CULTIVATED PADDY AREA IDENTIFICATION AND RICE YIELD ESTIMATION USING FREE SATELLITE IMAGES

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ABSTRACT

An effective pre-harvest rice yield estimation method is truly significant for the assessment of seasonal rice production in terms of strategic planning purposes. In Sri Lanka, a conventional method, crop-cut survey, is used to estimate seasonal rice production and it fails to forecast rice yield before harvest as this experiment is conducted during the harvest. This study is focused on identifying cultivated paddy lands and forecasting rice yield using free satellite data. 8-day composite images (250m spatial resolution) from Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard the NASA EOS Terra satellite were used from 2007 to 2014.

The challenge of identifying the cultivated paddy lands for considerable accuracy with 250m resolution satellite data has overcome with this study by suggesting a new method based on the analysis of temporal dynamics of paddy cultivation. Then linear and exponential yield forecasting models were built at different time intervals of the season based on NDVI and EVI2 vegetation indices. The results indicate that the suggested cultivated paddy lands identification method has the potential to identify cultivated paddy lands with 77% of average accuracy. According to the comparison of estimated yield with national statistical records, both NDVI and EVI2 based models provide more reliable estimations about 80 days after the beginning time of the season, but, EVI2 based model (derived at 80 days) gives more reliable estimations than NDVI based model with 92% average accuracy. Therefore seasonal rice yield can be successfully forecast one month before harvest time using EVI2 based model.

1. INTRODUCTION

The ability to estimate seasonal crop yield before a considerable time period to harvest is truly important to take precautions regarding seasonal crop production. Specially, it is of paramount importance in strategic planning and decision making regarding the food security and facilitation of safe harvest storages. On the other hand, proper import (in shortfall case) or export (in surplus case) policies can be taken based on such reliable yield estimations (Noureldin et al., 2013). Since there are such considerable advantages related with a pre-harvest yield estimation method, it is very significant to focus on the development of modern science and technology in building reliable yield forecasting models. Satellite Remote Sensing can be successfully applied for this particular research area as it is a powerful and effective tool for estimating and forecasting crop yields (Ferencz et al. 2004).

An accurate identification of crop cultivated lands using RS data is imperative before building yield forecasting models. In the case of paddy cultivation, unique physical characteristics (paddy plants are grown on flooded or irrigable soil) and unique temporal dynamics of paddy cultivation help distinguish paddy from other cultivations. Temporal dynamics of paddy cultivation can be characterized by three main periods; the flooding and rice transplanting period, the growing period (vegetative growth, reproductive and ripening stage) and the fallow period after harvest (Toan et al., 1997). The time dependent relationship between Land Surface Water Index (LSWI) and Normalized Difference Vegetation Index (NDVI) or Enhanced Vegetation Index (EVI) at the period of rice flooding and transplanting can be used to identify flooded pixels (Xiao et al., 2005a) and then paddy cultivated pixels can be isolated by applying water and forest mask or analyzing the changing pattern of vegetation index values (Xiao et al., 2002b, 2002c, 2005b; Lio et al., 2011). However, it has been posed a great challenge for remote sensing analyses at large spatial scales (Xiao et al., 2005b) since individual farmers follow diverse flooding and transplanting schedules in their paddy rice fields.

For yield prediction and estimation of crops, it is necessary to achieve a very high accuracy and reliability. This is being why even after a relatively long time (more than 20 years), no routine yield estimation method for a wide range of operational applications has been developed (Ferencz et al. 2004). But, considerable developments in this field have been achieved at present with the access of higher amount of free satellite data (MODIS, Landsat etc.). Before beginning a new experiment in this field, it is indispensable to study the results obtained from the previous experiments because considerable differences can be discovered among diverse experimental findings. For instance, some experiments have discovered a linear relationship between rice yield and vegetation indices (Cheng & Wu 2010) whereas some have showcased an exponential relationship (Nuarsa et al. 2011). One of the most important issues to be addressed by yield forecasting experiment is when the best relationship has occured between rice growth parameters and rice yield. For this issue, various solutions have been obtained by different experiments. According to an experiment conducted in Indonesia using Landsat ETM+ data, it had been disclosed that the best age of a paddy plant for yield prediction is after 63 days from the transplanting time period (Nuarsa et al. 2011). Another experiment conducted in Egypt had identified that the best age for yield prediction is after 90 days from paddy transplanting. (Noureldin et al. 2013). The factors such as soil attribute variations, climatic conditions, plant species varieties and different agricultural practices from one area to another have caused these diverse results. Thus, yield estimation models developed or tested locally are compatible solely for local use (Shresthan and Naikaset, 2003) and not for global use.

