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# Earth Observation Innovations for Accurate Crop Yield Estimation in Small-Scale Agriculture

Megha G S, Vivek D S, Tanujashree H V

Assistant Professor, Department of Computer Science and Engineering, CIT, Gubbi, Tumkur, Karnataka, India

UG Student, Department of Computer Science and Engineering, CIT, Gubbi, Tumkur, Karnataka, India

UG Student, Department of Computer Science and Engineering, CIT, Gubbi, Tumkur, Karnataka, India

**ABSTRACT:** Estimating how much crops will yield is really important for keeping an eye on agriculture, especially in small-scale farming areas like sub-Saharan Africa. The challenges here arise from small field sizes, broken-up landscapes, and the heavy data needs of crop growth models. This study looks into how combining data from different sensors can help make crop yield predictions better in Ethiopia's smallholder farms. We used high-resolution information from Landsat and MODIS by employing the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM). This allowed us to include inputs like leaf area index (LAI) and crop growth stages into the Simple Algorithm for Yield Estimation (SAFY) model. When we compared the yield predictions for maize and rice fields, we found that using data fusion really cut down on errors. For maize, we saw a relative RMSE of 16%, while for rice it was 23%. This is much better than the results from using MODIS data alone, which had 20% for maize and 35% for rice. The data fusion method also helped in adjusting specific parameters for each field and understanding yield differences, which could be a hopeful way forward for monitoring crops and ensuring food security in smallholder farming systems. These results highlight how valuable Earth observation technology can be in getting more accurate yield estimates and how it can be tailored to fit various small-scale farming environments and combined with machine learning for wider use.

**KEYWORDS:** Small farmer farming, predicting crop yields, watching the Earth, combining data from different sensors, images from satellites, modeling crop growth, differences in space, technology for seeing from a distance, keeping an eye on agriculture, leaf area measurement (LAI).

## I. INTRODUCTION

Small farms are essential for food production in many developing regions, yet they face significant difficulties such as unpredictable weather, poor soil, and a lack of resources. These problems can lead to inconsistent crop yields, which directly impacts the food available to local communities that rely on these farms. To use resources wisely and meet food demands, accurately estimating crop yields is key. However, traditional methods for assessing yields often involve lengthy field visits, which makes it hard to capture the specific conditions of small, dispersed plots. As a result, these approaches can be too slow and take too much effort for small farmers.

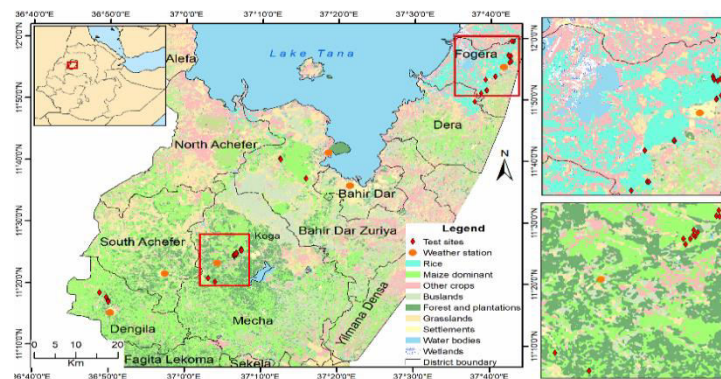
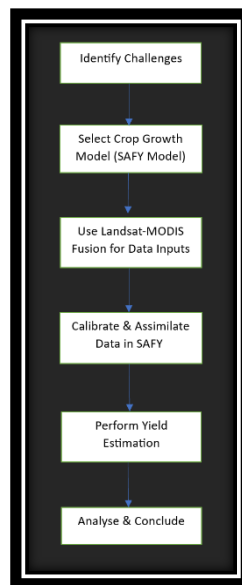


Fig.1. Map of the study area illustrating the locations of maize fields (south of Lake Tana) and rice fields (Fogera) samples, alongside a land cover map of the region for the 2019 growing season.

