Research article

Relationship between NDVI and Canopy Cover Sensed by Small UAV under Different Ground Resolution

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Abstract Canopy Cover (CC) is a significant indicator of crop development and estimation of the evapotranspiration volume of crop leaves within crop simulation models. During the last three decades, monitoring CC for crops using Normalized Difference Vegetation Index (NDVI) obtained from satellite sensors has been studied worldwide. However, a few studies have estimated the CC of crops using NDVI by UAVs. One of UAV imagery's crucial advantages is a high resolution of less than 0.10 m, while the resolution of satellite imagery is usually larger than 10 m. Now that the UAV has become a popular method in agriculture science, it is necessary to prove the interchangeability of UAV and satellite imagery of monitoring CC. In this study, small UAVs took RGB and multispectral images of the experimental peanuts field in Hokkaido. Orthomosaic and reflectance map of the field were constructed using the UAV imagery and then were obtained CC and NDVI values with GIS software. CC was calculated as the green canopy area ratio, extracted from the orthomosaic using a GIS supervised classification tool. CC was compared with NDVI values under various resolutions of 0.50 m, 1.0 m, 2.5 m, 5.0 m, and 10 m. The NDVI showed a highly correlated linear relationship with CC under each ground resolution from 0.10 m to 10 m (R^2 led a range of 0.88** to 0.94**). The shapes of NDVI and CC's regression equations closely resembled each other, with the slopes of 1.06 to 1.11 and the intercepts of 0.247 to 0.250, respectively. From the result of ANCOVA, the UAV imagery resolution has no significant impact on NDVI and CC's relationship. Although more irrelevant factors, such as soil and mulching seat, got included within one pixel of the images, the regression equations stayed the same with the increased ground resolution.

Keywords UAV, NDVI, canopy cover, ground resolution

INTRODUCTION

Canopy cover (CC) is a relatively easily measured property that is an indicator of crop growth and an important parameter in crop simulation models, such as the Aqua Crop (FAO, 2012) model. When simulating crop development, Aqua Crop model describes the development expansion of the CC using the percentage area of green canopy cover. According to the Food and Agriculture Organization (FAO), CC is defined as the ratio between the soil surface covered by the green canopy cover over the ground surface (FAO, 2012). CC value ranges from 0, when there is bare soil, to 1, where the vegetation canopy fully covered the ground. The crop characteristic decides the maximum value of CC. Aqua Crop model describes the development of the canopy between generation and the moment maximum CC is reached through a logistic type equation. Then, at the end of the season, when the senescence starts, the CC value declines (Steduto et al., 2009). Accurate and efficient CC estimation would allow improved scheduling and allocation of irrigation water (Bausch, 1995).

On the other hand, during the last three decades, Vegetation indices (VIs) have been extensively used to trace and monitor vegetation conditions such as health, growth levels, and water or nutrient stress (Silleo et al., 2006). Previous studies have shown that various spectral calculated from visible and near-infrared reflectance data are linearly related to the value of CC (Purevdor et al., 1998). Healthy canopies of green vegetation have a very distinct interaction with certain portions of the electromagnetic spectrum. In the visible region, chlorophyll causes strong absorption of energy, primarily for use in photosynthesis. This absorption peaks in the red and blue region s of the visible spectrum, while the green region is reflected by chlorophyll, thus leading to the green color of most leaves. This strong contrast between the reflectance of red and near-infrared regions of the electromagnet spectrum has been used to develop the Normalized Difference Vegetation Index (NDVI), a VI that has been widely used in the agricultural remote sensing field (Silleos et al., 2006). Region scale NDVI data could be obtained using high-resolution satellite sensors such as NOAA AVHRR, Terra MODIS, Landsat TM. This kind of traditional remote sensing data has been used to make better crop management, monitor the growing stress, and estimate the yield (Hirata, 2009). Furthermore, for the last decade, the research methodology and data analysis techniques from traditional remote sensing have been used to process aerial images with much higher spatial and temporal resolutions taken by Unmanned Aerial Vehicles (UAVs). This rapid development of remote sensing and precision agriculture provide aerial imagery with various resolution.

However, a few studies have estimated CC with UAV-obtained NDVI. It is still unclear if UAV-based NDVI has the same linear regression relationship with CC as satellite-based NDVI. To apply both satellite-sensed and UAV-sensed CC data to crop simulation models such as Aqua Crop, it is necessary to unravel whether the relationship between NDVI and CC remains the same under different ground resolutions. Therefore, This paper processed the UAV-sensed data into different resolutions, and compared the regression relationships between NDVI and CC.

