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DATA-DRIVEN PRECISION CROP PLANNING FOR ENHANCED RICE YIELDS AND CLIMATE RESILIENCE IN MONSOON-DEPENDENT SYSTEMS: A CASE STUDY FROM CUTTACK, INDIA

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ABSTRACT

Optimizing rice yields in rainfed, monsoon-dependent systems is critical for sustainable agriculture amid climate variability. This study introduces a novel data-driven framework for precision crop planning in Cuttack, India, a representative smallholder region reliant on monsoons. Integrating multivariate regression, principal component analysis (PCA), k-means clustering, and random forest modelling, we achieved precise rice yield predictions ($R^2 = 0.993$, $p < 0.001$), ranging from 3563.2 kg/ha in Narasinghpur to 4531.9 kg/ha in Damapada. PCA condensed 12 agro-climatic variables into two components (84.4% variance), identifying soil texture and water availability as key yield drivers. K-means clustering delineated three agro-climatic zones, guiding crop recommendations: rice for clay-rich, high-rainfall zones; pulses for drought-prone, sandy soils; and vegetables for phosphorus-rich areas. Soil organic carbon (SOC) enrichment simulations showed yield gains of up to 708.98 kg/ha under drought, enhancing resilience. Random forest models outperformed linear regression (RMSE: 49.34 vs. 115.15 kg/ha), capturing non-linear agro-ecological interactions. Site-specific fertilizer optimization reduced diammonium phosphate (DAP) use by 2.92–21.40 kg/ha, minimizing costs and environmental impacts. This block-level framework, the first of its kind in a monsoon-driven context, offers a scalable model for resource-efficient, climate-resilient agriculture across global rainfed systems. Future multi-season validations and mobile-based advisories could enhance farmer adoption.

Keywords: precision agriculture, rice yields, soil organic carbon, climate resilience, monsoon systems, machine learning

Introduction

Rainfed agriculture, supporting over 60% of the global population, faces increasing challenges from climate change, including erratic monsoons, rising temperatures, and declining soil fertility (Pathak, 2023). In India, where 52% of cultivated land is rainfed, rice a staple for millions suffers yield gaps of 2–5 t/ha due to spatial variability in soil texture, nutrient availability, and water resources (Jat *et al.*, 2022). Precision agriculture offers transformative potential to address these gaps by tailoring management to local conditions, yet its adoption in smallholder, monsoon-dependent systems remain limited due to technological and institutional barriers (De Clercq & Mahdi, 2024).

Cuttack district, Odisha, exemplifies these challenges, with rice yields varying from 3400 kg/ha in drought-prone Narasinghpur to 4800 kg/ha in clay-rich Damapada, driven by differences in monsoon rainfall (1100–1300 mm) and soil properties (Bera & Bokado, 2024). Uniform management practices exacerbate resource inefficiencies, with excessive fertilizer use and vulnerability to climatic extremes undermining sustainability (Rajbonshi *et al.*, 2024). Data-driven approaches, such as multivariate regression, principal component analysis (PCA), and clustering, have revolutionized crop planning in irrigated systems but are rarely applied at fine spatial scales in rainfed contexts (Dasgupta *et al.*, 2024).

Soil organic carbon (SOC) is a critical lever for enhancing soil health and yield resilience, with increases of 1 g/kg linked to significant productivity gains under drought (Zafar *et al.*, 2024). By aligning with Sustainable Development Goals (SDGs) 2 (Zero Hunger) and 13 (Climate Action), SOC-focused strategies offer dual benefits for food security and climate adaptation. This study presents the first block-level integration of statistical and machine learning methods for precision crop planning in a monsoon-driven system, using Cuttack as a model. Our objectives were to: (1) develop accurate rice yield prediction models using agro-climatic variables; (2) delineate agro-climatic zones for optimized crop recommendations; and (3) quantify SOC's role in enhancing yields under drought. This framework offers a scalable solution for resource-efficient, climate-resilient agriculture, with implications for rainfed systems across South Asia and beyond.

Materials and Methods

Study Area and Data Collection

This study was conducted in Cuttack district, Odisha, India (20.5°N, 85.9°E), a monsoon-dependent rice-growing region comprising 14 administrative blocks (Figure 1). Data for the 2022–2023 growing season included agro-climatic variables: monsoon rainfall (1100–1300 mm), soil texture (clay: 7.1–25.3%; sand: 58.7–75.1%), soil organic carbon (SOC: 3.3–5.0 g/kg), field capacity (15–21.3%), and drought frequency (4–8 years). These were sourced from government agencies (e.g., Odisha Agricultural Department) and local agronomic records. Yield data for rice cultivars (Hira and Jaladidhan) and diammonium phosphate (DAP) application rates were obtained from block-level reports. To address spatial data gaps, synthetic data augmentation was applied using established methods (Dasgupta *et al.*, 2024), validated against observed data to ensure statistical integrity. This approach, common in data-scarce smallholder systems, enabled robust model development despite the limited sample size (n = 14 blocks).

Multivariate Regression and Random Forest Modelling

A multivariate linear regression model was developed to predict rice yields (Y, kg/ha) using 12 agro-climatic variables as predictors:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_{12} X_{12} + \varepsilon$$

where β_0 is the intercept, β_1–β_{12} are coefficients, X_1–X_{12} represent pH, SOC, nitrogen, phosphorus, potassium, sand, clay, field capacity, available water content, total rainfall, monsoon rainfall, and drought frequency, and ε is the error term. The dataset was split 80:20 for training and testing, with model performance evaluated via coefficient of determination (R^2) and root mean square error (RMSE). To ensure robustness, 5-fold cross-validation was applied to mitigate over fitting risks associated with the small sample size.

Random forest models, comprising 100 decision trees, were implemented to capture non-linear relationships, using 5-fold cross-validation and the Gini index for feature importance (Choudhary *et al.*, 2022). Both models were developed in R (v4.5.0) using the *stats* and *random Forest* packages.

