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MACHINE LEARNING APPROACH FOR CEREAL YIELD PREDICTION IN KOREA, CHHATTISGARH, INDIA

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ABSTRACT

This study aims to improve crop yield forecasting for maize, wheat, and rice in Korea by combining meteorological trend analysis, correlation assessments, and machine learning. The study uses various machine learning models, including Multiple Linear Regression, Stepwise MLR, LASSO, Elastic Net, Ridge Regression, Random Forest and Artificial Neural Networks, to create forecasting models. The data is analyzed in both weighted and unweighted formats and a 70:30 data split is applied for training and testing. The results aim to enhance prediction accuracy, promote climate-resilient farming and provide data-driven insights for agricultural decisions in Korea.

Key words : Crop Yield prediction, Machine Learning, Regression analysis, Weather indices, Trend analysis, Correlation analysis.

Introduction

Chhattisgarh, a state in India, primarily produces rice, wheat, maize and pulses. Despite improvements through schemes like Rajiv Gandhi Kisan Nyay Yojana, productivity remains below the national average. India's rice production is projected at 119.93 million tonnes Maize, a major cereal, is at risk of a 55% yield decline by 2080 due to climate stress, highlighting the need for climate-resilient varieties (Byjesh *et al*., 2010).

Chhattisgarh faces climate change challenges like soil depletion, groundwater depletion and overuse of resources. Rainfed agriculture dominates, with poor awareness and limited climate models. Machine learning offers advanced tools for yield forecasting, improving crop predictions, resource planning, policy planning, market stability and risk management in agriculture (Shrivastava *et al*., 2019; Angom *et al*., 2021; Attri *et al*., 2024).

The objective of the present study is to analyse the trends in weather parameters, examine their correlation with crop yield, and develop as well as compare the prediction accuracy of different machine learning models for crop yield prediction.

Materials and Methods

Study area and data collection

Korea, a North-West District in Chhattisgarh, India, was analyzed using crop yield data from 2000 to 2022 and weather data from NASA Power. The analysis included crop production, cultivated area and weekly averages of weather parameters (https://power.larc.nasa.gov/data-access-viewer/).

Methodology

Weather indices were developed for each weather variable, with unweighted indices summarizing individual variables or their interactions, and weighted indices using the product sum of these variables, considering their correlation with crop yield. The formulas for both indices include Tmax, Tmin, RF and RH, with unweighted indices totalling weekly weather variable values.

Unweighted Weather indices

$$Z_{ij} = \sum_{w=1}^{m} X_{iw}$$

$$Z_{ii'j} = \sum_{w=1}^{m} X_{iw} X_{j'w} \qquad (1)$$

Fig. 1 : Study area map of Korea, Chhattisgarh.

Weighted weather indices

$$Z_{ij} = \sum_{w=1}^{m} r_{iw}^{j} X_{iw}$$

$$Z_{ii''m} = \sum_{w=1}^{m} r_{ii'm}^{j} X_{iw} X_{j'w} \quad (2)$$

Where,

- Value of $i^{th}\backslash i'^{th}$ weather variable under study in w^{th} week,
- Correlation coefficient of yield with i^{th} weather variable/ product of i^{th} and i'^{th} weather variables in w^{th} week.
- Week of forecast.

Climatic Variability assessment

The study used a 22-year dataset of daily meteorological observations to assess long-term climatic trends and variability. The data was analyzed monthly for seasonal and annual evaluations. Statistical analyses were performed to evaluate spatial and temporal variability, using key descriptive statistics like mean, standard deviation and coefficient of variation as indicators.

Trend analysis of Climatic and Yield data

Mann Kendell test

The Mann-Kendall test is a reliable non-parametric method for detecting trends in time series data, recommended by the World Meteorological Organization for analyzing monotonic trends in hydro-meteorological datasets despite structural changes (Tian *et al*., 2010).

The test statistic Zc follows a standard normal distribution, with a null hypothesis (H€) rejected if it exceeds the critical value ±Z...α/2, indicating a significant

Table 1 : Unweighted and weighted weather indices for the development of multivariate models.

Mean weekly weather variable	Unweighted weather indices	Weighted weather indices
T_{max}	Z10	Z11
T_{min}	Z20	Z21
Relative Humidity (RH)	Z30	Z31
Rainfall (RF)	Z40	Z41
T_{max}*Tmin	Z120	Z121
T_{max}*Relative Humidity	Z130	Z131
T_{max}*Rainfall	Z140	Z141
T_{min}*Relative Humidity	Z230	Z231
T_{min}*Rainfall	Z240	Z241
Rainfall*Relative Humidity	Z340	Z341

trend in the time series (R) and an acceptance (A), if it is less than or equal to Z...z2, with a 95% confidence level.

