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Estimating village-level potato yields using satellite remote sensing and ground data in Uttar Pradesh: An ensemble approach

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Abstract
Yield estimation is essential for effective crop management, market regulation, and agricultural planning. Uttar Pradesh, a leading contributor to India's potato production, requires reliable yield estimates to ensure food security and stabilize market dynamics.
This study proposes a robust, village-level yield estimation framework that leverages satellite remote sensing, meteorological data, ground observations, and advanced machine learning techniques. The approach addresses key limitations of traditional yield estimation methods, such as high data acquisition costs, low spatial resolution, and variability in data quality, which hinder accurate yield forecasting at fine spatial scales.
To overcome these challenges, the framework employs a multi-source ensemble approach that is scalable, cost-effective, and reliable. It integrates:
Sentinel-1 Synthetic Aperture Radar (SAR): Provides critical information on surface roughness and soil moisture, especially valuable during the planting and tuber development stages.
Sentinel-2 Multispectral Imagery: Offers high-resolution optical data for calculating vegetation indices such as NDVI, LSWI, and LAI, which are indicative of crop health and biomass accumulation.
Sentinel-3 FAPAR Products: Serve as proxies for photosynthetic activity, reflecting the physiological status of the crop.
Meteorological Data from IMD (Indian Meteorological Department): Includes rainfall and temperature variables to account for climatic influences on crop growth.
Ground-based Crop yield data Provide accurate, location-specific yield data that enhance model calibration and validation.
Given the absence of suitable historical yield data, the model uses current-season ground yield data for validation. These ground yield data were strategically collected based on categorized satellite and ground inputs to represent diverse ground realities, thereby improving the model's training and overall estimation accuracy.
This research demonstrates the power of integrating remote sensing and machine learning to address yield estimation challenges. The proposed framework is not only effective for potato yield estimation in Uttar Pradesh but is also scalable and adaptable to other crops and regions. By enabling data-driven decision-making, it supports more efficient and sustainable agricultural practices, enhances food security, and contributes to greater resilience in the agricultural sector.

Keywords: Potato-yield-estimation, remote sensing, AI/ML, ground yield, village-level estimation

1. Introduction
Potato is a crucial staple crop in Uttar Pradesh, India, contributing significantly to the state's agricultural economy and food security. As the largest potato-producing state in India, accounting for over 35% of the national potato yield, accurate and timely prediction of potato production is essential for effective market management, crop planning, and ensuring food availability for the rapidly growing population.
With its high carbohydrate content potato is considered a leading food ingredient and is one of the most popular and widely used vegetable in the world. It is the fourth largest food crop in the world following the Maize, wheat and rice respectively. Potato is consumed by more than one billion people all over the world and is grown in more than 100 countries in the world with a

production of around 364 million tons in the year 2012. China is now the biggest potato producer and almost one-third of all potatoes is harvested in China and India. At present, potato is high quality vegetable cum food crop in respect of world food scenario.

Existing methods for potato yield estimation in Uttar Pradesh primarily rely on manual field surveys, which are labour-intensive, costly, and often suffer from delays in data collection and processing. Consequently, there is a need for a more efficient and reliable approach to potato yield prediction that can provide granular, village-level estimates.

Recent advancements in remote sensing technology and artificial intelligence offer promising solutions to address this challenge. Remote sensing data from satellites, such as Sentinel-1 and Sentinel-2, provide detailed, multi-temporal information on crop conditions, which, when combined with machine learning algorithms, can enable accurate and scalable yield forecasting. (Lin *et al*., 2023) (Mahdi *et al*., 2020).

It's important to note that while ground yield are valuable, they are subject to certain limitations, such as sampling errors and potential biases if the selected plots are not truly representative. Modern techniques like remote sensing and crop modeling are increasingly being integrated with ground yield to improve the accuracy and efficiency of yield estimation. The use of remote sensing and modeling for yield estimation. While these sources don't specifically address Ground Yield methods in Uttar Pradesh, they highlight the broader context of yield estimation and the role of technology in improving its accuracy.

1.1 Objectives

- To estimate village-level potato yields by using multi-source remote sensing data with meteorological and ground-truth data.
- To evaluate the impact of agro-meteorological factors and biophysical parameters on potato yield variability, and to analyze their interactions with crop phenology.

1.2 Literature Review/Related Works

Estimating potato crop yield using satellite remote sensing has gained traction due to its ability to provide timely and accurate data for agricultural management. Various methodologies have emerged, integrating remote sensing with environmental variables and machine learning techniques to enhance prediction accuracy across different ecological settings.

Satellite data, particularly from sources like Sentinel-2B, is widely utilized for yield estimation, employing vegetation indices (VIs) such as NDVI and OSAVI to monitor growth stages and predict yields.

A semi-physical model using Hierarchical Linear Modeling (HLM) has shown strong generalization capabilities across different environments, achieving R^2 values of 0.57 to 0.60 during critical growth stages (Fan *et al*., 2024). Techniques like random forest regression and synthetic minority oversampling have been employed to improve yield predictions, particularly when training data is limited (Ebrahimy *et al*., 2023). The tuber initiation stage is identified as optimal for remote sensing data acquisition, enhancing the accuracy of yield predictions.

Environmental factors, including solar radiation and soil moisture, significantly influence yield outcomes, necessitating their integration into predictive models (Fan *et al*., 2024). While satellite remote sensing offers substantial benefits for potato yield estimation, challenges remain in data variability and model transferability across different regions and conditions. Future research should focus on expanding datasets and refining models to enhance predictive accuracy.

