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Paddy Yield Estimation Models Using Satellite Data: A Case Study in Kamburupitiya DS Division

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Abstract

In Sri Lanka, the crop cutting survey method is used to estimate the average paddy yield during the harvesting period, and it has failed to forecast the yield prior to harvesting. This method is time-consuming, expensive and make various errors. The yield prediction is worth to estimate yield before harvesting thousand tonnes of paddy. Satellite Remote Sensing is used to forecast crop yield using images during vegetative growth. The research was conducted in Kamburupitiya Divisional Secretariat (DS) division, Matara District, Sri Lanka, during *Yala* and *Maha* paddy growing seasons. Landsat 8 OLI/TIRS images with 30 m resolution were utilized to develop the paddy yield models using paddy yield records during 2016 to 2020. The simple linear regression models were developed using recorded average paddy yield data of the Kamburupitiya DS division and the average values of respective vegetation indices (Normalized Difference Vegetation Index (NDVI); Green Vegetation Index (GVI); Difference

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Vegetation Index (DVI); Infrared Percentage Vegetation Index (IPVI) and Ratio Vegetation Index (RVI) and reflectance values of three spectral bands (Green (G), Red (R) and near-infrared (NIR)). The validation process was carried out using Mean Absolute Percentage Error (MAPE) as the statistical indicator between modeled and predicted yield. When considering coefficient of determination (R^2) value, MAPE percentage, Durbin Watson statistics values, and Pearson correlation values, the yield model based on the GVI for *Maha* season and NDVI based model for *Yala* season are selected as the best models for paddy yield prediction using Landsat 8 OLI/TIRS imagery. The models will allow authorities to make effective decisions in paddy supply management.

Keywords: Paddy; Remote sensing; Spectral bands; Vegetative index; Yield prediction

Introduction

Rice is a major staple food crop that occupies 34% of the total cultivated lands in Sri Lanka (Department of Agriculture, 2020). Paddy is cultivated in Sri Lanka as a wetland crop in two major growing seasons, *Yala* and *Maha* (Census and Statistics, 2020). Generally, the "crop cutting survey" method estimates the average paddy yield during the harvesting period in Sri Lanka. This method was introduced by the Food and Agriculture Organization of the United Nations (FAO) in 1951(Census and Statistics, 2020). This is done using ground collected data (Census and Statistics, 2020), but crop cutting survey method is time-consuming, expensive, and has the potential to make various errors. Rather than that, it fails to predict the yield before harvesting. Due to unpredictable yield variations, food insecurity and management problems: scarcities and surpluses of paddy yield can happen. Hence, farmers will face issues in trading the products. Therefore, it is essential to forecast the yield of each crop within a considerable time before harvesting.

It leads to making better postharvest management decisions on the organization of the postharvest value chain within the country. This will help to manage the country's national food demand and food security (Bastiaanssen and Ali, 2003). Predicting the yield before harvesting using spatial distribution is a common practice in novel cropping systems. This Spatial analysis for the paddy lands can be applied to manage food security (Xiao *et al.*, 2005). As rice is the country's staple food, the spatial analysis of paddy is highly convenient for Sri Lanka. Satellite remote sensing can be considered an effective tool for estimating and predicting crop yield (Ferencz *et al.*, 2004). Spatial analysis can provide accurate data about land features. Also, these features can be used to identify the growth of the crops (Liu and Kogan, 2002).

Information acquired from the temporal dynamic remote sensing data closely relates to the identification of plant characteristics. Therefore, it can be applied for yield estimation before harvesting. Satellite images play an important role in providing geographical data (Shahbaz *et al.*, 2012). Quantitative and qualitative information is given by satellite and remote sensing images that reduce the difficulty of fieldwork and research time (Vaiphasa *et al.*, 2011). At periodic intervals, satellite remote sensing technologies capture data/images. The amount of data obtained from data centers is immense (Zheng *et al.*, 2013).Vegetation indices are optical measures of the greenness of the vegetation canopy and directly measure the photosynthetic properties. There is a correlation between the vegetation indices, such as NDVI, calculated based on satellite data and crop yield (Cheng and Wu, 2011).