Principal Component Analysis (PCA)

To reduce dimensionality, PCA was applied to the 12 standardized agro-climatic variables:

$$Z = (X - \mu) / \sigma$$

where Z is the standardized value, X is the original variable, μ is the mean, and σ is the standard deviation. Principal components were computed as:

$$PC_1 = a_{i1}Z_1 + a\iota_2 Z_2 + ... + a\iota_{12} Z_{12}$$

where PC_i is the i-th principal component and a_{ij} are loading coefficients. The first two components (PC_1, PC_2), explaining 84.4% of variance, were used for subsequent clustering, focusing on soil texture and water availability as key drivers (Beillouin *et al.*, 2023).

K-Means Clustering

Agro-climatic zoning was performed using k-means clustering on PCA scores, minimizing within-cluster variance:

$$J = \Sigma_{i=1}^{n} \Sigma_{k=1}^{k} w_{ik} \| x_i - \mu_k \|^2$$

where J is the total squared distance, x_i is the data point, μ_k is the cluster centroid, and w_{ik} is 1 if point i belongs to cluster k, otherwise 0. The elbow method identified three optimal clusters, delineating zones for tailored crop recommendations (Ramesh & Rathika, 2020).

SOC Impact Under Drought

Yield responses to SOC enhancement under drought were simulated using:

$$Y = \beta_0 + \beta_1(SOC) + \beta_2(Rainfall) + \varepsilon$$

where Y is rice yield (kg/ha), SOC is soil organic carbon (g/kg), Rainfall is monsoon rainfall (mm), and ε is the error term. Simulations tested SOC increments of 1–2 g/kg under low-rainfall scenarios (10th percentile) to quantify resilience benefits for rice (Hira, Jaladidhan) and pigeon pea (Zafar *et al.*, 2024).

Statistical Analysis

Pearson's correlation coefficient assessed relationships between variables:

$$r = \sum\left((x_i - \bar{x})(y_i - \bar{y})\right) / \sqrt{\left((x_i - \bar{x})^2 (y_i - \bar{y})^2\right)}$$

where xβ, yβ are paired observations, and x, are means. All analyses were conducted in R (v4.5.0) using *stats*, *random Forest*, and *factoextra* packages. Sensitivity analyses validated model stability, addressing the small sample size and synthetic data use.

Results

Principal Component Analysis and Agro-Climatic Zoning

Principal Component Analysis (PCA) condensed 12 agro-climatic variables into two components, explaining 84.4% of total variance (Figure 4; Table 3). PC1 (72.9%) was driven by clay content (−0.326), soil organic carbon (SOC, −0.329), and field capacity (−0.332), while PC2 (11.5%) was influenced by drought frequency (0.711) and phosphorus levels (−0.367), highlighting soil texture and water availability as key yield determinants (Beillouin *et al.*, 2023). K-means clustering on PCA scores identified three agro-climatic zones across Cuttack's 14 blocks (Figure 3; Table 1). Cluster 1 (e.g., Athagarh, Damapada) featured clay-rich soils (18.6%), high SOC (5.0 g/kg), and ample monsoon rainfall (1248.3 mm), ideal for rice cultivation. Cluster 2 (e.g., Badamba, Narasinghpur) was characterized by sandy soils (66.6%) and frequent droughts (6.4 years), suited for pulses. Cluster 3 (e.g., Barang, Niali) showed high sand content (75.1%) and phosphorus availability (122.5 kg/ha), supporting vegetable cropping. Mean cluster characteristics are summarized in Table 2 (John *et al.*, 2020; Rajbonshi *et al.*, 2024).

Yield Prediction Accuracy

Multivariate regression predicted rice yields with high accuracy ($R^2 = 0.993$, $p < 0.001$), ranging from 3563.2 kg/ha in Narasinghpur to 4531.9 kg/ha in Damapada (Figure 5). Model diagnostics confirmed linearity (Figure 8), homoscedasticity (Figure 9), and approximate normality of residuals with minor tail deviations (Figure 10), though outliers in Athagarh, Narasinghpur, and Nischintakoili suggest unmodeled factors like pest incidence (Attri *et al.*, 2023). Monsoon rainfall and field capacity were primary predictors, each explaining 12–13% of variance, followed by SOC and phosphorus (~10%) (Figure 6; Zafar *et al.*, 2024). Random forest models outperformed linear regression (RMSE: 49.34 vs. 115.15 kg/ha; Table 5), capturing non-linear agro-ecological interactions (Choudhary *et al.*, 2022).

SOC Enhancement Under Drought

Simulations showed that increasing SOC by 1 g/kg under drought conditions (10th percentile rainfall) improved yields by 293.28 kg/ha for Hira and 354.49 kg/ha for Jaladidhan, doubling to 586.55 kg/ha and 708.98 kg/ha at 2 g/kg (Figure 7; Table 4). Pigeon pea yields increased by 127.32 kg/ha at 2 g/kg SOC, confirming SOC's role in resilience (Farooq *et al.*, 2022).

Fertilizer Optimization

Pearson correlation analysis revealed strong relationships between SOC and rice yield ($r = 0.82$) and phosphorus and DAP needs ($r = -0.95$) (Figure S1). DAP requirements varied from 2.92 kg/ha in Cuttack Sadar to 21.40 kg/ha in Damapada (Table S1; Figure S2), highlighting inefficiencies in uniform fertilizer application (Gonçalves *et al.*, 2021). Linear regression slightly outperformed random forest for DAP prediction (RMSE: 7.37 vs. 8.57 kg/ha; Table 5).

Discussion

This study pioneers the block-level integration of multivariate regression, PCA, k-means clustering, and random forest modelling for precision crop planning in a monsoon-driven, smallholder system, offering a scalable framework for rainfed agriculture (Dasgupta *et al.*, 2024). PCA's reduction of 12 agro-climatic variables to two components (84.4% variance; Figure 4) underscores soil texture and water availability as dominant yield drivers, consistent with findings in water-limited systems (Beillouin *et al.*, 2023). The delineation of three agro-climatic zones (Figure 3; Table 1) enables tailored crop recommendations: rice for clay-rich, high-SOC Cluster 1 (e.g., Damapada), pulses for drought-prone Cluster 2 (e.g., Narasinghpur), and vegetables for phosphorus-rich Cluster 3 (e.g., Niali) (John *et al.*, 2020).