METHODOLOGY

Study Site

This study was conducted in the experimental field of the Obihiro University of Agriculture and Veterinary Medicine located in Obihiro City, Hokkaido, Japan (143.1709-143.1747°N, 42.8698-42.8671°E; Fig.1). The experimental field has a total area of 3.2 ha (200 m×160 m), separated into multiple sectors planted with various experimental crops. The peanuts sector inside the experimental field was selected as the study site to compare NDVI with CC. The peanuts usually have relatively spreading forms of about 30-50 cm high with long branches that grow close to the ground. This plant form makes peanut a good objective to study the relationship between NDVI and CC. Previous study shows that the NDVI tends to perform poor correlation to CC when the Leaf Area Index (LAI) value is high. In other words, if the leaf density under the vegetation canopy varies, the NDVI value could be different even though the CC value stays the same (Purevdorj et al., 1998). This kind of variation of LAI is relatively unapparent in peanuts because peanuts tend to grow with a horizonal pattern rather than a vertical pattern. The peanut field area is 1600m^2 (40 m×40 m), with a plant density of 7.7 plant/m^2. The surface of the planting area was covered by white mulch sheets made by plastic films, because insolation was important during the early stage of growth to ensure the basic vegetation growth of peanuts in low temperature region such as Hokkaido.

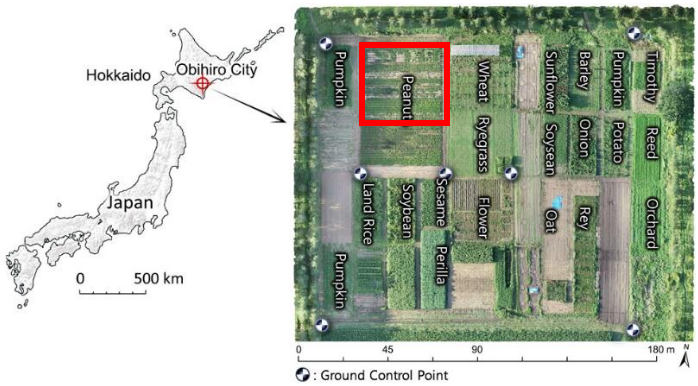

Fig. 1 Location and details of the study site

Investigation and Analyses

The RGB imagery of the experimental field was taken by Phantom 4 Pro (DJI) on 31st July 2019, and the reflectance imagery was made by a portable multispectral camera "Sequoia" (Parrot), which was mounted on Inspire 1(DJI) on 1st August 2019. The flight data is shown in Table 1.

Table 1 Flight conditions

Equipment	Date	Camera height from ground (m)	Speed (m/s)	Overlap (%) Top	Overlap (%) Side	Resolution (cm/pixel)
Phantom 4 Pro	31th July	50	4.8	80	80	1.3
Inspire 1 with Sequoia	1st August	40	3.0	80	80	5.9

NDVI and CC

After obtaining aerial imagery, RGB orthomosaic image and reflectance map of the experimental field were generated with the photogrammetric software, Pix4D Mapper 4.6.4 (Pix4D). The RGB orthomosaic image was used to separate the vegetation, soil and mulch films in ArcGIS Pro 2.3.0 (Esri), with a supervised image classification tool. The result of classification is shown in Fig.3. Based on the classified raster, the CC value of the peanuts field was calculated using Eq. 1.

$$CC = \frac{Vegetation}{Vegetation + Soil + Mulch\ film} \quad (1)$$

Where "Vegetation," "Soil," and "Mulch film" mean the number of pixels covered by green vegetation canopy, soil, and mulch films, respectively. To obtain the CC and NDVI values under different ground resolutions, we divided the peanut field into squared grids with a side length of 0.5 m, 1.0 m, 2.5 m, 5.0 m, and 10 m. As an example, the 1.0 m grids are shown in Fig.4. Based on the georeferenced reflectance map, the NDVI values were calculated by Eq. 2.

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (2)$$

Where "NIR" and "Red" mean the reflectance volume of the near-infrared region and the red region. The relationship between NDVI and CC values of each grid's size was determined using a least-squares fitting algorithm with python 3.7. An Analysis of Covariance (ANCOVA) was carried out to testify if there is a significant difference between NDVI and CC relationships under different ground resolutions. Finally, the accuracy of the regression equation was verified using RMSE.