Using satellite data, the maximum vegetative growth period could be the best time for the paddy yield prediction (Noureldin *et al.*, 2013). The vegetation indices can be used as a yield estimation tool before harvesting (Rasmussen, 1997). Vegetation Indices obtained from canopies based on remote sensing are quite simple and accurate algorithms. It is used for quantitative and qualitative purposes, such as evaluating the vegetation cover and growth dynamics (Xue and Su, 2017). Vegetation indices extracted from this light spectrum range can be attributed to several features outside plants' growth and vigor quantification. The indices are related to water, protein, sugar, pigment, carbohydrate content and aromatic content of crop (Foley *et al.*, 1998);(Batten, 1998).The NDVI is sensitive to the vigor of green vegetation. It is calculated using the visible and NIR light reflected by the target surface. Several studies have found that NDVI performs better in estimating Leaf Area Index (LAI), biomass and other vegetation characteristics when the amount of vegetation increases gradually to a certain value (Major, *et al.* 1990). The DVI is very sensitive to soil context changes. It can be used to detecting the ecological environment of foliage, hence, it is called as "Environmental Vegetation Index (EVI)" (Richardson and Wiegand, 1977). According to the previous studies, the green leaf Chlorophyll absorbed 80–90% of light in the Blue (B) or R portions of the spectrum (Gitelson *et al.,* 2003);(Xiao *et al.*, 2005).

The R and NIR band were found to be the most appropriate portions of the Electro-Magnetic Spectrum (EMS) for assessing crop conditions and biomass. The R spectral interval corresponds to the region of maximum chlorophyll absorption and the NIR spectral interval corresponds to the region of maximum reflectance of incident light by living vegetation (Rouse *et al.*, 1973). Information acquired from the temporal dynamic remote sensing data has a close relationship with the identification of plant characteristics. Therefore, it can be applied to yield estimation before the harvesting. Visible R, G and B bands and NIR regions of the electromagnetic spectrum are successfully used to monitor crop cover and crop yield (Magri *et al.*, 2005);(Baez-Gonzalez *et al.*, 2005). Shanmugam and Dammalage (2018) developed NDVI and EVI2 based models to forecast the paddy yield to the Polonnaruwa district of Sri Lanka.

This study was focused to develop the paddy yield estimation models using satellite data. The objectives of this were to identify the paddy cultivated areas in Kamburupitiya Divisional Secretariat (DS) division using satellite images, calculate the different vegetation indices and reflectance values of G, R and NIR spectral bands of paddy cultivation and validate the developed crop yield models from observed paddy yield data.

Materials and Methods

The research was conducted in Kamburupitiya DS division, Matara district, Sri Lanka during two paddy growing seasons (*Yala* and *Maha*). It is located in Southern province and its geographical coordinates are 6° 5' 0" North, 80° 34' 0" East. Kamburupitiya DS Division (68 km^2 land area) consists 38 Grama Niladhari (GN) Divisions. It provides a significant contribution to the total rice production in Matara District. The Figure 1 shows the map of the study area.

