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The Potential of Sentinel-2 for Crop Production Estimation in a Smallholder Agroforestry Landscape, Burkina Faso

Martin Karlson[1]*, Madelene Ostwald[2,3], Jules Bayala[4], Hugues Roméo Bazié[5], Abraham Sotongo Ouedraogo[5], Boukary Soro[5], Josias Sanou[6] and Heather Reese[7]

[1] Department of Thematic Studies/Environmental Change, Linköping University, Linköping, Sweden, [2] Department of Technology Management and Economics/Environmental Systems Analysis, Chalmers University of Technology, Gothenburg, Sweden, [3] Gothenburg Centre for Sustainable Development, Gothenburg, Sweden, [4] World Agroforestry (ICRAF), ICRAF-WCA/Sahel Node, Bamako, Mali, [5] Laboratoire Biosciences, Unité de Formation et Recherche en Sciences de la Vie et de la Terre, Université Joseph Ki-Zerbo, Ouagadougou, Burkina Faso, [6] Département Environnement et Forêts, Institut de l'Environnement et de Recherches Agricoles, Ouagadougou, Burkina Faso, [7] Department of Earth Sciences, University of Gothenburg, Gothenburg, Sweden

Crop production statistics at the field scale are scarce in African countries, limiting potential research on yield gaps as well as monitoring related to food security. This paper examines the potential of using Sentinel-2 time series data to derive spatially explicit estimates of crop production in an agroforestry parkland in central Burkina Faso. This type of landscape is characterized by agricultural fields where cereals (millet and sorghum) and legumes (cowpea) are intercropped under a relatively dense tree canopy. We measured total above ground biomass (AGB) and grain yield in 22 field plots at the end of two growing seasons (2017 and 2018) that differed in rainfall timing and amount. Linear regression models were developed using the *in situ* crop production estimates and temporal metrics derived from Sentinel-2 time series. We studied several important aspects of satellite-based crop production estimation, including (i) choice of vegetation indices, (ii) effectiveness of different time periods for image acquisition and temporal metrics, (iii) consistency of the method between years, and (iv) influence of intercropping and trees on accuracy of the estimates. Our results show that Sentinel-2 data were able to explain between 41 and 80% of the variation in the *in situ* crop production measurements, with relative root mean square error for AGB estimates ranging between 31 and 63% in 2017 and 2018, respectively, depending on temporal metric used as estimator. Neither intercropping of cereals and legumes nor tree canopy cover appeared to influence the relationship between the satellite-derived estimators and crop production. However, inter-annual rainfall variations in 2017 and 2018 resulted in different ratios of AGB to grain yield, and additionally, the most effective temporal metric for estimating crop production differed between years. Overall, this study demonstrates

that Sentinel-2 data can be an important resource for upscaling field measurements of crop production in this agroforestry system in Burkina Faso. The results may be applicable in other areas with similar agricultural systems and increase the availability of crop production statistics.

INTRODUCTION

Smallholder agricultural systems are the dominant livelihood strategy in most of sub-Saharan Africa (Morton, 2007), with a very high proportion of food and cash crop production coming from farms that are generally smaller than 2 ha (Gollin, 2014; Lowder et al., 2016). The importance of these systems in the light of the projected population growth and subsequent food production requirements on the continent cannot be overstated. At present, low actual crop yields relative to potential yields limit the possibilities to achieve food security and reduce poverty (World Bank, 2008). Such yield gaps and their causes need to be understood in order to design effective measures to increase crop production (Tittonell and Giller, 2013).

A basic requirement for conducting research on yield gaps is the availability of field level crop production estimates. Such data make it possible to understand causes of yield gaps and to evaluate the effectiveness of interventions and changes in land use techniques, as well as impacts resulting from changes in agricultural policy. However, agricultural statistics collected by field surveys in Africa are mainly reported on national level and generally considered to be unreliable (Carletto et al., 2015b; Burke and Lobell, 2017).

Satellite remote sensing represents an alternative method for deriving quantitative estimates of crop production and grain yield with a number of potential benefits, including the ability to cover large areas, repeated observations and low costs (Lobell, 2013; Chivasa et al., 2017). Crop production estimation has been a key research topic for several decades (Atzberger, 2013; Rembold et al., 2013). The main efforts have been directed toward intensive commercial systems where the fields are generally large, crops are homogeneous, and reliable agricultural statistics are accessible to calibrate and validate remote sensing based estimates (Lobell, 2013; Chivasa et al., 2017). Yields of these agricultural systems can be easily estimated even if the remotely sensed imagery has relatively coarse spatial resolution.
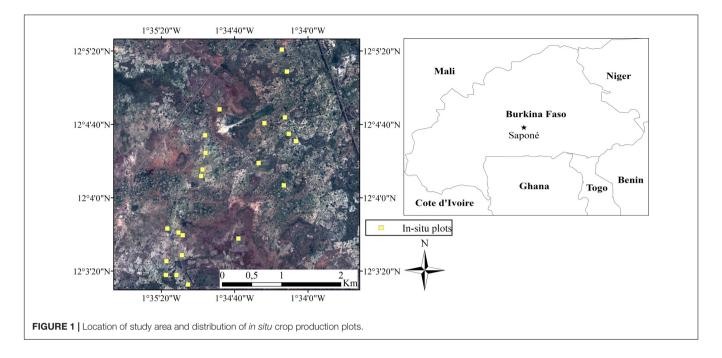
Such preconditions do not apply in the heterogeneous African smallholder systems where the agricultural fields are typically very small, irregular in shape and discontinuous in space and in crops cultivated (Burke and Lobell, 2017). Estimates based on household surveys from four African countries suggest that more than 50% of the fields are below 0.4 ha in size and 25% are smaller than 0.2 ha (Carletto et al., 2015a). In addition, a large proportion of the fields are intercropped, with high within-field heterogeneity in productivity (Bayala et al., 2014, 2015) and in situ measurements of crop production are generally unavailable (Tittonell et al., 2007; Bayala et al., 2014). A further complicating condition is that many of the smallholder farmers,

in particular in West Africa, practice agroforestry where trees and shrubs are integrated in the fields and thereby pose an additional challenge for remote sensing-based estimates of crop production (Vancutsem et al., 2013; Sweeney et al., 2015; Bégué et al., 2018).