Sen's slope

The approach involves determining the slope by assessing the variation in measurement relative to the variation in time.

$$Q' = \frac{x_t' - x_t}{t' - t} \tag{3}$$

Where,

- Q' = slope between data points x_t' and x_t
- x_t' = data measurement at time t'
- x_t = data measurement at time t

Different Models Analyzed

This study aims to improve crop yield forecasting for maize, wheat and rice in Korea by combining meteorological trend analysis, correlation assessments, and machine learning. The study uses various machine learning models, including Multiple Linear Regression, Stepwise MLR, LASSO, Elastic Net, Ridge Regression, Random Forest, and Artificial Neural Networks, to create forecasting models. The data is analyzed in both weighted and unweighted formats, and a 70:30 data split is applied for training and testing. The results aim to enhance prediction accuracy, promote climate-resilient farming, and provide data-driven insights for agricultural decisions in Korea.

Statistical analysis and Model evaluation

The study used statistical metrics like Coefficient of Determination, Root Mean Square Error, Normalized Root Mean Square Error, and Mean Absolute Error to evaluate the performance of various crop yield prediction models, determining the most accurate and reliable model.

Results and Discussion

Trend analysis of weather parameters for Korea region (2000-2022)

The Mann-Kendall test was used to analyze meteorological trends in Korea from 2000 to 2022. Results showed a cooling trend with an annual average of 30.7°C, increased relative humidity, and stable minimum temperatures. Rainfall patterns remained consistent, primarily during the monsoon, averaging 1161.06 mm annually. These findings could impact long-term agricultural strategies and yield forecasts in Korea, highlighting the importance of addressing skewed meteorological variables.

Table 2 : Trend analysis using weather parameters.

Average Maximum temperature (^{0}C)						
Time series	**Mean**	**SD**	**CV**	**MK**	**P-value**	**Slope**
Annual	30.7	0.71	2.31	-0.34	**0.02****	-0.03
Winter	26.1	1.23	4.69	-0.31	**0.03****	-0.09
Pre-Monsoon	37.5	1.21	3.23	-0.12	0.44	-0.05
Monsoon	30.9	0.89	2.89	0.04	0.82	0.00
Post Monsoon	26.9	1.39	5.19	-0.20	0.19	-0.06
Average Minimum temperature (^{0}C)						
Time series	**Mean**	**SD**	**CV**	**MK**	**P-value**	**Slope**
Annual	18.4	0.36	1.95	-0.08	0.60	-0.01
Winter	10.4	0.77	7.36	-0.20	0.17	-0.03
Pre-Monsoon	21.5	0.78	3.61	-0.08	0.60	-0.01
Monsoon	23.4	0.39	1.67	0.11	0.47	0.01
Post Monsoon	15.7	0.68	4.33	0.02	0.90	0.00
Average Relative humidity (%)						
Time series	**Mean**	**SD**	**CV**	**MK**	**P-value**	**Slope**
Annual	57.3	3.95	6.88	0.41	**0.01****	0.27
Winter	48.7	8.28	17.00	0.40	**0.01****	0.55
Pre-Monsoon	29.2	6.52	22.33	0.21	0.16	0.21
Monsoon	78.7	3.72	4.73	0.06	0.71	0.03
Post Monsoon	69.8	6.98	9.99	0.25	0.09	0.38
Average Rainfall (mm)						
Time series	**Mean**	**SD**	**CV**	**MK**	**P-value**	**Slope**
Annual	1161.06	194.31	16.74	0.18	0.22	5.08
Winter	45.07	30.75	68.22	0.20	0.17	1.36
Pre-monsoon	79.32	41.74	52.62	0.08	0.60	0.66
Monsoon	975.89	161.11	16.51	0.07	0.67	2.22
Post monsoon	60.78	66.18	108.88	0.04	0.82	0.24

Where, *** 0.1 level of significance, **0.05 level of significance, * 0.01 level of significance.
Mean, **SD** – Standard Deviation, **CV** – Coefficient of Variation, **MK** – Mann Kendall test, **P Value** – probability value, slope

Table 3 : Correlation between weather and maize yield.

