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Comparison between UAV and Satellite Data and Applying Deep Learning to Classify Satellite Images for Agriculture Practices In The Eastern Hokkaido

Short Communication

Matsumura K[1]* and Avtar R[2]
[1]Faculty of Bio industry, Tokyo University of Agriculture, Japan
[2]Faculty of Environmental Earth Science, Hokkaido University Japan

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***Corresponding author:** Kanichiro Matsumura Faculty of Bio industry, Tokyo University of Agriculture, Japan

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Abstract

Monitoring a crop's biophysical parameters such as the Leaf Area Index (LAI), crop coverage, growth stages, health, crop height etc. at a fine-scale is crucial for agriculture field management in regard to irrigation and fertilizer applications [1]. There has been a great demand for non-destructive and cost-efficient crop monitoring with high accuracy in precision agriculture. Field-based surveying and sampling methods have been used for crop monitoring. However, these traditional techniques are often time-consuming, laborious and not feasible in large areas [2]. The use of geospatial techniques such as remote sensing technology has been applied to estimate various biophysical parameters. However, inadequate spatial resolution, along with the low temporal resolution of satellite data weakens the application of geospatial data [3]. Recently, high-resolution satellite data with daily coverage from Planet (https://www.planet.com/) is a game-changer in the agriculture field with the constellation of more than 150 active miniature satellites in the system. The emergence of lightweight and cost-efficient Unmanned Aerial Vehicles (UAVs) system has expanded the field of precision agriculture. UAV facilitates the availability of high spatial and temporal resolution earth observation to reveal high spatial details of crops. The authors conducted satellite and UAV observation of glass land, corn, and wheat fields. An index that shows the growth conditions at a glance is proposed. The comparison between satellite and UAV is examined. The resolution of Planet images is 3meters and that of UAV data is 0.1 meters. Integrating Planet derived Normalized Vegetation Index (NDVI) data with that of UAV derived data can utilize and explore the potential of crop monitoring and is expected to support agricultural practices to monitor crop growth with fewer visits to the field and thus leads to cost reductions. This study can help the region which is facing a shortage of human resources in rural areas and will be helpful for sustainable agriculture practices in helping to provide stable supplies of agriculture products. Deep learning is currently paving new avenues in the field of digital image processing and the possibility of classifying satellite images these techniques is also examined.

Keywords: NDVI; Satellite data; UAV; Machine learning; GIS

Study Area

The Eastern part of Hokkaido is famous for dairy farming and grassland plays an important role in the feeding of cattle. Space-Agri company obtains satellite image data from Planet over Hokkaido and delivers visible images, NDVI images, and maps for fertilizing options to individual farmers. Planet derived NDVI data in this area is provided every day by Space-Agri Company Ltd, Obihiro, under clear sky conditions (Space-Agri, https://www.space-agri.com/). The authors conducted satellite and UAV observations for the glass land, corn, wheat and sugar beet fields shown in (Figure 1-5).

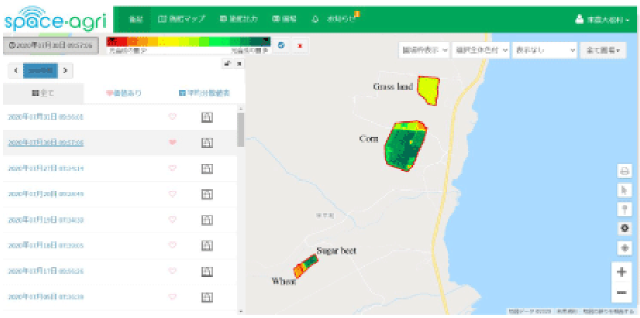

Figure 1: Satellite and UAV observed area, Eastern Hokkaido.

Figure 2: UAV with multispectral camera (Left), Observatory eastern part of Hokkaido (Middle) and Pre calculated course on grass land (Right).

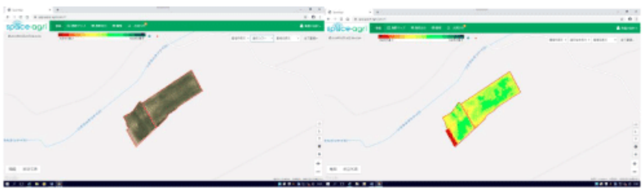

Figure 3: Satellite obtained Visible (Upper Right) and NDVI (Upper Left) image dated May16th, 2019.

