MEASURING GREEN VEGETATION COVER OVER AGRICULTURAL FIELDS: A MULTI-SCALE STUDY USING SMARTPHONES AND UAV

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Abstract
The fraction of green vegetation cover (fCover) is an important bio-physical parameter with a variety of applications in the fields of agriculture and forestry. fCover refers to the percentage of ground covered with photosynthetically active green parts of a plant. The main objective of this paper is to study the variation in fCover when estimated at various spatial scales using various methods and instruments. First, the effect of spatial resolution on fCover estimates is examined by using different smartphones and UAV images. Next, the influence of the method used for fCover estimation is studied by comparing two types of approaches – classification and regression. For the classification approach, an object-based image analysis technique was adopted. In the regression approach, various vegetation indices and their statistics were used as predictors in a random forests algorithm, which identifies the most important color and NIR indices to estimate fCover. Results show that minor differences in the resolution do not have major impact on the fCover estimates. But using too coarse spatial resolution can lead to substantial over- or underestimation of fCover. The comparision of the two approaches revealed that the regression method had less difficulties dealing with crops whose leaves are small and not well defined with respect to the background. Both approaches could poorly estimate fCover when the sun reflection was strong. Yet the regression method could deal much better with changing illumination.

Keywords: *fCover, machine learning, GEOBIA, UAV, smartphone*

INTRODUCTION

Estimating vegetation properties from remotely sensed images dates back to the Cold War when the USA used satellites to forecast wheat crop yield in the USSR and thus predict production shortfalls (Logsdon et al., 1998). Crop yield is still an important factor in national security because the failure of a country to produce sufficient quantities of agricultural products can lead to violent conflicts and mass migration (Campbell et al., 2007). This is especially true for developing countries in sub-Saharan Africa and South Asia not having the financial resources to import agricultural products and suffering from climate changes (Schmidhuber & Tobiello, 2007). Nowadays the access to high resolution imagery is not limited only to reconnaissance authorities. Optical remote sensing images with fairly high resolution such as those from Landsat-7 or Landsat-8 with up to 30 m resolution and Sentinel-2 with up to 10 m resolution are freely available. Farmers can use this information for predicting crop yield, monitoring diseases, planning irrigation and fertilizers application (Bastiaanssen et al., 2000; Seelan et al., 2003). Humanitarian organizations can also make use of it by identifying regions threatened by food shortages and thus planning in advance counter measures (Kaiser et al., 2003).

Besides these traditional remote sensing platforms, an increasing amount of data is being collected with unmanned aerial vehicles (UAVs) and smartphones making possible the estimation of vegetation properties for smaller agricultural fields and at better spatial resolution (Anderson & Gaston, 2013). UAVs do not only offer the possibility to collect higher resolution imagery than satellites, they have other advantages as well such as collecting data at different angles (Ren et al., 2017) and in cloudy weather conditions (Bondi et al., 2016). For the purposes of precision agriculture, topographic and atmospheric corrections are often not needed making the use of UAV images less laborious than the use of satellite images (Jakob et al., 2017). UAVs are able to carry various instruments ranging from hyperspectral to simple consumer grade RGB cameras (Salamí et al., 2014). Smartphones are more limited with respect to the cameras that they can carry but they might be equipped with sensors such as gyroscopes and inclinometers collecting information about the position, motion and surrounding environment (Pongnumkul et al., 2015). These sensors combined with the processing power of smartphones and dedicated applications can convert smartphones into effective tools for collecting vegetation properties information that might even replace more traditional field instruments (Campos-Taberner et al., 2015).

With the increased amount and availability of data, new methods are needed for its interpretation. While simple statistical techniques such as linear regression are still common, more sophisticated machine learning algorithms have gained popularity in recent times because of their good performance. However, this abundance of instruments, data and methods can be overwhelming. Therefore, this paper aims at comparing vegetation properties estimated using various instruments and analytical methods. This paper focuses on the fraction of green vegetation cover (fCover) as it is an important vegetation parameter having variety of applications in agriculture and forestry.