In Sri Lanka, rice yield estimation procedure is still based on a conventional and manual method called “the crop cutting survey on paddy”. It has failed to forecast rice yield before harvest because the crop cutting survey is conducted during the harvest time period. This method is often subjective, costly, laborious and time-consuming. According to this traditional method, yield can be only estimated during the harvest and it is prone to large errors due to incomplete ground observation. On the other hand, without the fullest cooperation of the selected farmers, it is truly difficult to conduct the experiment effectively. The main objective of this study was to check the potential of applying remote sensing technology for rice yield estimation and forecastin using MODIS satellite data by tarnishing the above mentioned draw backs in the present system. The main objective was achieved with the specific objectives of identifying paddy cultivated lands in each season (Yala and Maha) using satellite data and determining the best age of paddy plant for yield forecasting.

2. STUDY AREA, MATERIALS AND METHODS

2.1 Study Area

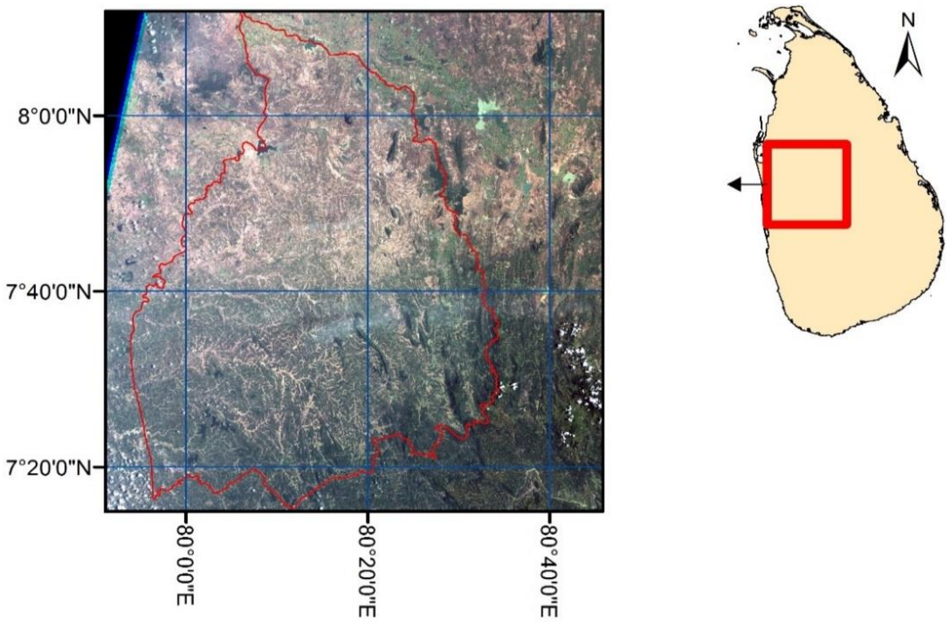

Figure 1. Spatial extent and location of the study area (Kurunegala district) in Sri Lanka with a subset of the Landsat 8 true color bands combination, acquired in 2015.

The study area encompassed Kurunegala district (total area - 481,600 hectares) in the North Western Province, Sri Lanka which provides a higher contribution for the total rice production in the country. According to the data released by Census and Statistics Department in Sri Lanka, its average paddy cultivated area is about 61,000 hectares and average rice yield was 3,775 kg per hectare from 2007 to 2014. The climatic condition of the study area is tropical with major changes in weather occurring during the monsoons from May to August and October to January. In these specific time periods, heavy rains can be expected. As a result of these two rainy seasons, two rice crops per year (Yala and Maha) are common in this region. Landsat 8 view of the area is given by the figure 1.