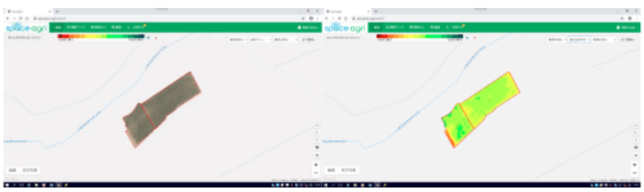

Figure 4: Satellite obtained Visible (Upper Right) and NDVI (Upper Left) image dated June 14th, 2019

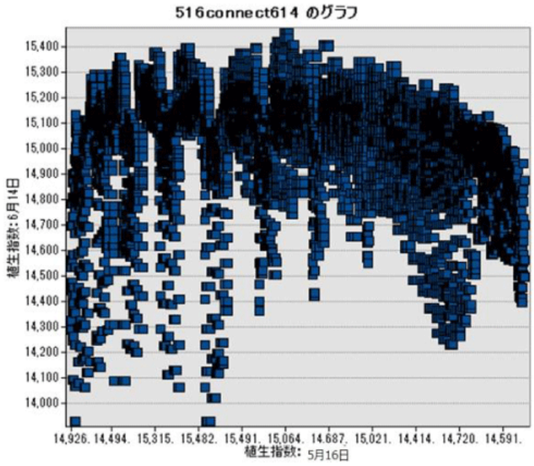

Figure 5: NDVI change from May 26th to June 14th, 2019.

Material used

The authors conducted surveys regularly using a UAV with a multispectral sensor camera and a sunshine sensor. The Parrot Sequoia+ with its two sensors, multispectral and sunshine is widely used for precision agriculture (https://www.parrot.com/business-solutions-us/parrot-professional/parrot-sequoia). The authors flew a UAV equipped camera over grassland regularly and obtained NDVI data. This UAV was operated automatically by using Litche software (https://flylitchi.com/hub) and Mission Planner (https://ardupilot.org/planner/index.html). The resolution of this UAV camera is 0.1meters and is good enough to judge the shape of items on the surface and provides useful information for precision agriculture.

Satellite data analysis for wheat field

The authors developed a methodology to understand the spatial crop growing conditions by using Space-Agri data. A wheat field is selected to conduct analysis. To compare NDVI datasets, cloud free conditions are required, otherwise appropriate NDVI images are difficult to obtain. Visible images were used for checking cloud free conditions. Visible and NDVI images dated March16th and June 14th were selected for analysis.

NDVI data obtained from Satellite ranges from 0 to 20000 expressed numerically in integers. By using GIS software, each grid has a GPS position, and compares the NDVI values for the two periods. The X-axis expresses NDVI values on May 26th and the Y-axis expresses that of June 14th, 2019. In the case of wheat, as it matured, the color changed from green to brown, and higher NDVI values decreased. This analysis is useful for understanding the complete situations.

Figure 6: Ground picture on wheat and sugar field.

Figure 7: Satellite image for the study area on April 29th to May 30th, 2020.

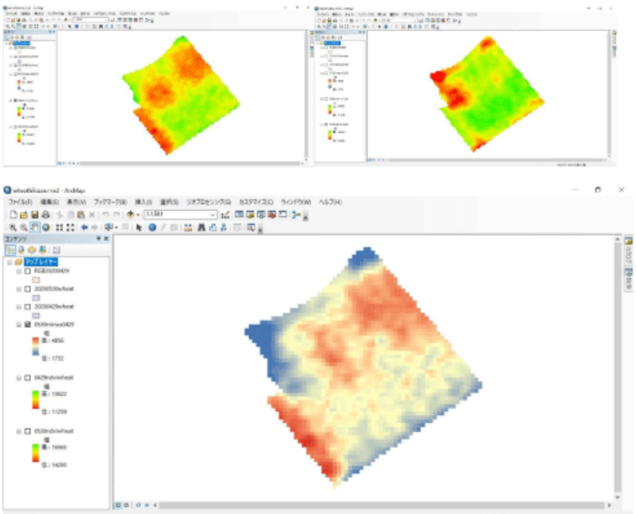

Figure 8: NDVI image for the study area on April 29th to May 30th, 2020 (Top) and subtraction (Bottom).

