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RESEARCH ARTICLE

Spatial yield estimation in rice using spectral indices derived from satellite datasets and DSSAT crop simulation model

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Abstract

An inter-comparison of two rice yield estimation procedures namely, the Semi-Physical model and the Crop Simulation model, Decision Support System for Agrotechnology Transfer (DSSAT), was conducted for the *Samba Season* (August 2023 to January 2024). This study focused on the Mayiladuthurai and Nagapattinam districts of Tamil Nadu. The Semi-Physical model utilized satellite-derived remote sensing data, including Photosynthetically Active Radiation (PAR), Fraction of Photosynthetically Active Radiation (FPAR), Water stress, Temperature stress and crop physiological parameters such as Radiation Use Efficiency (RUE) and Harvest Index (HI), to estimate crop yield. The DSSAT crop simulation model estimated rice yield using inputs such as soil properties, weather data, genetic coefficients and crop management practices. The simulated yield was further integrated with Synthetic Aperture Radar (SAR) data to generate spatial yield maps. The generated yields were validated with Crop Cutting Experiment (CCE) based yield estimates. The DSSAT model demonstrated superior performance, achieving an agreement of 88.2% in the Mayiladuthurai district and 86.8% in the Nagapattinam district.

Keywords

crop; remote sensing; semi-physical; spatial yield; stress

Introduction

Global food insecurity remains a pressing issue, driven by conflicts and severe environmental challenges as drought, which significantly impact cereal production in many regions worldwide. While Asia and Oceania have shown positive growth in cereal production, countries in Africa, Europe and America have experienced declines. India, ranked 111th out of 125 countries in the Global Hunger Index (GHI), highlights the nation's significant socio-economic challenges related to food security (1). Rice as a staple crop, plays a major role in ensuring food security for most South Asian countries. India's total food grain crop coverage spans approximately 1322 lakh ha. Among these, rice accounts for 477 lakh ha, followed by wheat at 318 lakh ha and pulses at 291 lakh ha (2). India's population is rising at a steady rate of 1% per year, projected to increase from 120 crores in 2011 to over 150 crores by 2036 (3). Population density in India is also expected to rise significantly, increasing from 368 persons per square kilometer in 2011 to 463 persons per square kilometer by 2036. The growing population demands increased agricultural production and productivity. To overcome these socio-economic barriers timely decision making and policies like the National Food Security Act (NFSA) should be prompted. The advent of geospatial technologies has revolutionized agricultural monitoring. Resources and crop production progress can now be tracked in near real-time using satellites imageries, drones and sensors-equipped machinery. Early prediction of crop production can significantly enhance mitigation strategies to combat food insecurity. Crop Simulation models like DSSAT, Aquacrop, Hydrocrop and APSIM enable data -driven planning and resource allocation.

Yield estimation has evolved significantly, transitioning from conventional methods such as manual field survey to advanced technologies like Unmanned Aerial Vehicle (UAV) and machine learning. Traditionally, yield estimation relied on techniques like the Whole Plot Harvest Method, which involves harvesting the entire plot to measure yield directly. While this method is free from bias, it is labor-intensive and time-consuming (4). Field survey have traditionally served as a foundational method for estimating crop area and yield. The visual calculations on plant population and physiological parameters were observed and weather variables were utilized for yield estimates (5). Crop cutting experiments developed by Mahalanobis and Sukhatme, are the conventional method that has been utilized for estimating crop yield over a longer period. However, the major downside of this method is the exclusion of harvest loss and the sampling of the experiment site which leads to a biased estimation of crop yields (6). The use of UAVs brought a breakthrough by enabling high-resolution spatial data collection for crop monitoring, enhancing scalability and efficiency. Incorporation of Vegetation Indices and crop factors from the multispectral drone into a Multiple Linear Regression model for field-level yield estimation. The accuracy of yield estimation can be enhanced using Extreme Gradient Boosting, machine learning algorithm that effectively captures complex, nonlinear relationships in data (7). Leaf Area Index (LAI) retrieved from Multispectral UAV-based Vegetation indices was integrated with the Simple Algorithm For Yield (SAFY) crop simulation model for yield estimation (8). Spectral Mixture Analysis decomposes the spectral signature of a mixed pixel into the proportions of UAV dataset which improves the estimation efficiency of rice crops at the heading stage (9, 10). Machine Learning (ML) and Deep Learning (DL) approaches further advanced this field by processing large datasets, such as UAV imageries, satellite imageries and environmental factors, improve prediction accuracy. With the use of AutoML (Automated Machine Learning), best Vegetation Indices and an ensemble of regression models were utilized for enhanced yield outputs (11). Ensembling is a machine learning technique that combines the less accurate classifiers altogether to obtain highly accurate classifiers (12). Remote sensing variables have been utilized for crop yield estimation through a combination of Deep Neural Networks (DNN) and Gated Recurrent Units (GRU), which enable advanced temporal and spatial data analysis (13). Meanwhile, crop simulation models such as DSSAT and APSIM have been widely used to simulate crop growth and estimate yield based on environmental and management data. These models offer scientifically grounded predictions but are dependent on detailed input data. The Ensemble Kalman Filter technique to improve the efficiency of the DSSAT-DA model by integrating it with Remote Sensing based Soil Moisture products (14). Recent research has focused on integrating multiple methods and data sources such as combining *In-situ* data, UAV data, ML and DL models and crop simulations to improve yield estimation accuracy. Integration of Satellite based indices and krigging with Census data provides effective yield estimation of crops (15). Leaf Area Index (LAI), derived from the Soil-Adjusted Vegetation Index (SAVI), has been integrated with the DSSAT crop simulation model to improve yield estimation (16). This hybrid approach leverages the strengths of each method while addressing individual limitations. As agriculture moves towards precision farming, integrating these advanced techniques will be key to enhancing the reliability and scalability of yield estimation across diverse environments.

Materials and Methods

Study Area

The study was conducted during *Samba 2023* season (August-January) in 2 coastal districts of the Cauvery Delta region, Mayiladuthurai and Nagapattinam, located in the eastern part of Tamil Nadu. Mayiladuthurai has 5 blocks, namely Kollidam, Kuthalam, Mayiladuthurai, Sembanarkoil and Sirkali with a total area of 1172 km^2 (17). Nagapattinam has 6 blocks, namely Keelaiyur, Kilvelur, Nagapattinam, Talanayar, Thirumarugal and Vedaranyam with a total area of 1940 km^2 (18). The major source of irrigation for this study area is the Cauvery River. The region's soils are enriched with soil nutrients deposited by the River Cauvery, making it highly suitable for agriculture (Fig. 1).