2.2 Satellite and Rice Yield Data

MODIS Surface Reflectance 8-Day L3 Global 250m (MOD09Q1) Product was used in this study. This product is a composite using eight consecutive daily 250 m images (MOD09GQ). The "best" observation during each eight day period, for every cell in the image, is retained. This has helped reduce and eliminate clouds or cloud shadows from a scene (The Center for Earth Observation, 2010). MOD09Q1 data products from 2007 to 2014 were freely downloaded from the USGS EROS Data Center (http://edc.usgs.gov/). This product contains three science data sets which are 250m surface reflectance band 1 (620-670 nm), 250m surface reflectance band 2 (841-876 nm) and 250m reflectance band quality data set.

Rice yield data and other required paddy statistics from 2007 to 2014 were obtained from Census and Statistics Department, Sri Lanka.

2.3 Vegetation Indices.

In order to minimize the effect on the canopy radiometric response, the factors such as optical properties of the soil background, illumination and view geometries, meteorological factors (wind, cloud) as well as single-band reflectance are combined into a vegetation index (Leblon, 1997). Vegetation Indices (VI) are the measures of vegetation "greenness" obtained by combining the results of measurements of surface reflectance of the vegetation canopy in different spectral bands. Their work is based on the principle that vegetation reflects different amounts of electromagnetic radiation in different spectral bands (Guzinski, 2010). However, vegetation indices are not indicative of one particular physical property of the vegetation, but they represent a combination of a number of properties such as leaf chlorophyll content, canopy cover and architecture or leaf area (Jiang et al., 2008). An ideal vegetation index must be able to distinguish the plant canopy conditions from background soil.

There are a number of different vegetation indices improved by researchers. The most commonly used vegetation indices include ratios of single-band or linear combined reflectance. This study was based on NDVI and EVI2 vegetation indices which are calculated by using red and near infrared bands.

NDVI

The first ratio-based vegetation index was the Reflectance Ratio or Ratio Vegetation Index (RVI) which is the ratio between near infrared and red bands (Pearson and Miller, 1972). Rouse et al. (1974) improved the ratio vegetation index and defined the Normalized Difference Vegetation Index (NDVI). It is too based on red and near infrared spectral bands. Those two bands are used 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%) (Gitelson, 2004).

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{1}$$

EVI2

The Enhanced Vegetation Index (EVI) (Huete et al., 1999) was developed as a standard satellite vegetation product for the Terra and Aqua Moderate Resolution Imaging Spectroradiometers (MODIS). EVI provides improved sensitivity in high biomass regions while minimizing soil and atmospheric influences. The major limitation of EVI is that it utilizes 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.

$$EVI2 = 2.5\frac{NIR - RED}{NIR + 2.4RED + 1} \tag{2}$$

2.4 Cultivated Paddy Fields Identification

Basically, there are two main paddy cultivation seasons in the study area called Yala and Maha. The beginning of the Yala season (flooding and transplanting) can alter from end of March to mid of May. Similarly, Maha season can vary from end of September to mid of December. Thus, it is distinct that there is no any exact time location which can be used as the exact beginning time of a particular season. Therefore, 24 composites (covering the whole season) for each season were taken for time series analysis.

Then NDVI values for all images were calculated using equation 1. Before calculating correlation coefficients, NDVI temporal profiles were smoothed using "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 by moving matching pattern along the NDVI temporal profile as illustrated in the figure 2. Then an appropriate threshold value for correlation coefficient was selected to extract cultivated paddy pixels by equalizing the total paddy area identified by this algorithm and census data. The pixels which included higher correlation coefficient values than threshold values, were classified as paddy cultivated lands. After that, a few pixels (identified as paddy) were randomly taken for verification of the classification result. In verification process, randomly selected paddy pixels were compared with Google earth to determine whether those pixels are truly paddy or not. This method was applied for all the other seasons to identify cultivated paddy lands in the study area.

