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Seasonal Pre-Planting Drought Impact-Based Forecasting of Crop Yield in India

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Key Points:

- District-level Random Forest models accurately predict drought impacts on rice and wheat yields up to 6 months before planting
- Integration of SEAS5-based seasonal drought forecasts extends the predictability of crop yields up to 6 months before the planting season
- We propose a scalable tool to cope with drought and support anticipatory agricultural decisions as well as early warning systems in India

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Accurate drought impact-based forecasting of crop yield in India remains challenging due to the country's hydro-climatic diversity and complex interactions between climate variability, ecosystem vulnerability, and agriculture. This study develops a framework integrating observed and forecasted drought indices across multiple accumulation periods to predict standardised crop yields at seasonal lead time before planting. Using district-level and cluster-based approaches, we apply Random Forest, Extreme Gradient Boosting, and Artificial Neural Networks to establish indicator–impact relationships for paddy rice (wet season) and wheat (dry season), leveraging historical yield data and seasonal forecasts. District-level models outperform cluster-based ones, with Random Forest showing the best performance. Over 80% of wheat districts and 70% of rice districts achieve strong predictive accuracy, with less than 20% deviation from the expected yield (defined as RMSE below 0.2 in the test set). Incorporating ECMWF's SEAS5 forecasts enables reliable rice yield predictions up to 6 months before the season—covering over 80% of wheat districts and 60%–70% of rice districts, depending on the lead time. Forecast skill assessed using Continuous Ranked Probability Score (CRPS) confirms robustness across space and time, especially in districts with moderate yield variability. Weighted CRPS shows forecasts for extremely low yields (below the 10th percentile) are accurate and reliable—crucial for early warning and preparedness. This work advances operational impact-based drought forecasting in India, offering a tool to inform anticipatory action among farmers, water managers, and supply chains. By linking drought observations and seasonal forecasts to crop yield outcomes, the study provides a replicable early warning approach to support targeted mitigation and enhance climate resilience in agriculture.

Plain Language Summary

Predicting how drought affects crop yields in India is difficult due to the country's diverse climates and the complex relationships between weather, ecosystems, and farming. This study developed a method to estimate rice and wheat yields before planting by using both observed and forecasted drought indicators. We applied three machine learning models—Random Forest, Extreme Gradient Boosting, and Artificial Neural Networks—using past yield records and seasonal climate forecasts. Models built for individual districts performed better than those built for broader regional clusters, with Random Forest showing the highest accuracy. Using forecasts from the European Center for Medium-Range Weather Forecasts (ECMWF), we could predict wheat yields accurately in over 80% of districts and rice yields in 60%–70% of districts up to 6 months ahead of the growing season. The models also performed well in identifying years when yields were extremely low (below the 10th percentile), which is critical for early warning and preparedness. This work supports more reliable drought impact forecasting in India and offers a decision-support tool for farmers, planners, and supply chains. By linking drought forecasts directly to crop outcomes, it enables earlier, more targeted action to reduce risks and build resilience in agriculture under changing climate conditions.

1. Introduction

Global food insecurity remains a critical challenge, with an estimated 757 million people facing chronic hunger in 2023 alone (FAO, IFAD, UNICEF, WFP & WHO, 2024). Among the key drivers of food crises are climatic extremes—particularly drought—which reduce agricultural productivity, disrupt food supply chains, and

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undermine the livelihoods of vulnerable populations (CRED & UNDRR, 2020; IPCC, 2022). In countries like India, where agriculture supports over 40% of the population and remains highly dependent on monsoon rainfall, droughts can have devastating consequences, including yield loss, income decline, and rural migration (ICAR, 2020; World Bank, 2021). Addressing these risks requires targeted, anticipatory measures and the capacity to predict when, where, and how drought-related agricultural impacts will emerge—well in advance of the planting season (Coughlan de Perez et al., 2015, 2016). Climate projections suggest that both the frequency and intensity of droughts will increase, particularly agricultural and ecological droughts, as global warming intensifies (Cook et al., 2020; IPCC, 2021). This trend underscores the urgency of developing robust, anticipatory tools that can translate climate signals into actionable insights for agriculture.

India's hydro-climatic gradient, marked by strong contrasts in precipitation, temperature, and hydrological patterns across its vast territory, is among the most pronounced globally (Dinesh Kumar et al., 2022; Pechlivanidis & Arheimer, 2015). This gradient results from the interaction of summer and winter monsoonal dynamics and varied topography across a broad range of latitudes, which together give rise to diverse climatic zones that span from hyper-arid deserts to tropical rainforests and alpine glaciers. The Western Ghats and the northeastern states receive more than 2,000 mm of rainfall annually (Singh et al., 2021). In comparison, the Thar Desert in Rajasthan gets less than 250 mm, while semi-arid regions such as western Uttar Pradesh and Gujarat receive between 500 and 1,000 mm (Ministry of Statistics and Programme Implementation, 2020). Summer temperatures in the Thar Desert can exceed 48°C, whereas the Himalayan north experiences sub-zero winters and the highest elevations are covered in snow throughout the year. The Indo-Gangetic Plains, characterized by a humid subtropical climate, face scorching summers with temperatures reaching or surpassing 45°C and also benefit from moderate winter precipitation (NBC, 2005). This degree of climatic variability plays a pivotal role in influencing water availability, agricultural output, and the resilience of ecosystems, which highlights the broader need to improve the understanding and forecasting of climate-induced hydrological extremes and their impacts (Widmann et al., 2019).

India's economy remains deeply intertwined with its agricultural sector, which contributes 15% to the country's GDP and provides employment to about 40% of the population (World Economic Forum, 2024). The country's varied climate significantly shapes agricultural outcomes. The summer monsoon season, responsible for nearly 75% of the annual rainfall (Guhathakurta et al., 2015), occurs between June and September and is vital for kharif crops like rice (paddy), maize, and pulses. Conversely, rabi crops (October–March) such as wheat, barley and mustard rely on cooler temperatures and the moisture retained in the soil during winter. Roughly 60% of Indian agriculture depends on rainfall, which making it highly susceptible to changes in precipitation patterns (ICAR, 2020).

Drought emerges from an extraordinary water deficit in the hydrological cycle and can severely disrupt the agricultural sector. Historically, major droughts in 1987, 2002, and 2009 have caused extensive agricultural damage across India and triggered distress migration. The 2002 drought, one of the most severe in recent decades, impacted nearly 300 million people and led to a 19% decline in food grain output (Government of India, 2004). The 2015–16 drought affected 330 million people, amounting to a quarter of India's population, across 255,923 villages in 254 districts spread across 10 states (Save the Children, 2015). More recently, the drought in 2023 significantly hindered rice production due to the late onset of the monsoon, erratic rainfall distribution, higher-than-usual temperatures, and declining groundwater levels, all of which contributed to water shortages and yield reductions (Farmonaut, 2023). The effects of drought on crop yield and the broader economy demand focused attention in order to prevent such widespread and damaging outcomes.

Crop yield prediction using drought inputs offers an opportunity for agricultural planning, grain transportation, and the distribution of agricultural inputs, helping to reduce the adverse impacts of drought. To translate meteorological or hydrological drought forecasts into expected impacts on crop yields, a second modelling step is often applied, using either process-based (physical) models or data-driven approaches. Process-based models, such as crop simulation models, predict agricultural drought impacts by simulating physiological processes driven by interactions among soil, crops, and the atmosphere (Kholová et al., 2013). For example, Rajasivaranjan et al. (2022) assessed water stress impacts on rice yield in North India using such models. Wanthanaporn et al. (2024) also applied a process-based crop model driven by seasonal forecasts to predict yield outcomes, demonstrating the integration of seasonal climate information into crop simulations; however, their study did not provide forecasts at lead times comparable to the longer-range, pre-planting predictions considered here. These models are also frequently used with future climate projections to assess long-term yield responses under drought stress (Debnath et al., 2021; Dixit et al., 2023; Kadiyala et al., 2015; Karan et al., 2022; Upreti et al., 2025). In contrast, data-driven models relate environmental variables to yield outcomes without explicitly modelling physiological processes. Several studies have applied these techniques using drought indices; for instance, Pandya and Gontia (2023) used multiple data-driven models, including multiple linear regression, artificial neural networks, and random forest algorithms, to predict cotton and groundnut yields in Gujarat. Moreover, Prasad et al. (2021) utilized the random forest algorithm to predict cotton yield in the state of Maharashtra. These data-driven approaches are particularly well suited for capturing complex, non-linear relationships between crop yields and environmental variables. Unlike crop models, they do not require detailed representation of phenological stages or periodic recalibration by domain experts (Deva et al., 2024). Despite substantial progress in data-driven yield modelling, very few studies, particularly for the Indian subcontinent, have coupled these models with seasonal meteorological or hydrological forecasts. This gap limits our ability to generate skillful, long-lead yield predictions specifically under drought conditions, which, in turn, constrains timely crop-management decisions. Moreover, no prior work has systematically evaluated forecast skill for extreme low-yield outcomes, which are most critical for drought-early-warning applications.

There is growing evidence that seasonal forecasts—particularly those produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) Seasonal Forecasting System 5 (SEAS5)—offer good predictability, especially for temperature in tropical and subtropical regions such as India (Johnson et al., 2019), which in turn enables the improved estimation of drought indices such as the SPEI. At the same time, the emerging field of drought impact-based forecasting, which directly links hydro-meteorological drought indicators with sector-specific impacts, remains underexplored in the Indian context, both in terms of research and practical implementation (Shyrokaya et al., 2024). This study aims to address that gap by developing a generalizable framework that connects drought observations and seasonal drought forecasts with actual impacts on rice and wheat yields. The goal is to provide more actionable, sector-specific information to support anticipatory decision-making in agriculture. Specifically, our objectives are: (a) to establish a replicable, step-by-step framework that links drought indicators to agricultural drought impacts; and (b) to forecast crop yield before the planting season, allowing for timely interventions. To achieve them, we apply data-driven models—Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN)—to predict crop yields under drought conditions, integrating them with drought observations and SEAS5 seasonal forecasts to enable yield forecasts up to 6 months in advance of the planting season.

The manuscript is structured as follows: Section 2 details the data sets and Section 3 the methodologies used to compute drought indices, build data-driven models, and incorporate seasonal forecasts. Section 4 presents the results on the seasonal predictability of crop yield. Sections 5 and 6 discuss the main findings, limitations, and provide concluding remarks.

