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Evaluation of Machine Learning Approaches in Estimating Crop Water Requirement

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INTRODUCTION & AIM

- Crop water requirement (CWR): total amount of water a crop needs from planting to harvesting; critical factor in plant growth
- Determined using empirical methods that rely on extensive climatic data which may not be accessible and also a time-consuming process
- Crop water requirement modelling - a suitable method
- Can be accomplished by using Machine Learning (ML), a subset of Artificial Intelligence (AI) concerned with the development of computational algorithms based on known data to make new prediction

The objectives :

1. To determine the suitable inputs of maize crop water requirement modelling for using Machine Learning models
2. To study the performance and competency of different Machine Learning models for predicting maize crop water requirement

METHOD

Collection of Temperature (T) (minimum, maximum), Relative Humidity (R) (minimum, maximum), Solar Radiation (N), Wind Speed (W) and Vapour Pressure Deficit (VPD) for 20 years (2001-2020) for Samastipur district, Bihar, India

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Estimation of CWR of maize by FAO- 56 Penman Monteith method and multiplying it by crop coefficient

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Application of Gamma Test for best input combination selection in WinGamma

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Division of data in training (80%) and testing (20%) datasets

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Multi Adaptive Regression Splines (MARS), Support Vector Machine (SVM) and Random Forest (RF) models in RStudio with 80% dataset

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Models' testing using 20% dataset

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Qualitative (scatter plots and time-series plots) and Quantitative analysis (statistical analysis by R^2, RMSE, NSE) for performance evaluation of best model

RESULTS & DISCUSSION

Table 1: Gamma test for input combination

Input combinations	Mask	Gamma (Γ)	V_{ratio}
(I_1): N, T1, T2, W, R1, R2, VPD	1111111	0.807	0.267
(I_2): N, T1, T2, W, R1, R2	1111110	0.805	0.266
(I_3): N, T1, T2, W, R1, VPD	1111101	0.799	0.264
(I_4): N, T1, T2, W, R2, VPD	1111011	0.773	0.255
(I_5): N, T1, T2, R1, R2, VPD	1110111	0.895	0.296
(I_6): N, T1, W, R1, R2, VPD	1101111	0.875	0.289
(I_7): N, T2, W, R1, R2, VPD	1011111	0.931	0.307
(I_8): T1, T2, W, R1, R2, VPD	0111111	1.722	0.569
(I_9): N, T1, T2, W, R1	1111100	0.829	0.274
(I_{10}): N, T1, T2, W, R2	1111010	0.775	0.256
(I_{11}): N, T1, T2, R1, R2	1110110	0.897	0.296
(I_{12}): N, T1, W, R1, R2	1101110	0.875	0.289
(I_{13}): N, T2, W, R1, R2	1011110	0.930	0.307
(I_{14}): T1, T2, W, R1, R2	0111110	1.720	0.568
(I_{15}): N, T1, W, R1, VPD	1101101	0.940	0.310

