Seeing the Invisible: How Soil Data and Remote Sensing Together Predict Crop Performance

Savita P Doni[1], Salma[2], Yallappa B Doni[3] and Mounika M N[4]

[1]Ph.D. Scholar, Department of Soil Science and Agricultural Chemistry, College of Agriculture, University of Agricultural Sciences, Dharwad - 580005, Karnataka, India.

[2]Young Professional, ICAR-IIPR, Regional Research Station, Dharwad - 580005, Karnataka, India.

[3]M.Sc. (Agri.), Department of Agronomy, University of Agricultural and Horticultural Sciences, Shivamogga – 577204, Karnataka, India.

[4]M.Sc. (Agri.), Department of Agronomy, College of Agriculture, University of Agricultural Sciences, Dharwad 580005, Karnataka, India.

Corresponding Author: savitadoni0806@gmail.com

Introduction

Improving crop productivity in a sustainable manner requires a deeper understanding of the soil-plant relationship and its spatial variability across fields. Soil properties such as texture, organic carbon, nutrient status and moisture dynamics directly influence crop growth, yet their effects often remain invisible at the field scale. Advances in remote sensing now allow continuous monitoring of crop vigour, stress and phenology using satellite-derived indices. When soil data are integrated with these remote sensing derivatives, they provide a powerful framework for accurately predicting crop performance and guiding precision management decisions. This combined approach is reshaping modern agriculture by enabling data-driven, site-specific farming.

From Underground Chemistry to Satellite Intelligence - A New Era of Precision Agriculture

Food security in the 21st century depends not only on increasing production but on understanding the invisible processes beneath our feet. Soil governs crop growth through its texture, nutrient status, moisture dynamics and biological activity. Yet, traditional soil analysis methods are time-consuming, labour-intensive and spatially limited.

Today, a powerful combination is transforming agricultural decision-making: integration of soil data with remote sensing derivatives. By merging laboratory-measured soil parameters with satellite-derived vegetation indices and thermal metrics, scientists can now predict crop performance with remarkable spatial precision. This integration allows farmers to diagnose stress early, optimize nutrient application, manage irrigation efficiently and forecast yields more reliably than ever before.

Why Soil Properties Matter for Crop Performance

Soil properties play a decisive role in determining yield potential and crop resilience.

1. Soil Texture

Texture determines water retention, aeration and root penetration. Clay-rich soils retain more water but may suffer from drainage constraints, whereas sandy soils are prone to drought stress. Optimal textures such as loam provide a balanced environment for root development (Choudhary and Mandal, 2021).

2. Soil Organic Carbon (SOC)

SOC enhances aggregation, microbial activity and nutrient cycling. Higher SOC improves water retention and nutrient availability, leading to increased biomass production. Remote sensing studies show a strong correlation between SOC levels and vegetation indices such as NDVI (Novak *et al.*, 2018; Baroudy *et al.*, 2020).

3. Soil pH

Soil pH regulates nutrient solubility. A slightly acidic to neutral range (5.5–7.0) ensures optimal nutrient uptake. Extreme pH levels restrict nutrient availability and reduce productivity (Choudhary and Mandal, 2021).

4. Macronutrients (N, P, K)

Nitrogen supports vegetative growth; phosphorus enhances root development and potassium strengthens stress tolerance. Nutrient deficiencies alter chlorophyll content and canopy reflectance patterns detectable through indices like NDRE and GCI (Karimli and Selbesoglu, 2023).

5. Soil Moisture and Water Holding Capacity

Moisture availability determines crop growth continuity. Remote sensing-derived indices such as NDWI and CWSI allow near real-time monitoring of water stress conditions (Barbanti *et al.*, 2018).

6. Bulk Density and CEC

Bulk density influences root penetration, while Cation Exchange Capacity (CEC) determines nutrient retention. Higher CEC soils sustain nutrient supply for longer crop growth phases (Choudhary and Mandal, 2021).

Remote Sensing: Monitoring Crop Health from Space

Remote sensing provides spatially continuous, time-series insights into crop vigour and stress.

- **Vegetation Indices:** The Normalized Difference Vegetation Index (NDVI) remains the most widely used indicator for crop vigour and biomass estimation. Enhanced Vegetation Index (EVI) improves sensitivity under dense canopy conditions, while Soil Adjusted Vegetation Index (SAVI) reduces soil background influence (Baroudy *et al.*, 2020). The Normalized Difference Red Edge (NDRE) and Green Chlorophyll Index (GCI) are particularly sensitive to nitrogen status (Karimli and Selbesoglu, 2023).