2. Data

2.1. Study Area

Climate and ecology shape crop patterns and farming practices across India's diverse agricultural regions. The Food and Agriculture Organisation (FAO) defines an agro-climatic zone (ACZ) as a land unit with specific climate and growing conditions suited to particular crops. During the 7th Five-Year Plan, the Planning Commission identified 15 zones (Figure S1 in Supporting Information S1) to enhance regional productivity, based on factors like temperature, rainfall, soil type, water resources, and terrain.

Each zone has distinct crop types and methods: the Himalayan Region uses terrace farming; the Gangetic Plains grow rice, wheat, and sugarcane (Ahmad et al., 2017); the semi-arid Central and Western Plateaus rely on pulses and millets; coastal zones produce rice and plantation crops; and the Western Dry Region focuses on livestock and drought-tolerant crops. Moreover, India's agricultural calendar revolves around two main cropping seasons: Kharif (monsoon) and Rabi (winter). Kharif crops like rice and maize are sown with the monsoon and harvested by autumn, while Rabi crops like wheat and mustard are planted post-monsoon and harvested in spring.

Water scarcity and heavy dependence on monsoon rains remain major challenges to agricultural sustainability (Samantaray et al., 2019). Semi-arid zones face erratic rainfall and limited irrigation, while over-extraction of groundwater in productive areas like the Gangetic Plains has led to falling water tables and salinity issues (Dangar

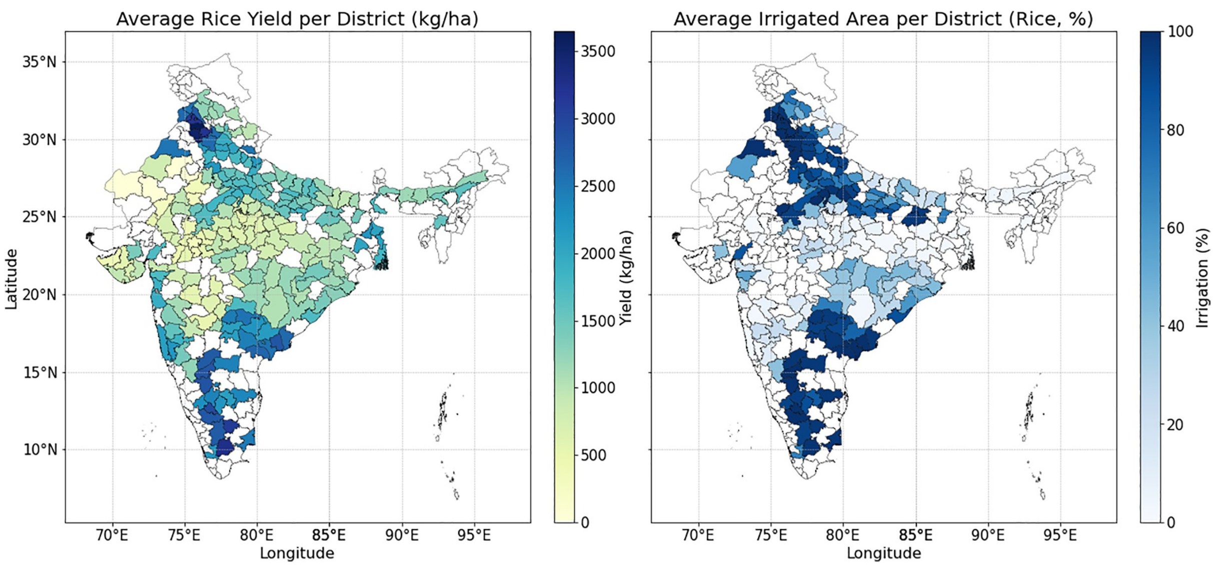

Figure 1. (Left) Average rice yield (kg/ha) and (right) irrigation (% of rice area) per district in India.

et al., 2021; Devineni et al., 2022; Jain et al., 2021). Coastal regions struggle with saline intrusion. These factors make farming uncertain and financially risky. Region-specific solutions—like improved irrigation, drought-resilient practices, and integrated water management—are essential. Understanding each zone's response to drought is key for long-term environmental, economic, and food security, requiring collaboration between policymakers, researchers, and farmers (Rizvi et al., 2025).

2.2. Drought Indicators and Impact Data

2.2.1. Drought Indicators

We obtained daily precipitation records (0.25° spatial resolution ∼28 km grid, 1960–2023) from the Indian Meteorological Department (IMD) as described in Pai et al. (2014) and aggregated them into monthly totals. Similarly, we downloaded potential evapotranspiration (PET) data for 1981–2022 from the same source and with the same spatiotemporal resolution, calculated using the Hargreaves method. District-level averages were then calculated for both total monthly precipitation and PET. Based on these, district-based Standardized Precipitation Index (SPI; McKee et al., 1993) and Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010) were computed at 3-, 6-, 9- and 12-month scales. Both SPI and SPEI are widely used as drought indicators (WMO, 2016) that enable comparison of wet and dry conditions across regions and time. Values below -1 generally indicate moderate to severe drought conditions, whereas values above $+1$ indicate unusually wet conditions. These indices frequently employed in drought monitoring (Peng et al., 2024) and early warning systems (Bachmair et al., 2016).

Additionally, we used the monthly Niño 3.4 index (anomaly of SST over 5°S–5°N, 170°–120°W) from NOAA Physical Sciences Laboratory's HadISST1.1 data set (1870—present) as an ENSO indicator (Rayner et al., 2003). ENSO phases influence monsoon rainfall in India: El Niño events (Niño 3.4 > 0) are typically associated with reduced precipitation, while La Niña events (Niño 3.4 < 0) often correspond to above-normal rainfall. Although the Indian Ocean Dipole (IOD) also strongly affects Indian monsoon variability, ENSO remains a key large-scale driver of seasonal rainfall anomalies and is widely used in operational forecasting (Cherchi & Navarra, 2013).

2.2.2. Drought Vulnerability and Crop Yield Data

Regional crop yield data for India, covering 360 districts from 1966 to 2017, was obtained from the International Crops Research Institute for the Semi Arid Tropics (ICRISAT) database (ICRISAT, 2021). This data set includes major crops, which are further categorized by their respective growing seasons, and provides information on the irrigated area, % of area within each district covered by irrigation (Figure 1 (rice) and Figure S2 in Supporting Information S1 (wheat)). As an example for rice, Figure 1 illustrates substantial spatial heterogeneity in both rice

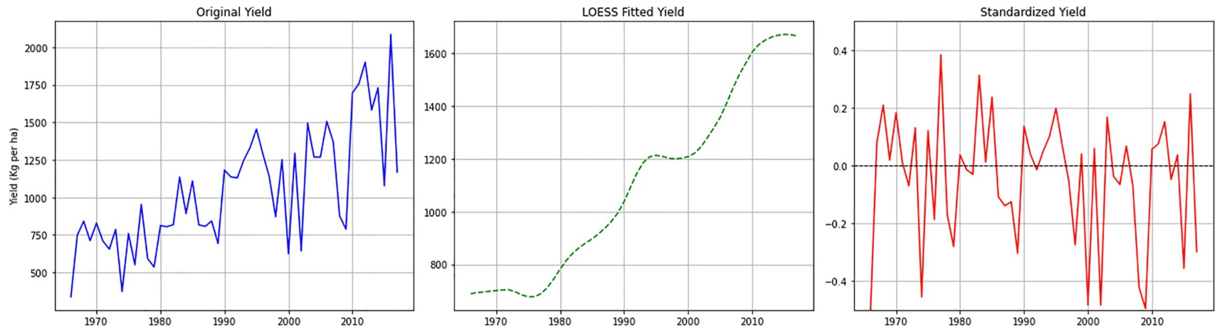

Figure 2. An example of the detrending and standardizing process for one district (Durg): original crop yield time series (left), LOESS-fitted trend used for detrending (center), and resulting standardized yield anomalies (right).

yield and irrigation coverage across India. Higher yields are concentrated in northern and eastern states, particularly Punjab and West Bengal, which also exhibit extensive irrigation (>60%). In contrast, central and southern regions show lower yields and more variable irrigation coverage, indicating potential vulnerability to rainfall variability. Districts with minimal irrigation (<20%) are primarily located in eastern and southern India, suggesting greater dependence on monsoon rainfall.

The data set further provides district-based information underscoring potential vulnerabilities, among which the following were used in the analysis: the amount of the fertilizer consumption (by respective growing season), field labor wages, and population of rural agricultural workers (Figure 3). Table 1 summarizes the data set used in this study.

To isolate inter-annual variability, crop yield data from 1966 to 2017 were detrended using Locally Estimated Scatterplot Smoothing (LOESS) and standardized. This method effectively removes long-term trends, ensuring that deviations reflect year-to-year fluctuations rather than gradual changes.

For each district and crop, LOESS was applied with Year as the predictor variable and Yield as the dependent variable. The LOESS model returned a smoothed yield estimate $\hat{Y}_{\text{model},i}$, which was used to compute the standardized yield anomaly:

$$\begin{aligned} \hat{Y}_{\text{model},i} &= \text{LOESS}(Y_{\text{obs},i}, t_i) \\ Y_{\text{obs\_std},i} &= \frac{Y_{\text{obs},i} - \hat{Y}_{\text{model},i}}{\hat{Y}_{\text{model},i}} \end{aligned} \tag{1}$$

Where $Y_{obs,i}$ is the observed crop yield for year t_i and $Y_{obs\_std,i}$ represents the relative deviation from the long-term trend. This approach expresses anomalies as proportional deviations, preserving interpretability in percentage

Table 1
Summary of Data Sets and Their Purposes in the Analysis

Data set	Variables used	Period covered	Resolution	Purpose
IMD	Precipitation	1981–2017	0.25° (~28 km)	To calculate SPI and SPEI
GLEAM v3.8	Potential Evapotranspiration	1981–2017	0.25° (~28 km)	To calculate SPEI
ICRISAT	Crop yield (wheat and paddy), irrigation, fertilizers, and field labor wages	1981–2017	District-level data	To build a crop yield monitoring model
SEAS5	Total precipitation, minimum, maximum, and mean temperature	2015–2016 (reforecast) and 2017 (forecast), 6-month lead time, monthly initialization	0.25° (~28 km), 25 ensemble members	To calculate SPI and SPEI used in crop yield forecasting model

