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Full Paper

Performance of UAV-derived Normalized Difference Vegetation Index (NDVI) for Early Estimation of Rice Yield

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Abstract

Traditionally, the rice yield is measured after the harvest, which is too late then to revert any agronomic practices to improve yield. The aerial spectral reflectance images of crops captured by a multispectral camera mounted in an Unmanned Aerial Vehicle (UAV) are capable of quantitatively measuring the internal physiological condition of crops directly associated with their health status. The aim of this study was to evaluate the performance of UAV-multispectral image derived-NDVI as a method for estimating rice yield. Multispectral drone images including single band images were acquired from a controlled rice field at Rice Research and Development Institute (RRDI), Sri Lanka. Rice variety Bg 300 was cultivated in the *Yala* season under four levels of Nitrogen (N) fertilizer treatment plots. According to the regression co-relation analysis the derived NDVI values at 15 and 25 m flying heights from the rice crops at the booting stage were moderately (R^2=0.65 and R^2=0.67, $p<0.05$, respectively) associated with the actual yield. The derived NDVI values indicated the rice crop vigor at the booting stage is a useful indicator for early estimation of the rice yield prior to actual harvest.

Keywords: NDVI, rice crop, UAV-Multispectral, yield

Introduction

In Asia, and particularly in Sri Lanka, rice (*Oryza sativa* L.) is one of the most popular cereal crops. Rice production involves a lot input, labor, time, and energy which are paid off at the end of the cropping season by the harvest, gained. By then the chances to revert any agronomic practices or to alter any ongoing cultural activities may not in use. If farmers can have a field-level crop assessment method to estimate the yield in the rice field in the ongoing cultivation before harvest, input application can be efficient or target application can be encouraged [1]. Traditional methods of measuring rice yield involve waiting until after the harvest to determine the actual yield. By this point, it is too late to make any agronomic adjustments to improve yield for that particular crop cycle. This method of yield measurement is not ideal as it does not allow for real-time monitoring of crop growth and yield potential, which can lead to missed opportunities for improving crop productivity [2, 3].

However, there are newer technologies and techniques available that allow for real-time monitoring of crop growth and yield potential. For example, remote sensing technologies such as satellite imagery, drones, and ground-based sensors can provide valuable data on crop growth and yield potential throughout the growing season. This allows farmers and agronomists to make more informed decisions about when and how to apply fertilizers, water, and other inputs, and to adjust their management practices accordingly to optimize yield [1]. Consequently, the traditional methods of measuring rice yield after harvest may still be used, newer technologies and techniques are available that allow for real-time monitoring and management of crop growth and yield potential, which can lead to improved crop productivity and higher yields [4].

Unmanned Aerial Vehicles (UAVs), commonly known as drones, equipped with sensors capable of capturing aerial spectral reflectance images of crops can provide valuable data on the health status and potential yield of rice crops [3, 5]. This real-time monitoring and management of crop growth and yield potential can lead to improved crop productivity and higher yields [6].

The advantage of using UAVs for crop monitoring is that they can capture high-resolution images of crops at a lower cost and with greater flexibility compared to traditional satellite imagery [2]. Moreover, the images can be captured at multiple time points throughout the growing season, allowing for continuous monitoring of crop growth and yield potential [7]. Additionally, the non-destructive nature of this technology means that crops can be monitored without causing any damage or harm to the plants [8]. The use of UAVs equipped with sensors for crop monitoring is a promising technology that has the potential to revolutionize the way crops are grown and managed, allowing for more precise and efficient use of resources while increasing crop yields [9].

The Normalized Difference Vegetation Index (NDVI) is a commonly used index derived from spectral reflectance data captured by remote sensing technologies such as satellite imagery, drones, and ground-based sensors. It is calculated as the difference between the near-infrared (NIR) and red spectral bands divided by their sum [7, 10]. By monitoring changes in NDVI over time, farmers and agronomists can identify areas of the crop that may be experiencing stress, such as from water or nutrient deficiencies or disease, and take appropriate action to correct the issue [11]. NDVI has become a popular tool for precision agriculture, as it allows for the real-time monitoring and management of crop growth and yield potential. The index can also be used to generate maps that can help farmers and agronomists identify areas of a field that may require more or less inputs, such as water, fertilizers, or pesticides [12, 13].