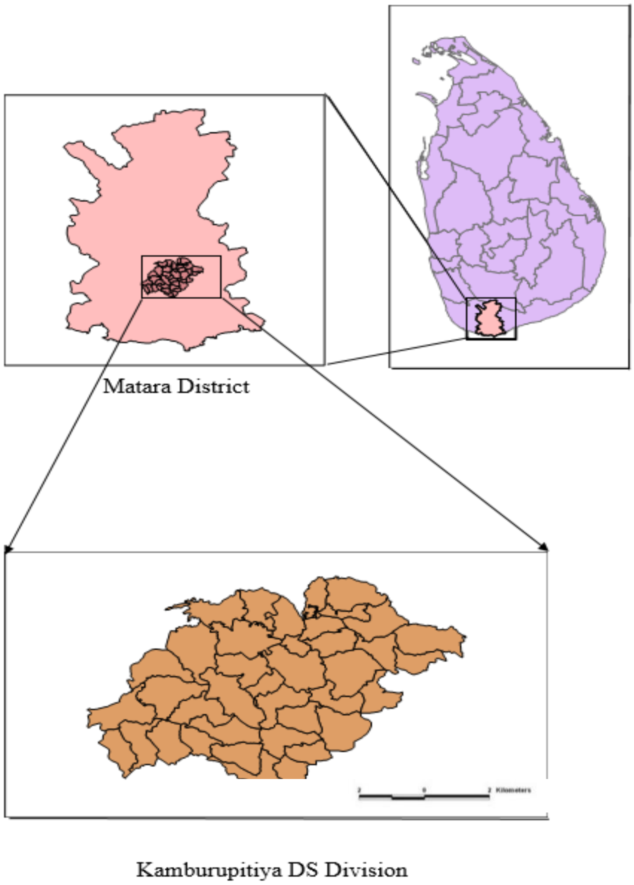


Figure 1: The study area

Three types of data were used as inputs to develop the paddy yield models. They are secondary crop reporting data, satellite data and Google Earth data. Paddy yield data (Crop cutting survey data) and other required local paddy statistics over 5 years in *Yala* and *Maha* seasons from 2016 to 2020 were obtained from Department of Agriculture, Matara. Free satellite images Landsat 8 OLI/TIRS imageries correspond to the years from 2016 to 2020 were selected approximately at the maximum vegetative growth stage of paddy in *Yala* and *Maha* seasons via USGE Earth Explorer Official Website. These Landsat 8 bands have a ground resolution of 30 meters. All images were downloaded from the

USGS Earth Explorer's collection 1 level 1 category and they were belonging to Datum- WGS84 and UTM Zone-44N. The Table 1 shows the acquired satellite images from 2016 to 2020.

Table 1: Acquired satellite images

Date of Acquisition	Path	Row	Scene cloud cover	Land cloud cover
2016.07.05	141	056	17.88	26.30
2017.01.29	141	056	12.27	4.07
2017.06.22	141	056	14.11	38.12
2017.12.31	141	056	22.50	28.99
2018.09.03	141	056	13.08	21.42
2019.01.13	141	056	7.33	6.63
2019.07.30	141	056	13.15	31.07
2020.01.06	141	056	4.62	7.48
2020.08.17	141	056	10.18	26.66

Geo-locations were assessed visually using Google Earth Pro Software application to identify and demarcate the locations of paddy cultivated lands in each growing season in Kamburupitiya DS division. Cultivated paddy lands were identified and marked as polygons (kmz files) in the growing stage of the paddy crops for each season in each year using Google Earth Pro Software Application. Nine images from Landsat 8 OLI/TIRS satellite were used for the time series analysis for both season. Band 1, 2, 3, 4, 5, 6 and 7 of those images were used for the image analysis. Extract by mask were done for each bands using a shape file of Kamburupitiya DS division. The satellite images were atmospherically corrected, as it is necessary for this study. Top of atmospheric corrections and solar zenith angle correction for each extracted bands of acquired Landsat 8 OLI/TIRS images were carried out using the data values of meta data files in each image. Then composite images were created for each season. Paddy polygons (kmz files) which were marked on the Google Earth map were applied as a layer on each composite image as kml files.

The vegetation indices were calculated for the Landsat 8 OLI/TIRS images approximately at the peak of growing stage at each growing season of paddy for all pixels under rice cultivation areas using Esri ArcMap 10.8 version. Five vegetation indices were calculated from different forms of algebraic ratios between R, NIR and G bands. They were NDVI, GVI, RVI, IPVI and DVI using the Raster calculator tool of ArcMap.

NDVI is determined using the R and NIR bands of the given satellite image (Equation 1) (Rouse *et al.*, 1973). R and NIR are spectral reflectance from the R and NIR-bands of the satellite image, respectively. The DVI is expressed in Equation 2 (Richardson and Everitt, 1992).

$$DVI = NIR - RED$$ Equation 1

The GVI was calculated using the relationship between G and NIR bands of the satellite image (Equation 3) (Panda *et al.*, 2010).

$$GVI = \frac{NIR-GREEN}{NIR+GREEN}$$

$$NDVI = \frac{NIR - RED}{NIR + RED}$$ Equation 2

Equation 3

There is a strong correlation with the season's progression between the GVI and grazed pasture green-up (Lecain *et al.*, 2000).