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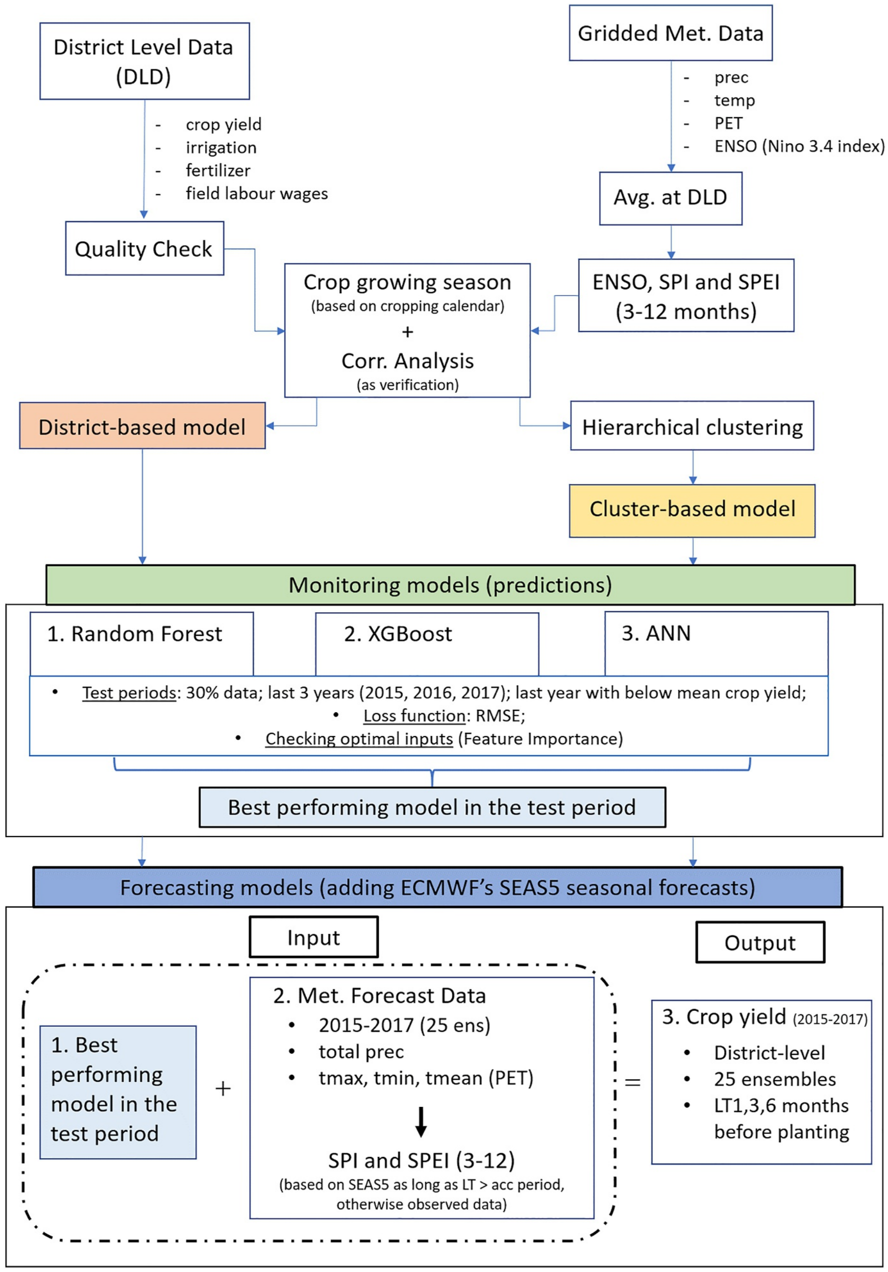

Figure 3. Schematic diagram of the steps involved in this study, accounting for both the district- and the cluster-based monitoring (prediction) and forecasting models.

terms. Figure 2 provides an example of the detrending process for one district (Durg). The original yield series shows a clear upward trend, reflecting technological improvements over time (Figure 2, left). The LOESS fit captures this long-term growth (Figure 2, center), while the standardized anomalies (Figure 2, right) highlight inter-annual fluctuations around the trend. These anomalies, ranging roughly between −0.4 and +0.4, indicate that year-to-year variability is significant despite overall yield improvements.

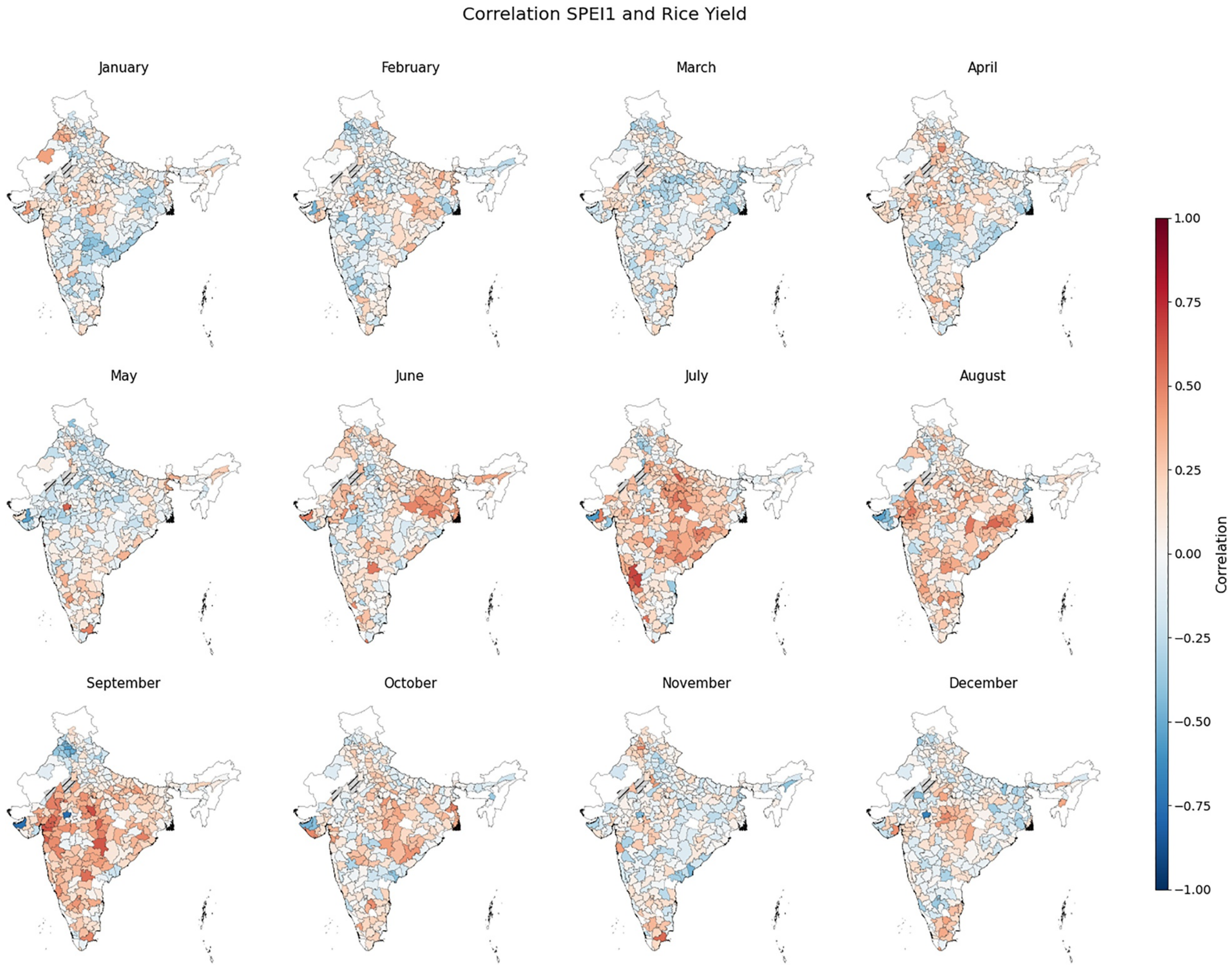

Figure 4. Correlation coefficient between SPEI1 and rice yield across districts for all months (January–December).

3. Methodology

3.1. Monitoring Model

After processing the data (see Table 1), we developed a monitoring (prediction) model based on historical data at two levels: districts (Section 3.1.1) and clusters of districts (Section 3.1.2). Figure 3 provides a schematic overview of the methodological steps in this study. Prediction refers to estimating known parts of the data set in real time. We later use the term "forecasting" to refer to predicting future values.

3.1.1. Monitoring Model: District-Based

To establish the district-based models, we first selected predictor variables limited to the months within the respective crop's growing season, ensuring that only periods likely to influence crop yield were included. According to crop calendars (United States Department of Agriculture [USDA], n.d.), rice is typically sown between May and July with the onset of the monsoon (Samantaray et al., 2022), and harvested between September and January. Wheat is usually sown between October and January and harvested between March and May. As an additional verification, we calculated the Pearson correlation between SPEI1 and crop yields for rice (Figure 4) and wheat (Figure S3 in Supporting Information S1) on a district-by-district basis. We selected SPEI1 because it captures short-term water balance anomalies and helps identify the early stages of the growing season on a monthly basis. For rice, although some districts showed notable correlations with SPEI1 in June, the majority exhibited stronger correlations in July. Therefore, for consistency, we adopted a common growing season for rice across all districts, with planting in July and harvesting in November. For wheat, the same procedure confirmed

