EVALUATION OF RGB VEGETATION INDICES DERIVED FROM UAV IMAGES FOR RICE CROP GROWTH MONITORING

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ABSTRACT:

The unmanned aerial vehicles (UAVs) are widely used for agricultural monitoring due to reduce the cost and time of crop monitoring via the acquisition of images with high spatial-temporal resolution. The normalized difference vegetation index (NDVI) is the most widely studied and used for mapping crop growth. A relatively expensive multispectral sensor is required to produce an NDVI map. The visible vegetation indices (VIs) derived from UAV images showed potential capabilities for predicting crop growth. The purpose of this paper is to evaluate the RGB indices to monitor the growth of the rice crop. The images were obtained from the study area by DJI PM4 multispectral UAV. The multispectral images were used to calculate NDVI as a reference vegetation index and different RGB indices were implemented and compared with the reference index. The results showed that RGB indices can be used as the vegetation index in the case of unavailable multispectral images.

1. INTRODUCTION

As a member of the cereal family, rice is the most widely used food item by a significant part of the world population, especially in Asia. As the world population increases, the demand for rice rises. So, the precise agriculture (PA) techniques have to be utilised to increase the crop yield. However, it is a challenge due to the fact that rice production is normally affected by major problems such as pests and diseases and the lack of supervision in the field.

Precision agriculture is an innovative and integrated approach, which enables farmers to make the best decisions for farm management. PA aims to improve the production of crops by maximizing crop yields. Technologies often used in PA include geographic information systems (GIS), remote sensing (RS) and geographic positioning systems (GPS), smart phones, and machine learning (Rudd et al., 2017a). A prerequisite for precision agriculture is data collection, which relies on the intelligent selection of sensors and their deployment in the field (Kelly et al., 2012; Rudd et al., 2017b).

Remote sensing technology is suitable for crop condition assessment based on the relationship between optical properties and biological parameters (Mac Arthur and Robinson, 2015). The plant phenotype, based on spectral reflectance information, relies on the optical properties reflected from the plant after multiple interactions (absorption, reflection, transmission, and emission) with plant tissues. Remote sensing data is used in various forms and sensors including satellites, and aerial in agriculture. Satellite or aerial remote sensing are widely used but have limitations such as resolution, availability and flexibility, complex image processing, and high costs (Mulla, 2013). These limitations can be overcome by substituting unmanned aerial vehicle (UAV) images.

Todays, UAVs are utilised in various fields of agriculture, including spraying, monitoring and management of farms, irrigation and disease detection, etc. (Abdullah et al., 2019; Hama et al., 2020; Starý et al., 2020). One of the main advantages of UAVs is capturing high-resolution RGB and multispectral images at low altitudes it is also light weight, easy to carry, lower cost and high manoeuvre.

Spectral characteristics of plants in different wavelengths are influenced by chlorophyll, nitrogen, water content of plants, and morphological factors (Liu et al., 2013). Chlorophyll plays an important role in the spectral behavior of plants. It is found that when there is enough chlorophyll in the plant, the near-infrared band is most reflective when the plant is under stress. The plant growth is less than optimal and its natural productivity is interrupted which may cause the production of chlorophyll to decrease or stop. If the amount of chlorophyll decreases, the spectral behavior of the plant changes and causes less absorption in the blue and red bands (Atkinson et al., 2012). Therefore, the red and blue bands are also reflected along with the green band and gives yellow or red color to the vegetation.

Remote sensing is used to quantitatively and qualitatively evaluation of vegetation and agricultural studies by examining vegetation indexes (VIs). The VIs are combinations of surface reflectance at two or more wavelengths designed to highlight specific vegetation characteristics (Liu et al., 2013; Zhou et al., 2021) . The VIs are calculated using operators and mathematical transformations on spectral reflectance in different spectral ranges of visible, near-infrared, middle and thermal. Therefore, by measuring the reflection of light after interacting with a plant, it is possible to determine the characteristics of a product based on the reflection values for different wavelengths of light.