Table 1. Soil Properties and Their Remote Sensing Indicators

Soil Property	Influence on Crop	Remote Sensing Indicator	Management Insight
Soil Texture	Water retention and aeration	NDVI variability	Drainage planning
SOC	Nutrient supply and structure	NDVI, LAI	Organic matter management
pH	Nutrient availability	Reflectance variations	Lime / gypsum application
Nitrogen	Vegetative growth	NDRE, GCI	Variable rate fertilization
Soil Moisture	Growth sustainability	NDWI, CWSI	Irrigation scheduling
Bulk Density	Root penetration	Stress indices	Tillage correction
CEC	Nutrient holding capacity	Indirect via vigour	Fertility planning

- **Thermal and Moisture Derivatives**

Land Surface Temperature (LST) and Crop Water Stress Index (CWSI) are powerful indicators of heat and drought stress (Barbanti *et al.*, 2018). NDWI and LSWI help detect canopy water content and waterlogging conditions.

- **Radar and Hyperspectral Tools:** Microwave backscatter and hyperspectral narrow-band indices detect structural and biochemical crop changes even under cloudy conditions (Baroudy *et al.*, 2020).

Techniques Used to Relate Soil and Remote Sensing Data

The real innovation lies in merging ground-based soil measurements with satellite-derived crop indicators.

1. Regression Approaches

Linear and multiple regression models have been widely used to correlate soil properties such as SOC and pH with NDVI and yield (Novak *et al.*, 2018).

2. Machine Learning Models

Advanced algorithms such as Random Forest and Support Vector Machines outperform traditional regression by capturing complex non-linear relationships between soil variables and spectral indices (Karimli and Selbesoglu, 2023). These models have shown significantly higher prediction accuracies in heterogeneous agricultural landscapes.

3. Geostatistical Techniques

Kriging and co-kriging combine soil sampling data with remote sensing covariates to generate spatial prediction maps (Baroudy *et al.*, 2020).

4. Crop Simulation Models

Models such as DSSAT and WOFOST integrate soil parameters with remote sensing-derived LAI and biomass estimates to simulate crop growth under varying environmental conditions (Barbanti *et al.*, 2018).

5. Principal Component Analysis (PCA)

Reduces dimensionality and identifies dominant soil–crop interaction factors.

Table 2. Comparison of Techniques Used for Integrating Soil Data and Remote Sensing for Crop Performance Prediction

Technique	Type of Relationship Captured	Data Requirement	Prediction Accuracy	Practical Advantage	Limitation
Simple/ Multiple Regression	Linear relationships between soil variables and RS indices	Moderate (soil + spectral indices)	Moderate	Easy to interpret and implement	Cannot capture complex non-linear interactions
Random Forest (RF)	Non-linear, multi-variable interactions	High (large training datasets)	High	Handles heterogeneous field variability effectively	Requires computational power
Support Vector Machine (SVM)	Non-linear boundary-based modeling	Moderate to High	High	Effective in small-to-medium datasets	Sensitive to parameter tuning
Artificial Neural Networks (ANN)	Complex non-linear patterns	Very High	Very High	Captures hidden soil–crop	Requires extensive training and

				interactions	validation
Geostatistical Co-kriging	Spatial correlation between soil and RS layers	Moderate	Moderate to High	Produces spatially explicit maps	Assumes spatial stationarity
Crop Simulation Models (DSSAT, WOFOST)	Process-based physiological modeling	High (soil + weather + RS + crop parameters)	High	Explains dynamic growth processes	Parameter intensive and complex

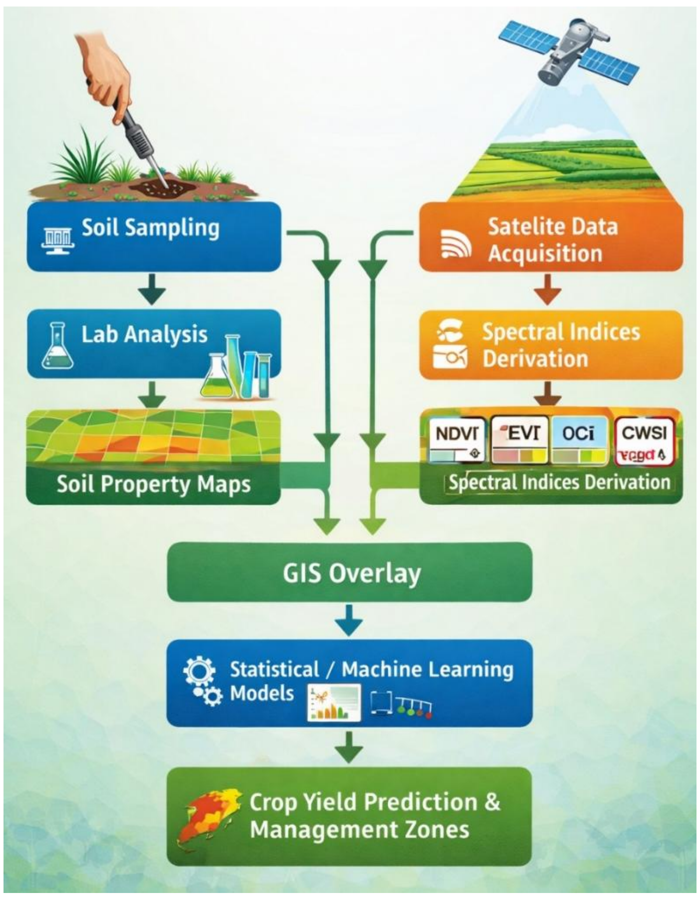

Fig. 1. Integrated Soil-Remote Sensing Framework

How Integration Works: Step-by-Step

Step 1: Soil Data Collection

- Grid or stratified sampling
- Laboratory analysis (texture, SOC, pH, EC, NPK)
- Spatial interpolation (kriging)

Step 2: Satellite Data Acquisition

- Sentinel-2
- Landsat
- MODIS
- UAV imagery

Step 3: Spectral Index Derivation

Calculate NDVI, EVI, NDWI, NDRE, etc.

