# MAPPING RICE PADDY CROPPING PATTERNS AND DROUGHT IMPACTS IN UGANDA USING MULTI-TEMPORAL MODIS IMAGES FROM 2001 TO 2018

Miwa Aoyama (1), Wataru Takeuchi (1),

[1] Institute of Industrial Science, The University of Tokyo, Meguro 4-6-1 Tokyo 153-8505
Email: aoyama-miwa078@g.ecc.u-tokyo.ac.jp; wataru@iis.u-tokyo.ac.jp ;

**KEY WORDS:** rice area mapping, vegetation index, East Africa

**ABSTRACT:** Rice is one of the most staple food which is cultivated across the world. These days growing rice is becoming popular in Uganda, but unplanned cultivation is said to deteriorate the environments of wetlands, which can cause their rapid loss. In spite of an advantage of rice map for environmental preservation, rice paddy cropping patterns have not revealed yet in Uganda. Therefore, this research aims to reveal how rice paddy fields have developed in Uganda by mapping their spatial distribution from 2001 to 2018. Normalized Difference Vegetation Index (NDVI) derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) is used to detect rice area, since it shows different responses on different land cover, especially vegetation. Change in rice cropping patterns is compared in relation to drought impacts, using annual precipitation and maximum temperature. The results indicate that low precipitation and high maximum temperature can give negative impacts on rice paddy expansion. Regional analysis is necessary for future work to specify relationships with rice area expansion and drought impacts.

## 1. INTRODUCTION

In Africa, growing rice is becoming popular as an income generating activity in recent years. It is believed as one of the effective ways for farmers to get out of poverty, since the international market value of rice remains relatively high and stable. NERICA rice is spreading with the help of Japan International Cooperation Agency across Africa, and Uganda, which published Plan for Modernization of Agriculture in 2000 to promote commercial rice farming, is not an exception. Uganda is rich in highland nature with 13% of national land being covered by wetlands (GoU, 2001), which can be converted into paddy fields. However, 30% of them was regarded to be lost in the last 14 years (Ramsar, 2018) owing partly to unplanned cultivation. Lack of a comprehensive management plan is said to deteriorate soil and water environments, which gives negative impacts on birds and fishes. It is also reported that decline in water level and soil erosion even caused reduction in rice yields. However, previous studies have not examined rice paddy cropping patterns for the last several decades across the nation. Therefore, this study aims to reveal how rice paddy fields have developed in Uganda by mapping their spatial distribution considering drought impacts. Understanding the current rice crop area and its past development are crucial when an agricultural strategy is planned, especially under highland climate which is subject to climate change.

## 2. METHOD

### 2.1. Study area

Study area is the whole area of Republic of Uganda, located in East-Central Africa. Figure 1 shows the image of study area, bordered with red line.