NDVI values derived from spectral reflectance data have been shown to be a useful indicator of rice crop vigor, particularly during the booting stage, which occurs about 50-60 days after planting. At this stage, the rice plants are in their reproductive phase and their biomass and yield potential are largely determined [14]. However, traditional ways of rice crop assessment techniques are challenging due to the requirement of crop level inspection on-ground and contact or destructive sampling methods, barriers in frequent (monthly) inspection, high time-dependency in covering larger fields, poor representation of the variability in the whole field and some methods need of laboratory facilities. Thus, the requirement of an advanced crop remote sensing technology i.e. unmanned aerial vehicle (UAV) is indispensable for assessing rice crop-based measurement, non-destructively. In this section, the limitation of traditional methods for measuring expected rice yield and the possibility of using the NDVI index by adopting a UAV imaging system is highlighted.

Though previous studies had used NDVI to monitor the crop status, the performance of the NDVI is not compared in estimating rice yield before the harvest in Sri Lanka. Furthermore, there is no evidence of past research work reported in Sri Lanka on the use of UAV multispectral imagery for estimating rice yield. Thus, an important research gap exists to investigate the accuracies of NDVI derived by UAV multispectral imagery over Sri Lankan rice ecosystem with locally used rice varieties.

Research has shown that there is a strong correlation between NDVI values during the booting stage and rice yield at harvest. Therefore, NDVI can be used as an early estimation tool for rice yield prior to actual harvest, which can help farmers and agronomists make informed decisions about crop management practices and optimize yield [8, 11]. Therefore, this study aimed to evaluate the performance of UAV-multispectral image-derived NDVI as a method for early estimating rice yield.

Materials and Methods

The initial calibration study with UAV surveying was carried out at the rice fields maintained by the Rice Research and Development Institute, Bathalagoda, Sri Lanka. Rice variety Bg 300 was established by transplanting seedlings at a spacing (4.5 m x 3 m and 49 plants/m^2 plant density) during the *Yala* season (April/July 2021). The rice field had a soil type of Red-Yellow Podzolic, supplied with abundant water through channel irrigation, no weeds, and agronomic practices conducted as recommended by the Department of Agriculture (DOA, Sri Lanka). The experimental layout was a complete randomized block design with four separate blocks of controlled levels of N-fertilizer dosages applied (0% (0 kg/ha), 50% (112.5 kg/ha), 100% (225 kg/ha), and 150% (337.5 kg/ha)) to create a rice growth variation in the field. Intermittent application of chemical pesticides was conducted whenever required while weeding was done manually by humans (Table 1).

Table 1. Average values of soil pH, P and K values of the experimental rice blocks

Block	pH	P, ppm	K, ppm
1	6.08	8.7	45.2
2	6.16	6.7	28.4
3	6.27	8.4	50.1
4	6.08	9.2	46.7

Image Acquisition by UAV and Image Processing

Mission planning was conducted using DJI GS Pro app and the images were improved into Pix4Dmapper for processing. UAV imagery of the field at the booting stage of the crop was captured at 15 and 25 m height (Figure 1) from 10:00 h to 11:00 h, respectively. The flight speed was 2 ms^{-1} and images were captured parallel to the path, resulting in front and side overlaps of approximately 80%. Segmentation targeted rice plants from the background was conducted using the NDVI as the threshold. The NDVI related to the rice plants was manually identified and thresholded from the ground NDVI. Normally the ground (soil, water) has a lower NDVI than the vegetation.

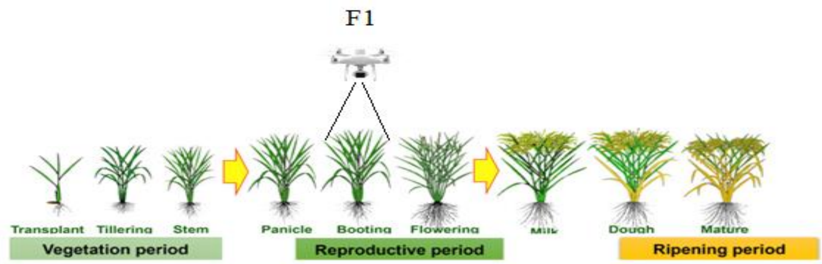

Figure 1. Growth stages of rice plant UAV imagery is acquired

This step was performed in QGIS software (Desktop 3.16.0) by following; drawing polygons on soil or water surfaces, calculating an average from the Zonal Statistics toolkit, and threshold using Raster Calculator toolkit. The final segmented image contained reflectance values of target rice and pixels coded as 'zeros' for associated soil or water areas (Figure 2).