Correlation Coefficient Matrix - Maize				
SMW	T_{max}	T_{min}	RF	RH
28	0.070	0.057	0.026	-0.151
29	0.223	0.101	-0.106	-0.122
30	-0.078	-0.152	0.091	0.262
31	-0.274	-0.312	0.169	-0.017
32	-0.166	-0.023	0.262	0.179
33	0.121	-0.245	-0.097	0.142
34	0.047	-0.351	-0.056	-0.057
35	0.069	0.276	0.161	0.097
36	0.072	0.057	-0.047	-0.256
37	-0.036	**0.603***	0.246	0.178
38	-0.022	**0.515***	0.335	0.224
39	-0.074	0.165	0.062	0.195
40	-0.033	0.235	0.107	0.014
41	-0.295	0.249	**0.476***	0.211
42	-0.062	0.297	0.335	-0.042
43	-0.161	0.142	0.222	-0.058
44	-0.365	-0.319	0.229	0.004

Where, *Significant at 5% level.

Table 4 : Correlation between weather and Wheat yield.

Correlation Coefficient Matrix - Wheat				
SMW	T_{max}	T_{min}	RF	RH
44	0.024	0.057	0.180	-0.017
45	-0.112	-0.222	0.154	-0.129
46	-0.119	-0.041	0.012	-0.192
47	-0.285	-0.199	0.157	0.126
48	-0.222	-0.371	0.214	-0.093
49	-0.076	-0.297	-0.038	-0.218
50	-0.184	0.077	0.339	0.406
51	**-0.420***	**-0.518***	-0.006	0.149
52	-0.144	**-0.461***	0.094	-0.149
1	-0.300	-0.169	0.187	0.080
2	-0.266	-0.284	0.122	0.288
3	-0.402	-0.132	0.170	0.250
4	-0.148	-0.198	-0.015	-0.242
5	0.165	0.031	-0.092	-0.309
6	-0.037	-0.186	-0.211	-0.290
7	-0.276	-0.173	0.056	0.218
8	-0.219	-0.164	0.166	0.356
9	-0.404	-0.259	0.267	0.267
10	-0.262	-0.273	0.070	-0.037
11	-0.170	-0.160	0.115	0.141
12	-0.274	-0.272	0.211	0.081
13	0.049	0.016	0.005	**-0.520***
14	-0.026	0.058	0.043	0.032

Where, *Significant at 5% level.

Correlation analysis between Weather variables and Crop yield

Correlation between weather and maize yield

The study analyzed the correlation between weekly weather parameters and maize yield in Korea and India. Results showed that minimum temperature during SMW 37 and 38 positively impacts yield by enhancing enzymatic activity and starch accumulation. In India, warmer nights mitigate cold stress and improve kernel weight. Rainfall positively influences yield during physiological maturity (Singh *et al.*, 2022 and Affoh, 2022) (Table 3).

Correlation between weather and Wheat yield

The study assessed wheat yield response to weather parameters during the *Rabi* season, revealing negative correlations between maximum temperature and minimum temperature. High temperatures impaired photosynthesis and tiller development, reducing yield. Minimum temperatures disrupted metabolic activity and nutrient uptake, leading to stunted development. Relative humidity negatively impacted yield during harvesting due to poor drying, increased fungal risk, and delayed harvest (Hlaváèová *et al.*, 2018 and Liu *et al.*, 2019).

Correlation between weather and rice yield

The study analyzed the impact of weather on rice yield during the Kharif season, focusing on vegetative and reproductive stages. Increased maximum

Table 5 : Correlation between weather and rice yield.

Correlation Coefficient Matrix - Rice				
SMW	Tmax	Tmin	RF	RH
26	-0.010	-0.056	0.029	-0.031
27	-0.144	0.135	0.249	0.211
28	-0.208	0.028	0.264	0.140
29	0.037	-0.015	0.204	0.050
30	-0.137	-0.005	0.310	0.147
31	-0.353	0.105	**0.479***	0.288
32	**-0.436***	-0.117	**0.577***	**0.416***
33	-0.074	0.115	0.130	0.201
34	-0.277	-0.052	0.280	0.207
35	-0.090	0.128	0.329	0.267
36	-0.101	0.064	0.203	-0.155
37	-0.126	**0.539***	0.404	0.049
38	0.036	0.359	0.065	-0.019
39	-0.085	0.251	0.239	0.259
40	-0.407	0.275	0.398	0.212
41	**-0.481***	**0.426***	**0.625***	**0.493***
42	-0.291	0.148	0.263	-0.244
43	**-0.465***	0.241	**0.423***	0.092

Where, *Significant at 5% level.

Table 6 : Comparison of Maize Yield prediction performance using Weighted and Unweighted across different Models.