Estimating potato yield using satellite remote sensing involves several factors that influence the accuracy of predictions. These factors include the type of satellite data, the vegetation indices used, the timing of data collection, the machine learning models applied, and the incorporation of additional information such as cultivar differences and soil conditions.

Higher resolution satellite images, such as those from Sentinel-2, generally provide more accurate yield predictions compared to lower resolution images like those from Landsat-8 or MODIS (Al-Gaadi *et al*., 2016; Gómez *et al*., 2019; Bala & Islam, 2009; Vallentin *et al*., 2021) [1, 2, 4, 7]. Frequent data collection can help mitigate issues caused by cloud cover and other temporal gaps, improving the robustness of yield predictions (Awad, 2019) [5].

The normalized difference vegetation index (NDVI) and the soil adjusted vegetation index (SAVI) are commonly used and have shown good correlation with actual yields (Al-Gaadi *et al*., 2016; Bala & Islam, 2009) [1, 4]. Different vegetation indices may perform better depending on the specific conditions and crop stages. For example, NDVI, LAI, and fPAR have shown high correlation coefficients (R^2 values) in various studies (Bala & Islam, 2009; Huang & Han, 2014) [4, 6].

Data collected during specific growth stages, such as the tuber initiation stage, can be more predictive of final yields. Early-season data often provide better correlations with marketable yields (Li *et al*., 2021) [3]. The timing of data collection (e.g., July, August, September) can significantly impact the accuracy of yield predictions, with some models performing better with data from specific months (Gómez *et al*., 2019) [2].

Different machine learning models, such as Random Forest Regression (RFR), Support Vector Regression (SVR), and Regression Quantile Lasso, have varying levels of accuracy. Feature selection and preprocessing steps are crucial for improving model performance (Gómez *et al*., 2019; Li *et al*., 2021) [2, 3].

Models that incorporate feature selection to reduce multicollinearity among predictors tend to perform better. For instance, the Regression Quantile Lasso and Leap Backwards models showed lower RMSE and higher R^2 values when correlated predictors were removed (Gómez *et al*., 2019) [2].

Incorporating cultivar-specific data can significantly improve the accuracy of yield predictions. Different cultivars may respond differently to environmental conditions, and including this information helps tailor the models more precisely (Li *et al*., 2021) [3].

Soil fertility and climate conditions (e.g., precipitation, temperature) also affect the accuracy of yield predictions. Studies have shown that correlations between yield and remote sensing data vary with soil types and climate systems (Huang & Han, 2014) [6].

Table 1: Comparison of Different ML Models Used for Potato Yield Estimation

Model Type	Key Features	Performance Metrics	References
Regression Quantile Lasso	Utilizes feature selection to reduce multicollinearity; based on red, red-edge, and infra-red bands from Sentinel 2 data.	RMSE: 11.67%, R^2: 0.88, MAE: 9.18%	(Gómez *et al*., 2019) [2]
Leap Backwards	Similar to Lasso with feature selection; uses Sentinel 2 data.	RMSE: 10.94%, R^2: 0.89, MAE: 8.95%	(Gómez *et al*., 2019) [2]
Support Vector Machine Radial (svmRadial)	No feature selection; uses Sentinel 2 data.	RMSE: 11.7%, R^2: 0.93, MAE: 8.64%	(Gómez *et al*., 2019) [2]
Random Forest (RF)	Uses Sentinel 2 bands and Potato Productivity Index (PPI); better than NDVI.	RMSE: 15.42%, R^2: 0.77	(Gómez *et al*., 2021) [9]
Multiple Linear Regression (MLR)	Uses agronomic, phytophenological, and meteorological data.	MAPE: <15%	(Piekutowska *et al*., 2021) [11]
Adaptive Neuro-Fuzzy Inference System (ANFIS)	Uses energy inputs; better than ANN.	RMSE: 0.029, R: 0.987, MAPE: 0.2	(Khoshnevisan *et al*., 2014) [12]
Support Vector Machine Polynomial (svmP)	Uses meteorological and NDVI data; best for summer cycle.	RMSE: 14.9%, R^2: 0.858	(Salvador *et al*., 2020) [14]

The table above compares various machine learning models used for potato yield estimation. Models like Regression Quantile Lasso and Leap Backwards show high accuracy with feature selection, while Support Vector Machine Radial performs well without it. Random Forest models using the Potato Productivity Index outperform those using NDVI. ANFIS model demonstrates strong predictive capabilities, with ANFIS showing superior performance due to its fuzzy logic integration.

2. Materials and Methods

2.1 Study Area

Uttar Pradesh, India's largest potato-producing state, plays a crucial role in the country's agricultural economy. Among its prominent agricultural districts, Kannauj stands out for its significant contribution to potato farming. Located in the fertile Indo-Gangetic Plain, Kannauj spans approximately 1,993 square kilometres and lies between 26°54'N to 27°06'N latitude and 79°44'E to 80°01'E longitude. The district comprises three tehsils and over 716 villages. It is bordered by Farrukhabad to the west, Kanpur Nagar to the south, and Hardoi to the east, forming a vital agricultural hub. The district is known for cultivating key crops such as potato, wheat, rice, mustard, and sugarcane, with potato being particularly noteworthy due to its contribution to Uttar Pradesh's dominance in national potato production. The fertile alluvial soils and reliable irrigation systems, including canals and tube wells, provide ideal conditions for intensive agriculture.

Kannauj experiences a subtropical climate, with temperatures ranging from 5 °C in winter to 45 °C in summer. The potato-growing season is primarily during the winter months from October to February. The district receives an average annual rainfall of 800-1,000 mm, mostly during the monsoon season, with supplemental irrigation supporting rabi crops like potato. Kannauj was chosen as the study area for this research because of its high potato productivity.