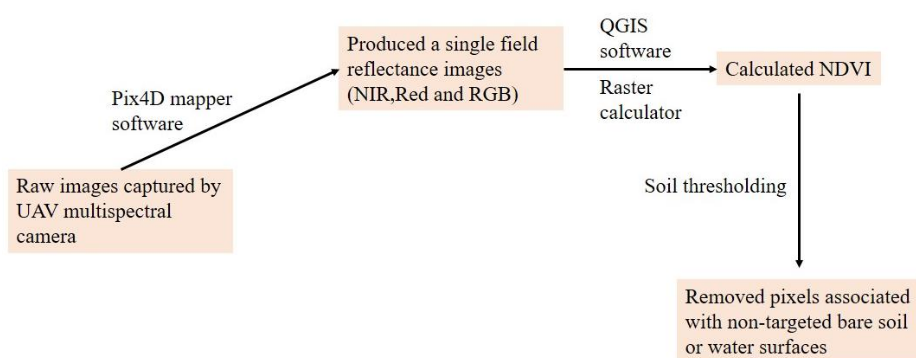

Figure 2. Steps involved in image processing and segmentation

And at the harvesting stage the rice yield was measured according to the sampling units. Regression analysis was done using R studio software (4.1.3) to determine the correlation between NDVI and yield data according to the two heights. Besides R^2 and RMSE were computed.

Results and Discussion

Regression analysis produced yield potential estimation equation at 15 and 25 m. The NDVI values were highly correlated with the yield at the booting stage. Results showed a higher R^2 value for 25 m (R^2=0.67, $p<0.05$) height than the 15 m height (R^2=0.65, $p<0.05$) (Figure 3). It may be the structure changes due to wind-induced movements of rice leaves, so that features may shift their relative position from image-to-image, completing the matching of multiple views that required for the reconstruction of reliable point cloud [2].

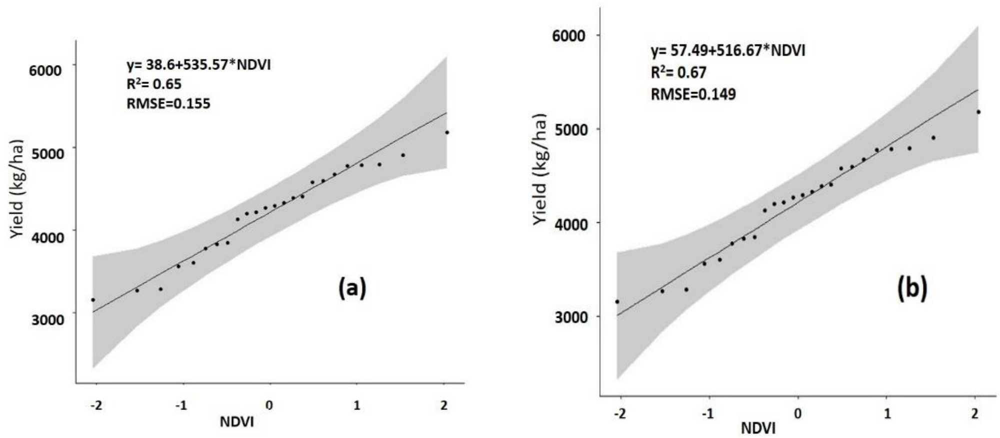

Figure 3. Linear regression between yield and NDVI according to the flying heights, (a) 15 m and (b) 25 m

Table 2 shows that there is a positive relationship and significant correlation between NDVI and rice yield.

Table 2. Readings of rice yield, and NDVI according to the N level

N Level	NDVI (paddy)
0%	0.584
50%	0.701
100%	0.765
150%	0.790

Furthermore, the NDVI was applied separately on commercial farmer field ground-truth and multispectral reflectance data to understand the behavior of NDVI and their fitness of association. The coefficient of determination of the relationship between the observed and estimated RY was R^2=0.61 and RMSE=0.161 kg/ha (Table 3), which is low compared to the coefficient of determination of the controlled field. The difference of the results may be due to the cultivation ecosystems, soil types can influence the expression of crop signal and that can be signaled by specific VI that are localized for the field or area.