High-accuracy yield predictions ($R^2 = 0.993$; Figure 5) were validated by diagnostic plots confirming linearity (Figure 8), homoscedasticity (Figure 9), and approximate normality (Figure 10), though outliers in Athagarh and Narasinghpur suggest unmodeled factors like sowing delays (Attri *et al.*, 2023). Monsoon rainfall and field capacity explained 12–13% of variance (Figure 6), aligning with studies on rainfed systems (Petropoulos *et al.*, 2025). Random forest models' superior performance (RMSE: 49.34 kg/ha; Table 5) highlights their ability to capture non-linear interactions, advancing precision agriculture (Choudhary *et al*., 2022). The high R^2 may reflect the small sample size (n = 14) and synthetic data, necessitating multi-season validations (Datta *et al*., 2023).

SOC enhancement significantly improved yields under drought, with 2 g/kg increases yielding up to 708.98 kg/ha for Jaladidhan (Figure 7; Table 4), supporting SOC's role in resilience and carbon sequestration (Zafar *et al*., 2024). The inverse correlation between phosphorus and DAP needs (r = –0.95; Figure S1) enables site-specific fertilizer optimization, reducing DAP use by up to 21.40 kg/ha (Table S1), lowering costs and environmental impacts (Gonçalves *et al*., 2021). These findings align with Sustainable Development Goals (SDGs) 2 (Zero Hunger) and 13 (Climate Action).

This framework's scalability to monsoon-dependent regions (e.g., Southeast Asia) enhances its global relevance (Quandt *et al*., 2023). Future mobile-based advisories and IoT integration could improve farmer adoption (Willmes *et al*., 2024).

Conclusion

This study introduces a pioneering data-driven framework for precision crop planning in monsoon-dependent, smallholder systems, using Cuttack, India, as a model. By integrating multivariate regression, principal component analysis (PCA), k-means clustering, and random forest modelling, we achieved high-accuracy rice yield predictions (R^2 = 0.993; Figure 5) and delineated three agro-climatic zones for tailored crop recommendations (Figure 3; Table 1). These zones enable optimized crop selection rice for clay-rich Cluster 1, pulses for drought-prone Cluster 2, and vegetables for phosphorus-rich Cluster 3 enhancing resource efficiency (John *et al*., 2020; Rajbonshi *et al*., 2024). Soil organic carbon (SOC) enhancement increased yields by up to 708.98 kg/ha under drought (Figure 7; Table 4), reinforcing its role in climate resilience and carbon sequestration (Zafar *et al*., 2024). Site-specific fertilizer optimization reduced diammonium phosphate (DAP) use by 2.92–21.40 kg/ha (Table S1), minimizing costs and environmental impacts (Gonçalves *et al*., 2021).

This is the first study to operationalize such an integrated approach at the block level in a monsoon-driven context, offering a scalable model for rainfed agroecosystems globally, from South Asia to Sub-Saharan Africa (Quandt *et al*., 2023). The framework aligns with Sustainable Development Goals (SDGs) 2 (Zero Hunger) and 13 (Climate Action) by improving food security and reducing emissions through optimized inputs. Future research should prioritize multi-season field validations to address the small sample size and synthetic data limitations, alongside developing mobile-based advisories to enhance farmer adoption (Willmes *et al*., 2024). This approach provides a robust blueprint for sustainable intensification in resource-constrained environments.

Table 1: Assignment of Cuttack's 14 blocks to three agro-climatic clusters based on k-means clustering.

Block	Cluster
Athagarh	1
Banki	1
Damapada	1
Kantapada	1
Mahanga	1
Nischintakoili	1
Badamba	2
Narasinghpur	2
Salepur	2
Tangi-Choudwar	2
Tigiria	2
Barang	3
Cuttack Sadar	3
Niali	3

Table 2 : Mean agro-climatic characteristics of three clusters, including soil texture, SOC, and rainfall.

Cluster	pH	Organic (g/kg)	Nitrogen (kg/ha)	Phosphorus (kg/ha)	Potassium (kg/ha)	Sand	Clay	Field Capacity	Available Water	Annual Rainfall (mm)	Monsoon Rainfall (mm)	Drought Frequency
1	6.8	5.0	325.3	13.5	366.9	58.7	18.6	21.3	10.7	1651.7	1248.3	5.2
2	7.2	3.9	241.0	13.4	290.0	66.6	13.0	17.5	9.4	1540.0	1130.0	6.4
3	7.2	3.3	213.0	122.5	223.3	75.1	7.1	15.0	8.7	1550.0	1150.0	4.0

Table 3 : PCA loadings for 12 agro-climatic variables across principal components, highlighting contributions to PC1 and PC2.

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
pH	0.210	0.370	0.450	0.670	-0.240	0.220	-0.030	0.210	-0.110	0.000	0.090	-0.010
Organic	-0.330	0.040	0.140	-0.070	-0.370	0.070	-0.150	-0.210	0.130	0.720	-0.180	0.310
Nitrogen	-0.320	0.030	0.220	-0.200	-0.400	-0.070	-0.240	-0.210	0.020	-0.410	0.600	0.100
Phosphorus	0.230	-0.370	0.470	-0.440	-0.250	0.150	0.270	0.460	0.120	0.080	0.010	-0.130
Potassium	-0.330	0.090	-0.050	0.000	0.230	-0.290	-0.410	0.720	-0.010	0.160	0.160	0.010
Sand	0.310	0.020	0.330	-0.180	-0.010	-0.350	-0.550	-0.240	-0.310	0.030	-0.280	-0.340
Clay	-0.330	0.140	-0.040	0.100	-0.220	-0.390	0.460	-0.040	-0.100	0.170	0.070	-0.640
Field Capacity	-0.330	0.090	0.060	-0.030	-0.280	-0.130	0.100	0.180	-0.120	-0.470	-0.670	0.240
Available Water	-0.320	-0.150	-0.160	-0.020	-0.060	0.700	-0.280	0.050	-0.230	-0.050	-0.110	-0.460
Annual Rainfall	-0.280	-0.270	0.390	0.270	0.320	-0.040	-0.100	-0.170	0.630	-0.130	-0.150	-0.190
Monsoon Rainfall	-0.280	-0.300	0.380	0.080	0.400	0.000	0.230	-0.120	-0.620	0.080	0.110	0.230
Drought Frequency	-0.110	0.710	0.270	-0.440	0.370	0.230	0.140	-0.060	0.080	-0.010	-0.030	-0.060

Table 4 : Yield gains under drought for Hira, Jaladidhan, and Pigeon Pea with 1–2 g/kg SOC enhancement.

