A Semi - Physical Approach using Remote Sensing based Net Primary Productivity (NPP), Spatial, Spectral & Temporal Paddy Yield Model Development for the State of Assam

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Abstract: ***India, renowned as the leading rice exporter and the second - largest rice producer globally, faces the crucial task of ensuring an adequate rice supply to meet the demands of its growing population. Consequently, accurate yield prediction plays a vital role in enabling policymakers and planners to devise effective strategies concerning import - export dynamics to achieve food security objectives. Additionally, such predictions serve as a valuable tool for crop insurance purposes. This research focuses on Assam, a state in India known for its significant cultivation of paddy. In Assam, paddy is cultivated three seasons, namely Ahu (Autumn rice), Sali (Winter rice), and Boro (summer rice). The study primarily focuses on the "Sali" season, given its prominence as the dominant crop, occupying approximately 77.5% of the rice - growing area (dmagri. in) and contributing to nearly 75% of the overall rice production in the state (dmagr. in). The selection of the Sali season is further influencedby its vulnerability to flood - related challenges, rendering it an ideal period for investigation. To achieve cost - effective and efficient crop monitoring, remote sensing technology is employed. This study adopts a semi - physical approach for predicting crop yield, utilizing remote sensing data for crop masking in the study area, coupled with essential physiological parameters including temperature stress, water stress, and insolation. The estimation of Net Primary Productivity (NPP) is accomplished through Monteith's model, leveraging variables such as Photosynthetically Active Radiation (PAR), Fraction of Absorbed Photosynthetically Active Radiation (fAPAR), Radiation Use Efficiency (RUE), water stress, and temperature stress. The NPP and Harvest Index (HI) are then utilized to compute rice/paddy yield. The investigation spans a period of five years (2018 - 2022) and encompasses the entirety of Assam. Comparisons with existing data from the Directorate of Economics and Statistics (DES) demonstrate slight deviations in yield, primarily attributed to the relatively coarse resolution of the remote sensing data (500m or 1km). Nonetheless, this research model exhibits promising potential for semi - operational utilization in forecasting rice crop yield.***

Keywords: Remote Sensing, Monteith equation, NPP, Yield Estimation, INSAT 3D

1. Introduction

Rice, one of the staple food crops in India, plays a crucial role in ensuring food security for the nation's ever - growing population. With an extensive cultivation area of 43.86 million hectares and an impressive output level of 130.29 million tonnes in the fiscal year 2021 - 2022, India stands as the world's second - largest rice producer and top exporter. However, despite these notable achievements, India's rice productivity remains relatively low compared to many other rice - producing nations. Enhancing rice yield and addressing the challenges associated with it are imperative to meet the rising demand and sustain food availability. Rice cultivation in India is taken up across diverse climatic and soil conditions, encompassing various regions such as the northeastern part (including Assam, Arunachal Pradesh, and Manipur), the eastern region (Orissa and West Bengal), northern parts (Punjab and Uttar Pradesh), western part (Maharashtra and Gujarat), and the southern tip (Tamil Nadu, Andhra Pradesh, etc.). It is estimated that over 60% of India's population heavily relies on rice consumption, emphasizing the significance of maintaining a consistent and abundant rice supply.

Over the years, significant progress has been made in expanding the area under rice cultivation and increasing rice production in India. From a modest 30.81 million hectares in 1950 - 1951, the rice cultivation area has witnessed a substantial growth to 46.38 million hectares in 2021 - 2022, representing an impressive increase of approximately 142%. The surge in rice output has been even more remarkable, expanding from 20.58 million tonnes in 1950 - 1951 to 130.29 million tonnes in 2021 - 2022, reflecting a fivefold increase. This progress has resulted in a notable rise in rice yield, with an increase from 668 kg/ha in 1950 - 1951 to 2809 kg/ha in 2021 - 2022. The Kharif season, characterized by the southwest monsoon, is crucial for rice production, accounting for the majority of the country's rice output. Successful rice cultivation relies on implementing appropriate agronomic practices, including land preparation, nursery bed preparation, sowing of nursery, and transplanting of 25 to 30 - day - old saplings. To further augment rice productivity, the Department of Agriculture and Farmers Welfare (DAC & FW) 's Crops Division has implemented various programs and schemes. Notable initiatives include the National Food Security Mission (NFSM) for rice and the Bringing Green Revolution to Eastern India (BGREI) program, which aim to boost rice production and productivity.

Despite these efforts, there are several factors contributing to the lower yield rates observed in different parts of India. These factors encompass imbalanced fertilizer usage, reliance on traditional farming methods, soil pH stress, pest incidences, and inadequate plant population. The identification of yield determinants and their correlation with management techniques is of paramount importance for farmers to enhance crop productivity and address these concerns effectively. In this context, remote sensing techniques present a valuable tool for enabling farmers to manage their crop practices at the field level. Remote sensing data offers the capability to monitor crop phenology throughout the growing season, capturing changes in color content and primary characteristics. Satellite and aerial imagery serve as valuable planning tools for crop mapping, intra - season crop health monitoring, agro - cultural practice monitoring, and evaluating crop suitability. Vegetation indices derived from spectral coefficients, facilitating easy interpretation of reflectance coefficients at specific wavelengths, play a pivotal role in assessing plant characteristics. Various remote sensing data sources, ranging from high to low resolution, such as MODIS, NOA, and SPOT, are employed for agricultural purposes based on specific requirements. Several models, including regression models utilizing normalized difference vegetation index (NDVI) and leaf area index (LAI), as well as statistical models like multiple linear regression and moving averages, have been used for crop yield estimation. Strong correlations have been observed between vegetation indices, plant canopy attributes, and grain yield.

