INTEGRATING CNN DEEP LEARNING AND BIOMASS CORRELATION APPROACHES FOR PADDY LAND DETECTION AND YIELD ESTIMATION IN NORTH CENTRAL PROVINCE, SRI LANKA

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Abstract: Accurate paddy land monitoring and production forecasting are critical for ensuring food security and making informed import decisions. This research focuses on integration of Convolutional Neural Network (CNN) deep learning models with vegetation index-based analyses to enhance paddy land identification and yield estimation in the North Central Province of Sri Lanka. The research design outlined involves two overall stages. First stage involves two steps. First, CNN models are applied to high-resolution satellite imagery to detect paddy lands in the region accurately. Second, the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) are utilized to classify active and inactive paddy fields during cultivation seasons. The second stage is the production estimation using a biomass correlation approach by employing NDVI and the Enhanced Vegetation Index (EVI) to predicting yield before harvesting. The study addresses a major problem in Sri Lanka's agricultural sector—inaccuracy of data, which typically leads to inefficient decisions in rice import and compromises food security at national level. By providing timely and accurate information on active paddy lands and expected production, the proposed method offers a scientific basis for better planning and policy-making in the agricultural sector.

Keywords: *Convolutional Neural Network (CNN), NDVI, NDWI, EVI, biomass correlation*

1. Introduction

1.1. BACKGROUND OF THE STUDY

In Sri Lanka, rice is regarded as a fundamental food resource and this directly impacts the economy of the country. Most Sri Lankans depend on rice as their primary source of calories, and therefore rice and paddy cultivation are important components of the agricultural sector which supports the income of rural folk (Wickramaarachchi & Jeevika Weerahewa, 2016). Nonetheless, in recent years, Sri Lanka has faced a consistent decrease in paddy crops which will impacts the availability of rice and food security. The Sri Lankan rice crisis is a serious food security issue in the nation. The research makes an effort to bridge significant gaps in the data on paddy land usage and yield estimation with remote sensing technology and deep learning algorithms. The results of this study may inform future programs aimed at ensuring long-term food security in Sri Lanka.

1.2. RESEARCH PROBLEM

Inaccurate data on paddy land extent and yield hinder effective decision making in addressing Sri Lanka's current food security challenges. The motivation for this study arises from the absence of precise, up-to-date information regarding paddy land use and yields, which obstructs effective decision-making in agricultural policy and intervention. Conventional approaches to track paddy production, including field surveys and manual observations, are labour-intensive and susceptible to inaccuracies (Nakano et al., 2004; Morales et al., 2011). These techniques fall short in delivering the extensive, real-time data necessary for policymakers to develop effective strategies to secure food availability. Thus, Sri Lanka is under tremendous pressure to track paddy land use change and production variations, thus hindering the capacity to respond to the underlying causes of falling output.

During the past few years, remote sensing technology has been effective enough to address such challenges. Based on satellite imagery and enhanced data analysis software, remote sensing has the ability to furnish enhanced and up-to-date evaluation of land use and agricultural produce (Misra et al., 2005; Zhang et al., 2018). These techniques can be combined with Convolutional Neural Networks (CNNs), a type of deep learning, to develop more precise models for land use, and yield forecasting. (Sri Silpa Padmanabhuni et al., 2023).

1.3. OBJECTIVES OF THE STUDY

Objective: To suggest a consistent method of paddy field detection and yield estimation.

Sub objectives:

1: Identify and calculate the area of paddy lands using Deep learning model.
2: Estimate paddy yield based on the detected land area using biomass correlation approach.

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1.4. SCOPE OF THE STUDY

This research will focus on Sri Lanka's North Central Province, the Anuradhapura and Polonnaruwa districts. The two districts are selected since they have been found to possess a relatively higher paddy production level. Current remote sensing methods, using satellite images and Geographic Information System (GIS) techniques, will be employed to estimate and determine paddy yield. The addition of deep learning algorithms, i.e., Convolutional Neural Networks (CNNs), will allow for more accurate impact assessments.

The geographical location of this study is confined within the North Central Province, although the findings of this research would be applicable for other parts of Sri Lanka as well as nations facing similar agricultural challenges. This research will yield critical results for policy makers, farm planners, and other stakeholders responsible for enhancing food security and sustainable agriculture development.

2. Literature review

2.1. OVERVIEW OF THE PADDY PRODUCTION IN SRI LANKA

Paddy farming is at the core of Sri Lanka's agricultural sector and is at the core of the country's economy. Sri Lankan rice farming is significantly reliant on small farmers, with most paddy crops depending on rain sources, supplemented by a high percentage of irrigated areas (Sivapathasundaram & Bogahawatte, 2015). Sri Lanka has a rich history of rice cultivation, with methods tracing back over 2,500 years, supported by ancient irrigation channels and water management techniques (Weerahewa, 2007). Rice farming is characterized by two cropping seasons: the Maha season from October to March, and the Yala season from May to August. The Maha season is favoured by monsoon rains, whereas the Yala season greatly relies on irrigation facilities (Sivapathasundaram, 2012).

