

Use of Satellite Remote Sensing for Rice Yield Estimation: A Case Study of Polonnaruwa District, Sri Lanka

ABSTRACT

In Sri Lanka, a conventional method named as the Crop-cut survey is currently used to estimate the seasonal rice production. However, it fails to forecast rice yield before the harvest as it is conducted during the harvest. Therefore, this study focusses on to test a pre-harvest rice yield estimation method using satellite remote sensing data. Landsat 8 OLI/TIRS images (30m spatial resolution) from Earth explorer and 8-day composite images (250m spatial resolution) from Moderate Resolution Imaging Spectro-radiometer (MODIS) sensor on-board NASA EOS Terra/Aqua satellite were used from 2014 to 2017. Cultivated paddy lands were identified by land cover classification, using field-training samples and Landsat 8 OLI/TIRS data. Besides, the temporal change of Normalized Differenced Vegetation Index (NDVI) for paddy and forest were analysed to validate the classification. The observed minimum accuracy of the land cover classification, out of the tested four (4) seasons, was 99.4%, and the minimum kappa coefficient was 0.9916. The correlation between reference net harvested paddy area and identified paddy cultivated area by Landsat 8 was 0.93. Linear and exponential yield forecasting models developed for Kurunegala District were validated and tested, based on NDVI and EVI2 vegetation indices obtained through MODIS (MOD09Q1v006) surface reflectance images of Polonnaruwa District. The comparison of estimated yield with national statistical records denotes that both NDVI and EVI2-based models provide more reliable estimations about 80-days after the transplanting of each season. Nevertheless, the EVI2-based model (derived at 80 days) provides more reliable estimates than the NDVI-based model with 83.7% average accuracy. Therefore, the seasonal rice yield can be successfully forecasted one-month before the harvest time using the EVI2-based model in Polonnaruwa district.

Keywords: Rice yield, Landsat 8 OLI/TIRS, MODIS, NDVI, EVI2

1. INTRODUCTION

Rice is one of the staple foods for more than three billion people worldwide. Rice paddies accounted for approximately 11.5% of the World's arable land area during 2012. Rice provided ~19% of the global dietary energy in recent times and its annual average consumption per capita was ~65 kg during 2010–2011 [8]. Therefore, rice area mapping and forecasting its production is important for food security. Paddy occupies approximately 37 per cent (0.77 million ha) of the cultivated land area of Sri Lanka [1]. It is cultivated during two major seasons, *yala* and *maha*. The beginning of the *yala* season (flooding and transplanting) can alter from the end of March to mid-May. Similarly, *maha* season can vary from the end of September to mid of December. Approximately 1.8 million farm families are dependent on paddy farming throughout the country, and the demand for paddy in Sri Lanka will increase at a rate of 1.1 percent per year, which necessitates the production to grow annually at a rate of 2.9 percent [1]. Sri Lanka produced around 2.9 million tons of paddy during the 2015/2016 cultivation season [1].

The yield estimation for crops in Sri Lanka is based on conventional techniques of data collection and uses ground-based field visits and reports. It is time-consuming, subjective, and prone to significant discrepancies due to insufficient ground observations that cause inefficient crop production assessment. The outcomes are made available to the government and public several months after crop harvesting, and thus, ineffective for food security purposes. The process is costly, depending on the survey areas, and frequently, when the data become available, it is late for any suitable action to be taken to avert food shortage.

Crop-yield prediction using remotely sensed data has already represented a very active field of research and application [10]. Notable advances in remote-sensing technology over the last several decades are now providing scientists with valuable information for yield and production forecast. Satellite remote sensing is popular and recognised as a powerful and useful technology for identifying agriculture crops [5]. The ability to estimate seasonal crop yield before a considerable time period to harvest is vital for taking precautions regarding seasonal crop production. It is of paramount importance in strategic planning and decision-making in the food security and facilitation of safe harvest storages [3]. Alternatively, proper import (in shortfall case) or export (in surplus case) policies can be materialised based on such reliable yield estimations [11]. Due to the significant advantages of the pre-harvest yield estimation method, it is essential to focus on the development of modern science and technology to build reliable yield forecasting models. Satellite Remote Sensing can be successfully applied to this particular research area as it is a highly efficient tool to estimate and forecast crop yields [4].

