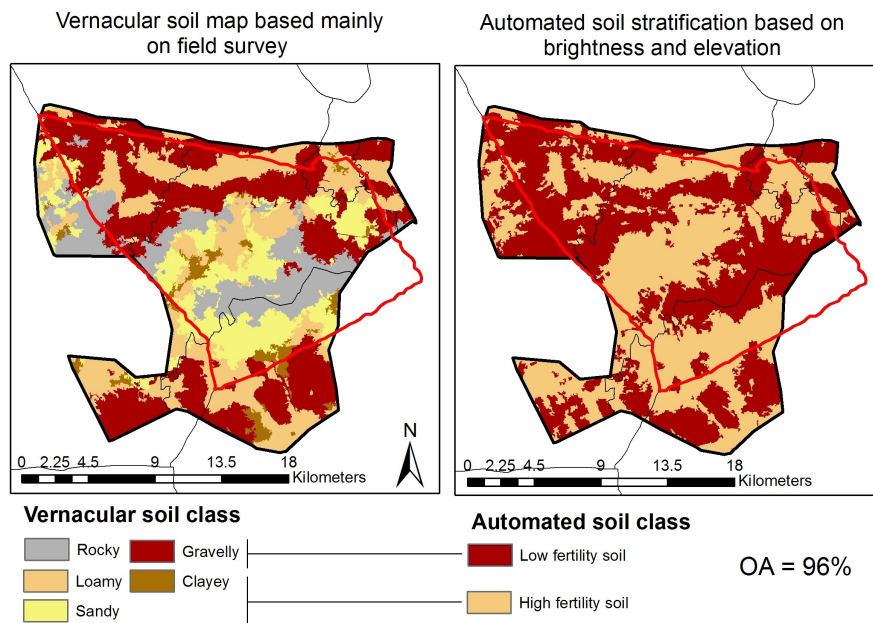


Figure A5: Vernacular soil map compared to automated soil classification

D. Interview guide

The interview guide used during the 2016 field campaign is presented here below. The questionnaire is in French as the interpreter was a French-speaker.

Guide d'entretien

Préparatif :

- Impression des cartes des parcellaires de chaque agriculteur
- Imprimer le questionnaire
- Charger l'enregistreur et le GPS
- Mémoriser le nom, le prénom et les informations personnelles disponibles

Ce tableau est à remplir avant d'arriver chez l'agriculteur et à compléter au cours de l'entretien.

	Information générale
Date (jj/mm/yyyy)	
Village	
Nom de l'enquêteur	
Nom de l'interlocuteur	
Nom du traducteur	
Numéro du ménage dans l'échantillon	
Présence de femmes (oui /non)	
	Information géographique
Latitude du ménage (°)	
Longitude du ménage (°)	
Code GPS	
	Information sur le chef de ménage
Nom du chef de ménage	
Prénom du chef de ménage	
Âge approximatif du chef de ménage	
Sexe du chef de ménage	1. Féminin 2. Masculin
Niveau d'instruction du chef de ménage	1. Aucun 2. Primaire 3. Secondaire 4. Technique 5. Alphabétisation

Observation : type de lieu de rencontre, matériel des murs de la maison (2), du toit de la maison (3), présence d'électricité (panneau solaire), présence d'eau courante ¹

¹ (1) 1. Hameau, concession, (2) ciment, banco, mélange ciment + banco, (3) tôle, paille

PRÉSENTATION + MISE EN CONFIANCE**5 min**

La présentation en début d'interview est cruciale pour la suite. Il est nécessaire d'expliquer clairement les objectifs de l'étude afin de collecter des données de qualité. Il faut mettre l'agriculteur en confiance.

« Bonjour Mrs/ Mr

Mon nom est Marie-Julie et je suis étudiante dans une université en Belgique. Je ne parle pas votre langue donc Birama Sissoko va m'aider dans la traduction. J'étudie les écarts de rendement dans votre région. J'aimerais discuter avec vous pour comprendre comment fonctionne votre ferme. J'aimerais savoir quels sont les problèmes que vous rencontrez.

