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Machine Learning-Based Analysis of Climatic and Agricultural Factors for Crop Yield Prediction

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Abstract

Crop yield in India depends on both the climate in which crops grow and the way in which they are managed, yet the relative importance of these two groups of factors is rarely quantified within a single statistical framework. This study examines the influence of five climatic factors (temperature, rainfall, relative humidity, sunshine duration and wind speed) and five agricultural factors (irrigation, fertilizer use, soil quality, seed quality and pesticide use) on the yields of wheat, rice and soybean. It uses 299 district-season records from six major producing states, with Madhya Pradesh as the focal state. Pearson and partial correlation analysis, hierarchical multiple regression with crop dummy variables, Shapley decomposition, dominance analysis, bootstrap inference and ten-fold cross-validation were applied, and the model assumptions were verified through standard diagnostic tests. The full model explained 88.8 per cent of the variation in yield (adjusted $R^2 = 0.884$; $F = 189.91$, $p < 0.001$). Temperature had a significant negative effect (−0.114 t/ha per °C). Rainfall, sunshine, irrigation, fertilizer use, soil quality and seed quality had significant positive effects, while humidity, wind speed and pesticide use were not significant. Agricultural factors accounted for about 66 per cent and climatic factors for about 34 per cent of the within-crop variance explained, and the difference was significant. The model predicted yield accurately on independent data (cross-validated RMSE = 0.335 t/ha). The results indicate that improved input management offers substantial scope for raising yields, while adaptation to rising temperatures remains essential.

Keywords: crop yield; climate; agricultural inputs; multiple regression; dominance analysis; India

1. Introduction

1.1 Agriculture and Food Security

Agriculture remains central to food security and rural livelihoods in India. Although its share in national income has declined, it continues to support a large part of the population, and fluctuations in crop output affect food prices, farm incomes and rural demand. The need to raise agricultural productivity is becoming more urgent as population and incomes grow while the area available for cultivation remains essentially fixed. Since further expansion of cropland is limited, most future growth in production must come from higher yields on existing land. Understanding what determines crop yield, and how much each determinant matters, is therefore a question of direct policy importance.

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1.2 Climate Sensitivity of Crop Production

Crop production is highly sensitive to weather and climate. Temperature governs the rate of crop development and the duration of grain filling, rainfall supplies the water on which rainfed crops depend, and humidity and sunshine influence evaporative demand and photosynthesis. The Intergovernmental Panel on Climate Change (IPCC, 2022) has concluded that climate change has already slowed the growth of agricultural productivity, especially in warm regions, and that the risks will increase with further warming. Global analyses estimate that each 1 °C rise in temperature reduces average yields of wheat, rice and soybean by several per cent (Zhao et al., 2017). Extreme weather events, such as droughts and heat waves, have caused significant losses in national cereal production (Lesk et al., 2016). India, with its high temperatures and dependence on the monsoon, is among the most exposed countries.

1.3 Agricultural Inputs and Productivity

Climate sets the environmental conditions for crop growth, but the yield obtained depends heavily on management. Irrigation, fertilizers, improved seed and plant protection were the foundations of the Green Revolution, and they remain the principal means through which farmers raise yields. In India, irrigation has contributed substantially to wheat yield growth and has reduced the sensitivity of the crop to heat (Zaveri & Lobell, 2019). Large yield gaps persist between farmers working under similar climatic conditions, which shows that management differences matter (Jain et al., 2017). Unlike climate, these inputs can be influenced by farmers and governments, so evidence on their effects is directly relevant to agricultural policy.

1.4 Regression Modelling in Agriculture

Because climatic and agricultural factors act together and are often correlated, their separate effects cannot be judged from simple comparisons. Multiple regression analysis estimates the effect of each factor while holding the others constant. It provides tests of significance and measures of goodness of fit, and it can be used to predict yield from observed conditions (Montgomery et al., 2021). Regression-based approaches have been widely used to study climate impacts on crop yields in India and neighbouring countries (Guntukula, 2020; Ali et al., 2017). In addition, techniques such as dominance analysis allow the explained variance to be divided among correlated groups of predictors in a way that does not depend on the order in which they are entered.