2.2. PROBLEMS OF PADDY PRODUCTION IN SRI LANKA

Paddy cultivation in Sri Lanka is confronted with a number of challenges, both short- and long-term. They not only pose threats to the stability of rice supply but also to food security and sustainable agriculture in the country as a whole.

Climate change is bringing about changes in rain patterns, more intense and frequent droughts, and uncertain monsoon cycles, which are also altering windows of planting and harvesting. The drought experienced during 2016-2017 was a classic example of this and seriously impacted the rice cultivation industry in Sri Lanka, particularly for the dry zone in which irrigation does not take place evenly (Amaratunga et al., 2020). These climatic fluctuations result in sub-normal supply of water, poor yield of crops, and decrease in production overall. The climatic volatility also makes it harder to control paddy cultivation and adds the risk for the farmers while lowering productivity.

The rice farmers of Sri Lanka are also facing economic issues. The country's economic crisis, combined with its all-time high inflation rates, impacts the cost of inputs such as seeds, labour, and more notably, fertilizers. The 2021 government prohibition on chemical fertilizers in a nationwide push for organic cultivation has been particularly disastrous. This policy, with an aim to minimize harm to the environment, caused a substantial decrease in crop yields, and numerous farmers have suffered significantly by way of shortage of nutrients (Dulanjani & Shantha, 2022). Moreover, the economic crisis and the resulting economic pressures have led to diminishing agricultural subsidies, thus making necessary inputs even more out of reach.

Government policies have long affected the paddy cultivation trend in Sri Lanka. Where there have been efforts to boost productivity through improving irrigation and mechanization, the lack of long-term strategic planning has resulted in unpredictable policies. Such policies tend not to address deeper causes of inefficiency, for instance, land fragmentation, use of outdated cultivation methods, and failure to deploy modern technology to agricultural production. Additionally, unsound tenure systems for land and incremental reform speeds have given rise to the environment where land is used inefficiently and growth in agriculture is constrained (Tharindu Dananjaya Weerasinghe & Gamage, 2023).

2.3. PADDY LAND EXTENT CALCULATION METHODS

Proper estimation of paddy land area is essential in successful monitoring of agricultural land use, planning, and policy formulation. Different techniques have been applied to measure the area of paddy land such as traditional field surveys, Maximum Likelihood Classification, Random Forest-Machine Learning method, CNN-Deep Learning method.

Recent advancements in deep learning methods, particularly Convolutional Neural Networks (CNNs), have significantly transformed land use mapping. CNNs can extract features automatically from satellite images, enhancing the accuracy of paddy land identification compared to conventional classification approaches (Zhang et al., 2018). Unlike conventional machine learning algorithms, CNNs have the capability to learn hierarchical representations and fine-grained spatial relations in images, which can be used to differentiate between paddy fields and other land cover types. This capability to handle high-resolution satellite images makes CNNs particularly effective in identifying intricate spatial patterns, which are important in fragmented land ownership regions (Sri Silpa Padmanabhuni et al., 2023). Thus, CNN-based approaches are highly accurate and efficient and are the best approach to use in calculating paddy land extent.

To identify paddy fields using CNNs, it stands to reason that U-Net architecture would be heavily relied upon in tasks such as land use detection, involving semantic segmentation. U-Net is a potent deep learning architecture for image segmentation that is best known for being able to produce accurate predictions at the pixel level. For the present case, U-Net serves the useful purpose of being able to work with high-resolution images such as those captured from a high-resolution image.

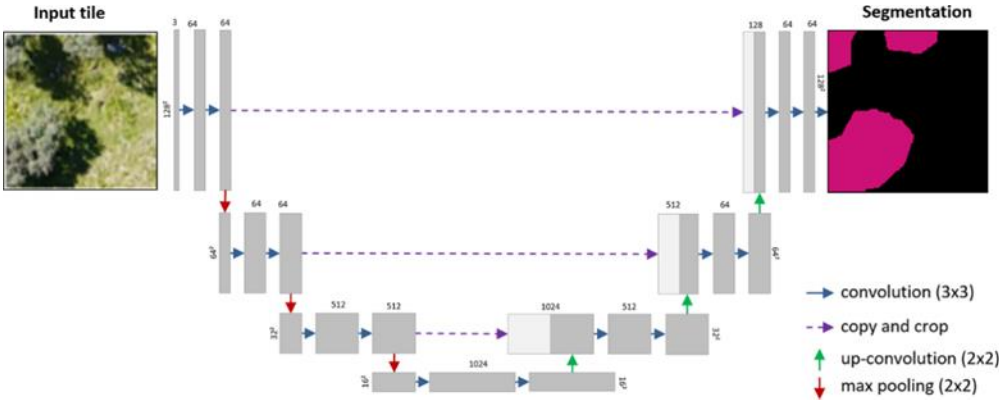


Figure 1: CNN-Deep Learning; Image Segmentation
(source: Kattenborn et al., 2019)

Convolutional layers are first applied to extract features, followed by ReLU (Rectified Linear Unit) activation functions to introduce the necessary non-linearities. The learning rate adaptation during training provided by the Adam optimizer is employed quite often for improving convergence and general model performance. The model performance is assessed with metrics such as IoU (Intersection over Union) and its accuracy in classifying paddy versus non-paddy areas.

