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Estimation of rice crop acreage using Remote Sensing and GIS

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Abstract

It is critical to obtain the paddy yield for national food security and nutritional assessment. An attempt was made in this study to estimate the acreage under rice cultivation in Visakhapatnam, Andhra Pradesh, which is one of India's major cities. Nearly 14 ground truth points were obtained in this analysis, and one-third of them were included in the supervised classification method. The remaining ten percent were used for confirmation, resulting in an accuracy of over 85 percent. Sentinel-2 L1C images were used in the study. The spectral response was recorded for the crop. The area under the paddy crop was differentiated from other vegetation by using the spectral reflectance from appropriate bands. The yield obtained from crop cutting studies was compared to the yield obtained from remote sensing data, and a deviation of about 10% was found. The paddy cultivated area in Visakhapatnam was estimated to be 91,708 ha and the gross was yield was estimated to be 154986.52 tonnes.

Keywords: Data; remote sensing; rice; yield.

Introduction

Environmental conditions, as well as technological intervention in agricultural science, have an effect on crop development. Since the mid-1920s, the global population has been growing at an exponential rate, with an estimated growth of three billion people in the next five decades (Wang *et al.* 2008). As a result, global food demand will increase, and competition for the fertile land and water supplies needed to produce more agricultural food products is anticipated (Seelan *et a.l* 2003). According to Rijsberman *et al.* (2001), overall food production must increase by around 40% while water supplies used in agriculture must be reduced by 10%–20%. However, these assumptions must account for the possibility of any anticipated climate change, which may have a detrimental effect on crop production as well as other critical agricultural resources such as water supply (Nelson *et al.* 2014). Other essential resources that ensure food production include land, fossil fuels, and nutrients, while their current intake exceeds their global regeneration rate (Bindraban *et al.* 2012).

Rice is a staple meal for over three billion people worldwide. Rice covers about 11.5 percent of the world's available land area and generates about 19 percent of global dietary nutrition in recent years, with an annual average intake per capita of about 65 kilograms. In terms of rice yield, a ground-based field survey is still needed, despite the fact that this necessary survey is often considered to be time-consuming. Precision agriculture arose in response to significant global threats such as food security (Conijn *et al.* 2018), natural resource degradation (Windfuhr *et al.* 2005), and anthropogenic climate change (Doran, 2002). Precision agriculture's main aim is to maximize profits while minimizing the effect of farming on the environment.

New technology, such as satellite data, Geographic Information Systems (GIS), or Global Positioning Systems (GPS), can help to increase crop yield production and quality, thus assisting in the long-term security of food supply while also reducing the negative effects of agricultural activities. Satellite remote sensing data has a variety of uses in agriculture, including soil property identification, crop type recognition, crop yield forecasting, crop health tracking, soil moisture retrieval, and weather data analysis. Sentinel 2 optical datasets were used for crop growth analysis in this study because they have higher spatial, spectral, and temporal resolutions. On a temporal basis, supervised classification was carried out using spectral resolution. These signatures were derived from photographs that had been time composited. Finally, the crop areas in hectares were measured and compared to the paddy field at the district level (Louis *et al.* 2016). There was a 10% margin of error in these comparisons. Rice mapping and forecasting are critical for food security in areas where demand sometimes exceeds supply due to rising population. The aim of the forecast is to include accurate, reliable, and independent crop yield predictions as early as possible during the growing season by taking into account the effects of weather and climate (Ajith *et al.* 2017). The methods for forecasting regional rice yield using remote sensing are discussed in this article.

Study area

Visakhapatnam city of Andhra Pradesh is located near the Bay of Bengal (Fig.1). It is the most populated city of Andhra Pradesh. Visakhapatnam is irrigated mostly by Gostahani and Sarada Rivers. These are mostly non-perennial in nature. The city has a tropical wet and dry climate with the average temperatures ranging from 24˚C to 30˚C. The maximum temperature is observed in the month of May whereas the minimum temperature is observed in the month of January. It receives an average annual rainfall of 1,118.8 mm

Fig.1. Image showing Visakhapatnam in India Map

Materials and Methods

The yield of paddy can be estimated conventionally by obtaining field data from all the farmers who have adopted rice cultivation in the selected area. This method is considered as accurate but it is more time consuming and labour intensive than the yield estimation using remote sensing. Therefore, remote sensing is increasing being adopted to obtain timely data about acreage and yield of rice. However, the accuracy of obtaining yield through remote sensing depends on the resolution of the raster datasets used for analysis. It is reported that the error rate is lower for datasets which are higher in resolution as the number of mixed pixels can be minimized. It is also important to select the appropriate algorithm for classifying the area under paddy to obtain reliable results. In this study, Spectral Angle Mapper (SAM) algorithm was used for the classification purpose. The SAM is a supervised classification algorithm that can distinguish various classes present in the image based on the spectral angle calculation. The detailed information was extracted from the hyperspectral imagery in order to identify and distinguish between features which are unique but have similar spectral reflectance.