1.5 Context of the Present Study

Most earlier studies have analysed either climatic factors or agricultural inputs, often for a single crop or with national aggregate data, and few have compared the contributions of the two groups formally. The present paper addresses this gap. It analyses five climatic and five agricultural factors together for three major crops (wheat, rice and soybean) across six states of India, with Madhya Pradesh as the focal state. The paper examines the relationships between these factors and yield, quantifies the relative contributions of the two groups, develops and validates a prediction model, and identifies the key factors influencing yield. The remainder of the paper is organised as follows: the literature is reviewed, the methodology is described, the results are presented and discussed, and conclusions are drawn.

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2. Literature Review

2.1 Climatic Factors and Crop Yield

There is now strong evidence that high temperatures reduce the yields of major crops. Zhao et al. (2017) combined crop models, statistical regressions and field experiments and estimated that, without adaptation, each 1 °C increase in global mean temperature reduces yields by about 6.0 per cent for wheat, 3.2 per cent for rice and 3.1 per cent for soybean. Liu et al. (2016) found that three independent methods gave similar estimates of a 4.1 to 6.4 per cent decline in global wheat yield per degree of warming. Ortiz-Bobea et al. (2021) estimated that anthropogenic climate change has reduced global agricultural total factor productivity by about 21 per cent since 1961. In India, Birthal et al. (2021) used district-level fixed-effects regression for 1966–67 to 2011–12 and found that heat stress reduces wheat yield, with the impact increasing over time.

Rainfall and moisture are equally important. Lesk et al. (2016) showed that droughts and extreme heat reduced national cereal production by roughly 9 to 10 per cent. Matiu et al. (2017) demonstrated that the combination of heat and drought is more damaging than either alone, and Vogel et al. (2019) found that climate extremes account for 18 to 43 per cent of the explained variance in yield anomalies. Rigden et al. (2020) showed that atmospheric evaporative demand, which is closely related to humidity, improves yield prediction beyond soil moisture alone. In South Asia, Guntukula (2020) found that rainfall and maximum and minimum temperatures significantly affect the yields of major Indian crops over 1961–2017, with effects differing across crops. Ali et al. (2017), analysing Pakistan, found that maximum temperature adversely affects wheat, while minimum temperature has a positive effect on all the major crops studied.

2.2 Agricultural Factors and Crop Yield

Irrigation is one of the most important determinants of yield in India. Zaveri and Lobell (2019) estimated that national wheat yields in the 2000s were 13 per cent higher than they would have been without the expansion of irrigation since 1970, and that irrigated wheat shows only about one-quarter of the heat sensitivity of rainfed wheat. Birthal et al. (2021) likewise found that irrigation moderates the harmful effect of heat stress. Kumar et al. (2016), using state-level panel data, found that land productivity in India is positively associated with irrigated area and fertilizer use and negatively associated with maximum temperature.

At the global level, Agnolucci et al. (2020) analysed 18 crops and showed that fertilizer application and irrigation raise yields and can partly offset the effect of rising temperatures. Soil quality also matters. Oldfield et al. (2019) found in a global meta-analysis that yields increase with soil organic carbon up to about 2 per cent. Seed quality determines the genetic yield potential of the crop, and Atlin et al. (2017) argued that rapid varietal replacement is critical for adapting cropping systems to climate change. Jain et al. (2017) found that improving management could raise wheat yields in the eastern Indo-Gangetic Plains by up to 32 per cent, with late sowing and high temperatures being the factors most associated with low yields.