Consequently, coarse-to-medium spatial resolution systems, such as MODIS and Landsat, provide limited possibilities for accurate crop production estimation in these heterogeneous agricultural landscapes because of the inability to distinguish small individual fields. Under such conditions, these satellite systems integrate the spectral measurement over an area that goes beyond the field boundaries, which means that other landscape components influence the signal and thereby results in mixed pixels. An important technological development was achieved when the Sentinel-2 satellite systems became operational (2A in 2015 and 2B in 2017). Sentinel-2 combines key spectral wavelengths at 10–20 m spatial resolution with a relatively short revisit-period (5 days at Equator) and an open-access data policy. These improvements have opened up new possibilities for more frequent high-resolution observations of agricultural fields, which is a precondition for satellite-based crop production estimation in African smallholder systems (Duncan et al., 2015).

Recent research in both eastern and western Africa has demonstrated the feasibility of satellite-based crop production estimation in smallholder systems. Burke and Lobell (2017) used 1 m Terra Bella Skysat imagery to estimate maize production during two growing seasons in Kenya and found promising agreement between satellite and in situ crop production estimates at individual field level. These authors concluded that the low availability of cloud-free imagery was an important limitation for improving accuracy in the estimates. Jin et al. (2017, 2019) expanded on the research in Kenya by also assessing the utility of satellite imagery from RapidEye and Sentinel-2. They found that the inclusion of red-edge wavelengths was useful for crop production estimation and reported considerable improvements in accuracy when aggregating field scale estimates to district level. Also using Sentinel-2 imagery, Lambert et al. (2018) developed crop type specific regression models to estimate production of millet, sorghum, maize and cotton in Mali. They showed that peak growing-season values of vegetation index (VI) and leaf area index (LAI) were the best estimators for the different crops.

The aim of this study is to assess the utility of Sentinel-2 data to estimate crop production at individual field scale in a smallholder farming system in central Burkina Faso. The landscape type in focus is referred to as agroforestry parklands in which the fields include a significant tree component and represents an important subsistence base in West Africa (Bayala et al., 2014). We investigated several critical aspects of satellite-based crop production estimation in this farming system,

FIGURE 1 | Location of study area and distribution of *in situ* crop production plots.
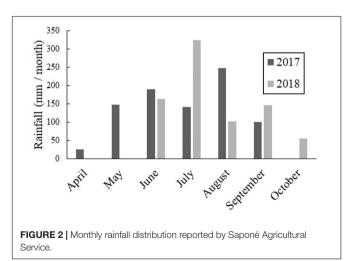
including (i) choice of vegetation indices (VI), (ii) effectiveness of different periods for image acquisition and temporal metrics, (iii) consistency of the method between years, and (iv) influence of intercropping and trees on accuracy of the estimates. We also assessed the relationship between crop above ground biomass (AGB) and grain yield based on the reasoning that AGB has a stronger influence on the remote sensing data and is therefore easier to estimate.

MATERIALS AND METHODS

Study Area

The study area is an agroforestry parkland system situated in the rural commune of Saponé ($12°04'48''$N, $1°34'00''$W) located 30 km south from Ouagadougou in central Burkina Faso (**Figure 1**).

FIGURE 2 | Monthly rainfall distribution reported by Saponé Agricultural Service.

This is a typical Sudano-Sahelian smallholder landscape where the fields are rainfed and farmers primarily grow pearl millet (*Pennisetum glaucum* (L.) *R. Br.*), sorghum (*Sorghum bicolor* (L.) *Moench*) and legumes, such as cowpea (*Vigna unguiculata*), for household consumption. Parklands are the main production system throughout this region. Farmers apply various forms of organic amendment to the fields, including manure, crop residues, woody litter and compost, but rarely mineral fertilizers (Koussoubé and Nauges, 2016). Doses of applied manure vary from 0.8 to 15 t ha^{-1}, with an average dose of 5.5 $\pm$ 0.72 t ha^{-1} (Sanou, 2010). Crop residues also represent an important source of fodder for the small-scale livestock production, which is a common activity throughout this region.

The local terrain is relatively flat with small variations in elevation (293–363 m above sea level). The soils are shallow (on average ca. 60 cm), sandy loamy reosols (FAO classification) with very low nutrient content in terms of nitrogen, phosphorus and organic material (Bazié et al., 2012). In addition, the soils are weakly acidic with low cation exchange capacity (Bayala et al., 2002). Mean tree canopy cover is 15% and mainly consists of traditional agroforestry species, in particular *Vitellaria paradoxa*, *Parkia biglobosa*, *Lannea microcarpa*, and *Mangifera indica* (Karlson et al., 2015).