New advances in the technology used for observing the Earth are proving to be a great help for farmers. They can now get timely updates on how their crops are doing, when they are growing, and the surrounding environmental conditions over wide areas. Satellites like MODIS and Landsat allow for regular crop monitoring, which helps farmers and planners make smarter choices. MODIS provides updates frequently but at a lower quality, while Landsat gives high-quality images, though not as often. For farmers managing smaller, scattered fields, having both quick and detailed information is essential. To meet this need, techniques that merge data, like the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM), work by combining details from different satellites. This approach produces clear, high-resolution images that support crop monitoring, even in challenging weather conditions.



**Fig.2.** Flowchart - the process of using Earth Observation data fusion and model calibration to enhance crop yield estimation in small-scale agriculture.

This study focuses on making the Simple Algorithm for Yield Estimation (SAFY) model better by bringing together data from various sources. The SAFY model estimates crop yields by considering things like leaf area index and the stages of crop growth. By combining information from Landsat and MODIS, the research hopes to improve how accurately we can predict yields, particularly for smallholder farms in Ethiopia. This approach gives us a clearer picture of how crops are developing in different areas, which can help with yield estimates in various farming environments. The results should enable small-scale farmers to make more informed decisions, and this method might also benefit other farming communities, ultimately aiding food security in similar regions.

## II. LITERATURE SURVEY

Understanding crop yields accurately is really important for ensuring we have enough food, especially in regions like sub-Saharan Africa where small farms play a vital role. Traditional methods of predicting yields can be quite slow and often rely on local information, which can be hard to gather in areas with many small, scattered farms. Fortunately, Earth Observation (EO) technologies offer a fresh perspective. By using satellite imagery and remote sensing, we can make crop yield predictions for larger regions. Tools such as MODIS and Landsat provide us with consistent and detailed updates on crop health, growth stages, and environmental conditions. This allows us to identify stress in crops early on and makes it easier to estimate the expected harvest.

A significant advancement in crop monitoring using EO is the combination of data from multiple sensors. This technique merges information from different satellite sources, addressing challenges related to image clarity and timing. For instance, MODIS delivers regular but lower-resolution images, while Landsat provides clearer images less frequently. By employing methods like the Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model (ESTARFM), we can create high-quality, cloud-free images that track crop growth over time. This approach has proven

effective in improving the accuracy of yield estimation models by reducing prediction errors, especially when leveraging data from various sensors to enhance coverage.

Bringing together crop growth models and satellite data can open up great opportunities for smallholder farmers. For instance, consider the SAFY model. It's designed to work effectively in areas where there's not much information available and requires few resources. By using satellite images to gather data on things like the Leaf Area Index (LAI) and different stages of plant growth, we can significantly enhance our ability to predict crop yields. When we update the model with real data through methods like Particle Swarm Optimization (PSO), the accuracy of these predictions improves even further. Although there are still hurdles to overcome, such as dealing with cloudy weather and field differences, the future looks promising for using satellite data to estimate crop yields. By merging this information with machine learning tools like convolutional neural networks (CNNs), we can provide smallholder farmers with timely and accurate assistance.

### III. MATERIALS

In the Lake Tana area of Ethiopia, many farmers work on small plots of land, usually less than one hectare, where they mainly grow maize and rice. This region sits at elevations between 1,700 and 3,500 meters and has a variety of climates, with temperatures and rainfall changing with the seasons. The main rainy season, known as "Kiremt," lasts from June to September and is vital for the growth of crops. To gain a clearer picture of how crops perform in this diverse setting, researchers turned to satellite images along with other types of data. They aimed to give small-scale farmers useful information to help them make better choices, promote sustainable farming, and support food security in the area.

For this study, we used the SAFY model to figure out crop yields in places where traditional data isn't easily available. This model considers important growth factors like how much light is absorbed, leaf area, and biomass to make better predictions about yields. By adding Earth observation data, such as temperature and plant health indicators, the model provides more precise information on how crops are doing. To improve our method, we looked at data from Landsat-8 and MODIS satellites, correcting for atmospheric effects and combining the data to better identify crops and estimate yields. This method showed how effective high-resolution satellite images and data merging can be in dealing with challenges like cloud cover, which ultimately helps in monitoring agriculture for smallholder farms in complicated landscapes.

