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

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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ABSTRACT

In Sri Lanka, a conventional method named the Crop-cut survey is currently used to estimate the seasonal rice production. However, it fails to predict rice yield before the harvest as it is conducted during the harvest. Therefore, this study focuses on testing rice yield estimation models based on satellite remote sensing data. Landsat 8 OLI/TIRS images (30m spatial resolution) from Earth Explorer and 8-day composite images (250 m spatial resolution) from Moderate Resolution Imaging Spectro-radiometer (MODIS) sensor onboard NASA EOS Terra/Aqua satellite from 2014 to 2017 were used. Cultivated paddy lands were identified by land cover classification, using field-training samples and Landsat 8 OLI/TIRS data. In addition, the temporal change of Normalised 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,

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based on NDVI and EVI2 (Enhanced Vegetation Index) indices obtained through MODIS surface reflectance images of Polonnaruwa District. Both NDVI and EVI2-based models derived after about 80-days of transplanting provide more reliable estimations with compared to national statistical records. Nevertheless, the EVI2-based model provides more reliable estimates than the NDVI-based model with 83.7% average accuracy. Therefore, the rice yield can be successfully estimated for each season before one-month to 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 [1]. According to the reports of the Food and Agriculture Organization, rice was cultivated for about 11.5% of the World's arable land area during 2012. The annual average consumption of rice per capita was ~65 kg during 2010- 2011 [1]. It further records that rice provides almost 19% of the global dietary energy [2]. Accordingly, Rice is considered to be one of the most important crop/food. Hence, cultivated area identification and forecasting of its production are vital for global food security. Paddy occupies approximately 37% (0.77 million ha) of the cultivated land area of Sri Lanka [3]. It is cultivated during two major seasons, *Yala* and *Maha*. Flooding and transplanting of the *Yala* season can alter from the end of March to mid-May. Similarly, *Maha* season can alter from the end of September to mid of December. Approximately 1.8 million farmer families depend on paddy farming throughout the country, and the demand for paddy in Sri Lanka increases at a rate of 1.1% per year, which necessitates the production to grow annually at a rate of 2.9% [3]. Sri Lanka produced around 2.9 million tons of paddies during the 2015/2016 cultivation season [3].

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

Satellite remote sensing based crop-yield prediction has already represented a very active field of research and application [4]. Satellite and drone- based remote sensing technologies are now capable of providing researchers with cost-effectiveness and timely 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 substantial time to harvest is vital for strategic planning and for proper decision-making regarding seasonal crop production. For instance, proper imports in a shortfall case or arrange exports in a surplus case and import-export policies can be materialised based on such reliable yield estimations [6]. Due to the significant advantages of the pre-harvest yield valuation method, it is essential to focus on highly efficient data acquired based on remote sensing technologies to build reliable yield estimating models [7].

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 of 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 [8]. 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 use and validate the MODIS images-based rice yield estimation models proposed by Dammalage et al. [12] for Kurunagala District, Sri Lanka. In addition, this study uses Landsat 8 OLI/TIRS images to identify the paddy cultivated area and determine the best age of paddy plants for yield forecasting in Polonnaruwa district.

2. STUDY AREA, MATERIALS AND METHODS

Polonnaruwa district is situated in a plain valley of Mahaweli river in the North Central Province of Sri Lanka and 216 kilometres away from Colombo. It is located between the Northern latitude 7’40” – 8’ 21” and Eastern longitude 80’ 44” – 81’ 20”, and at an elevation of 50-500 meters. The selected study area indicated in Fig. 1, is one of the major paddy cultivation regions in Sri Lanka. According to the 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. Throughout the district there are 04 major reservoirs, 03 middle scale reservoirs, 62 functioning small- scale reservoirs, 35 defunct small- scale reservoirs, to provide required water resources for agriculture and other basic needs. Average annual rainfall is 1000 mm – 1500 mm and the average temperature ranges from 24°C (minimum) – 31°C (maximum).

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 the year 2014 to 2017 for six cultivation seasons. This product consists of 30 m spatial resolution without a suitable temporal resolution from paddy growth analyses. Cloud images were frequent during the *Maha* season. In 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. Also, this study used the MODIS surface reflectance 8-Day L3 Global 250 m (MOD09Q1) image product, which is a composite using eight consecutive daily 250 m images (MOD09Q1) from 2014 to 2017. Rice yield and paddy area statistics for 2014 to 2017 were obtained from the Census and Statistics Department of 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 250 m surface reflectance band 1 (620-670 nm), band 2 (841-876 nm), and band quality data sets.