The use of satellite data for crop classification and crop yield estimation has a long history. For classification and identification of cultivated paddy lands, a few usable images during the growing season sometimes suffice the needs. However, for yield-estimation, both are needed, i.e., high spatial-resolution for field-level information, and high temporal-resolution for growth condition or phenology; however, free data at both high spatial and temporal resolutions are not available [12]. MODIS satellite images are in low spatial and high temporal resolution. However, the Landsat imagers are moderate resolution free satellite data with low temporal resolution. Therefore, this study aims to validate the MODIS images-based rice yield estimation models proposed by Dammalage et al., (2017). In addition, this study uses Landsat 8 OLI/TIRS images for identify the paddy cultivated area and determine the best age of paddy plants for yield forecasting in Polonnaruwa district.

2. STUDY AREA, MATERIAL AND METHODS

Polonnaruwa, located in the North central province of Sri Lanka, at $7^{\circ} 56'$ latitude $81^{\circ} 0'$ longitude (Figure 1), was selected as the study area because it is one of the major paddy cultivation regions in Sri Lanka. According to Irrigation Department of Sri Lanka, this area consists of approximately 85,505 acres (34,629.525 ha) of rice fields and due to the extensive rice cultivation lands, remote sensing can easily monitor this type of farming system.

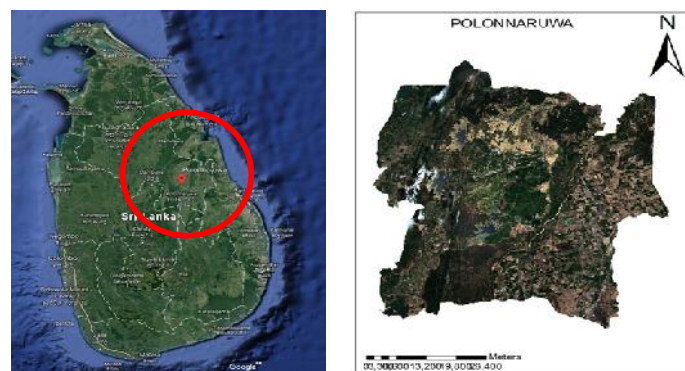


Fig. 1. Spatial extent and location of the study area (Polonnaruwa district) in Sri Lanka with a subset of the Landsat 8 true colour bands combination, acquired in 2017 from Earth explorer

2.1 Satellite and Rice Yield Data

Free satellite images of Landsat 8 OLI/TIRS level 1 were downloaded from USGS Earth Explorer website (<https://earthexplorer.usgs.gov/>) from year 2014 to 2017 for 6 cultivated seasons. This product consists of 30m spatial resolution without a suitable temporal resolution from paddy growth analyses. Cloud images were frequent during the *maha* season. The year 2017 *yala* season had four images without or with fewer clouds, but it can be used by removing clouds utilising the cloud mask technique. In addition, this study used the MODIS surface reflectance 8-Day L3 Global 250m (MOD09Q1) image product, which is a composite using eight consecutive daily 250m images

(MOD09Q1) from 2014 to 2017. Rice yield data and other required paddy statistics for 2014 to 2017 were obtained from the Census and Statistics Department, Sri Lanka.

To achieve the primary objective of improving the MODIS images-based rice yield estimation model with the Landsat 8 OLI/TIRS images and determine the best age of paddy plants for yield forecasting in Polonnaruwa conditions, the study first proposed a method to identify paddy cultivated lands in each growing season, using Landsat 8 OLI/TIRS data and MODIS satellite data. Radiometric and FLAASH atmospheric corrections were conducted for Landsat 8 OLI/TIRS images, and clouds were removed. The MODIS satellite images consisted of three science data sets, which held 250m surface reflectance band 1 (620-670nm), 250m surface reflectance band 2 (841-876nm), and 250m reflectance band quality data sets.

2.2 Vegetation Indices

The Normalized Difference Vegetation Index (NDVI) is a measure of the vegetative cover on the land surface over extensive areas. The imagery strongly points out the dense vegetation and visibly identify the areas with little or no vegetation [7]. NDVI also recognises water and ice. The NDVI values were calculated based on Landsat 8 OLI/TIRS images by using NIR band-5(0.845-0.885µm) and Red band-4 (0.630-0.680µm) in ENVI software. NDVI values were assigned for each feature by 2017 *ya/a* season images, and the feature classes were correctly identified with the help of training samples and Google earth. The NDVI ranges were then assigned for different classes from the values and derived the NDVI temporal change of the paddy and forest.