Crop Area Estimation

This study utilized a C-band Synthetic Aperture Radar (SAR) product from Sentinel-1 mission of the European Space Agency's Copernicus Program. The Sentinel-1A Level-1 Ground Range Detected (GRD) dataset, featuring dual polarisation (VV+VH), an interferometric wide-swath mode, a 250-km swath, 20-m spatial resolution and 12-day temporal resolution, was used to delineate the rice crop area (19). The automated Pre-processing steps (Strip mosaicking of SAR datasets from same orbit and acquisition date, Co-registration of temporal images acquired in same area, Speckle filtering of images with differences in radar backscatter, Calibration of radiometric parameters, Normalization of radar range dependency, Smoothening of homogeneous targets, Removal of atmospheric attenuation) and Post-processing (Multi-temporal raster generation from pre-processed dataset, Layer Stacking of multi-temporal raster, Parameterized rice classification) were performed using MAPSCAPE software for estimation of the rice crop area. An accuracy assessment was conducted using Ground Truth verification points to evaluate crop area estimates derived from satellite imagery. The assessment achieved an overall accuracy of 84.5%. The generated rice area map was used as a crop area mask. Rice area estimation process was illustrated in Fig. 2.

Semi Physical Approach

Generation of Photosynthetically Active Radiation (PAR)

INSAT-3DR is successor of INSAT-3D, it's a Geo-Stationary satellite of Indian National Satellite System (INSAT) developed by Indian Space Research Organisation (ISRO). It has Incoming Solar Radiation (Insolation) data at 4000 m spatial resolution with a daily temporal revisit period. These datasets for the study area were downloaded from the website Meteorological and Oceanographic Satellite Data Archival Centre | Space Applications Centre, ISRO (http://mosdac.gov.in) covering a period from August 2023 to January 2024 for further processing.

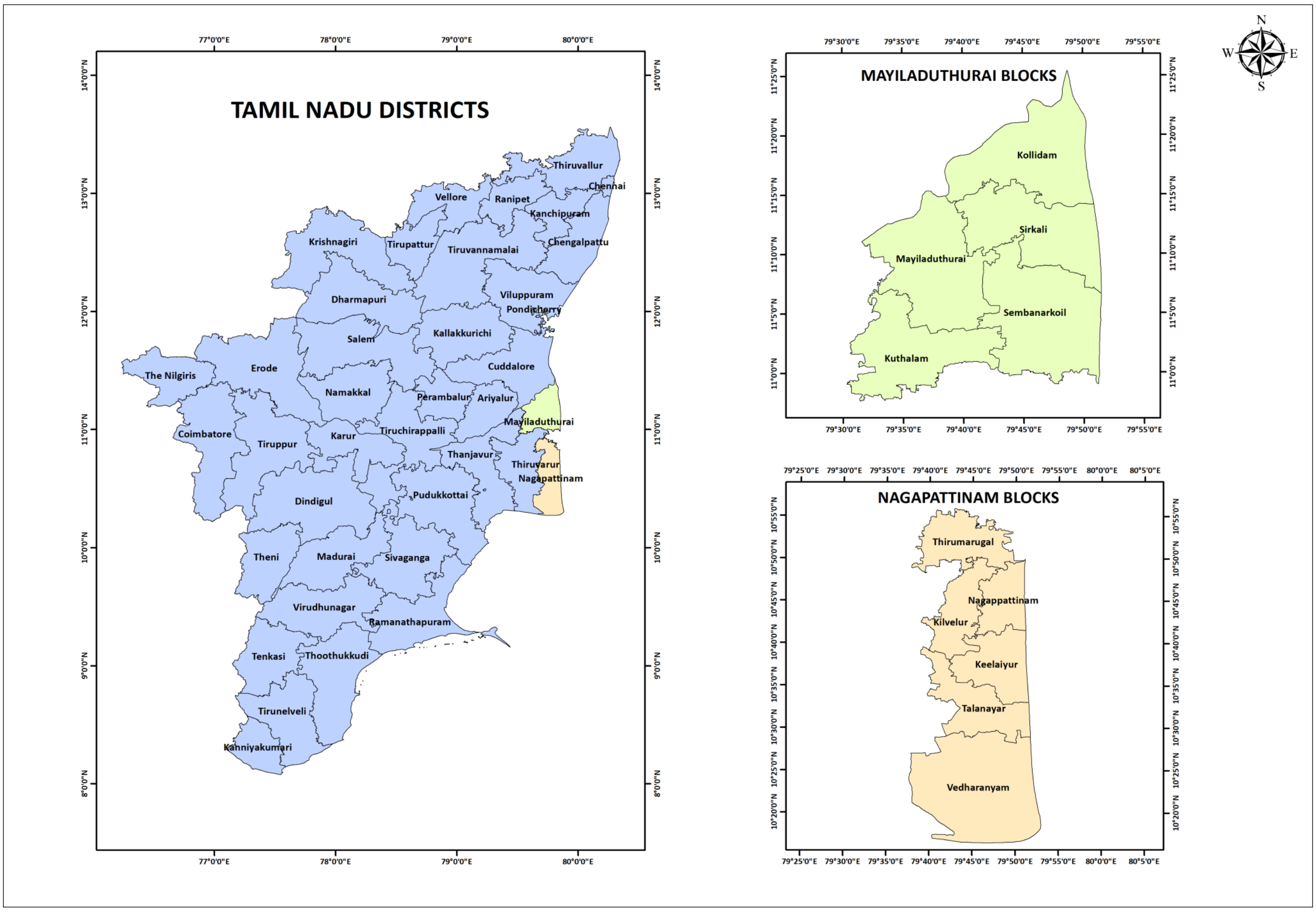

Fig. 1. Study area map.

