Estimating Crop Extent using Neural Networks and Remote Sensing Data

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RESEARCH QUESTION

Rice is considered as one of the main cereal grains and more than half of world's population consume as the staple food (Consultative Group for International Agricultural Research [CGAIR], 2018). Farmers in Asia Pacific region contribute to over 90 percent of the world's rice production. Rice cultivation occupies 34 percent of the total cultivated area in Sri Lanka. About 1.8 million farm families depend on rice cultivation in Sri Lanka (Rodrigo, 2013). Common practice in Sri Lanka is to cultivate rice in two seasons, namely Maha and Yala targeting two monsoons. In Sri Lanka, it happens in the three main climate zones that are identified as the wet zone, the intermediate zone, and the dry zone. Rice cultivation in the wet and intermediate zones particularly rely on rainfall for water. Farmers in the dry zone rely mostly on irrigation for water. Recent bad weather conditions and major disease outbreaks have negatively affected rice cultivation for paddy farmers. Paddy diseases have caused huge yield losses annually around the world (Rodrigo, 2013).

According to the Food and Agriculture Organization of the United Nations, increasing the productivity of farmers is one of the key approaches to eradicating poverty and food security (Food and Agriculture Organization of the United Nations, 2017). It can also help achieve zero hunger, which is one of the UN Sustainable Development Goals. Nevertheless, certain decisions taken based on erroneous information has led to the decline of productivity for farmers in Sri Lanka (Dharmaratne, 2007). For example; In 2013, due to the short sighted decision of redistributing paddy lands among individuals selected by Mahaweli officials, a farmer who had faithfully cultivated his land for 26 years had committed suicide due to the loss of previously cultivated paddy fields (Newsfirst.lk, 2013). Similarly, many farmers refused to sell and eventually resorted to composting their harvest when the farm gate price of 1kg of leeks dropped to Rs.5.00, even though the estimated production cost was Rs. 20.50 according to 2009 data from the Department of Agriculture. In the subsequent 2011/2012 Maha peak harvesting period, which falls during February, the situation became even worse, leading to over 50 tonnes of vegetables being discarded due to issues resulting from price volatility (Champika, 2016). Therefore, accurate and timely estimation of the extent of cultivation and crop yield prediction is essential for stakeholders such as farmers, government and traders in order to make precise decisions on planting, insurance premium calculation, buying, importing and exporting.

The current approach of paddy extent estimation and crop yield predictions in Sri Lanka is based on the availability of human resources.. Field officers are employed around the country by the government to collect data regarding the status of paddy cultivation for analysis and estimation purposes. Decisions taken by stakeholders are highly susceptible to factors such as insurance premium calculation, price volatility, and import extent of crops, which in turn is susceptible to flaws in existing paddy extent estimation procedure. Moreover, the cost of acquiring required human resources, the burden of handling human resources and the time consumption related to handling human resources, getting estimates and doing analyses have been also identified as limitations of the current approach (Shiu et al., 2010). Stakeholders, including the government of Sri Lanka, are willing to put alternative efficient mechanisms of paddy extent calculation and crop yield estimation into practice.

THE RESEARCH

Multiple studies have shown that remote sensing data can be used as a potential alternative for providing valuable insights about various aspects of agriculture (Xiao et al., 2005; Shao et al., 2010;

Zheng et al., 2015;). Remote sensing data acquired by the Moderate Resolution Imaging Spectroradiometer (MODIS) (National Aeronautics and Space Administration [NASA], 2000) and Landsat (United States Geological Survey [USGS], 1972) satellite are heavily used in agricultural analysis particularly targeting larger continuous agricultural lands.

Vegetation indices are widely used for agricultural monitoring purposes such as crop land classification and crop yield prediction. Significant research has proven that the Normalized Difference Vegetation Index (NDVI) has a substantial potential of using it as a parameter to classify cropped lands (Shao et al., 2010). Rice yield is heavily influenced by the water supply for paddy plants. This distinct characteristic of paddy during the initial growing stage can be monitored by the Land Surface Water Index (LSWI) (Xiao et al., 2005).

Xiao et al. (2005) developed an algorithm to identify cultivated paddy fields incorporating three vegetation indices; NDVI, Enhanced Vegetation Index (EVI), LSWI derived by MODIS imagery. A research conducted by Yang Shao et al. (2010) revealed the capability of MODIS NDVI time series to classify several crop types (corn, soybeans, wheat, and hay) in Great Lakes Basin (GLB) areas. They claimed that the models have an accuracy of 84 percent for crop type classification. Zheng et al. (2015) applied Support Vector Machine algorithm to Landsat NDVI time-series data in order to classify nine types of crops. The proposed system has shown over 86 percent of overall accuracy.