Average annual rainfall is around 800 mm with high inter-annual variability, which strongly influences crop development and production. Total rainfall was 850.7 mm in 2017 and 789.1 in 2018, with relatively large inter-annual differences in the monthly distribution (**Figure 2**). Annual mean potential evapotranspiration (PET$_{Penman}$) is 1900 $\pm$ 210 (Bazié et al., 2018). The rainy season generally extends between May and October, with high variability between seasons, and the main proportion of rain is usually falling between July and September. The cropping season starts between May and July, depending on crop type and the onset of the rainy season, whereas harvesting generally

takes place at the end of October to November. However, unreliable rainfall at the start and end of the rainy season can lead to large windows for both sowing (May 15–July 15) and harvesting (October 15–December 15). This is even more variable nowadays due to high climate variability, as evidenced by farmers sometimes continuing to sow in August, as well as rains continuing to the beginning of November.

Crop Production Data

We measured total AGB and grain yield in 22 plots (20 × 20 m) during the harvest period (late October to early November) in 2017 and 2018 (**Figures 1**, **3**). The plot locations included agricultural fields with different tree canopy cover and crop combinations, where agreements with the local landowners were organized. Tree canopy cover within and around the fields ranged between 1 and 34% (see section "Analysing the Influence of Tree Cover and Intercropping on Estimation Accuracy"). Each plot was geo-referenced using a Garmin Oregon GPS device with a locational error <3 m. Three different crops were cultivated in the sampled fields, including sorghum, pearl millet and cowpea. The plots included both intercropped and single crop fields. For each plot and crop, we cut, dried and weighed the different plant components. The millet and sorghum plant components included ears, grain and straw, and for cowpea the components included pods, grain and residues. Total AGB represents all dried plant components, including the grain.

Satellite Data

Sentinel-2 A/B data from 2017 to 2018 growing seasons (June-October) were processed to Level 2A using version 1.8.3 of the Sentinel-2 for Agriculture system (Bontemps et al., 2015; Defourny et al., 2019). Following these protocols, atmospheric correction, detection of clouds and shadows and retrieval of aerosol optical thickness were done using the MACCS algorithm (Hagolle et al., 2010, 2015). From the two growing season time series, images with cloud cover below 30% were selected for further processing, resulting in six 100 × 100 km granules (30PXU) from 2017 (9/6, 29/6, 29/7, 7/9, 7/10, 22/10) and seven from 2018 (14/6, 14/7, 24/7, 17/9, 27/9, 7/10, 22/10). The image acquisition aimed to select dates from similar points in time for each of the 2 years. MACCS output enabled masking of clouds and shadows in the time series images. Sentinel-2 acquires red-edge and shortwave infrared bands at 20 m resolution. These bands were resampled to 10 m using bilinear interpolation to allow integration with the visible and near-infrared bands.

In addition, we acquired a cloud free Pléiades image (0.5 m spatial resolution) in October 2017 and used it to delineate tree crowns around the field plots. This ancillary dataset enabled an assessment of the potential influence of parkland trees on the Sentinel-2-based crop production estimation.

Vegetation Indices

We used various spectral VI derived from the Sentinel-2 data as estimators of crop production. **Table 1** presents candidate VI previously used for estimating crop production in similar agricultural systems. These were identified in recent studies focusing on satellite based estimation of crop production and yield at high spatial resolution in smallholder systems located in comparable agro-ecological zones with similar crops, including Burkina Faso (Forkuor et al., 2018), Mali (Lambert et al., 2018), and Kenya (Jin et al., 2017). Our review indicated that VI with a strong relationship to crop production often included red-edge wavelengths or were designed to be sensitive to canopy chlorophyll content. We also included traditional VI, such as NDVI and EVI, for reference.

Temporal Metrics for Crop Production Estimation

The image dates used to derive VI, as well as the method used to integrate a time series of vegetation index values to derive temporal metrics, such as peak or mean values, are critical issues that strongly affect the accuracy of crop production estimation (Chivasa et al., 2017). First, clouds limit the possibility to acquire gap free observations during the growing season, especially in tropical areas, and thereby generally reduces the possibility to acquire dense time series (Roy et al., 2010). Secondly, the phenological phase characterized by the observations is critical for establishing strong relationships between VI and crop production (Duncan et al., 2015). The optimal timing of image acquisition or method for deriving temporal metrics can differ between years, geographical regions and crops, and also depends on the planting period and climatic factors, in particular rainfall (Rasmussen, 1992; Maselli et al., 2000). We evaluated both individual dates and temporal metrics (**Table 2**) as estimators of crop production. The temporal metrics were derived from the

TABLE 1 | Vegetation indices (VI) selected for crop production estimation in Saponé, Burkina Faso.

Vegetation index (VI)	Equation	References
Normalized Difference Vegetation Index (NDVI)	$\frac{(B8-B4)}{(B8+B4)}$	Rouse et al., 1974
Enhanced Vegetation Index (EVI)	$\frac{2.5 \times (B8-B4)}{(B8+6 \times B4+7.5 \times B2+1)}$	Huete et al., 1997
Red Edge 1 NDVI	$\frac{(B8-B5)}{(B8+B5)}$	Forkuor et al., 2018
Red Edge 2 NDVI	$\frac{(B6-B4)}{(B6+B4)}$	Forkuor et al., 2018
Triangular Vegetation Index (TVI)	$0.5 \, (120 \, (B4 - B3) - 200(B4 - B3)$	Broge and Leblanc, 2001
MERIS Terrestrial Chlorophyll Index (MTCI)	$\frac{(B8-B5)}{(B5-B4)}$	Dash and Curran, 2004

The equation references the Sentinel-2 band numbers.

full growing season (GS; June–October), as well as the end of the growing season (EGS) defined here as September to October.

Crop Production Estimation

In order to identify the most effective estimators for crop production, we compared average and maximum Pearson correlation coefficients ($p < 0.05$) between *in situ* measurements of crop production and the candidate VI. The comparison was done for both the temporal metrics and individual acquisition dates. In the final selection of VI to use as estimators in the crop production models, we gave preference to those that provided high correlation coefficients for both 2017 and 2018. The reason for this was to test whether a crop production model developed in 1 year (2017) was applicable for estimation of crop production in the following year (2018).