Est-ce que vous auriez un peu de temps pour discuter ? Si c'est possible, j'aimerais aussi aller voir avec vous quelques-unes de vos parcelles.

Pour ne rien oublier de notre conversation, j'aimerais enregistrer. Est-ce que cela vous dérange ? Je peux arrêter l'enregistrement si besoin.»

Question de transition :

Q1 : Moi mon nom c'est Marie-Julie, et vous quel est votre nom, votre prénom, et votre métier ?

Q2 : Vous avez à peu près quel âge ?

Q3 : Avez-vous été à l'école ? Jusqu'à quel niveau ?

ACTE 1 : information générale – système de culture**15 min**

Questions / Dialogue	Info recherchée	Statut
Q1 : Qu'est-ce que vous cultivez cette année ? [Coton, mil, sorgho, maïs, arachide, niébé, sésame, soja, fonio, riz]	Le type de cultures 2016 et 2015, le type de rotations	
Q2 : Combien de champs de X avez-vous et quelle est la superficie de chacun (à répéter pour chaque culture) ?		
Q3 : Vous cultivez le mil, le sorgho, le maïs, pour la consommation, la vente ou autre chose ?		
Q4 : Est-ce que vous avez cultivé les mêmes cultures que l'année passée ?		
Q5 : Comment faites-vous les rotations des cultures chaque année dans les champs ?		
Q6 : Quels sont les avantages des rotations des cultures chaque année dans les champs ?		
Q7 : Est-ce que vos champs sont regroupés dans un même lieu ? Si pas, comment sont répartis les champs ? [Sur la colline, près du village]	La localisation par rapport à la maison et la superficie	
Q8 : Comment allez-vous jusqu'à votre parcelle ? Combien de temps ça vous prend pour aller à vos parcelles ?		

ACTE 2 : informations existentielles en lien avec les hypothèses

1h15

Questions	Info recherchée	Statut
1. GESTION FERTILISATION – ENGRAIS CHIMIQUES		10 min
Q1 : Utilisez-vous des engrais chimiques ? - Si non, pourquoi ?	Engrais minéraux : provenance, type, sur quoi, quantité, pourquoi	
Q2 : Sur quelle culture mettez-vous de l'engrais chimique ?		
Q3 : Quelle quantité d'engrais chimiques mettez-vous sur chaque culture ? Et quelle sorte ?		
Q4 : Comment obtenez-vous les engrais chimiques ?		
Q5 : Est-ce que les engrais chimiques sont suffisant ?		
Q6 : Si vous aviez plus d'engrais chimiques, dans quels champs, vous les mettriez ? Pourquoi ?		
Q7 : Pourquoi est-ce que vous n'utilisez pas plus d'engrais chimiques ?		
2. GESTION FERTILISATION – FUMURE ORGANIQUE		20 min
Q1 : Est-ce que vous mettez de la fumure organique sur vos champs ?	Production de matière organique : comment, où, sur quoi, transport.	
Q2 : D'où vient la fumure organique ?		
Q3 : Comment produisez-vous la fumure organique ? [Fumier, composte à la concession, en champs, tas d'ordure, terre de parcs des bovins]		
Q4 : <i>Rebondir sur la question précédente</i> : Avec quoi faites-vous le composte ? Vous avez donc des animaux ... Quel type d'animaux et combien ?		
Q5 : Sur quelle culture mettez-vous de la fumure organique ?		
Q6 : Quel est le champ que vous priorisez pour apporter la fumure organique ? Pourquoi ?		
Q7 : Comment transportez-vous la fumure organique dans les champs ?		
Q8 : Combien avez-vous de charrettes ?		
Q9 : Vous apportez combien de sacs / charrettes de fumure organique dans un champ de X (répéter pour chaque culture) ?		
Q10 : Est-ce que tu penses que c'est suffisant ?		