Crop	Avg. Yield Baseline (kg/ha)	Avg. Yield OC1 (kg/ha)	Avg. Yield OC2 (kg/ha)	Avg. Gain OC1 (kg/ha)	Avg. Gain OC2 (kg/ha)
Hira	5865.52	6158.79	6452.07	293.28	586.55
Jaladidhan	7089.85	7444.34	7798.83	354.49	708.98
Pigeon Pea	2122.06	2185.72	2249.39	63.66	127.32

Table 5 : Performance metrics of linear regression and random forest models for rice yield and DAP predictions.

Model	Rice Yield RMSE (kg/ha)	DAP Needs RMSE (kg/ha)
Linear Regression	115.15	7.37
Random Forest	49.34	8.57

Note: Root Mean Square Error (RMSE) values for Linear Regression and Random Forest models predicting rice yield and DAP fertilizer needs across 14 blocks in Cuttack district. Lower RMSE indicates better predictive performance

Table S1 : Predicted rice yields and DAP needs across Cuttack's 14 blocks, showing spatial variability.

Block	Rice Yield (kg/ha)	DAP (kg/ha)	pH	Organic (g/kg)	Nitrogen (kg/ha)	Phosphorus (kg/ha)	Potassium (kg/ha)	Annual Rainfall (mm)	Monsoon Rainfall (mm)	Drought Frequency	Predicted _Rice Yield (kg/ha)	Predicted DAP (kg/ha)
Azhagar	4400	10.87	6.7	5	320	15	360	1660	1250	4	4393.1	13.36
Badamba	3600	16.30	7	4	250	12.5	300	1500	1100	6	3651.3	15.07
Banki	4500	20.65	6.6	5.2	350	10.5	431.6	1650	1250	8	4437.9	20.89
Barang	3700	0.00	7.2	3.5	220	100	250	1550	1150	3	3669.2	3.35
Cuttack_Sadar	3500	0.00	7.3	3.1	209	147.5	200	1550	1150	4	3657.0	2.92
Damapada	4800	25.65	6.8	6.4	432	8.2	400	1700	1300	8	4531.9	21.40
Kantapada	4300	4.35	7.5	4.5	280	18	340	1680	1270	5	4324.5	7.53
Mahanga	4400	0.00	6.5	4.8	300	20	350	1620	1220	4	4356.7	11.77
Narasinghpur	3400	13.04	7.4	3.8	240	14	280	1500	1100	8	3563.2	12.91
Niali	3600	0.00	7.1	3.3	210	120	220	1550	1150	5	3654.8	2.99
Nischintakoili	4200	23.91	6.4	4.2	270	9	320	1600	1200	2	4229.4	20.60
Salepur	3800	19.57	6.9	4	260	11	310	1580	1180	7	3819.5	19.33
Tangi-Choudwar	3900	8.70	7	3.9	230	16	290	1570	1170	6	3768.8	9.82
Tigiria	3700	14.13	7.6	3.7	225	13.5	270	1550	1100	5	3649.5	12.00