The most popular VI is the normalized difference vegetation index (NDVI) which is widely used in vegetation measurement and agriculture due to its remarkable ability to detect vegetation compared to other indices in the literature (Li et al., 2019; Sun et al., 2017). The popularity of NDVI in vegetation sensing is due to the availability of infrared and red channels, because the reflectance of green and young vegetation increases in the near infrared channel and decreases in the red channel. Thus, a multispectral imaging sensor with infrared channel is required to exploit the NDVI for agricultural applications. However, multispectral sensors are expensive and require more processing and calibration. Currently, high resolution RGB cameras are more affordable and several plant indices based on color spectrum were used in recent years (Rabatel et al., 2011). Several research works have been conducted to use RGB UAV

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images instead of multispectral images in various precision agriculture applications including pest identification, plant identification, and yield estimation.

The capability of RGB and multi-spectral UAV images was evaluated to estimate nitrogen accumulation in rice crop (Zheng and Cheng, 2018). The results have shown that the use of the UAV images is a reliable approach to monitor N accumulation in the crop. Rice yield was estimated using multispectral imaged collected by UAV in northern Italy, showed that the UAV is a potential platform for investigating crop growth (Stroppiana et al., 2015). Also, the early growth stages of rice crops were investigated using the normalized difference index (Science, 2019). In another research, UAV derived plant indices such as canopy height and canopy cover were used to improve rice yield prediction under different nitrogen levels (Wan et al., 2019). In addition, the yield of rice crop was increased via the use of RGB UAV images in the early stage of crop (Norasma et al., 2018). In this research work, RGB and multispectral UAV images were used for rice plant growth monitoring. The obtained results from RGB and multispectral images were compared, and finally, the performance of the NDVI and RGB indices for rice crop growth were evaluated.

2. STUDY AREA

The study area is located in Babul city, the north of Iran, and the largest cities in Mazandaran province. The UAV images were collected during the ripening period of rice crop in 24 October 2020. The study area is shown in Figure 1.

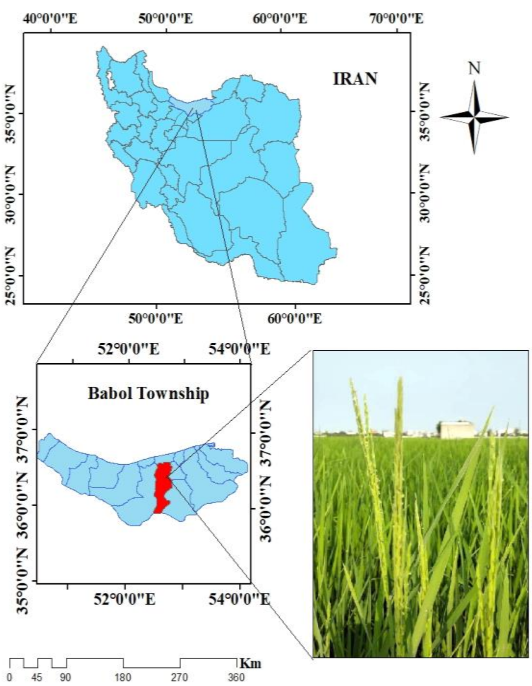


Figure 1. Study area

3. MATERIAL AND METHODS

3.1 Dataset

In this study, DJI Phantom 4 Multispectral (P4M) was used for imaging (Figure 2). It has a gimbal-based imaging system and includes RGB camera images and a multi-spectral camera array with five blue, green, red, red-edge and infrared cameras comprising 1600x1300 pixel resolution. More detailed information about the imaging sensor is provided in Table 1. Real-time, centimetre-accurate positioning data on images captured by all six cameras within DJI built-in system is used to align the RGB and multispectral images.

Figure 2. DJI PM4 UAV

Flight planning of 70 meters altitude with 65% forward- and side- overlaps was designed and image collection was carried out over the rice field at noon to minimize the shadow effect.

Focal length	5.74 mm
Image size	1600*1300 pixels
Size of the sensor	4.87 x 3.96 mm
Spectral bands	Blue, green, red, near red edge and infrared

Table 1. Specifications of the DJI PM4 UAV

3.2 Methods

The procedure of the proposed method is presented in Figure 3.