RVI is the ratio vegetation index (Equation 4) (Jordan, 1969), and it can be used to eliminate various albedo effects.

$$RVI = \frac{NIR}{RED}$$ Equation 4

IPVI is the infrared percentage vegetation index (Equation 5)
(Crippen, 1990), and it is determined using the R and NIR bands of the given satellite image.

$$IPVI = \frac{NIR}{NIR+RED} \quad \text{Equation 5}$$

G, R and NIR spectral bands of each satellite images at each
growing season of paddy for all pixels under rice cultivation areas were considered to calculate the reflectance values. Purposive samples of pixel values of the direct spectral data collected from satellite imagery (reflectance values of R, G and NIR bands) and five calculated vegetation indices under the cultivated paddy lands were selected for model building. These pixel values were collected from the paddy cultivated lands in respective GN divisions by crop cutting survey. Then simple linear regression models based on the relationship between the recorded average paddy yield data of Kamburupitiya DS division collected by Department of Agriculture, Matara with the average values of respective Vegetation indices and reflectance values of three spectral bands were developed for both two season using Minitab statistical software. MAPE was used as the statistical indicator for Validation and Accuracy Assessment (Equation 6).

$$M = 1/n \sum_{t=1}^{n} \frac{(At-Ft)}{At} \quad \text{Equation 6}$$

M	=	mean absolute percentage error
n	=	number of times the summation iteration happens
At	=	actual value
Ft	=	forecast value

For the accuracy validation of the derived models, the average rice yield data of 2020 *Yala* season and 2019/2020 *Maha* season were used, which were not used for modeling. After validating and checking the accuracy of each model, the most accurate models were selected for yield prediction in Kamburupitiya DS division.

Results and Discussion

Development of the paddy yield models

After the cultivated paddy lands were demarcated in the growing stage of the paddy crops for each season in each year using Google Earth Pro Software

Application, the average pixel values of the direct spectral data collected from satellite images (reflectance values of green, red and near infrared bands). Five vegetation indices under the cultivated paddy lands were calculated for the model development process for both *Maha* and *Yala* season.

Linear relationships between paddy yield with the average values of vegetation indices and average reflectance values of G, R and NIR spectral bands have been calculated for respective GN divisions. The regression models on NDVI and RVI for *Maha* Season (Figure 2) showed a higher determinants of coefficient (R^2) values of 77.5% and 76.8%, respectively. The R^2 values with positive relationship were 77.5%, 76.8%, 73.3%, 72.7% 52.1% and 35.9% for NDVI, RVI, GVI, IPVI, DVI and NIR band in *Maha* season, respectively (Table 2. Negative relationship was observed in R and G band with the R^2 values with 73.3% and 46.4 %, respectively.