2.3 Regression and Yield Prediction

Multiple regression remains the standard tool for estimating the effects of several factors on yield. It provides interpretable coefficients and formal tests, and its assumptions can be verified through diagnostic procedures (Montgomery et al., 2021). In India, Das et al. (2018) compared stepwise multiple linear regression, artificial neural networks and penalised regression for predicting rice yield from weather variables. They found that the linear models performed as well as the neural networks. In a systematic review, van Klompenburg et al. (2020) found that temperature, rainfall and soil type are the most frequently used predictors in crop yield prediction studies. They also stressed the importance of validating models on independent data. Despite this literature, few studies have combined climatic and agricultural predictors for several crops within one validated regression model and decomposed the explained variance between the two groups. The present study is designed to fill this gap.

3. Research Methodology

The study follows a quantitative, explanatory and correlational design based on secondary data. The study area comprises six major producing states of India: Madhya Pradesh, Uttar Pradesh, Maharashtra, Punjab, Rajasthan and West Bengal. Madhya Pradesh is the focal state because of its diverse agro-climatic zones and its importance in wheat and soybean production. The unit of observation is the district-season record, defined as the yield of one crop in one district in one agricultural year, over the period 2014–15 to 2023–24. A multistage stratified random sample of 312 records was drawn, with 104 records allocated to each crop. After data screening, 299 records were retained: 100 for wheat, 102 for rice and 97 for soybean. This sample comfortably exceeds the minimum of 184 records required to detect a medium effect ($f^2 = 0.15$) with 95 per cent power at the 5 per cent significance level with twelve predictors.

Crop yield (t/ha) was the dependent variable. The climatic factors were the growing-season mean temperature, seasonal rainfall, mean relative humidity, sunshine duration and mean wind speed, obtained from India Meteorological Department records and aggregated over the crop-specific season. The agricultural factors were the percentage of crop area irrigated, fertilizer use ($N + P_2O_5 + K_2O$ per hectare), a soil quality index and a seed quality index (both composite scores from 1 to 10 built from weighted, normalised indicators), and pesticide use per hectare. These were compiled from official agricultural statistics and Soil Health Card data. Crop type was represented by two dummy variables, with wheat as the reference category.

Records with missing values were removed by listwise deletion, and multivariate outliers were identified using the Mahalanobis distance at the 0.001 level. The analysis combined descriptive statistics, Pearson and partial correlation (controlling for crop), and hierarchical multiple regression estimated by ordinary least squares. The full model is shown in Equation (1).

$$Y_i = \beta_0 + \gamma_1 D_{1i} + \gamma_2 D_{2i} + \sum_{j=1}^{5} \beta_j X_{ji} + \sum_{j=6}^{10} \beta_j X_{ji} + \varepsilon_i \qquad (1)$$

Here Y_i is crop yield, D_1 and D_2 are the rice and soybean dummies, X_1 to X_5 are the climatic factors, X_6 to X_{10} are the agricultural factors and ε_i is the random error. The predictors were entered in three blocks: crop type (Model 1), climatic factors (Model 2) and agricultural factors (Model 3). The contribution of each block was tested by the F-change statistic in Equation (2).

$$F_{\text{change}} = \frac{\left(R_f^2 - R_r^2\right)/m}{\left(1 - R_f^2\right)/\left(n - k_f - 1\right)} \tag{2}$$

Because block contributions depend on the order of entry, the within-crop explained variance was also partitioned by Shapley decomposition and by dominance analysis over all 1,024 sub-models of the ten factors. The difference between the climatic and agricultural shares was tested with 2,000 bootstrap resamples. Predictive accuracy was evaluated on a 20 per cent hold-out sample and by ten-fold cross-validation, using the root mean square error (RMSE), mean absolute error and mean absolute percentage error (MAPE). The model assumptions were verified through variance inflation factors, the Shapiro–Wilk test on residuals, the Breusch–Pagan test and the Durbin–Watson statistic. All tests were conducted at the 5 per cent significance level.