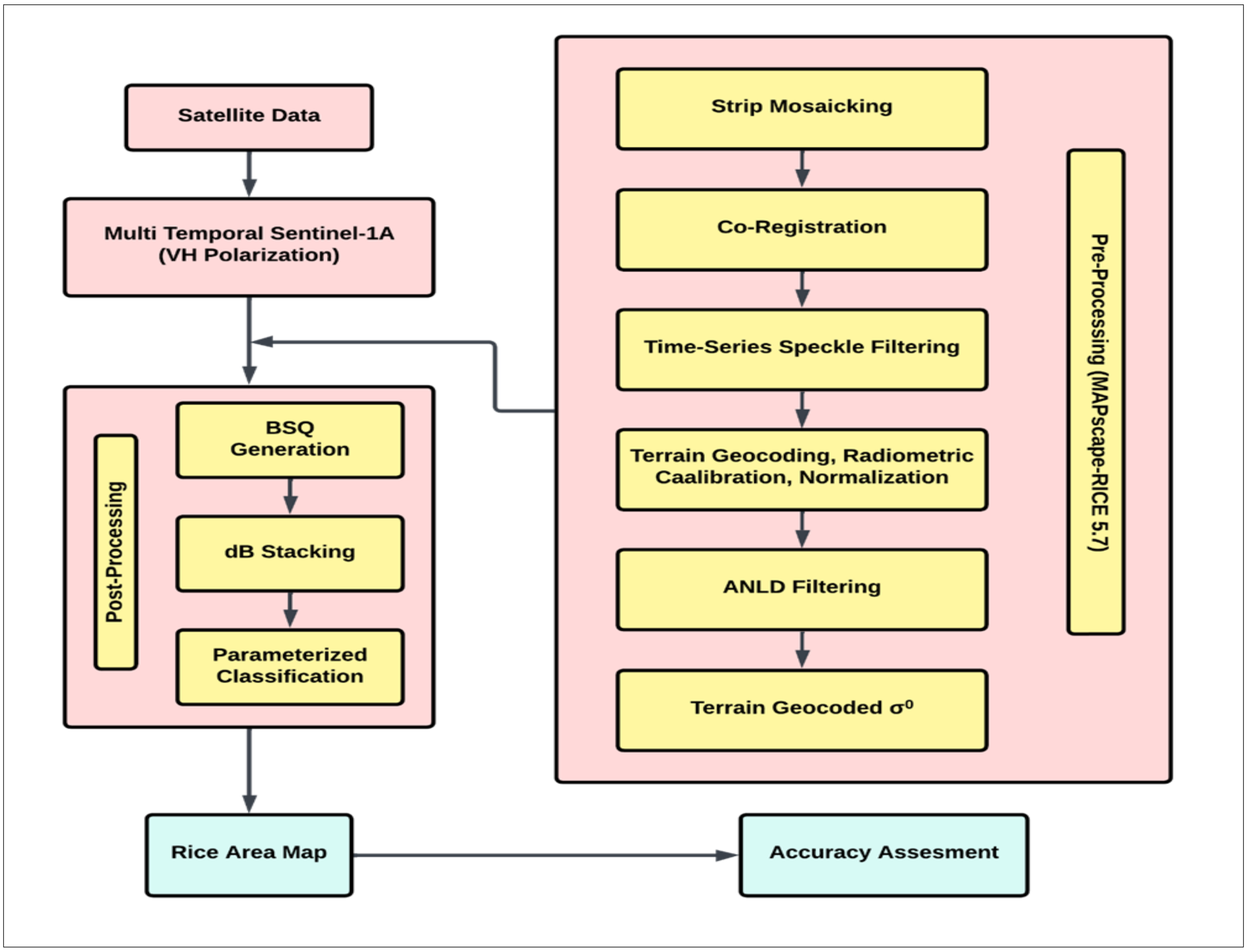

Fig. 2. Flow chart depicting rice area estimation.

Daily Insolation data from INSAT-3DR is multiplied by 0.48 to generate daily Photosynthetically Active Radiation (PAR). Daily PAR is then composited into an 8-day Composite raster with respect to the acquisition dates of Moderate Resolution Imaging Spectroradiometer (MODIS) datasets (20). PAR is the amount of radiation utilised by plants for photosynthesis.

Generation of Fraction of Photosynthetically Active Radiation (FPAR)

MODIS is a Polar Orbiting satellite of NASA's Earth Observation Program. For this study, an 8-day composite MCD15A2H Level-1B product with 2 Spectral bands (Leaf Area Index and Fraction of Photosynthetically Active Radiation), Spatial resolution of 500 m is used for retrieving Fraction of Photosynthetically Active Radiation. These data for the study area were downloaded from the website (http://earthdata.nasa.gov) covering a period from August 2023 to January 2024 for further processing (21). FPAR is the fraction of PAR that is absorbed by vegetation for photosynthesis.

Generation of Water Stress

For this study, an 8-day composite MOD09A1 Level-1B product with 16 Spectral bands, Spatial resolution of 500 m is used for generating Land Surface Water Index (LSWI) (22). And downloaded for a period from August 2023 to January 2024 for further processing.

LSWI was generated using the spectral bands retrieved from MOD09A1 using the Equation 1

$$LSWI = \frac{NIR - SWIR}{NIR + SWIR} \quad \text{(Eqn. 1)}$$

Where, *LSWI=Land Surface Water Index, NIR=Near-Infrared and SWIR=Shortwave Infrared.*

Further, the Water Stress was generated from LSWI using the Equation 2

$$W_{stress} = \frac{1 + LSWI}{1 + LSWI_{max}} \quad \text{(Eqn. 2)}$$

Where, ***W***W_{stress}*=Water Stress, **LSWI**=Land Surface Water Index and* $LSWI_{max}$*=Maximum Land Surface Water Index of the area.*

Generation of Temperature Stress

NASA POWER (National Aeronautical and Space Administration - Prediction of Worldwide Energy Resources) is a part of NASA's Earth Science Research Program has Global, Regional and Point level Meteorological datasets from weather forecast models and satellite (22). Temperature data for the study area was retrieved in CSV format from the NASA POWER data portal, with a grid size of about 0.5 x 0.625 degrees covering a period from August 2023 to January 2024 for generating Temperature Stress. Temperature Stress was generated using the Equation 3

$$T_{stress} = \frac{(T - T_{min})\,(T - T_{max})}{(T - T_{min})\,(T - T_{max}) - (T - T_{opt})^2} \quad \text{(Eqn. 3)}$$

Where, T_{stress}*=Temperature Stress, **T**=Daily Mean Temperature,* T_{min}*= Minimum Temperature for Photosynthesis (°C),* T_{max}*= Maximum Temperature for Photosynthesis (°C) and* T_{opt} *=Optimum Temperature for Photosynthesis (°C).*

Generation of Net Primary Product

Net Primary Product (NPP) for the cropping season from sowing to harvest was computed at an 8-day interval using the periodical PAR, FPAR, W_{stress}, T_{stress} and Maximum Radiation Use Efficiency (RUE) using the Equation 4. RUE quantifies the efficiency with which absorbed PAR is converted into biomass.

$$NPP = PAR * FPAR * RUE * W_{stress} * T_{stress} \quad \text{(Eqn. 4)}$$

Yield estimation from Net Primary Product

NPP_{sum} was computed for the entire cropping season from 8-day composite datasets. The crop yield for the study area was estimated from the product of NPP_{sum} and Harvest Index using the Equation 5. Harvest Index (HI) was generated from the CCE data using the Equation 6.

$$Yield = NPP_{sum} * HI \quad \text{(Eqn. 5)}$$

$$HI = \frac{\text{Economic Yield}}{\text{Biological Yield}} \quad \text{(Eqn. 6)}$$

The methodology for rice yield estimation using the Semi -Physical model was depicted in Fig..3.