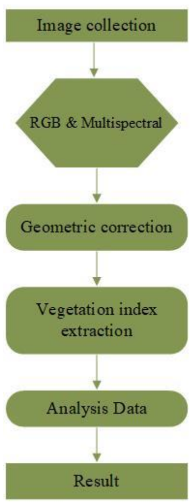


Figure 3. Procedure of the proposed method.

3.2.1 Geometric correction

The multi-camera sensors, such as DJI PM4 UAV camera, provide separated images for each band. Since the images have different perspective point, the raw images cannot be used without co-registration procedure.

In this paper, a feature-based registration technique, Speed-up Robust Feature algorithm (SURF), has been used to co-register the images collected via different band cameras. The extracted features have been used to estimate geometric transformation, and then, moving image was registered to the reference image with 1-pixel level of accuracy (Cruz et al., 2019).This technique was implemented in MATLAB and red band image was considered as the reference image and the rest of the images were registered to the reference. Figure 4 shows the red, green and blue bands before and after registration procedure.

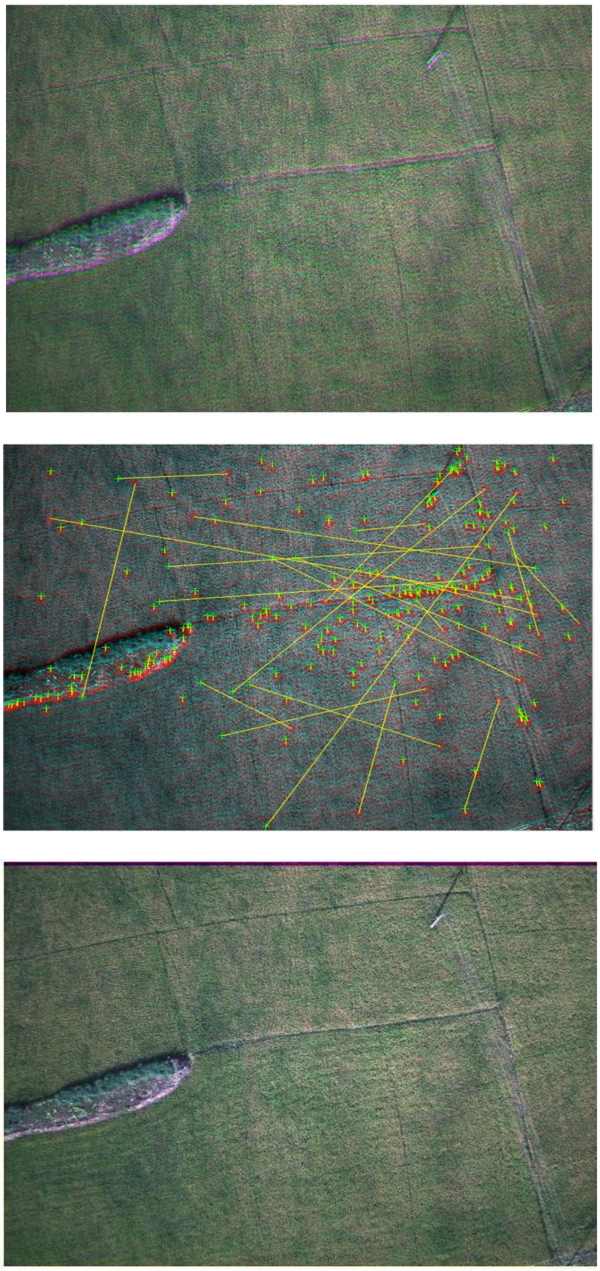


Figure 4. UAV multispectral image before (top) and after (bottom) registration.

3.2.2 Vegetation indices calculation

After co-registering the band images, three RGB vegetation indices including the Modified Green Red Vegetation index (MGRVI) (Bendig et al., 2015), Red Green Blue Vegetation index (RGBVI) (Bendig et al., 2015), Green Leaf Index(GLI) (Louhaichi et al., 2001), Modified excess green (MExG) (Burgos-artizzu et al., 2011) as well as NDVI have calculated. These indices have been widely used for crop health monitoring and were indicated in Table 2.

