OBSERVING PADDY PHENOLOGY WITH UAV IMAGERY

Jong-geol Park

Tokyo Univ.y of Information sciences, 4-1 Onaridai Wakaba-ku Chiba-city, Chiba, 2658501, Japan

Email: amon@rsch.tuis.ac.jp

KEY WORDS: Paddy field, Phenology, Timeseries imagery, UAV

ABSTRACT: The Phenology is a periodic plant life cycle event, which is to study how it is influenced by the seasonal and interannual variations of the climate. Time-series satellite images are widely used for global vegetation phenology analysis. MODIS satellite data has a wide observation width and high frequency observation, but low resolution (250m, 500m and 1000m). Therefore, it is not suitable for regional analysis. Therefore, in this study, we investigated the detailed phenology changes of paddy fields using UAV. In this research, we propose Greenness index of paddy field using RGB data from UAV. In addition, we performed time series analysis using Greenness index and extracted Onset time, duration time, offset time etc. of paddy field.

1. INTRODUCTION

Grasping the height and color of crops such as rice and wheat is an important means for determining whether crops have been growing steadily since ancient times. However, it takes time and effort to look around a wide field and measure the plant height and color. The average cultivated area per farmhouse in Japan (Ministry of Agriculture, Forestry and Fisheries 2014) is as small as 23.35 hectares in Hokkaido, 2.26 hectares in the Tohoku region, and 1.39 hectares in other prefectures, and there is also a large difference in cultivation conditions between fields. More than 70% of family-run agriculture in the world is less than 1 hectare (United Nations World Food Security Commissioner Expert High Level Panel 2014). For this reason, remote sensing research has progressed to reduce the burden on agriculture. Shiga et al. have shown the possibility of yield prediction from satellite data in the lower reaches of Hokkaido Ishikari, and Wakiyama et al. created a rice yield prediction formula for Fukui, Ishikawa, Toyama, and Nagano from yields over three years, meteorological data during the ripening period, and satellite data during the heading period. It also suggests that Shinsu et al. can estimate branching characteristics at the growth stage and the protein content and amylose content of rice. When estimating the yield and protein content in wide-area observation using satellite data, there is a concern that the estimation accuracy may be reduced due to differences in the growth stage from differences in cultivation conditions (rice planting time, topdressing, etc.) by field. (Sugaya et al., 2012).

Many studies have been conducted on the observation accuracy and analysis method of paddy field, with the free use of Landsat satellite data, the improvement of spatial resolution (500m to 30m), and the improvement of spectral resolution (by the addition of a red edge band). However, in rice cultivation areas with a monsoon climate, many clouds are generated during the growing season, so optical sensor remote sensing using satellites has many restrictions (the observation period is long and the image acquisition date is determined). As a result, a decrease in the frequency and certainty of observation became an issue (Akiyama et al., 2014) (Landsat acquisition probability). Also, aerial photography is not suitable for continuous monitoring because of cost and operational procedures. Currently, many monitoring are being done by SAR (Synthetic Aperture Radar) that use microwaves that can be observed regardless of weather conditions. The possibility of estimating the growth and yield of paddy rice from the backscattering coefficient of SAR has been suggested (Kimura et al., 2013). Although SAR data can be observed regardless of the weather, it is more expensive than optical sensor data, and the current technology has less information on vegetation information than optical sensors.

Understanding locality is a prerequisite for natural research and solving environmental problems on a scale directly related to people's lives and livelihoods. Locality determines the environmental cycle of the region, and natural development and appropriate management can be performed only by means adapted to it (Kondo 2003). Proximity remote sensing using UAV (Unmanned Aerial Vehicle) as a flat form is expected to become increasingly important as on-demand remote sensing that can be adapted to the region. In addition, the UAV has a low price, ease of handling, improved safety performance, maneuverability (UAV of fixed and rotary wings), development of UAV-equipped sensors, automatic flight with GPS, etc. Frequency data acquisition is now possible. As a result, UAV has been used in many proximity remote sensing fields. As a previous study using UAV in the agricultural field, Tsuji et al. (2014) showed the effectiveness of paddy field monitoring using a radio-controlled electric multicopper and Tanaka et al. Using a small UAV. Mukaiyama et al. used SPAD values for estimation of brown rice protein content in an industrial unmanned helicopter using a hyperspectral image sensor. In the research example using a multicopter, 3D models (CSMs: Crop Surface Models) are created by using SfM-MVS (Structure from Motion and Multi-View Stereo) technology using multiple photos from a small camera, and biomass from the community height was measured (Bendia et al., 2014). Uto et al. conducted paddy rice monitoring with a small hyperspectral sensor for UAV. Tsuji et al. (2016) performed time-series growth monitoring of rice using SfM-MVS using multi-period UAV data. In this study, we investigate the time-series phenology change of rice using RGB image of UAV.