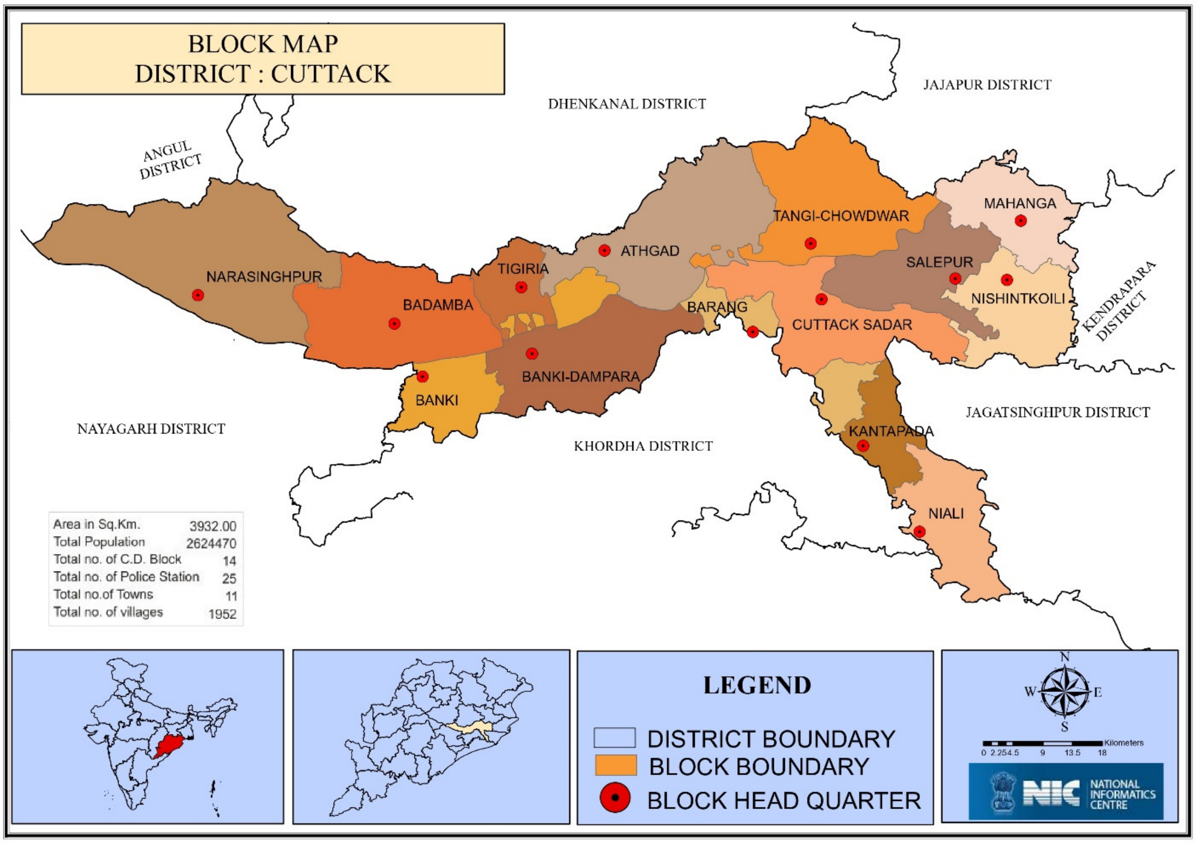

Fig. 1: Block map of Cuttack district

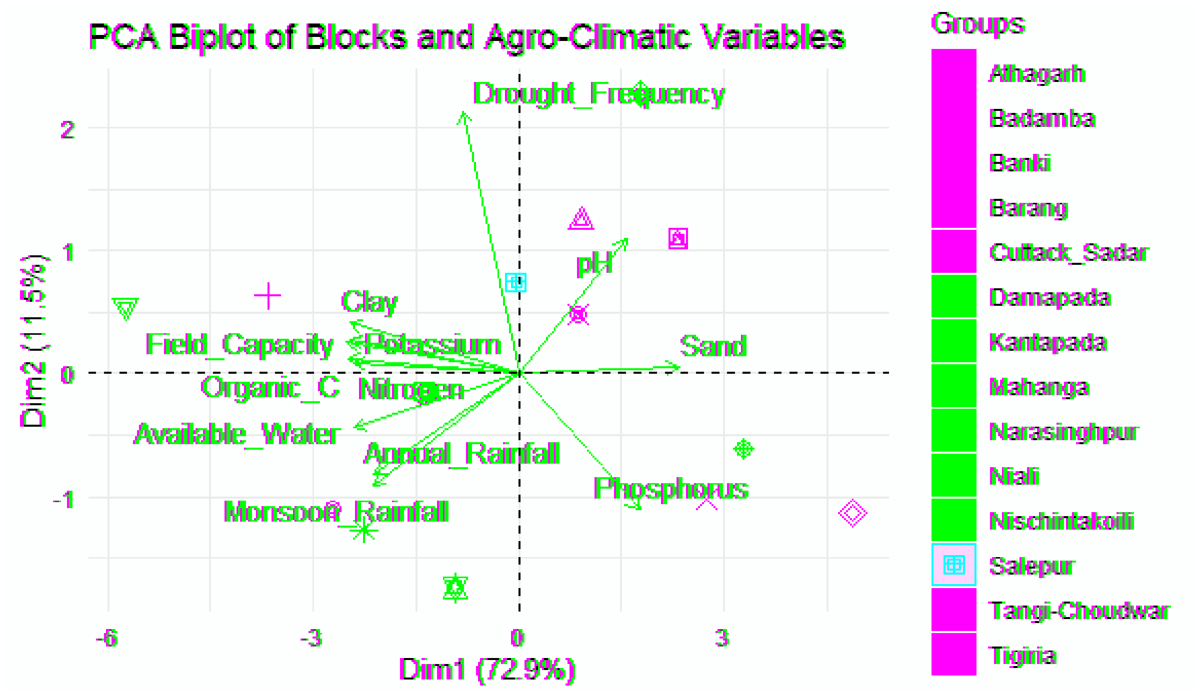

Fig. 2 : PCA biplot of Cuttack's 14 blocks and 12 agro-climatic variables, showing PC1 (72.9%) and PC2 (11.5%) driven by soil texture and water availability.

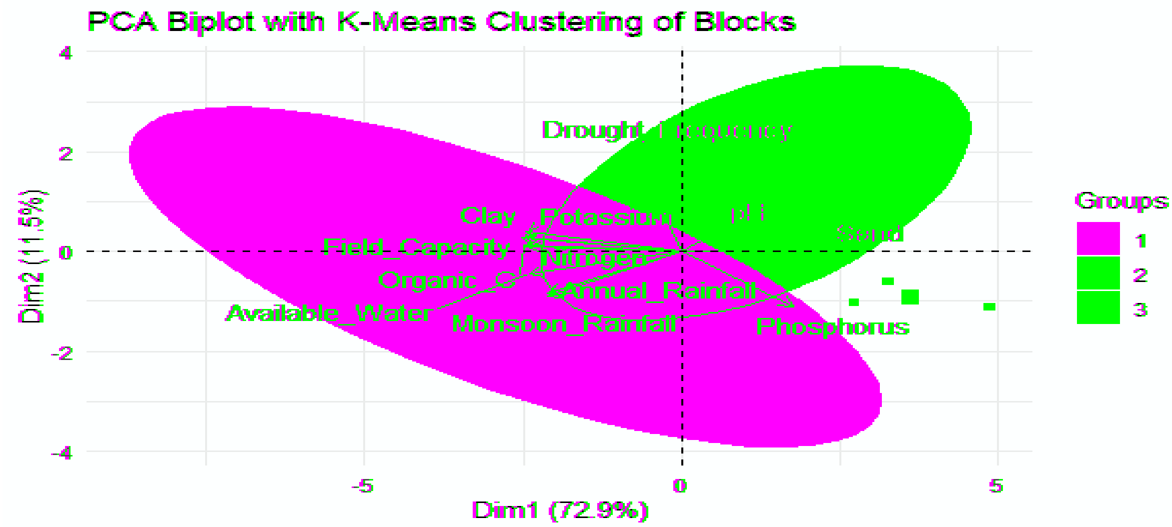

Fig. 3 : PCA biplot with k-means clustering, illustrating three agro-climatic zones based on soil and rainfall variables across Cuttack's 14 blocks.

