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Assessing yield and fertilizer response in heterogeneous smallholder fields with UAVs and satellites

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ABSTRACT

Agricultural intensification and efficient use and targeting of fertilizer inputs on smallholder farms is key to sustainably improve food security. The objective of this paper is to demonstrate how high-resolution satellite and unmanned aerial vehicle (UAV) images can be used to assess the spatial variability of yield, and yield response to fertilizer. The study included 48 and 50 smallholder fields monitored during the 2014 and 2015 cropping seasons south-east of Koutiala (Mali), cropped with the five major crops grown in the area (cotton, maize, sorghum, millet and peanuts). Each field included up to five plots with different fertilizer applications and one plot with farmer practice. Fortnightly, in-situ in each field data were collected synchronous with UAV imaging using a Canon S110 NIR camera. A concurrent series of very high-resolution satellite images was procured and these images were used to mask out trees. For each plot, we calculated vegetation index means, medians and coefficients of variation. Cross-validated general linear models were used to assess the predictability of relative differences in crop yield and yield response to fertilizer, explicitly accounting for the effects of fertility treatments, between-field and within-field variabilities. Differences between fields accounted for a much larger component of variation than differences between fertilization treatments.

Vegetation indices from UAV images strongly related to ground cover ($R^2 = 0.85$), light interception ($R^2 = 0.79$) and vegetation indices derived from satellite images (R^2 values of about 0.8). Within-plot distributions of UAV-derived vegetation index values were negatively skewed, and within-plot variability of vegetation index values was negatively correlated with yield. Plots on shallow soils with poor growing conditions showed the largest within-plot variability. GLM models including UAV derived estimates of light interception explained up to 78% of the variation in crop yield and 74% of the variation in fertilizer response within a single field. These numbers dropped to about 45% of the variation in yield and about 48% of the variation in fertilizer response when lumping all fields of a given crop, with Q^2 values of respectively 22 and 40% respectively when tested with a leave-field-out procedure. This indicates that remotely sensed imagery doesn't fully capture the influence of crop stress and management. Assessment of crop fertilizer responses with vegetation indices therefore needs a reference under similar management. Spatial variability in UAV-derived vegetation index values at the plot scale was significantly related to differences in yields and fertilizer responses. The strong relationships between light interception and ground cover indicate that combining vertical photographs or high-resolution remotely sensed vegetation indices with crop growth models allows to explicitly account for the spatial variability and will improve the accuracy of yield and crop production assessments, especially in heterogeneous smallholder conditions.

1. Introduction

Yields in smallholder fields are often only 20% of attainable yields (Tittonell and Giller, 2013). Yield gaps are usually defined as the difference between water-limited and actual yields (van Ittersum et al., 2013). These yield gaps may be caused by many factors, including management (choice of crop variety, suboptimal plant density and sowing dates, limited use of fertilizers, weeding, pest and disease

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control) and biophysical constraints (pH, macro- and micro nutrient availability). There is an urgent need to sustainably intensify to feed the fast growing populations in sub-Saharan Africa, while limiting expansion of agricultural land-use (van Ittersum et al., 2016). Reliable estimates of attainable yields and realized production at field and farm scales are needed to better inform policy makers, farmers and suppliers of inputs and credit, to more effectively intensify and ensure that inputs are targeted efficiently. Farmer investments in intensification are driven by the expected return on investment, for which reliable knowledge about the expected yield response (the additional kg of yield per kg of nutrient applied) is key information but known to vary strongly over small distances, governed mostly by influence of past management (Zingore et al., 2011). Better information about the differences in the response to applied nutrients within and between fields may help maximize financial returns for smallholders and other investors.

Quantitative information about crop management and crop growth may help inform government agencies and actors in agricultural value chains. This will help to accelerate the intensification of smallholder farming systems by improving credit facilities, input supply mechanisms and market options. Smallholder farming systems in sub-Saharan Africa are highly diverse. Spatial variability is large intra-field, as trees are omnipresent in fields and inter cropping or relay cropping (e.g. peanuts and watermelon) is common. Environmental conditions (soil type, fertility and water availability) vary strongly within landscapes and even within fields (Tittonell et al., 2008). Natural spatial variability is further compounded by heterogeneous management practices (Tittonell et al., 2005a). Socio-economic factors also play an important role as nutrient re-distribution by grazing animals and use of crop residues cause strong gradients in soil fertility, typically decreasing with distance to the homestead (Tittonell et al., 2005b).