Q11 : Si vous aviez plus de fumure organique, dans quels champs vous la mettriez ? Pourquoi ? Q12 : Comment est-ce que vous mettez la matière organique dans les champs ? [Épandage ou à la volée, par poquet, charrue à 3 lames] Q13 : êtes-vous en collaboration avec des éleveurs pour obtenir de la matière organique ? Comment cela se passe-t-il ? Quand ?		
3. TYPES DE SOLS		10min
Q1 : Quels sont les difficultés que vous rencontrez dans les sols de vos champs ? Q2 : Quelles sont les différents types de sols que vous avez dans vos champs ? Quel est le sol qui a le plus de force ? Comment s'appelle-t-il ? Q3 : Comment lutez-vous contre l'érosion du sol ?	Présence de jachère / culture continue Types de sols, qualité, fertilité	
4. MAIN D'ŒUVRE		10 min
Q1 : Quelles sont les personnes de votre foyer qui participent aux travaux de fertilisation ? Q2 : Est-ce que les personnes qui font les travaux de fertilisation font aussi les autres travaux du champ ou il y a d'autres personnes ? Q3 : Est-ce que la main d'œuvre est suffisante ? Pour quels travaux manque-t-il de la main d'œuvre ? Q4 : Si vous aviez plus de main d'œuvre, à quoi servirait-elle ? Q5 : Vous avez en charge combien de personnes ? Combien d'enfants, combien de femmes, combien d'hommes ? Q6 : Est-ce que les personnes à votre charge travaillent dans les champs ? Quels sont les travaux des enfants, des femmes et des hommes ? Q7 : Est-ce qu'il arrive souvent de prendre de la main d'œuvre extérieure ? Pour quels travaux ?	Taille du ménage, main d'œuvre disponible, contrat extérieur	
5. ACCES AU FONCIER		10 min
Q1 : Avez-vous hérité des terres que vous cultivez ou bien est-ce qu'on vous les a prêté ou donné ? Q2 : Est-ce que vous faites tout ce que vous voulez sur les parcelles qui ne sont pas à vous ?	Propriété, accès au bas fond	

Q3 : Est-ce que vous faites des jachères ? Où et pourquoi ?		
Q4 : Qu'est-ce-que vous cultivez dans vos vergers / potagers si vous en avez ? Où sont-ils situés ?		
6. ACTIVITES EXTRA AGRICOLE – MIGRATION		15 min
Q1 : Est-ce que dans la famille il y a des personnes qui font d'autres activité que l'agriculture ? - Qui font ces activités ? - A quelle période ?	Activité extra-agricole : vente des produits	
Q2 : Est-ce que vous vendez certaines de vos récoltes sur les marchés ? - Si oui, quelle culture, comment et où ?		
Q3 : Qu'est-ce que vous vendez le plus ?		
Q4 : Est-ce que vous vendez les animaux ? - Si oui, quel type ?		
Q5 : Est-ce qu'il y a un ou plusieurs membres de la famille qui est en aventure ? - Quel est le membre de la famille qui est parti ? - Où est-il parti ? - Il y a combien d'années qu'il est en aventure ? - Est-ce qu'il est parti car les récoltes sont mauvaises ou pour autre chose ? - Est-ce qu'il vous envoie des aides ? - Est-ce que ça contribue ?	Migration	

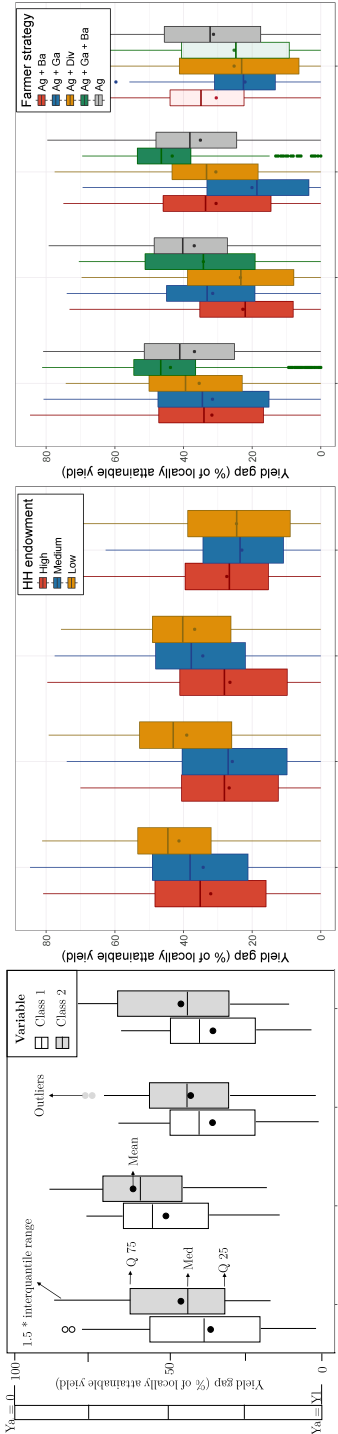
ACTE 3 : sortie et demande sur l'évolution de l'exploitation**15 min**