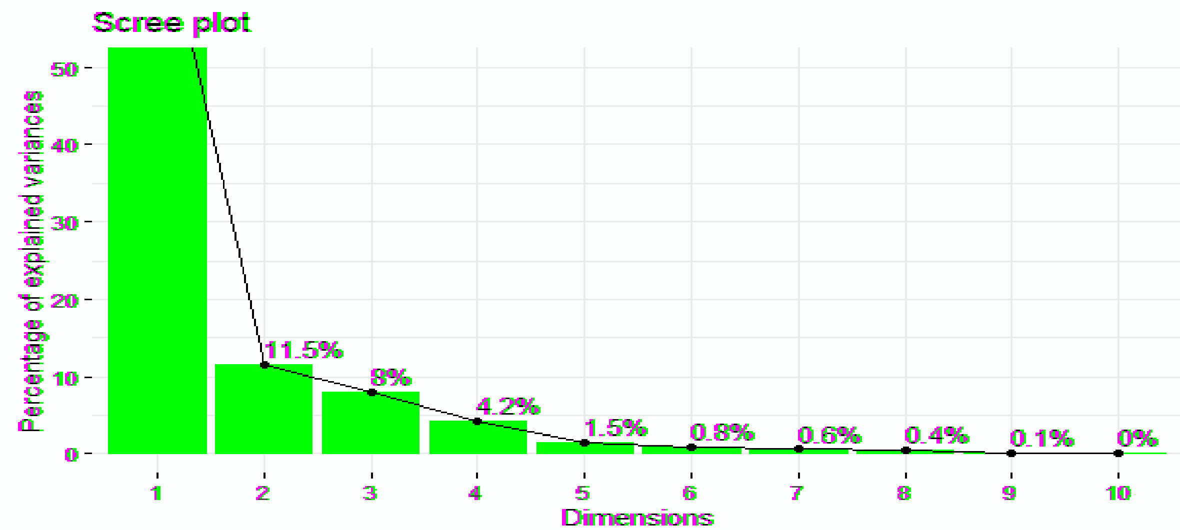

Fig. 4 : Scree plot showing variance explained by each principal component, with PC1 and PC2 explaining 84.4%.

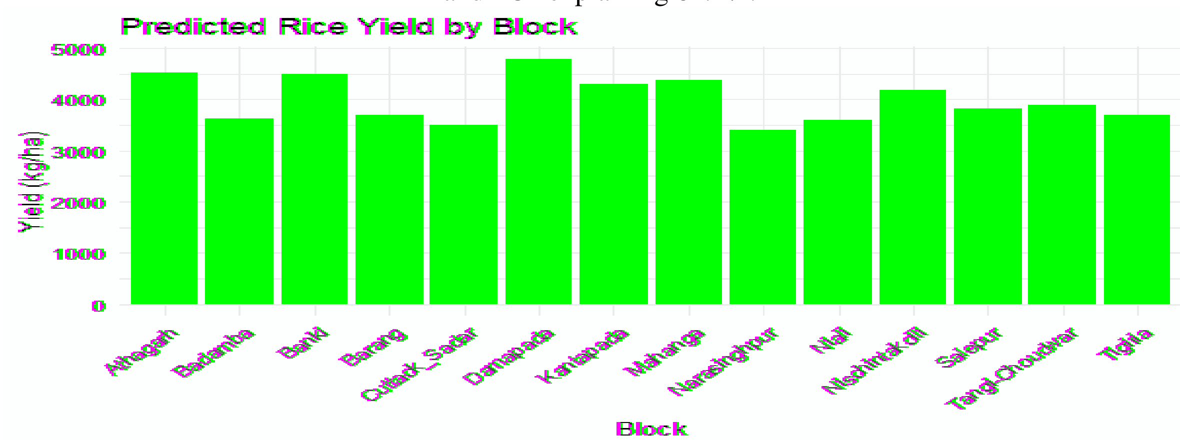

Fig. 5 : Predicted rice yields (kg/ha) across Cuttack's 14 blocks, ranging from 3563.2 kg/ha (Narasinghpur) to 4531.9 kg/ha (Damapada), with error bars representing random forest prediction uncertainty (RMSE: 49.34 kg/ha).

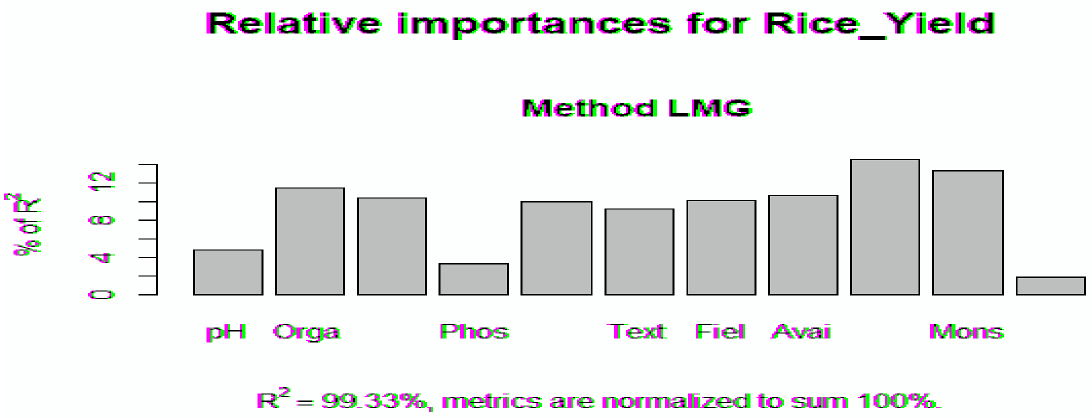

Fig. 6: Bar plot of relative importance of predictors for rice yield, with monsoon rainfall and field capacity explaining ~12–13% of variance.