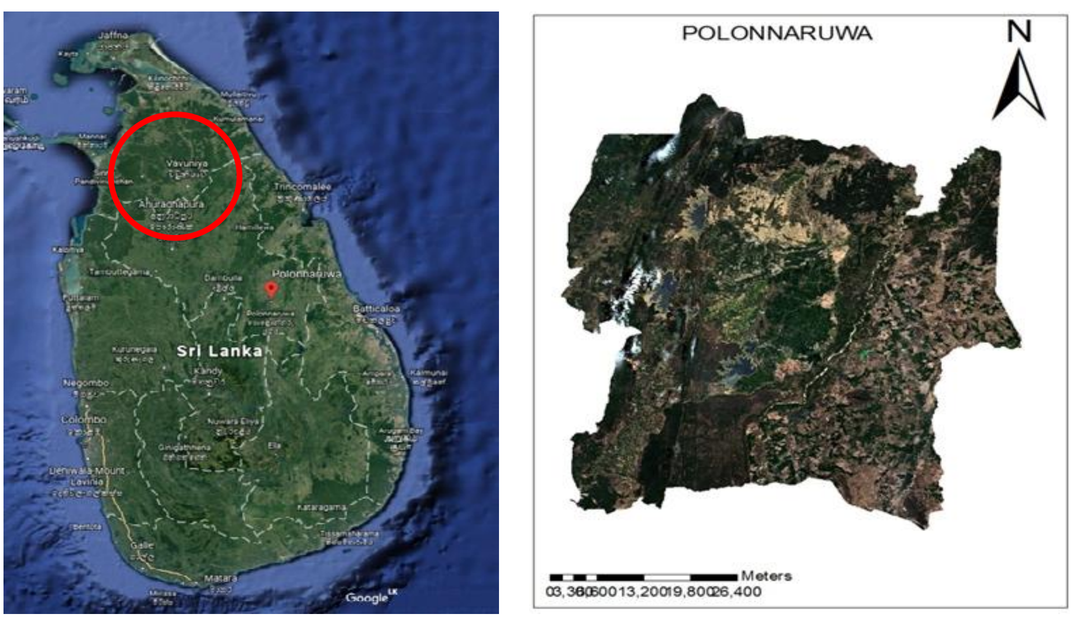

Fig. 1. Location of the study area (Polonnaruwa district) in Sri Lanka with a subset of the Landsat 8 true colour bands combination, acquired in 2017 from earth explorer

2.2 Vegetation Indices

The Normalized Difference Vegetation Index (NDVI) gives several measures of the vegetative cover on the land surface over extensive areas. The imagery strongly points out the dense vegetation and visibly identifies the areas with little or no vegetation [9]. NDVI also recognises water and ice. The NDVI values were calculated based on Landsat 8 OLI/TIRS images by using NIR band-5(0.845-0.885 μm) and Red band-4 (0.630-0.680 μm) in ENVI software. NDVI values were assigned for each feature by 2017 *Yala* 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.

Healthy vegetation shows strong absorption in the red wavelength region of the spectrum (reflectance of around 3-5%) and weak absorption in the NIR portion (reflectance around 40 - 60%) [10]. Hence, the red and NIR bands of MODIS images are used to calculate NDVI. The MOD09Q1 images calculated NDVI from the equation 1, using 250 m surface reflectance band 1 (620-670 nm) and 250m surface reflectance band 2 (841-876 nm).

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

Enhanced Vegetation Index (EVI) provides enhanced sensitivity in high biomass regions while minimising soil and atmospheric influences than NDVI [11]. The main limitation of EVI is that it utilises blue band in addition to the red and near-infrared bands. Jiang et al. [13] developed and evaluated a further improved 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.

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

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 contained the 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 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 was high or low.