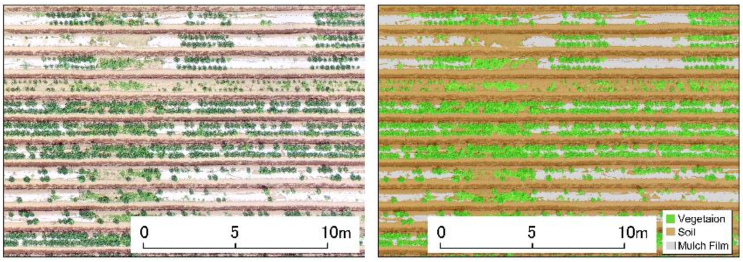

Fig. 3 Classification result (Left: RGB orthomosaic image; Right: Classified raster)

Fig. 4 Example of squared grid dividing the peanuts field (Grid size: 1.0 m)

RESULTS AND DISCUSSION

Fig. 5a and Fig. 5b show the spatial distribution of NDVI and vegetation cover under the original resolution of the peanuts field. NDVI tended to be high in the area covered by vegetation and low in the area covered by soil or mulch films. This is because the vegetation surface has a lower reflectance rate in the red region and a higher reflectance in the near-infrared region. In contrast, the soil and the plastic mulch films have similar reflectance in both regions. Besides, the mulch film has a lower NDVI than soil because the PVC material has a relatively higher reflectance of red, and at the meantime, a lower reflectance of near infrared than soil (Corradini et al., 2019). The spatial distribution of NDVI of the other grid sizes (0.5m, 1.0m, 2.5m, 5.0m, and 10m) showed the same tendency. The NDVI value varied from -0.47 to 0.68 under the original resolution, from -0.37 to 0.61 under 0.5 m grid size, from -0.29 to 0.40 under 1.0 m, grid size, from -0.25 to 0.24 under 2.5 m grid size, from -0.10 to 0.13 under 5.0 m grid size, and from -0.05 to 0.08 under 10 m grid size. Unlike the crops or forests with the vertical growth pattern, the maximum NDVI value of peanuts was less than 0.7. This is because peanuts have low-height, wide-expanding, and horizontal-trained canopies, which cause relatively low LAI within the canopies. The CC values varied from 0.00 to 1.00 under the original resolution, from 0.00 to 1.00 under 0.5 m grid size, from 0.00 to 0.74 under 1.0 m grid size, from 0.03 to 0.53 under 2.5 m grid size, from 0.14 to 0.42 under 5.0 m grid size, and from 0.19 to 0.35 under 10 m grid size. The range of both NDVI and CC values decreased with grid sizes.

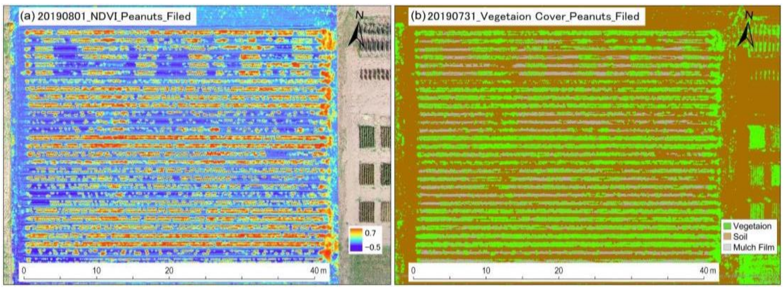

Fig. 5 Spatial distribution of NDVI (a) and vegetation cover (b)

Fig. 6a to Fig. 6e show the correlation between NDVI and CC under each grid size. NDVI was strongly correlated with CC under the resolution of 0.5m, 1.0m, 2.5m, 5.0m, and10m (R^2=0.88**, 0.92**, 0.94**, 0.89**, and 0.93**, respectively). The shape of the linear regression line ($y=ax+b$) of NDVI and CC closely resembled each other; the slopes (a) such as 1.16, 1.11, 1.09, 1.08, and 1.06, respectively, and the intercepts (b) such as 0.25, 0.25, 0.25, 0.25, and 0.25, respectively. The incept values indicate that a grid with 25 percent of it covered by peanuts canopies has an approximately NDVI value of 0. The slope values slightly decreased with the increasing grid size, resulting in the grid's NDVI values without any vegetation cover varying from 0.5m to 10m (-0.21, -0.22, 0.23, -0.23, and -0.24 respectively). This difference of slopes is considered to be caused by two kinds of abnormal values of NDVI. One was the abnormally high NDVI value due to relatively high LAI. The other one was the abnormally low NDVI value caused by the mulch sheets. These two kinds of abnormal NDVI became outliers when the grid size was small, because there were grids that include only canopies or only plastic. However, they cancelled each out when the grid size was large, so that the regression line was closer to the ideal state where there were simply vegetation and soil.