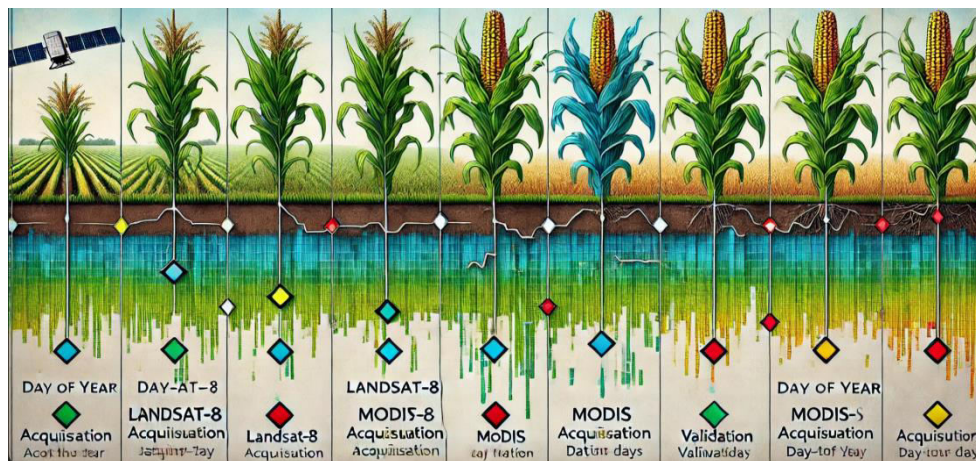


Fig.3. The acquisition dates for Landsat and MODIS (Black diamond markers represent the data points used for prediction, while the red marker indicates those used for validation).

### IV. METHODOLOGY

This study combined information from Landsat-8 and MODIS to improve crop yield estimates for smallholder farms. It considered various farming methods and field sizes by using a crop calendar and matching similar land cover. The Enhanced Vegetation Index (EVI) was helpful in tracking how crops grow through different stages and estimating the Leaf Area Index (LAI), which led to more accurate yield predictions. Additionally, the research utilized TIMESAT

software and the Savitzky-Golay smoothing technique to monitor crop growth patterns, identifying key growth stages and refining predictions for small-scale farmers.

The SAFY model improved by incorporating LAI values from Landsat and MODIS data, alongside the smoothed EVI time series. This approach reduced the impact of cloudy weather, making yield predictions for maize and rice more trustworthy. We also calculated radiation-use efficiency (fAPAR) to understand how much light crops absorbed, which further enhanced the model's accuracy. By using data assimilation methods like Particle Swarm Optimization (PSO), we fine-tuned vital parameters such as LAI and ELUE, increasing the model's precision. Thanks to these enhancements, smallholder farmers can now rely on better yield forecasts, aiding them in making informed decisions for sustainable farming.

Parameters	Unit	Rice: Range/Value	Maize: Range/Value	Source
<b>Input Variables</b>				
Daily incoming global radiation	MJ m <sup>-2</sup> d <sup>-1</sup>	-	-	METRAZ and weather station
Daily mean air temperature	°C	-	-	Weather stations
<b>Fixed Parameters</b>				
Initial LAI	m <sup>2</sup> /m <sup>2</sup>	0.02	0.1	LAI estimated
Initial dry aboveground mass	kg ha <sup>-1</sup>	2.0	4.0	Various references
Climatic efficiency	-	0.5	0.5	In situ measurement
Light-interception coefficient	-	0.55	0.5	In situ measurement
Temperature for crop growth	°C	10, 31, 42	10, 30, 45	Various sources
Polynomial degree	-	2	2	Various sources
Specific leaf area	m <sup>2</sup> g <sup>-1</sup>	0.019	0.024	Various sources
Harvest index	-	0.25	0.5	In situ/other measurements
<b>Input Parameter Values</b>				
Emergence date	DOY	[185, 220]	[170, 190]	Phenology detection
Date of senescence	DOY	-	-	Phenology detection
Sum of temperature for senescence	°C	[1839, 2226]	[1365, 1920]	Ta from DO to DOS
End of simulation	DOY	-	-	Phenology detection
<b>Calibrated Parameters</b>				
Partition-to-leaf function: parm a	-	[0.1, 0.5]	[0.1, 0.5]	Calibrated
Partition-to-leaf function: parm b	-	[0.0007, 0.0059]	[0.0007, 0.002]	Calibrated
Rate of senescence	°C d <sup>-1</sup>	[4000, 15000]	[3000, 10000]	Calibrated
Effective LUE	g MJ <sup>-1</sup>	[1.2, 4]	[1.5, 4]	Calibrated