4. Results and Discussion

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics of the study variables. Mean yield was 2.82 t/ha overall, 3.42 t/ha for wheat, 3.30 t/ha for rice and 1.72 t/ha for soybean. The crop differences were highly significant ($F = 276.81$, $p < 0.001$). Temperature varied little (CV = 6.6 per cent), whereas rainfall (CV = 25.1 per cent) and the agricultural inputs varied considerably across districts and seasons. Most variables were approximately normally distributed; wind speed showed moderate positive skewness.

Table 1: Descriptive statistics of study variables (n = 299)

Variable	Mean	SD	Minimum	Maximum	CV (%)
Crop yield (t/ha)	2.82	0.96	0.56	4.75	33.83
Temperature (°C)	25.58	1.69	20.82	30.96	6.61
Rainfall (mm)	1066.22	267.51	291.37	1769.52	25.09
Relative humidity (%)	61.38	7.91	39.82	83.03	12.88
Sunshine (h/day)	7.24	0.72	5.29	8.85	9.98
Wind speed (km/h)	7.74	2.35	3.32	15.16	30.38
Irrigation (% area)	62.35	16.28	12.85	98.00	26.11
Fertilizer (kg/ha)	151.25	35.34	59.05	260.00	23.37
Soil quality index	6.16	1.36	2.63	9.32	22.04
Seed quality index	6.45	1.39	2.62	10.00	21.61
Pesticide (kg a.i./ha)	0.83	0.26	0.15	1.51	31.51

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4.2 Correlation Analysis

Table 2 reports the Pearson correlation of each factor with yield and the partial correlation controlling for crop type. The correlations are also displayed in Figure 1. Temperature was negatively correlated with yield (r = −0.204), and the association strengthened to −0.395 after controlling for crop. Rainfall, irrigation, fertilizer use and soil quality were positively correlated with yield. Fertilizer had the strongest partial correlation (0.535). Seed quality was not significant in the pooled analysis but became highly significant once crop was controlled (partial r = 0.259). This shows that pooling crops without control can conceal genuine relationships. Humidity was strongly correlated with rainfall (r = 0.71).

Table 2: Correlation of climatic and agricultural factors with crop yield

Factor	Group	Pearson r	p-value	Partial r (crop controlled)	p-value
Temperature (°C)	Climatic	−0.204***	< 0.001	−0.395***	< 0.001
Rainfall (mm)	Climatic	0.119*	0.039	0.274***	< 0.001
Relative humidity (%)	Climatic	0.037	0.527	0.176**	0.002
Sunshine (h/day)	Climatic	0.030	0.607	0.067	0.251
Wind speed (km/h)	Climatic	−0.062	0.284	−0.049	0.402
Irrigation (% area)	Agricultural	0.240***	< 0.001	0.499***	< 0.001
Fertilizer (kg/ha)	Agricultural	0.252***	< 0.001	0.535***	< 0.001
Soil quality index	Agricultural	0.242***	< 0.001	0.341***	< 0.001
Seed quality index	Agricultural	0.082	0.157	0.259***	< 0.001
Pesticide (kg a.i./ha)	Agricultural	−0.035	0.542	−0.004	0.946

Note: * p < 0.05, ** p < 0.01, *** p < 0.001.