Questions	Info recherchée	Statut
Q1 : Quelles sont les différences dans l'état de vos champs et ceux de vos voisins ?	Perspective	
Q2 : Est-ce que les pratiques culturales sont différentes ?		
Q3 : Quelles sont les causes qui font que dans un même champ, les cultures n'ont pas les mêmes niveaux de développement ?		
Q4 : Comment s'annoncent les récoltes cette année par rapport aux autres années ?		
Q5 : Qu'est-ce qui limite votre production ?		
Q6 : Quelle est la place du coton pour votre unité de production et pour le revenu aujourd'hui ?		

E. Distribution of yield gaps according to the variable of interest.

The Figure A6 represents the distribution of yield gaps per crop type and for each variables of interest: household endowment level, farmer strategy, previous crop, organic manure and field potential. These variables are related either to field or farm levels. The subplot (a) explains the construction of the graphs. On subplots c, d and f the transparency indicates variable with less than 400 pixels which is considered as too small to be analyzed.

Distribution of yield gaps for each variable at farm level

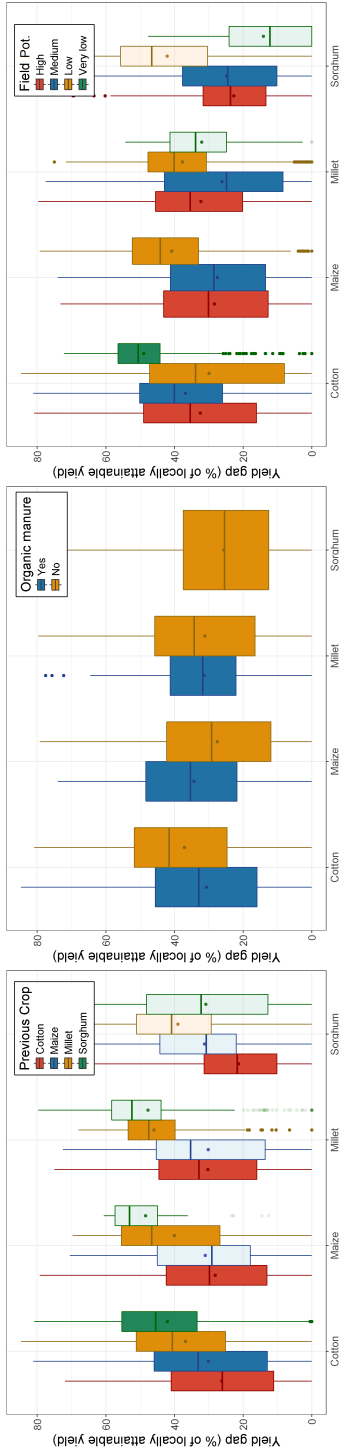


(a) Theoretical boxplot

(b) Household endowment level

(c) Farmer strategy

Distribution of yield gaps for each variable at field level



(d) Previous crop

(e) Organic manure

(f) Field potential

Figure A6: Yield gaps as percentage of locally attainable yield explained by variables for the four crop types.

F. 2017 Crop classification in Mali *

Taking advantage of the spatial and temporal resolutions of Sentinel-2 and Landsat 8, this study aims to map the cropland extent and the crop type in the southern region of Mali. It offers a demonstration of the possibilities to map the crop types in challenging heterogeneous smallholder farming systems in near real-time conditions (2017 growing season). Thanks to a robust field data collection and image digitalization, the ESA Sen2-Agri system is run for the 2017 season to produce both cropland and crop type maps.