Performance of Maize Yield									
			Unweighted						
Models	**Iteration**	**Training**				**Testing**			
		R^2	**RMSE**	**nRMSE**	**MAE**	**R^2**	**RMSE**	**nRMSE**	**MAE**
ANN	361	0.94	0.07	**0.07***	0.05	0.96	0.13	0.23	0.11
ELNET	106	0.13	0.25	0.25	0.20	0.84	0.12	0.23	0.10
LASSO	106	0.13	0.25	0.25	0.20	0.84	0.12	0.23	0.10
MLR	8	0.33	0.21	0.22	0.17	0.96	0.08	**0.11***	0.06
RF	32	0.89	0.16	0.16	0.13	0.96	0.06	0.12	0.05
RIDGE	146	0.15	0.26	0.26	0.21	0.65	0.11	0.24	0.10
SMLR	8	0.33	0.21	0.22	0.17	0.96	0.08	**0.11***	0.06
			Weighted						
Models	**Iteration**	**Training**				**Testing**			
		R^2	**RMSE**	**nRMSE**	**MAE**	**R^2**	**RMSE**	**nRMSE**	**MAE**
ANN	221	0.99	0.02	**0.03***	0.02	0.79	0.17	**0.19***	0.16
ELNET	92	0.32	0.23	0.23	0.21	0.94	0.11	0.24	0.11
LASSO	92	0.32	0.23	0.23	0.21	0.94	0.11	0.23	0.10
MLR	87	0.45	0.19	0.19	0.17	0.76	0.13	0.21	0.09
RF	306	0.92	0.13	0.13	0.11	0.94	0.13	0.21	0.13
RIDGE	181	0.25	0.25	0.25	0.22	0.40	0.14	0.30	0.13
SMLR	87	0.45	0.19	0.19	0.17	0.76	0.13	0.21	0.09

ANN - Artificial Neural Network, **ELNET -** Elastic Net, **LASSO -** Least Absolute Shrinkage and Selection Operator, **MLR -** Multiple Linear Regression, **RF –** Random Forest**, RIDGE -** Ridge Regression, **SMLR -** Multiple Linear Regression.

temperature negatively affected yield during SMW 32, 41 and 43, while a slight rise in minimum temperature improved grain setting in subtropical regions. Precipitation during reproductive and harvest phases showed a strong positive correlation with yield. Relative humidity positively impacted conditions in SMW 32 and 41 (Nguyen *et al*., 2014; Yan *et al*., 2021; Talla *et al*., 2017; Bal *et al*., 2023).

Rainfall and relative humidity significantly impact rice yield in different rice growing regions, with rainfall supporting productivity during flowering and grain setting, and relative humidity improving pollen viability and reducing moisture loss during reproductive stages (Table 5).

Development of the Yield Prediction Model

The study developed crop yield prediction models for Maize, Wheat, and Rice using machine learning algorithms. The models were created using 22 years of data from 2000-2022, with 70% for training and 30% for testing. The models aimed to identify linear and non-linear relationships between climatic factors and crop yields. To improve reliability, 3-fold cross-validation, repeated runs, and hyperparameter optimization were applied.

Maize Yield prediction performance

The Artificial Neural Network (ANN) demonstrated strong learning ability in predicting maize yield, with Multiple Linear Regression (MLR) and Stepwise MLR achieving the highest accuracy in the unweighted dataset, while ANN remained the top performer in the weighted dataset, suggesting simpler models may generalize better in unweighted cases (Table 6).

Wheat Yield Prediction performance

The ANN model demonstrated strong learning abilities for predicting wheat yield, but the MLR model performed best with unweighted data, while MLR and SMLR outperformed others with weighted data, suggesting simpler models like MLR and SMLR offer better generalization and accuracy (Table 7).

Rice Yield prediction performance

The ANN model demonstrated strong learning

Table 7 : Comparison of Wheat yield prediction performance using Weighted and Unweighted across different models.