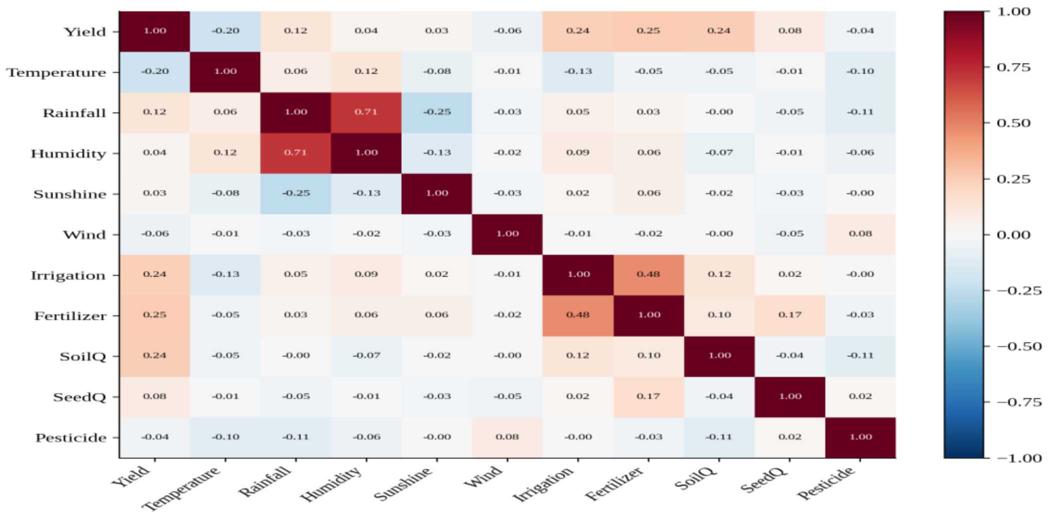

Figure 1: Correlation heat map of crop yield and the ten explanatory variables (n = 299)

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4.3 Hierarchical Regression and Model Fit

Table 3 summarises the hierarchical regression. Crop type alone explained 65.2 per cent of the variation in yield. Adding the climatic factors increased R^2 by 0.091 (F-change = 20.55, $p < 0.001$), and adding the agricultural factors increased it by a further 0.146 (F-change = 74.88, $p < 0.001$). The final model achieved R = 0.943, $R^2 = 0.888$ and adjusted $R^2 = 0.884$. The ANOVA in Table 4 confirms that the model is highly significant ($F(12, 286) = 189.91$, $p < 0.001$). The small gap between R^2 and adjusted R^2 indicates that the model is not over-fitted.

Table 3: Hierarchical regression model summary

Model	R	R^2	Adjusted R^2	SE of estimate	ΔR^2	F change	Sig.
Model 1: Crop type	0.807	0.652	0.649	0.566	0.652	276.81	< 0.001
Model 2: + Climatic factors	0.862	0.743	0.736	0.490	0.091	20.55	< 0.001
Model 3: + Agricultural factors	0.943	0.888	0.884	0.326	0.146	74.88	< 0.001

Note: Dependent variable: crop yield (t/ha). Durbin–Watson (Model 3) = 1.970.

Table 4: Analysis of variance for the full regression model

Source	Sum of squares	df	Mean square	F	Sig.
Regression	241.562	12	20.130	189.91	< 0.001
Residual	30.316	286	0.1060		
Total	271.878	298			

4.4 Regression Coefficients

The estimated coefficients are presented in Table 5, and the standardised coefficients are shown in Figure 2. Temperature had a significant negative effect: each 1 °C increase reduced yield by 0.114 t/ha, or about 4.0 per cent of mean yield, with other factors held constant. This finding is consistent with global and Indian evidence (Zhao et al., 2017; Birthal et al., 2021). Each additional 100 mm of rainfall raised yield by 0.071 t/ha, and each additional hour of daily sunshine raised it by 0.087 t/ha. The effect of sunshine appeared only once rainfall was controlled. Humidity and wind speed had no significant effect, so the bivariate association of humidity with yield reflects its correlation with rainfall.

Among the agricultural factors, each additional 10 percentage points of irrigated area raised yield by 0.086 t/ha, and each additional 10 kg/ha of fertilizer raised it by 0.052 t/ha. A one-point improvement in the soil quality and seed quality indices raised yield by 0.114 and 0.092 t/ha respectively. These results agree with the evidence on irrigation and inputs in India (Zaveri & Lobell, 2019; Kumar et al., 2016). Pesticide use was not significant. All variance inflation factors were below 2.2, so multicollinearity does not affect these estimates.