Despite the wide use of fCover, the multiple terms being used to describe it are not yet standardized which makes the comparison of studies using this bio-physical parameter difficult (Godínez-Alvarez et al., 2009). In literature, fCover can be often regarded to as (fractional/fraction of/percentage of) (green) foliage, ground, plant, vegetation or canopy cover. Depending on the purpose for which it is used, cover may refer only to certain types of vegetation such as tree and shrub canopies, only to green vegetation, to all types of vegetation including litter or in the case of ground cover also to non-vegetation material such as rocks (Bonham, 2013). fCover can be expressed in different ways - as percentage, proportion or using a categorical scale (Bonham, 2013). In this paper, fCover is expressed as percentage and refers only to the photosynthetically active green parts of a plant.

STUDY AREA, DATA AND METHODS

The study area is located in Bangladesh which is characterized by sub-tropical humid climate. The field surveys took place in Barisal, Kalapara and Patuakhali located in the south part of the country (Fig. 1).

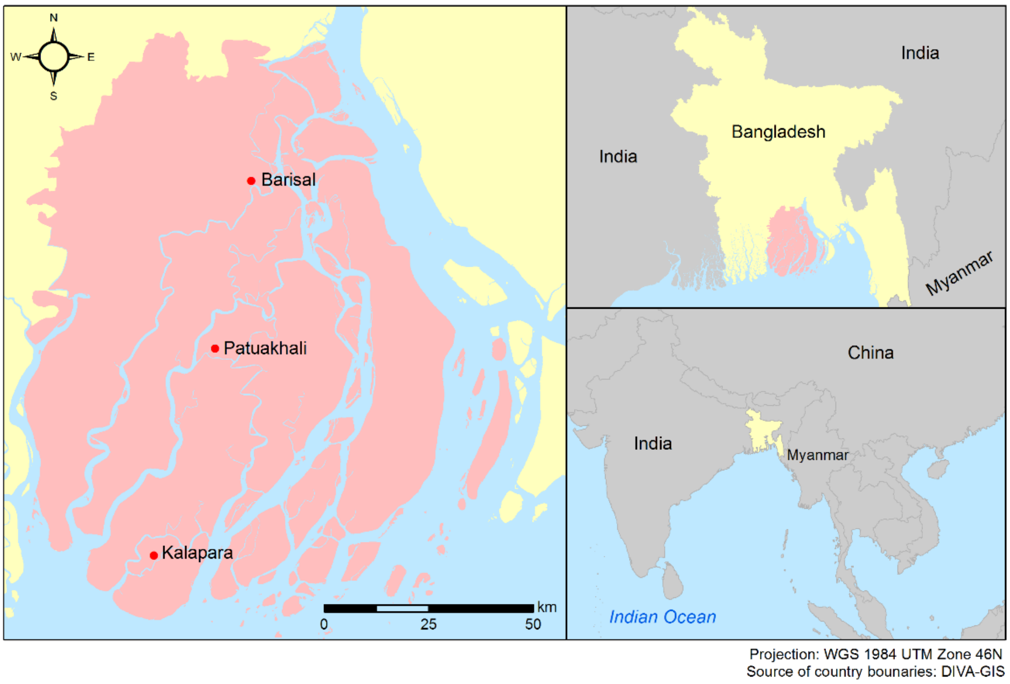

Figure 1. Map showing the three study sites – Barisal, Kalapara and Patuakhali, located in the administrative division of Barisal (depicted in light red)

Several fields were visited and photos were collected using different brands of smartphones and an octocopter. Each of the smartphone pictures was taken vertically above ground and covered approximately 1 m^2 as measured by a square frame placed on the ground during the field surveys. The green pixels in the pictures were manually annotated with CAN-EYE - software that allows the extraction of fCover from RGB images (Weiss & Baret, 2016). RGB images of the fields were collected with the octocopter at several different altitudes ranging from 7 m to 65 m. Multispectral images were collected as well at an altitude of 100 m. In total, five spectral bands were covered – 530 nm, 680 nm, 710 nm, 740 nm and 800 nm, with 10 nm band width.