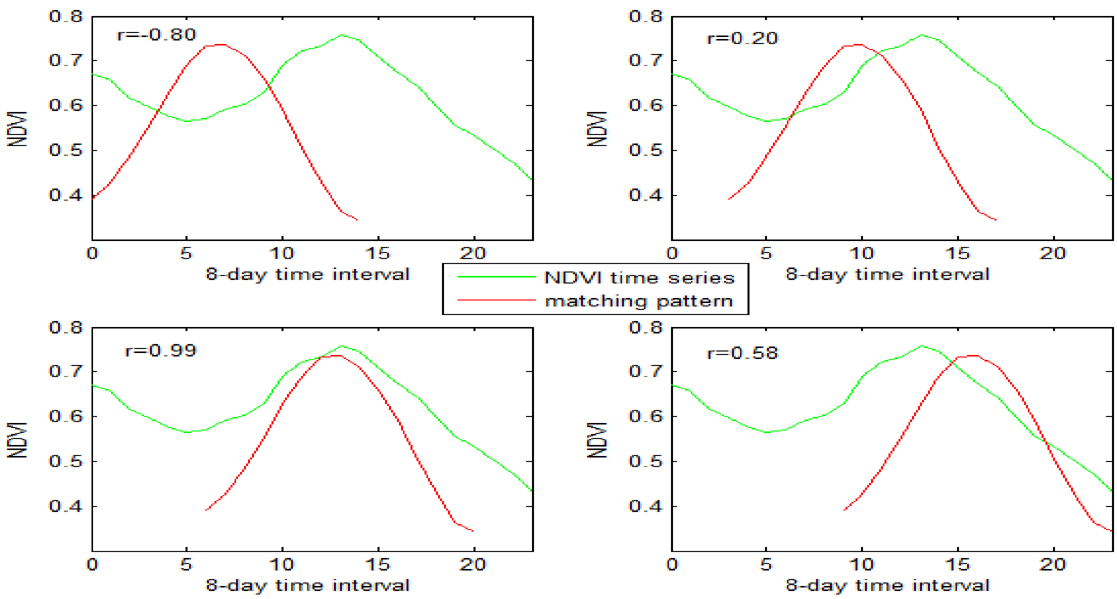

Figure 2. The cultivated paddy lands identification process by moving matching pattern (Red) along a NDVI temporal profile (Green) derived from MODIS 8 day composites data.

As illustrated in the figure 2, correlation coefficient (r) has taken a higher value at some points when the specific NDVI time series corresponded to a cultivated paddy land. Required seasonal parameters were obtained based on the number of times that the matching pattern was shifted to right occurring the highest correlation coefficient value. In the above situation, maximum value of the correlation coefficient is 0.99 and it is highly correlated with the matching pattern. Therefore that pixel is classified as paddy cultivated pixel. Using this method, all pixels were classified into two classes as paddy cultivated and not cultivated lands.

2.5 Building Rice Yield Forecasting Models.

The average NDVI and EVI2 values for all pixels identified as paddy were calculated with different time intervals of paddy growth for all seasons from 2007 to 2014 (14 seasons). Then the relationship between calculated average vegetation indices values and rice yield for six different stages of paddy growth with a 16 day time interval was calculated using average rice yield data from 2007 to 2012. Remaining average rice yield data from 2013 to 2014 were used to perform the accuracy assessment of built up models. Accuracy assessment results obtained from linear and exponential models were compared to identify the best method to represent the relationship between rice yield and vegetation indices. By analyzing the value of determinant of coefficient (R^2) corresponding to each model and also utilizing remote sensing data, the most suitable time period of paddy growth to forecast rice yield was identified. Apart from the above mentioned methods, another rice yield forecasting model was developed by taking seasonal average cumulative NDVI (ΣNDVI) values of paddy growth. Cumulative NDVI values were calculated in two different methods. In the first method, the area traced out by the original NDVI temporal profile was calculated. In the second method, the original NDVI temporal profile was smoothed using moving average method and cumulative NDVI was computed by using the smoothed profile.