Study area

The study area covers 135,500 km² and includes the entire Sikasso region and part of the Koulikoro and Ségou regions (Figure A7). It is covering most of the CMDT region. Two major natural regions from the Projet d'Inventaire des Ressources Terrestres (PIRT) are observed in the study regions: Haut Bani-Niger and Koutiala (named southern and northern strata). Millet, sorghum, maize, rice, and cotton are the major crop types in the study area.

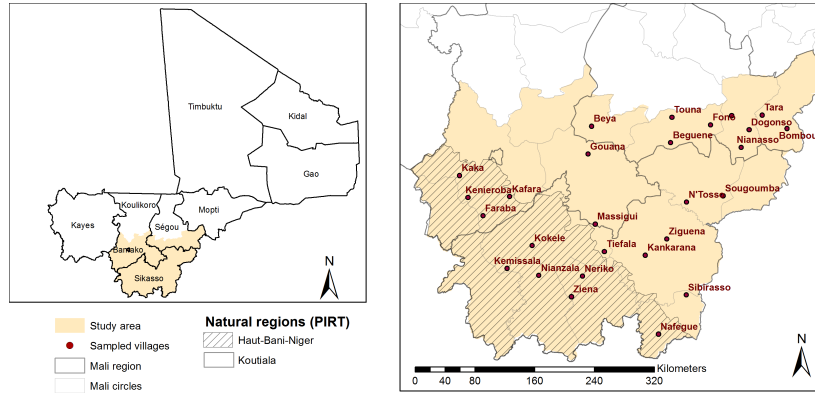


Figure A7: Study region (in orange) covering the whole Sikasso region and part of the Ségou and Koulikoro administrative regions. Field data were collected around 27 villages spatially distributed over the study region (in red). The natural regions of the PIRT are presented in stripped line for the Haut-Bani-Niger's region and in transparent for the Koutiala's region.

Data

All Sentinel-2 and Landsat 8 imageries acquired during the 2017 growing season and covering the region of interest were automatically downloaded from the ESA's Scientific data Hub (<https://scihub.copernicus.eu/>) and United States Geological Survey (USGS) (<https://landsat.usgs.gov/>) data provider platforms. Sentinel-2 and Landsat 8 satellite data were atmospherically-corrected using the

*Adapted from a draft of paper realized in collaboration with N. Bellemans, S. Traoré, P.S. Traoré, S. Bontemps and P. Defourny. This paper should be submitted by the end of the year.

MACCS algorithm (Hagolle *et al.*, 2010), included in the ESA Sen2-Agri system.

Field data were collected by the Institut d'Economie Rural (IER) in Bamako during the 2017 growing season in 27 villages spread over all regions and circles (Figure A7). The crop type field dataset is composed of 6,591 cultivated fields including both major and minor crop types. The data were collected along the roads associated with crop type information following the Joint Experiment for Crop Assessment and Monitoring (JECAM) guidelines. A non-cropland dataset including more than 2,100 polygons over other land cover classes, was built by visual interpretation of Sentinel-2 and various freely available VHR imagery such as Google or Bing.

Methods

The ESA Sen2-Agri system is a free and open-source operational standalone processing system made of modules generating a series of four agricultural products from Sentinel-2 and Landsat 8 TS acquired along the growing season of interest (Defourny *et al.*, 2018). The two products of interest for this experiment are (i) the dynamic cropland mask, and (ii) the cultivated crop type map for the main crop types, both at 10 m resolution. The categorization of the cropland extent is conducted following the method introduced in Valero *et al.* (2016) and complemented in Defourny *et al.* (2018). The processing chain for the generation of the crop type map follows a supervised RF classification approach built on field data (more information in Inglada *et al.* (2015)). The *in situ* information was split between training samples used to feed the classification process and validation samples used to assess the product accuracy (OA, and F-score).