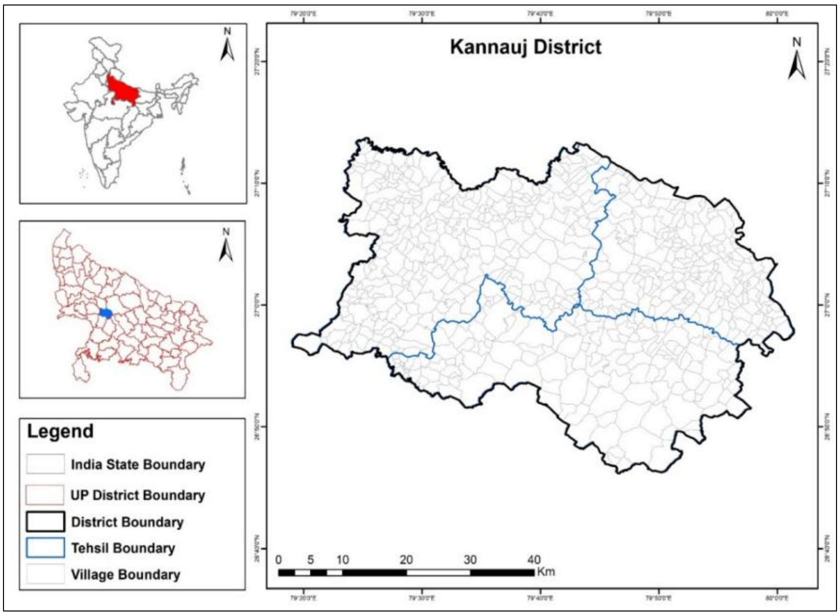


Fig 1: Study Area Map of Kannauj District

2.2 Materials

2.2.1 Ground Truth Data

Ground truth data for this study was systematically collected using the GT App developed by Star Agribazaar Technology Pvt. Ltd., enabling efficient and precise data acquisition. Ground personnel, trained and deployed across Kannauj district, gathered crop-specific information in the form of geospatial polygon data. These polygons delineated the boundaries of potato fields and included vital agronomic details such as crop type, growth stages, sowing dates, crop health, expected yield and management practices.

Additionally, geotagged photographs of the fields were captured alongside the polygon data, ensuring spatial accuracy and visual validation of the recorded information. This comprehensive dataset provided a rich repository of ground-level observations that complemented remote sensing data, enhancing the model's ability to identify and characterize potato fields.

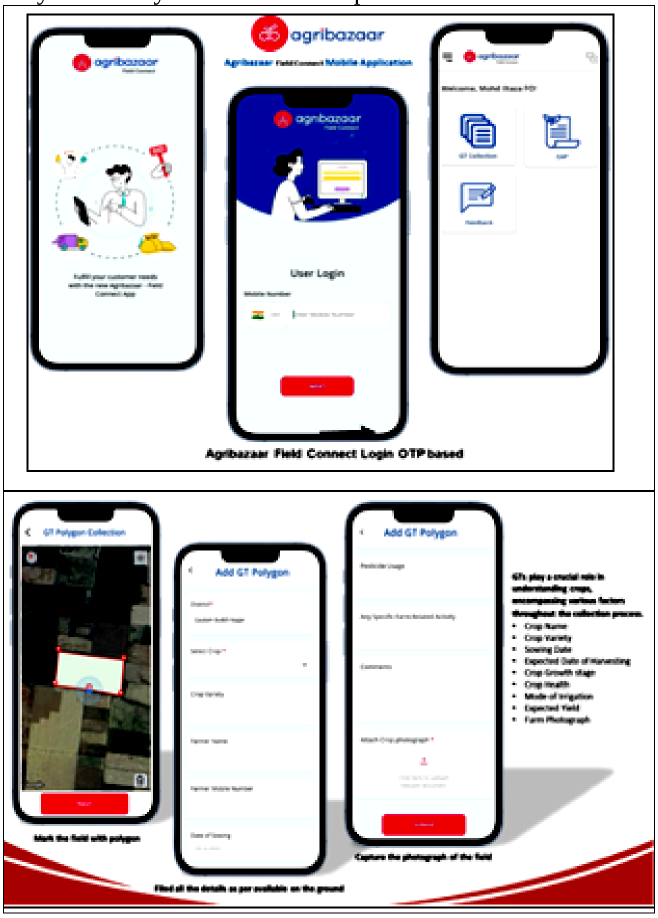


Fig 2: Application used for GT and Ground Yield Data collection

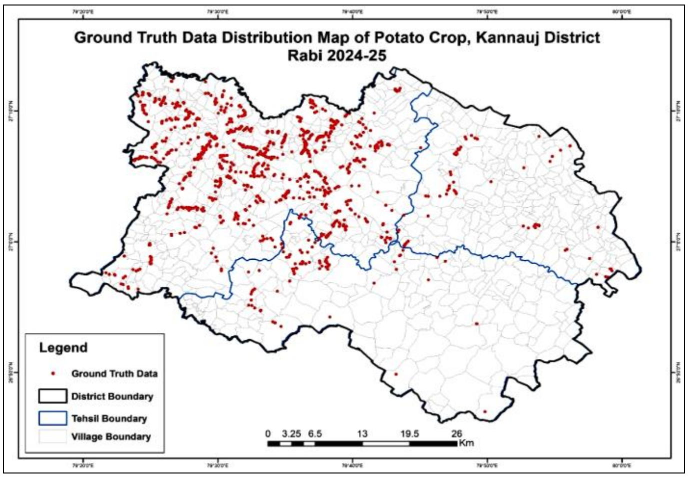


Fig 3: Potato GT Point Distribution Map

2.2.2 Ground Yield Data

Yield data was collected at the time of crop harvesting for validation purposes. The traditional Crop Cutting Experiment (CCE) methodology was not applied in this approach. Instead, a Smart Sampling method was used to select fields based on satellite remote sensing-based proxy yield parameters and crop health indicators such as NDVI, LSWI, and FAPAR, supported by ground truth data.