2. STUDY AREA

This study was conducted at Inba Marsh. Inba Marsh is located in the northern part of Chiba Prefecture, about 40-50 km from Tokyo. The water of Inba Marsh flows into the Tone River and is poured from the Choshi into the sea. Inba Marsh is a lake in the Tone River system with an elevation of about 1.5m.

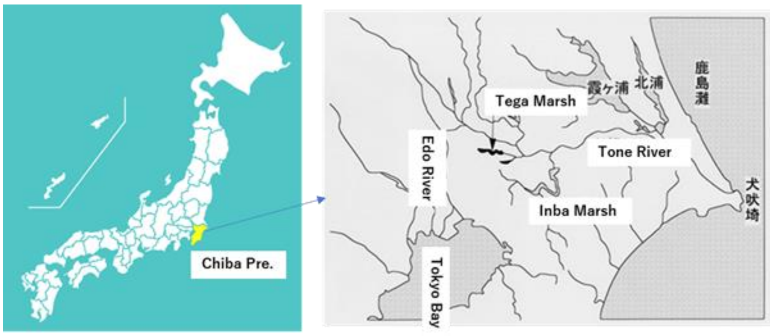


Fig. 1 Test site location

The area around Inba Marsh is one of the leading rice districts in the prefecture with 7,000 ha of vast rice fields. Agricultural water is distributed from the Inba marsh to every corner of the vast paddy field through pumping stations and irrigation channels. And the Inba Marsh Land Improvement District maintains these agricultural and irrigation facilities so that the effects of irrigation can be fully demonstrated.

3. DATA AND VEGETATION INDEX

The data collected in this research consist of 2 type of data including Landsat 8 and UAV image data. Landsat 8 data was download from official web site (https://earthexplorer.usgs.gov/). UAV image taken every one month from April to September, 2019. Images are taken using Mavic Pro camera. Field surveys were conducted to obtain rice productivity data.

Paddy vegetation index calculated using NDVI (Normalized Difference Vegetation Index) with following equation:

$$NDVI = [\rho NIR - \rho Red] / [\rho NIR + \rho Red]$$

The visible atmospherically resistant index (VARI) was proposed by Gitelson et al. It is an improvement of GRVI (Rouse et al) that reduces atmospheric effects. Although this is not an expected severe effort in low flying UAV platforms, it might locally be so. At Mediterranean sites with large amounts of bare soil. In addition, it has been reported to correlate better than GRVI with vegetation fraction (Asier and Lluis). It is defined as:

$GRVI = [\rho Green - \rho Red] / [\rho Green + \rho Red]$
$VARI = [\rho Green - \rho Red] / [\rho Green + \rho Red - \rho Blue]$

4. RESULT

Figure 2 shows the result of orthomosaic image using 800 images observed by Metashape software on June 9th. The pixel resolution is 1.2cm. Since UVA has only an RGB camera, only VARI was analyzed. Moreover, The NDVI value was obtained using a near infrared camera (Yubaflex). We performed phenological changes of vegetation using time series VARI images (Fig. 3). VARI values tended to increase from the rice planting time to before heading and decreased after the heading time. As can be seen from the RGB image, a lot of green is seen by stems and leaves before heading, but it appears yellow after the heading due to the addition of rice. The same trend was observed for NDVI values.