Crop production estimation models were calibrated using the most effective estimators identified in the previous step as independent variables in simple Ordinary Least Squares regression. Due to the relatively small sample size ($n = 22$), we used 10-fold cross validation for model calibration and for computing model accuracy measures (Hastie et al., 2008), including coefficient of determination (R^2), root mean square error (RMSE), relative RMSE (relRMSE), and standard deviation (SD).

Analysing the Influence of Tree Cover and Intercropping on Estimation Accuracy

Using the 2017 Pléiades image as reference, we manually delineated individual tree crowns in 60 m × 60 m areas centred over the crop harvest plots and tree canopy cover (%) was calculated within each 3600 m^2 area. From the *in situ* crop production data, we also computed the proportional contribution of cowpea to total AGB, which enabled an assessment of the influence of intercropping on the crop production estimation. Cowpea is a low growing legume and represents the primary crop to combine with cereals (millet and sorghum). We hypothesized that a higher proportion of cowpea in the fields would increase the error in the estimates since this crop is partly obscured from the view of the satellite sensor by the taller cereal canopy. Separate linear regression models were computed to analyse the relationships between residuals from the crop production estimation models and the field level proportion of cowpea AGB, as well as percent tree cover.

TABLE 2 | Temporal metrics used for crop production estimation based on full growing season (GS) and end of growing season (EGS) VI time series.

Temporal metric	Time period
GS mean VI	June–October
GS median VI	June–October
GS peak VI	June–October
EGS mean VI	September–October
EGS sum VI	September–October

RESULTS

Crop Production Measurements

Crop production measured *in situ* differed substantially between the 2 years, in particular for AGB, which was higher in 2018, whereas inter-annual differences in mean grain yield was comparatively small (**Table 3**). On the other hand, maximum and minimum values, and consequently the range of AGB and grain yield showed large differences between the 2 years with considerably higher values in 2018. The higher AGB in 2018, when total rainfall was lower compared to 2017, can be explained by variations in the interannual rainfall distribution. Relatively high rainfall in July (2018) can provide more favorable conditions for plant growth, whereas heavy rains in August (2017) can damage the more developed plants through effects of sustained flooding of the soil.

There was strong linear relationship between AGB and grain yield in both years, with an R^2 of 0.88 and 0.86 in 2017 and 2018, respectively (**Figure 4**). However, the slope of the regression line differed between the years with a lower AGB to grain yield ratio in 2018 compared to 2017. This suggests that AGB is a very strong indicator of grain yield despite the high prevalence of intercropping of cereals and legumes, which differ markedly in their structure. The results also show that the relationship can be subject to considerable inter-annual differences. We choose to focus the remaining analysis of satellite-based crop production estimation on total AGB instead of grain yield for two reasons. Firstly, AGB is what influences the signal in the Sentinel-2 data and any attempt to estimate grain yield is dependent on the strength of this relationship. Secondly, in addition to the grain yield, all other crop material constitutes an important source of fodder for livestock, which represents a key component of the area's livelihood (Bayala et al., 2014).

Identification of Crop Production Estimators

The strength of relationships between the candidate VI and AGB varied slightly with no clear consistency between the years, with the exception of MTCI that did not provide a significant correlation in either 2017 or 2018 (**Table 4**). When considering both 2017 and 2018, RENDVI 2 proved to be the most stable VI and was therefore selected as the VI to develop regression models for crop production estimation. The temporal metrics with the strongest relationship to AGB also differed between the years, with GS peak VI consistently ranking highest in 2017 and GS median VI in 2018.

In addition to the temporal metrics, we also investigated the potential of the most effective VI (i.e., RENDVI 2) from individual dates as estimators of AGB. **Figure 5** shows a relatively similar temporal pattern for both years, where RENDVI 2 from early to mid-September appears to provide the strongest correlation to AGB. The difference in the September image acquisition dates between 2017 and 2018 needs to be considered when comparing the maximum correlation coefficients.

TABLE 3 | Descriptive statistics of *in situ* crop production measurements in Saponé, Burkina Faso.

Year	Crop combination	AGB ton ha^{-1}			Grain yield ton ha^{-1}		
		Min	Max	Mean	Min	Max	Mean
2017	Sorghum (*n* = 4)	0.74	2.09	1.18	0.17	0.57	0.33
	Millet (*n* = 6)	0.06	1.79	0.66	0.01	0.38	0.15
	Sorghum – cowpea (*n* = 7)	0.10	2.19	1.10	0.05	0.89	0.36
	Millet – cowpea (*n* = 1)	0.73	0.73	0.73	0.15	0.15	0.15
	Millet-sorghum – cowpea (*n* = 4)	0.56	1.85	0.99	0.16	0.87	0.41
	Total	0.06	2.19	0.96	0.01	0.89	0.30
2018	Sorghum (*n* = 8)	0.29	4.67	1.92	0.04	1.12	0.37
	Millet (*n* = 5)	0.53	4.89	2.1	0.08	0.82	0.35
	Sorghum – cowpea (*n* = 3)	0.29	2.51	1.13	0.05	0.73	0.31
	Millet – cowpea (*n* = 5)	0.65	1.38	0.98	0.14	0.26	0.22
	Millet-sorghum – cowpea (*n* = 1)	1.73	1.73	1.73	0.36	0.36	0.36
	Total	0.29	4.89	1.62	0.04	1.12	0.32

FIGURE 3 | Two examples of field plot locations. Early growing season **(left)** and before harvest **(right)**.