In the Kannauj district, selected fields were physically measured, and the entire field area was considered for yield assessment. During harvesting, the crop was harvested and threshed, and both biomass and grain weight were recorded from the actual measured area to calculate yield for model validation.

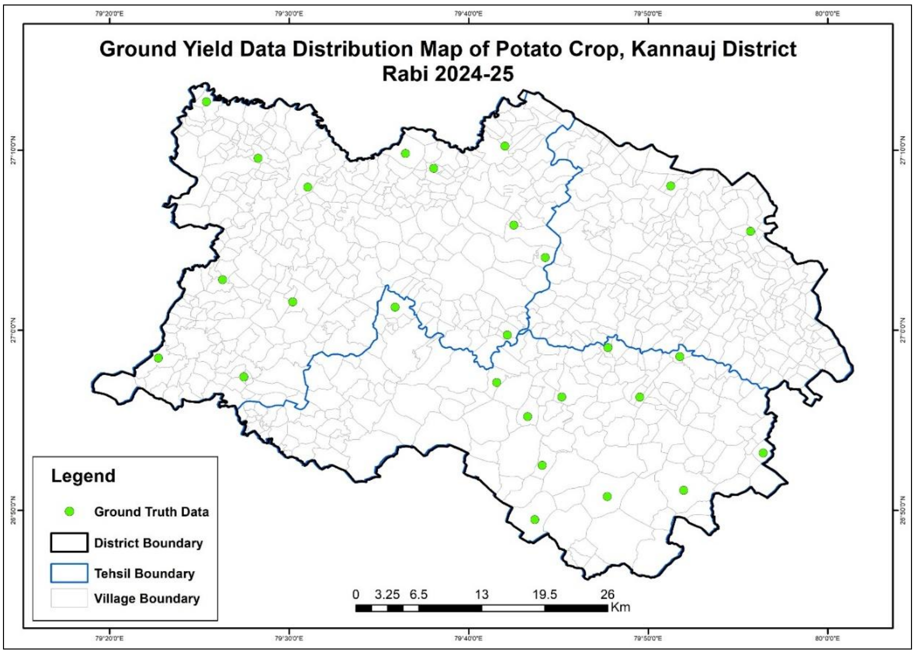


Fig 4: Potato Ground Yield Point Distribution Map

2.2.3 Crop Mask

Accurate identification of the crop sown area is essential for reliable yield estimation, as it ensures that the analysis is confined to relevant agricultural zones. In this study, the potato crop mask was provided by the Department of Technology, Star Agribazaar Technology Pvt. Ltd. Spanning an area of 66,091 hectares, the mask was developed using time-series Sentinel-2 satellite imagery at a spatial resolution of 10 meters for the Rabi season of 2024-25. This high-resolution crop mask precisely delineates regions under potato cultivation and serves as a foundational dataset for data preprocessing and yield estimation. The crop mask overlaying village boundary is illustrated in Figure 5, showcasing the spatial distribution of potato fields across the study area.

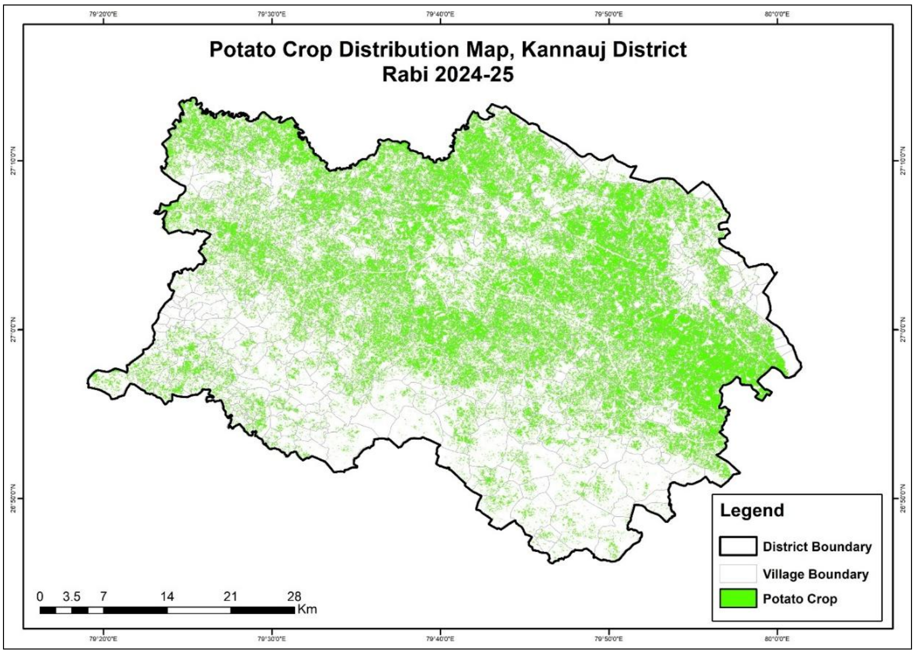


Fig 5: Potato Crop Distribution Map of Kannauj District

2.2.4 Remote Sensing Data

This study utilized data from Sentinel-1, Sentinel-2, and Sentinel-3 satellites to integrate optical, radar, and biophysical parameters for potato yield estimation during the Rabi 2024-25 season. The combination of these datasets provided a comprehensive view of crop health, structure, and photosynthetic activity.