The supervised image classification technique was used in this study. The location and the identity of the land under paddy cultivation of several points were known beforehand through field work and analysis of aerial photography. The sites with similar spectral characteristics were located and they were treated as training sites. The spectral characteristics of these sites were used for training the classification algorithm for identification of sites under paddy cultivation. The pixels were evaluated and assigned to the class where it had the highest likelihood of being a member.

Sentinel-2 L1C images were downloaded from the Sentinel website to cover the periods between crop sowing and harvesting of paddy. The Sentinel satellites are twin-polar orbiting satellites that provide a revisit time of five days. They convey a Multi-Spectral Instrument which has 13 spectral bands: six bands at 20 m, four bands at 10m and three bands at 60 m spatial resolution (Pantazi *et al.* 2016). The images were pre-processed in order to make them suitable for detailed analysis. The atmospheric corrections and the Top of Atmosphere (TOA) reflectance were obtained by the sen2 core processor. TOA reflectance provides the ratio of radiation that is reflected from a given surface to the solar radiation that incident upon a given surface. The TOA reflectance can be calculated from the spectral radiance and the solar zenith angle. Atmospheric correction process involved tasks such as removal of atmospheric error, aerosol effect, terrain effect and stratosphere reflectance. Basically the DN values were converted into radiance values during this process to make the images more related to the features like water, soil and their characteristics. Other pre-processing work like mosaicking and layer stacking were also carried out using ArcGIS.

The cloud free images were utilized to create a time composited image. A vector shape file was created by using appropriate latitude and longitude in the ArcGIS. The vector shape file that was created had the same projection system as that of the raster layer. Temporal signatures were obtained for paddy by using the sample training ground truth points and the time composited image. The signatures required for the supervised classification were then provided in ArcGIS. Those signatures were given as an input for supervised classification in ArcGIS. A thematic map of the paddy layer was obtained from the classification which is a unit map (values are 0 and 1) and value 1 was classified as paddy area. Number of pixels was then counted and pixel area was obtained from histogram. The area represented by a pixel was multiplied by the number of pixels to compute the area. The area was initially obtained in square meters and then it was converted into hectares. The standard data of paddy yield per unit area obtained after literature survey were considered in the study for computation of the yield of paddy.

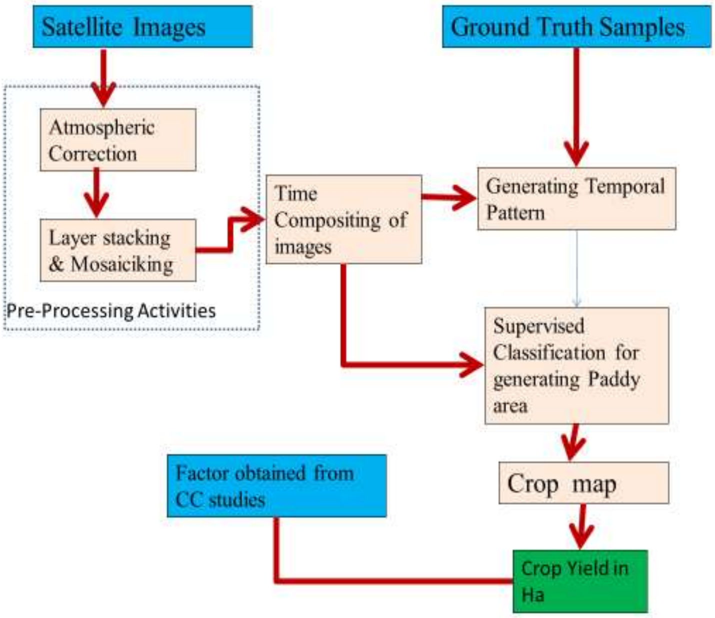

Fig 2. Flow chart of rice yield estimation

Results and Discussion

The False Colour Composite (FCC) image was obtained in ArcGIS using the standard combination of bands (Fig. 3). The red colour in the FCC image represents vegetation. The satellite images in the monsoon were cloudy and therefore not suitable for reliable classification. Therefore, the scenes of 8th October and 24th November were used in the study. All the 10 bands were used for classification which includes VNIR, Veg Red Edge and SWIR. The spectral profiles of paddy for the dates used for classification were also obtained (Fig. 4). It was found that the reflectance in the red band and the Near Infrared (NIR) band was in the range of 2500 to 2800 on 08/10/2018 whereas it was in the range of 2000 to 2500 on 24/11/18. The spectral profile of paddy was used for distinguishing it from other vegetation. SWIR-1 and SWIR-2 are absorbed in water so the values are lower and NIR was reflected by chlorophyll so they have high reflectance values. The reflectance was found to be low on both the dates in the green, blue and short wave infrared (SWIR) bands. However, as the paddy fields were flooded most of the time, the SWIR bands were found to be useful in separating paddy fields from the non-paddy fields and other vegetation (Zhao *et al*. 2004).