Images of Sentinel-2 were taken during June and July of 2022 as a source for training the CNN model due to most recent freshest updates already available from Google Earth Pro with satellite data extension up to mid-2022. Sentinel-2 offers imagery at a spatial resolution of 30 meters and is thus appropriate for paddy field detection (Zhang et al., 2018; Sri Silpa Padmanabhuni et al., 2023).

2.4. ACTIVE AND NON-ACTIVE PADDY LAND CLASSIFICATION

Active and non-active paddy land will be categorized by employing NDVI and NDWI values derived from Sentinel-2 imagery. The fields that show high NDVI (indicating presence of healthy, vigorous vegetation) and moderate NDWI (indicating presence of water during flowering) are considered to be active paddy lands; whereas fields with low NDVI and low NDWI will be classified as non-active paddy lands, either in fallow or abandoned. NDVI and NDWI formulated as;

$$NDVI = (NIR - R) / (NIR + R) \quad (1)$$

NIR = Reflectance in the near-infrared band (Sentinel-2 Band 8)
R = Reflectance in the red band (Sentinel-2 Band 4)

$$NDWI = (Green - NIR) / (Green + NIR) \quad (2)$$

Green = Reflectance in the green band (Sentinel-2 Band 3)

No universally fixed threshold values exist for NDVI and NDWI to separate active from non-active fields, hence their classification must basically follow patterns of distribution for the given study area and corresponding season.

Sentinel-2 imagery from the flowering periods of Maha (October to December) and Yala (June to July) had been selected to map paddy lands since these flowering periods are when paddy fields would be most active and observable. The flowering season is the time when paddy fields show signature characteristics such as water presence in fields and maximum NDVI (Normalized Difference Vegetation Index) values that depict healthy crops. Therefore, using Sentinel-2 high-resolution multispectral bands at peak growing seasons will give precise and reliable results in mapping paddy lands by using both NDVI and NDWI indices to differentiate water-covered land paddy fields from other land uses (Zhang et al., 2018; Sri Silpa Padmanabhuni et al., 2023). Selection of correct date of imagery would have a direct relation to the accuracy of estimates for paddy production, since the timing directly influences the identification of active paddy fields, and yield estimation.

2.5. PADDY PRODUCTION ESTIMATION

Accurate estimation of paddy yield is crucial in planning agricultural resources, food security, and policy formulation. Various methods have been developed to estimate paddy yield from conventional to advanced methods such as traditional methods and biomass correlation approach.

The biomass correlation approach is widely employed to estimate the agricultural production through the use of remote sensing-derived vegetation indices. The most frequently used indices within this method are NDVI and EVI. NDVI is the index indicating vegetation health, which is calculated from the red (R) and near-infrared (NIR) bands using the following equation:

$$NDVI = (NIR-R) / (NIR+R) \quad (1)$$

The EVI corrects some of the atmospheric distortions, thus better enhances the signal in areas of thick biomass, e.g., dense paddy fields. The mathematical expression representing EVI is:

$$EVI = G\times \{(NIR-R) / (NIR+C1\times R-C2\times B+L)\} \quad (3)$$

where G represents the gain factor, C1 and C2 are coefficients for atmospheric correction, B denotes the blue band reflectance, and L is a canopy background adjustment factor. Paddy production is estimated in this study as follows:

First, biomass estimation is executed through:

$$Biomass = (\{(NDVI \times Biomass\ Factor) + (EVI \times Biomass\ Factor)\})/2 \times Active\ Paddy\ Area \quad (4)$$

The biomass factor of 9.0 tonnes/ha is obtained from pre-existing literature concerning paddy cultivation in the North-Central Province of Sri Lanka.

Then yield (production) is estimated through:

$$Yield = Biomass \times Production\ Factor \quad (5)$$

Depending on regional studies, a production factor of 0.45 was accepted for estimation, signifying the common conversion rate from biomass into grain yield for paddy fields.

To estimate paddy production accurately, satellite images taken before harvest have been selected. Because most biomass accumulation in crops has taken place before this time, this timing offers excellent reflection of actual yield conditions. Satellite images during this period were January to March for Maha, and July to August for Yala. Pre-harvest images are ideal because they capture the biomass peak for NDVI and EVI values, making them critical for reliable production estimation, using a biomass correlation approach.

2.6. GAP IN THE LITERATURE

Although substantial research has been conducted on paddy production, and land utilization, notable gaps persist in the literature. While numerous research in Sri Lanka emphasizes either the traditional aspects of paddy land identification or prediction models, few have incorporated cutting-edge technologies, such as deep learning and remote sensing, to connect land identification with yield estimation.

3. Methodology

The study has two stages for paddy land detection and production estimation.