Estimating Crop AGB Production

The regression equations and the validation metrics for the AGB estimations based on temporal metrics and individual dates are presented in **Table 5**. The strength of the linear regression models between *in situ* AGB and VI estimates is generally high, with R^2 ranging between 0.41 and 0.80. However, there are clear

TABLE 4 | Correlation coefficients between vegetation index (VI) temporal metrics and aboveground biomass (AGB) in Saponé, Burkina Faso.

Vegetation index (VI)	2017		2018	
	Average	Max	Average	Max
EVI	0.63 (4)	0.69 – Peak	0.68 (5)	0.73 Median
NDVI	0.68 (4)	0.77 – Peak	0.65 (5)	0.75 Median
RENDVI 1	0.70 (1)	0.70 – Peak	0.53 (4)	0.58 Median
RENDVI 2	0.68 (6)	0.76 – Peak	0.73 (5)	0.83 Median
TVI	0.62 (4)	0.77 – Peak	0.57 (5)	0.60 Peak
MTCI	–	–	–	–

Numbers in parentheses indicate the number of temporal metrics with a significant (p ≤ 0.05) relationship to AGB that were used to compute the mean value.

differences in accuracy between the 2 years when using VIs from individual dates as estimators. Specifically, the regression model based on RENDVI 2 from September 7 (2017) resulted in the most accurate estimates overall, with an R^2 of 0.80 and relRMSE of 32.2%. This contrasts with the lowest accuracy for AGB estimates that were derived using RENDVI 2 from September 17 in 2018, both in terms of R^2 (0.41) and relRMSE (63%). Using temporal metrics (GS peak and median) derived from the full growing season time series as estimators resulted in relatively high accuracy for both 2017 and 2018 with small inter-annual differences.

Above ground biomass estimates in 2017 were within the range of the *in situ* measurements and the estimation models did not show any signs of bias (**Figure 6**). In 2018, the AGB estimates were mostly between 0.5 and 3 ton ha^{-1} and generally smaller as compared to the *in situ* measurements. The 2018 temporal metric (median) showed less tendency for bias and clearly outperformed the individual date (September 17, 2018) in terms of accuracy.

Inter-Annual Consistency

As an additional experiment, we applied the 2017 peak RENDVI 2 regression model to estimate AGB in the

FIGURE 4 | Relationships between *in situ* aboveground biomass (AGB) and grain yield in 2017 (**left**; R^2 0.88) and 2018 (**right**; R^2 0.86) in Saponé, Burkina Faso.
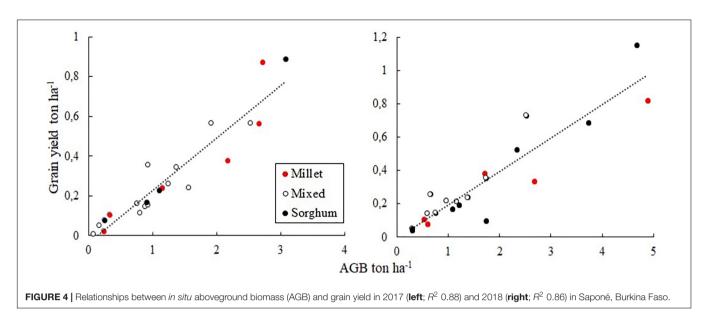
TABLE 5 | Linear regression models used for aboveground biomass (AGB) estimation and validation metrics for 2017 and 2018 for the Saponé site in Burkina Faso.

Year	Regression model	R^2	RMSE (ton ha^{-1})	Rel RMSE (%)	SD (ton ha^{-1})
2017	AGB (ton ha^{-1}) = −4.0 + 12.7 × *peak RENDVI 2*	0.62	0.54	56.2	0.68
	AGB (ton ha^{-1}) = −2.7 + 10.4 × *Sep 7 RENDVI 2*	0.80	0.31	32.2	0.76
2018	AGB (ton ha^{-1}) = −8.3 + 31.9 × *median RENDVI 2*	0.68	0.77	47.5	0.93
	AGB (ton ha^{-1}) = −2.1 + 9.6 × *Sep 17 RENDVI 2*	0.41	1.02	63.0	0.80

Remotely sensed estimators are highlighted in italics.

following year using the 2018 Sentinel-2 time series as input data. The 2017 peak RENDVI 2 model was able to produce relatively accurate AGB estimates in 2018 in terms of R^2 (0.66), RMSE (0.81 ton ha^{-1}) and relRMSE (50%; **Figure 7**). However, the AGB ranges and mean values are different between the years, and AGB in 2018 was generally underestimated when using the model developed in 2017. The
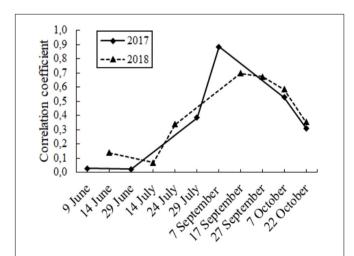
estimates for plots with only millet in particular resulted in large errors, whereas AGB in plots with mixed crops were accurately estimated.

Influence of Tree Cover and Intercropping on Estimation Accuracy

We found no significant correlations between residuals and percent tree cover inside and around the fields (**Figure 8**), nor between regression residuals and the proportional contribution of cowpea to the total AGB. Consequently, these factors do not appear to significantly influence the satellite-based estimation of AGB in this study.