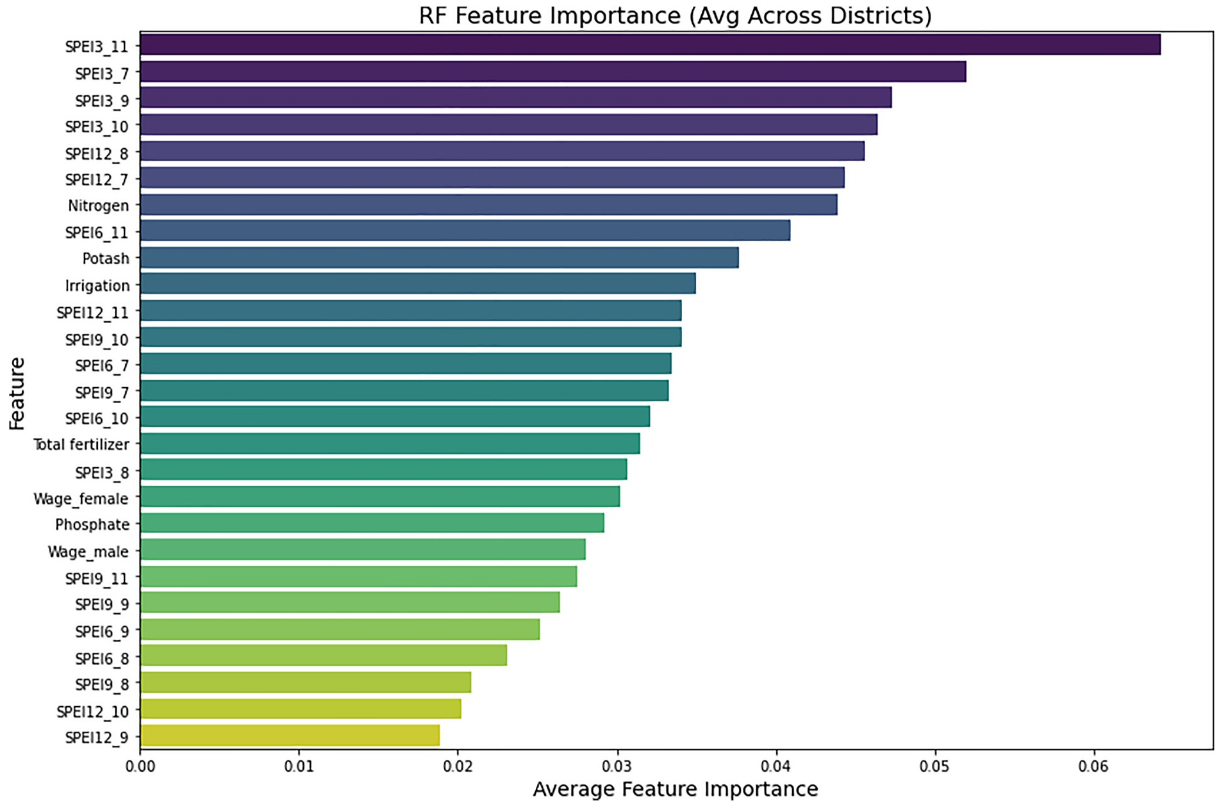

Figure 5. Average feature importance for 198 district-based RF models (rice), arranged in descending order.

November as the typical planting month and May as the harvesting period (Figure S3 in Supporting Information S1). We excluded meteorological and climatic predictors outside the respective growing seasons.

We employed three data-driven methods: Random Forest, XGBoost, and Artificial Neural Networks. RF, an ensemble of decision trees, is relatively easy to interpret and tune while capturing non-linear relationships and reducing overfitting through bootstrap aggregation (Breiman, 2001). It has also been used to derive drought-impact functions from indices such as SPI and SPEI (Bachmair et al., 2017) and to model drought-related impacts in different settings (Bachmair et al., 2017; Shyrokaya et al., 2024; Sutanto et al., 2019). XGBoost is likewise tree-based but uses gradient boosting and built-in regularization to enhance predictive accuracy and efficiency (Chen & Guestrin, 2016), and it has often outperformed RF in tabular prediction tasks (Westerveld et al., 2021; Zhang et al., 2023). It has also been applied to forecast drought-related indicators such as scPDSI and SPEI (Ekmekcioğlu, 2023; Zeng et al., 2025). ANN, a layered computational model that transforms inputs through weighted connections and non-linear activations (Maier et al., 2023), can represent more complex interactions than tree ensembles (Goodfellow et al., 2016) but typically requires larger data sets and more tuning (Maier et al., 2023). ANNs have similarly been used for future drought prediction (Oyounalsoud et al., 2024; Poudel et al., 2024).

Given the high number of potential meteorological and non-meteorological predictors (Figure 3), we initially built RF, XGBoost, and ANN models using all variables within the respective growing seasons and iteratively reduced the feature set based on feature importance analysis (Figure 5). Besides SPEI indicators, Nitrogen (for rice) application and Irrigation (for wheat) showed relatively high importance across several districts and were considered for inclusion. However, for both RF and XGBoost for rice and wheat, the model tuning revealed that the best-performing district-based models were obtained using only SPEI at 3-, 6-, 9-, and 12-month scales during the growing season. Including irrigation data yielded comparable results, while the addition of Nitrogen for rice—despite its importance in some districts—led to reduced model performance. Since our primary aim is prediction rather than explanation (Tredennick et al., 2021), we opted for a simpler, yet more predictive model.

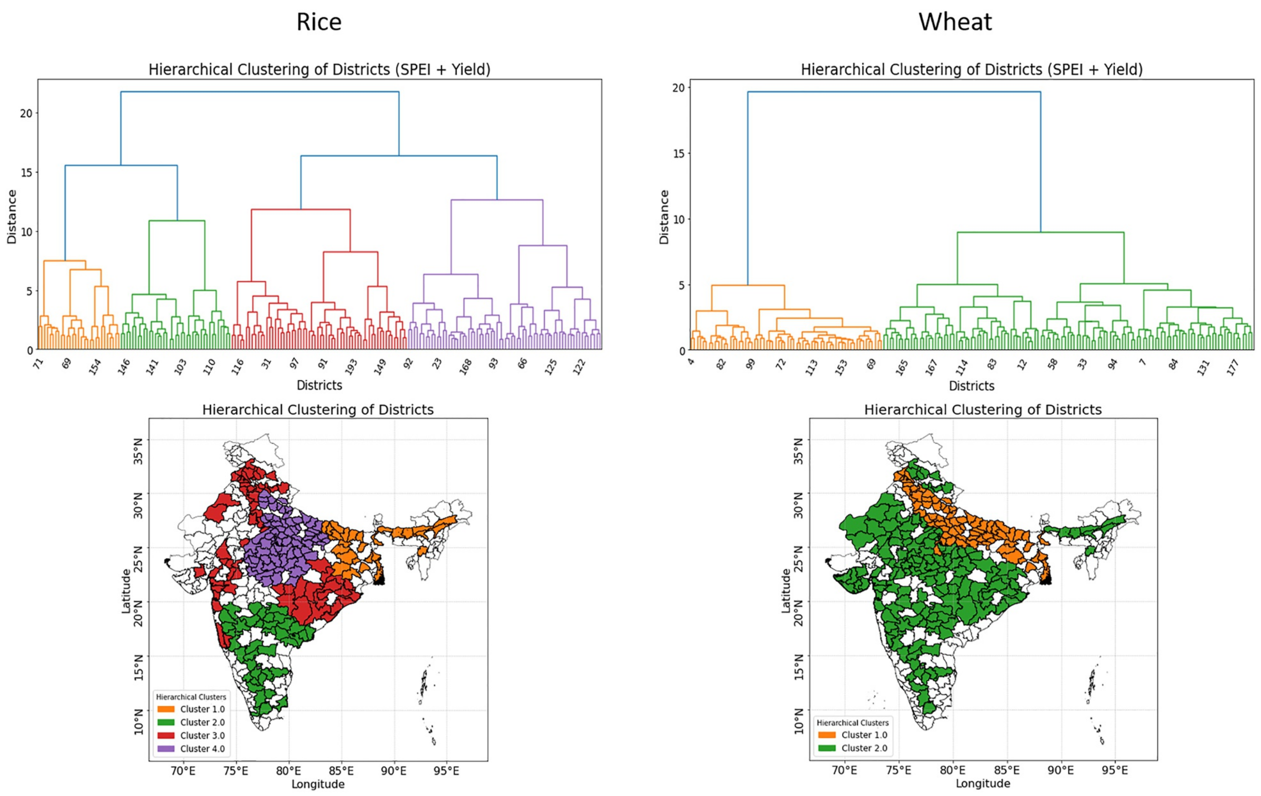

Figure 6. Clustering of the districts (left—rice, right—wheat): upper panel—dendrogram of hierarchical clustering using Ward linkage; lower panel—hierarchical clustering results.

For ANN, the conventional feed-forward neural network approach was implemented for predicting the crop yield over districts of India using district-wise input features as shown in Figure 3. Further details on the ANN setup are provided in Text S4, while Figure S5 of Supporting Information S1 presents a schematic overview of the neural network-based crop yield prediction model used in this study. We proceeded to develop district-level RF, XGBoost, and ANN models for rice and wheat, with each district having 38 years of data (1981–2017). The start year of 1981 was chosen based on the availability of observed PET data.

3.1.2. Monitoring Model: Cluster-Based

We then proceeded with clustering the 198 (for rice) and 211 (for wheat) districts using a hierarchical clustering approach with two key conditions. First, we identified the top three predictors based on feature importance from the RF models across all districts. The first condition for clustering was the correlation between districts based on these three predictors, while the second condition was the correlation in crop yield across districts. To visualize the clustering structure, we generated a dendrogram (Figure 6, upper panel), which revealed four distinct clusters for rice and two for wheat, as shown by the colored branches. This hierarchical clustering structure was based on the Ward linkage method, minimizing variance within clusters and ensuring a clear separation between them. Given this result, we adopted a four-cluster (for rice) and a two-cluster (for wheat) approach and further analyzed the clustering outcomes. We compared the hierarchical clustering results (Figure 6, lower panel) with k-means clustering (Figure S6 in Supporting Information S1). Both methods yielded comparable results, but hierarchical clustering provided a more spatially coherent representation of the clusters, especially for rice. Therefore, we proceeded with the hierarchical clustering approach for further analysis for both crops (Figure 6, lower panel).

We next applied the best-performing district-level model, as described earlier in Section 3.1.1, at the cluster level instead of individual districts. To avoid data leakage due to correlated information within clusters, we ensured that the train-test split was performed consistently across all districts in a given cluster. This means that no district's test data could be indirectly learned from the training data of another district within the same cluster. Using this approach, we predicted 30% of the data, and the results are presented in Section 4.1.