Rußwurm et al. (2017) conducted a research using remote sensing data captured by Sentinel 2A (European Space Agency [ESA], 2015) to emphasize the importance of multi-temporal approaches over mono-temporal approaches for land cover classification using Long Short-Term Memory (LSTM) neural networks. Immitzer et al. (2016) conducted a research based on pre-operational Sentinel 2 data for mapping crop types and tree species in Lower Austria. Due to the lack of temporal data at the time they conducted the research, only single date acquisitions have been available for the study.

Research on crop type classification has been conducted more frequently in larger countries. However, a fewer number of such studies have been conducted in small developing countries (Immitzer et al., 2016; Rußwurm et al., 2017). This is partly due to the lack of freely available high resolution remote sensing data sources, as well as due to lack of awareness on available medium to low resolution data sources. In our approach, we have used two different data sources and two different neural network models to enhance the quality of the classification.

CONCERNS IN USING REMOTE SENSING DATA

There are many concerns about using remote sensing data for estimating the extent of cultivation of paddy fields. These concerns relate to the problems of getting high-quality remote sensing data, using technologies to extract knowledge from data and evaluation of the results. Some of the challenges are listed below.

- A tradeoff between resolution and cost: Data at highest resolution is not available freely.
- Clouds and cloud shadows: Due to the coverage of clouds in 2/3 of the earth's surface area at any given time, it causes significant loss in accuracy for optical wavelength remote sensing (Wang et al., 2009).
- A significant effort is needed for data fusion: Data fusion is used to combine multiple sensors' images using appropriate fusion algorithms for more reliable results (Hall & Linas, 1997). The additional accuracy afforded by data fusion is necessary to develop better models.
- Low and distributed upwelling signal to the sensor (National Environmental Research Institute, 1999)
- Remote sensing data is error prone: Geometrically inaccurate because of errors in the scanner, platform, ephemeris and altitude of the satellite in addition to errors due to earth's rotation, curvature and atmospheric refraction.
- Difficult and expensive field sampling
- Lack of remote sensing infrastructure and expertise in this field
- Processing and analysing the data takes a considerable amount of time, which may be of concern as the results need to be delivered to the relevant stakeholders in a timely fashion.
- Availability of ground truth data to evaluate the accuracy of models: Obtaining ground

truth data from government agencies can be difficult due to legal or regulatory constraints.

- Cannot easily verify the accuracy of the available ground truth data

COMPARISON BETWEEN AVAILABLE REMOTE SENSING DATA

Several satellite platforms provide space-based remote sensing data. Different remote sensing sources are used to examine different environmental issues (such as infrastructure, disease and poverty) according to the spectrum and resolution of the resources. Some of those data sources are freely available while others are commercial.

Landsat and MODIS remote sensing data are being extensively used in research regarding mapping agriculture croplands, but these resources have crucial limitations when the precision is important. In general, depending on latitude value one or two MODIS satellite image pixels might cover the entire cropland of some developing countries. Hence, it would be challenging to derive meaningful and accurate insights about agricultural productivity.

Recent developments of technology persuade private institutions to launch satellite constellations which have the capability of offering inexpensive high and medium spatial and temporal imagery.

Satellite Pour l'Observation de la Terre (SPOT) (Centre for Remote Imaging, Sensing and Processing [CRISP], 2002), IKONOS (CRISP, 1999) and QuickBird (DigitalGlobe, 2003) sources offer high spatial and temporal imagery. But those are commercial products. So accessing those images is expensive.

In this study, time series data from two remote sensing data resources are used for the better performance of the model. PlanetScope (Traub et al., 2008) and Sentinel 2 (freely available) image sources are selected to balance the tradeoff between cost and resolution. PlanetScope satellite constellation consists of approximately 120 satellites providing 3m resolution images of entire earth every day. Sentinel 2, a mission developed by European Space Agency (ESA), provides remote sensing data with 10m of spatial resolution and 4 days of temporal resolution. Further details of the remote sensing data sources are mentioned in Appendix I.

METHODOLOGY

The rapid development of deep neural networks in recent years has encouraged researchers to use various types of deep neural networks in agriculture-related research.

Accordingly, we built machine learning models to evaluate the performance of each remote sensing data source as well as evaluate the performance when the two remote sensing data sources are combined. Moreover, the performances of two neural networks; Long Short-Term Memory Network and Convolution Neural Network, are compared with Support Vector Machine (as a baseline) in terms of paddy land classification into two classes; cultivated and not-cultivated.

Experiment was conducted using the remote sensing data and ground truth data related to 2017-2018 Maha Season. A sample set of paddy fields covering all three climate zones are selected to conduct our study. At least 17 PlanetScope remote sensing imageries have been used to derive NDVI time series of each sample paddy field and at least 9 sentinel 2 remote sensing data were used to derive NDVI and NDWI time series for each sample paddy field. Due to low revisit time and cloud contamination we could only use about 9 Sentinel 2 images.