Vegetation index	Equation
NDVI	$\frac{NIR - R}{NIR + R}$
MExG	$1.62 \times G - 0.884 \times R - 0.311 \times B$
MGRVI	$\frac{\boldsymbol{G}^2 - \boldsymbol{R}^2}{\boldsymbol{G}^2 + \boldsymbol{R}^2}$
RGBVI	$\frac{G - (R \times B)}{G + (R \times B)}$
GLI	$\frac{2G - R - B}{2G + R + B}$

Table 2. Vegetation indices used in the study (R: Red, G: Green and B: Blue bands)

4. RESULT AND DISCUSSION

The maps of NDVI, MExG, RGVBI and MGRVI indices, R^2 and RMSE are extracted from the processed image and shown in Figure 4. All VI evaluated were probably affected by the solar reflection angle, which was not evaluated in this study, or by the presence of shadows.

NDVI ranges from -1.0 to 1.0, where positive values indicate vegetation and negative values indicate non-vegetation features such as water, barren areas, ice, snow, or clouds (Pettorelli et al., 2005). But due to the fact that the surface of the rice field is in the harvest stage, which does not have active photosynthesis activity, the NDVI index values decrease to ranges between −0.6 and 0.6, Because the active photosynthesis in the young and healthy rice product in the vegetative stage gives a good reflection in the NIR sensor and absorbs the red reflection. Therefore, in the period of rice growth, the NDVI values are between 0.6 and 1 (Figure 5, b).

The GLI index behaved visually similar to that observed for NDVI (Figure (5, c)). Areas with lower values of GLI indicates that rice is in the growing stage. The RGBVI index does not show good results for the level of the greenness of rice in comparison with NDVI since the rice is in the harvesting stage (Figure (5, d)). According to (Bendig et al., 2015), the MGVRI index is suitable for biomass prediction. As shown in Figure (5, e), it has good results and compared to other indicators, it shows that the rice is ready for harvesting. In contrast, the MExG index does not provide acceptable results (Figure (5, f)). Figure 6 shows the results (determination coefficient, R^2, RMSE and regression model) of the correlation analysis between the NDVI and other calculated indices. It shows that the MGVRI index has the best result among the four calculated indices. Figure (6, a) shows the Pearson correlation between NDVI and MGVRI, which has a R^2 of 0.72, while Figure (6, b) shows the correlation of NDVI with RGBVI with a R^2 = 0.65. The lowest performance is for the MExG index and GLL with R^2 = 0.44 and R2 = 0.46, respectively. Also, in all four indices MGVRI, RGBVI, GLI and MExG the RMSE value was 0.11, 0.21, 0.32 and 0.45, respectively, compared to NDVI.