2.4 Cultivated Paddy Field Identification

The basic statistics of the maximum likelihood classification was used to identify the paddy cultivated area or the extent, and subsequently, it is possible to detect the accuracy of the census and the data of statistics department (reference data) regarding the extent of paddy cultivation. The NDVI values were calculated using equation 1 for all the selected images. Before calculating the correlation coefficients, NDVI temporal profiles were smoothed using the ‘moving average’ method. As suggested by Dammalage et al. [12], correlation coefficients between NDVI changing pattern of normal paddy cultivation and smoothed profiles were calculated, and ten correlation coefficients were calculated for one smoothed NDVI temporal profile. By equalising the total paddy area identified by this algorithm and census data, a suitable threshold value for the correlation coefficient was then selected to extract the cultivated paddy pixels. 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. To verify the identification process, Google earth and field data were used to randomly validate the identified paddy pixels. 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. [12] have proposed several yield estimation models for Kurunegala district using MODIS data. In their study, the paddy cultivated lands from 2007 to 2014 in Kurunegala district were identified using time-series 250 m spatial resolution MODIS satellite imagery data (MOD09Q1). They have proposed,the linear and exponential relationship between vegetation indices and rice yield. A number of rice yield forecasting models were built based on average NDVI, maximum NDVI, cumulative NDVI and average EVI2 at different age of paddy plants commencing from 32 days after transplanting. According to their analysis, the paddy plants of about 80 days after transplantation gave the best relationship between rice yield and tested vegetation indices. However, the yield forecasting models derived based on EVI2 values showed higher R^2 values of correlation than NDVI based models.

Cumulative NDVI based models reflected 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 provided higher correlated yield estimations at the paddy age of 80 days after the transplanting. The R^2 of models between estimated and reference yield data was 0.82 and 0.96 for NDVI and EVI2 model derived at 80 days respectively. 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.

$$y = 2213e^{0.8498x} \tag{3}$$

$$y = 1603e^{2.0827x} \tag{4}$$

Where,

y - Rice yield (kg per hectare)
x - Corresponding vegetation index

3. RESULTS AND DISCUSSION

3.1 Identification of Cultivated Paddy Fields

The temporal pattern of NDVI values in the cultivated paddy lands based on the field samples were identified for each season. A 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 the end of August were used for the analysis. 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 were 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. Fig. 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.

The training samples 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). The same method was used for all the other seasons to classify the cultivated paddy lands of that specific season in the study area. A suitable threshold value for the correlation coefficient was selected for each season to identify the image pixels of cultivated paddy lands by equalising the total paddy area recognised by the derived models and census data. Accordingly, the pixels which represent equal of correlation coefficient values greater than the selected threshold values were classified as paddy cultivated lands of the season. The matching pattern was shifted to the right along with the NDVI time series to obtain the highest correlation coefficient value. At certain cultivated paddy land pixels, the resulted correlation coefficient (r) remains high with a maximum value of 0.9 and highly correlated with the matching pattern. Therefore, that pixel is classified as a paddy cultivated pixel for that specific season. By applying the same method, all pixels were classified into two classes as ‘cultivated’ and ‘not cultivated’ paddy lands.

The entire area was classified as paddy and the respective threshold value for the correlation coefficient for each season is listed in Table 1. However, the analysis revealed that identification of a common threshold value distinguishes cultivated paddy lands and other land uses which are complicated to define. The difference between identified paddy area and the statistical records obtained from sensors and statistics department for each season were also tested and are listed in Table 1. The difference was recorded as percentage of difference, and it was maximum for 2015 *Yala* and minimum for 2016 *Yala* season. However, it was recommended to investigate to define a unique threshold value by changing the shape of the matching NDVI pattern by applying smoothing and filtering methods for NDVI time series data. This provides a potential area for future research.