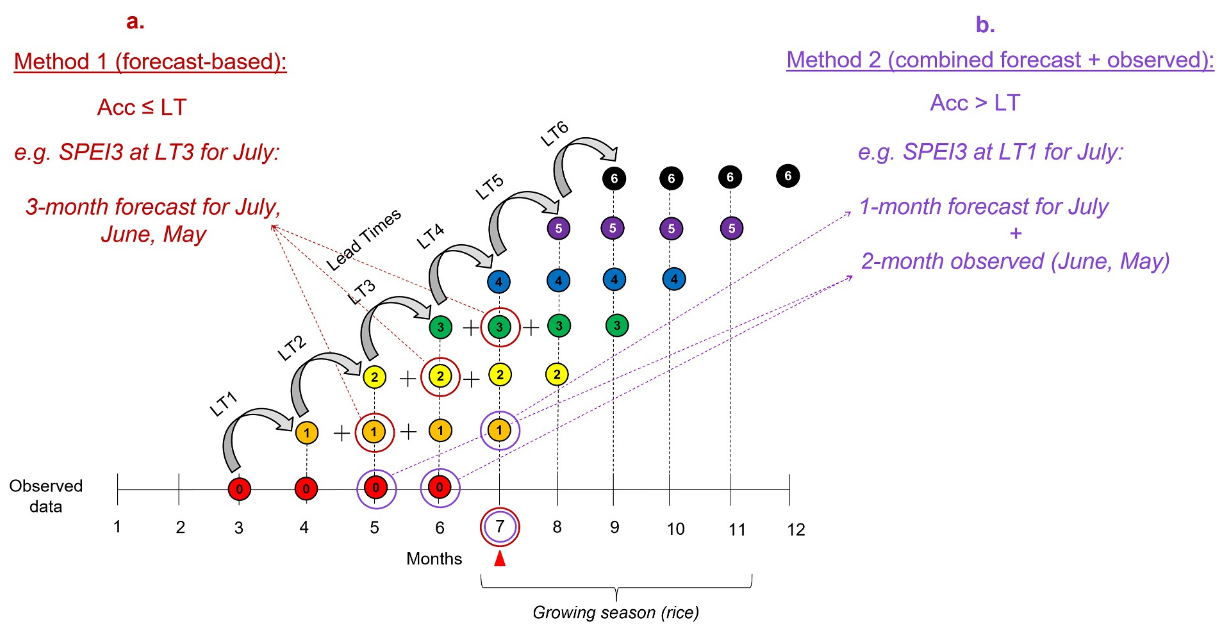

Figure 7. The forecast-based method ((a), method 1 in red) of calculating SPEI3 at LT3 (initialization in April) and the combined method ((b), method 2 in purple) of calculating SPEI3 at LT1 (initialization in June), both for the target month of July. Acc refers to the accumulation period (redrawn after Shyrokaya et al., 2025).

3.2. Forecasting Model: District and Cluster-Based

Seasonal meteorological forecasts from the ECMWF SEAS5 prediction system (Johnson et al., 2019) were used to compute SPI and SPEI for accumulation periods of 3, 6, 9 and 12 months, focusing on the last 3 years in our analysis period (2015–2017). For 2015 and 2016, we used the 25 available members from the SEAS5 hindcasts, while for 2017—the first year of real-time SEAS5 forecasts—we randomly selected 25 out of the 51 available members. Two forecasting setups were implemented, both targeting the start of the rice (July sowing) or wheat (November sowing) growing season, with 1-, 3-, and 6-month lead times (LT). For example, SPEI3 for July at LT1 was computed using a 1-month forecast for July (targeting July with initialization in June), combined with 2 months of historical data for June and May (Figure 7b). In contrast, SPEI3 at LT3 for the same target month of July was calculated by combining SEAS5 forecasts for May (LT1), June (LT2), and July (LT3), all initiated in April (Figure 7a). However, certain indicators, such as SPEI12 for August, cannot be computed at LT1 or LT3, as they fall outside the lead time window for the target months (July), making only LT6 viable in such cases. Combining forecasted and observed data to estimate drought indices with accumulation periods exceeding the forecast lead times has proven to be both effective and practical (Shyrokaya et al., 2025).

The forecasts of crop yield were then evaluated based on the last 3 years by incorporating forecasted or a combination of forecasted and observed drought indicators into the models. This step generated crop yield forecasts for lead times of 1, 3, and 6 months (LT1, LT3, and LT6). The forecasted yields were then compared against predictions based solely on observed data, separately for the district-based and cluster-based models.

3.3. Performance Evaluation

To evaluate the monitoring models and ensure robustness while avoiding overfitting or underfitting, we compared the Root Mean Square Error (RMSE) values of predicted and observed crop yields during both five-fold cross-validation (hereafter, CV) and Test phases across districts. Since crop yield values were detrended and standardized, RMSE values represented the percentage deviation of model predictions from the LOESS fitted crop yield. For instance, an RMSE of 0.15 corresponds to an average deviation of ∼15.78% from the LOESS trend.

We conducted three validation approaches (Figure 3):

1. A random split of the data set into 70% training and 30% testing, followed by prediction (Figure 8a in Section 4).

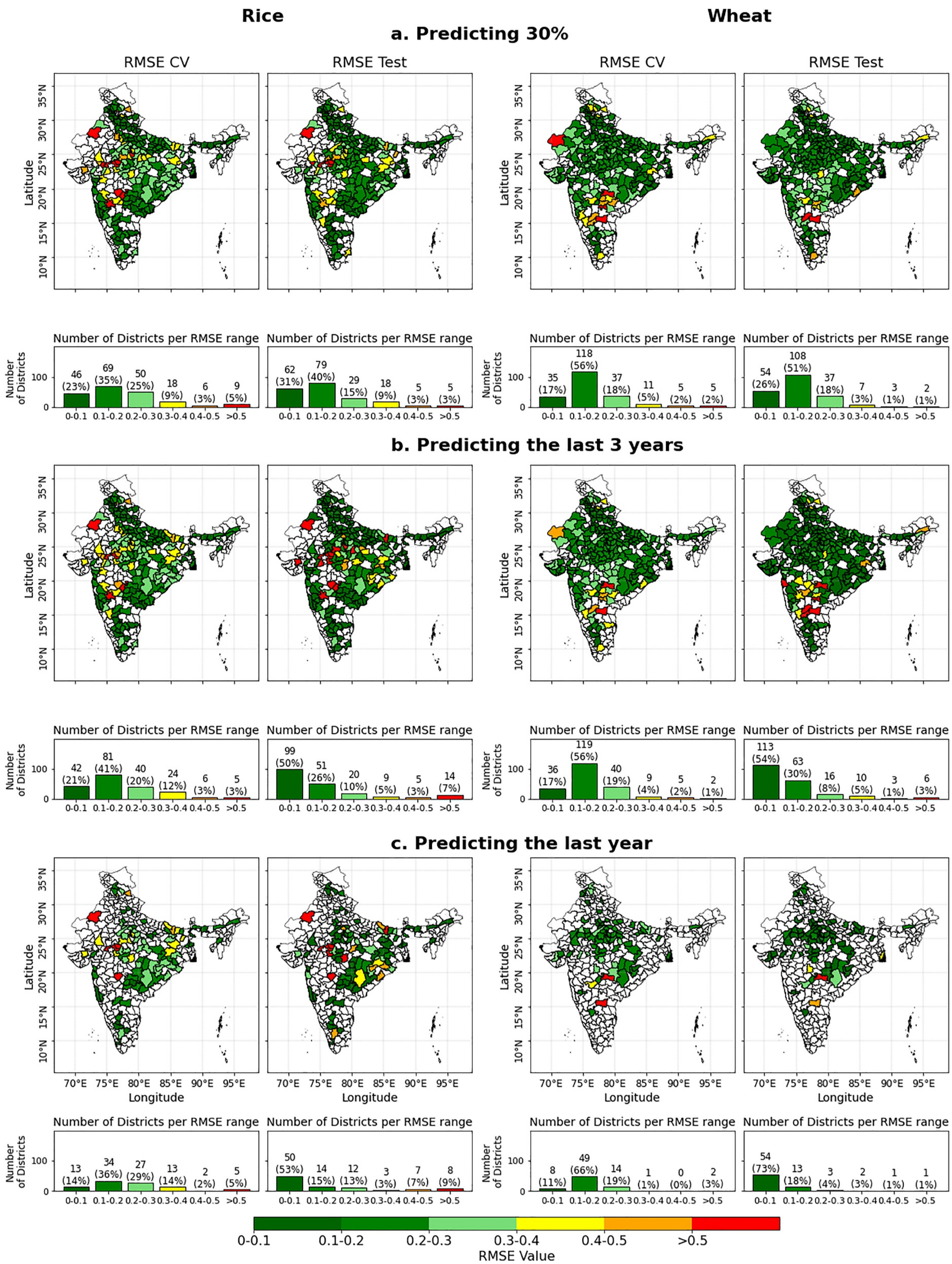

Figure 8. Spatial distribution of district-based RMSE values from the RF model for cross-validated performance (CV) and test for rice (left) and wheat (right) under three scenarios: (a) 30% test data; (b) the last 3 years, and (c) the last year for 94 districts where rice yield was below the mean.

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2. A strictly chronological evaluation in which the data set was split into a training–validation period (1981–2014) and an independent test period (2015–2017); cross-validation using random 70%–30% splits was applied only within the training–validation period, and performance was assessed out of sample for 2015–2017 (Figure 8b in Section 4).
3. A targeted evaluation of low-yield conditions, in which only districts experiencing below-average crop yield during the last year were selected, and the ability of the models to reproduce these low-yield outcomes was assessed (Figure 8c in Section 4).

Approach (2), focusing on predicting the last 3 years, was implemented to establish a validation framework for integrating forecasts into the models (Section 4.2), allowing a comparison between models based solely on historical data and those incorporating the forecasts for the most recent years.

In addition to inter-model comparisons, model performance was benchmarked against two simple baseline approaches to contextualize skill: (a) a district-wise climatology, defined as the mean detrended and standardized yield over the training period, and (b) a district-wise multiple linear regression using the same set of predictors as the machine-learning models.

For the evaluation of the forecasting model, we used RMSE, CRPS (Continuous Ranked Probability Score), and weighted CRPS (wCRPS; Taillardat et al., 2023), all calculated at a district level. RMSE was calculated as the average over 25 ensemble members and across the 3 years (2015–2017). Here, it measures the average magnitude of the error between the forecasted and observed yields, with lower values indicating better agreement. CRPS, averaged over the 3 years, evaluates the quality of probabilistic forecasts by combining both accuracy (closeness to observations) and reliability (calibration of the forecast distribution), where lower CRPS values indicate better forecast performance. wCRPS emphasizes forecast performance for extreme low yield values (10th percentile) and is influenced by the choice of weight function, which can be tailored to user priorities (Gneiting & Ranjan, 2011; Lerch et al., 2017; Taillardat et al., 2023).

wCRPS modifies the standard CRPS by incorporating a weight function to emphasize specific regions of the predictive distribution, such as the tails. We used non-negative weight functions like $w(x) = 1 - \phi(x)$ for left tail and $\phi(x)$ for the right tail to focus on low-value events and high value events, respectively. Then we computed the corresponding cumulative weight function $W(x)$ using numerical integration. For each forecast-observation pair, we calculated three terms: the integrated weight at the observed value (T1), the average difference in weight values when ensemble members exceed the observation (T2), and a weighted average of the forecast values based on their empirical cumulative distribution (T3). wCRPS was then derived by combining these terms (T1 +2*T2 −2*T3) as suggested by Taillardat et al. (2023). Given the short forecast period (2015–2017), we report bootstrap percentile intervals (1,000 resamples) as an indicative measure of variability across the available cases, and interpret these intervals cautiously rather than as precise confidence intervals.