DISCUSSION

The ability to produce accurate and spatially explicit estimates of crop production at sub-field level from freely available satellite data would be a major development for the monitoring and analysis of smallholder farming systems in Africa. This study demonstrates that this may be feasible even in the highly heterogeneous and complex agroforestry parklands that extend over large parts of the Sudano-Sahel in West Africa. The following section discusses the relevance of our results for the application of the method to estimate crop production at regional or national level.
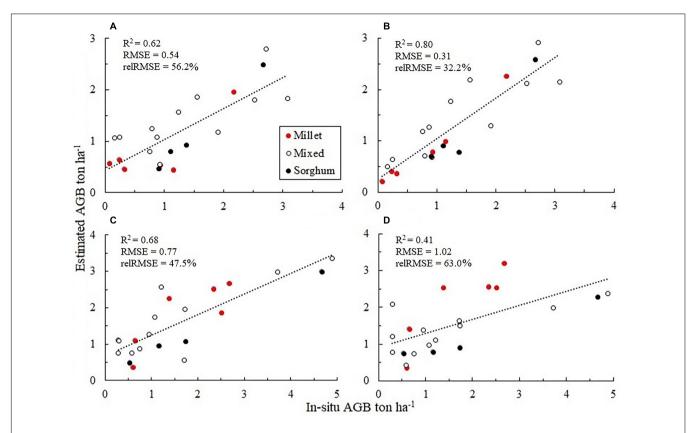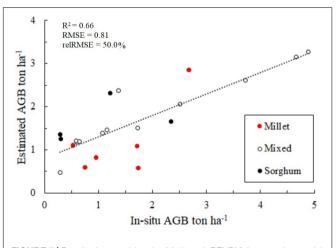

FIGURE 5 | Correlation between RENDVI 2 from different image acquisition dates and aboveground biomass (AGB) at harvest in Saponé, Burkina Faso.

FIGURE 6 | Relationship between in situ and estimations of aboveground biomass (AGB) based on peak VI 2017 **(A)**, 7 September 7, 2017 **(B)**, median VI 2018 **(C)**, and September 17, 2018 **(D)** for Saponé site in Burkina Faso.
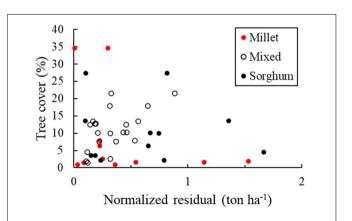
Comparison to Previous Crop Production Estimation Based on Satellite Imagery

Depending on the estimator used and the year considered, our method was able to explain between 41 and 80% of the variation in the *in situ* crop production measurements, with RMSE ranging between 0.31–0.54 and 0.77–1.02 ton ha^{-1} AGB in 2017 and 2018, respectively. Previous research on the use of medium to high spatial resolution satellite imagery for crop production estimation in Africa is limited compared to other continents. In addition, comparing results from this study to previous research is complicated due to differences in the crops in focus, the spatial scale used for estimating crop production and measures used to report accuracy. While the commonly reported RMSE

FIGURE 7 | Result when applying the 2017 peak RENDVI 2 regression model to the 2018 time series data for Saponé site in Burkina Faso.

FIGURE 8 | Relationship between normalized residuals from AGB estimation based on RENDVI 2 temporal metrics (peak 2017; median 2018) and percent tree cover in and around in situ plots for Saponé site in Burkina Faso.

provides a quantitative measure of accuracy, its interpretation is dependent on the local crop production conditions, in particular the production per spatial unit.

Earlier efforts that focused on similar crops (i.e., millet and sorghum) primarily used coarse resolution AVHRR imagery for estimating crop production at district level (Rasmussen, 1992; Maselli et al., 2000), with limited relevance for comparison with our sub-field level results. In terms of accuracy, our results are comparable to the study in Mali by Lambert et al. (2018) who used peak LAI derived from Sentinel-2 imagery acquired at the end of August to estimate crop yield of millet, sorghum and maize. These authors report results from crop type specific regression models, with R^2 ranging between 0.48 and 0.80 and RMSE between 0.5 and 1.0 tons ha^{-1}. Other studies in Africa have also focused on single crop agricultural systems, mainly maize production, with varying results. For example, Jin et al. (2017) achieved R^2 between 0.28 and 0.36 for field level estimates of maize production in western Kenya using Sentinel-2 imagery but did not report RSME. In the same area, Burke and Lobell (2017) estimated maize production using Terra Belle high spatial resolution imagery and reported R^2 of 0.4 at field level. Other studies have estimated maize production at a higher level of spatial aggregation. Azzari et al. (2017) used peak VI from coarse spatial resolution MODIS data at province level in Zambia and reported R^2 of 0.55 and RMSE of 0.4 ton ha^{-1}. In Kenya and Tanzania, Jin et al. (2019) reported district level results with an accuracy of R^2 of 0.5 and RMSE of 0.39–0.54 ton ha^{-1}. Consequently, the accuracy of our estimates is in the same range as those previously reported even though a large proportion of the sampled fields in this study included both mixed crops and trees.

Effectiveness of Crop Production Estimators

We assessed several VI for their effectiveness in estimating crop production. Correlation analysis did not show substantial differences in the strength of the relationship between the different VI and AGB, in particular in 2017. In 2018, RENDVI 2 marginally outperformed the other VI and was therefore selected as the principle VI for crop production estimation in this study. The importance of the Sentinel-2 red-edge bands confirms previous research on crop mapping applications in the Sudano-Sahel (Forkuor et al., 2018; Lambert et al., 2018). A main reason for the high correlation between AGB and RENDVI 2 is likely the sensitivity of the Sentinel-2 red-edge bands, in our case particularly band 6, to key elements in photosynthesis, including canopy content of chlorophyll and nitrogen. However, the small differences in predictive performance suggests that the choice of VI does not appear to be a critical consideration in this particular agricultural system. The main exception was MTCI, which previously has been identified as an effective estimator of maize production (Jin et al., 2019), but was not in our study.