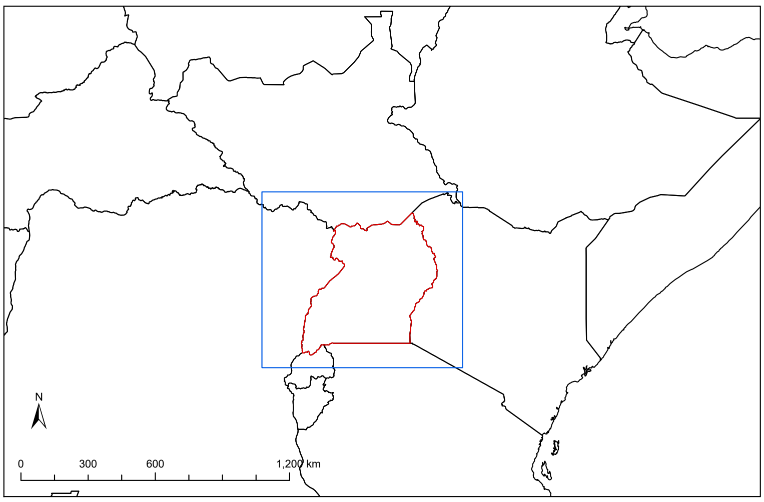


Figure 1. Image of study area

## 2.2. Mapping rice paddy cropping patterns

**2.2.1. Data:** Optical remote sensing images are often used to map rice paddy area since multi-temporal and multi-spectral reflectance data are obtained. In this study, images from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard the NASA EOS Terra Satellite, especially the 16 day composite MOD13A2 dataset from 2001 to 2018 are used as a main data source. It consists of four bands: bands 1 (red), 2 (near-infrared), 3 (blue), and 7 (mid-infrared). The images are processed with Kalman filter, which is an optimal recursive data processing algorithm, to get smooth NDVI images.

**2.2.2. NDVI:** This study uses the normalized difference vegetation index (NDVI) to detect rice area. The change of NDVI shows the crop growing season, and it shows different responses depending on land cover type. The calculation formula is expressed as:

$$NDVI = \frac{\rho_{nir} - \rho_{red}}{\rho_{nir} + \rho_{red}}$$

where $\rho_{nir}$, $\rho_{red}$ are spectral responses of the pixel in near infrared and visible red bands, respectively.

**2.2.3. Algorithms for identifying paddy rice field:** In case of mapping rice areas, remote sensing images are acquired over every stage of rice production from sowing to harvesting. NDVI of rice would be low at sowing stage and increases gradually over the vegetative-to-reproductive stage which often takes 60 to 100 days depending on the variety (Mosleh et al., 2015). After reaching its peak, it decreases suddenly over the ripening-to-harvesting stage, which often takes 30 days. Since rice production in Uganda is double-crop, the NDVI value shows the lowest value from 0.3 to 0.5 at sowing stage in March-April and August-September (Son et al., 2014). Meanwhile, it shows the highest from 0.75 to 0.9, however, rice production in Uganda is predominantly rainfed (GoU, 2009; FAO, 2010), which reduces the peak value of NDVI to 0.6-0.7. Considering these thresholds, land cover in Uganda is classified by Classification and Regression Trees (CART) classifier. However, it is quite difficult to distinguish rice paddy from other croplands only with NDVI when creating training data. Therefore, another threshold is referred to support detection of rice paddy field when creating training data. A unique physical feature of paddy rice fields is that rice is grown on flooded soils. Therefore, the temporal dynamics of rice paddy field is characterized by flooding and transplanting period, where the pixel satisfies the following threshold (Xiao et al., 2005) expressed as:

$$LSWI + 0.05 \geq NDVI$$

where LSWI represents land surface water index calculated with the formula expressed as:

$$LSWI = \frac{\rho_{nir} - \rho_{swir}}{\rho_{nir} + \rho_{swir}}$$

where $\rho_{swir}$ is spectral responses of the pixel in short-wave infrared. Then, land cover is classified by the classifier based on annual temporal dynamics of NDVI.

## 2.3. Mapping drought impacts

A number of studies examine precipitation and temperature when they evaluate drought impacts. As one of drought indices, Keetch-Byram Drought Index (KBDI), incorporates precipitation and maximum temperature, these two factors are crucial for evaluating droughts. Therefore, in this study, drought impacts are roughly evaluated by mapping multi-temporal spatial distribution of annual precipitation and maximum temperature.

**2.3.1. Precipitation:** Main data source is Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), a 30+ year quasi-global rainfall dataset. CHIRPS incorporates 0.05° resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring. Annual precipitation is calculated by summing up the amount of rainfall throughout the year.

**2.3.2. Maximum temperature:** Main data source is TerraClimate, a dataset of monthly climate and climatic water balance for global terrestrial surfaces. TerraClimate incorporates 2.5 arc minutes resolution. It uses climatically aided interpolation, combining high-spatial resolution climatological normals from the WorldClim dataset, with coarser spatial resolution, but time-varying data from CRU Ts 4.0 and the Japanese 55-year Reanalysis (JRA55). Temporal information is inherited from CRU Ts 4.0 for most global land surfaces for temperature, but JRA55 data is used for regions where CRU data had zero climate stations contributing. Annual maximum temperature is calculated by averaging maximum temperature throughout the year.