Fig.4. Table presents the initial and calibrated values of the SAFY model parameters.

The research (Model Evaluation and Validation) looked into how well the SAFY model can predict crop yields. It did this by comparing information from Landsat–MODIS fusion and MODIS with actual data from the fields. The focus was on the effect of different data resolutions—30 m for Landsat and 500 m for MODIS—on how accurate the yield predictions were for maize and rice. To see how the model performed, they used measures like R<sup>2</sup>, RMSE, and bias, comparing the predicted outcomes to real field numbers. The study also examined how changes in the data and model settings influenced yield estimates, highlighting the importance of Earth observation in helping improve yield forecasts for small-scale farming.

Crops	Calibration Input	D <sub>0</sub> (DOY)	Pl <sub>a</sub>	Pl <sub>b</sub>	S <sub>IT</sub> (°C)	R <sub>S</sub> (°C)	ELUE (g MJ <sup>-1</sup> )	RMSE	rRMSE (%)
Rice	Ground	198 ± 5	0.29	0.0016	990 ± 30	6575	2.30 ± 0.19	0.4	26
	Fused	197 ± 6	0.29	0.0016	947 ± 85	6575	2.30 ± 0.33	0.54	26
	MODIS	190 ± 6	0.29	0.0016	889 ± 96	6575	2.10 ± 0.37	0.38	28
Maize	Ground	179 ± 5	0.375	0.0015	729 ± 95	6619	2.64 ± 0.50	0.33	16
	Fused	175 ± 3	0.375	0.0015	681 ± 130	6619	2.75 ± 0.46	0.44	17
	MODIS	167 ± 11	0.375	0.0015	728 ± 83	6619	2.62 ± 0.36	0.49	22

Fig.5. This table provides a comparison of SAFY parameter calibration values for rice and maize using different calibration inputs.