The effectiveness of the temporal metrics used as crop production estimators differed between the 2 years. In 2017, growing season peak values provided the strongest relationship between AGB for all VI, whereas median VI values were generally

the most effective estimator in 2018. This is likely caused by a combination of differences in i) availability of cloud free imagery between the years, and ii) local growing conditions related to rainfall amount and temporal distribution. The rainfall distribution differed substantially between 2017 and 2018, which may have affected both the total crop production, as well as the relationship between VI and AGB. Growing season peak values are the most commonly used estimator in comparable studies (Azzari et al., 2017; Lambert et al., 2018; Jin et al., 2019). However, our results suggest that the optimal estimator is likely a function of annual crop growth dynamics and crop density, which in the Sudano-Sahel is tightly coupled to the amount and distribution of rainfall (Rockström and de Rouw, 1997; Gibon et al., 2018).

Inter-Annual Consistency of VI-AGB Relationships

There was a relatively large disparity in estimation accuracy between the 2 years in this study with relRMSE ranging between 32.2–56.2% in 2017 and 47.5–63% in 2018. The rather high relRMSE is mainly an effect of the generally low AGB values resulting from unfavorable growing conditions (soil and rainfall) in the area. The higher relRMSE in 2018 can be explained by a combination of two factors: the substantially higher mean AGB and a weaker relationship between the VI based estimators and crop production. The large difference in AGB between the 2 years is the result of high climate variability that characterize this region (Sultan and Gaetani, 2016). In addition, clouds restricted the collection of imagery during late August and early September in 2018. This relatively short window of time appears to be crucial for achieving a strong relationship between VI and AGB at the EGS (see **Figure 5**), and likely corresponds to the period when crops reach maximum growth and greenness in this region (Lambert et al., 2018). From mid-September, the crops start to ripen with accompanying leaf senescence and chlorophyll breakdown, which results in reduced correlation between AGB and VI based estimators. Since the harvest of millet, sorghum and cowpea usually takes place between late October and early November, this time window opens up for using imagery from this period as an important source of information for predicting the harvest 1–2 months before the end of the growing season. Such information is a key component of early warning systems focusing on food security (Meroni et al., 2014a). However, the duration of this study is too limited to characterize the high inter-annual climate variability and its influence on crop development, as well as the ratio between AGB and grain yield. A longer time series of *in situ* crop production measurements is needed to derive well-founded conclusions.

In 2017, the use of RENDVI 2 from an individual date (September 7) resulted in slightly more accurate AGB estimates compared to using growing season peak values. When applying this method to map larger areas, the potential increase in accuracy achieved from using single date imagery needs to be contrasted with the possibility of increased data gaps caused by high cloud cover coinciding with the period of maximum vegetation growth. The use of a temporal metric, such as peak VI, has the benefit of limiting the impact of clouds by combing VI values from multiple

image acquisitions and thereby increasing the possibilities for deriving gap free data coverage.

The results from this study using 2 years of data represent conditions in a relatively small area, which needs to be kept in mind. Several factors may influence the timing of maximum crop growth and therefore the relationship between VI and AGB, including inter-annual rainfall variability, soil moisture, sowing date and differences between crop varieties or combinations (Meroni et al., 2014b; Sanon et al., 2014; Wolf et al., 2015). These factors are highly variable in space within the Sudano-Sahelian zone, which makes it difficult to predict optimal timing for image acquisition in a specific area. When applying this method for estimating crop production on a regional or national scale, it is therefore advisable to use temporal metrics as estimators instead of individual dates for image acquisition. Besides reducing the influence of clouds, the use of temporal metrics can also compensate for local differences in the timing of maximum crop growth, and consequently strengthen the relationship between VI and AGB. However, further research using both longer time series of in situ crop production, as well as sampling plots distributed in a larger area is needed to clarify this issue.

The collection of *in situ* crop production measurements is a work intensive and time demanding task. Hence, it would be advantageous if a crop production model developed for 1 year could be applied to estimate crop production for future years. Identifying a temporal metric that is stable through time and space will be an important task in this context in order to facilitate operational application of satellite-based crop production estimation. Our initial attempt to test this showed that reasonably accurate estimates in terms of R^2 and RMSE could be achieved when using the 2018 Sentinel-2 time series as input to the 2017 peak RENDVI 2 model. However, the results also showed that large inter-annual differences in the range of *in situ* AGB could cause problems for the estimation model. In our study, this generally resulted in severe underestimation (relRMSE = 50%) of the 2018 crop production. Another explanation for the high relRMSE in 2018 when using the model developed in 2017 can be that the crop combination changed substantially between the 2 years. More accurate predictions may be possible in areas where the crop rotation cycle is more stable, and the same crops or crop combinations are grown in the fields in consecutive years.

Effects of Intercropping and Tree Cover on Crop Production Estimation

When considering that previous research reported accuracies for single crops or used crop specific prediction models, our results derived from a high proportion of intercropped fields are encouraging. Intercropping cereals with a significant proportion of legumes is a common agricultural strategy in Sudano-Sahel for improving food and nutrition security and replenish soil nitrogen (Franke et al., 2018; Kulkarni et al., 2018). We did not find evidence suggesting that a high degree of intercropping affected the relationship between VI and AGB, and consequently did not affect the ability

to estimate crop production from Sentinel-2 imagery. Crop specific regression models may increase estimation accuracy but require a land-cover map in which fields are classified based on crop type or crop combinations. This adds a layer of uncertainty that needs to be considered. In northern Burkina Faso, Forkuor et al. (2018) showed that it is possible to separate mono-crop fields with either cereals or legumes with relatively high accuracy using Sentinel-2 image classification. However, accurately distinguishing intercropped fields in remote sensing imagery is virtually impossible (Bégué et al., 2018). In addition, separation between millet and sorghum using image classification is generally not reliable due to their similar structure and spectral properties (Lambert et al., 2018). Taken together, this limits the applicability of crop specific regression models in smallholder agricultural systems in the Sudano-Sahel.