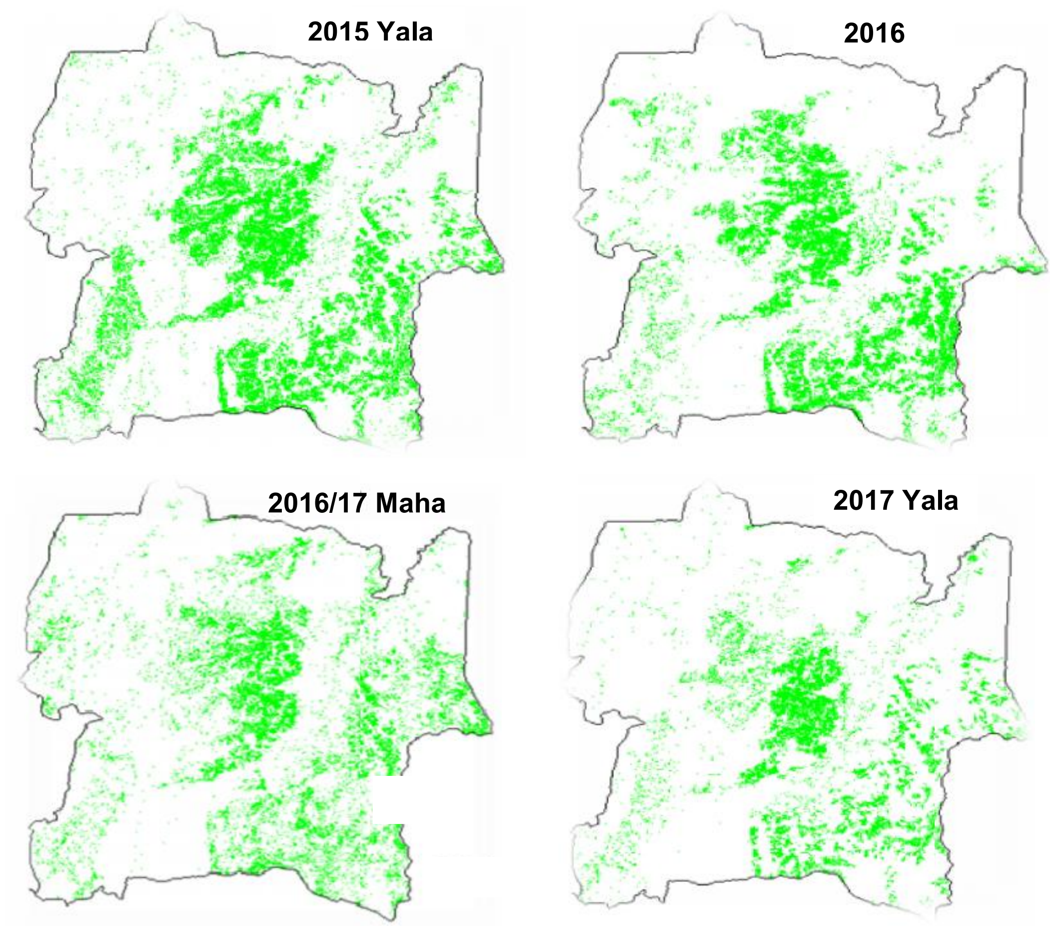

Fig. 2. Landsat 8 OLI/TIRS classified images by maximum likelihood classifier

Table 1. Identified threshold values to classify 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	0.2%
2015 Y	0.8454	54,513	155	0.28%
2015/2016 M	0.8990	57,650	42	0.07%
2016 Y	0.8920	49,731	23	0.05%
2016/2017 Y	0.9057	42,306	38	0.09%
2017 Y	0.8615	35,625	40	0.11%

3.2 The Relationship between Vegetation Indices and Rice Yield

At about 80-days after transplanting paddy plants 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. [12]. Accordingly, the rice yield is estimated for Polonnaruawa district by using the two models present in equation 3 and 4.

An accuracy assessment was performed for six paddy cultivation seasons of Polonnaruwa district 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.

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

Table 3 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 3, the NDVI model offers 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, it 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.

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.

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	$y = 2213e^{0.8498x}$	73.23	77.83	79.02	79.41	78.22
EVI2	$y = 1603e^{2.0827x}$	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*

Table 3. Accuracy analysis of total rice yield production by models

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

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 250 m resolution MODIS (terra) spectral surface reflectance (MOD09Q1) data acquired from 2014 to 2017, and 30 m 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 initiation 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 might 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 model could be increased 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 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 influencing factors of the growing stage is rice variety. Different verities 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 suitable for the country estimations. Hence, rebuilding the models to suit the entire country is essential 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 the accuracy of that model was lesser than EVI2. The EVI2 model has high accuracy, but not highly correlated. When compared to NDVI and EVI based models, EVI2 values-based models were the best for rice yield forecasting using satellite imagery (This study was only based on NDVI and EVI2 indices). Therefore, it can be concluded that rice yield can be accurately forecasted, approximately one month before harvest with considerably higher accuracy.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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