The area of Visakhapatnam is estimated to be about 2, 58,334 ha out of which 91,708 ha was found to be the paddy cultivated area. Spectral angle mapper was used for classifying the dataset, because it uses spectral matching techniques (comparing unknown spectra with known signatures). As sentinel 2 has a 5-day revisit period and 10-meter resolution the chances of classifying mixed pixels were less. The classification could be considerably improved if the images during the sowing period were not clouded. The yield was paddy was estimated by multiplying the acreage of 91708 hectares with the average yield of paddy per hectare commonly produced in the area.

Several researchers published similar findings with good agreement between actual and estimated yield using the approach of acreage estimation by remote sensing (Mosleh *et al*. 2015; Patra *et al.* 2017). Li *et al.* (16) utilized three RADARSAT- images acquired during early, middle, and prior-to-harvesting stages for rice yield estimation over Guangdong Province, Southern China. Chen and McNairn (17) utilized RADARSAT-1 (C-band with HH polarization) for rice forecasting over Munoz and Santo Domingo, Philippine. The area was estimated and then neural network model was used to predict rice yield which provided an accuracy of 94 %.

It was found that the actual and the estimated yield had a decent relationship. This approach of obtaining the acreage by remote sensing and then estimating the yield could be useful in evaluating the yield potential from the cultivated rice prior to harvest.

Conclusion

In comparison to manual surveying, which is time intensive and vulnerable to human error, remote sensing provides quicker and more accurate knowledge about crop acreage and yield. Nearly 14 ground truth points were obtained in this case study, and one-third of them were included in the supervised classification method. The remaining ten percent was used for confirmation, resulting in an accuracy of over 85 percent. The paddy cultivated area in Visakhapatnam was estimated to be 91,708 ha and the gross was yield was estimated to be 154986.52 tonnes. The yield obtained from remote sensing was compared to the data obtained from crop cutting tests, and a variance of less than 10% was found. Before the crop is harvested, the acreage under paddy field and the yield can be estimated using remote sensing.

Fig 3. False Colour Composite raster image (Red colour Indicates Vegetation)

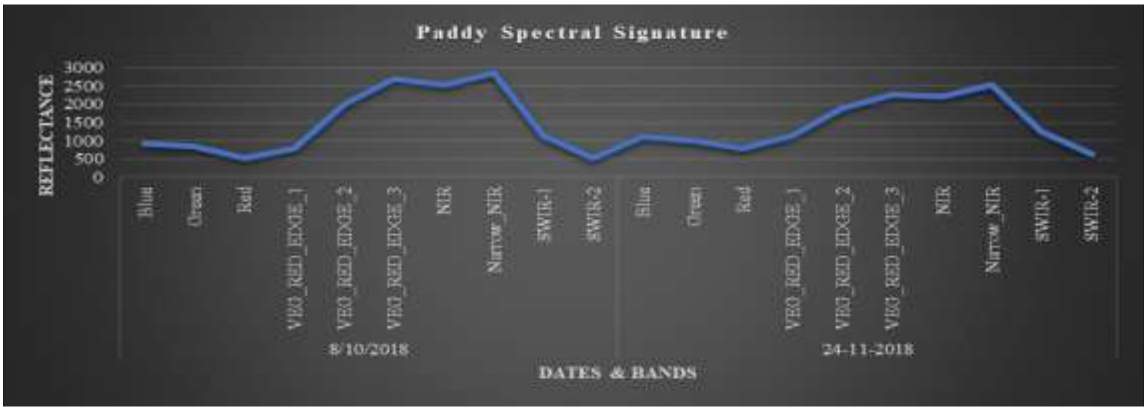

Fig 4. Spectral Profile of Paddy for the dates used for classification

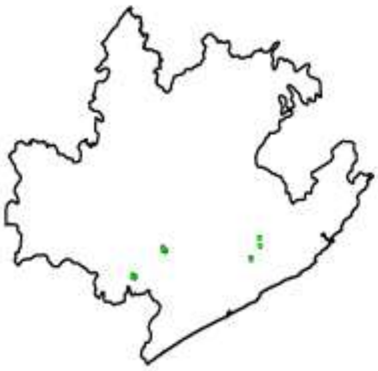

Fig 5. Ground Truth point map

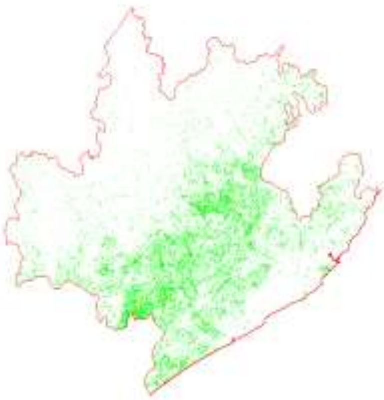

Fig 6. Thematic maps showing paddy-distributed areas in Visakhapatnam.

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