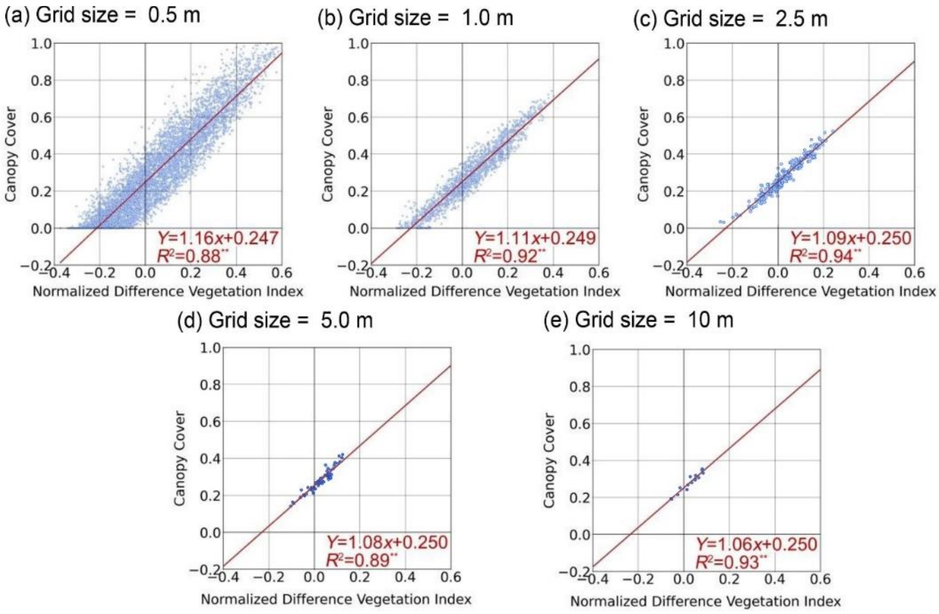

Fig. 6 Relationship between NDVI and CC

To testify the significance of each regression equation's differences, an ANCOVA was conducted with an Excel data analysis add-in, XLSTAT (ver 2020.5.1, Addinsoft), where CC as the dependent variable, while NDVI and ground resolution as the explanatory variables. The result is shown in Table 2. The p-value of all kinds of grid sizes except for 10.0 m was near 1.000, indicating that the grid sizes have no significant effect on NDVI and CC's relationship.

Table 2 Model parameters of ANCOVA

Factor	Coefficient	Standard deviation	t	Pr > |t|
Intercept	24.775	1.980	12.512	**<0.0001**
NDVI	115.735	0.466	248.448	**<0.0001**
Ground Resolution-0.5	-0.021	1.983	-0.011	0.991
Ground Resolution-1	0.004	1.990	0.002	0.998
Ground Resolution-3	0.078	2.072	0.038	0.970
Ground Resolution-5	0.000	2.214	0.000	1.000
Ground Resolution-10	0.000	1.310	0.000	1.000

Therefore, despite the slight difference between the regression equations of the five kinds of grid sizes, it is considered that the NDVI value of peanuts remains the same relationship with CC under different ground resolution. Since the offset effect of two abnormal values of NDVI was most remarkable at the 10 m grids, the equation derived from the data of 10m grid size was used to predict CC using NDVI. The RMSE of CC estimation of each grid size from 0.50 m to 10 m was 0.081, 0.089, 0.048, 0.025, 0.020, 0.014, respectively.

CONCLUSION

Herein, we analyzed the relationships between NDVI and CC values of peanuts in the experimental field using UAV-sensed data under five kinds of ground resolutions. As a result, the NDVI showed a highly correlated linear relationship with CC under each ground resolution. Slight differences of slopes and intercepts were found between the regression equations, however this kind of difference was found not significant due to an ANCOVA. The regression equation of 10 m grid size performed a moderate estimation accuracy of CC with the RMSE less than 0.01. This result demonstrated that CC estimation tend to keep consistent despite of the change of resolution, suggesting the possibility that both UAV-sensed and satellite-sensed NDVI could be used to estimate CC for the usage of crop simulation models such as Aqua Crop.

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