Stage 1: Active Paddy Land Identification
Stage 2: Production Estimation

3.1. ACTIVE PADDY LAND IDENTIFICATION

The paddy land extent as it currently is at this moment in time is the foremost feature of the analysis. This is because without this spatial data on the current active extent of paddy land, estimation of paddy production could not be carried out properly. This includes 3 steps.

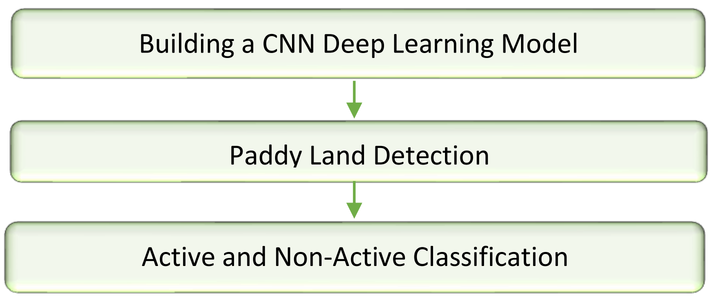


Figure 2: Active paddy land extent Identification

3.1.1. Step 1: Building a CNN Deep Learning Model

The reasoning behind modelling the CNN is that one wants to design a model that can be trained accurately to detect paddy lands. Training samples include 5000-paddy and 5000-non-paddy samples and satellite images. From this input, a paddy-detection model emerges. Once trained, the model can perform paddy detection in various seasons with no further need for retraining.

Table 1: cnn model building

Architecture	U-Net
Activation function	ReLu
Optimizer	Adam
Model evaluation methods	IoU

3.1.2. Step 2: Paddy Land Detection

The purpose of this step is to adapt the detection model to perform accurately during different flowering seasons. The input is satellite imagery from the flowering season and the output is spatial maps of paddy lands of each season. Model accuracy is validated using 500 paddy and 500 non-paddy samples for each season.

3.1.3. Step 3: Active and non-active paddy land classification

This phase's goal is to classify the detected paddy lands into active and non-active areas, which is critical for fragmentation and production estimation purposes. The input is the extent of paddy land detected during the previous step, and NDVI/NDWI threshold values are computed based on that specific season. The output active paddy land was validated with published sown paddy land extent. The output is the extent of active paddy land, which serves as the major input for the subsequent phases of analysis.

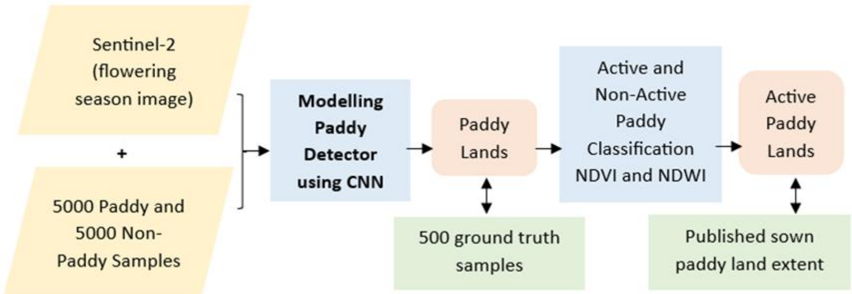


Figure 3: flow diagram for active paddy identification method

3.2. PADDY PRODUCTION ESTIMATION

This is the purpose of this stage: estimating paddy production, which is one of the aspects of looking at the relationship between land fragmentation and the production. The input includes the active paddy land extent mask and satellite imagery of the pre-harvest season. Output is given as estimated paddy production in metric tons (MT), which will directly support evaluating how fragmentation impacts production. The main method of production estimation is the biomass correlation approach, pertaining to NDVI and EVI values. Biomass factor and production factor are derived from literature review findings relevant to the study context.

Table 2: Biomass and Production Factor of the region

Biomass factor	**9**
Production factor	0.45

The validation of these estimated values against published production data is done.