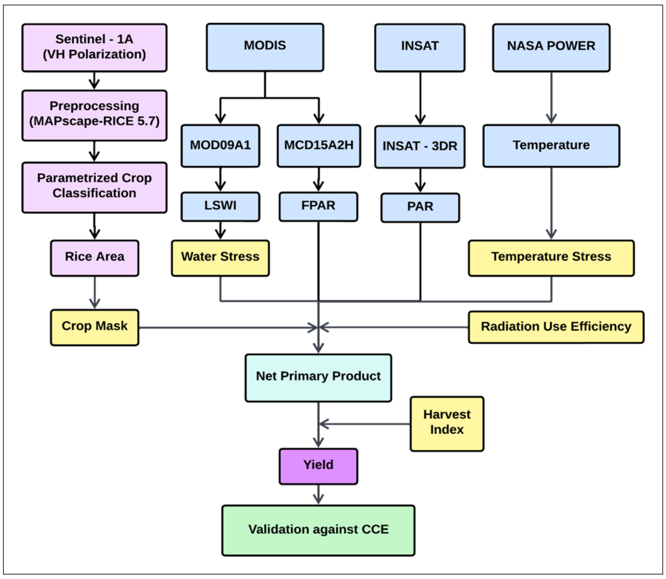

Fig. 3. Flow chart depicting semi physical model-based yield estimation.

DSSAT Approach

Soil Data

Soil data generated by utilizing the available soil database of Tamil Nadu from the Department of Remote Sensing and GIS, Tamil Nadu Agricultural University is used as input for the DSSAT model as soil input.

Weather Data

NASA POWER (National Aeronautical and Space Administration - Prediction of Worldwide Energy Resources) is a part of NASA's Earth Science Research Program has Global, Regional and Point level Meteorological datasets from Weather forecast models and satellite. Weather variables (Minimum Temperature, Maximum Temperature, Precipitation, Solar Radiation, Relative Humidity and Wind speed) for the study area was retrieved in CSV format from the NASA POWER data portal, with a grid size of about 0.5 x 0.625 degrees covering a period from August 2022 to January 2023 for further processing (23).

Genetic Coefficient

Genetic Coefficients such as P1 (Photoperiod-insensitive period), P20 (Critical photoperiod at maximum development rate), P2R (Extent to which the crop phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above P20), P5 (Time period from beginning of grain filling to physiological maturity), G1 (Potential spikelet number coefficient), G2 (Single grain weight under ideal growing conditions), G3 (Tillering coefficient) and G4 (Temperature tolerance coefficient) generated for the rice varieties (CR1009, ADT(R) 45 and BPT 5204) prevailed in the study area. These coefficients were then input into the DSSAT GENCALCULATOR, a software tool to generate metrics for various crop growth stages (24).

Crop Management

The crop management practices from nursery to harvest were generated using the DSSAT XBuild tool for creating and editing the input files such as the experimental conditions and field characteristics like irrigation management, fertilizer management, environmental modifications, harvest management and simulation controls and output options (25).

Leaf Area Index

Leaf Area Index (LAI) is a crucial parameter in DSSAT. It quantifies the total leaf area per unit ground surface area beneath the plant canopy. LAI plays a pivotal role in simulating crop growth. It depicts the interception of solar radiation, which significantly influences the rate of photosynthesis. LAI calculation considers various factors, including plant population density, leaf growth rates and senescence processes (26, 27).

DSSAT Yield Estimation

The back scatter values retrieved from the processed Sentinel 1A SAR data was integrated with the Simulated LAI from CERES-Rice module available in the DSSAT to retrieve spatial LAI and a linear regression carried to generate spatial rice yield from spatial LAI and DSSAT simulated yield. DSSAT yield, Spatial LAI and Spatial rice yield estimation using the DSSAT crop simulation model and SAR dataset was depicted in Fig. 4.

Results

Rice Area Estimation

The rice area map distinctly reveals the availability of crop area nearby the water resources. Rice area in Mayiladuthurai district covers about 49556 ha and Nagapattinam district covers about 42321 ha (Table. 1, Fig. 2). A total of 208 ground truth points were collected on different stages of crop growth for validation of estimated crop area. A confusion matrix was computed to

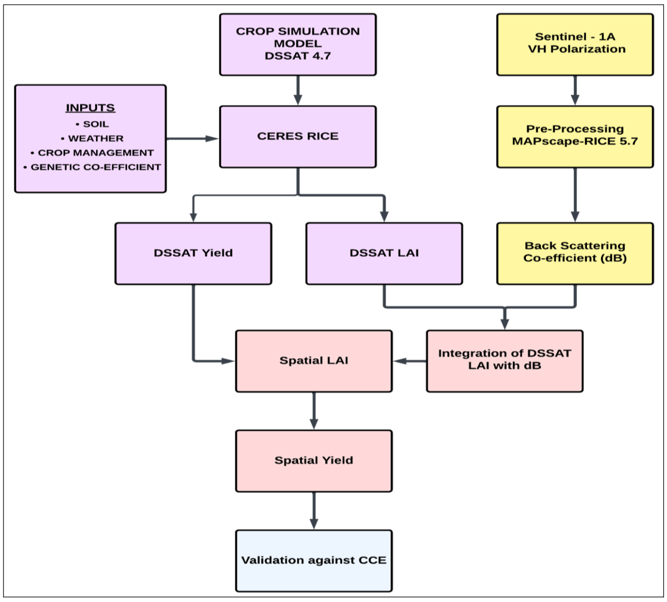

Fig. 4. Flow chart depicting DSSAT model-based yield estimation.

estimate the accuracy of the crop classification. The assessed accuracy for the estimated rice crop was 88%, meanwhile accuracy for non-rice crop was 82%. The seasonal rice area for Mayiladuthurai and Nagapattinam districts were shown in Fig. 5.

Model Evaluation

Model performances were validated by comparing simulated yields with actual yields from Crop Cutting Experiments (CCE) conducted within the study area. CCE data, while providing valuable ground truth, may have inherent limitations. Spatial variability within fields and across the broader landscape may not be fully captured by the limited number of CCE sampling points. Additionally, manual harvesting procedures in CCE can introduce potential biases due to sampling errors and inconsistencies in measurement techniques.

Model performances were evaluated using the metrics including Agreement percentage, Root Mean Square Error (RMSE) and Normalized Root Mean Square Error (NRMSE). Agreement percentage quantifies the overall model accuracy by comparing simulated and actual yields. Higher agreement percentages indicate better model performance. RMSE provides a measure of the average deviation between predicted and actual values. NRMSE, a normalized version of RMSE, facilitates comparisons of model performance across datasets with varying scales.

