THE POTENTIAL OF VERY HIGH SPATIAL RESOLUTION REMOTE SENSING IN APPLICATIONS IN SMALLHOLDER AGRICULTURE

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ABSTRACT: Smallholder farmers contribute to more than 50% of the world's annual production of cereals, meat and dairy products and they cultivate more than 80% of the total agricultural area in Asia and Sub-Saharan Africa. Conversely, it is estimated that more than 2.5 billion people depend directly on the agricultural sector. Earth Observation has been a tool for agronomists with ever-increasing capability, however, the case of agriculture in low-income countries imposes challenges, for instance in recognizing mixed- and inter-cropping, the small size of the farm plots and lack of sound crop management systems, which increase the uncertainty of information derived from remotely sensed data.

The Spurring a Transformation for Agriculture through Remote Sensing (STARS) project aims to investigate the potential of Very High Spatial Resolution remote sensing in delivering data products that can better inform decisions around smallholder agriculture. Data are collected throughout the growing season via *in-situ* measurements, Unmanned Aerial Vehicles equipped with NIR and multispectral cameras and VHSR satellite images. One important STARS' objective is to analyze the spectral information of this multi-scale and multi-temporal dataset and establish implementation flows to support stakeholders in their decision making and economic development.

In this study, we demonstrate the usefulness of VHSR images in mapping and monitoring smallholder crop fields in Bangladesh. UAV-based and satellite data at a variety of spatial scales are presented and the degree to which delineation of crop fields and related agronomical information can be extracted is discussed. This study aims to demonstrate potentials and limitations of the use of remote sensing for monitoring crop fields of smallholder farmers.

1. INTRODUCTION

Smallholder farmers contribute to more than 50% of the world's annual production of cereals, meat and dairy products (Kremen et al. 2012) and they cultivate more than 80% of the total agricultural area in Asia and Sub-Saharan Africa. More importantly, it is estimated that globally more than 2.5 billion people depend directly on the agricultural sector, primarily people suffering from poverty and undernourishment. Hence, increasing agricultural production can have a significant impact on poverty alleviation.

Earth observation has become an increasingly valuable source of data for agricultural and food information systems over the past decades in high-income countries. Nevertheless, in low-income countries (LICs) the agricultural landscape is fundamentally different in a number of respects. Sound crop management recommendations either are not available or do not reach the farmers sufficiently either farmers do not have access to inputs for various reasons. While smallholder farmers depend on their own crops as the primary source of their livelihoods, many barely manage to produce enough food to feed themselves and their families. Production levels can vary greatly and for some crops a wide range of varieties are grown. Mixed- and inter-cropping are also being practiced in small land plots, in order to increase land use intensity and establish food security. These factors pose fundamental challenges to the use of Remote Sensing (RS) for smallholder farmers. Established practices valid for the case of high-income countries, such as the deployment of satellite images with medium or even fine spatial resolution, may not apply to LICs.

Despite the fact that RS is a technology well-established since the 1970s and smallholder agriculture is an important livelihood component of millions of people, the application of RS to the latter is still primitive, mainly due to the limited spatial resolution of RS monitoring systems. With the advent of very high spatial resolution (VHSR) satellite systems and Unmanned Aerial Vehicles (UAVs), the spatial resolution problem is alleviated and insight of the usability of RS on smallholder farming needs to be developed. For example, it is worth investigating which role remote sensing can play in agricultural information such as crop vigor and health, nutrient and water content, water availability, yield, species and weed detection, and hence increase productivity and decrease vulnerability. Moreover, and despite the fact that agronomy is one of the main applications of RS and conversely RS is a valuable agronomic tool (Hatfield at el. 2006), economic benefit estimates for farmers are rarely addressed (Tenkorang and Lowenberg-DeBoer, 2008) and RS can be a source of material on agricultural economics.

The Spurring a Transformation for Agriculture through Remote Sensing (STARS) project aims to investigate the potential of VHSR remote sensing to assist smallholder farmers in sub-Saharan Africa and South Asia. STARS is an ongoing effort to collect data at different spatial resolutions (Figure 1) using UAVs and VHSR satellite images and complementing them with a wide array of *in-situ* measurements. One of STARS' main objectives is to analyze the spectral information of this multi-scale and multi-temporal dataset and establish implementation flows to support stakeholders involved in decision-making for economic development.