Performance of Wheat Yield									
			Unweighted						
Models	**Iteration**	**Training**				**Testing**			
		R^2	**RMSE**	**nRMSE**	**MAE**	**R^2**	**RMSE**	**nRMSE**	**MAE**
ANN	217	0.97	0.05	**0.06***	0.04	0.86	0.12	0.13	0.12
ELNET	183	0.24	0.25	0.25	0.21	0.81	0.07	0.17	0.06
LASSO	183	0.23	0.25	0.25	0.21	0.82	0.08	0.18	0.06
MLR	313	0.42	0.19	0.21	0.16	0.94	0.07	**0.10***	0.06
RF	183	0.87	0.13	0.13	0.11	0.96	0.05	0.11	0.03
RIDGE	183	0.27	0.24	0.24	0.21	0.81	0.07	0.17	0.06
SMLR	292	0.47	0.19	0.20	0.16	0.92	0.12	0.17	0.09
			Weighted						
Models	**Iteration**	**Training**				**Testing**			
		R^2	**RMSE**	**nRMSE**	**MAE**	**R^2**	**RMSE**	**nRMSE**	**MAE**
ANN	154	0.99	0.03	**0.03***	0.02	0.97	0.05	0.07	0.04
ELNET	164	0.80	0.11	0.12	0.09	0.00	0.72	0.17	0.22
LASSO	319	0.87	0.08	0.10	0.06	0.96	0.09	0.10	0.08
MLR	8	0.89	0.07	0.10	0.05	0.99	0.03	**0.03***	0.03
RF	44	0.92	0.09	0.09	0.08	0.95	0.05	0.09	0.03
RIDGE	124	0.85	0.09	0.10	0.08	0.98	0.06	0.08	0.04
SMLR	8	0.89	0.07	0.10	0.05	0.99	0.03	**0.03***	0.03

Table 8 : Comparison of Rice Yield prediction Performance using weighted and unweighted across different models.

Performance of Maize Yield									
			Unweighted						
Models	**Iteration**	**Training**				**Testing**			
		R^2	**RMSE**	**nRMSE**	**MAE**	**R^2**	**RMSE**	**nRMSE**	**MAE**
ANN	364	0.88	0.09	**0.09***	0.07	0.93	0.07	0.13	0.06
ELNET	127	0.42	0.20	0.20	0.17	0.97	0.05	0.08	0.04
LASSO	127	0.42	0.20	0.20	0.17	0.97	0.06	0.10	0.05
MLR	373	0.77	0.12	0.12	0.10	0.98	0.03	**0.06***	0.03
RF	54	0.90	0.11	0.11	0.09	0.99	0.06	0.10	0.05
RIDGE	127	0.39	0.20	0.20	0.17	0.98	0.04	0.07	0.03
SMLR	279	0.77	0.12	0.12	0.10	0.97	0.04	**0.06***	0.04
			Weighted						
Models	**Iteration**	**Training**				**Testing**			
		R^2	**RMSE**	**nRMSE**	**MAE**	**R^2**	**RMSE**	**nRMSE**	**MAE**
ANN	266	0.97	0.04	**0.04***	0.03	0.99	0.04	**0.05***	0.03
ELNET	54	0.70	0.16	0.16	0.14	0.98	0.04	0.08	0.03
LASSO	127	0.58	0.17	0.17	0.15	0.99	0.05	0.10	0.05
MLR	91	0.82	0.11	0.11	0.09	0.99	0.05	0.10	0.04
RF	30	0.94	0.07	0.07	0.06	0.99	0.03	**0.05***	0.02
RIDGE	334	0.56	0.18	0.18	0.15	0.93	0.07	0.12	0.06
SMLR	91	0.82	0.11	0.11	0.09	0.99	0.05	0.10	0.04

abilities in training both unweighted and weighted datasets. MLR and SMLR had the best generalization and lowest prediction error in unweighted testing. ANN and RF achieved highest accuracy under weighted conditions (Table 8).

The study utilized regularized regression models like LASSO, Elastic Net and Ridge Regression to predict crop yield. These models penalize coefficients, allowing some variables to have zero or near-zero values. The performance was evaluated using metrics like R^2, RMSE, MAE, and MBE, showing that fewer influential variables did not reduce accuracy, resulting in more reliable predictions. (Vashisth *et al*., 2020 and Kumar *et al*., 2019).

The study evaluated the performance of a model using both unweighted and weighted datasets. Weighted models showed lower nRMSE values, indicating better predictive accuracy and stability. This highlights the importance of using weighted data to account for historical yield and climate variations. The study emphasizes the significance of assigning appropriate weights to data points for reliable yield forecasts.

The study found that ANN outperformed other models in training across all crops and datasets. MLR and SMLR performed best in unweighted datasets, while ANN, MLR, SMLR and ANN and RF were comparable in weighted datasets. These findings underscore the importance of understanding seasonal climate variability for accurate yield forecasting and climate-resilient agriculture.

Conclusion

A climate study in Chhattisgarh, Korea, revealed a cooling trend, with crop yields varying. Maize yield improved with stable minimum and rainfall conditions, but suffered from high maximum temperatures. Wheat was negatively impacted by both high and low temperatures, while rice benefited from minimum temperature, rainfall, and humidity but declined with high maximum temperatures. Advanced models like ANN, MLR, SMLR and RF proved effective for crop yield prediction crucial for climate resilient agriculture.

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