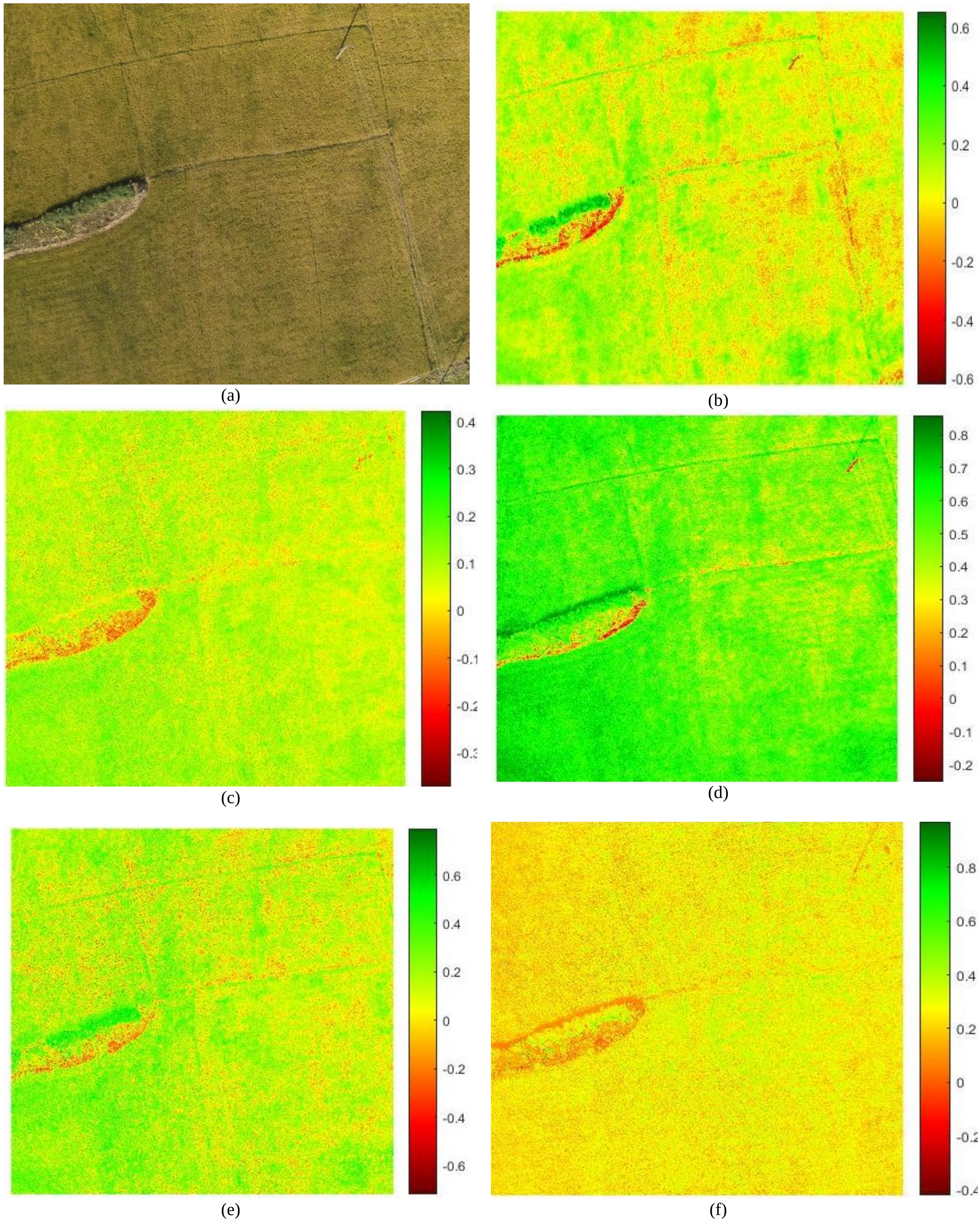
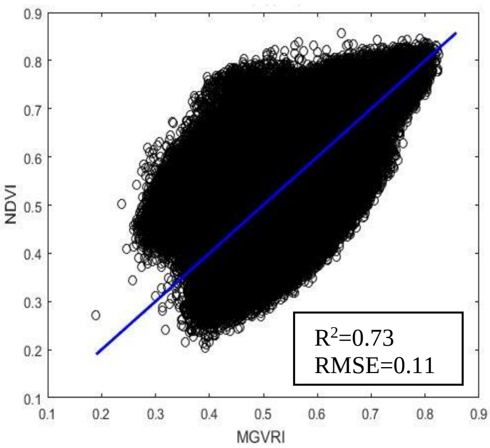
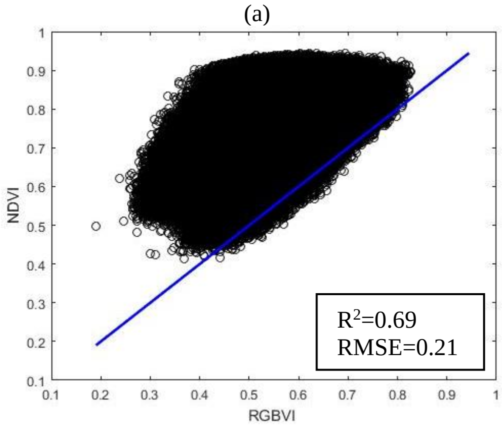


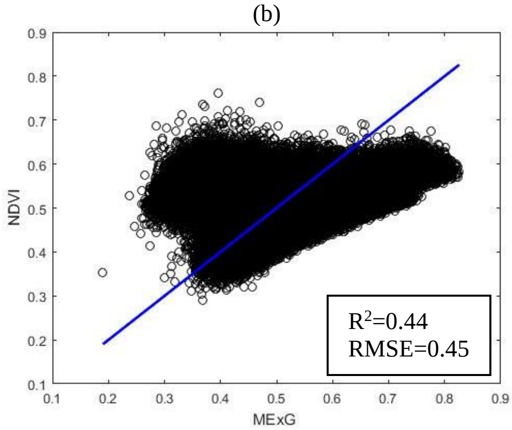
Figure 5. RGB image and calculated indices of a UAV image covering rice field,
(a) RGB; (b) NDVI; (c) GLI; (d) RGBVI; (e) MGRVI; (f) MExG.