Step 4: Data Integration

Overlay soil and vegetation maps in GIS.

Step 5: Model Development

Apply regression or machine learning models to relate soil properties and vegetation indices with yield.

Integrating ground-based soil data with satellite-derived indices enables spatially precise crop performance prediction.

Why Integration Improves Yield Prediction

When soil maps are overlaid with vegetation indices in GIS, patterns emerge:

- High SOC + High NDVI = High productivity zones
- High EC + Low NDVI = Salinity stress areas
- Adequate N + Low NDVI = Possible moisture constraint

Integrated models consistently show better predictive performance compared to soil-only or remote sensing-only approaches (Karimli and Selbesoglu, 2023; Baroudy *et al.*, 2020).

Benefits of Soil-RS Integration

1. Precision Nutrient Management

- High SOC + High NDVI zones = optimized fertilizer use
- Low NDVI + adequate soil N = possible moisture stress

2. Water Use Optimization

CWSI + Soil moisture maps = efficient irrigation scheduling

3. Stress Detection at Early Stage

Thermal anomalies combined with soil salinity maps detect hidden yield constraints.

4. Yield Forecasting

Time-series NDVI + soil fertility + weather data = accurate pre-harvest yield estimates.

Integrated models combining soil and remote sensing data significantly improve yield prediction accuracy.

Case Insights from Research

Studies integrating multispectral satellite data with soil sampling have demonstrated:

- Positive correlation between NDVI and SOC levels.
- Strong relationship between soil texture and colour indices.

- Improved yield prediction accuracy when soil moisture maps are combined with thermal indices.
- Machine learning models outperform traditional regression in heterogeneous conditions.

These findings confirm that spatial variability in soil properties directly influences crop reflectance behaviour, enabling predictive mapping of productivity zones.

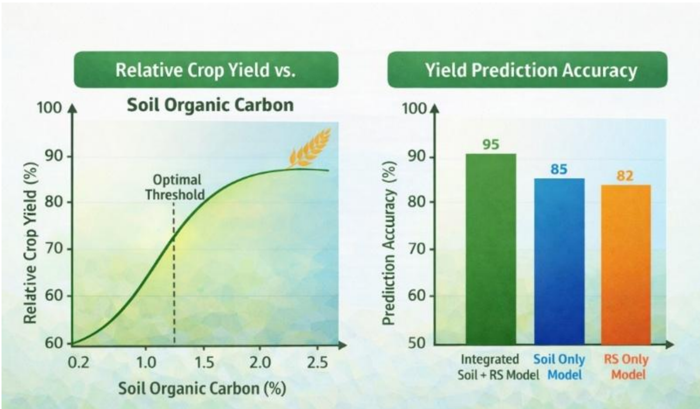

Fig. 2. Soil Property vs Yield Response Curve

Challenges and Considerations

Despite promising results, certain limitations remain:

- High-quality soil sampling is still essential.
- Cloud cover affects optical satellite data.
- Machine learning models require large datasets.
- Spatial variability demands periodic recalibration.

However, advancements in open-access satellite platforms and computational tools are rapidly addressing these constraints.

Future Directions

The future of agriculture lies in:

- Real-time soil health monitoring
- AI-powered yield forecasting systems
- Integration of weather, soil and satellite big data
- Site-specific nutrient management at sub-field scale
- Digital soil mapping linked to farm advisory apps

The integration of soil science and space technology is redefining sustainable intensification.

Implications for Farmers and Agronomists

The combined use of soil data and satellite analytics enables:

- Site-specific nutrient management
- Variable-rate fertilizer application
- Irrigation scheduling based on real-time stress
- Early warning systems for crop failure
- Accurate pre-harvest yield forecasting

Such integration supports climate-resilient agriculture while reducing input costs and environmental footprint.

Conclusion

The integration of soil data with remote sensing derivatives represents a paradigm shift in agricultural monitoring. By linking below-ground soil intelligence with above-ground spectral signatures, this approach provides a comprehensive understanding of crop performance. As demonstrated across multiple studies (Novak *et al.*, 2018; Baroudy *et al.*, 2020; Karimli and Selbesoglu, 2023), integrated models significantly enhance prediction accuracy and decision-making precision. This synergy between soil science and space technology is paving the way toward smarter, more sustainable farming systems.

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