Table 3. Performance of NDVI in controlled rice field, and transferability of NDVI at controlled field to commercial farmer field

Description	RY		
	VIs	R^2	RMSE
Controlled rice field	NDVI	0.67*	0.149 kg/ha
Transferability of VIs (controlled field to farmer field)	NDVI	0.61	0.161 kg/ha

**The associations are significantly different at p<0.05*

The derived NDVI values indicated the rice crop vigor at the booting stage which was proven by this study to be a useful indicator for early estimation of the rice yield at early at six weeks prior to actual harvest [3, 15]. Zhou et al., suggested that vegetation index, such as Normalized Difference Vegetation

Index (NDVI), could be used to estimate rice yield. Furthermore, using the NDVI values, it was possible to generate NDVI distribution map for the expected yield category at the levels of fertilizer application for rice crop (Figure 4).

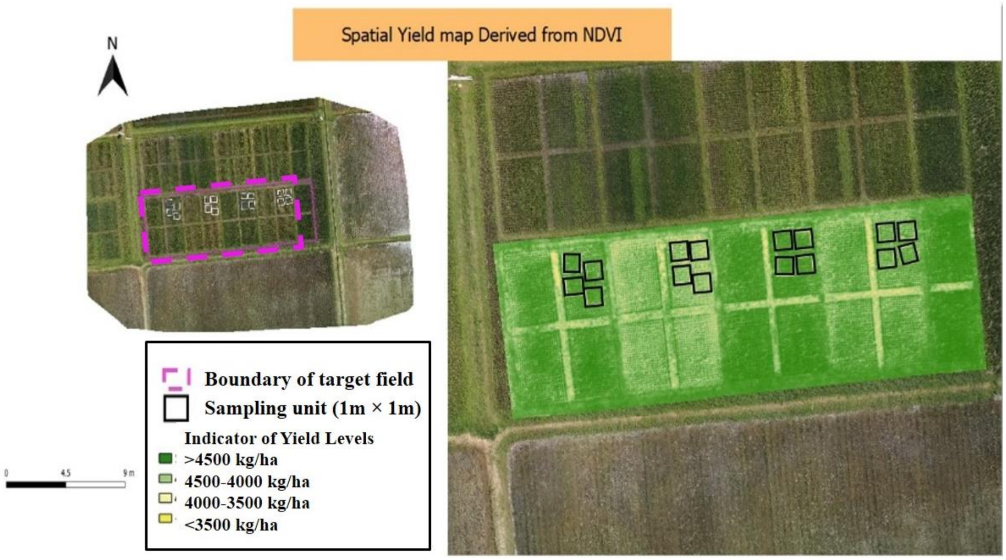

Figure 4. Spatial distribution of the estimated rice yield depicted in a NDVI map

There are few reports describing rice crop yield estimation based on NDVI [8, 11, 14] but there is lack of researches in Sri Lanka based on the UAV derived NDVI to estimate rice yield before the harvest. In this study, the relationships between rice grain yield and the spectral indices from multispectral images were studied at booting stage (1.5 month before the harvest) based on images taken by a UAV.

Conclusion

The findings from this experimental work suggest that crop remote sensing technology can be used as a surrogate for traditional subjective crop monitoring methods in rice fields. UAV-based multispectral imagery was capable of estimating rice yield with high accuracy and can be used to estimate rice yield 1 ½ month before the harvest encouraging more environmentally sustainable agriculture. Future work needs to carry out investigating on additional vegetation indices in order to assess their performance in estimating yield more accurately and testing the method in different environmental conditions or assessing the scalability of the approach.

Conflicts of Interest

The authors declare no conflict of interest. The founding sponsors had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results.

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References

[1] J.J. Assmann, Kerby, J.T., Cunliffe, A.M., and Myers-Smith, I.H., Vegetation monitoring using multispectral sensors — best practices and lessons learned from high latitudes. *Journal of Unmanned Vehicle Systems*, **2019**. *7(1)*,54-75.DOI: 10.1139/juvs-2018-0018.

[2] J. Berni, Zarco-Tejada, P.J., Suarez, L., and Fereres, E., Thermal and Narrowband Multispectral Remote Sensing for Vegetation Monitoring From an Unmanned Aerial Vehicle. *IEEE Transactions on Geoscience and Remote Sensing*, **2009**. *47(3)*,722-738.DOI: 10.1109/tgrs.2008.2010457.