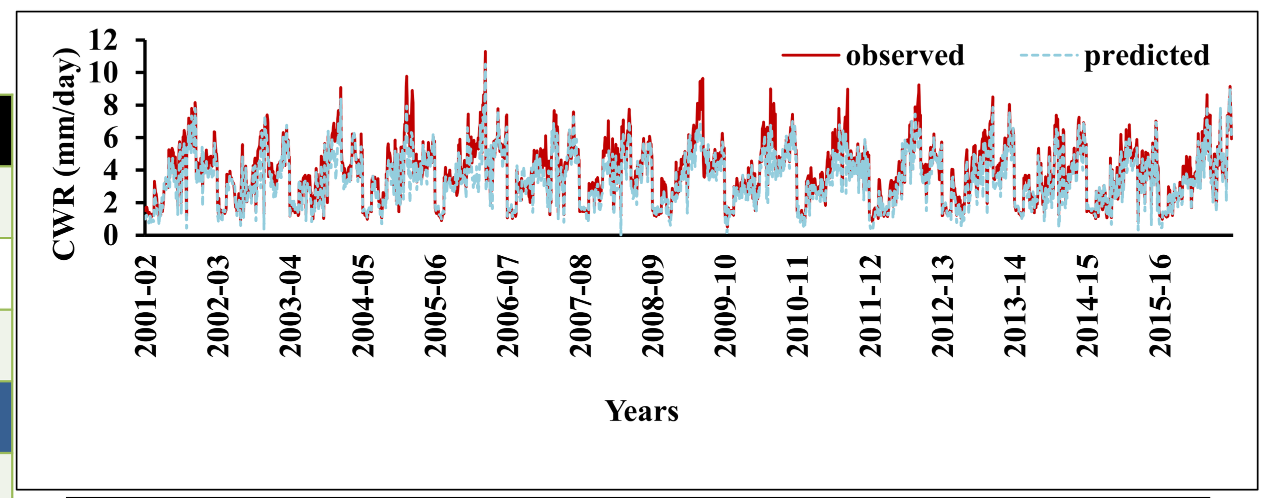

Figure 1: Time-series plot of MARS for training phase

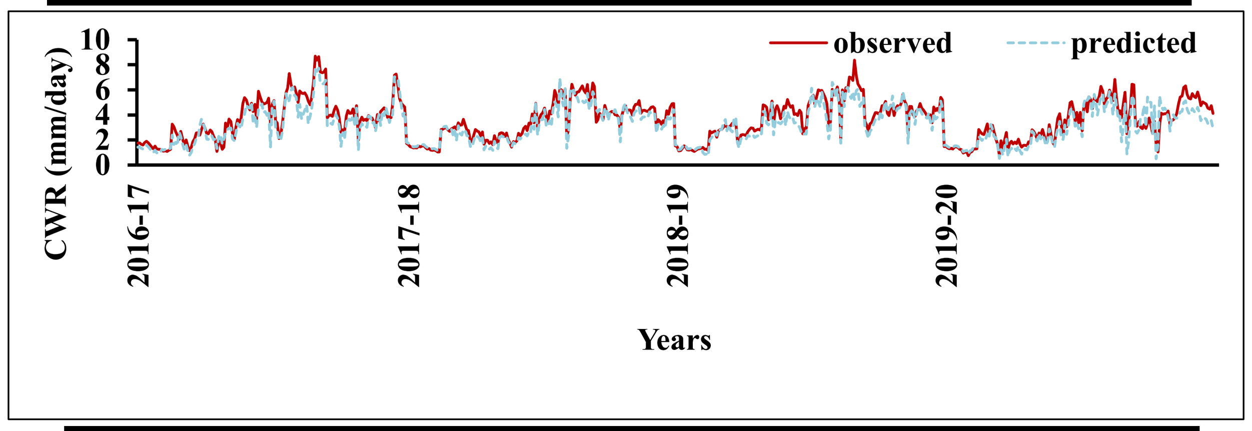

Figure 2: Time-series plot of MARS for testing phase

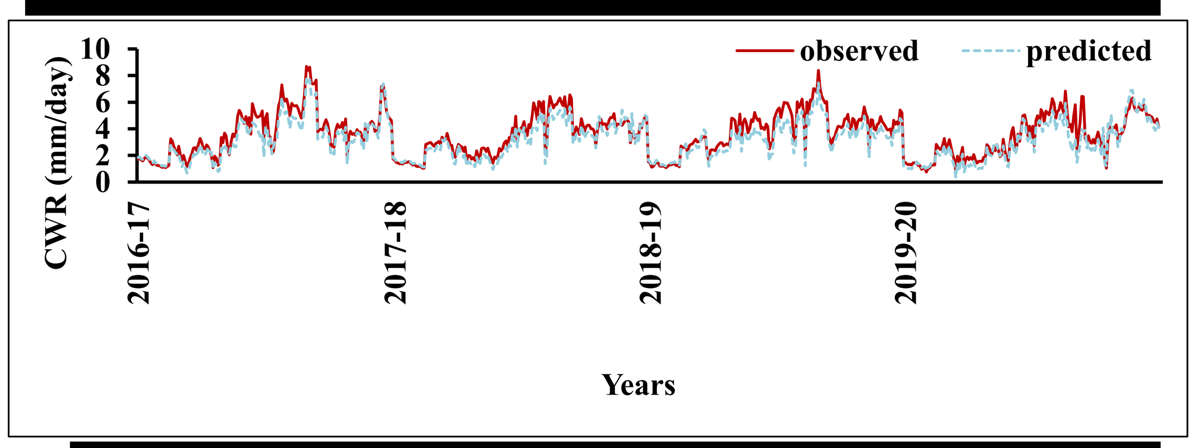

Figure 3: Time-series plot of SVM for training phase

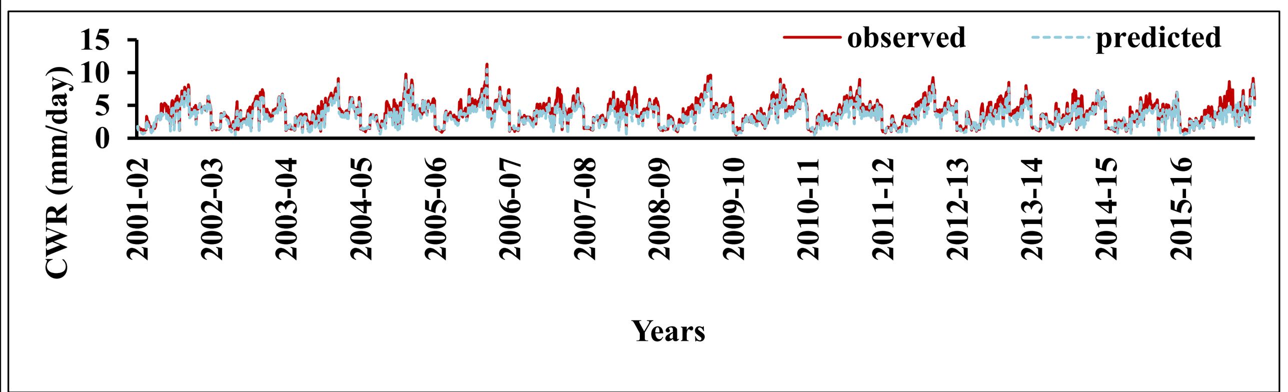