4. Results

4.1. Monitoring Models: RF District-Based Modeling Outperforms Other Approaches

To benchmark forecasting skill, we first evaluated monitoring models—without forecast inputs—using both district-level and cluster-based setups across the three ML methods: RF, XGBoost, and ANN. For all three methods, a total of 198 for rice and 221 for wheat district-based models were developed, which included all top districts producing both crops (Figure 8).

Among the three ML algorithms tested, RF clearly outperforms the others, achieving lower RMSE values and capturing yield variability. We use RMSE as a simple summary of typical error magnitude in standardized yield anomaly units and consider RMSE <0.2 as a conservative screening threshold for identifying models with comparatively low errors. Previous studies have suggested that RMSE values below roughly half the standard deviation of the observed series (i.e., $\text{RMSE}/\sigma < 0.5$) indicate relatively low error in a normalized sense (e.g., Moriasi et al., 2007; Singh et al., 2004), noting that such thresholds are heuristic and context-dependent. Using this conservative threshold, the majority of models—70% for rice (out of 198) and 80% for wheat (out of 221)—show low RMSE on the 30% test set (Figure 8a). The RMSE CV serves as an internal check against overfitting or underfitting, as each prediction is made on data unseen during training within the cross-validation folds. Furthermore, as an example (Figure 9), we present results for a district with high model performance (RMSE = 0.06) and a district with low model performance (RMSE = 0.38). The results for predicting the last

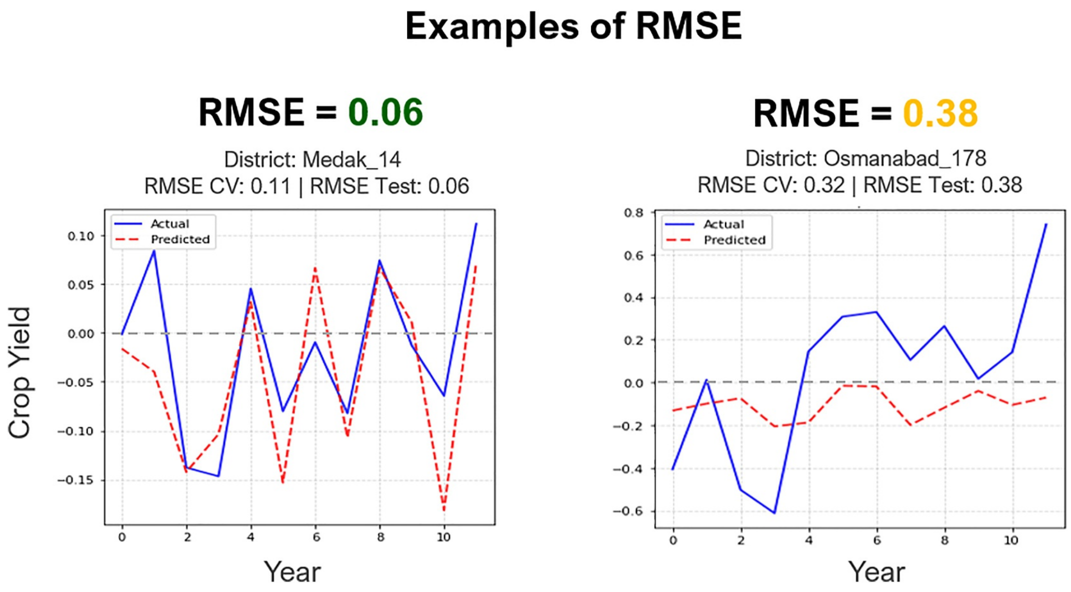

Figure 9. The two example districts with contrasting performances between predicted (in red) and observed (actual) (in blue) yield: RMSE of 0.06 (left) and 0.38 (right).

3 years (Figure 8b) closely align with those obtained from the test set, demonstrating the model's robustness. Additionally, Figure 8c presents predictions for districts where rice and wheat yields in the last year only were below the mean, revealing that 68% of these rice districts and 91% of wheat districts achieved RMSE values below 0.2 on the test set. A comparable yet poorer performance was observed with the XGBoost (Figure S7 in Supporting Information S1) and ANN (Figures S8 and S9 in Supporting Information S1) models for rice, with the XGBoost model also showing signs of overfitting.

To further contextualize model performance, the district-based monitoring models were benchmarked against two simple baseline approaches: a district-wise climatology and a district-wise multiple linear regression using the same predictors. This comparison confirms that climatology represents a strong reference at the district scale, while the machine-learning models, particularly RF, exhibit systematically lower RMSE values and a reduced frequency of high-error cases relative to both baselines (Figure S12 in Supporting Information S1). The linear regression baseline generally performs worse than climatology, indicating that the improved performance of the machine-learning models arises from their ability to capture nonlinear relationships rather than from predictor selection alone.

We next assessed the performance of the cluster-based approach (Section 3.1.2) as compared to the district-based approach (Section 3.1.1), focusing on RF. Similar to the district-based approach, running RF models for the four rice (Figure 10, upper panel) and the two wheat (Figure 10, lower panel) clusters produced CV and test RMSE values for the majority of districts below 0.2 when predicting 30% of the data.

Plotting the predicted 30% of data for each district (Figures 10a and 10b) shows that cluster-based models perform slightly worse than district-specific models for rice, with 31% of districts achieving an RMSE below 0.1 using district-based models compared to 16% using cluster-based models, but yield comparable results for wheat (for RMSE below 0.2). Consequently, for the next forecasting step, we used only RF and district-based models for rice, while applying both district- and cluster-based RF models for wheat. The weaker performance of the cluster-based models for rice likely reflects the higher interannual variability of rice yields, which reduces the stability of the drought–yield relationship across districts. This pattern is supported by the analyses (Figures S10 and S11 in Supporting Information S1) showing that model accuracy decreases systematically as yield variability increases. In addition, rice-growing districts exhibit more heterogeneous management practices and crop calendars (e.g., transplanting vs. direct-seeding, and multiple growing seasons), which reduce the coherence of the drought–yield signal captured by monthly SPEI. In contrast, wheat cultivation follows a more consistent seasonal pattern and a more stable relationship with the aggregated drought indicators used in this study.

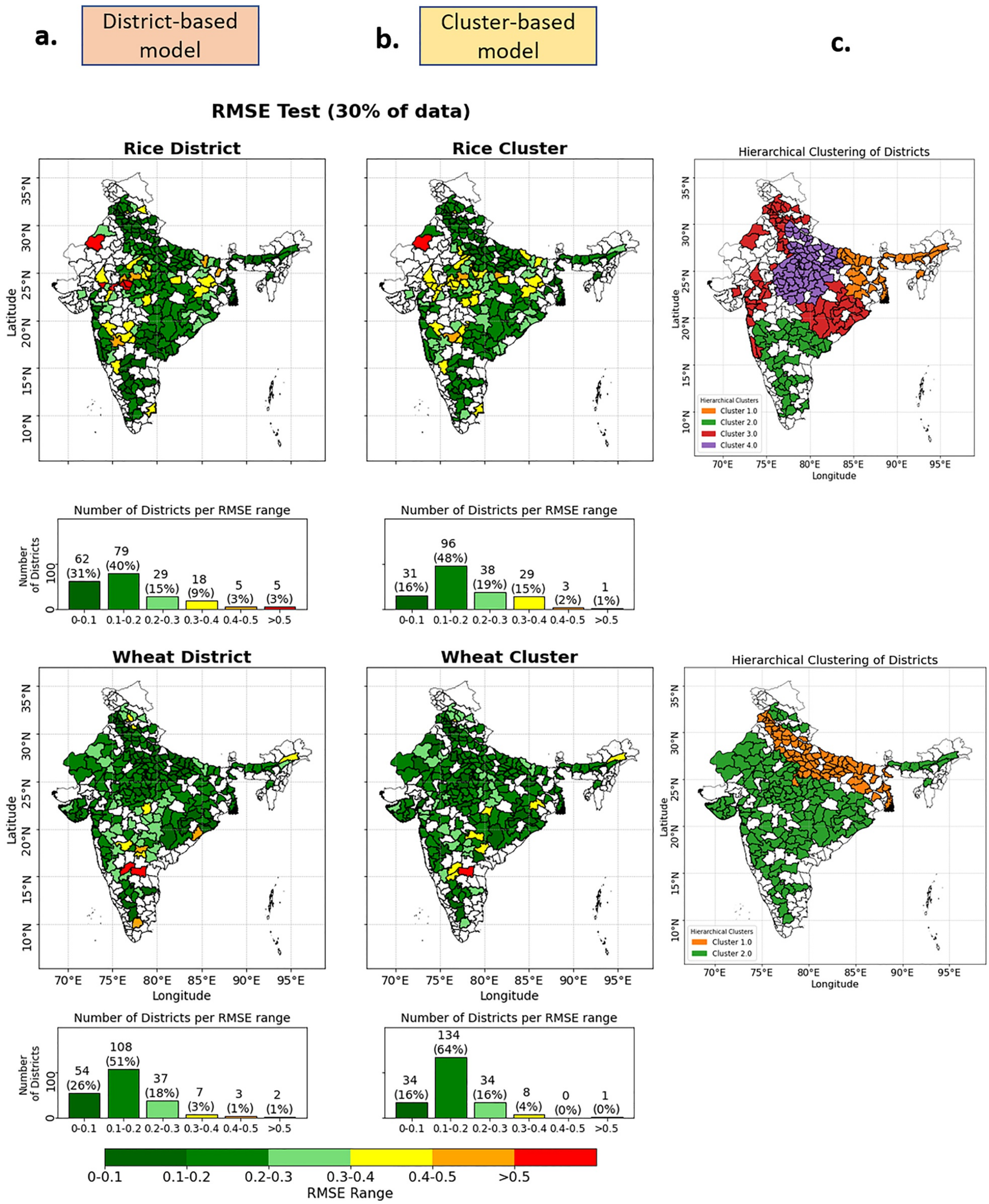

Figure 10. The spatial plot with the prediction of 30% of data for rice (upper panel) and wheat (lower panel): (a) district-based models; (b) cluster-based models evaluated on the district level; (c) the four or the two formed clusters (see Section 3.1.2).