3. RESULTS

3.1 Cultivated Paddy Area Identification

One of the most significant parts of this study was the identification of cultivated paddy lands in Kurunegala district. It was practically difficult with regard to the complexity of different paddy cultivation practices in a specific area. In expounding on the fact, the amount of paddy cultivated lands changes from season to season and the beginning of flooding and transplanting time can also vary from location to location even for the same season. In overcoming those issues, correlation coefficients between known NDVI pattern of paddy cultivation and NDVI time series have been calculated. The table 1 demonstrates, the interdependency between the amount of area identified as paddy and the threshold value for correlation coefficient. According to the table 1, there is no unique or common threshold value which can be used to distinguish cultivated paddy lands from other land uses. However, by changing the shape of the matching NDVI pattern and smoothing and filtering methods of time series data, a unique threshold value can be discovered and it provides food for thought for further studies.

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

Season	Threshold for correlation coefficient	Total amount of area identified as paddy (hectares)	Net harvested area (hectares)
2007/08 Maha	0.938	75050	75243
2008 Yala	0.889	67969	68188
2008/09 Maha	0.985	76206	76812
2009 Yala	0.875	46088	46516
2009/10 Maha	0.978	71381	68023
2010 Yala	0.943	55125	56386
2010/11 Maha	0.855	79494	80206
2011 Yala	0.943	66600	67458
2011/12 Maha	0.962	56600	56718
2012 Yala	0.965	14913	15153
2012/13 Maha	0.946	80581	80851
2013 Yala	0.920	51631	52300
2013/14 Maha	0.984	55156	55480
2014 Yala	0.942	51924	52587

Figure 3 shows the spatial distribution of cultivated paddy fields from 2007 to 2014 in Kurunegala district at 250m spatial resolution. Paddy rice agriculture sporadically occurred throughout the study area because increased complexity of topography and land-use restrict the size of the rice fields that can occur. Most of paddy fields are not continuously cultivated each and every season and it basically depends on the weather condition and individual farmers aspects. However, the main factor which is controlling the paddy cultivation is the water availability for paddy growth. This can be clearly observed by studying the spatial distribution of paddy cultivated lands in less harvested seasons like 2012 Yala season (Figure 3-j), because in that kind of situation paddy cultivated lands have concentrated around major water tanks which have capability of supplying the necessary water requirement of the paddy cultivation.