MODIS images had two bands to calculate NDVI. Those two bands acting as green vegetation displays strong absorption in the red part of the spectrum (reflectance of around 3-5%) and weak absorption in the NIR part (reflectance around 40 - 60%) [9]. The MOD09Q1 images calculated NDVI from the equation 1, using 250m surface reflectance band 1 (620-670 nm) and 250m surface reflectance band 2 (841-876 nm).

$$NDVI = (NIR - RED) / (NIR + RED) \quad (1)$$

The Enhanced Vegetation Index (EVI) was developed as a standard satellite vegetation product for the Terra and Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) [2]. EVI provides improved sensitivity in high biomass regions while minimising soil and atmospheric influences. The main limitation of EVI is that it utilises blue band in addition to the red and near-infrared bands. Jiang et al. (2008) developed and evaluated a 2-band EVI (EVI2), without a blue band, which has the best similarity with the 3-band EVI, particularly when atmospheric effects are insignificant, and data quality is good. EVI2 index of the MOD09Q1 images was calculated based on equation 2.

$$EVI2 = 2.5 \times \{ (NIR - RED) / (NIR + 2.4RED + 1) \} \quad (2)$$

2.3 Ground Truth Data Collection

The field route was selected by Google earth application to collect paddy field locations before the field work. Accordingly, the middle part of the study area was chosen, which contains a majority of paddy fields. GPS coordinates of the paddy fields and the forest were collected by CT Droid Sri Lanka application on mobile phones, and approximately 50 paddy samples were collected. The ground truth data were used for the classification, and the identification of paddy area and sample collections (approx. 30 samples) from the remaining places were made by using Google Earth application. Several classification methods were used, but Maximum Likelihood classification, with high accuracy, was chosen for further analysis. The areas regarding percentage and hectares were computed, the accuracy assessments captured and checked whether the accuracy level of the land cover classification is high or low.

2.4 Cultivated Paddy Field Identification

The basic statistics of the maximum likelihood classification can identify the paddy cultivated area or the extent, and subsequently, it is possible to detect the accuracy of the census and statistics department data (reference data) regarding the extent of paddy cultivation. Then NDVI values for all images were calculated using equation 1. Before calculating the correlation coefficients, NDVI temporal profiles were smoothed using the 'moving average' method. Correlation coefficients between

NDVI changing pattern of normal paddy cultivation and smoothed profiles were calculated. In this respect, 10 correlation coefficients were calculated for one smoothed NDVI temporal profile. An appropriate threshold value for correlation coefficient was then selected to extract the cultivated paddy pixels by equalising the total paddy area identified by this algorithm and census data. The pixels which included higher correlation coefficient values than threshold values were then classified as paddy cultivated lands.

Subsequently, a few pixels (identified as paddy) were randomly taken to verify the classification result. In the verification process, randomly selected paddy pixels were compared with Google earth and field data to determine whether those pixels are paddy (or not). This method was applied to all the other seasons to detect cultivated paddy lands in the study area, and paddy cultivated area was identified using the Landsat 8 and MODIS images. Both cultivated paddy area extents were compared with reference data and checked whether those extents are the actual cultivations (or not) with the training samples. The cultivated paddy extent was determined by analysing those extents.

2.5 Validate the Model Equation and Yield Prediction

Dammalage et al. (2017) have proposed several yield estimation models for Kurunegala district using MODIS data. In their study the cultivated paddy fields in Kurunegala district were identified using time-series 250m resolution MODIS (terra) spectral surface reflectance (MOD09Q1) satellite imagery data acquired from 2007 to 2014. They have proposed, linear and exponential relationship between rice yield and vegetation indices on four different methods; average NDVI, maximum NDVI, cumulative NDVI and average EVI2. Number of rice yield forecasting models were built based on NDVI and EVI2 vegetation indices at different age of paddy starting from a rice age of 32 days. Based on the statistical analysis, the paddy plant at about 80 days after transplanting has given the best relationship between vegetation indices (NDVI and EVI2) and rice yield. However, the yield forecasting models which are derived based on EVI2 index had higher R^2 values than NDVI based models.