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Table 5: Estimated regression coefficients of the full model

Predictor	B	SE	Beta	t	Sig.	VIF
Constant	2.4044	0.4454	—	5.398	< 0.001	—
Rice dummy	−0.0897	0.0464	−0.045	−1.934	0.054	1.363
Soybean dummy	−1.7804	0.0470	−0.874	−37.900	< 0.001	1.364
Temperature (°C)	−0.1137	0.0115	−0.201	−9.922	< 0.001	1.055
Rainfall (mm)	0.00071	0.00010	0.198	6.764	< 0.001	2.197
Relative humidity (%)	−0.00140	0.0035	−0.012	−0.402	0.688	2.138
Sunshine (h/day)	0.0867	0.0273	0.066	3.172	0.002	1.095
Wind speed (km/h)	−0.00495	0.0081	−0.012	−0.613	0.540	1.014
Irrigation (% area)	0.00865	0.0013	0.147	6.452	< 0.001	1.338
Fertilizer (kg/ha)	0.00519	0.00062	0.192	8.360	< 0.001	1.352
Soil quality index	0.1136	0.0143	0.161	7.958	< 0.001	1.056
Seed quality index	0.0919	0.0139	0.134	6.618	< 0.001	1.054
Pesticide (kg a.i./ha)	0.0768	0.0739	0.021	1.040	0.299	1.046

Note: Dependent variable: crop yield (t/ha). Wheat is the reference crop.

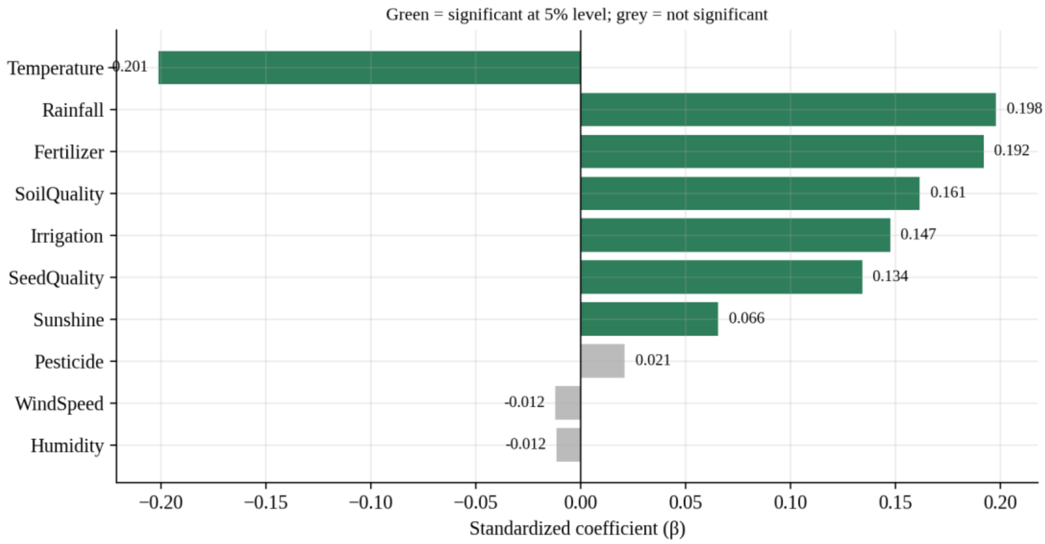

Figure 2: Standardised regression coefficients of climatic and agricultural predictors (green: significant at 5 per cent level)

4.5 Relative Contribution of Climatic and Agricultural Factors

Table 6 and Figure 3 present the relative contributions of the two groups of factors. Crop type accounted for 65.2 per cent of the total variance. Of the within-crop variance explained by the ten factors, agricultural factors contributed 65.9 per cent and climatic factors 34.1 per cent. The bootstrap 95 per cent confidence interval for the difference between the two shares, [0.032, 0.116], excludes zero, so agricultural factors make a significantly larger contribution. The dominance analysis ranked fertilizer use first (25.1 per cent), followed by irrigation (19.8 per cent) and temperature (19.6 per cent). Taking significance, standardised coefficients, unique variance and dominance together, the seven key factors were temperature, fertilizer use, soil quality, rainfall, irrigation, seed quality and sunshine.