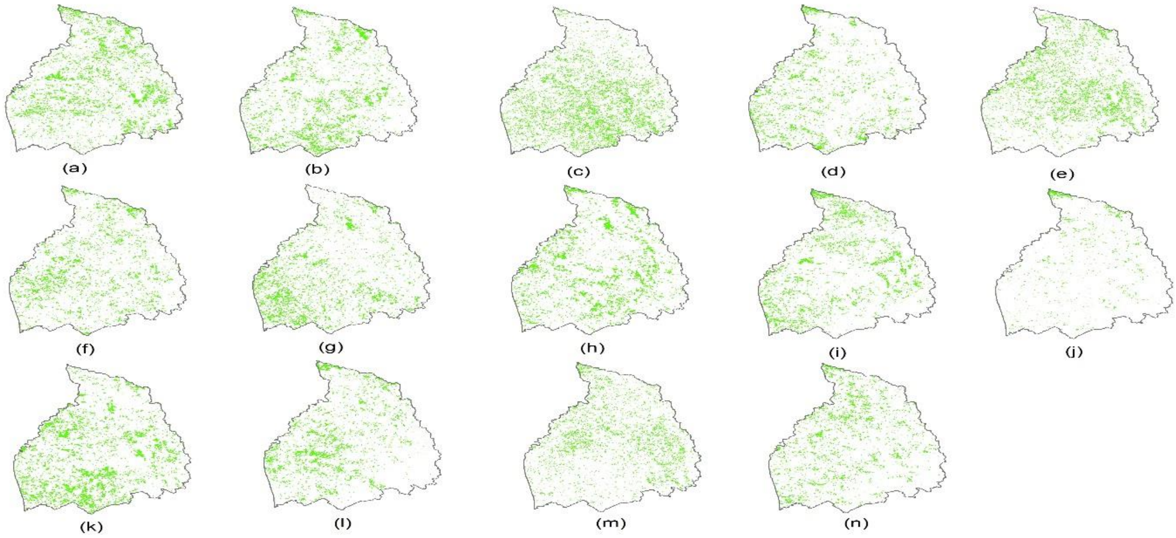

Figure 3. Spatial distribution of cultivated paddy fields (Green color) in Kurunegala district as derived from the analysis of MODIS 8 – day surface reflectance data (at 250m spatial resolution) from (a) 2007/08 Maha season to (n) 2014 Yala season.

3.2 Accuracy Assessment of Identified Paddy Lands.

Randomly selected sample points from six different seasons were utilized for this process. Accuracy assessment results are given in the table 2.

Table 2. Accuracy assessment results of cultivated paddy area identification process

Season	No of sample points (Classified as paddy)	Actual land use		Accuracy
		Paddy	Other	
2008 Yala	25	18	7	72%
2009/10 Maha	25	19	6	76%
2010/11 Maha	25	18	7	72%
2012 Yala	25	21	4	84%
2012/13 Maha	25	19	6	76%
2014 Yala	25	20	5	80%

According to the accuracy assessment result, cultivated paddy area identification algorithm has been effectively implemented and it has produced reliable results. Most of points which are classified as “Other” in the table 2 are located near large paddy fields. Thus, they are represented in the image as a mixed pixel which contains higher amount of paddy cultivation. The main reason for such a problem is the low spatial resolution (250m) of MODIS09Q1 data product. As a result of this low resolution, some lands which are located near large paddy lands may be represented as a paddy pixel in the image. On the other hand, small paddy fields which are surrounded by another land use may not be represented by a paddy pixel in the image. There by, the total area identified as paddy may be equal to the real amount as the mixed pixels problem tends to be canceled itself. However, cultivated paddy lands may be precisely isolated if high resolution images are utilized.

3.3 Relationship between Vegetation Indices and Rice Yield

A number of rice yield forecasting models have been built up based on NDVI and EVI2 vegetation indices at different age of paddy starting from a rice age of 32 days. Figure 4 shows how determinant of coefficient (R^2) values of derived linear models change with the age of the paddy plant. The trend of R^2 slightly decreased from the age of 32 days to 64 days, then it has reached its maximum value at the age of 80 days and again it decreased until the harvest time. Based on this 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 in most of stages, yield forecasting models which are derived based on EVI2 index have higher R^2 values than NDVI based models.

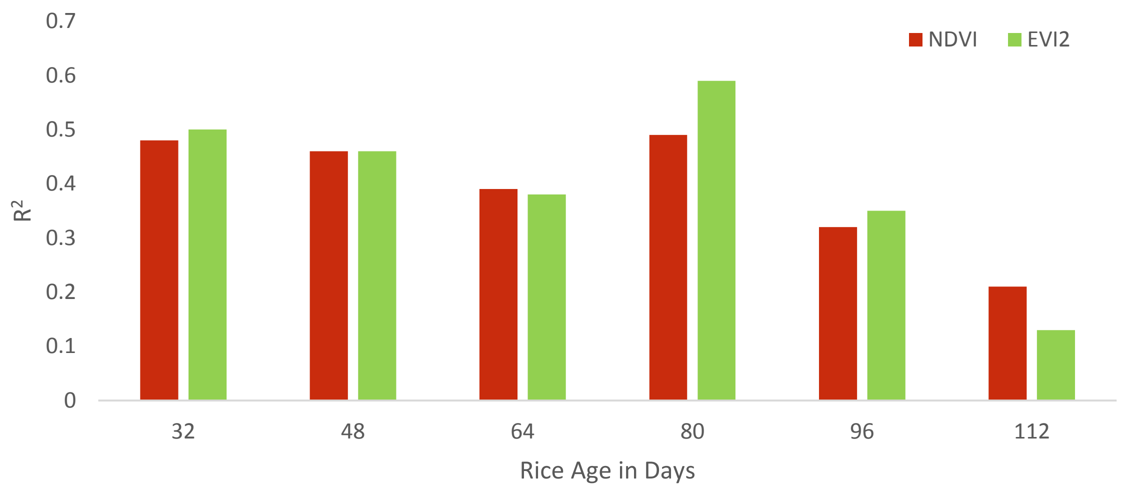

Figure 4. The relationship between rice age and Determinant of Coefficient (R^2) values of linear yield forecasting models which have been derived based on NDVI or EVI2 vegetation indices.