When NDVI based models are considered, cumulative NDVI based models have higher R^2 values (normal $R^2 = 0.55$ and smoothed $R^2 = 0.56$) compared to other NDVI based models. Both cumulative NDVI and EVI2 based models were provided more accurate yield estimations at 80 days after the transplanting. The R^2 of models between estimated and reference yield data is 0.82 for NDVI and 0.96 for EVI2 model derived at 80 days. The derived NDVI and EVI2 models were shown in equation 3 and 4 respectively, and they were used for yield estimation of Polonnaruwa District in this study.

$$y = 2213e^{0.8498x} \quad (3)$$

$$y = 1603e^{2.0827x} \quad (4)$$

Where, y - rice yield (kg per hectare) and x - corresponding vegetation index

3. RESULTS AND DISCUSSION

3.1 Identification of Cultivated Paddy Fields

The temporal pattern of NDVI values in the cultivated paddylands based on the field samples were identifier for each season. Set of samples at a particular point was selected to detect the NDVI values for all the seasons because of the low temporal resolution in Landsat 8 images. Although the *yala* season extends from May to August, it is not always precise. Hence, the images of mid-April to end of August were used for the analyses. In April there were no paddy fields, but at the beginning of May, paddy fields at the early stage could be identified. The NDVI values then increased closer to forest NDVI values. In July, NDVI values were high and was near to 80 days. Cultivated paddy fields were identified by using this temporal pattern of NDVI values. However, the cultivated paddy fields could not be identified precisely for every season using Landsat 8, due to the low temporal resolution of the Landsat 8 images and the cloud cover. Ground truths were then used for land cover classification to identify the paddy lands with moderate resolution Landsat 8 images. Figure 2 presents the classified

images over the study area in 2015 yala, 2016 yala, 2016/17 maha, and 2017 yala seasons. Green colour indicates the paddy cultivated area.