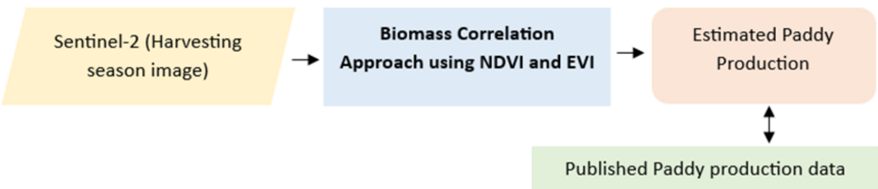


Figure 4: flow diagram for production estimation method

4. Analysis and Results

4.1. REAL TIME ACTIVE PADDY LAND EXTENT

4.1.1. CNN-Deep learning model building

The paddy land identification using the trained CNN model delivered the model's performance as 88.5% accuracy. The training was carried out for 14 epochs, and no signs of overfitting were observed in the training and validation process. Such high accuracy sets the validity of the model for further spatial analysis for different seasons.

```
Epoch 1/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 64ms/step - accuracy: 0.6639 - loss: 0.7055 - val_accuracy: 0.7009 - val_loss: 0.5764 - learning_rate: 5.00e
Epoch 2/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 54ms/step - accuracy: 0.6584 - loss: 0.7140 - val_accuracy: 0.7009 - val_loss: 0.5759 - learning_rate: 5.00e
Epoch 3/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 56ms/step - accuracy: 0.6816 - loss: 0.7217 - val_accuracy: 0.7009 - val_loss: 0.5751 - learning_rate: 5.00e
Epoch 4/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 47ms/step - accuracy: 0.6837 - loss: 0.7251 - val_accuracy: 0.8850 - val_loss: 0.1150 - learning_rate: 5.00e
Epoch 5/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 29ms/step - accuracy: 0.6764 - loss: 0.6480 - val_accuracy: 0.8850 - val_loss: 0.1150 - learning_rate: 5.00e
Epoch 6/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 1s 30ms/step - accuracy: 0.6905 - loss: 0.6900 - val_accuracy: 0.8850 - val_loss: 0.1150 - learning_rate: 5.00e
Epoch 7/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 26ms/step - accuracy: 0.6976 - loss: 0.6489 - val_accuracy: 0.8850 - val_loss: 0.1150 - learning_rate: 2.50e
Epoch 8/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 25ms/step - accuracy: 0.6859 - loss: 0.6451 - val_accuracy: 0.8850 - val_loss: 0.1150 - learning_rate: 2.50e
Epoch 9/50
14/14 ━━━━━━━━━━━━━━━━━━━━ 0s 24ms/step - accuracy: 0.6568 - loss: 0.7096 - val_accuracy: 0.8850 - val_loss: 0.1150 - learning_rate: 2.50e
```

```
test_loss, test_accuracy = model.evaluate(X_test_resized, y_test)
print(f"Test Loss: {test_loss}")
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
```

```
7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - accuracy: 0.8850 - loss: 0.1150
Test Loss: 0.1150101208686829
Test Accuracy: 88.50%
```