## 3. RESULT

### 3.1. Mapping rice paddy cropping patterns

In this study, land cover in Uganda is classified into 7 classes; urban, water, rice, forest, cropland, vegetation, and sparse vegetation. Figure 2 shows the result of estimating multi-temporal spatial distribution of paddy rice fields across Uganda. Most rice area appears in the middle of Uganda and some appears in the south-west, but in general rice area is not very large compared to other land cover types. Hence, estimated rice area is calculated to get an idea of its change as shown in Table 1. It is calculated by multiplying the number of pixels classified as 'rice' by pixel area (resolution, $964 \times 844$ m$^2$). It is compared with ancillary data, a statistical data of rice until 2014 from Ricepedia. Ancillary data shows the constant increase from 2001 to 2008, followed by a sudden decrease to 86 in 2009 and gradual recovery afterwards. On the other hand, estimation results show increase from 2001 to 2010 and drastic decrease afterwards, overestimating rice area throughout the period.

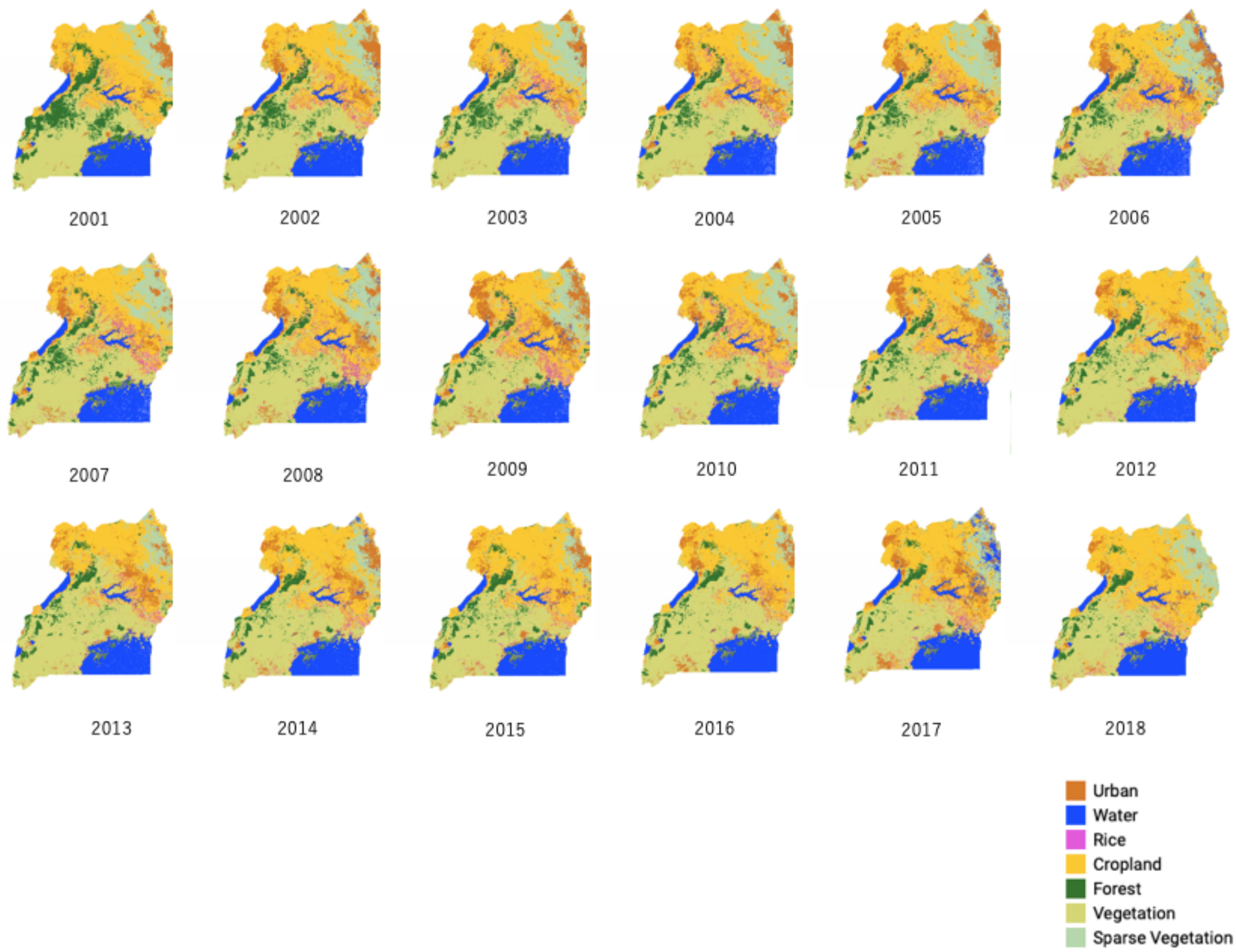


Figure 2. Estimated multi-temporal spatial distribution of rice paddy fields in Uganda

Table 1. Changes in rice area and estimated rice area

| | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rice area (1000ha) | 76 | 80 | 86 | 93 | 102 | 113 | 119 | 128 | 86 | 87 | 90 | 92 | 93 | 95 | N/A | N/A | N/A | N/A |
| Estimated rice area (1000ha) | 212 | 484 | 560 | 503 | 550 | 682 | 664 | 600 | 680 | 721 | 596 | 372 | 399 | 399 | 330 | 248 | 429 | 376 |

### 3.2. Mapping drought impacts

Figure 3 shows the multi-temporal spatial distribution of annual precipitation in the area around Uganda, the blue rectangle area of Figure 1. Figure 4 shows change in annual precipitation averaging across study area (not the rectangle area). Annual precipitation reaches its bottom in 2009, and it does not seem to have a strong relationship with the change in rice area. Figure 5 shows the multi-temporal spatial distribution of annual maximum temperature around Uganda. It neither seem to have a strong relationship with the change in rice area.