4.2. Forecasting Models - Accurate and Reliable Seasonal Pre-Planting Prediction of Rice and Wheat Yields

The integration of SEAS5 seasonal forecasts with district- and cluster-based (for wheat only) RF models enabled robust crop yield predictions up to 6 months before planting (Figure 11). For rice, over 60%–70% of districts achieved forecast RMSE values below 0.2 at all lead times (1, 3, and 6 months before the growing season), indicating robust predictive skill even at long lead times (Figure 11). Wheat yield forecasts showed even better performance, with over 80% of districts reaching RMSE values below 0.2 across all the lead times (Figure 11).

The RMSE of the crop yield forecasts slightly increases at longer lead times but not significantly, and remains only slightly worse than the test set predictions (Figure 10). However, cluster-based wheat forecasts show a clear decline in performance compared to district-based models as lead time increases, particularly for the cluster located in northern India. Further, certain districts that performed poorly in the test set (monitoring model) also show similarly poor or even worse performance in the forecasting mode. In addition, a number of districts in central India consistently exhibit high RMSE values, suggesting the influence of local factors—such as storms, pests, or other unmodeled stressors—that may impact crop yield in these areas.

Analysis of CRPS values across districts and lead times (Figure 12) shows that good performance is achieved in most districts at all lead times. Districts with high RMSE values also tend to show poor performance in terms of CRPS, suggesting that in these areas, forecasts fail to adequately capture the variability in crop yield and are less accurate and less reliable.

Comparing CRPS with the range of crop yield (maximum minus minimum) in each district (Figures S10 and S11 in Supporting Information S1) reveals that CRPS tends to increase with greater yield variability, as expected. However, most districts still show CRPS values below 0.2 for yields standardized as proportional deviations from the LOESS trend (typically within a range of ±0.5, i.e., a total amplitude of 1), indicating sufficiently accurate and reliable forecasts.

Because decision-makers are primarily concerned with yield shortfalls, we further evaluate probabilistic skill using a left-tail weighted CRPS that emphasizes the lowest 10% of the yield distribution (wCRPS_low). For completeness, we also use a right-tail wCRPS for the top 10% of yields. Positive values indicate error, with zero denoting a perfect forecast. In around 70%–80% of districts, we find that wCRPS_low <0.2, confirming robust skill for extreme low yields (Figure 13). For rice, districts where wCRPS_low >0.2 coincide with arid central–western India, where water-limited conditions may interact with unmodelled local stressors such as pest outbreaks (Juroszek & von Tiedemann, 2013), potentially reducing model performance.

5. Discussion: Practical Implications and Limitations

This work has significant practical implications for India's agriculture and related sectors. With a 6-month lead time, the yield forecasts can help smallholder farmers make informed decisions before sowing, such as choosing climate resilient crop varieties, or switching to alternative crops, thereby reducing input costs and improving income stability (Olesen et al., 2011; Palka & Manschadi, 2024; Sharafi et al., 2021). Water managers, particularly in irrigation dependent states like Punjab, Tamil Nadu, or Maharashtra, can use the forecasts to plan reservoir releases, manage irrigation schedules, and prepare for water stress (Stone & Meinke, 2005). Policymakers and local governments can prioritize regions forecasted to face low yields for timely interventions such as input subsidies, public procurement, or fertilizer support under schemes like PM PRANAM and the Nutrient Based Subsidy program (Patel & Thallam, 2024). Additionally, they can initiate early distribution of subsidized seeds through state agriculture departments or national schemes like the National Food Security Mission (NFSM), ensuring that farmers have access to suitable inputs well in advance (Acharya Balkrishna et al., 2022; Lakshmi et al., 2024). Financial institutions, including rural banks and crop insurers, can integrate forecasts into credit risk models, premium pricing, and disbursement planning, enhancing the viability of weather and yield indexed products (Birthal et al., 2022; Elabed et al., 2013; Ghosh et al., 2021). State authorities can also plan for food price stabilization and supply management. Finally, NGOs and anticipatory action organizations can use these forecasts to trigger early responses, such as distributing inputs, scaling advisory services, or launching livelihood support programs (Nobre et al., 2019; Westerveld et al., 2021), especially in vulnerable regions, making agricultural risk management in India more proactive, targeted, and data driven (Kalkuhl et al., 2016).

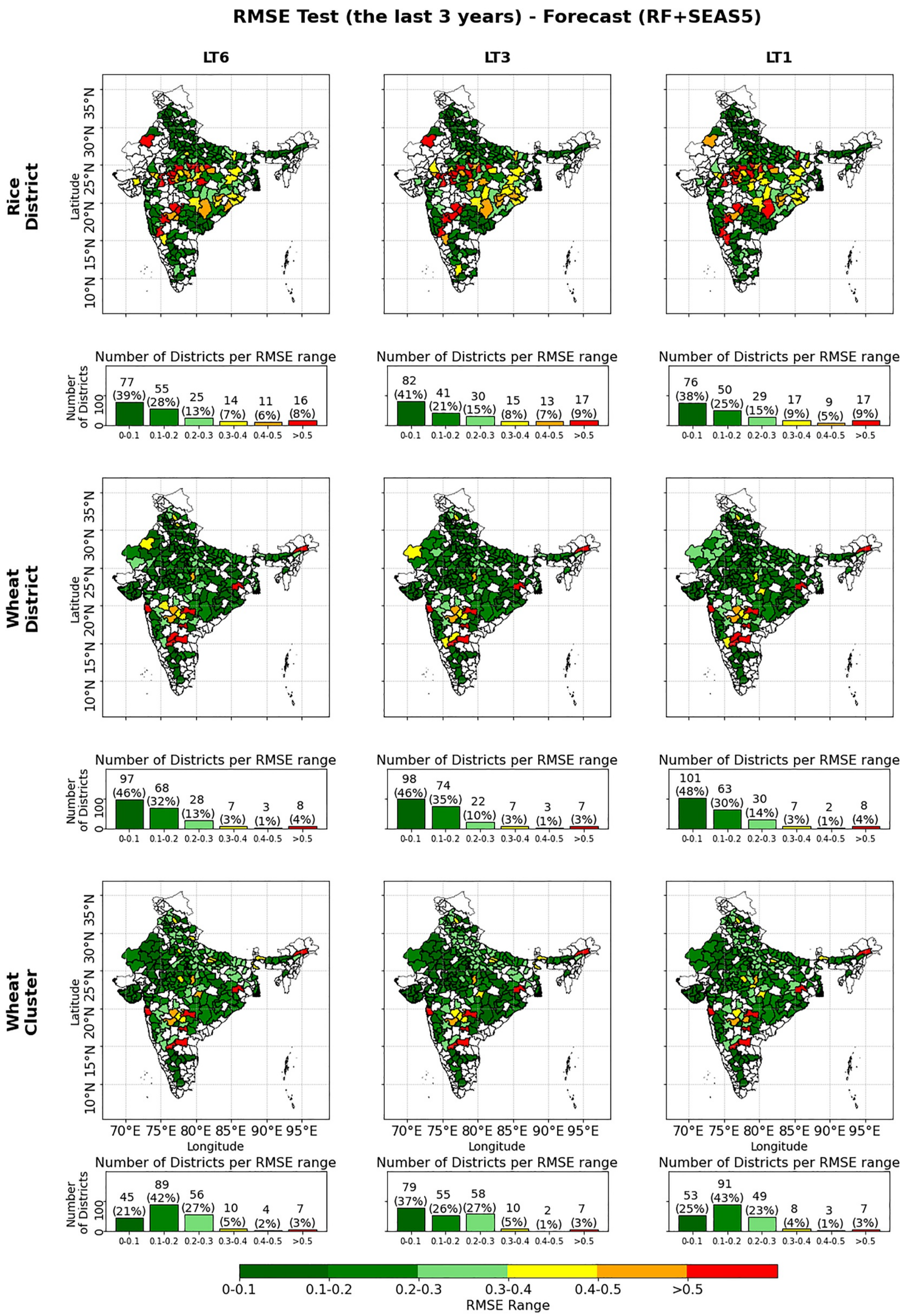

Figure 11. Comparison of district-level RMSE values for district (for both rice and wheat) and cluster-based (for wheat only) models: forecasted crop yield at lead times of 1, 3, and 6 months before the start of the growing season (July for rice, November for wheat).