Precise monitoring of crop growth in smallholder fields with abundant trees requires a time-series of very high resolution (VHR) images, as observed spatial patterns in vegetation indices over cropland areas change through time due to interactions between site, weather and management. Interpreting these spatial patterns is therefore not straightforward. For example, spatial patterns in the landscape may emerge during the season due to staggered planting practices and differences between crops in phenology, such as greening up rate and plant senescence (Schut et al., 2010). Interpreting such spatial patterns in smallholder landscapes in terms of yield or nutrient response is therefore not straightforward, especially if only one single image is available as sowing windows are typically wide, with frequent re-sowing or transplanting when needed. A time-series of images may resolve these temporal aspects in the observed spatial patterns, and may be much more useful to assess differences in yield than one in-season image. Further, a very high-resolution dry season-image provides means to map evergreen tree locations, needed to eliminate the influence of trees on signals from the crop. Available optical satellite products are limited in that regard by their temporal resolution and their cost (e.g. DigitalGlobe, Pleiades), by their spatial resolution (e.g. MODIS, SPOT-Vegetation, Proba-V), and by cloud cover during the growing season (all).

Unmanned Aerial Vehicle (UAV) systems do not suffer from such strong cloud cover limitations and may present a useful alternative to monitor crop growth. Also, they can be used to upscale plot data collected at a limited number of locations to wider areas (van der Heijden et al., 2007), providing means to upscale plot-based assessments at relatively low costs. Unmanned aerial vehicles have been widely used experimentally to monitor crops, e.g., for assessment of plant survival and necrosis (Khot et al., 2016), precision agriculture (Zhang and Kovacs, 2012), and plant phenotyping (Sankaran et al., 2015). With UAV high-resolution images, crop height can be derived from surface models (Bendig et al., 2014), and strong relationships with biomass have been reported (Li et al., 2016). Most uses of UAV images are in the context of high-input farming systems. To our knowledge, there is no example of UAVs used to assess crop yield and its response to nutrients in smallholder landscapes (Burke and Lobell, 2017).

In previous work, we showed that only about 50% of the within-field variation in vegetation index values can be explained by fertilization treatments (Blaes et al., 2016). We further showed that on a landscape scale, the fraction in normalized difference vegetation index (NDVI) variability attributable to fertilization treatment (1–23%) was much smaller than the fraction attributable to between-field differences arising from soil variability or other field management practices. Fields within the same soil catena position were shown to be more alike, indicating that catena and the interaction with farm management strongly affect vegetation index values. Vegetation indices most strongly respond to ground cover, while both ground cover and vegetation indices correlate with light interception by the crop. Interception of photosynthetically active radiation is causally related to the crop growth rate (Sinclair and Muchow, 1999) and accumulated crop growth rates during grain filling determine crop yield (Goudriaan and Van Laar, 1994).

Combining vegetation indices from image time-series with crop growth models may provide means to develop a better understanding of underlying processes (Bouman and Goudriaan, 1989). Images may also inform about field conditions and crop status, e.g. spatial variability at small scales may inform about plant density variations. We aim to improve quantitative information on smallholder crop growth that enable better links between crop growth models and actual farmer yields using UAV and satellite data. The objective of this work is to test whether UAV images can be used to assess differences in light interception and crop yields between smallholder fields, and responses to fertilizer therein. The latter may be interpreted as an approximation of the nutrient gap, i.e. the extra yield that can be obtained when comparing to an adequate fertilization reference. Secondly, we expect that small-scale spatial variation may be an indicator of plant heterogeneity and a proxy for poor crop growth conditions. We hypothesize that knowledge of light interception and coefficients of spatial variation helps to assess and explain differences in crop yield and response to fertilizer between fields.

2. Materials and methods

2.1. Field data

During the 2014 and 2015 growing seasons, we collected ground data in respectively 48 and 50 farm fields near Sukumba (Koutiala District, Mali). The Sukumba village is located in the Sudano-Sahelian climate zone, with an average annual rainfall of about 900 mm (Traore et al., 2013). Crops monitored included Maize, Peanut, Sorghum, Millet and Cotton. Fields were located along a catena, covering light colored alluvial valley soils with deep sandy loams (subsoil: clay loams), shallow red colored sandy loams with gravelly material on intermediate landscape positions and again somewhat deeper soils with sandy loam topsoils and higher sub-surface clay contents, on plateau positions. Fields were thus grouped into three broad strata (valley, intermediate and plateau) based on combinations of soil type and elevation. Soil types were derived from a map used for a regional study (PIRT-Projet Inventaire des Ressources Terrestres, 1983). Each field included five or six plots of 225 m^2 (15 × 15 m) with different crop-specific fertilizer application rates. Plot A reflected farmer practice, plot B did not receive fertilizer and plots C to F received increasing amounts of fertilizer. These plots were located at least 5 m away from the crown of trees, ensuring that trees did not influence crop growth or UAV images. On average, fields were sown around June 2nd (millet), June 5th (cotton) and June 19th (maize, peanut and sorghum). Crops were mostly manually sown, leading to wide sowing windows with standard deviations around these mean sowing dates of 16.4, 9.6, 7.9, 9.2 and 21.7 days for millet, cotton, maize, peanut and sorghum, respectively in 2014. Harvest dates varied a bit more: peanut was harvested first around October 3rd (± 5.2 days), followed by cotton (November