Sentinel-1

It provided Synthetic Aperture Radar (SAR) data in VV and VH polarizations, which are sensitive to crop structure, density, and moisture content. The VH backscatter coefficients were calculated to monitor crop canopy, soil conditions and to assess vegetation density and differentiate between crop stages.

Sentinel-2

Sentinel-2's high-resolution (10 m) multispectral imagery was used to derive key vegetation indices that are critical for assessing crop Vigor and health. The indices included:

- **Normalized Difference Vegetation Index (NDVI)**

NDVI = (NIR - RED) / (NIR + RED)

- **Enhanced Vegetation Index (EVI)**

EVI = 2.5 × (NIR - RED) / (NIR + 6 × RED - 7.5 × BLUE + 1)

- **Normalized Difference Red Edge (NDRE)**

NDRE = (NIR - REDEDGE) / (NIR + REDEDGE)

Sentinel-3 FAPAR Product

Sentinel-3 provided Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) at a coarser resolution, representing the fraction of sunlight absorbed by vegetation for photosynthesis. FAPAR is a biophysical parameter directly linked to crop productivity and was critical for assessing photosynthetic efficiency. Sentinel-3's near-daily temporal resolution ensured continuous monitoring of potato photosynthesis activity.

Leaf Area Index: LAI (Leaf Area Index) derived from Sentinel-2 imagery using vegetation indices and radiative transfer models provides critical insights into crop canopy structure and photosynthetic activity. Sentinel-2's high-resolution red and near-infrared (NIR) bands enable accurate LAI estimation. Frequent revisit times ensure timely monitoring of potato growth, biomass production, and stress conditions, supporting effective crop management and productivity enhancement.

$LAI = a \cdot VI + b$

Where:
VI is the vegetation index, and a and b are coefficients determined through calibration with field data.
Soil Moisture (Sentinel-1)-Soil moisture can be estimated using Sentinel-1 Synthetic Aperture Radar (SAR) data due to its sensitivity to surface moisture content. Sentinel-1's dual-polarized (VV and VH) C-band radar provides valuable information on soil conditions, even under cloudy or low-light conditions. Regular soil moisture mapping with Sentinel-1 supports monitoring of potato fields, aiding in irrigation scheduling, drought assessment, and optimizing water use efficiency. Its high temporal resolution ensures frequent updates, enabling precise management of agricultural practices to enhance productivity and sustainability.

$SM = \alpha \cdot \ln(\sigma VV0) + \beta$

Where:
α\alphaα and β\betaβ are coefficients obtained through calibration with in-situ soil moisture data.

2.2.5 Meteorological Data

Daily rainfall and temperature data for the Rabi 2024-25 season were sourced from the Indian Meteorological Department (IMD). These datasets included minimum and maximum temperatures, which are critical for assessing thermal stress and its impact on crop growth and development. Rainfall data provided insights into precipitation patterns, essential for evaluating water availability during the crop's phenological stages. This meteorological information was integrated with satellite-derived parameters to enhance the accuracy of potato yield estimation by accounting for environmental variability.

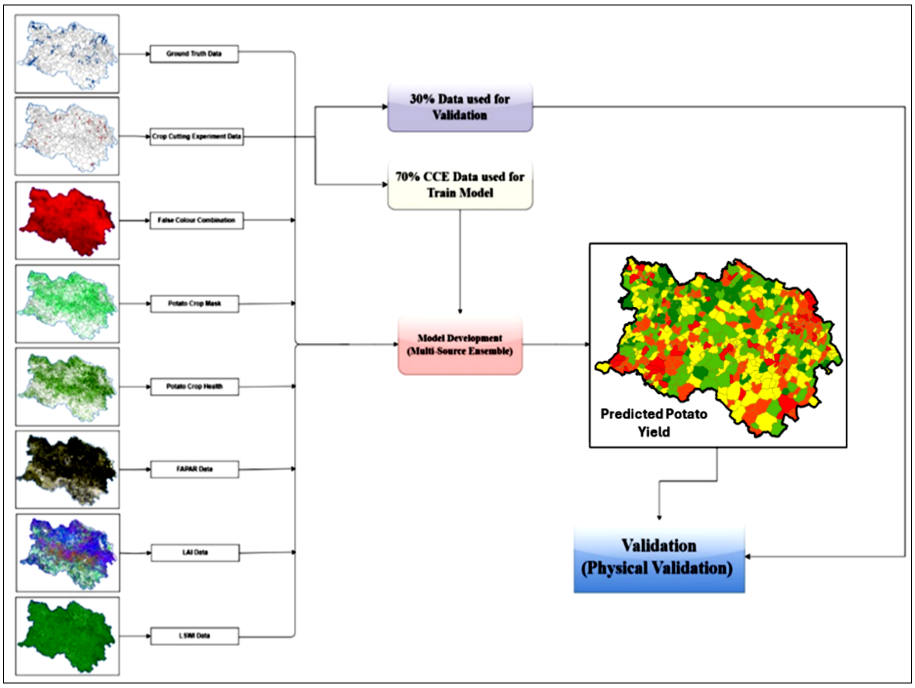


Fig 6: Flow Chart of Input dataset and validation process

2.3 Methods

The following methodology chart (Figure 6) outlines the step-by-step approach employed in this study for estimating village level potato yields.

