Assessment of a New Scalable Non-near Infrared Vegetation Index for Crop Assessment

David Kramar

Introduction

Monitoring and mapping of agricultural systems and land cover/land use is not new. The use of aerial imagery to quantify land cover and land use change is a widely applied and accepted remote sensing process that has been in practice for decades. In recent years there has been an increase in the use of small unmanned aerial systems (UAS). The ability to capture high resolution imagery from small UAS platforms provides a low cost alternative to traditional aerial surveys and has been widely used in recent years for agricultural monitoring (Lelong et al. 2008), weed mapping (Pflanz, Nordmeyer, and Schirrmann 2018), and grass monitoring (Barbosa et al. 2019). As the use of UAS has increased, so has the interest in applying vegetation indices that do not rely on the near-infrared (NIR) portion of the electromagnetic spectrum (EMS). Whereas the normalized difference vegetation index (NDVI) is a well-known index based on the ratio of red and NIR radiation, the application of this metric is limited to UAS platforms that are outfitted to collect information in the NIR portion of the EMS. Furthermore, the NDVI is subject to atmospheric, anisotropic, and spectral error. Typical “off-the-shelf” UAS such as the DJI Phantom 4 Pro require aftermarket modification in order to collect NIR information. Notwithstanding, several indices have been developed that use only the red, green, and blue (RGB) components of the EMS, with varied levels of success. These indices include the Green-Red Vegetation Index (GRVI) (Motohka et al. 2010), the Green Leaf Index (GLI) (Louhaichi, M., Borman, M.M., Johnson 2001), a scalable Visible Vegetation Index (VVI) from the Planetary Habitability Laboratory at the University of Puerto Rico (PHL-UPR 2017), and the triangular greenness index (TGI) (Hunt et al. 2012)) (Table 1).

Index	Formula
Green-Red Vegetation Index	GRVI=(Green-Red)/(Green+Red)
Green Leaf Index	GLI=(2*Green-Red-Blue)/(2*Green+Red+Blue)
Visible Vegetation Index	$\mathrm{VVI}=[(1-\lvert(\mathrm{Red}-R_0)/(\mathrm{Red}+R_0)\rvert)(1-\lvert(\mathrm{Green}-G_0)/(\mathrm{Green}+G_0)\rvert)(1-\lvert(\mathrm{Blue}-B_0)/(\mathrm{Blue}=B_0)\rvert)]^{(1/w)}$ where R_0, G_0, and B_0 represent a vector of the reference green color; and w is a weight exponent
Visible Atmospherically Resistant Index	VARIGreen=(Green-Red)/(Green+Red+Blue)

Methods

The study was conducted using a Phantom 4 Pro (P4P) and the 20-megapixel RGB sensor that is standard on the P4P platform. Secondary analysis used information derived from an AgBOT UAS with a 5-band MicaSense Multispectral sensor. Imagery was typically collected at either 150’ or 250’ on both airframes. The selection of the P4P was to gain insight as to how useful an inexpensive UAS could be to precision agriculture applications, and the ease at which vegetation indexes that do not rely on the near infrared portion of the spectrum could be calculated. Data were collected across numerous trials at the CREC, however, this project focuses on one area of soybean. Qualitatively, visual inspection of the VVI, GLI, and GRVI, and TGI was performed in conjunction with the true color imagery collected from the UAS platform and NDVI collected from a MicaSense 5-band sensor mounted on a secondary platform (AgBOT). Given the exceptionally high resolution, it was adequate for preliminary evaluation of the performance of each of the indices. Implementation of the vegetation indices was completed using ArcGIS 10.6 and the raster calculator.

Results

There was variation in how the different indices performed. Not surprisingly, the more commonly known GRVI and the GLI performed adequately. The VVI also performed adequately, and in some cases resulted in a more granular representation (e.g. GRVI and GLI were more “washed out”) of the vegetative health. That said, both GRVI and GLI tend to classify healthy vegetation adequately (Figure 1). The TGI appeared to most closely resemble the output of the NDVI index, with less overall variability in “greenness”. In terms of overall applicability, any one of the other three (GRVI, GLI, VVI) indexes would suffice for approximating plant health. Note that the scalability of the VVI is particularly useful when “fine-tuning” the index, and offers some flexibility when imagery is collected in sub-par conditions.

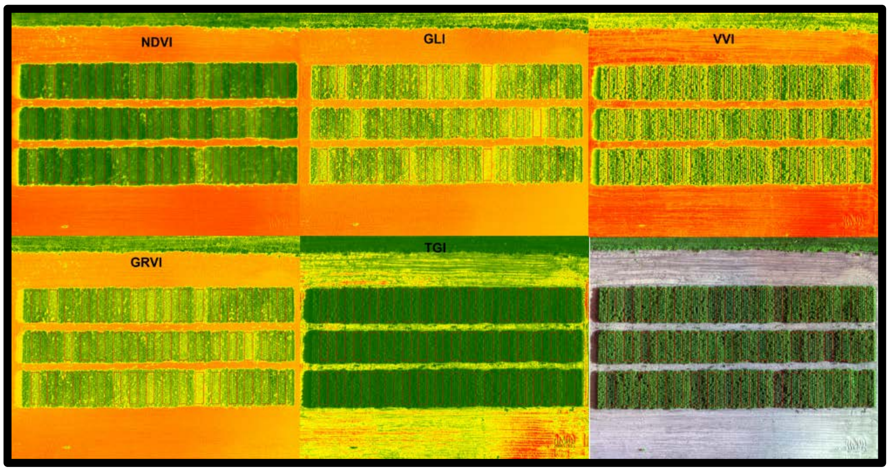

Figure 1: Comparison of the GRVI, GLI, VVI and TGI against the standard NDVI Index. While there is variability among the different indexes, overall patterns can still be determined upon visual inspection. Zoomed in, we lose some granularity among the more common indexes.

Discussion

The application of non-NIR vegetation indices, as well as classification of ultra-high resolution imagery presents significant challenges, particularly in ecosystems characterized by homogenous vegetation types, such as agricultural fields. A number of techniques were evaluated to identify and classify healthy vegetation using a mix of non-NIR vegetation indices. Using GRVI, GLI, or VVI resulted in adequate representation of vegetative health, with the VVI resulting in a more granular result that was less “washed out” than either GRVI or GLI. These results are not surprising given that GRVI and GLI are relatively well-established, and GLI was designed for low-altitude applications. We are enthusiastic about the VVI, particularly due to the scalability of the vectors. Future work will focus on further identifying the most suitable vector values for each portion of the EMS. Given the ultra-high resolution, many areas had an abundance of shadows that proved difficult to manage. It is likely that many of these areas were vegetation however; future work needs to include a field component to verify the percentages that are, or are not, vegetation.

References

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