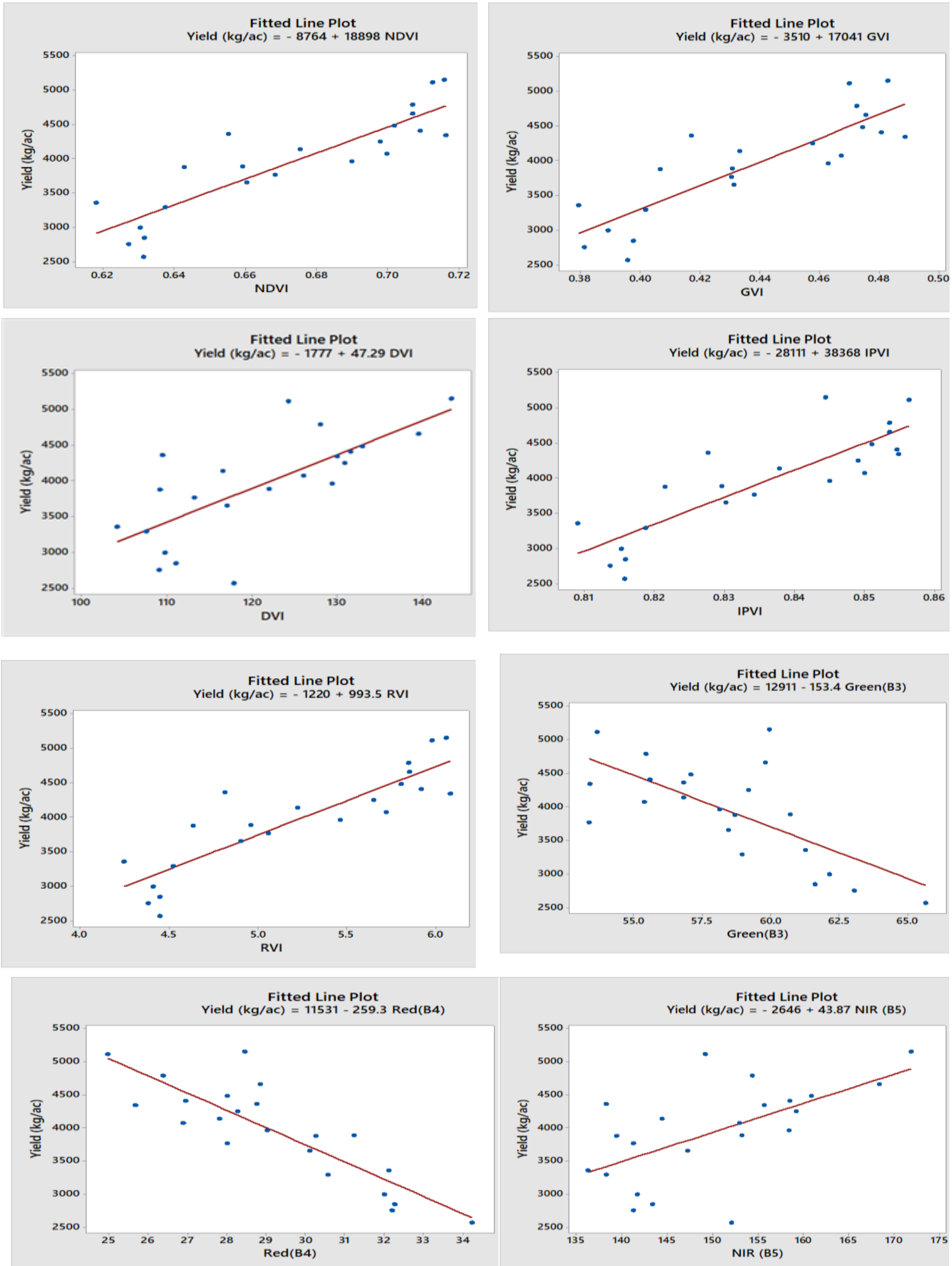
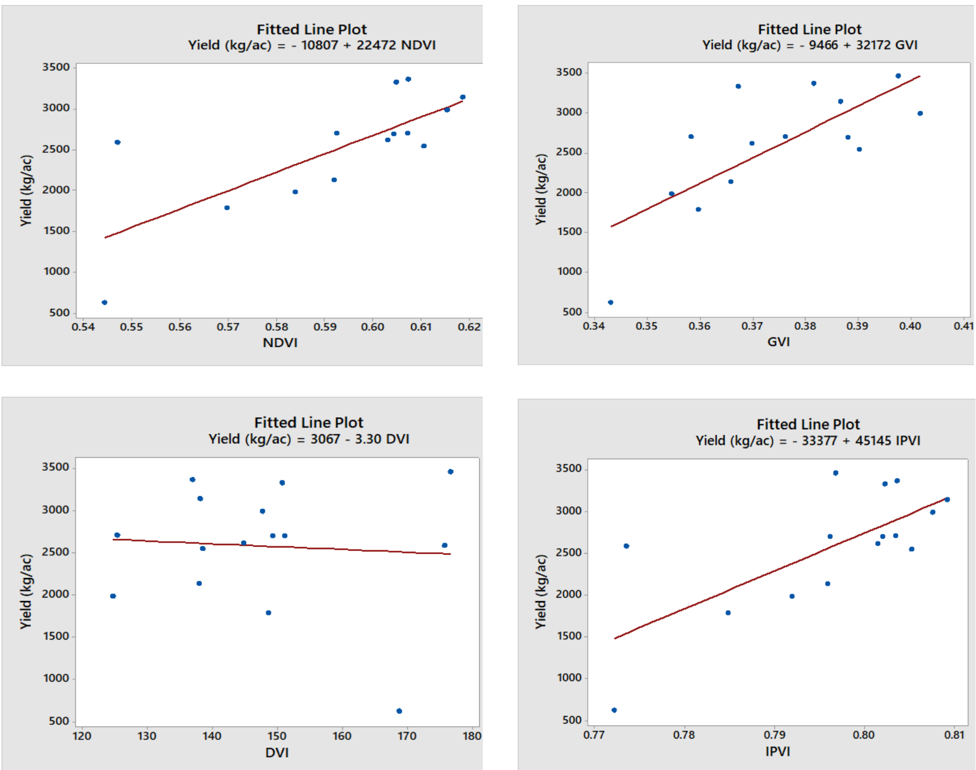