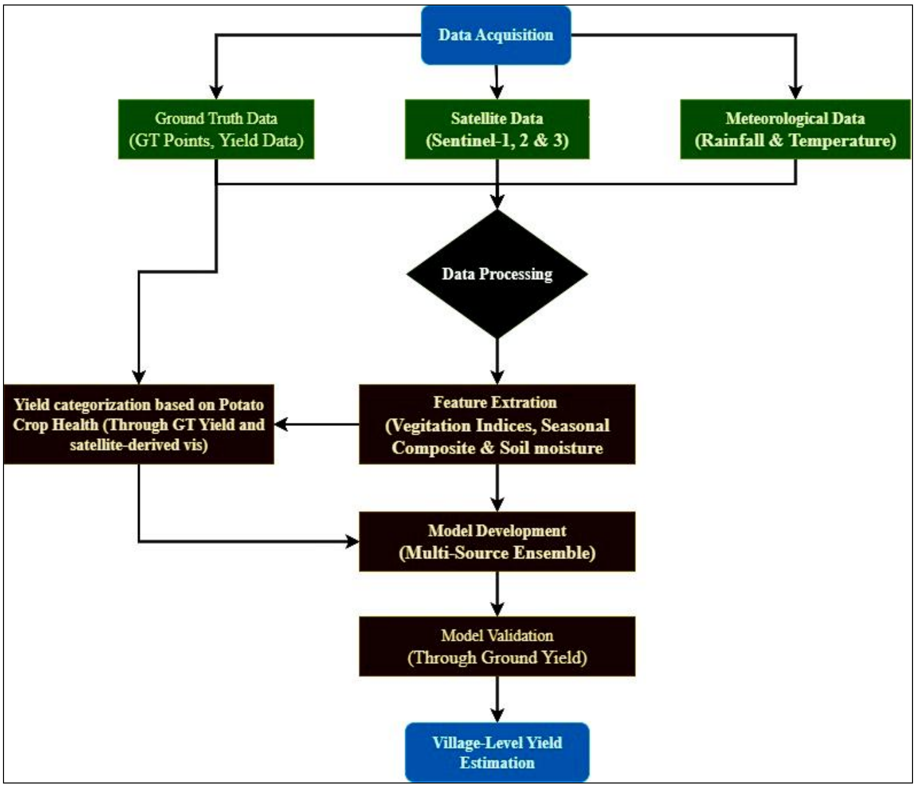


Fig 7: Methodology Chart used in this study

2.4 Data Preparation/processing

Data preparation and processing are crucial steps in the analysis of potato yield prediction using satellite remote sensing data. The process begins with the acquisition of Ground data such as Ground Truth (GT) points and Ground Yield data. These datasets provide essential reference information for validation and yield categorization. Along with ground data, Satellite Remote Sensing Data from Sentinel-1, Sentinel-2, and Sentinel-

3 are collected to capture a comprehensive view of the agricultural conditions over time.

The next step is Data preprocessing, where the raw satellite data is cleaned and prepared for analysis. This includes steps like georeferencing, atmospheric correction, and noise removal to ensure data quality. Once the data is pre-processed, Feature extraction is performed to derive vegetation indices (such as NDVI, LAI, FAPAR), seasonal composites, and soil moisture content, which are critical for assessing crop health and productivity.

These features serve as the input for model development, where a multi-source ensemble approach is used to build predictive models for potato yield estimation. The models are then validated by comparing the predicted results with actual ground data. Finally, the Village level yield estimation is carried out, using the validated models to estimate the potato yield at a fine spatial resolution. This comprehensive processing workflow allows for accurate yield predictions and effective agricultural management.