In this study, a semi - physical model to estimate paddy yield is used, considering factors like crop variety, classification, transplanting, harvest, and environmental variations, which include factors such as weather conditions, temperature, precipitation, and other ecological influences that can affect the growth and productivity of paddy crops. The model incorporates Photosynthetically Active Radiation (PAR), within the insolation transmission range of 0.4–0.7 μm, as a critical component. The Net Primary Productivity (NPP) is calculated using the model proposed by Kumar and Monteith (1982), which directly relates NPP to variables such as Fraction Absorbed Photosynthetically Active Radiation (fAPAR) and Radiation Use Efficiency (RUE), representing the conversion of absorbed radiation into biomass. This study aims to integrate PAR, fAPAR, water stress, and temperature stress elements within the NPP model to accurately estimate rice yield. By combining crop models with remotely sensed information, it is anticipated that the limitations associated with yield prediction, especially at regional scales, can be overcome. The findings of this research hold significant potential in guiding farmers' decision - making processes and contributing to the overall improvement of rice crop management and productivity.

2. Material and Methods

2.1 Study Area

Assam, located in northeastern India, serves as the primary study area for this research. Rice cultivation is the dominant agricultural activity in the state, covering approximately 2.54 million hectares out of a total cultivated area of 4.16 million hectares. Remarkably, rice production in Assam accounts for 96% of the state's total food grain production. Over time, natural selection and farmer preferences have contributed to the emergence of a wide range of rice varieties, showcasing the state's rich genetic diversity in rice. The Sali season, corresponding to winter rice cultivation, holds particular significance in Assam, constituting 70% of the total paddy production. The state's unique physical characteristics, geographical location, and historical background have contributed to its distinct rice diversity. Additionally, the migration and immigration of ethnic communities to Assam have introduced various genetic stocks of rice. As a result, Assam's indigenous rice germplasm contributes significantly to the National Rice Research Institute's collection of 12, 256 rice germplasms, representing approximately 20% of the total collection.

However, due to the increasing demand for higher yields, farmers in Assam are gradually transitioning from traditional rice varieties to modern ones. Efforts by institutions such as Assam Agriculture University (AAU) and the Department of Agriculture, Government of Assam, aim to facilitate this transition and promote the adoption of improved rice varieties.

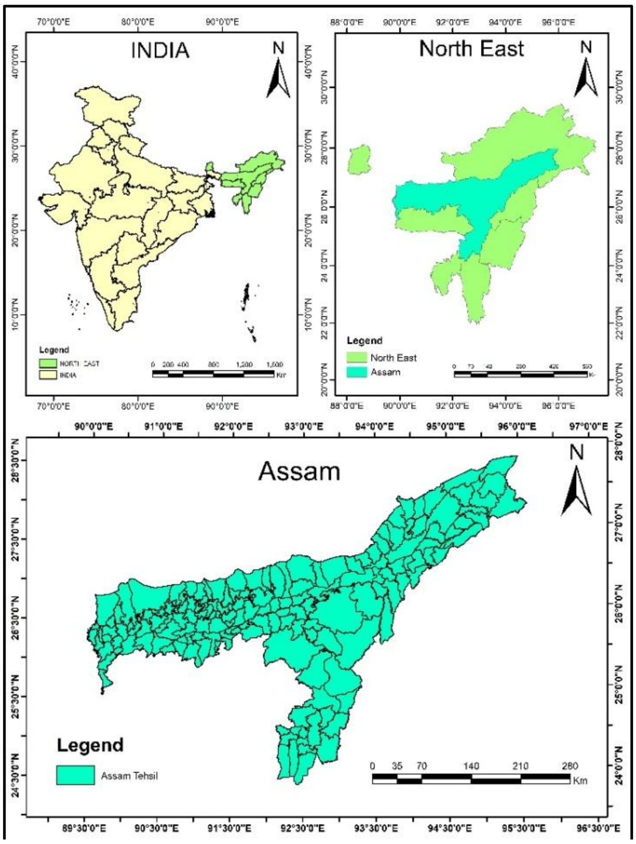

Figure 1: Study Area

3. Methodology and Data Used:

The data and materials used in this study are as follows:

Table 1: showing the data and materials used for the study

Data	Satellite/Ground	Resolution	Source
Daily insolation/PAR	INSAT - 3D	4km resampled to 1km	MOSDAC
10 days composite fAPAR ver.2	PROBA V and SPOT - VGT	1km	Copernicus Land Service
8 days composite surface reflectance	Terra - MODIS	500m to 1km	MODIS Time Series Tool
Rice Mask	Sentinel 1	10m to 1km	ESA Copernicus
Temperature	Gridded data from NASA Power website	1km interpolated	NASA Power
Light - use efficiency			Literature
Harvest Index	Ground	CCE	Ground/Paper

The software we used to process the data are ArcGIS, Erdas Imagine and RStudio.