Estimated yields of Mayiladuthurai District

For Mayiladuthurai district the DSSAT model performed better with an average simulated yield of 3862.6 kg ha^{-1}than the Semi-Physical model with an average simulated yield of 3641.1 kg ha^{-1}. The estimated yield for both models were shown in the Fig. 6, 7. The statistical comparisons were tabulated in Table 2 and graphically visualized in Fig. 8.

Table 1. Block-wise rice area of study area

District	Block	Area in ha	District	Block	Area in ha
Mayiladuthurai	Kollidam	7269.60	Nagapattinam	Keelaiyur	6582.96
Mayiladuthurai	Kuthalam	9446.36	Nagapattinam	Kilvelur	7484.52
Mayiladuthurai	Mayiladuthurai	12574.44	Nagapattinam	Nagappattinam	4446.04
Mayiladuthurai	Sembanarkoil	12342.72	Nagapattinam	Talanayar	6476.16
Mayiladuthurai	Sirkali	7923.36	Nagapattinam	Thirumarugal	7413.36
			Nagapattinam	Vedharanyam	9918.76

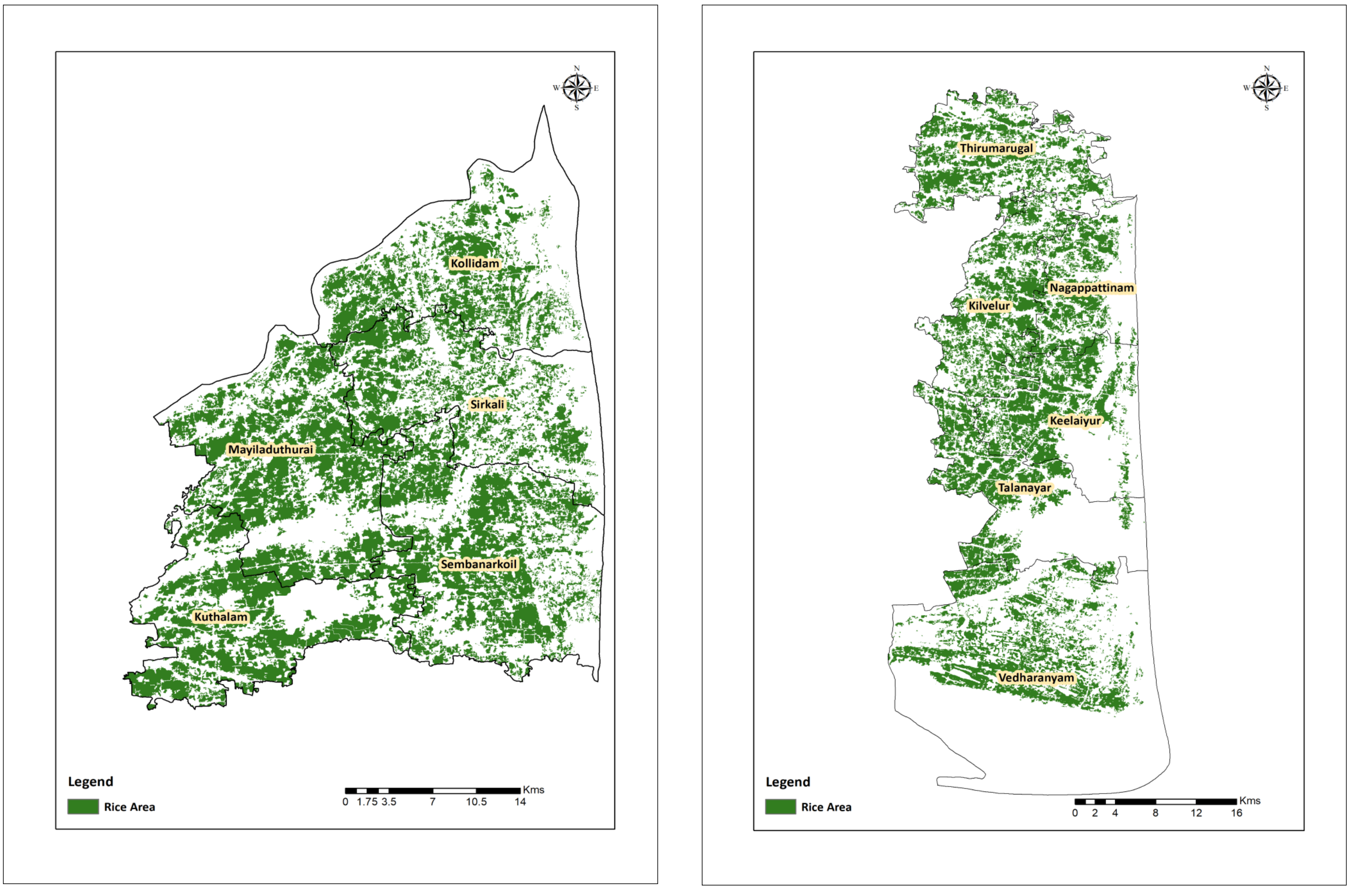

Fig. 5. Rice area map of Mayiladuthurai and Nagapattinam districts for *Samba 2023.*