3. Results and Discussion

3.1 Village-Level Potato Yield Estimation

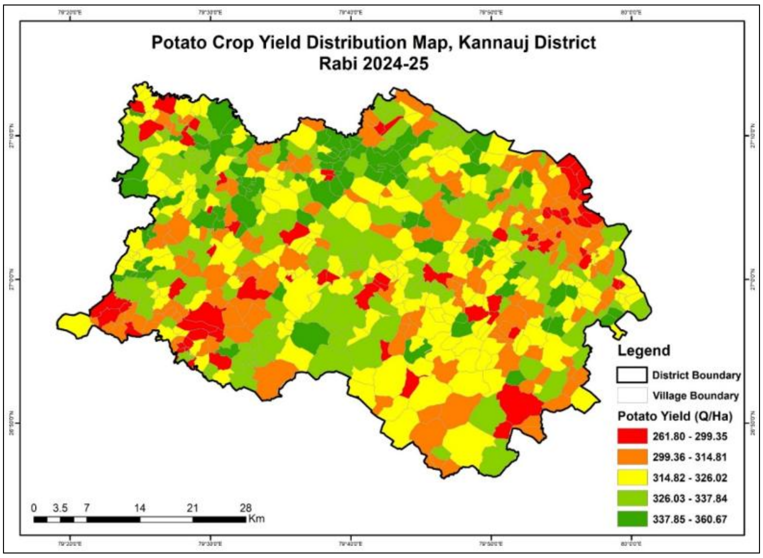


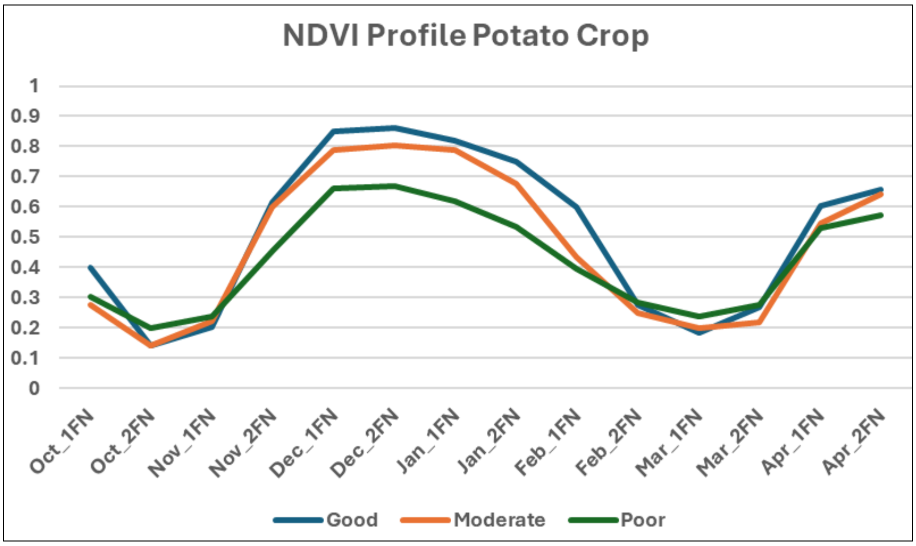
Fig 8: Village Level Potato Yield Distribution Map

3.2 Interactions potato yield with satellite derived biophysical parameters during different crop phenological stages

The study evaluated the temporal dynamics of satellite-derived biophysical parameters such as NDVI, LSWI, FAPAR, and LAI for yield categories—good, moderate, and poor—across different phenological stages. Line charts were used to depict the variation of these indices over time.

These temporal profiles provide insights into how different growth conditions influence yield. However, the results also revealed that some indices, particularly at peak growth stages, reached saturation or displayed non-linear correlations with yield, deviating from theoretical expectations. This highlights the need to account for index saturation and integrate additional parameters for more accurate yield modeling.

Good-yield locations consistently exhibited higher NDVI, LSWI, FAPAR, and LAI values, indicating robust canopy growth, water availability, and photosynthetic activity. Moderate-yield locations showed lower peaks, while poor-yield areas demonstrated subdued profiles, reflecting stress factors like limited water or suboptimal growing conditions. However, it was observed that these indices sometimes reached saturation points or did not directly correlate with yield as expected, indicating potential limitations in their standalone predictive capacity.



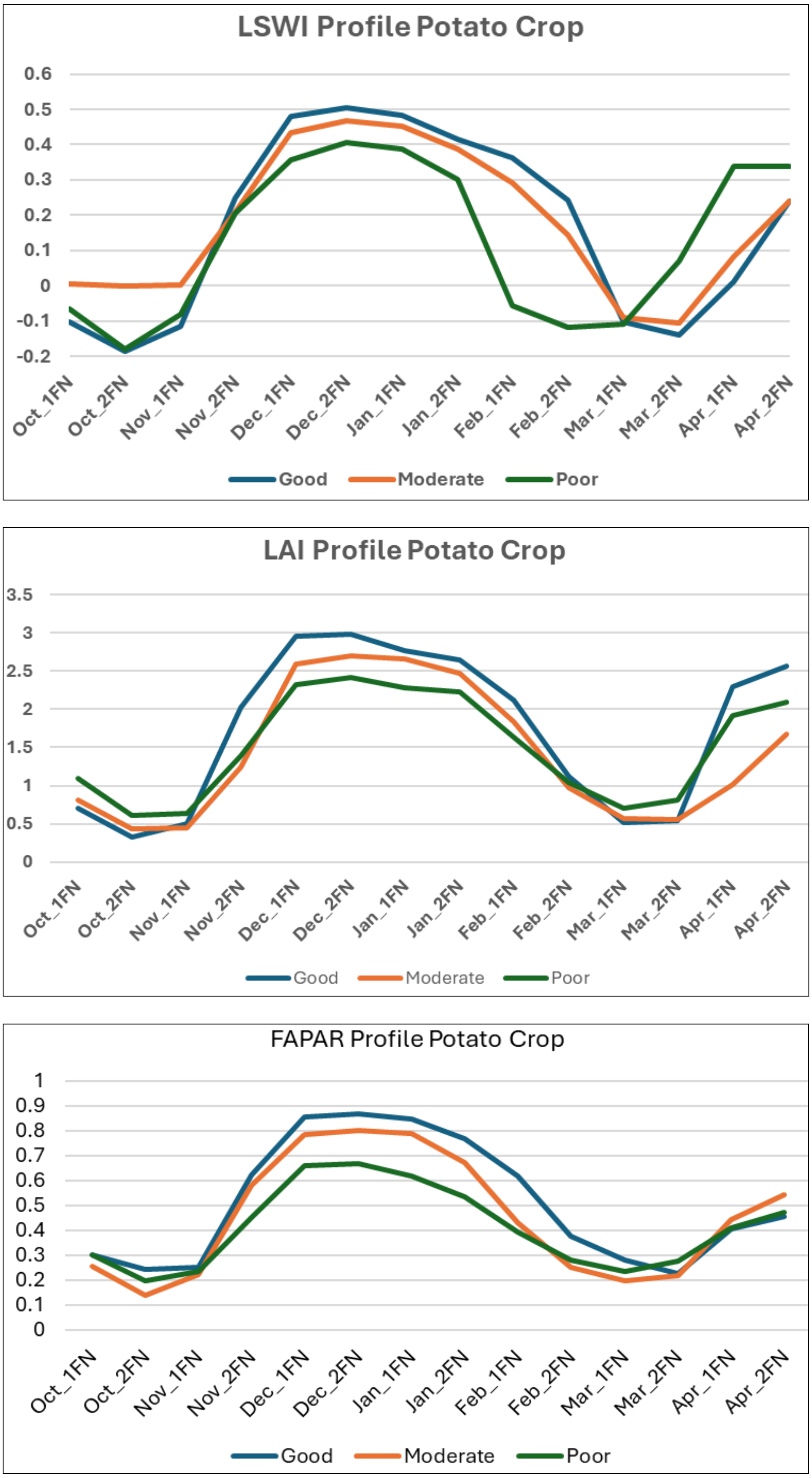


Fig 4: Crop Phenology Stages for Potato Crop

3.3 Relationships between Effect of Agro-Meteorological Factors and potato yield

Correlation of Potato Yield with Temperature & Rainfall-

We have analysed Rainfall and temperature data, and no significant relationship found between Potato Yield with Temperature and Rainfall.