Figure 2: Regression models for *Maha* Season

Linear relationships between rice yield with the average values of vegetation indices and average reflectance values of G, R and NIR spectral bands in *Yala* season are shown in Figure 3. The Coefficients of determination (R^2) of the forecasting models for *Yala* were lower value due to cloud percentages of selected satellite images for *Yala* season were higher than the selected images for *Maha* season. But, the R^2 values of NDVI, RVI, GVI and IPVI based models were higher than 0.5 coefficient of determination as 56.0%, 55.8%, 54.5% and 50.2%, according to the descending order, respectively. Therefore, according to regression equations in this statistical analysis, paddy yield has considerable relationship with NDVI, RVI, GVI and IPVI based models, while DVI, G, R and NIR band models have a lower R^2 value. In this season, the relationships based on NDVI and RVI showed a higher determinant of coefficient (R^2) values than determinant of coefficients of other forecasting models.



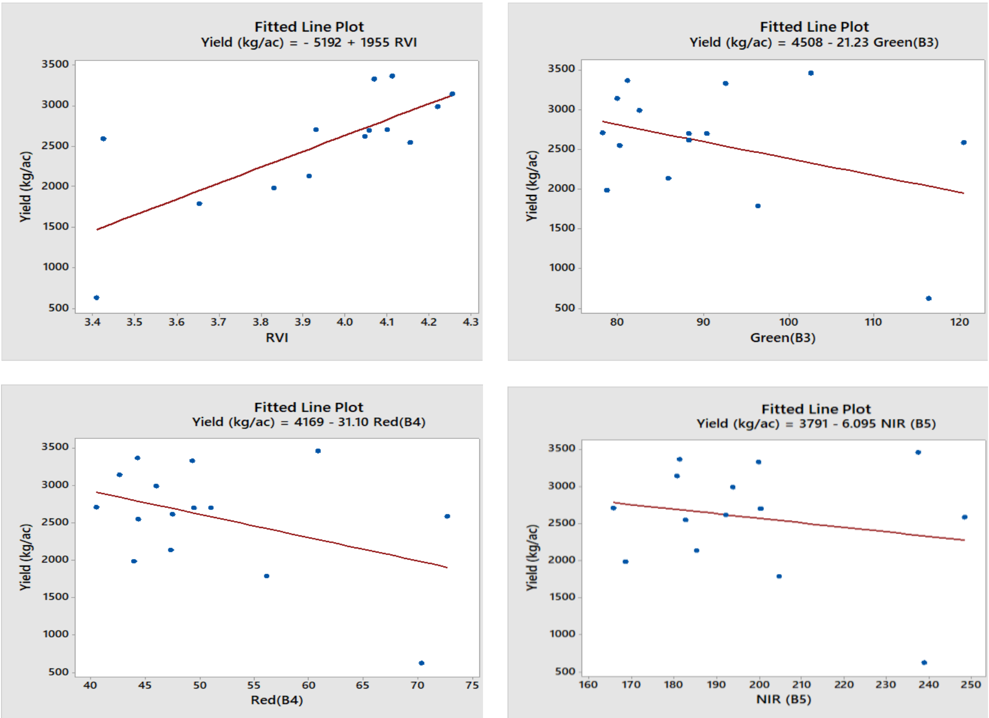


Figure 3: Regression models for *Yala* Season

Validation and accuracy assessment of paddy yield models

Rice yield was predicted for the 2019/2020 paddy cultivated *Maha* season and 2020 *Yala* season based on the derived models to evaluate the yield forecasting. In Tables 2 and 3, the accuracy of validated results is shown as a percentage difference between model-based yield and reported data of Department of Agriculture based on the traditional "Crop-cutting survey" method using MAPE. Other than that, Durbin Watson statistical test was used as an adequacy for validation of these model.