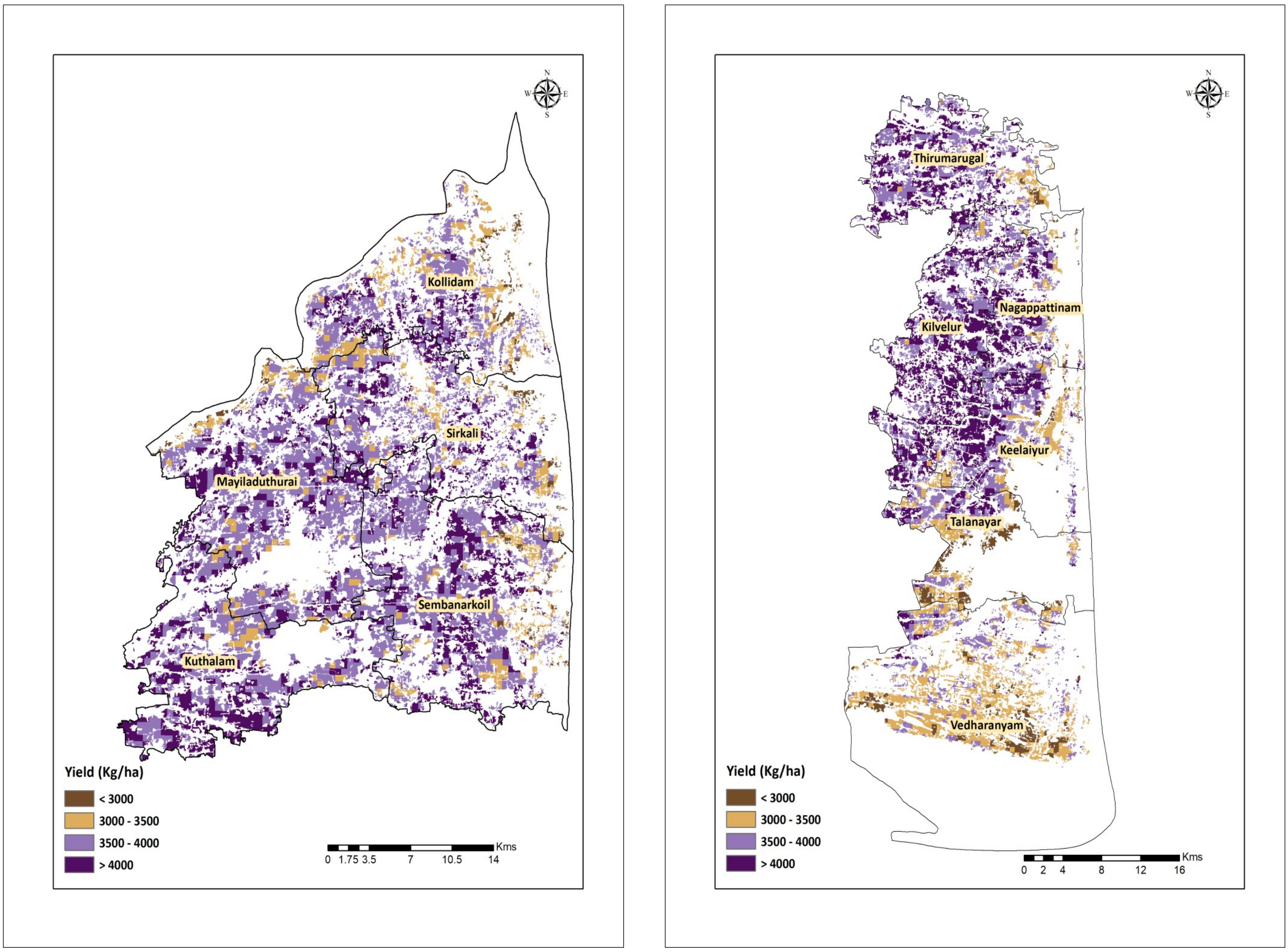

Fig. 6. Semi-physical model-based yield map of Mayiladuthurai and Nagapattinam districts.

Table 2. Block-wise yield comparison of Mayiladuthurai district

Block	CCE Yield (Kg/ha)	Semi-Physical Model based Yield (Kg/ha)	DSSAT Model based Yield (Kg/ha)	Semi-Physical Model based RMSE (kg/ha)	Semi-Physical Model based NRMSE (%)	Agreement (%) Semi-Physical vs CCE	DSSAT Model based RMSE (kg/ha)	DSSAT Model based NRMSE (%)	Agreement (%) DSSAT vs CCE
Kollidam	4154.5	3499.9	3682.2	680.5	15.7	84.3	478.1	11.0	89.0
Kuthalam	4421.1	3784.7	3858.5	680.9	14.5	85.5	567.1	12.1	87.9
Mayiladuthurai	4438.3	3660.3	4006.1	781.8	16.9	83.1	469.2	10.0	90.0
Sembanarkoil	4356.9	3655.7	3904.9	710.6	15.5	84.5	518.0	11.3	88.7
Sirkali	4505.9	3606.7	3861.4	912.0	19.7	80.3	683.4	14.7	85.3

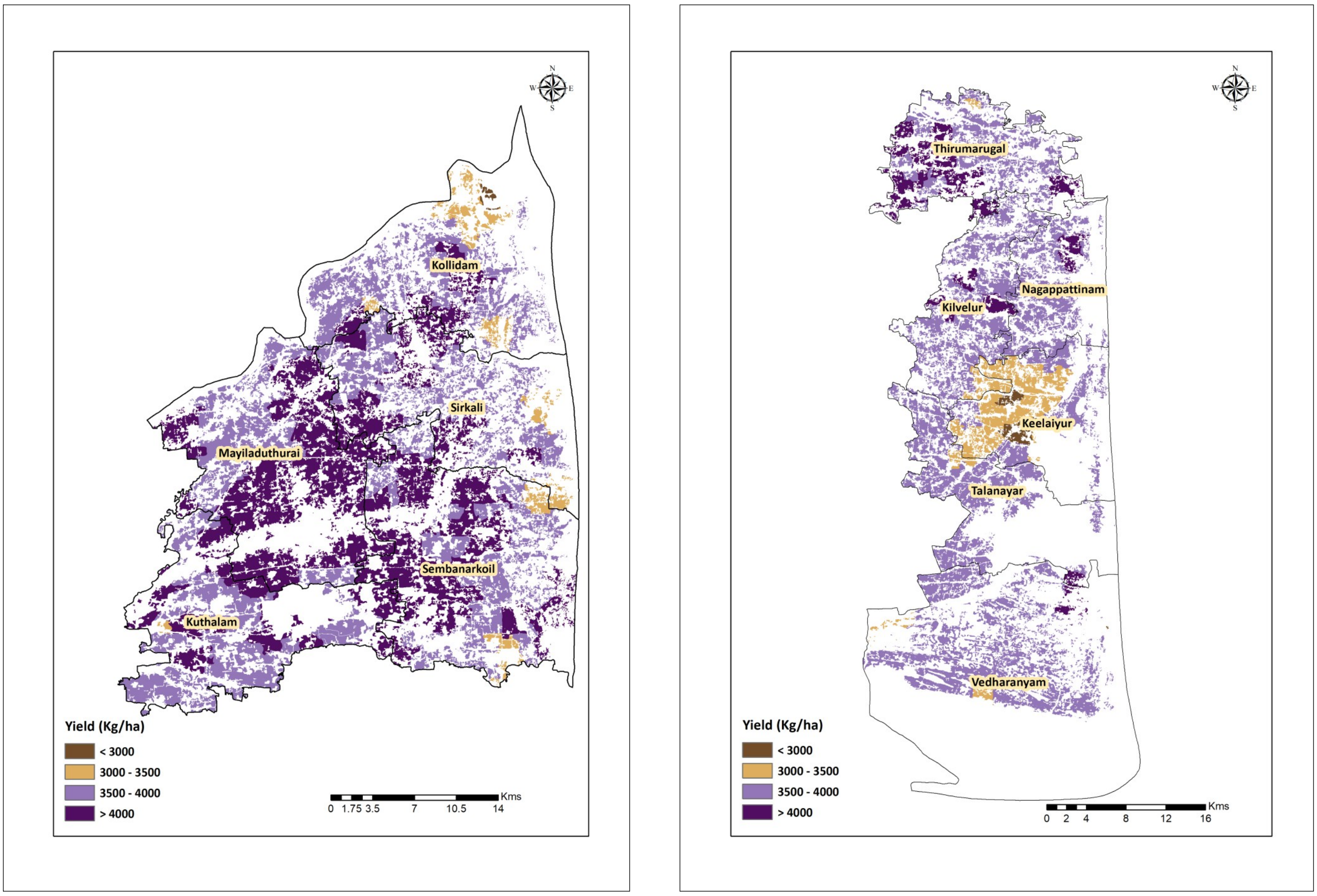

Fig. 7. DSSAT model-based yield map of Mayiladuthurai and Nagapattinam districts.