Figure 4: Time-series plot of SVM for testing phase

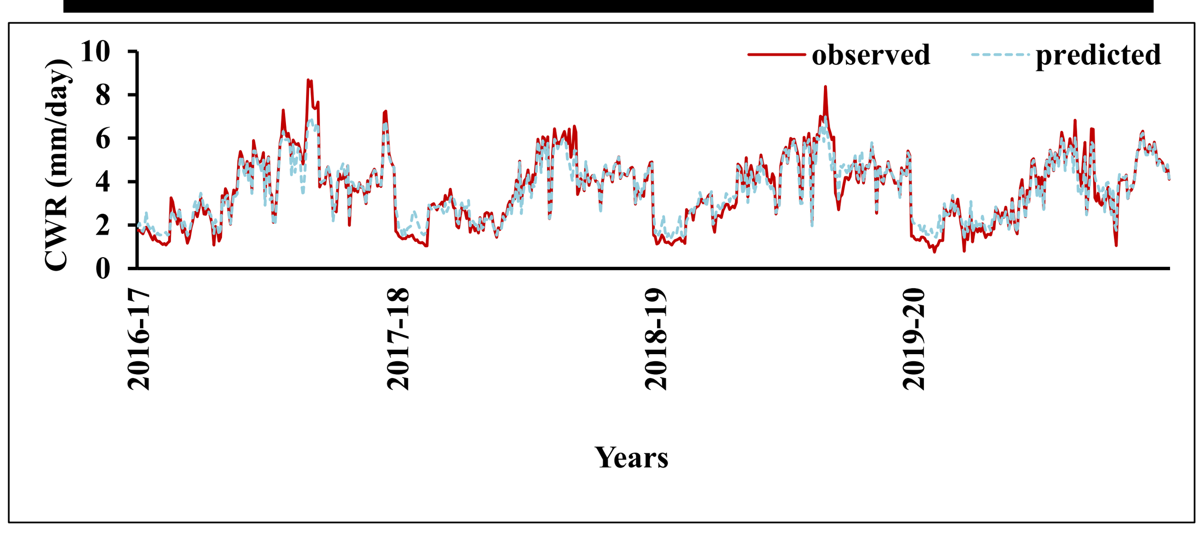

Figure 5: Time-series plot of RF for training phase

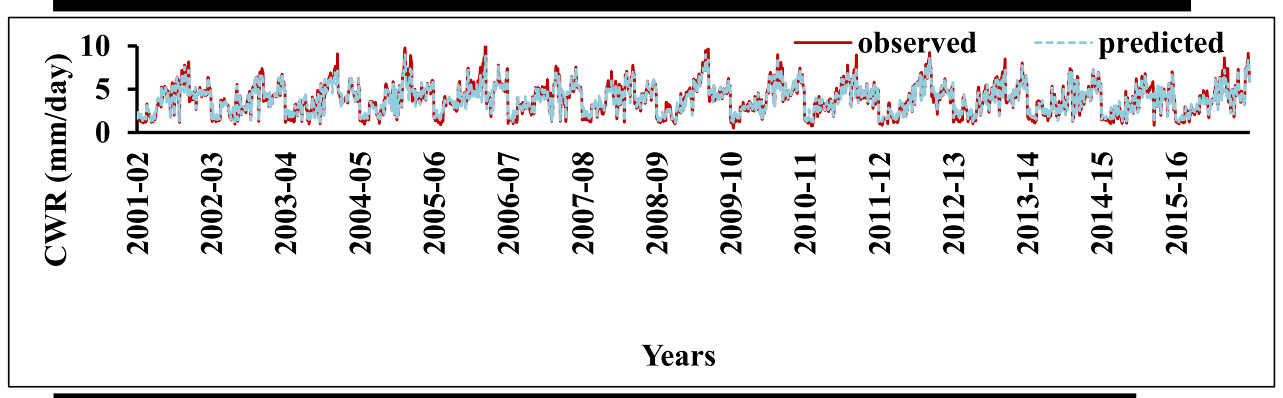

Figure 6: Time-series plot of RF for testing phase

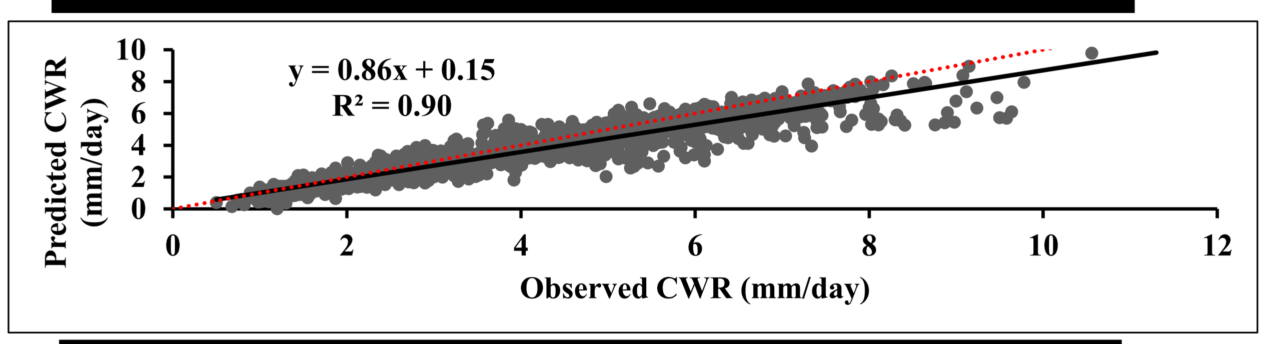

Figure 7: Scatter plot of MARS for training phase

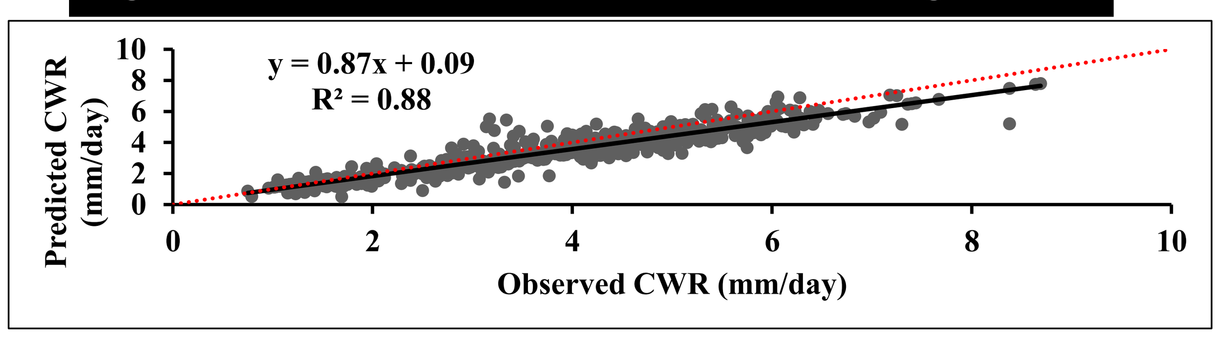