The methodology is as follows:

Photosynthetic Absorbed Radiation (PAR):
PAR is calculated from daily insolation data. The daily insolation data is converted to 8 - day composite (sum) for the whole period.50% insolation is considered as PAR. This daily insolation data is collected from MOSDAC from INSAT - 3D satellite, source link (www.mosdac. gov. in) for the crop season from 2018 to 2022.
PAR= 8 - day composite * 0.5

Fraction Absorbed PAR (FAPAR):
The FAPAR data is from Copernicus Land Service, source link is (https: //land. copernicus. eu/global/index. html). the 10 - day composite product with 1 km data is used. The range of FAPAR lies between 0 and 1. The physical values are retrieved from the Digital Number (DN).
Light Use Efficiency (Ɛ):
The light use efficiency is relatively constant for crops like Paddy (with a value of about 1.8 g•MJ - 1).

Temperature Stress (T_{stress}):
The daily average temperature data is downloaded from NASA Power website, source link is (https: //power. larc. nasa. gov/data - access - viewer. html). It is a gridded data with a resolution of 1°0 * 1°0 latitude and longitude.

The T_{stress} is calculated in the following way:

$$\mathbf{T_{stress} = (T - T_{min}) * (T - T_{max}) / [(T - T_{min}) * (T - T_{max}) - (T - T_{opt})^{2}]}$$

[T = Daily average temperature]

Based on Paddy optimum photosynthesis, Tmin = 14°C; Tmax = 40°C and Topt = 30°C, if air temperature falls below Tmin, Tscalar is set be 0.

Water Stress (W_{stress}):
The Wstress is calculated from Land Surface Water Index (LSWI). The MODIS time series tool (MODIStsp) used to download and process the MODIS 8 day composite (MOD09A1) source link is (https: //lpdaac. usgs. gov/products/mod09a1v006), and LSWI is calculated for the entire period with the formula –

$$\mathbf{LSWI} = \frac{(\mathrm{p}NIR - \mathrm{p}SWIR)}{(\mathrm{p}NIR - \mathrm{p}SWIR)}$$

LSWI value range from - 1 to 1, and higher positive values indicate the vegetation and soil water stress.

Further, the Wstress is calculated from 8 days LSWI output –

$$\mathbf{W_{stess}} = \frac{(1 - LSWI)}{(1 + LSWImax)}$$

The $LSWI_{max}$ value has been taken from the spatial maximum of paddy crop mask of the entire state.

WHEAT CROP MASK:
The paddy crop mask was generated using Sentinel 1 data from ESA Copernicus for the period of July to October 2022. Supervised Classification using Erdas Imagine software was done.

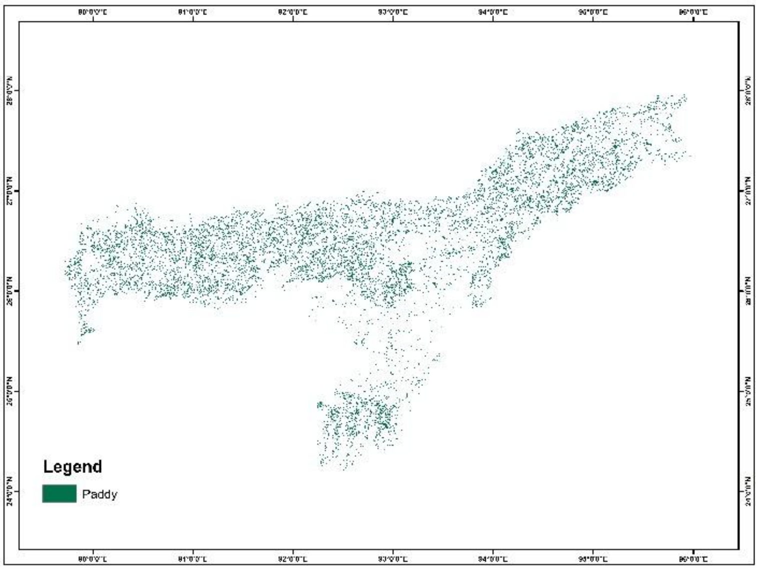

Figure 2: Crop Mask for Paddy

CALCULATION FOR NPP AND GRAIN YIELD:

To compute the final NPP and its Grain Yield, the formula and equation is used as follows:

NPP = PAR * FAPAR * Ɛ * Tstress * Wstress (Logic *of Monteith Equation 1972)*

The HI value for study area is considered 0.50, based on literature. The NPP sum has been multiplied with HI to estimate per pixel yield.