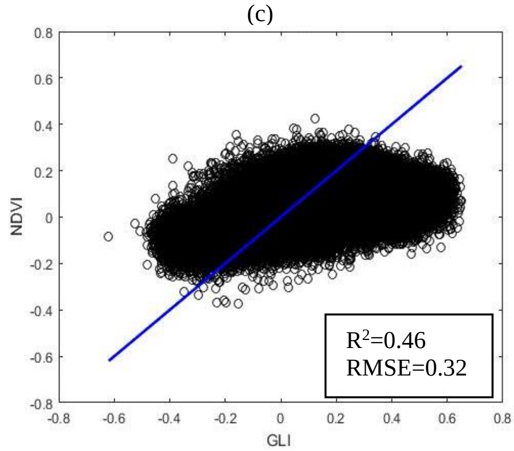
(a)



(b)



(c)



(d)

Figure 6. The relationship between the calculated RGB indices and the obtained NDVI.

5. CONCLUSION

The use of drones for monitoring and management in agricultural products is very promising. This is because the images obtained from the uav have a very high spatial resolution. And they are flexible and easy to work with. On the other hand, plant indices are a useful and efficient tool for evaluating crops. Since multi-spectral sensors have a high cost, in this study they were used to evaluate RGB indexes for rice growth management. The results showed that it is possible to use RGB index for management in the field and prevent damage in crop production to a minimum.

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REFERENCES

Abdullah, S., Tahar, K.N., Rashid, M.F.A., Osoman, M.A., 2019. Camera calibration performance on different non-metric cameras. Pertanika Journal of Science and Technology 27, 1397–1406.

Atkinson, P.M., Jeganathan, C., Dash, J., Atzberger, C., 2012. Inter-comparison of four models for smoothing satellite sensor time-series data to estimate vegetation phenology. Remote Sensing of Environment 123, 400–417. https://doi.org/10.1016/j.rse.2012.04.001

Bendig, J., Yu, K., Aasen, H., Bolten, A., Bennertz, S., Broscheit, J., Gnyp, M.L., Bareth, G., 2015. International Journal of Applied Earth Observation and Geoinformation Combining UAV-based plant height from crop surface models , visible , and near infrared vegetation indices for biomass monitoring in barley 39, 79–87.

Burgos-artizzu, X.P., Ribeiro, A., Guijarro, M., Pajares, G., 2011. Real-time image processing for crop/weed discrimination in maize fields. Computers and Electronics in Agriculture 75, 337–346.

Cruz, A., Ampatzidis, Y., Pierro, R., Materazzi, A., Panattoni, A., De Bellis, L., Luvisi, A., 2019. Detection of grapevine yellows symptoms in Vitis vinifera L. with artificial intelligence. Computers and Electronics in Agriculture 157, 63–76. https://doi.org/10.1016/j.compag.2018.12.028

Hama, A., Tanaka, K., Mochizuki, A., Tsuruoka, Y., Kondoh, A., 2020. Estimating the Protein Concentration in Rice Grain Using UAV Imagery Together with Agroclimatic Data. Agronomy 10, 431.

Kelly, M., Vehicle, U.A., Algorithm, L., 2012. Object-Based Approach for Crop Row Characterization in Uav Images for Site-Specific Weed Management. Procedings of the 4th GEOBIA 426–430.