Figure 5: paddy detection model-performance assessment

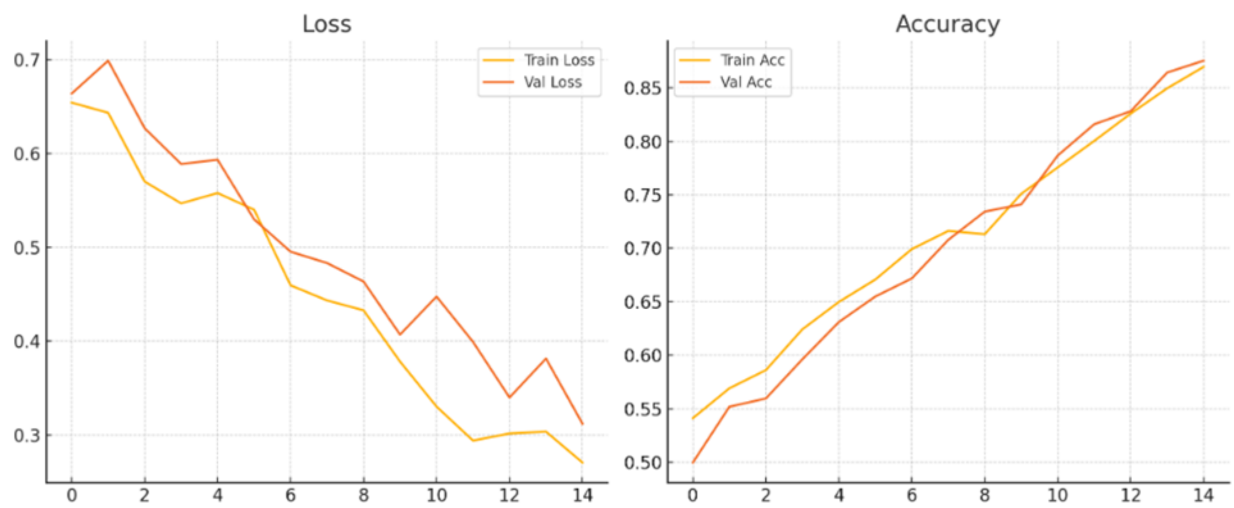


Figure 6: loss and accuracy of the model

4.1.2. real time paddy land extent

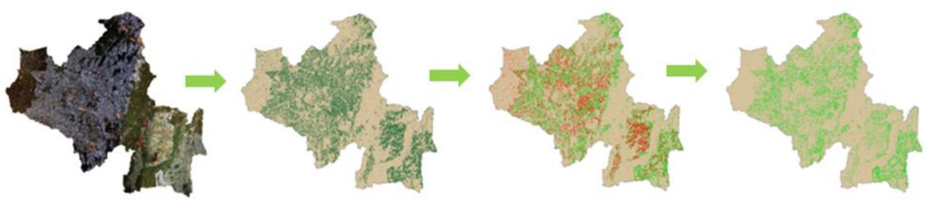


Figure 7: active paddy land identification process

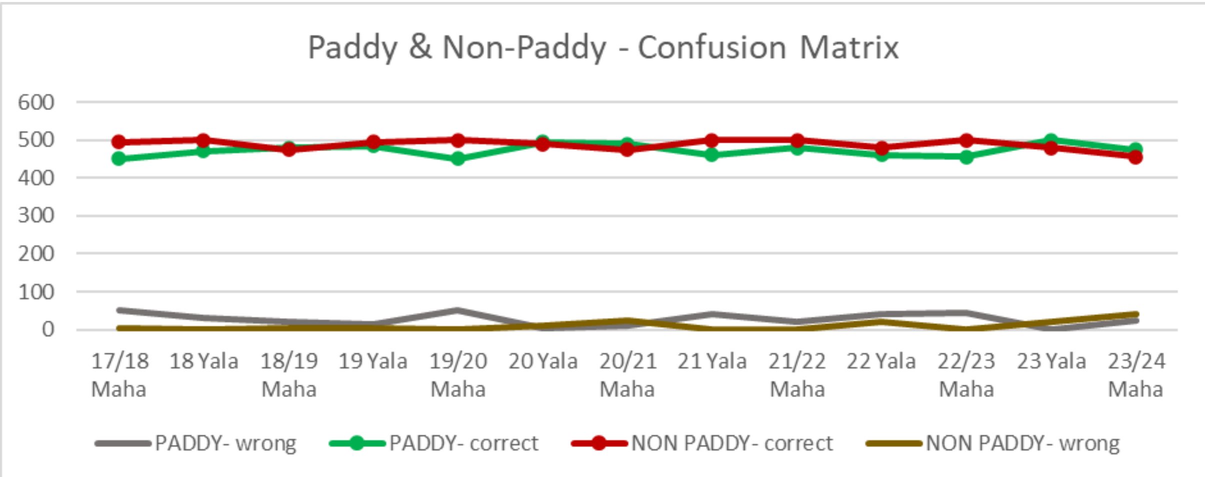
The results indicate that the actual paddy land areas were properly identified using the CNN deep learning model. Classification accuracy was validated by a confusion matrix using ground truth samples, which provides correct and incorrect class labels of the paddy and non-paddy lands.

Table 3: model validation

		PADDY		NON- PADDY	
SEASON-YEAR	ACCURACY	wrong	correct	correct	wrong
17/18 MAHA	94.50%	50	450	495	5
18 YALA	97%	30	470	500	0
18/19 MAHA	97.5%	20	480	475	5
19 YALA	98%	15	485	495	5
19/20 MAHA	95%	50	450	500	0
20 YALA	98.50%	5	495	490	10
20/21 MAHA	96.5%	10	490	475	25
21 YALA	96%	40	460	500	0
21/22 MAHA	98%	20	480	500	0
22 YALA	94%	40	460	480	20
22/23 MAHA	95.50%	45	455	500	0
23 YALA	98.00%	0	500	480	20
23/24 MAHA	93.50%	25	475	455	40

In the verification of paddy land detection for all seasons, the model achieved a more than 90% accuracy rate across all seasons. Confusion matrices were developed for all seasons, confirming the high classification performance of the model with high true positive rates and low misclassification. The accuracy assessment graph also illustrates the classification performance correctly and incorrectly classified samples.

Graph 1: model accuracy check: confusion metrics



4.1.3. real time active paddy land extent

Following the initial classification, active and non-active paddy lands were discriminated using NDVI and NDWI values. Active paddy land extent for the season was then quantified. *Table 1.2 gives the active paddy land area found, to which government-publicized sown paddy land area data has been compared in order to check its validity. Percentage variation of official records versus the found values by the model is also shown, which demonstrates the credibility of the model result.

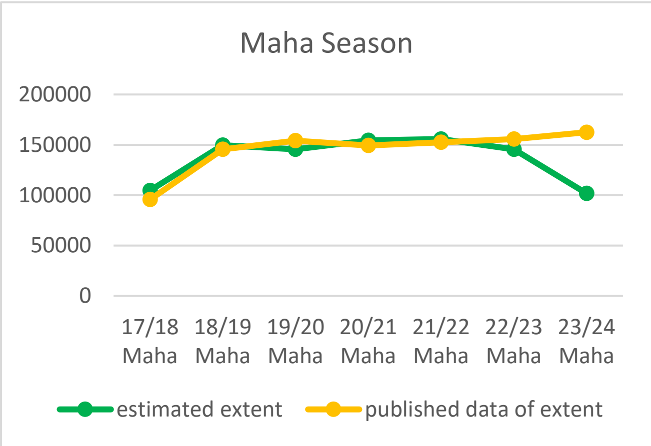
Table 4: comparison with published data

season	*estimated extent*	*Published data of extent*	*% of error*	*season*	*estimated extent*	*Published data of extent*	*% of error*
17/18 Maha	104490.9	95571.00	-9.33324	18 Yala	74062.42	69240.00	-6.96479
18/19 Maha	149628.9	145517.00	-2.8257	19 Yala	73476.68	80145.00	8.320319