In this study, we demonstrate the usefulness of VHSR images in mapping and monitoring smallholder crop fields in Bangladesh, one of the study areas where STARS investigates the potential of production-enhancing techniques with an emphasis on irrigation for winter crops. A time series of VHSR images from commercial satellite providers (i.e., DigitalGlobe and BlackBridge) and UAVs data was used to derive information at this fine spatial scale. We present a semi-automated processing flow from the satellite image to spectral information assigned to an individual smallholder farm plot and the associated products that can be extracted. Several spectral indices derived from the images signpost the potential advantage of the narrowband configuration of RS systems. This study aims to demonstrate potentials and limitations of the use of RS for monitoring fields of smallholder farmers.

Figure 1: Wheat plot at Barisal from very low height (a) single shot of a field at Kalapara from low height (b) and crop fields at Barisal from a higher height (c).

2. MATERIALS AND METHODS

2.1 Datasets

A wealth of remotely sensed datasets are available within the STARS project. Here, we demonstrate the usefulness of VHSR images from UAV and satellite platforms as collected over three sites in Bangladesh. Time series of DG images (WV-2/3, Quickbird, Ikonos and GeoEye) and Rapideye images are available during the crop growing season. For UAV data, we used a Tetracam miniMCA6 mounted on a geo-X8000 octocopter. The footprint of the UAV is considerably smaller than the satellite coverage and covers a few farm plots per flight and per image mosaic. The Tetracam narrowband pass filters were configured to emphasize on the red-edge region as shown in Figure 2.

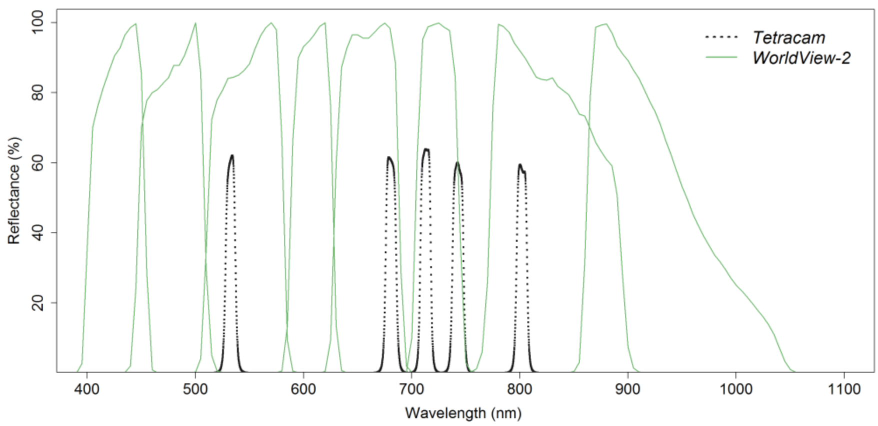

Figure 2: Spectral Response Functions of the Tetracam miniMCA used in the Bangladeshi STARS site and of the WorldView-2 images.

2.3 Processing

Processing workflows in the project are primarily based on free and open source software for reasons of following recent scientific trend and the fact that proprietary software licenses are expensive for LIC-based institutions. Moreover, we plan to release our workflows to allow for full reproducibility of the methods and to facilitate their uptake by any interested stakeholder.

The processing workflows for the satellite images consist of: (1) atmospheric correction, (2) tile mosaicing (3) orthorectification (4) image-to-image registration and (5) extraction of field-specific statistics. The 6s radiative transfer model (Vermote et al., 1997), R programming language (R Core Team, 2015) and Orfeo Toolbox (Inglada and Christophe, 2009) are used for these aforementioned tasks.

The UAV images were stitched to produce a single image encompassing the area of interest using proprietary software. The latter image was then spectrally calibrated using ground spectral targets and then geometrically registered. Additional agronomic information was obtained during field visits. Subsequently we derive vegetation narrowband spectral indices on the basis of the fact that such information is one of the most important products disseminated form RS data. For instance, Candiago et al. (2015) presented some examples of vegetation indices derived from a UAV-mounted Tetracam camera and discussed the application of such information in the context of precision farming. They presume that UAV-derived vegetation indices maps have a great potential in the agricultural sector. In this study we derived three narrowband spectral indices typically used in vegetation studies, namely the Normalised Difference Vegetation Index (NDVI), the Red Green Index (RGI) and the Simple Ratio Index (SRI), calculated as described in Table 1. Finally the band-to-band correlation is finally computed for the miniMCA image.