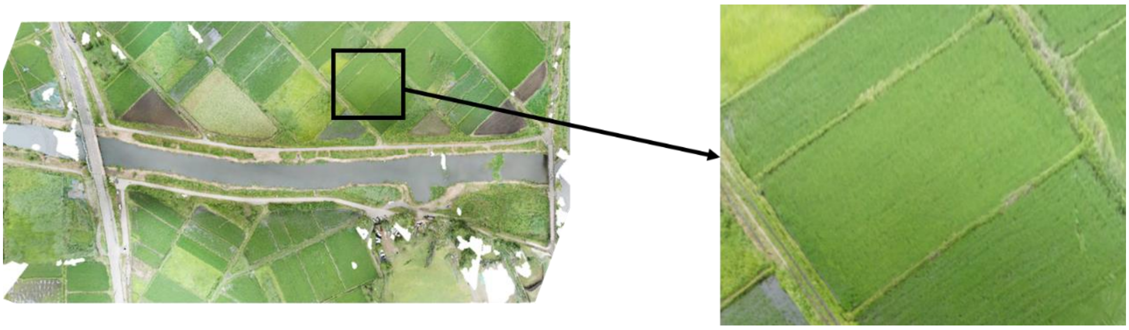
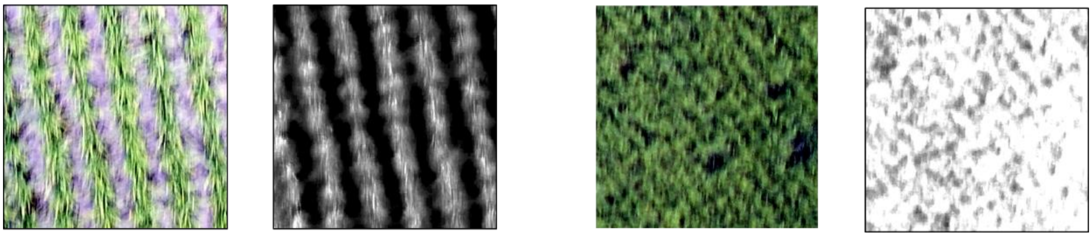


Fig. 2 Orthomosaic image on June 9th



June 9 (RGB and VARI) July 11 (RGB and VARI)

Fig. 3 Comparison of June 9 and July 11 VARI

In this study, it was found that rice growth could be estimated using time-series RGB data. It was found that the growth of rice in the field can be estimated without an expensive near-infrared camera.

References

Hiroyuki Shiba and Daiki Asaka, 1995, Mapping of Rice yield distribution using Landsat TM data and MOS-1/MESSR data, J. Soil Sci. Plant Nutr., 66, pp. 625-631.

Yasuyuki Qakiyama, Kimio Inoue and Kou Nakazono, 2003, A simple Model for yield prediction of rice based on vegetation index derived from satellite and AMeDAS data during ripening period, J. Agric. Meteorol., 59(4), pp. 277-286.

Bandig J, Bolten A,Bennertz S, Broscheit J, Eichfuss S, Bareth G, 2014, Estimatin Biomass of Barley Using Crop Surface Models (CSMs) Derived from UVA-Based RGB Imaging. Remote Sensing 6 : pp. 10395-10412.

Shinji Mukoyama, Yukio Kosugi, Kuniaki Uto, Genya Saito and Kunio Oda, 2011, SPAD value estimation of paddy leaves using a hyperspectral sensor mounted on a radio-controlled helicopter, J. photogrammetry and remote sensing, 50(2), pp. 90-95.

Akira Hama, Yaka Hayazaki, Atsushi Mochizuki, Yasuo Tsuruoka, Kei Tanaka, Akihiko Kondoh, 2016, Rice Growth Monitoring Using Small UAV and SfM-MVS Technique, J. Japan Soc. Hydrol. And Water Resour. 29(1), pp.44-54
Gitelson, A.A.; Kaufman, Y.J.; Stark, R.; Rundquist, D. 2002, Novel algorithms for remote estimation of vegetation fraction. Remote Sens. Environ. 80, pp. 76–87.
Asier R. Larrinage and Lluis Brotons, 2019, Greenness Indecies from a Low-Cost UAV Imagery as Tools for Monitoring Post-Fire Forest Recovery, Drones, 3(6) doi:10.3390/drones3010006