[3] B. Duan, Fang, S., Zhu, R., Wu, X., Wang, S., Gong, Y., and Peng, Y., Remote Estimation of Rice Yield With Unmanned Aerial Vehicle (UAV) Data and Spectral Mixture Analysis. *Front Plant Sci*, **2019**. *10*,204.DOI: 10.3389/fpls.2019.00204.

[4] J.L. Gabriel, Zarco-Tejada, P.J., López-Herrera, P.J., Pérez-Martín, E., Alonso-Ayuso, M., and Quemada, M., Airborne and ground level sensors for monitoring nitrogen status in a maize crop. *Biosystems Engineering*, **2017**. *160*,124-133.DOI: 10.1016/j.biosystemseng.2017.06.003.

[5] T.N. Carlson and Ripley, D.A., On the relation between NDVI, fractional vegetation cover, and leaf area index. *Remote Sensing of Environment*, **1997**. *62(3)*,241-252.DOI: 10.1016/s0034-4257(97)00104-1.

[6] D.A. García Cárdenas, Ramón Valencia, J.A., Alzate Velásquez, D.F., and Palacios Gonzalez, J.R. Dynamics of the Indices NDVI and GNDVI in a Rice Growing in Its Reproduction Phase from Multi-spectral Aerial Images Taken by Drones. in *Advances in Information and Communication Technologies for Adapting Agriculture to Climate Change II*. 2019. Cham: Springer International Publishing.

[7] S. Guan, Fukami, K., Matsunaka, H., Okami, M., Tanaka, R., Nakano, H., Sakai, T., Nakano, K., Ohdan, H., and Takahashi, K. Assessing Correlation of High-Resolution NDVI with Fertilizer Application Level and Yield of Rice and Wheat Crops Using Small UAVs. *Remote Sensing*, 2019. **11**, DOI: 10.3390/rs11020112.

[8] J. Huang, Wang, X., Li, X., Tian, H., and Pan, Z., Remotely sensed rice yield prediction using multi-temporal NDVI data derived from NOAA's-AVHRR. *PLoS One*, **2013**. *8(8)*,e70816.DOI: 10.1371/journal.pone.0070816.

[9] N. Jalinus, Design and Need Analysis of Computer Devices' Expert System Using Forward Chaining Method. *International Journal of GEOMATE*, **2019**. *17(61)*.DOI: 10.21660/2019.61.icee408.

[10] C.J. Tucker, Holben, B., Elgin Jr, J., and Mcmurtrey III, J., Relationship of spectral data to grain yield variation. *Photogrammetric Engineering and Remote Sensing* **1980**. *46*.

[11] I. Wahab, Hall, O., and Jirström, M. Remote Sensing of Yields: Application of UAV Imagery-Derived NDVI for Estimating Maize Vigor and Yields in Complex Farming Systems in Sub-Saharan Africa. *Drones*, 2018. **2**, DOI: 10.3390/drones2030028.

[12] D.A. Walker, Epstein, H.E., Jia, G.J., Balser, A., Copass, C., Edwards, E.J., Gould, W.A., Hollingsworth, J., Knudson, J., Maier, H.A., Moody, A., and Raynolds, M.K., Phytomass, LAI, and NDVI in northern Alaska: Relationships to summer warmth, soil pH, plant functional types, and extrapolation to the circumpolar Arctic. *Journal of Geophysical Research: Atmospheres*, **2003**. *108(D2)*.DOI: 10.1029/2001jd000986.

[13] Z. Jingyong, Wenjie, D., Congbin, F., and Lingyun, W., The influence of vegetation cover on summer precipitation in China: A statistical analysis of NDVI and climate data. *Advances in Atmospheric Sciences*, **2003**. *20(6)*,1002-1006.DOI: 10.1007/bf02915523.

[14] X. Zhou, Zheng, H.B., Xu, X.Q., He, J.Y., Ge, X.K., Yao, X., Cheng, T., Zhu, Y., Cao, W.X., and Tian, Y.C.,

Predicting grain yield in rice using multi-temporal vegetation indices from UAV-based multispectral and digital imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, **2017**. *130*,246-255.DOI: 10.1016/j.isprsjprs.2017.05.003.

[15] F. Maselli and Rembold, F., Analysis of GAC NDVI data for cropland identification and yield forecasting in Mediterranean African countries. *Photogrammetric engineering and remote sensing*, **2001**. *67(5)*,593-602.