Linear and exponential relationship between rice yield and vegetation indices have been studied based on four different methods; average NDVI, maximum NDVI, cumulative NDVI and average EVI2. Yield forecasting models that have given more reliable results in each method have been tabulated in Table 3. R^2 values of linear models are always greater than that of exponential models and it demonstrates that a linear relationship is more suitable to model the relation between rice yield and vegetation indices.

To determine the accuracy and reliability of estimations provided by yield forecasting models, an accuracy assessment has been done for four seasons by using rice yield data provided by the Department of Census and Statistics in Sri Lanka. The accuracy of the estimations are given in table 3 and those results have shown the reliability of yield estimations provided by each model which are based on remote sensing data.

Table 3. Different type of rice yield forecasting models and a comparison of their forecasting results with national statistical data.

Forecaster	Model*	R^2 value	Accuracy (model/crop cutting)×100%			
			12/13 Maha	2013 Yala	13/14 Maha	2014 Yala
NDVI after 80 days	$y = 2542x + 2087$	0.49	81.19	96.41	94.44	94.18
	$y = 2391e^{0.6862x}$	0.47	81.21	96.46	94.39	94.32
NDVI maximum	$y = 6685x - 1816$	0.36	80.77	93.59	92.27	99.36
	$y = 825.2e^{1.817x}$	0.35	80.75	93.76	92.15	99.45
Normal cumulative NDVI	$y = 152.3x + 2297$	0.55	75.78	91.77	92.64	95.19
	$y = 2532e^{0.0410x}$	0.53	75.68	92.15	92.49	95.34
Smooth cumulative NDVI	$y = 147.1x + 2370$	0.56	77.78	92.12	94.24	94.47
	$y = 2580e^{0.0397x}$	0.55	77.65	92.46	94.12	94.64
EVI2 after 80 days	$y = 8402x + 174.3$	0.59	83.56	97.32	86.78	93.25
	$y = 1410e^{2.295x}$	0.57	83.77	97.21	86.68	93.45

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

4 CONCLUSION

In this study, cultivated paddy fields in Kurunegala district were identified using time series satellite imagery analysis. This imagery was generated from the 250m resolution MODIS (terra) spectral surface reflectance (MOD09Q1) data acquired from 2007 to 2014. The algorithm for identifying cultivated paddy fields was developed based on temporal dynamics of paddy cultivation. The developed algorithm retains the capacity to find out the beginning time period of paddy cultivation though it alters from one location to another. It showcases 77% average accuracy in cultivated paddy lands' identification process. However, the accuracy of this algorithm can be improved by using high resolution images. A unique threshold value to identify cultivated paddies could not be discovered during this study. This method can be successfully applied to identify any cultivation which has unique temporal dynamics.

A number of rice yield estimation models have been developed based on various methods at different stages of paddy growth. According to the statistical data comparison between linear and exponential models, the best way to describe the relationship between rice yield and related VI (NDVI or EVI2) is fitting those data into a linear model. 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. Therefore, taking the sum of NDVI values in the entire season (from transplanting time to harvesting) is better than taking NDVI values at one fixed stage to build up models since it indicates the condition of paddy growth for the entire season rather than one growing stage. Both NDVI and EVI2 based models provide more accurate yield estimations at 80 days after the transplanting. The R^2 of linear models between estimated and reference yield data is 0.82 for NDVI and 0.96 for EVI2 model derived at 80 days. Thus, estimations provided at this time have highly correlated with reference yield data. 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 forecast approximately one month (4 month paddy) before harvesting.

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