Grain Yield= HI$^{*}\sum \textit{Harvesting Sowing NPP}$

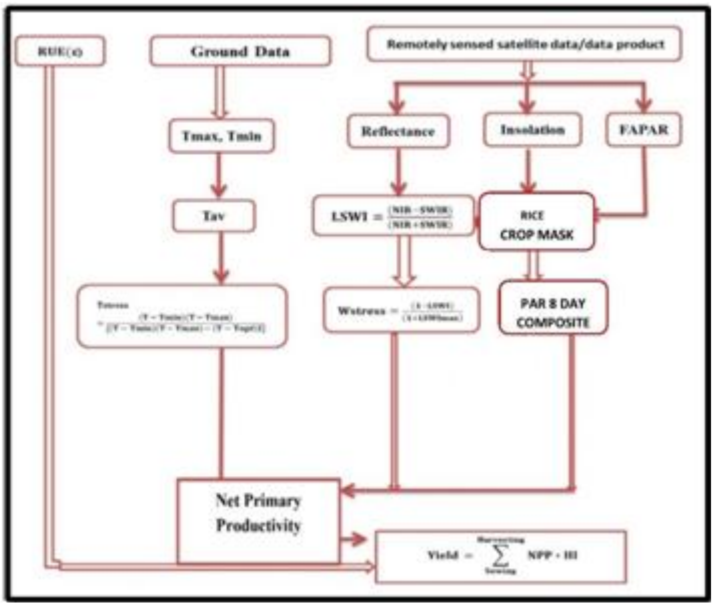

Figure 3: Flow Chart of Methodology

VALIDATION:

The accuracy of our model was evaluated on the basis of DES government data (Directorate of Economics and Statistics) for the crop season of (2017 - 2018, 2018 - 2019, 2019 - 2020, 2020 - 2021, 2021 - 2022).

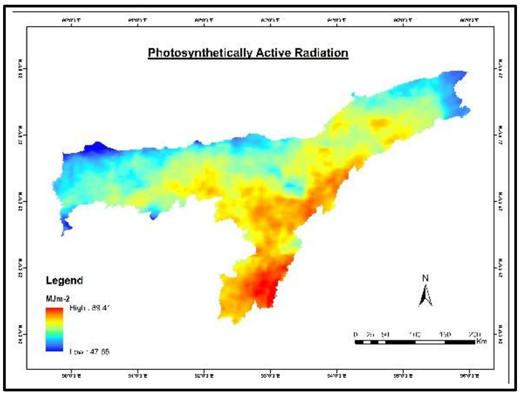

Figure 4: PAR for Assam 2022

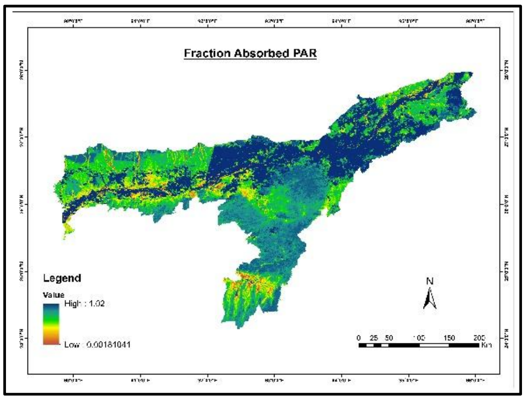

Figure 5: FAPAR for Assam 2022

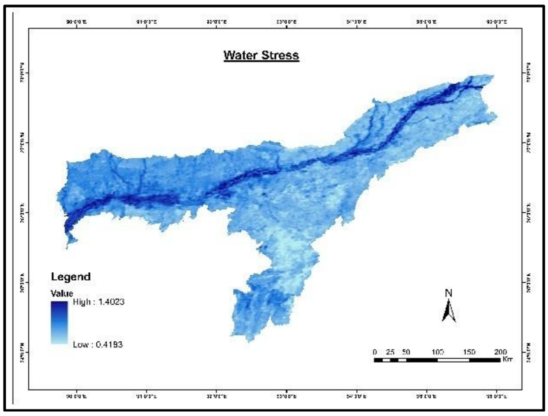

Figure 6: Water stress for Assam 2022

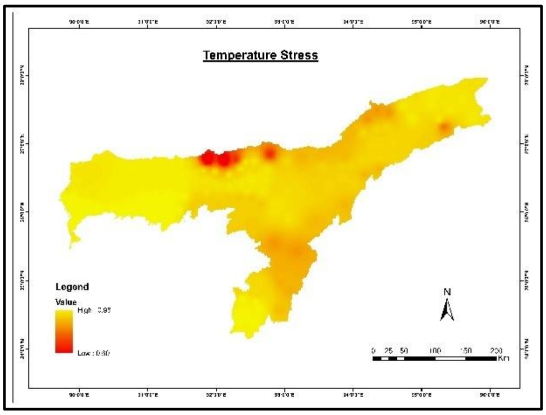

Figure 7: T stress for Assam 2022

4. Result and Discussion

The analysis of grain yield for the paddy crop over the five - year period (2018 - 2022) revealed notable variations across different districts in Assam. In 2021, Hojai district exhibited the highest yield of 3.01 tons/ha, while Sonitpur district recorded the lowest yield of 1.48 tons/ha. Similarly, in 2020, Hojai district achieved a yield of 3.2 tons/ha, whereas Dhemaji district had the lowest yield of 1.3 tons/ha. The highest yield in 2019 was observed in Udalguri district with 3.34 tons/ha, while Tinsukia district again had the lowest yield of 2.01 tons/ha. In 2018, Dhemaji district had the lowest yield consistently across the analyzed years, with 1.5 tons/ha, while Nalbari district recorded the highest yield of 2.94 tons/ha. To assess the accuracy of our data, a comparison was made with the Decision Support System (DES) data provided by the government. Linear regression analysis was conducted to evaluate the consistency between our data and the DES data. The obtained R - squared (R2) values were 0.7, 0.5, 0.6, and 0.7 for the respective years. The maximum difference between our data and the DES data ranged from 0.70 tons/ha, while the minimum difference was as small as 0.02 tons/ha.