Table 2: Validation of *Maha* Season

Forecaster	Model	R^2 Value (%)	MAPE (%)	Pearson Correlation	P Value	Durbin-Watson Statistic
NDVI	Y= -8764+18898*NDVI	77.5	8.76	0.881	0	1.42093
GVI	Y= -3510+17041*GVI	73.3	9.23	0.856	0	1.81667
DVI	Y= -1777+47.29*DVI	52.1	8.30	0.722	0	1.77318
IPVI	Y= -28111+38368*IPVI	72.7	9.38	0.853	0	1.55955
RVI	Y= -1220+993.5*RVI	76.8	9.88	0.877	0	1.44413
Green	Y= 12911-153.4*Green	46.4	37.36	-0.681	0	1.46014
Red	Y= 11531-259.3*Red	73.3	28.11	-0.856	0	1.60496
NIR	Y= -2646+43.87*NIR	35.9	12.4	0.599	0.003	1.80735

When considering R^2 value, MAPE percentage, Durbin Watson statistics values and Pearson correlation values all together, It was noted in *Maha* season that G, R and NIR band, and DVI as predictors for paddy yield prediction models were not applicable. All other models, with the exception of three spectral bands-based models, have shown less than a 10% difference between model-based (predicted) yield and crop reporting data. Out of those, the GVI-based model had the highest accuracy, with just 9.23 percent of discrepancy and 1.82 of Durbin Watson statistics value. So, according to the results of this research study area, the GVI-based model was the most appropriate one for forecasting rice yield through other yield forecasting models. Hence, the yield model based on GVI values can be selected as the best model for rice yield forecasting using Landsat satellite 8 OLI/TIRS imagery in this particular study area according to this research study for *Maha* season.

Table 3: Validation of *Yala* season

Forecaster	Model	R^2 Value (%)	MAPE (%)	Pearson Correlation	P Value	Durbin Watson Statistic
NDVI	Y=10807+22472*NDVI	56.0	12.72	0.748	0.002	1.87192
GVI	Y=-9466+32172*GVI	54.5	39.27	0.738	0.003	2.20609
DVI	Y=3067-3.3*DVI	0.5	25.28	-0.072	0.799	1.52904
IPVI	Y=-33377+45145*IPVI	50.2	14.68	0.709	0.003	1.61259
RVI	Y=-5192+1955*RVI	55.8	16.72	0.747	0.002	1.933
Green	Y=4508-21.23*Green	14.8	19.15	-0.384	0.157	1.46106
Red	Y=4169-31.10*Red	17.5	15.17	-0.418	0.121	1.45992
NIR	Y=3791-6.095*NIR	4.4	21.60	-0.209	0.455	1.49944

When considering R^2 value, MAPE percentage, Durbin Watson statistics values and Pearson correlation values all together, it was noted in that NDVI, IPVI and RVI as predictors for paddy yield prediction models were applicable for *Yala* season. All these models have shown less than a 20% difference between model-based (predicted) yield and crop reporting data. Out of those, the NDVI-based model had the highest accuracy, with around 12% of discrepancy and 1.87 of Durbin Watson statistics value. So, according to the results of this research study area, the NDVI based model was the most appropriate one for forecasting rice yield for *Yala* Season. Rahman and Robson, (2016) developed yield prediction model derived from maximum Green Normalized Difference Vegetation Index (GNDVI) for predicting sugarcane yield in Bundaberg region using Landsat data with significant correlation with R^2 value of 0.69 and RMSE value of 4.2 t/ha at the peak of the growing stage of the crop.

Conclusion

The yield model based on GVI for the *Maha* season and the NDVI-based model for the *Yala* season can be selected as the best model for rice yield forecasting using Landsat 8 OLI/TIRS imagery at the peak of the growing stage of the paddy. If the limitations are overcome, the models will enable authorities to make successful decisions about rice supply management before the harvesting without incurring high costs and drudgery. The accuracy of the research can be improved using satellite images with high spatial resolution. This study will guide to improve development of prediction models by using Landsat 8 OLI/TIRS satellite imagery time series for paddy yield estimation for the Matara District.

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