3.4 Validation

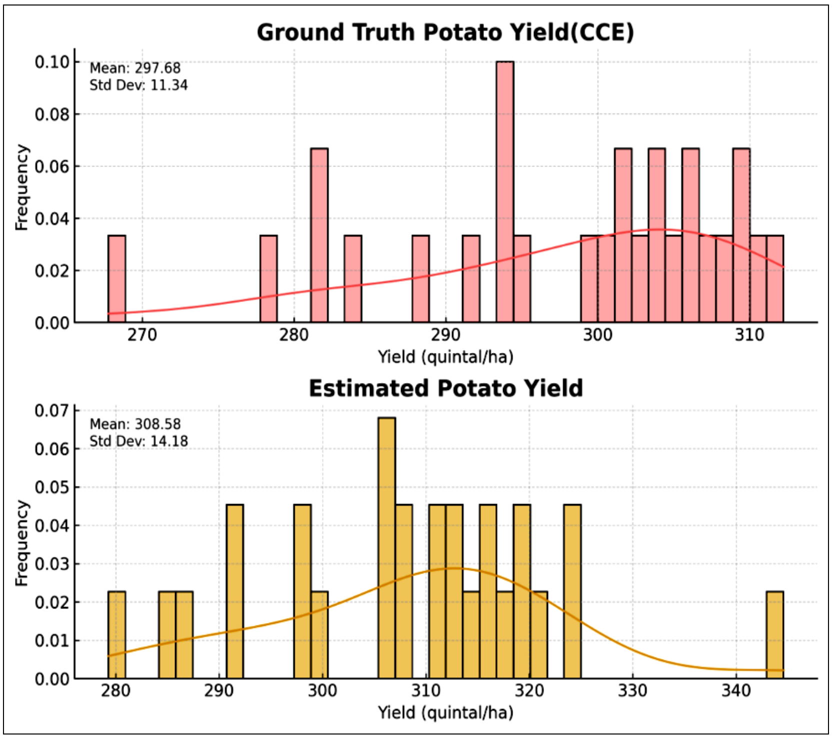


Fig 10: Distribution of Ground Yield and Estimated Potato Yields

Figure 10 compares the distribution of Ground Yield and estimated potato yields in quintals per hectare (Q/ha). The ground yields have a mean of 297.68 Q/ha with a standard deviation of 11.34, indicating moderate variability around the mean, which reflects the natural fluctuations observed in the field. The estimated yields, however, have a mean of 308.58 Q/ha, which is very close to the ground truth mean, suggesting that the model has accurately predicted the overall yield. The standard deviation of the estimated yields is 14.18 Q/ha, which is slightly higher than the grounds yields, indicating that the model has captured the core distribution of the yields with slightly reduced variability. This suggests that the model has high accuracy in predicting the yields, with a narrower spread in the predicted values compared to the actual data. The slight reduction in variability for the predicted yields reflects the model's consistency and its ability to predict yield trends with high precision, closely matching the observed field data. This indicates that the model is highly effective and accurate in estimating potato yields, with minimal error and a high degree of reliability in predicting yield variations.

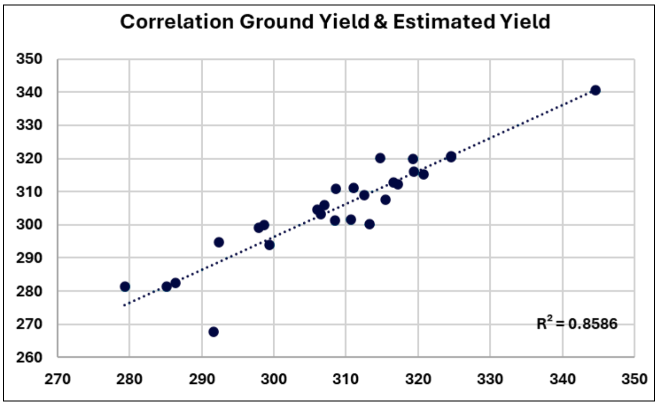


Fig 12: Correlation between Ground yield and Estimated Potato Yields

The validation of predicted yield against ground-collected yield data demonstrated an excellent correlation, with a coefficient of determination (R^2) of 0.85. This high R^2 value indicates a strong agreement between the predicted and observed yields, validating the accuracy and reliability of the prediction model for yield estimation.

4. Conclusion

Estimating potato yields accurately requires a comprehensive approach that incorporates cultivar-specific information, as yields are significantly influenced by tuber size and cultivar type. Solely relying on satellite-derived data often falls short, emphasizing the need for integrating additional agronomic and ground-level data. Previous studies also underscore the importance of these supplementary inputs for improving prediction accuracy.

This study highlights that potato yield estimation using remote sensing is influenced by various factors, including the resolution and type of satellite data, the selection of vegetation indices, the timing of data acquisition, and the machine learning models used. Incorporating critical factors like cultivar differences and soil conditions further enhances model reliability. By optimizing these components, yield prediction accuracy can be significantly improved, offering valuable insights for agricultural planning, market regulation, and food security. This integrative approach lays a foundation for scalable, data-driven solutions in agricultural management.

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