Training data set consists of 8000 data points while the test data set consists of 1000 data points. We followed 10 fold cross validation for neural network training and validation.

In our study, we compared the capabilities of each remote sensing resource individually and their combinations with two neural network models in terms of classifying harvested paddy pixels as described in Figure 1.
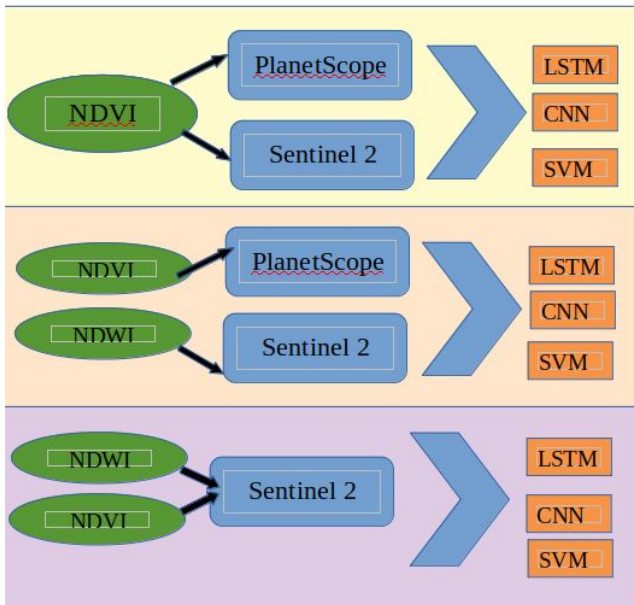
Figure 1 Overview of classifying paddy fields

The extent of cultivated paddy fields are then calculated by accumulating the area covered in each pixel which is identified as cultivated pixels. Then we have compared the paddy land extent from ground truth data in selected regions and estimated paddy land extent from each machine learning model.

RESULTS AND DISCUSSION

Accuracy metrics of different LSTM, CNN machine learning models along with the SVM baseline model in terms of classifying using PlanetScope and Sentinel 2 data are calculated. The results of the different experiments are summarized in Table I.

TABLE I. PERFORMANCE EVALUATION OF MACHINE LEARNING MODELS

Classification Scenario	Observation
Only Planetscope NDVI data	SVM outperforms compare to other models, LSTM better than CNN
Only Sentinel 2 NDVI data	Better results than PlanetScope NDVI data models, LSTM gives best results
Both Planetscope NDVI data and Sentinel 2 NDWI data	CNN models accuracies improved than above scenarios, LSTM models didn't show improvement over other LSTM models
Sentinel 2 NDVI and	Achieved the highest accuracies
Sentinel 2 NDWI data	among all four experimental setups, CNN performs better than other models

We have obtained the highest score of 97.94% from the CNN model built based on Sentinel 2 NDVI data and Sentinel 2 LSWI. However, LSTM model with 150 LSTM cell units and two LSTM layers achieved an accuracy which is very close to the accuracy of aforesaid CNN model.

Even though the highest accuracy of paddy classification is attained by leveraging Sentinel 2 NDVI and Sentinel 2 LSWI data, results when using Sentinel 2 data without Planetscope data had become worse in estimating paddy extent. Hence, the model based on Planetscope NDVI data and Sentinel 2 LSWI data output approximately accurate paddy extent with the least impact of false positive and false negative pixels. Further, Table II shows the evaluation result of the paddy extent estimation by region wise using the different data sources.

TABLE II. PADDY EXTENT ESTIMATION PERFORMANCE EVALUATION

	Actual Extent	Planet Scope NDVI	Sentin el 2 NDVI	Planet scope NDVI + Sentin el 2 LSWI	Sentin el 2 NDVI + LSWI
Dry Zone	25.47	26.9	27.33	26.61	27.14
Intermediate Zone	37.62	30.61	21.01	40.09	36.61
Wet Zone	8.96	11.81	11.54	8.71	5.29
Total Extent	72.05	68.32	69.88	75.41	69.04

Table III shows the error between obtained extent and actual extent of the paddy by region wise using the different data sources.

TABLE III. PADDY EXTENT PERFORMANCE ERROR IN TOTAL EXTENT AND ZONE WISE

	PlanetScope NDVI	Sentinel 2 NDVI	Planetscope NDVI + Sentinel 2 LSWI	Sentinel 2 NDVI + LSWI
Dry Zone	+1.43 (5.61%)	+1.86 (7.30%)	+1.14 (4.48%)	+1.67 (6.56%)
Intermediate Zone	-7.01 (18.63%)	-16.61 (44.15%)	+2.47 (6.57%)	-1.01 (2.68%)
Wet Zone	+2.85 (31.81%)	+2.58 (28.80%)	-0.25 (2.79%)	-3.67 (40.96%)
Error in Total Extent Est.	-3.73 (5.17%)	-2.17 (3.01%)	+3.36 (4.66%)	-3.01 (4.18%)
Mean Region-wise Error	3.76	7.02	1.28	2.12