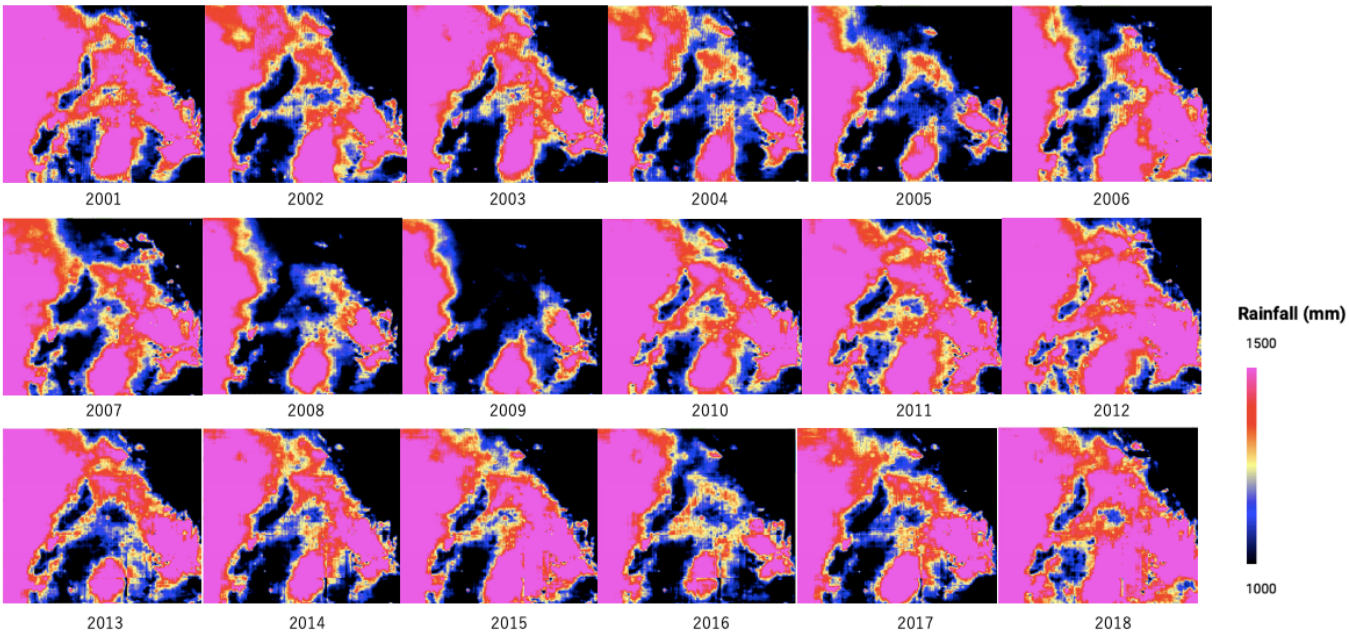


Figure 3. Multi-temporal spatial distribution of annual precipitation

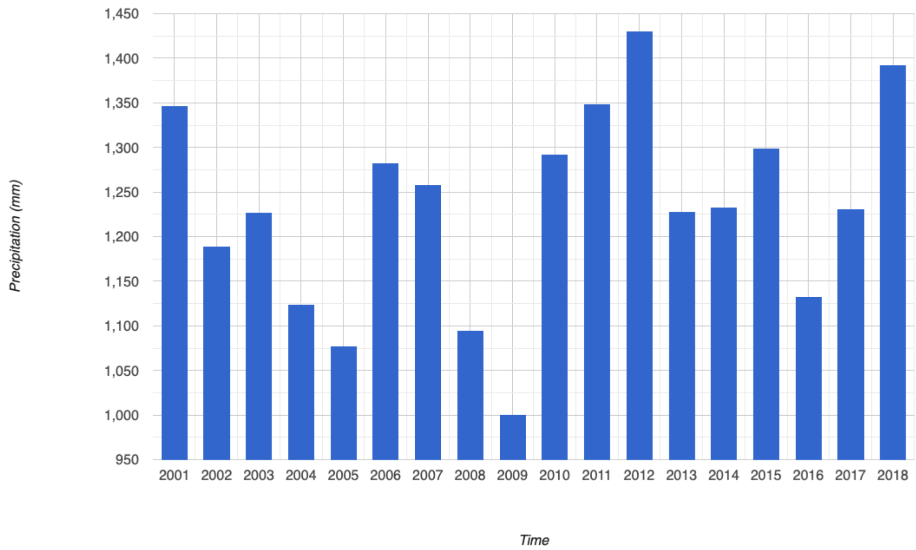


Figure 4. Annual precipitation in Uganda from 2001 to 2018

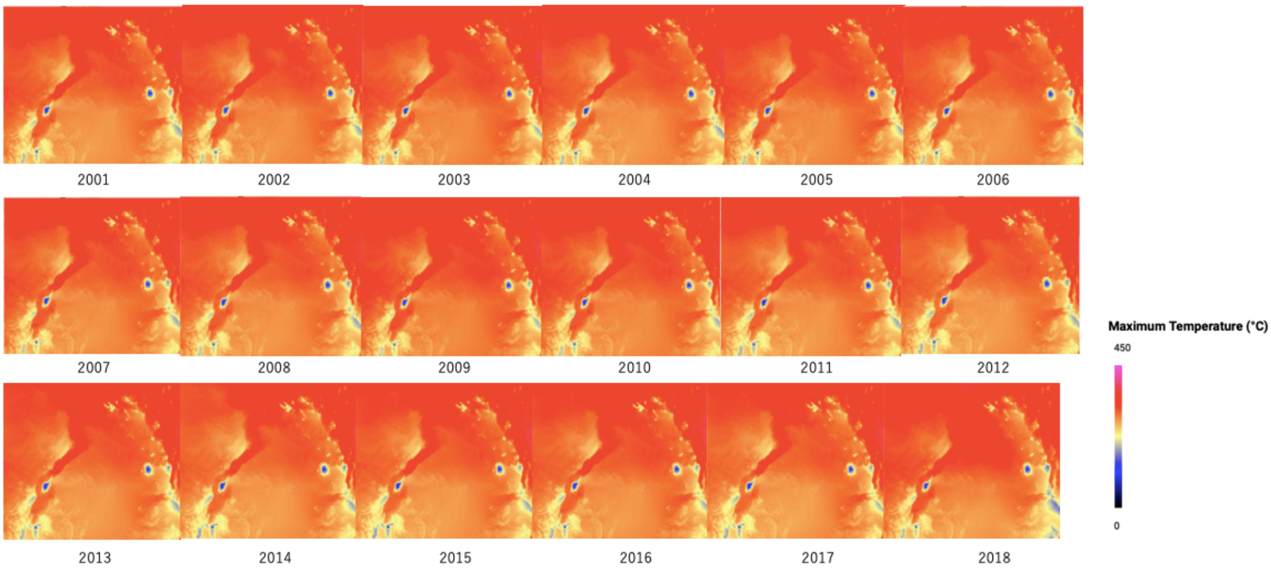


Figure 5. Multi-temporal spatial resolution of annual maximum temperature

## 4. DISCUSSION

Estimated rice area always shows larger values than statistical data. Overestimation would be caused by the image resolution, which is approximately 1km × 1km, in spite of small rice paddy plots expected in Uganda. Hence the use of MODIS products with higher resolution or calculating fractional cover rate of rice area in a pixel is suggested to obtain more accurate values. Despite overestimation of the result, similar trend is observed in change in rice area over the period. Estimated rice area increases until 2010 followed by a sudden decline, while statistical rice area increases until 2008. Low annual precipitation and high maximum temperature in 2009 can be one of possible events that gives negative impacts on the expansion of rice area. However, low precipitation and its decline in other years such as 2005 does not seem to give negative impact on rice area. Since this nationwide analysis can eliminate regional characteristics, analysis by region would be necessary for future work to specify the relationship with rice area expansion and precipitation/temperature. It would also contribute to regional analysis to validating our results by comparing with rice paddy map derived from SAR images with higher resolution.