Table 6: Relative contribution of factor groups and leading individual factors

Component	% of total variance	% of explained within-crop variance
Crop type (control)	65.16	—
Climatic factors (Shapley share)	8.07	34.06
Agricultural factors (Shapley share)	15.62	65.94
Unexplained	11.15	—
Fertilizer (kg/ha) (dominance)	5.96	25.14
Irrigation (% area) (dominance)	4.69	19.82
Temperature (°C) (dominance)	4.65	19.61
Soil quality index (dominance)	3.14	13.26
Rainfall (mm) (dominance)	2.28	9.62
Seed quality index (dominance)	1.98	8.34

Note: Individual dominance weights are shown for the six most important factors.

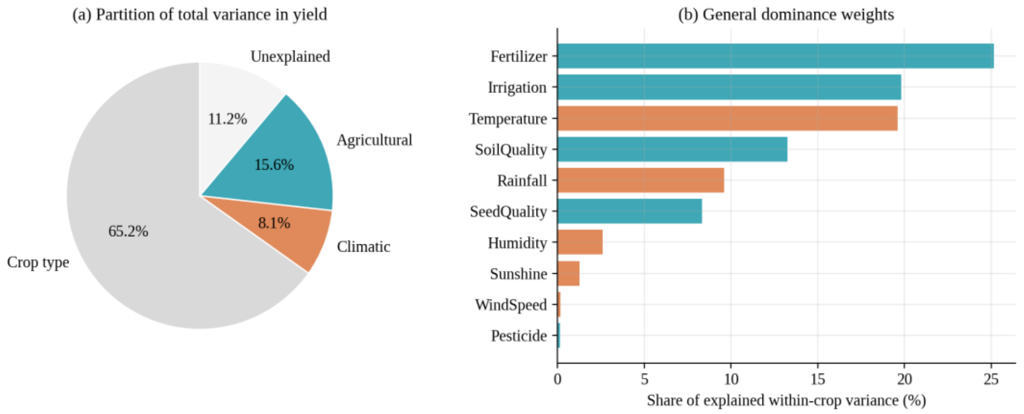

Figure 3: Relative contribution: (a) partition of total variance by factor group, (b) dominance weights of individual predictors

4.6 Prediction Accuracy and Model Diagnostics

The model predicted yield accurately. On the 20 per cent hold-out sample, it achieved R^2 = 0.886 and RMSE = 0.328 t/ha. In ten-fold cross-validation, R^2 was 0.877, RMSE was 0.335 t/ha and MAPE was 11.6 per cent, close to the in-sample RMSE of 0.318 t/ha. The observed and predicted yields in Figure 4 lie close to the 45-degree line for all three crops. The residuals were normally distributed (Shapiro–Wilk p = 0.651; Figure 5), homoscedastic (Breusch–Pagan

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p = 0.530) and independent (Durbin–Watson = 1.970). The classical regression assumptions are therefore satisfied. These results support the finding of Das et al. (2018) that well-specified linear models perform well in weather-based yield prediction.