Table 1: Empirical spectral indices proposed frequently in vegetation studies.

Index	Reference	Formula (proposed)	Formula (miniMCA adapted)
NDVI (Normalised Difference Vegetation Index)	Tucker (1979)	$(R_{NIR}-R_{RED})/(R_{NIR}+R_{RED})$	$(R_{740}-R_{680})/(R_{740}+R_{680})$
RGI (Red Green Index)	Zarco-Tejada et al. (2005)	R_{690}/R_{550}	R_{680}/R_{530}
SRI (Simple Ratio Index)	Jordan (1969)	R_{800}/R_{680}	R_{800}/R_{680}

3. RESULTS AND DISCUSSION

The STARS dataset brings up the diversity of spectral information collected by the different sensors used in this study, from different heights and consequently different spatial resolutions. It is evident from Figure 3 that with coarser spatial resolution the land cover information is aggregated and the resulting spectral homogenization is broad. The UAV dataset shows explicit information over the structure of the field plots and the canopy status in a well-developed agricultural test site in Barisal, Bangladesh from images acquired during two consecutive days. The respective DG panchromatic image retains much of the information, while the DG multispectral image is resulting in spectral degradation over the field plots. This is an indication that a pan-sharpened product might eventually provide a comparable to the UAV image inheriting both the spectral and the spatial fidelity. It is worth noting that both DG products are sufficient for delineating field boundaries in this ideal case, however typical smallholder farms are not always as distinguishable as here. Field boundaries are non-detectable at the RapidEye spatial resolution of 5 m. A single land cover type encompassing all the plots can be identified, however, it is spectrally inconsistent in comparison to the higher spatial resolution products.

Figure 4 presents the crop development from UAV data within a period of one month (i.e. 2nd March to 3rd April). It is important to note that from the UAV images it becomes feasible to identify structures otherwise indistinguishable from the satellite image; the importance of this information lies not in the fact of identification itself, but mainly in the opportunity of distinguishing structures and objects which otherwise would contribute to the spectral signal of a single satellite image pixel and hence blur the spectral signature. For instance, the individual haystacks, human and animal presence, pathways and even plantation rows at this spatial scale become crisp thematic objects for visual interpretation or classification schemes. Nevertheless, the very high within-class variability has to be stressed, a fact that is not present in lower spatial resolution satellite images due to the homogeneity of land cover encountered within a single pixel; with increased spatial resolution, the individual scene elements are evident and the spectra found in the scene become more diverse, therefore the representation of each traditionally thematic class is rendered less consistent (Barnsley and Barr, 1996).