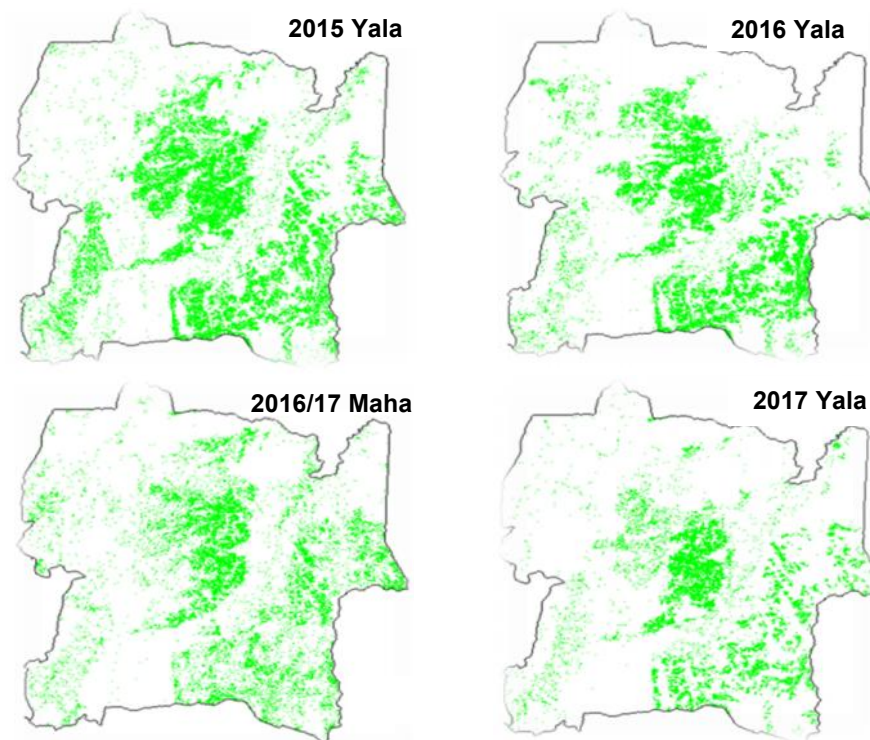


Fig. 2. Landsat 8 OLI/TIRS classified images by maximum likelihood classifier

The training samples alone are not sufficient to check the identified cultivated paddy extent accuracy. The problem of the designated paddy extent by Landsat 8 image still prevails. Those images were then compared with the ground truths (training samples). This method was applied to all the other seasons to identify the cultivated paddy lands in the study area. An appropriate threshold value for correlation coefficient was selected to extract the cultivated paddy pixels by equalising the total paddy area identified by this algorithm and census data. The pixels which included higher correlation coefficient values than the threshold values were classified as paddy cultivated lands. The correlation coefficient (r) held a higher value at some points when the specific NDVI time series corresponded to cultivated paddy land. The necessary seasonal parameters were obtained based on the number of times that the matching pattern was shifted to the right, providing the highest correlation coefficient value. In the above situation, the maximum value of the correlation coefficient was 0.90 and highly correlated with the matching pattern. Therefore, that pixel is classified as a paddy cultivated pixel. All pixels were classified into two classes as 'paddy cultivated' and 'not cultivated' lands, using this method.

The total area identified as paddy and the respective threshold value for the correlation coefficient for each season is listed in Table 1. However, no unique or common threshold value exists to distinguishes cultivated paddy lands from other land uses. The difference between identified paddy area and the statistical records obtained from sensors and statistics department for each season is also tested and listed in table 1. The difference was recorded as percentage of difference and it was maximum from 2015 *yala* and minimum for 2016 *yala* season. By changing the shape of the matching NDVI pattern and by applying a smoothing and filtering methods for time series data, a unique threshold value could be discovered. This provides a potential area for future research.

Table 1. Appropriate thresholds to identify cultivated paddy lands from other land uses in each season

Season	Threshold for correlation coefficient	Area identified as paddy (hectares)	Difference between statistical and identified paddy area	
			hectares	%
2014/2015 M	0.8116	65,756	135	20%
2015 Y	0.8454	54,513	155	28%
2015/2016 M	0.8990	57,650	42	7%
2016 Y	0.8920	49,731	23	5%
2016/2017 Y	0.9057	42,306	38	9%
2017 Y	0.8615	35,625	40	11%

3.2 The relationship between Vegetation Indices and Rice Yield

Paddy plants at about 80-days after transplanting produced the best relationship between vegetation indices (NDVI and EVI2) and rice yield estimated according to the study of Kurunagala district done by Dammalage et al. (2017). Accordingly, the rice yield is estimated for Polonnaruwa district by using the two models present in equation 3 and 4.

An accuracy assessment was performed for Polonnaruwa district for over six seasons to determine the accuracy and reliability of estimations provided by the yield forecasting models, using rice yield data obtained from the Department of Census and Statistics in Sri Lanka. Table 2 presents the accuracy of the estimations, and the results demonstrate the reliability of yield estimations provided by each model based on remote sensing data.

Table 2. Accuracy of yield forecasting models with national statistical data

Yield Forecasting Models after 80 days		Yield Accuracy (model/crop cutting) ×100%				
		14/15 M	2015 Y	15/16 M	2016 Y	16/17 M
NDVI	$y = 2391e^{0.6862x}$	73.23	77.83	79.02	79.41	78.22
EVI2	$y = 1410e^{2.295x}$	72.93	90.62	81.60	94.41	78.85

*y represents rice yield (kg per hectare) and x represents corresponding vegetation index or related yield forecaster.

After 80 days, NDVI gives an overall accuracy of 77.54% while that of the EVI2 model gives an overall accuracy of 83.68% for all the five seasons. However, the R^2 of models between estimated and reference yield data is 0.89 for NDVI, and 0.27 for an EVI2 model derived at 80 days. Thus, estimations provided at this time were highly correlated with reference yield data in NDVI model, but accuracy of that model was lesser than EVI2. The EVI2 model has high accuracy, but not highly correlated.

Table 3 presents the comparison of cultivated paddy area identified by Landsat 8 and MODIS data. According to the classification accuracy analysis with ground truth data, the identified cultivated area by Landsat 8 was more accurate than MODIS. However, these data still carry an issue due to the challenges of classification and paddy area identification.

Table 3. Comparison of Identified Paddy cultivated area

Season	Landsat 8 OLI/TIRS	MODIS
2014/15 M	No images	65,756
2015 Y	67,223.61	54,513
2015/16 M	No images	57,650
2016 Y	54,847.53	49,731
2016/17 M	47,185.47	42,268
2017 Y	36,739.80	35,625

Table 4 presents the accuracy analysis of estimated total rice yield by NDVI after 80-days and EVI2 after 80-days models. Therefore, the total paddy cultivated extent was calculated from the Landsat 8 images and estimated total yield. According to Table 4, the NDVI model offers an accuracy closer to crop cutting survey method, but the EVI2 model gives better results than the crop cutting survey method. Hence, these two models are applicable for estimations if the reference yield data are assumed as correct. Besides, for the accuracy as crop cutting survey, can replace this NDVI after 80 days model because one month before harvesting can estimate rice yield near to crop cutting survey accuracy. Therefore, it is not necessary to wait until the crop cutting survey.