Figure 6,7 shows a ground photo for the study area. In 2019, the whole area was planted with wheat, in 2020, the area was rotated to sugar beets and the back area remains as a wheat field. Studying the wheat field, a comparison between field conditions was conducted between April 29th and May 30th. The spatial differences of NDVI for the wheat field was calculated and is shown in Figure 8.

Comparing UAV and Satellite images for grassland

The authors collected satellite image datasets both from UAV and clear sky satellite data on September the 3rd, 2019. NDVI data from the UAV observation ranges from 0 to 1. The satellite based NDVI data is given in integers and it ranges from 0 to 20000. Dividing the Integer values by 10000 and subtract 1 changes the satellite based data sets to the same scale used by the UAV datasets. Figure 9 shows the comparison between UAV data and Satellite based data.

Both of the NDVI datasets are in raster format. The authors used ArcGIS software provided by ESRI company and its functions, the spatial analyst function makes it possible to transform the data into one column and compare it to another column. The concept of this transformation is shown in Figure 10.

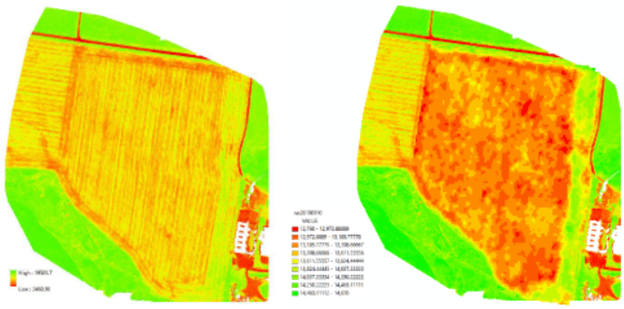

Figure 9: UAV (Left) and Satellite (Right) obtained NDVI integer image on September the 3rd, 2019.

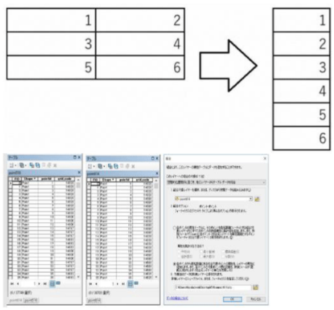

Figure 10: Transforming from raster to row data based on its position.

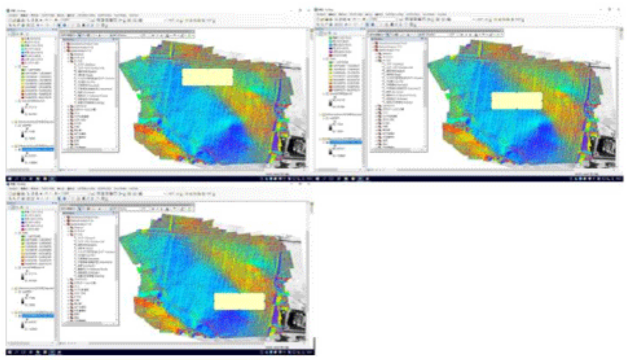

Figure 11: Extracting 3 small areas from the study area

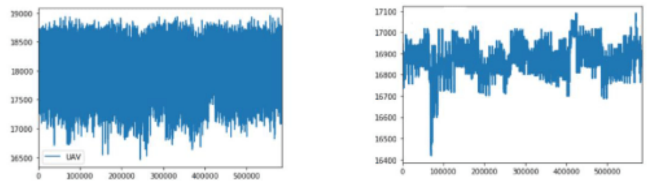

Figure 12: UAV (Left) and Satellite (Right) NDVI in Integer value.

A topographical map can be obtained by using the UAV. In the study area, the grassland area was too big an area for the computer to analyze using both the UAV and Satellite NDVI data. Three areas from the topographical map were extracted to reduce data size and to allow UAV and Satellite NDVI data to be shown in Figure 11,12.

The relationships were examined with a hope that extrapolations from only the satellite data can produce accurate measurements of crop conditions so reducing the necessity for onsite UAV data collection. 1 of 3 areas is transformed to row data with its position. Original NDVI of UAV ranges from 0 to 1, so that 1 is added and then multiplied 10,000 to compare with that of satellite ranging from 0 to 20000. There are 58445 rows. Each row has latitude and longitude information.