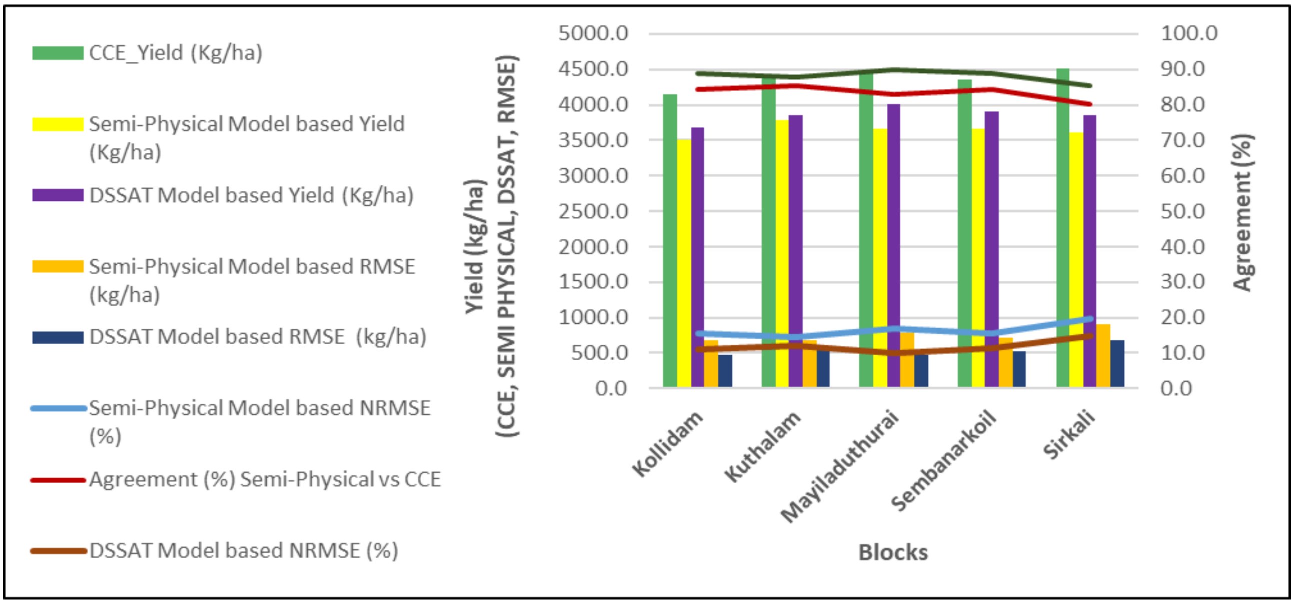

Fig. 8. Block-wise yield comparison of Mayiladuthurai district.

Among the 5 blocks in the Mayiladuthurai district, the Semi-Physical model estimated the highest yield of 3784.7 kg ha^{-1} in the Kuthalam block, while the Kollidam block recorded the lowest estimated yield of 3499.9 kg ha^{-1}. Estimated yields were compared with yields from CCE obtained from Department of Agriculture were used for estimating RMSE, NRMSE and Agreement percent. The average RMSE, NRMSE and Agreement percentage for the Mayiladuthurai district were 753.2 kg ha^{-1}, 16.5% and 83.5% respectively.

Among the 5 blocks in the Mayiladuthurai district, the DSSAT model estimated the highest yield of 4006.1 kg ha^{-1} in the Mayiladuthurai block, while the Kollidam block recorded the lowest estimated yield of 3682.29 kg ha^{-1}. Estimated yields were compared with yields from CCEs for estimating RMSE, NRMSE and Agreement percent. The average RMSE, NRMSE and Agreement for Mayiladuthurai district were 543.2 kg ha^{-1}, 11.8% and 88.2% respectively.

Estimated yields of Nagapattinam District

For Nagapattinam district the DSSAT model performed better with an average simulated yield of 3792.3 kg ha^{-1}than the Semi-Physical model with an average simulated yield of 3725.2 kg ha^{-1}. The estimated yield for both models were shown in the Fig. 6 and fig. 7. The statistical comparisons were tabulated in Table 3 and graphically visualized in Fig. 9.

Among the 6 blocks from Nagapattinam district, Semi-Physical model estimated the highest yield of 4115.5 kg ha^{-1} in Kilvelur block, while Vedharanyam block recorded the lowest estimated yield of 3311.3 kg ha^{-1}. Estimated yields were compared with yields from CCEs for estimating RMSE, NRMSE and Agreement percent. The average RMSE, NRMSE and Agreement for Mayiladuthurai district were 664.0 kg ha^{-1}, 14.8% and 85.2%.

Among the 6 from Nagapattinam district Thirumarugal block attained maximum yield of 3996.6 kg ha^{-1} and Keelaiyur block attained minimum yield of 3522.4 kg ha^{-1}. Estimated yields were compared with yields from Crop Cutting Experiments (CCE) for estimating Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE) and Agreement percent. The average RMSE, NRMSE and Agreement for Mayiladuthurai district were 602.4 kg ha^{-1}, 13.2% and 86.8%.

Discussion

The DSSAT crop simulation model represents crop growth by incorporating key growth factors such as variety, soil, weather conditions and crop management practices. Predicted spatial yields were highly sensitive to variations in the LAI, highlighting the interplay among soil properties, weather conditions and cultivation practices across different regions. In the semi-physical model, yield estimation was influenced by the amount of Photosynthetically Active Radiation (PAR) received during the cropping season and the Radiation Use Efficiency (RUE) of the crop under specific conditions. PAR and RUE quantify the

Table 3. Block-wise yield comparison of Nagapattinam district

Block	CCE Yield (Kg/ha)	Semi-Physical Model based Yield (Kg/ha)	DSSAT Model based Yield (Kg/ha)	Semi-Physical Model based RMSE (kg/ha)	Semi-Physical Model based NRMSE (%)	Agreement (%) Semi-Physical vs CCE	DSSAT Model based RMSE (kg/ha)	DSSAT Model based NRMSE (%)	Agreement (%) DSSAT vs CCE
Keelaiyur	4318.8	3682.0	3522.4	644.6	14.7	85.3	796.4	18.0	82.0
Kilvelur	4739.8	4115.5	3900.1	624.3	12.7	87.3	841.8	17.4	82.6
Nagappattinam	4333.7	3764.9	3896.9	568.8	12.8	87.2	476.3	10.4	89.6
Talanayar	4204.4	3560.4	3773.7	644.1	15.2	84.8	484.5	10.8	89.2
Thirumarugal	4604.4	3917.1	3996.6	687.3	14.6	85.4	629.0	13.2	86.8
Vedharanyam	4005.5	3311.3	3663.9	815.1	18.7	81.3	386.2	9.1	90.9
Keelaiyur	4318.8	3682.0	3522.4	644.6	14.7	85.3	796.4	18.0	82.0