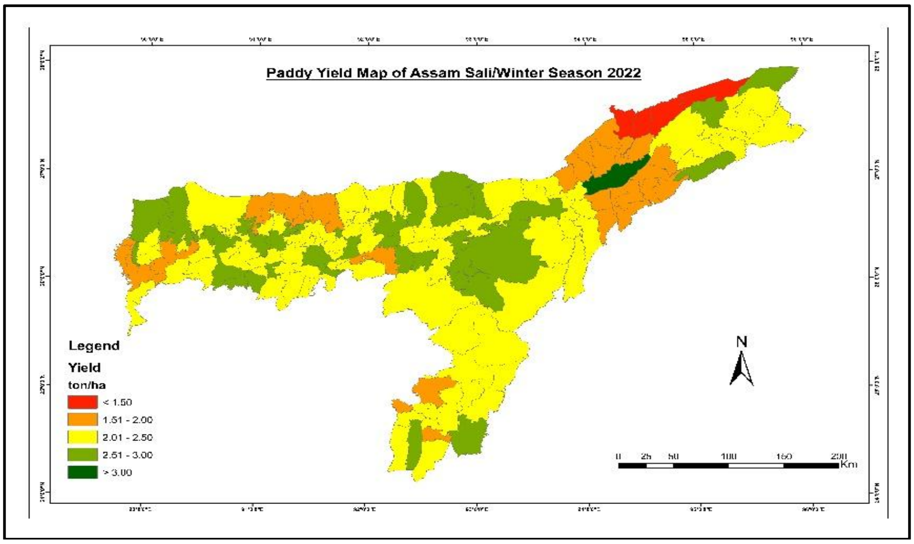

Figure 8: Winter Rice/Sali season Yield Map for Assam 2022

These findings indicate that our data aligns well with the DES data, demonstrating the reliability and accuracy of our yield estimation model. The slight discrepancies observed can be attributed to factors such as differences in data sources, measurement techniques, and resolution. Overall, the results affirm the effectiveness of our approach in predicting rice crop yield and its potential for practical application in yield estimation and agricultural planning.

Table 2: Yield of DES in tons/ha, yield derived by RS Data in tons/ha and Error in yield 2018

District	DES (tons/ha)	RS Data (tons/ha)	Difference
1. Baksa	2.2	2.1	- 0.1
2. Barpeta	1.94	2.5	0.56
3. Bongaigaon	1.46	1.7	0.24
4. Cachar	2.21	2.5	0.29
5. Chirang	1.61	1.89	0.28
6. Darrang	2.38	2.7	0.32
7. Dhemaji	1.28	1.5	0.22
8. Dhubri	1.8	2.2	0.4
9. Dibrugarh	1.88	2.3	0.42
10. Dima Hasao	2.23	2.32	0.09
11. Goalpara	2.39	2.72	0.33
12. Golaghat	2.22	2.6	0.38
13. Hailakandi	2.37	2.82	0.45
14. Jorhat	2.5	2.6	0.1
15. Kamrup	2.72	2.91	0.19
16. KamrupMetro	2.62	2.2	- 0.42
17. Karbi Anglong	1.99	2.11	0.12
18. Karimganj	2.17	2.36	0.19
19. Kokrajhar	2.14	2.25	0.11
20. Lakhimpur	2.23	2.5	0.27
21. Morigaon	2.13	2.3	0.17
22. Nagaon	2.47	2.72	0.25
23. Nalbari	2.82	2.94	0.12
24. Sibsagar	1.94	2.03	0.09
25. Sonitpur	2.08	2.3	0.22
26. Tinsukia	1.72	1.9	0.18
27. Udalguri	2.55	2.73	0.18

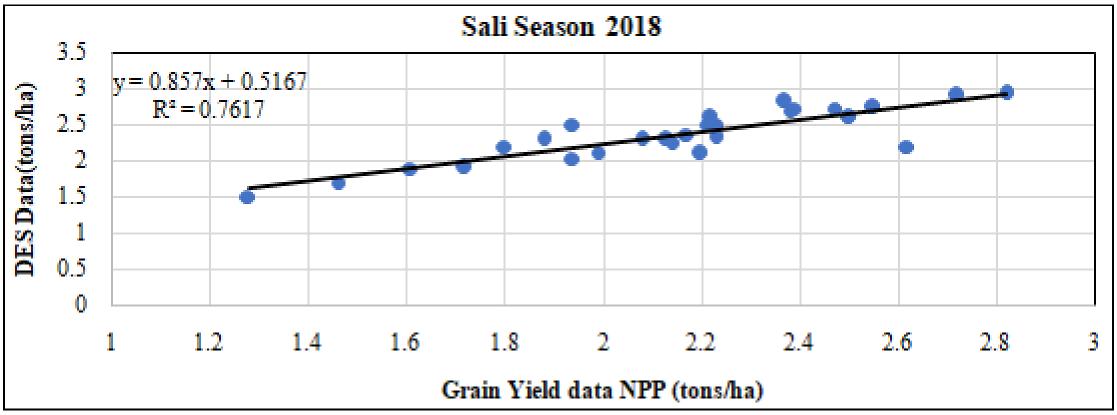

Figure 9: Comparison of DES yield data with RS yield data 2018

Table 3: Yield of DES in tons/ha, yield derived by RS Data in tons/ha and Error in yield 2019