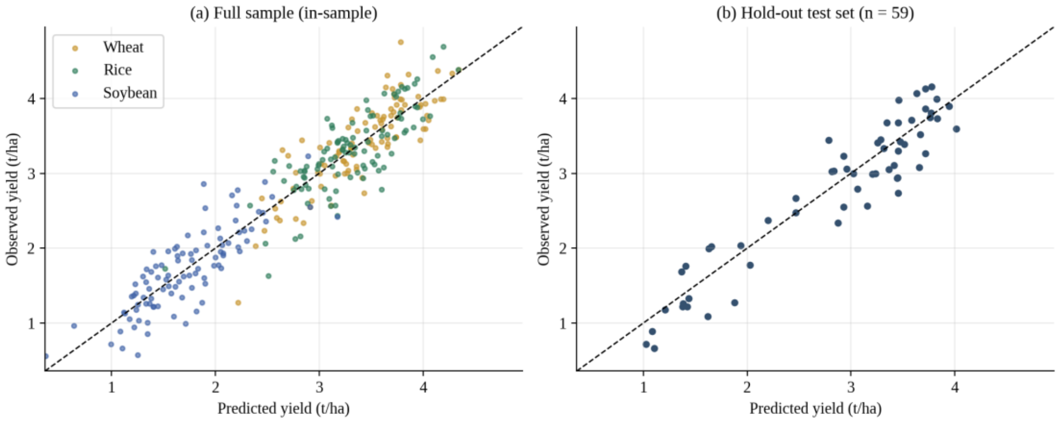

Figure 4: Observed versus predicted crop yield: (a) full sample, (b) hold-out validation sample

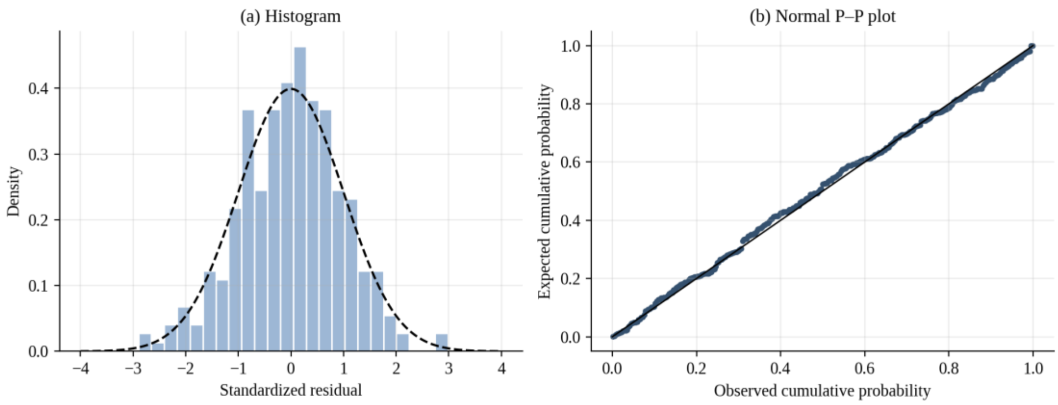

Figure 5: Normality of regression residuals: (a) histogram of standardised residuals, (b) normal P–P plot

5. Conclusion

This study assessed the impact of climatic and agricultural factors on the yields of wheat, rice and soybean in India using hierarchical multiple regression. The model explained 88.8 per cent of the variation in yield, satisfied all diagnostic tests and predicted yields accurately on independent data. Temperature was the most influential single factor, and its effect was adverse. Rainfall and sunshine had positive effects, while humidity and wind speed had no independent effect. Irrigation, fertilizer use, soil quality and seed quality all raised yields significantly.

The central finding is that agricultural factors contribute about twice as much as climatic factors to within-crop variation in yield (66 per cent versus 34 per cent). This indicates that productivity is, to a considerable degree, within the reach of management and policy. Priority should be given to balanced fertilizer use guided by soil testing, expansion of efficient irrigation, soil health improvement and wider use of certified seed. At the same time, the adverse effect of temperature means that heat-tolerant varieties and timely sowing are essential adaptation measures. The study relies on district-level secondary data and seasonal climatic averages, so its estimates are associations rather than proven causal effects. Future research could use farm-level data, measures of climate extremes and panel methods to extend these findings.

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