## 5. CONCLUSION

This study implements mapping spatial distribution of rice paddy cropping patterns in relation to drought impacts, and our result suggests that low precipitation and high maximum temperature can give negative impacts on rice paddy expansion. In order to specify relationships with rice area expansion and drought impacts, regional analysis is necessary for future work.

**References**

FAO (2010) Crop Calendar, available from: http://www.fao.org/agriculture/seed/cropcalendar/welcome.do [accessed on August 30th].
Government of Uganda (GoU) (2009) Uganda National Rice Development Strategy.
Government of Uganda (GoU) (2001) Wetland Sector Strategic Plan.
Mosleh, M., Hassan, Q., & Chowdhury, E. (2015). Application of remote sensors in mapping rice area and forecasting its production: A review. *Sensors*, *15*(1), 769-791.
Ramsar (2018) Ramsar Advisory Mission Report N° 90.
Son, N. T., Chen, C. F., Chen, C. R., Minh, V. Q., & Trung, N. H. (2014). A comparative analysis of multitemporal MODIS EVI and NDVI data for large-scale rice yield estimation. *Agricultural and forest meteorology*, *197*, 52-64.
Xiao, X., Boles, S., Liu, J., Zhuang, D., Frolking, S., Li, C., ... & Moore III, B. (2005). Mapping paddy rice agriculture in southern China using multi-temporal MODIS images. *Remote sensing of environment*, *95*(4), 480-492.