District	DES (ton/ha)	RS data (tons/ha)	Difference
1. Baksa	2.04	2.54	0.5
2. Barpeta	2.06	2.7	0.64
3. Bongaigaon	1.69	2.05	0.36
4. Cachar	2.28	2.83	0.55
5. Chirang	1.8	2.11	0.31
6. Darrang	2.63	2.89	0.26
7. Dhemaji	1.27	2.4	1.13
8. Dhubri	2.09	2.51	0.42
9. Dibrugarh	1.81	2.34	0.53
10. Dima Hasao	2.34	2.92	0.58
11. Goalpara	2.57	2.83	0.26
12. Golaghat	2.21	2.89	0.68
13. Hailakandi	2.8	3.13	0.33
14. Jorhat	2.44	2.87	0.43
15. Kamrup	2.61	2.9	0.29
16. KamrupMetro	2.12	2.63	0.51

17. Karbi Anglong	1.99	2.43	0.44
18. Karimganj	1.92	2.57	0.65
19. Kokrajhar	1.92	2.45	0.53
20. Lakhimpur	1.69	2.4	0.71
21. Morigaon	2.06	2.42	0.36
22. Nagaon	2.14	2.61	0.47
23. Nalbari	2.66	2.2	- 0.46
24. Sibsagar	2.06	2.77	0.71
25. Sonitpur	2.05	2.64	0.59
26. Tinsukia	1.63	2.01	0.38
27. Udalguri	2.82	3.34	0.52

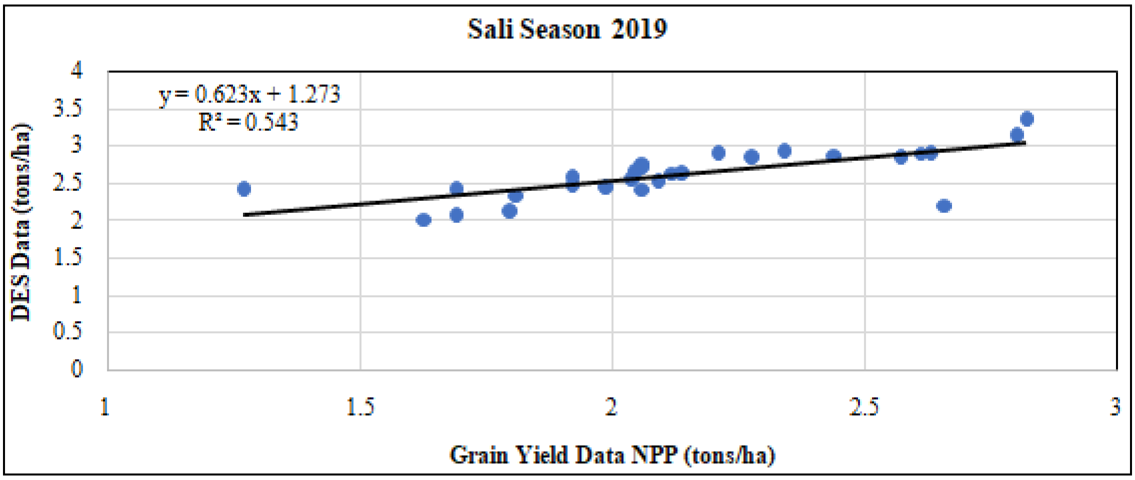

Figure 10: Comparison of DES yield data with RS yield data 2019

Table 4: Yield of DES in tons/ha, yield derived by RS Data in tons/ha and Error in yield 2020

District	DES Data (tons/ha)	RS Data (tons/ha)	Difference
1. Baksa	2.02	1.8	- 0.22
2. Barpeta	2.11	2.3	0.19
3. Biswanath	1.81	1.6	- 0.21
4. Bongaigaon	1.88	2	0.12
5. Cachar	2.18	2.3	0.12
6. Charaideo	1.95	1.6	- 0.35
7. Chirang	2	1.8	- 0.2
8. Darrang	2.54	2.7	0.16
9. Dhemaji	1.5	1.3	- 0.18
10. Dhubri	2.11	2.2	0.09
11. Dibrugarh	2.18	2.2	0.02
12. Dima Hasao	2.48	2.7	0.22
13. Goalpara	2.31	1.9	- 0.41
14. Golaghat	2.08	2.3	0.22
15. Hailakandi	2.52	2.8	0.28
16. Hojai	2.96	3.2	0.24
17. Jorhat	2.13	1.9	- 0.23
18. Kamrup	2.25	2	- 0.25
19. KamrupMetro	2.09	2.2	0.11
20. Karbi Anglong	2.05	2.4	0.35
21. Karimganj	2.01	2.3	0.29
22. Kokrajhar	2.07	2.2	0.13
23. Lakhimpur	1.93	1.8	- 0.13
24. Majuli	2.67	2.4	- 0.27
25. Morigaon	2.03	1.5	- 0.53
26. Nagaon	1.77	2.1	0.33
27. Nalbari	2.56	2.1	- 0.46
28. Sibsagar	1.96	2.2	0.24
29. Sonitpur	2.01	1.6	- 0.41
30. South Salmara Mancachar	2.35	2.7	0.35
31. Tinsukia	1.75	1.5	- 0.25
32. Udalguri	2.62	2.4	- 0.22
33. West Karbi Anglong	2.24	2.5	0.26