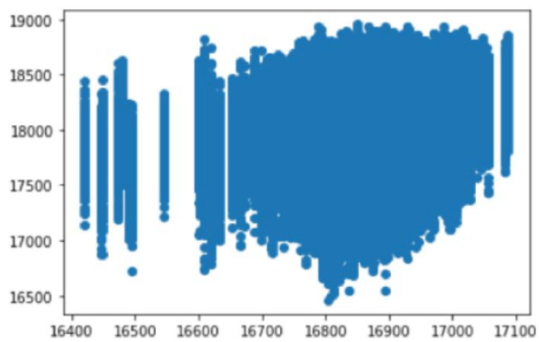

Figure 13: Scatter plots of UAV (Y-axis) and Satellite (X-axis) based NDVI.

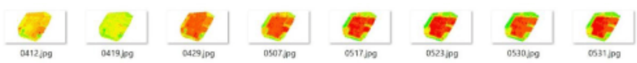

Figure 14: NDVI absolute values for corn from April 12th to May 31st

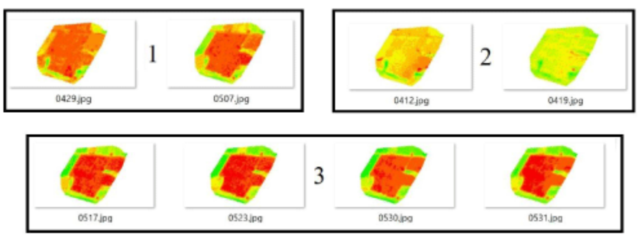

Figure 15: NDVI absolute values classified into 3 groups.

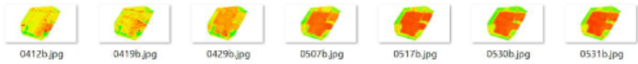

Figure 16: NDVI extended values for corn from April 12th to May 31st

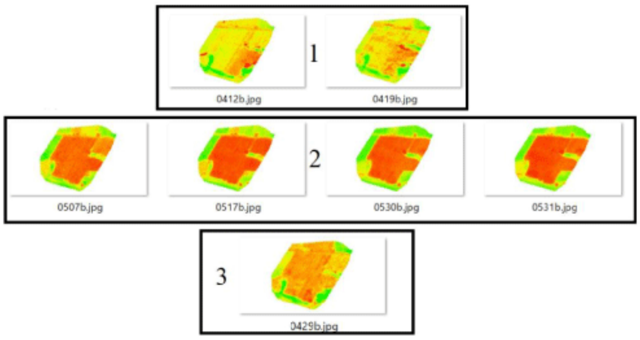

Figure 17: NDVI extended values classified into 3 groups.

The resolution of satellite image is 3meters and that of UAV is 0.1 meter. 3 meters by 3meters=9 square meters. In 1 square meter, 100 grids of UAV obtained data. One grid obtained by satellite includes 300 grids of UAV obtained data. The relationships between UAV and Satellite obtained NDVI values in Integer value is expressed on scatter plots shown in Figure 13-17.

Deep learning methodology for Satellite images

K-means clustering is used to automatically partition a data set into k groups. It proceeds by selecting k initial cluster centers and then iteratively refining them as follows:

1. Each instance di is assigned to its closest cluster center.
2. Each cluster center Cj is updated to be the mean of its constituent instances. The algorithm converges when there is no further change in assignment of instances to clusters [4-7].

Python program, scikit-learn is applied to satellite image data sets and is classified into 3 categories based on K-means clustering. The authors prepared for corn field NDVI datasets. One set was in absolute values and the other set was extended value. Both datasets are automatically classified into 3 categories.

Conclusion

The possibilities of operational agriculture support systems with the synergistic use of Planet data with UAV data were examined. The authors conducted satellite and UAV observations for glass land, corn, and wheat fields. When wheat matures, the wheat field turns from green to brown, reducing NDVI values, Spatial difference is calculated for wheat field and it enables farmers to understand the wheat situation at a glance. Comparing UAV data with The Planet imagery for grassland was examined. Integrating Planet derived Normalized Vegetation Index (NDVI) with that of UAV derived data can utilize and explore the potential of Planet data in crop monitoring and is expected to support agricultural practices to monitor crop growth with fewer visits to the field and leads to cost reductions. Applying deep learning for corn field was also examined. This method is based on Unsupervised learning based on K-means clustering and have possibilities to classify crop conditions.

Acknowledgement

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