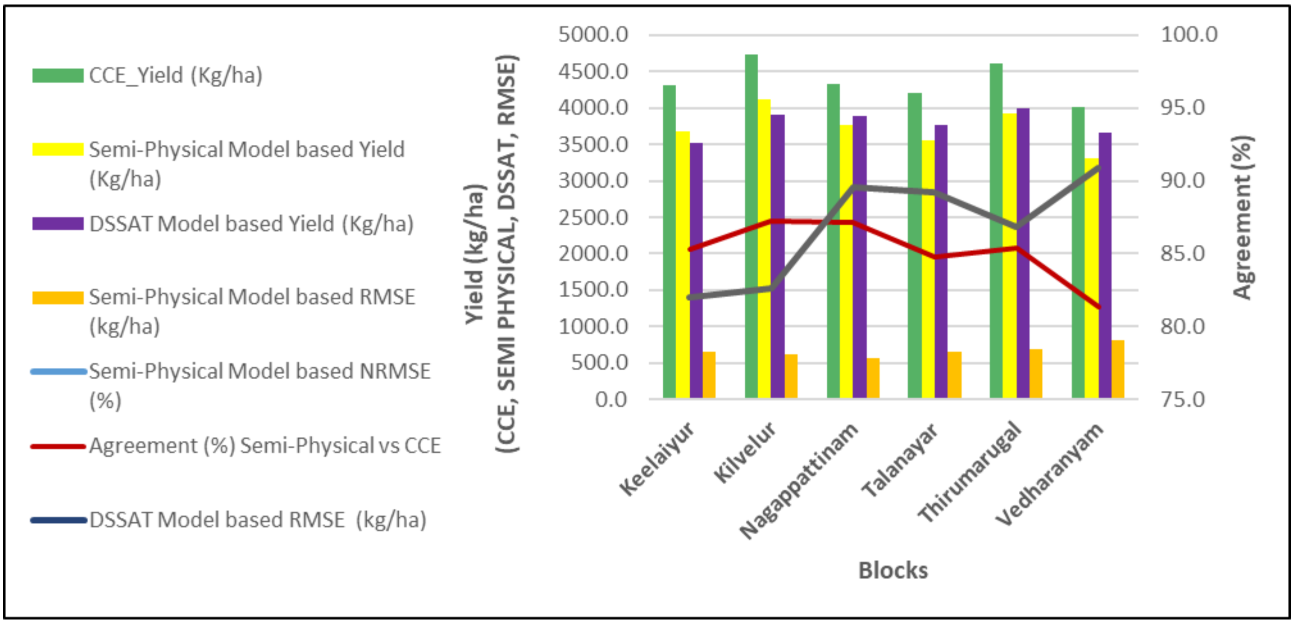

Fig. 9. Block-wise yield comparison of Nagapattinam district.

amount of radiation received and converted into biomass by that specific crop (28). The results of this study align with findings from (16, 28), which demonstrated that DSSAT consistently predicted higher average yields across the study area.

It was evaluated yield estimates using various approaches and reported the highest mean R^2 value for the DSSAT model, followed by spectral indices-based regression analysis, with the Semi-Physical model showing the least predictive performance (29). A correlation coefficient of 0.81 found between observed and DSSAT simulated yields, while 0.85 between model LAI and yield. DSSAT found to be sensitive to the timing of sowing and the quantity of applied fertilizer (27). Application of Nitrogen improves the estimated yield in DSSAT model upto a threshold level of 200 kg ha^{-1}, a decline in yield was found beyond the threshold level (30). Increase in LAI improves the dry matter production and it also hinders the light incidence of lower leaves (31). CERES-RICE model predicted improvement in estimated yield for the plant population of 11-44 plants m-2 and a decline after that range (32).

Identification of CCE sites and crop growth stages using crop mask and NDVI improves the reliability and accuracy of CCE for validation (16). It was achieved higher R^2value while comparing the semi-physical model-based yield estimates with government yield estimates (33). Another study was achieved an R^2 value of 0.58 from a Semi-physical model based yield estimation (34).

Semi-physical based approach can estimate yields at administration units at village level and the yield. Yield estimates from PAR and FPAR on wheat crop shows 10% deviation from the actual yields (35, 36). Semi-physical and machine learning approach on pearl millet shown a nominal deviation of 10 and 6% from the actual yields (37).

Conclusion

This research aimed to showcase the performance ability of 2 models *viz.,* DSSAT-Crop Simulation model and Semi-Physical model. In comparison with CCE based yield estimates the overall performance in the study area was topped by the DSSAT model while the Semi-Physical model performed better in some areas. As the DSSAT model includes most of the necessary parameters responsible for crop yield it has an advantage over the Semi-Physical model. But DSSAT requires quality input data, including soil properties, crop management practices and weather data. Obtaining these data can be challenging in regions with limited data availability and record-keeping. Inaccurate data, particularly for soil characteristics and historical weather patterns, can significantly impact the reliability of model predictions.

The complexity of DSSAT can pose challenges for users with limited technical expertise. Similarly, Semi-physical approach also requires quality input datasets and insufficient datasets might create error gaps. The input datasets used in the Semi-Physical model had a coarse spatial resolution which impacts the final yield estimate. Some alternative sources such as Sentinel-2 have a better spatial resolution but it has a drawback in terms of cloud cover during monsoons of this study area. DSSAT can be utilized in precision farming to identify and implement efficient management practices, including optimizing fertilizer application, designing effective irrigation schedules and determining the ideal plant population density. Usage of DSSAT and Semi-physical outputs by insurance and government agencies improved a lot in recent years. Automation of data acquisition and processing of inputs for these models using programming language and machine learning tools improves the computation time and overall efficiency of these techniques.

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Authors' contributions

SM carried out the experiment, observation and drafted the manuscript. SP guided the research by formulating the research concept and approved the final manuscript. KPR guided the research by formulating the research concept and helped in securing research funds. RK performed the statistical analysis. APS conceived of the study and participated in its design and coordination. MR participated in the data analysis and revised manuscript. All authors reviewed the results and approved the final version of the manuscript.

Compliance with ethical standards

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Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT by OpenAI to enhance language clarity and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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