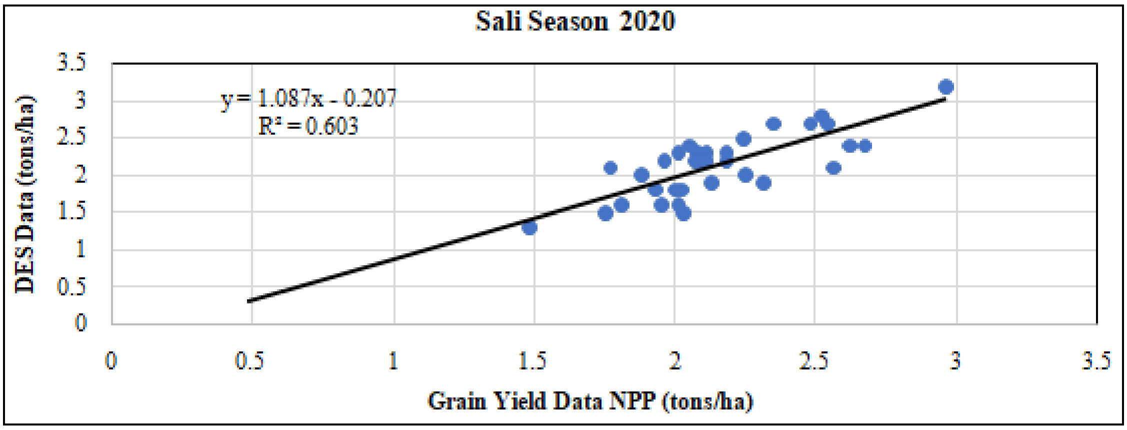

Figure 11: Comparison of DES yield data with RS yield data 2020

Table 5: Yield of DES in tons/ha, yield derived by RS Data in tons/ha and Error in yield 2021

District	DES Data (Tons/ha)	RS Data (Tons/ha)	Difference
1. Baksa	2.02	2.32	0.3
2. Barpeta	2.11	2.42	0.31
3. Biswanath	1.81	2.01	0.2
4. Bongaigaon	1.88	2.13	0.25
5. Cachar	2.18	2.34	0.16
6. Charaideo	1.95	2.15	0.2
7. Chirang	2	2.5	0.5
8. Darrang	2.54	2.73	0.19
9. Dhemaji	1.48	1.73	0.25
10. Dhubri	2.11	2.46	0.35
11. Dibrugarh	2.18	2.38	0.2
12. Dima Hasao	2.48	2.62	0.14
13. Goalpara	2.31	2.7	0.39
14. Golaghat	2.08	2.43	0.35
15. Hailakandi	2.52	2.82	0.3
16. Hojai	2.96	3.01	0.05
17. Jorhat	2.13	2.56	0.43
18. Kamrup	2.25	2.43	0.18
19. KamrupMetro	2.09	2.17	0.08
20. Karbi Anglong	2.05	2.25	0.2
21. Karimganj	2.01	2.32	0.31
22. Kokrajhar	2.07	2.19	0.12
23. Lakhimpur	1.93	2.11	0.18
24. Majuli	2.67	2.89	0.22
25. Morigaon	2.03	2.23	0.2
26. Nagaon	1.77	1.97	0.2
27. Nalbari	2.56	2.79	0.23
28. Sibsagar	1.96	2.03	0.07
29. Sonitpur	2.01	1.4	- 0.61
30. South SalmaraMancachar	2.35	2.67	0.32
31. Tinsukia	1.75	1.83	0.08
32. Udalguri	2.62	2.78	0.16
33. West Karbi Anglong	2.24	2.43	0.19