From the results observed from the experiments, overall, Neural network models built based on Sentinel 2 datasets outperforms the Planetscope datasets and combined datasets. If only unmixed paddy pixel data are used for training machine learning models, Sentinel 2 will demonstrate good paddy pixel classification accuracies even though the resolution and revisit time are less than Planetscope imageries. Planetscope data can be suggested as a perfect input remote sensing data resources for paddy land classification as well as paddy extent estimation

Results in this research show a significant improvement of paddy land classification accuracies by incorporating LSWI data along with NDVI data over models built only using NDVI data.

LIMITATIONS AND FUTURE WORK

This section points out limitations of the current work, and also outlines directions for future research.

Our work mainly focuses on paddy due to the advantages in the paddy cultivation such as

- Cultivate larger spatial area: Able to distinct the paddy fields using low/medium spatial resolution images.
- Recursive cultivation: Estimation methodology can be repeated next few years.
- Rice cultivation occupies 34 percent of the total cultivated area

- Not able to do intercropping with other plants

However, we need to focus on cash crops, as well as they directly impact the economy.

In this research, we were able to collect only 9000 data points due to the manual annotation of remote sensing image pixels. According to the data related to paddy cultivation provided by field officers of department of agriculture, we have to annotate in order to train the system. But 9000 data points are not sufficient for the models we used. So we are currently in the process of negotiating more data from the department of agriculture to enhance the quality.

We have used free remote sensing data with high/medium spatial and temporal resolution. Some remote sensing data sources with high spatial and temporal resolution also offer images for freely/reduced price for research purposes. Currently we are investigating those resources to obtain high-quality data.

We have mostly completed the works for estimating paddy extent as it is an essential prior step for paddy yield prediction. By extending the current research work for estimating crop yield using sensing technologies and machine learning techniques would greatly overcome the issues in the current decision-making procedures.

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Appendix I

Sources	Commercial/Free	Spatial Resolution	Revisit time	Globally available	Applicability
Meteosat	Free	1-3 m	15 minutes	No, Cover Europe and Africa only	Wavelengths: Both infrared and visible. Display: Weather oriented image of the planet Use cases: Assist to detect and forecast weather up to 6 hours ahead. Applicable for monitoring thunderstorms, fog. (National Research Council, & Geographical Sciences Committee, 2007)
Advanced Very High Resolution Radiometer (AVHRR)	Free	Approximately 1km	Daily	Yes	Use cases: Monitor cloud cover, determine the temperature of sea and land surfaces, forecasting forest fires and hurricanes, Using variations in vegetation to monitor land cover. (National Research Council, & Geographical Sciences Committee, 2007)
Systeme Pour l'Observation de la Terre (SPOT)	Commercial	from 2.5 to 20 m	Daily	Yes	Use cases: Monitor land use, agricultural monitoring, forecasting forestry and water resources (National Research Council, & Geographical Sciences Committee, 2007)
Medium Resolution Imaging Spectrometer (MERIS)	Free	Ocean: 1040m x 1200 m, Land & coast: 260m x 300m	3 days	Yes	Focus: Ocean carbon cycle and temperature of upper ocean Use cases: Monitoring ocean temperature, Investigating and monitoring of fisheries and coastal zones. (National Research Council, & Geographical Sciences Committee, 2007)
Moderate Resolution Imaging Spectroradiometer (MODIS)	Free	250 to 1,000 m	1-2 days	Yes	Focus: Biological and meteorological changes Use cases: Studying interaction between earth, sea and atmosphere, monitoring climate change (National Research Council, & Geographical Sciences Committee, 2007)
Landsat	Free	30m	16 days	Yes	Focus: Land surface Use cases: Monitoring land surface, agricultural monitoring (National Research Council, & Geographical Sciences Committee, 2007)
IKONOS	Commer	1-4m	Every 98	Yes	Focus: Natural resources of urban and rural

			minutes		area Use cases: Predicting and monitoring natural resources, Analysing agriculture and forest, social science analysis (National Research Council, & Geographical Sciences Committee, 2007)
QuickBird	Commercial	0.61m	1-3.5 days, depending on latitude	Yes	Focus: Environmental data Use cases: Analyses related to agriculture, land use, forest and social science. Can get the details of house size, quality of roofing, and presence of vehicles. (National Research Council, & Geographical Sciences Committee, 2007)
Sentinel 2	Free	10-20m	Every 4 days	Yes	Use cases: Analysis related to agricultural and forestry practices (ESA, 2015)
PlanetScope	Free	3m	Daily	Yes	Use cases: Urban monitoring, monitoring agriculture, forestry management, hydrology analysis (Traub et al. 2008)