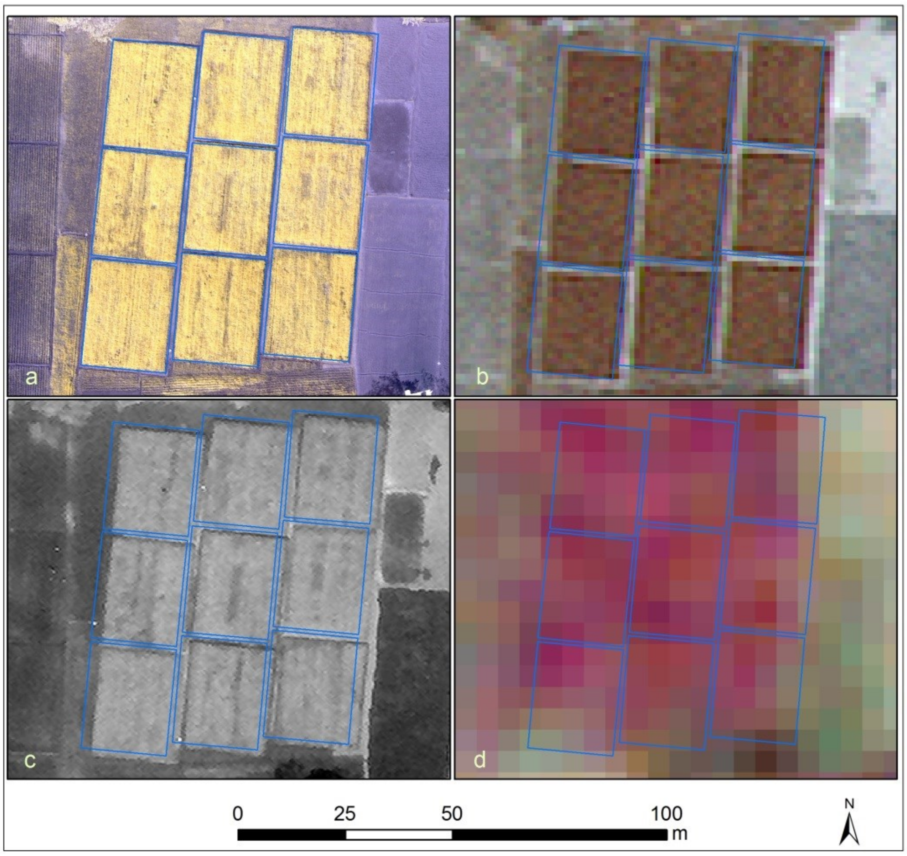

Figure 3: Spatial resolution of four remotely sensed images over Barisal. Tetracam image from UAV (a), WV-3 multispectral (b), WV-3 panchromatic band (c) and RapidEye (d). The UAV image was acquired on 12 February 2015 and the WV-3 (multispectral and panchromatic) and RapidEye scenes on 13 February 2015. Sub-figures b and c are provided for STARS by © 2015 DigitalGlobe, Inc. Sub-figure d includes material © 2015 BlackBridge S.àr.l. All rights reserved.

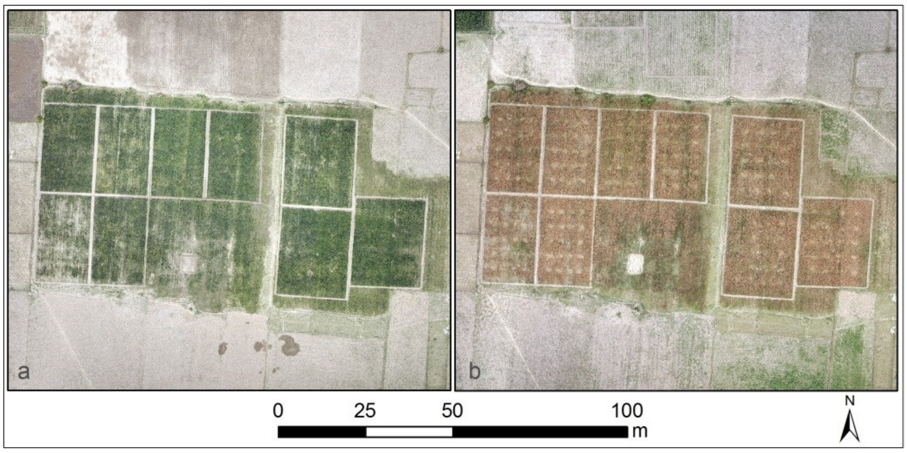

Figure 4: RGB image acquired from the miniMCA Tetracam from an UAV platform over Putuakali in two different moments of crop development on 02 March 2015 (a) and 03 April 2015 (b).

Figure 5 and Table 2 demonstrate the spectral information derived from the Tetracam for the test site over Kolopara, Bangladesh. In comparison to the RGB camera, the Tetracam presents coherent classes and tends to underestimate the shadows between the plants. The band-to-band correlation for the spectral configuration set for the Tetracam at this site shows a very high correlation between two groups: the first three bands (530 nm, 680 nm and 710 nm) and the last two bands (740 nm and 800 nm).

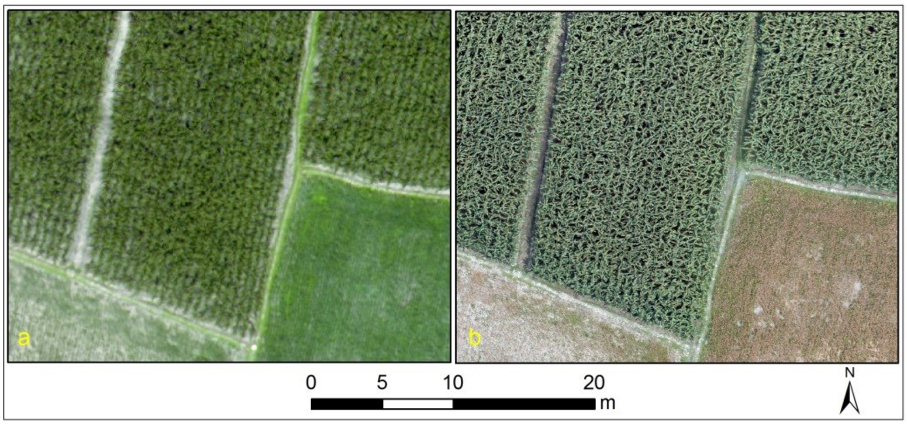

Figure 5: True-colour representation of canopy from UAV-mounted sensors over Kolopara, a Tetracam miniMCA on 13 March 2015 (a) and RGB imager on 29 March 2015 (b).