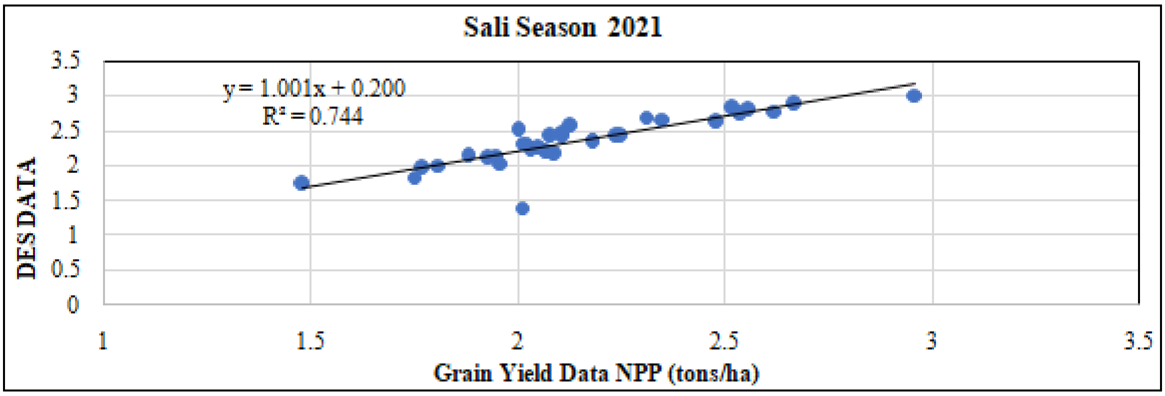

Figure 12: Comparison of DES yield data with RS yield data 2021

The analysis of yield prediction in Assam has revealed interesting insights into the factors influencing rice productivity. Several reasons contribute to the observed variations in yield across districts in the state. Firstly, districts like Dima Hasao, Karbi Anglong, and Cachar exhibited unexpectedly high yields despite having relatively smaller cultivated lands. This anomaly can be attributed to the presence of tropical rainforests in these areas. Tropical rainforest regions are known to have the highest Net Primary Productivity (NPP) globally, which likely influenced the higher yields observed in these districts. Another significant factor impacting yield in Assam is the presence of the mighty Brahmaputra River. Assam is prone to frequent floods and riverbank erosions, resulting in excessive water inundation in paddy fields. The fluctuating intensity of floods and rainfed waters from year to year has negatively affected rice productivity in the state. Remote sensing data, with its varying spatial resolutions, plays a crucial role in enhancing image interpretation. In the case of Assam, which has a vast geographical area, a coarse resolution of 1000m or 1km was chosen for data analysis. However, this coarse resolution poses certain challenges in accurately capturing yield factors, particularly in narrow land strips with scrubs and non - forest regions. Accounting for such factors becomes complex when calculating yield at the tehsil level in Assam.

Majuli, the world's largest riverine island located in Assam, has unique characteristics that impact yield. Districts surrounding Majuli, such as Shibsagar and Karbi Anglong East, contain wetlands and marshes, which contribute to higher biomass and potentially amplify yield in these regions. The presence of estuarine and wetland biomes has a significant influence on rice productivity. Additionally, forest cover depletion in Assam has been observed, particularly in the year 2020 and 2021, with a reduction of approximately 9 to 13%. This depletion of forest cover coincided with the lowest average recorded yield of 2.14 tons/ha during the year of 2020. These findings highlight the empirical support provided by the semi - physical model in understanding the complex dynamics of yield and its underlying factors.

Overall, the study emphasizes the multifaceted nature of yield prediction in Assam, taking into account factors such as tropical rainforests, flood vulnerability, remote sensing data resolution, wetland ecosystems, and forest cover. By considering these factors, the semi - physical model offers valuable insights into rice yield dynamics and can contribute to better - informed decision - making processes in agricultural planning and management.

5. Conclusion

This analysis utilized a framework based on the estimation of net primary productivity (NPP) to predict paddy yield in the tehsils of Assam. The results highlight the diverse nature of yield determination in Assam, where various secondary and tertiary factors, in addition to active radiation, play a significant role. The harvest index (HI) emerges as a crucial parameter influencing yield. While the semi - physical model demonstrated promising results, it also revealed certain disparities with government data. Further improvements are necessary to enhance the spatial efficiency of the model. One aspect that requires attention is the availability of accurate data, particularly regarding sowing and harvest dates, which greatly influence NPP modelling and yield prediction accuracy. The model achieved a satisfactory R - square (r2) value ranging from 0.75 to 0.5, indicating a reasonably good fit. Despite its limitations, remote sensing data proved invaluable in providing a deeper understanding of the underlying realities and factors affecting yield prediction. Therefore, it can be concluded that the semi - physical NPP model holds potential for predicting the yield of various crops in an altruistic manner.

In summary, this study highlights the importance of considering multiple factors and leveraging remote sensing techniques for accurate yield prediction. Further research and refinements to the model can lead to more robust and reliable predictions, enabling farmers, policymakers, Insurance companies and stakeholders to make informed decisions and optimize agricultural practices for improved crop productivity.

Disclosures

No potential conflict of interest is reported by the authors.

Acknowledgements

We extend our heartfelt gratitude to the individuals who have contributed to the successful completion of our project titled "A semi - physical approach using Remote Sensing based net primary productivity (NPP), spatial, spectral & temporal Paddy Yield Model Development for the state of Assam. "

We express our sincere thanks to Mr. Sairam Iyer for his invaluable guidance, mentorship, and insightful inputs throughout the course of this project. His expertise and encouragement have been instrumental in shaping our research.

We are immensely thankful to Mr. Surya Narayan Dash for his constant support and expert advice. His willingness to share his knowledge and provide meaningful suggestions greatly enriched our project.

Our gratitude also goes to Mr. Kiran Prajapati, whose assistance in data analysis and technical discussions significantly contributed to the advancement of our research.

We extend our appreciation to Mr. Pradip Patil for his valuable contributions and his assistance in navigating various aspects of our project.

We would like to acknowledge the dedicated efforts of our team members, Upasana Singh, Gargi Gaydhane, and Ashutosh Pawar. Our collective commitment and collaboration have been pivotal in bringing this project to fruition.

We acknowledge with gratitude the support, guidance, and contributions of all individuals mentioned above, without whom this project would not have been possible.

Lastly, we are grateful to the data provided by MODSAC, MODIS, NASA and ESA COPERNICUS, as due them and their data collection, the project went smooth without any hassle.

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