Results

The cropland mask reaches an OA of 97% with a F-score of 98% and 89% for non-cropland and cropland respectively (Figure A8a). The Figure A8b presents the very first 10 m crop type map produced over the South of Mali at the end of the season (December 2017). The accuracy of the crop type map produced over the two strata is presented in the Figure A9. The crop type map reaches 63% OA in the northern strata (Figure A9a) and 54.6% OA in the southern strata (Figure A9b) with pixel-based validation. In the northern strata, cotton crop yields to higher accuracy with a F-score of 80% and is followed by millet 71%), sorghum (64%), maize (62%), rice (59%), other crops (43%) and groundnut (22%). In the southern strata, rice presents the highest F-score of 89% and is followed by maize, cotton, sorghum, groundnut, other crops and millet with a F-score of respectively 69%, 59%, 56%, 41%, 30% and 17%.

Conclusion

These preliminary results highlight the possibilities to map cropland with high accuracy in complex smallholder farming systems at the regional scale thanks

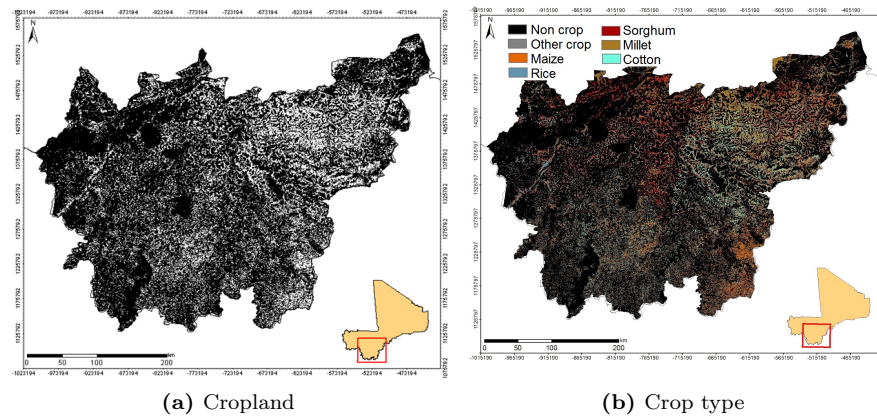


Figure A8: 10 m cropland mask (a) and crop type map (b) over south of Mali for 2017 growing season, obtained at the end of the season using Sentinel-2 and Landsat 8 data. White and black represent cropland and non-cropland classes respectively.

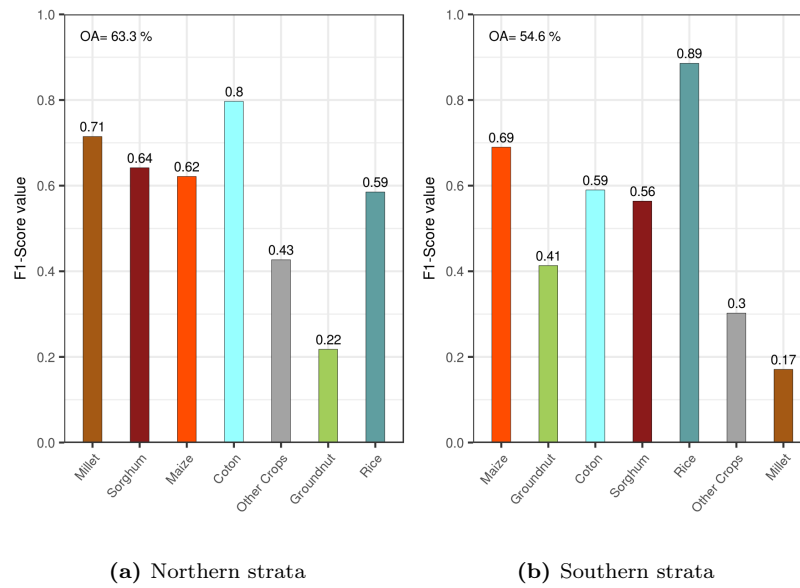


Figure A9: Classification accuracy of the main crop type classes over the study area with object based validation (a) Koutiala's strata (b) Haut-Bani-Niger's strata.

to high resolution open source imagery and robust field campaign. Crop type mapping is more challenging but present encouraging results.