Figure 8: Scatter plot of MARS for testing phase

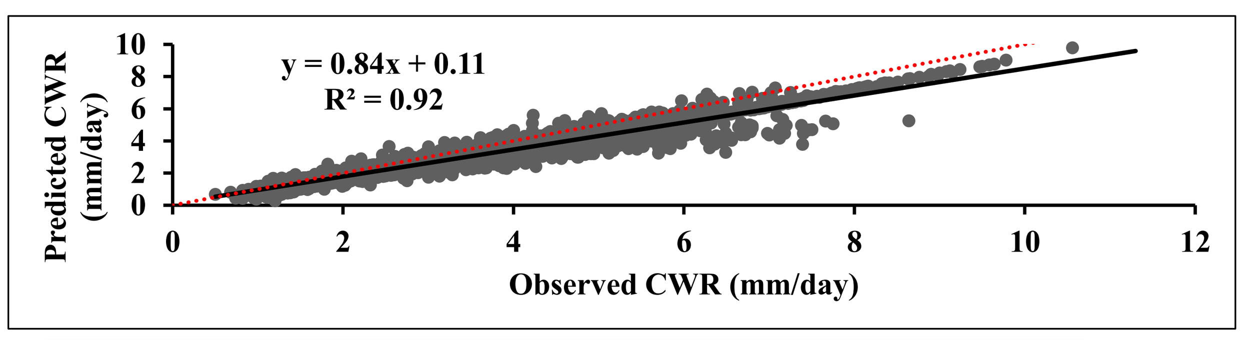

Figure 9: Scatter plot of SVM for training phase

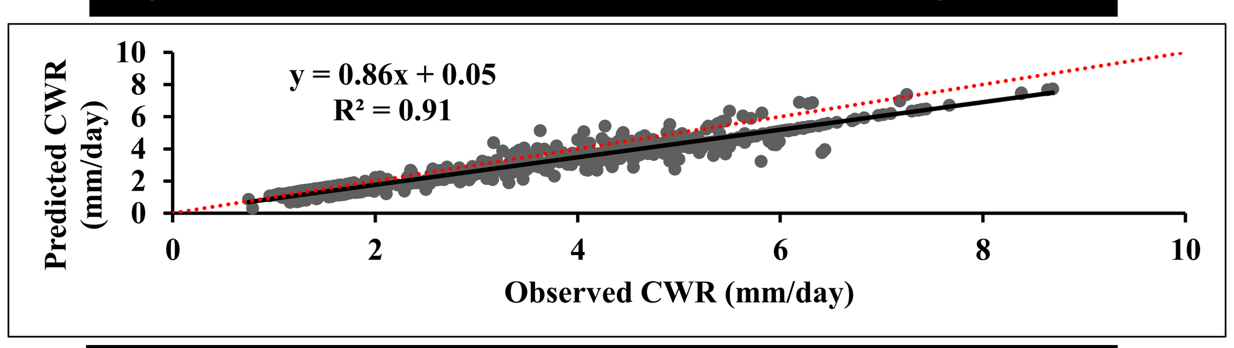

Figure 10: Scatter plot of SVM for testing phase

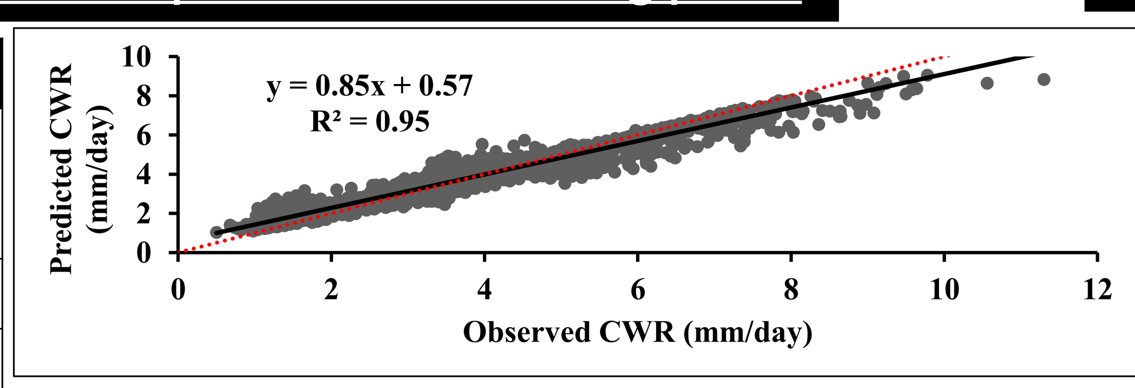

Figure 11: Scatter plot of RF for training phase

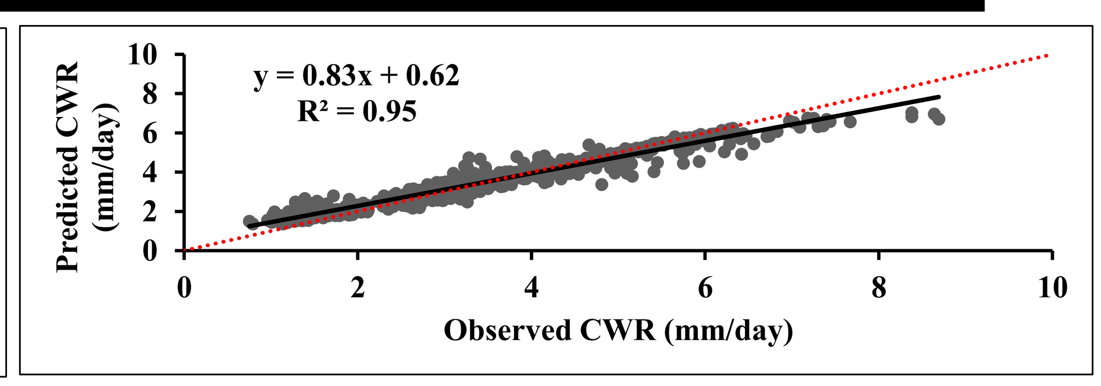

Figure 12: Scatter plot of RF for testing phase

Table 2: ML models statistical parameters

Models	Training			Testing		
	R^2	RMSE (mm/day)	NSE	R^2	RMSE (mm/day)	NSE
MARS	0.90	0.70	0.84	0.88	0.66	0.83
SVM	0.92	0.73	0.83	0.91	0.67	0.82
RF	0.95	0.43	0.92	0.95	0.42	0.91

CONCLUSION

- The Gamma test showed that the input I_4 combination having (N, T1, T2, W, R2, VPD) was the best for maize crop
- The models' performance-wise rankings were RF, MARS and SVM
- From the results attained, RF model beat MARS and SVM throughout training and testing phases for maize crop emphasizing the value of ML models for precise maize water requirement prediction

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