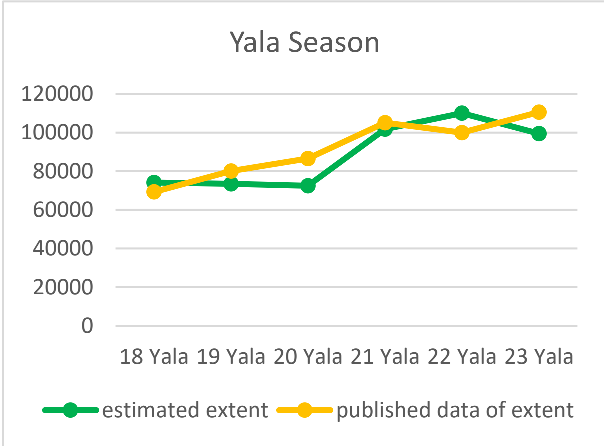
19/20 Maha	145468.2	154057.00	5.575079	20 Yala	72440.82	86542.00	16.29403
20/21 Maha	154447.6	149199.00	-3.51785	21 Yala	101819.7	105067.00	3.090742
21/22 Maha	155785.4	152588.00	-2.09547	22 Yala	109971.5	99976.00	-9.99791
22/23 Maha	145540.1	155801.00	6.585888	23 Yala	99384.84	110523.00	10.07769
23/24 Maha	101744.7	162513.00	37.39286				

Although the model had achieved acceptable accuracy in past seasons, validation for recent years revealed a significant gap, reflecting the inaccuracy of information in subsequent years. This gap reflects a bigger issue, reflecting inefficient government import decisions on rice, which had impacted the accuracy of detection of paddy land. In addition, the temporal dynamics of active paddy land cover are presented in Graphs 2 and 3, representing the seasonal trends of Maha and Yala seasons, respectively. These findings present the active paddy cultivation changes over different years, providing data on seasonal and long-term paddy land changes.

Graph 2: comparison with maha season published data



Graph 3: Comparison with yala season published data



The temporal changes in active paddy land areas have been mapped spatially in the maps provided below. The maps show a visual representation of the temporal changes in paddy cultivation in the area, indicating locations where paddy lands have been continuously active, abandoned, or newly cultivated.