Li, Congcong, Li, H., Li, J., Lei, Y., Li, Chunqiang, Manevski, K., Shen, Y., 2019. Using NDVI percentiles to monitor real-time crop growth. Computers and Electronics in Agriculture 162, 357–363. https://doi.org/10.1016/j.compag.2019.04.026

Liu, L., Waters, D.L.E.E., Rose, T.J., Bao, J., King, G.J., 2013. Phospholipids in rice: Significance in grain quality and health benefits: A review. Food Chemistry 139, 1133–1145. https://doi.org/10.1016/j.foodchem.2012.12.046

Louhaichi, M., Borman, M.M., Johnson, D.E., 2001. Spatially located platform and aerial photography for documentation of grazing impacts on wheat. Geocarto International 16, 65–70.

Mac Arthur, A., Robinson, I., 2015. A critique of field spectroscopy and the challenges and opportunities it presents for remote sensing for agriculture, ecosystems, and hydrology, in: Remote Sensing for Agriculture, Ecosystems, and Hydrology

XVII. p. 963705. https://doi.org/10.1117/12.2201046

Mulla, D.J., 2013. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. Biosystems engineering 114, 358–371.

Norasma, C.Y.N.N., Abu Sari, M.Y., Fadzilah, M.A., Ismail, M.R., Omar, M.H., Zulkarami, B., Hassim, Y.M.M.M., Tarmidi, Z., Sari, M.Y.A., Fadzilah, M.A., Ismail, M.R., Omar, M.H., Zulkarami, B., Hassim, Y.M.M.M., Tarmidi, Z., 2018. Rice crop monitoring using multirotor UAV and RGB digital camera at early stage of growth, in: IOP Conference Series: Earth and Environmental Science. https://doi.org/10.1088/1755-1315/169/1/012095

Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J., Tucker, C.J., Stenseth, N.C., Lyon, C.B., 2005. Using the satellite-derived NDVI to assess ecological responses to environmental change. Trends in ecology \& evolution 20, 503–510. https://doi.org/10.1016/j.tree.2005.05.011

Rabatel, G., Gorretta, N., Labbé, S., Rabatel, G., Gorretta, N., Getting, S.L., 2011. Getting NDVI spectral bands from a single standard RGB digital camera: A methodological approach. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 7023 LNAI, 333–342. https://doi.org/10.1007/978-3-642-25274-7_34

Rudd, J.D., Roberson, G.T., Classen, J.J., 2017a. Application of satellite, unmanned aircraft system, and ground-based sensor data for precision agriculture: A review, in: 2017 ASABE Annual International Meeting. p. 1. https://doi.org/10.13031/aim.201700272

Rudd, J.D., Roberson, G.T., Classen, J.J., 2017b. Application of satellite, unmanned aircraft system, and ground-based sensor data for precision agriculture: A review. 2017 ASABE Annual International Meeting 1–8. https://doi.org/10.13031/aim.201700272

Starý, K., Jelínek, Z., Kumhálová, J., Chyba, J., Balážová, K., 2020. Comparing RGB - based vegetation indices from UAV imageries to estimate hops canopy area 18.

Stroppiana, D., Migliazzi, M., Chiarabini, V., Crema, A., Musanti, M., Franchino, C., Villa, P., 2015. Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy, in: 2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS). pp. 4664–4667.

Sun, L., Gao, F., Anderson, M.C., Kustas, W.P., Alsina, M.M., Sanchez, L., Sams, B., Mckee, L., Dulaney, W., White, W.A., Alfieri, J.G., Prueger, J.H., Melton, F., Post, K., others, 2017. Daily mapping of 30 m LAI and NDVI for grape yield prediction in California vineyards. Remote Sensing 9, 317. https://doi.org/10.3390/rs9040317

Wan, L., Cen, H., Zhu, J., Li, Y., Zhu, Y., Sun, D., Weng, H., He, Y., 2019. Combining UAV-based vegetation indices, canopy height and canopy coverage to improve rice yield prediction under different nitrogen levels, in: 2019 ASABE Annual International Meeting. p. 1.

Zheng, H., Cheng, T., 2018. Evaluation of RGB , Color-Infrared and Multispectral Images Acquired from Unmanned Aerial Systems for the Estimation of Nitrogen Accumulation in Rice. https://doi.org/10.3390/rs10060824

Zhou, X., Zhang, D., Lin, F., 2021. UAV Remote Sensing: An Innovative Tool for Detection and Management of Rice Diseases, in: Diagnostics of Plant Diseases. IntechOpen.