Two different approaches were proposed for estimating fCover: a regression and a classification. For the regression approach, a machine learning technique – random forests (RF), was used. RF can be used not only for prediction but also for assessing variable importance (Breiman, 2001). In the proposed approach, the dependent variable fCover was estimated using a number of independent variables represented by various vegetation indices. The vegetation indices were first calculated on pixel level and then aggregated over the whole photo for smartphones or over the whole field for UAV images using their statistics (minimum, maximum, mean, and standard deviation). Using the ability of the RF algorithm to measure variable importance, the different vegetation indices were ranked according to their ability to predict fCover. Due to the lack of measurements in the NIR band for the smartphone photos, only color vegetation indices (Table 1) were used for the estimation of fCover from them. For the UAV images, both NIR and color indices were used as predictors (Table 2).

Table 1. List of vegetation indices using only the blue, green and red bands (color indices)

Vegetation Index	Author(s)
Red Green Ratio Vegetation Index (RGVI)	Jordan (1969)
Excess Green Index (ExG)	Woebbecke et al. (1995)
Excess Red Index (ExR)	Meyer et al. (1999)
Normalized Difference Index (NDI)	Perez et al. (2000)
Excess Green minus Excess Red index (ExGR)	Meyer & Neto (2008)
Improved Normalized Difference Vegetation Index (INDI)	Meyer & Neto (2008)
Modified Excess Green index (MExG)	Burgos-Artizzu et al. (2011)
Color Index of Vegetation Extraction (CIVE)	Kataoka et al. (2003)
Vegetation index (VEG)	Hague et al. (2006)
Combined index (COM1)	Guijarro et al. (2011)
Modification of the combined index (COM2)	Guererro et al. (2012)

Table 2. List of vegetation indices using also the NIR band

Vegetation Index	Author(s)
Difference Vegetation Index (DVI)	Roujean & Breon (1995)
Normalized Difference Vegetation Index (NDVI)	Rouse et al. (1974)
Renormalized Difference Vegetation Index (RDVI)	Roujean & Breon (1995)
Green Normalized Difference Vegetation Index (GNDVI)	Gitelson et al. (1996)
Soil Adjusted Vegetation Index (SAVI)	Huete (1988)
Simple Ration Index (SR)	Gitelson et al. (1996)
Green Chlorophyll Index (GCI)	Gitelson et al. (2006)
Red Edge Chlorophyll Index (RECI)	Gitelson et al. (2006)
Global Environmental Monitoring Index (GEMI)	Pinty & Verstraete (1992)
Modified Soil Adjusted Vegetation Index (MSAVI)	Qi et al. (1994)
Triangular Vegetation Index (TVI)	Broge & Leblanc (2001)
Adjusted Transformed Soil Adjusted Vegetation Index (ATSAVI)	Baret & Guyot (1991)

For the classification approach, object based image analysis (GEOBIA) was used. GEOBIA is suitable for classifying very high resolution images or images in which the object of interest is represented by several pixels (Blaschke et al., 2014). When the estimation of bio-physical variables is carried out on a pixel level, information such as texture, context and shape is often neglected (Hay & Castilla, 2008). GEOBIA makes use of this information by exploring the characteristics of features in the images and the relationships between them (Blaschke, 2004). In a typical GEOBIA workflow, an image is first segmented and then classified (Blaschke, 2004). During the segmentation step, similar pixels are grouped together into objects (Addink et al., 2012) or "objects candidates" – homogenous and semantically meaningful groups of pixels (Blaschke, 2010). The fCover estimates retrieved with the classification and regression approaches were compared to those obtained with CAN-EYE.