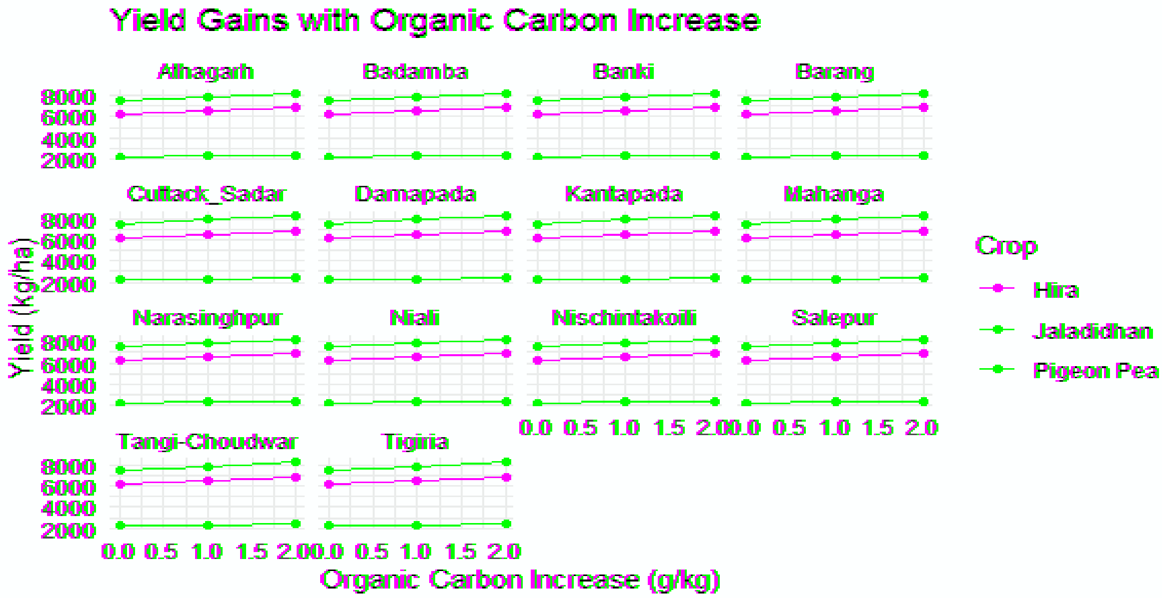

Fig. 7: Bar plot of yield gains for Hira, Jaladidhan, and Pigeon Pea under drought with 1–2 g/kg SOC enhancement.

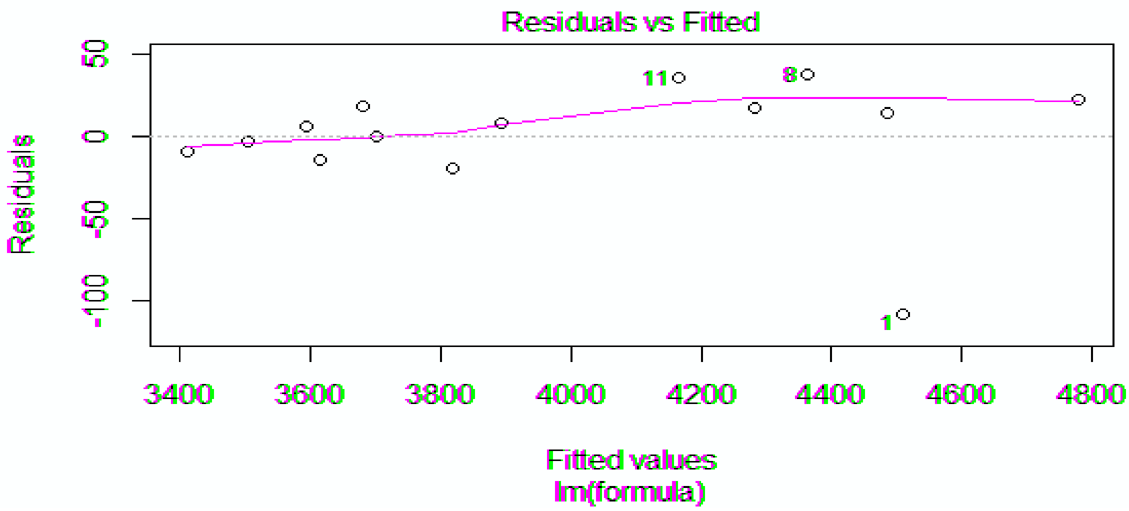

Fig. 8 : Residuals vs. fitted plot for the rice yield regression model, confirming linearity with outliers in Athagarh, Narasinghpur, and Nischintakoili.

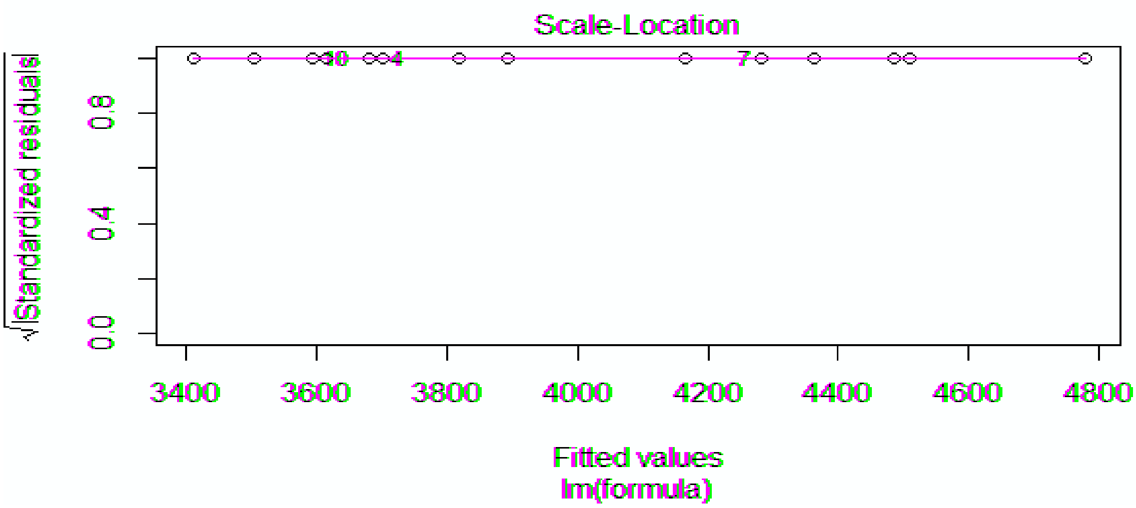

Fig. 9 : Scale-location plot, indicating homoscedasticity of residuals across fitted values.