Season	Reference total yield (MT)	Estimated by NDVI after 80 days model (MT)	Estimated by EVI2 after 80 days model (MT)	Accuracy (model/crop cutting) ×100%	
				NDVI After 80 days	EVI2 after 80 days
2015 Y	280,476	268,470.049	312,556.336	95.70	over production
2016 Y	251,131	219,826.870	261,353.471	87.53	over production
2016/2017 M	214,722	187,489.516	189,029.050	87.32	88.03
2017 Y	173,595	143,881.257	173,033.421	82.88	99.68

Table 4. Accuracy analysis of total rice yield production by models

The total estimation of an EVI2-based model was higher than the crop cutting survey output. Therefore, it is also applicable here, but further investigations are necessary to analyse the accuracy of the total yield production. More assessments are required to confirm the accuracy of the reference data before using that model for further analysis, as such testing was hindered by limited time allocation.

4. CONCLUSION

The cultivated paddy fields in Polonnaruwa district were identified in this study, using time series satellite imagery and high spatial resolution imagery analysis. This imagery was generated from the 250m resolution MODIS (terra) spectral surface reflectance (MOD09Q1) data acquired from 2014 to 2017, and 30m resolution Landsat 8 OLI/TIRS data obtained from 2015 to 2017.

The algorithm to identify the cultivated paddy fields was developed based on high spatial resolution images of paddy cultivation. This developed algorithm retains the capacity to find out the beginning time of paddy cultivation though it varies from one location to another. Average accuracy was produced in 99.9% cases of the identification process in cultivated paddy lands. However, the cultivated paddy land identification process using Landsat 8 images was still doubtful. Hence, the area has to be analysed to detect whether the paddy area was cultivated (or not) in that particular season. Therefore, it could be possible to visit the field and check or collect district-wise paddy statistics for that specific season and collect the field verifications done by the irrigation department of the district. However, the accuracy of this algorithm can be improved by using high temporal resolution images. Therefore, combined results were used to estimate the rice yield. A unique threshold value to identify the cultivated paddies could not be discovered during this study. This method can be successfully applied to detect any cultivation with unique temporal dynamics.

Both Landsat and MODIS have issues; therefore, recommending one method for this analysis is by using drones that can capture high spatial and temporal resolution images. The process is to send the drone above the paddy fields and obtain the imagery with high temporal and spatial resolution. By analysing those images according to their requirements, it may be possible to find cultivated paddy lands accurately and modify the models for the estimations. Many rice yield estimation models have been developed based on various methods at different stages of paddy growth. However, both NDVI and EVI2-based models provide more accurate yield estimations at 80 days after transplanting. Rice

yield estimation models are usually variety-dependent. However, these models are variety-independent, and hence, do not consider the rice variety. One of the important influence factor of the growing stage is rice variety. Different varieties may need to be cultivated on different days after transplanting, demand various weather factors and have varied water requirements. Therefore, considering the rice variety may produce a higher accuracy. Preferably, the tested NDVI and EVI2 models after 80 days are suitable for large areas of paddy cultivations; they are unsuitable for small patches. These models were initially tested in the Kurunegala district and then in Polonnaruwa district because of the availability of substantial paddy regions. They were not be suitable for whole country estimations. Hence, rebuilding the models to suit the entire country needs considering many additional factors.

The R^2 of linear models between estimated and reference yield data is 0.89 for NDVI, and 0.27 for an EVI2 model derived at 80 days. Thus, estimations provided at this time were highly correlated with reference yield data in NDVI model, but accuracy of that model was lesser than EVI2. The EVI2 model has high accuracy, but not highly correlated. Finally, it can be concluded that the model based on EVI2 values is the best model for rice yield forecasting using satellite imagery (This study was only based on NDVI and EVI2 indices). Therefore, rice yield can be accurately forecasted, approximately one month before harvest with considerably higher accuracy.

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