Table 2: Band -to-band correlation for the Tetracam MCA-UAV image over Kolopara.

Correlation	***530 nm***	***680 nm***	***710 nm***	***740 nm***	***800 nm***
530 nm	1	0.98	0.97	0.84	0.80
680 nm		1	0.95	0.78	0.72
710 nm			1	0.92	0.88
740 nm				1	0.99
800 nm					1

Of specific interest to this study is the information that can extracted from the image after calculating spectral vegetation indices. Here in Figure 6, we present popular spectral indices used traditionally in vegetation studies. These indices were derived from the UAV-Tetracam data. The degree to which NDVI is saturated is remarkable; fields with crops in well-developed stages appear homogenous based on the NDVI index and the in Near Infrared false-colour (RGB: 740, 680, 530); on the other hand, SRI and RGI provide more detail with regard to the canopy of interest and pick up the difference from the spectral bands they are built on. However, the latter two indices are not able to discriminate between fields non-predominantly covered with vegetation as the three fields on the right of the study area; this is an indication that these spectral indices are more appropriate for studying the crop canopy specifically; on the other hand, a more holistic mapping of the smallholder farms including non-vegetated parcels seems to be better represented by NDVI.

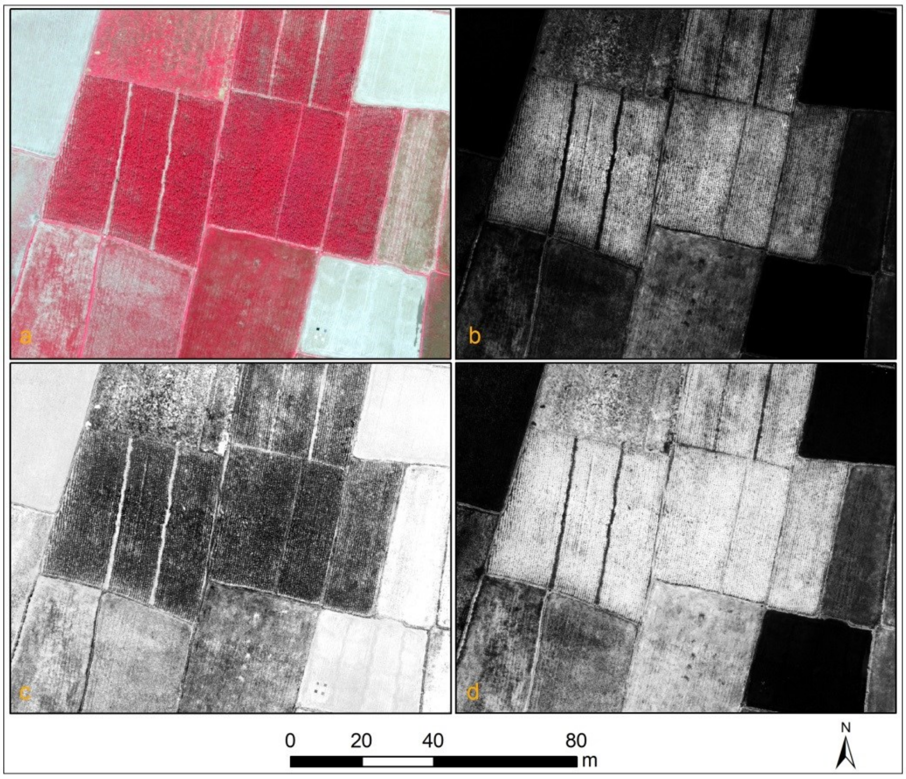

Figure 6: Agricultural field over Kolopara on 13 March 2015 through a NIR false-colour composite (RGB: 740, 680, 530) of Tetracam miniMCA (a), the SRI (b), the RGI (c) and the NDVI (d) indices.

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