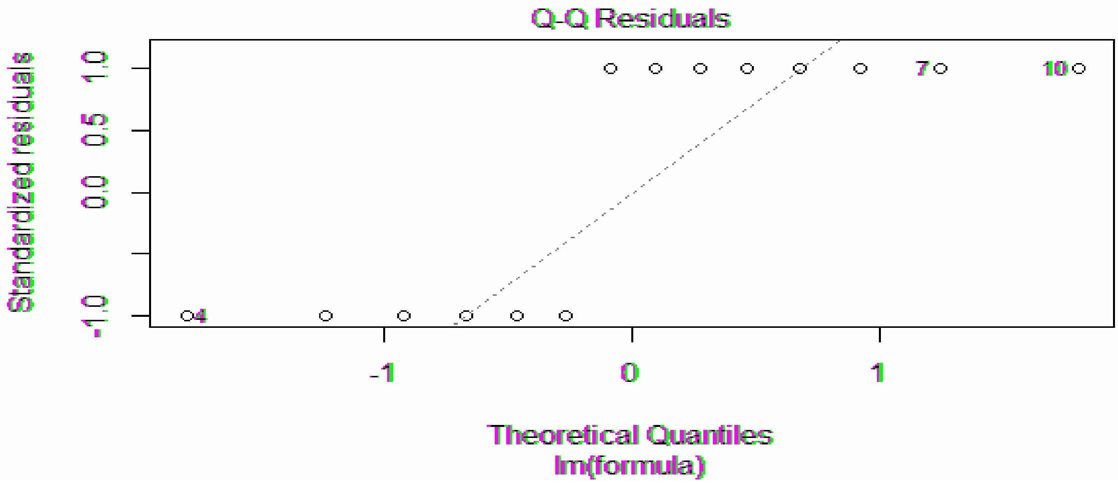

Fig. 10 : Q-Q plot of standardized residuals, showing approximate normality with minor tail deviations.

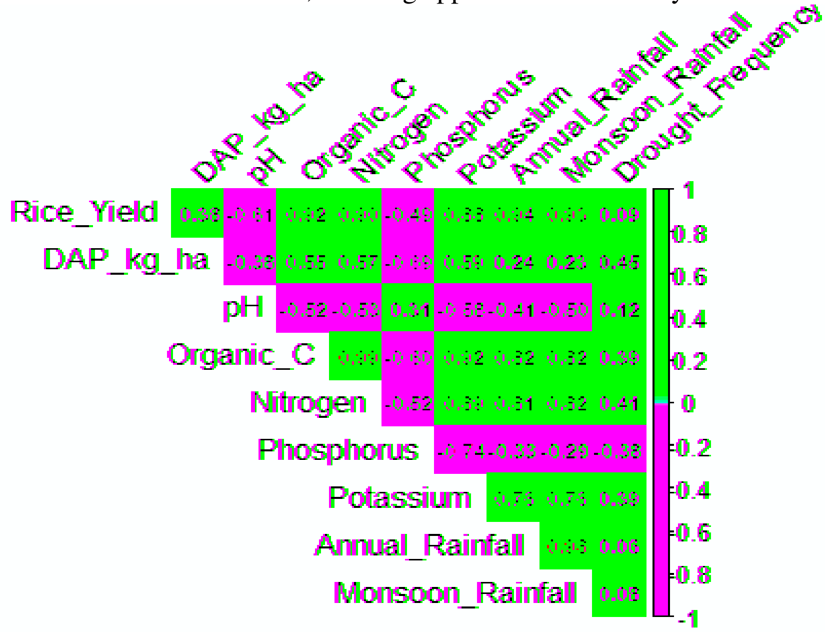

Fig. S1 : Correlation matrix of soil properties, climate factors, and agronomic outcomes in Cuttack.

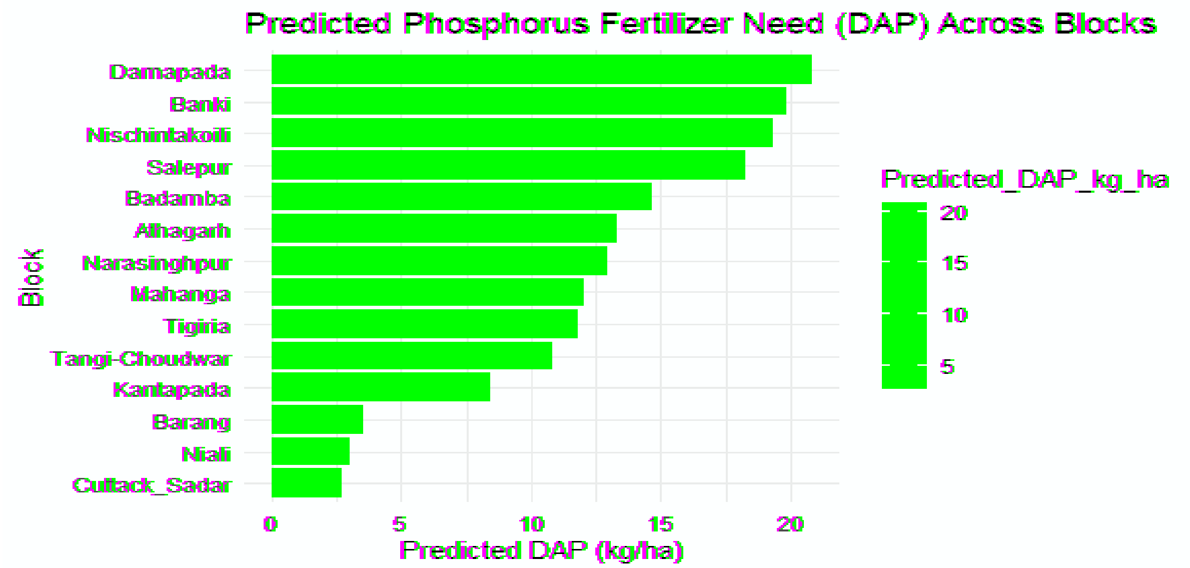

Fig. S2 : Spatial variability in predicted DAP needs (kg/ha) across Cuttack's 14 blocks.

Highlights

- Novel framework predicts rice yields with high accuracy ($R^2 = 0.993$) in Cuttack, India.
- PCA and k-means clustering identify three agro-climatic zones for tailored crop management.
- SOC enhancement increases rice yields by up to 708.98 kg/ha under drought stress.
- Optimized DAP use (2.92–21.40 kg/ha reduction) enhances sustainability in rainfed systems.

Scalable model for precision agriculture in global monsoon-dependent agroecosystems.

Conflicts of Interest/Competing Interests: The authors declare no conflicts of interest.

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