In addition to intercropping, the prevalence of a substantial tree cover in the fields is generally considered an important factor that restrict remote sensing for agricultural applications in African smallholder systems (Lobell, 2013; Sweeney et al., 2015). In this study, tree cover inside or in close proximity to the fields did not seem to influence the crop production estimation negatively. However, other sources of error may have disturbed the relationship between VI and AGB and reduced the accuracy of the estimations. Quantitative measures of weeds or shrub coppices in the field were not recorded during the *in situ* data collection. A high presence of such vegetation is likely to influence the performance of the satellite based estimation (Burke and Lobell, 2017), but could not be assessed here due to lack of this information in the collected reference data. The collection of such data is a key issue for future studies.

Potential Applications of Satellite-Based Crop Production Estimates

High-resolution crop production estimates of sufficient accuracy have several applications of prime importance, especially in an African context. Firstly, collection of field level data on crop production is expensive and seldom reported systematically in African countries, including in the Sudano-Sahel (Burke and Lobell, 2017). Lack of such data limits the possibilities to understand the causes of yield gaps in different types of agricultural systems. Knowledge about yield gaps and their causes is a key prerequisite for improving crop production and increasing food security through various interventions (Tittonell and Giller, 2013). In the agroforestry parkland system, such interventions could include different strategies for managing the tree cover, including crown pruning, tree species selection and modifying tree densities in the fields (Bayala et al., 2015). Detailed characterization of parkland tree cover, including canopy structure and species composition can be achieved using satellite remote sensing (Karlson et al., 2014, 2016). The combination of detailed and spatially explicit information on both trees and crops opens up new ways of studying the mechanisms of this important agriculture system.

Crop production statistics reported at district to national levels are generally considered unreliable in many African countries (Carletto et al., 2015b), including Burkina Faso. While limited in geographical scope, our results indicate that Sentinel-2 imagery may represent an important complementary data source to improve the situation. Other researchers have shown that the accuracy can be improved when crop production estimates are aggregated at a coarser spatial unit, including districts and provinces (Azzari et al., 2017; Jin et al., 2019). In Burkina Faso, national statistics of the main crops are based on field level estimates that are aggregated at regional and national level. These surveys are conducted throughout the different regions of the country and thereby captures the spatiotemporal variability in crop types and combinations, and crop production capacity. If quality of the surveys can be ensured and the field level measurements are accurately geo-references, these data could be used to calibrate Sentinel-2 based crop production estimation models, which allow national scale mapping. An important prerequisite for such an approach is, however, accurate maps of agricultural field boundaries. Previous research has demonstrated that such maps can be derived from optical satellite systems, such as Landsat 8 and Sentinel-2, even in the heterogeneous smallholder systems of Sudano-Sahel (Forkuor et al., 2018). Another option for this task may be high-resolution cubesat imagery with daily revisit periods provided by systems such as PlanetScope to capture this highly dynamic landscape where fields are regularly fallowed, and new land is subsequently cleared.

CONCLUSION

This study investigated the potential of Sentinel-2 data for mapping crop production at 10 m pixel resolution in a smallholder agroforestry area situated in central Burkina Faso. Several factors contribute to making this a challenging landscape for this type of mapping, including pervasive cloud cover during the growing season and heterogeneous agricultural fields in terms of size, shape and a high prevalence of intercropping of cereals and legumes, as well as interspersed trees and shrubs. Our results based on 2 years of *in situ* crop production data show that inter-annual variability in climate conditions can lead to relatively large differences in the relationship between crop development and VI, which constitutes the basis for estimating crop production from satellite data. This was manifested by interannual differences in the effectiveness of satellite data acquisitions and the method used for deriving VI temporal metrics. While the temporal dimension of crop production estimation appears to be highly influential on mapping accuracy, the choice between different VI appears to be of lesser importance in the agroforestry parkland system, which was in focus here. A way forward would be research targeting a wider area, additional years of *in situ* data and different crop combinations and densities to confirm these observations.

The method presented here based on freely available satellite data and processing tools was able to explain between 41 and 80% of the variability in the *in situ* crop production data, depending on year and approach used for deriving temporal metric from VI time-series. This relatively high mapping accuracy is encouraging, especially since a high proportion of the *in situ* data represented fields where cereals and legumes were intercropped. From an operational mapping perspective targeting regional or national scales, such field conditions are to be expected for large areas of the Sudano-Sahelian zone. These results contribute to a growing body of research showing that sufficiently accurate and spatially explicit estimates of crop production at landscape scale may be feasible not too far into the future, even for the challenging smallholder systems that dominates African agricultural systems. Such information is of prime importance to improve the quality, extent and resolution of national crop statistics, as well as for research analyzing the causes of yield gaps. While the quality may be questionable, field surveys collecting national crop statistics are regularly conducted in many African countries, including Burkina Faso. Relatively small modifications in such survey protocols to better align with the requirements of calibrating satellite-based crop production estimates could be an efficient investment to improve field data availability in this region.

DATA AVAILABILITY STATEMENT

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

MK, MO, HB, HR, and JB conceived and planned the study. HB, AO, BS, and JS planned and carried out the field data collection. MK took the lead in analyzing the data, interpreting the results, and writing the manuscript. All authors provided critical feedback and helped shape the research, analysis, and manuscript. All authors contributed to the article and approved the submitted version.

FUNDING

ACKNOWLEDGMENTS

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