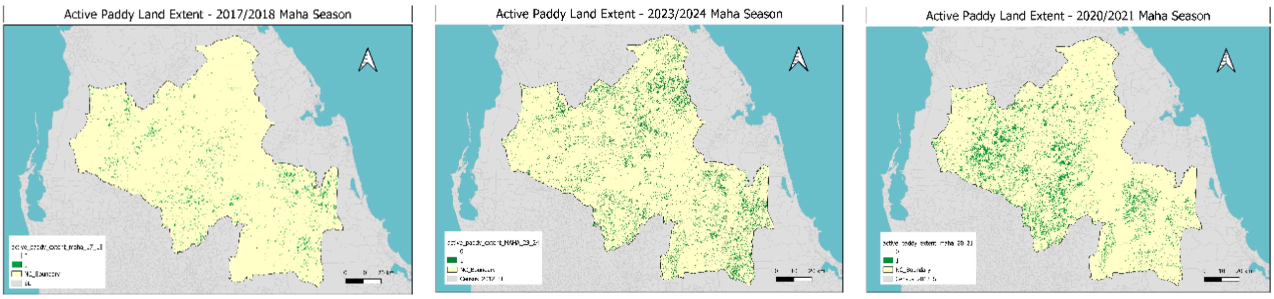


Figure 8: Active paddy land over the time-Maha season

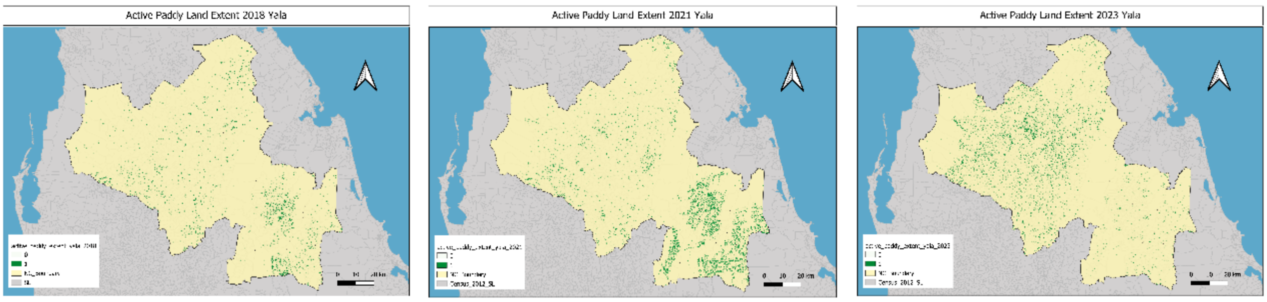


Figure 9: Active paddy land over the time-Yala season

4.2. PADDY PRODUCTION ESTIMATION

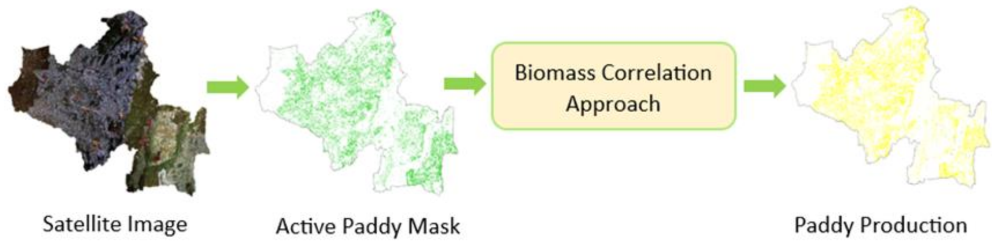


Figure 10: production estimation process

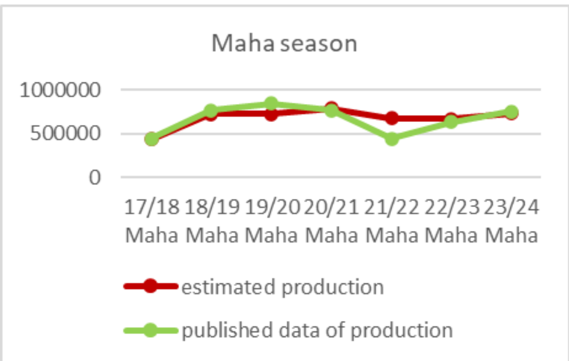
Estimated paddy production of the study area is presented in Table 6. They were estimated by using the biomass correlation method for NDVI and EVI values derived from Sentinel-2 images during harvest times. The government-agency-published paddy production data was also compared to the estimated production figures for purposes of verification, and percentage variations between these two datasets are also presented in Table 5.

Table 5: Comparison with published production data

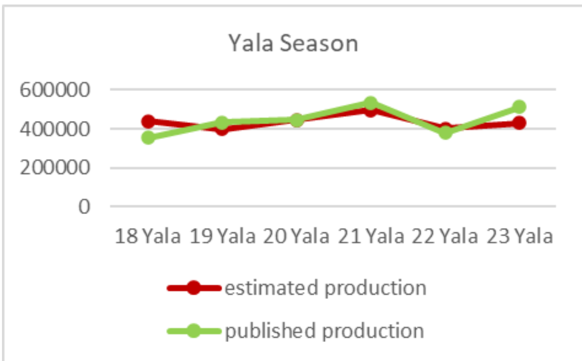
Season	*estimated production*	*published production*	*% of error*	*Season*	*estimated production*	*published production*	*% error*
17/18 Maha	436782.9	446665	2.212416	18 Yala	439885.9	354163	-24.2044
18/19 Maha	729505.1	768282	5.047217	19 Yala	397794.4	431571	7.826432
19/20 Maha	728270.6	848708	14.19068	20 Yala	446602.8	444119	-0.55926
20/21 Maha	788805.1	767775	-2.73909	21 Yala	495692.2	534265	7.219788
21/22 Maha	679485.9	443076	-53.3565	22 Yala	401173.7	378697	-5.93526
22/23 Maha	668482.1	634552	-5.3471	23 Yala	430637.5	511426	15.79671
23/24 Maha	737697.5	757266	2.5841				

The validation of estimated production showed an acceptable difference in the past years, but for the recent Yala season and 2019 Maha season, there was a large deviation. The deviation in 2023 yala might be due to data accuracy issues that occurred between late 2024 and early 2025. Also, deviation in 2019/2020 Maha reflecting the period in between Drought and Economic crisis in Sri Lanka. Seasonal variation in paddy output is better represented in Graphs 4 and 5, the estimated production trend of the Maha season and the Yala season, respectively. The trends reflect the variation in paddy yields across different years, reflecting how climatic factors, farming practices, and land use influence levels of production.

Graph 4: comparison with published production data-maha season



Graph 5:comparison with published production data-Yala season



5. Conclusion and Recommendations

5.1. RESEARCH FINDINGS

The Convolutional Neural Network (CNN) model was used to detect and spatially map paddy fields within the Maha and Yala seasons of 2017-2024. It calculated the total paddy cultivated area for each season, in hectares. Furthermore, it evaluated the estimated area under paddy production in metric tons using a biomass correlation method.

5.2. PRACTICAL APPLICATIONS

Accurate paddy land detection using CNN deep learning models, combined with biomass correlation for yield estimation, enables early prediction of production levels before harvesting. This timely information supports informed decision-making in agricultural planning and helps authorities manage rice imports more efficiently, reducing the risk of shortages or oversupply.

5.3. LIMITATIONS AND RECOMMENDATIONS

While the research is thorough, limitations were encountered that are of future potential to overcome. The production predictions were contrasted against government-released figures, which are subject to reporting delay or reporting inaccuracies and thus could contaminate the accuracy assessment. To address this, it is recommended that future studies incorporate field-level validation methods, e.g., direct farmer interviews, to validate satellite-based classifications. Subsequent research should adopt an interdisciplinary approach that merges urban planning, agriculture, remote sensing, and deep learning.

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