RESULTS

As part of the regression approach several different models were created. The RF algorithm trained with manually annotated smartphone photos is referred to as RF.model. This model was applied to a selected set of UAV images in order to create a training dataset for the models using UAV images because annotated data from the octocopter field surveys was not available. Two models using UAV images were trained - RF.model_NIR which uses both color and NIR vegetation indices, and RF.model_NIRO which uses only vegetation indices containing the NIR band. All models provided a satisfactory fit to the data as it can be seen from the variance explained and the mean of squared residuals (Table 3). The variance explained showed in Table 3 was calculated based on the out of bag (OOB) samples. These samples were not used during the training of the models and therefore give the opportunity to realistically test the ability of the regression approach to predict fCover. The models with NIR indices clearly outperformed the model relying only on color indices. However, color indices also contributed to the accurate estimation of fCover as it can be seen by the comparison of the RF.model_NIR and RF.model_NIRO.

Table 3. The percentage of variance explained and mean of squared residuals of out of bag (OOB) samples

	% Variance explained	**Mean of squared residuals**
RF.model	66.73%	0.0104
RF.model_NIR	97.04%	0.0005
RF.model_NIRO	92%	0.0013

In the RF.model, the most important parameter was the mean value of the ExR index. In this model, it was evident that the mean values of the indices were more important variables than any other statistics (minimum, maximum values and standard deviation). While the fCover estimates derived from manually annotated photos best aligned with those taken by the device with the best resolution, the percentage of variance explained for all types of devices was high and no substantial difference among the different estimates was found. In the RF.model_NIR, both the mean and the standard deviation of the VIs played an important role. Similarly to the RF.model, the most important parameter was the mean value of the ExR index. The most important parameter based on a vegetation index containing the NIR band was the standard deviation of the RECI index using the red edge at 710 nm. The same held true for the RF.model_NIRO.

fCover estimates derived from images at two different altitudes – 12 m and 65 m, were compared. The fCover estimates at an altitude of 12 m and 65 m were not correlated as evidenced by the low variance explained ($R^2 = 0.04$). The fCover estimated at the height of 65 m was approx. twice higher than the fCover estimated at 12 m. No conclusion could be made which one of the estimates was over-/underestimated due to the lack of ground truth data. It was assumed that this outcome was related to the difference in the spatial resolution obtained at the two different altitudes.

The classification approach was applied only on smartphone photos due to computational constraints. The percentage of variance explained when the training samples were excluded amounted to 76%. However, this measure cannot be directly compared to the variance explained for the regression models (Table 3) because different amount of training samples was used. Similarly to the regression approach, higher resolution photos did not always outperform lower resolution photos when used for fCover estimation. However, in contrast to the regression approach for some devices this relationship was very weak. The classification of some photos was more challenging than for others. Such photos were those containing crops other than mung beans, maize and wheat that had rather small and not easy to distinguish leaves. Misclassification was often present when there was difference between the illumination in the photos on which the classifier was trained and the photos to be classified. Strong reflectance of sun light in some of the photos was also a common reason for the inaccurate estimation of fCover both for the classification and regression approaches.

CONCLUSION

The difference between the predicted fCover retrieved with the regression approach and the actual fCover from the annotated photos was small. The inclusion of information from the NIR part of the spectrum contributed to the more accuarate estimation of fCover. However, best results were obtained when both color and NIR indices were used. The most import color indeces were ExR (color only) and RECI (with NIR info at 710 nm). The difference between the predicted fCover retrieved with the classification approach and the actual fCover was also small. However, the percentage of variance explained for the different devices varied greatly. In this respect, the regression approach is more robust. The regression approach could also deal better with changing illumination and crops with small and difficult to distinguish leaves. Both approaches had difficulties estimating fCover for photos with strong sun glint. Minor differences in the photos resolution of smartphone devices were not strongly correlated to the fCover estimates. However, substantial difference in the spatial resolution of UAV images led to under-/overestimation of fCover by as much as a factor of two.

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