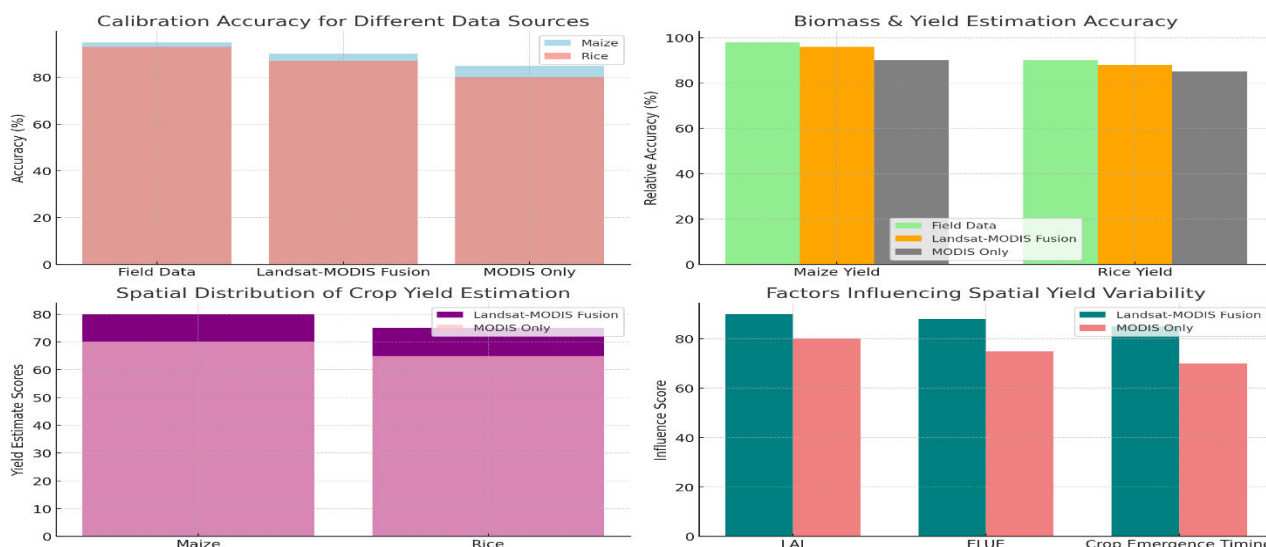
### V. EXPERIMENTAL RESULT

**Calibration Accuracy For Different Data Sources** -The SAFY model did a good job estimating crop yields when it used field data for calibration. However, things got even better when it combined data from Landsat and MODIS. This blend made it easier to get accurate estimates of Leaf Area Index (LAI), especially for maize. On the other hand, using just MODIS data often resulted in lower LAI values, particularly in rice fields. This shows how important it is to use multiple sources of Earth observation data to get better yield predictions, since relying on a single source like MODIS can overlook important details, especially in varied smallholder farm areas.

**Biomass and Yield Estimation Accuracy** -When researchers included the combined Landsat and MODIS data, they found that the SAFY model became better at predicting biomass and yield. This improvement was especially clear for maize, where the updated LAI data matched up more closely with actual yield numbers. However, the model struggled more with rice yields because of the differences in LAI and how grains were distributed, indicating that the model needs some tweaks for rice-specific parameters. This difference shows how much data quality matters and highlights how data fusion can lead to more accurate predictions for various crops.

**Spatial Distribution of Crop Yield Estimation** - By fusing Landsat and MODIS data, researchers got a better picture of how yields varied across different types of farms and landscapes. The predictions indicated that larger, mechanized farms usually had higher yields, while smaller, mixed-crop farms reported lower estimates. This clear distinction helps us understand how the type and size of a farm can affect yield distribution, showing that detailed spatial data from unified Earth observation sources can notably improve the model’s ability to show yield patterns in diverse farming areas.

**Factors Influencing Spatial Yield Variability** - In this study, the accuracy of the yield predictions was largely tied to how precise the LAI values were and how well the radiation-use efficiency adjustments worked. By fine-tuning these factors with the combined LAI data, the model was able to better reflect how environmental and management influences affect crop performance. This method highlighted that practices in crop management, environmental conditions, and the spatial detail all play important roles in yield differences across smallholder farms. Overall, this study illustrates how combining Earth observation practices data can help small-scale farmers get more dependable yield forecasts, ultimately aiding in better agricultural practices and improved resource management.



### VI. CONCLUSION

This research focused on better predicting crop yields for small farms in sub-Saharan Africa, where farming is often disjointed and good data is hard to find. By merging satellite information from Landsat and MODIS into the SAFY model, the study took advantage of both sources: Landsat provides sharp images, while MODIS offers updates

frequently. This combination helped tackle the problem of having limited ground data in the area and made it easier to monitor important growth factors like leaf area index (LAI) and different stages of crop development, which can differ widely depending on farming methods.

The results showed that using both Landsat and MODIS data produced more accurate predictions for crop yields compared to just using MODIS data or field observations alone. By bringing these data sources together, the model managed to lower errors in measuring important crop aspects like LAI, biomass, and yield, especially in smaller, more scattered fields. This was an important advancement in dealing with the difficulties of predicting crop success in places where resources and infrastructure for monitoring are limited.

This method, boosted by satellite technology, offers a dependable and scalable approach to tracking crop growth over large and uneven landscapes. It not only improves yield predictions but also aids in assessing food security, providing vital information that helps farmers make better choices. By promoting the use of modern technology in agriculture, this research plays a part in encouraging sustainable farming practices in Africa's varied environments, assisting smallholder farmers in boosting their productivity and adapting to environmental challenges.

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