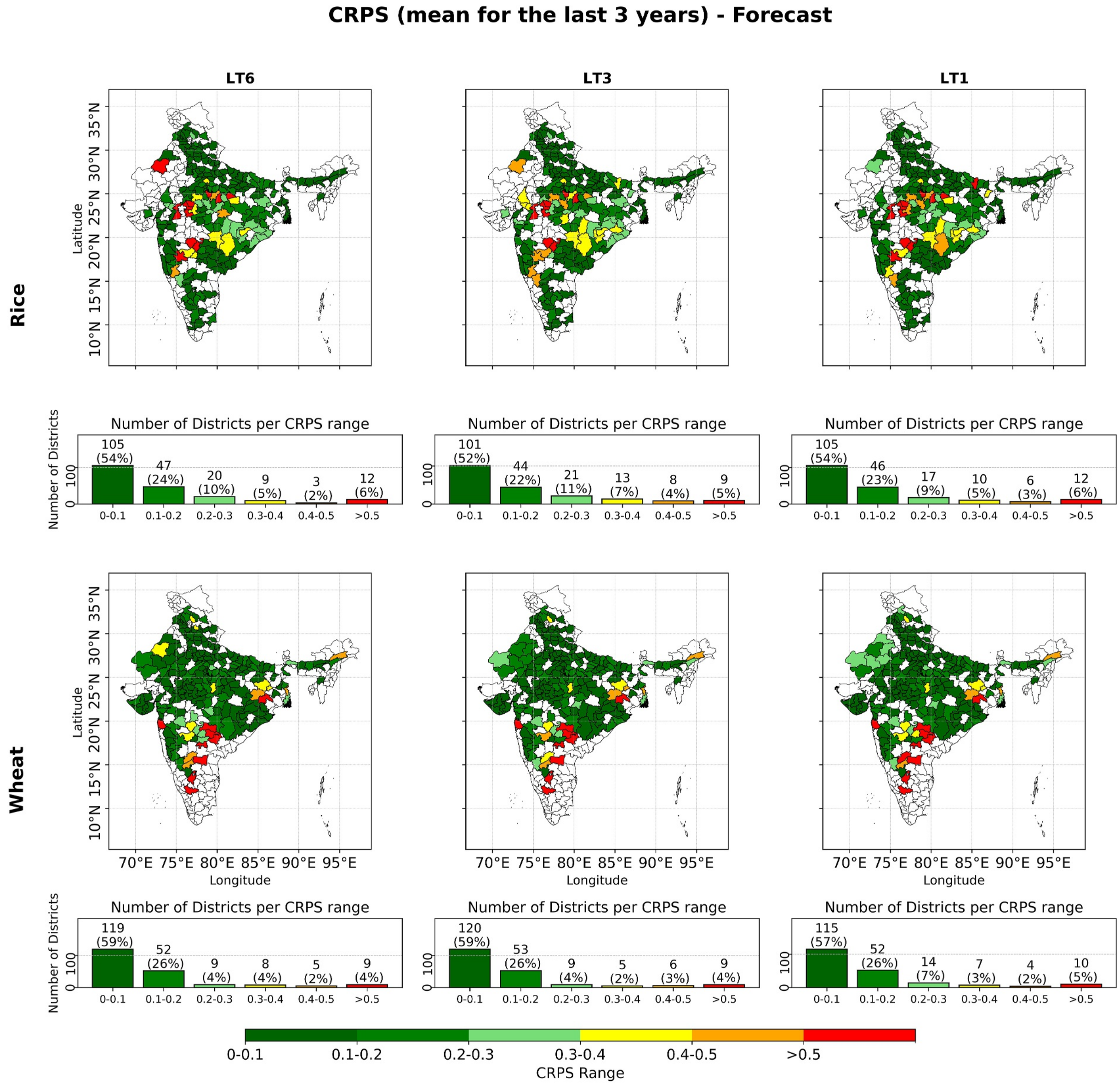

Figure 12. CRPS values for rice (upper panel) and wheat (lower panel) yield forecasts at the district level lead times of 1, 3, and 6 months before the start of the growing season (July for rice, November for wheat).

While this study focuses on India, the framework's reliance on standardized drought indices, open-access seasonal forecasts, and flexible machine learning models makes it adaptable to other regions. However, effective transfer requires local retraining and sufficient observational meteorological and crop yield data to ensure reliable performance. Countries with similar challenges, such as high drought risk, reliance on rainfed agriculture, and limited impact data, could benefit from adapting this approach to their local contexts.

This study comes with certain limitations. First, uncertainties in both the observed yield data (e.g., measurement errors) and the SEAS5 forecasts (e.g., model prediction errors) may independently introduce bias into the yield models. The model's reliability is reduced in highly irrigated districts due to limited data from drought years without irrigation. It also excludes important factors such as pests, diseases (Nóia Júnior et al., 2023), and farm management practices beyond irrigation, such as soil and land management, which can significantly influence yields (Gerber & Mirzabaev, 2017) but are difficult to quantify consistently across regions. Management variables such as irrigation intensity and nitrogen input were tested but ultimately excluded due to the lack of spatially and temporally consistent, district-level data. Available information was either too coarse or binary

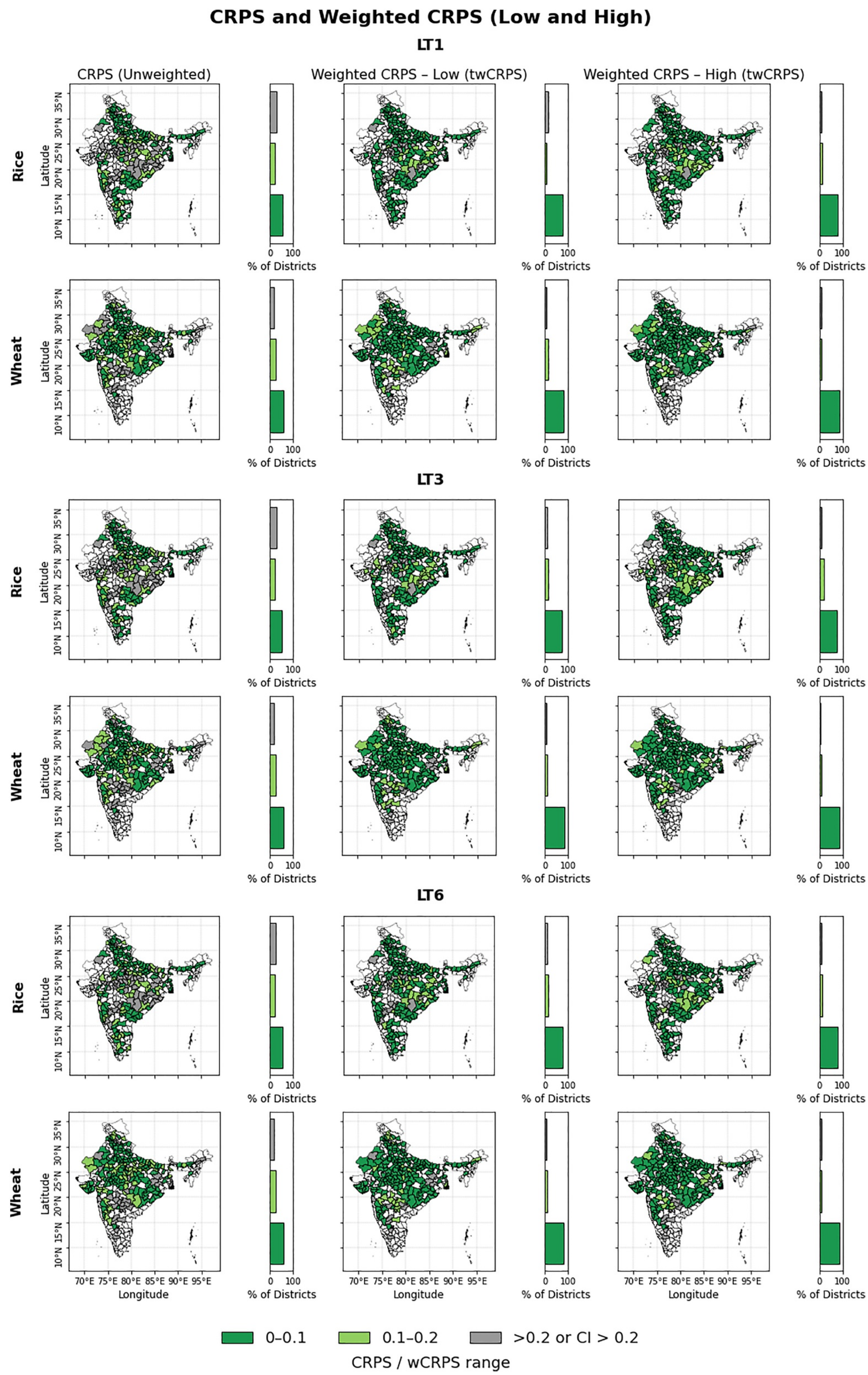

Figure 13. Forecast model performance in terms of the CRPS and weighted CRPS for the low (left) and high (right) tails of the rice and wheat yield values, all at LT1, 3, and 6 months. CI refers to the Confidence Intervals from the bootstrap procedure (Section 3.3).

(e.g., irrigated/non-irrigated), which did not improve, and in some cases degraded, the performance of the machine learning models. We therefore treated their exclusion as a data-availability limitation rather than a modeling choice. Drought was analyzed at a monthly scale, which may overlook short, highly sensitive crop stages (e.g., heading/flowering in wheat). In addition, probabilistic verification would benefit from a longer test period to increase the number of independent forecast observation cases. Future work should evaluate finer temporal aggregations (e.g., weekly) to better capture short, high-impact dry spells. Additionally, the use of a uniform crop calendar may oversimplify regional and crop specific variability. Future studies could incorporate the climate change component to better contextualize long term trends. The study also does not address yield losses due to floods or other natural hazards, which could be considered in future research. While we tested XGBoost, Random Forest, and ANN, other advanced algorithms such as LightGBM or Rotation Forests (Gu et al., 2023) remain unexplored and could also be evaluated in future work. Despite these limitations, our study demonstrates the potential of integrating seasonal forecasts with machine learning for anticipatory agricultural planning and highlights key avenues for methodological refinement and broader integration in future research and operational systems.

6. Conclusions

This study presents a scalable, data-driven framework that links seasonal drought indicators to pre-season crop yield forecasts in India. By integrating ECMWF SEAS5 forecasts with Random Forest models across district and cluster levels, we demonstrate strong predictive skill for both paddy rice and wheat, even at lead times up to 6 months before planting.

In the monitoring phase, namely real-time yield estimation, district-level models consistently outperform cluster-based approaches, with more than 80% of districts for wheat and 70% for rice achieving RMSE values below 0.2. Importantly, the framework accurately identifies years and locations of extremely low yields, highlighting its relevance for developing early warning systems.

Forecast-based models, which predict future yield, showed similarly robust performance. Over 80% of wheat-growing districts and 60%–70% of rice-growing districts achieved RMSE values below 0.2 across all forecast lead times (1, 3, and 6 months before planting). Wheat forecasts were especially accurate, with minimal decline in skill even at longer lead times. Rice forecasts also remained reliable under extended lead times, indicating that early-season climatic signals from SEAS5 are sufficiently informative for both crops. The probabilistic evaluation confirmed that forecasts are both accurate and reliable with low uncertainty in most districts and strong skill in predicting extreme low yield years, which is critical for early warning, while lower performance in some districts likely reflects unmodeled local stressors such as pests.

Our findings mark a step forward in operationalizing impact-based forecasting in data-scarce, climatically diverse regions. The generalizability of the framework, along with the use of globally accessible data sets and models, makes it suitable for adaptation in other countries facing agricultural drought risks, thereby supporting broader efforts in anticipatory action and climate resilience. The ability to forecast agricultural drought impacts before sowing offers a valuable decision-support tool for farmers, policymakers, and supply chain actors. Future research should explore ensemble modeling approaches, integration with additional socio-economic vulnerability data, and real-time application through national or regional forecasting platforms.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

All crop yield and vulnerability data used in this study are publicly available from the International Crops Research Institute for the Semi Arid Tropics (ICRISAT) database (ICRISAT, 2021), accessible at http://data.icrisat.org/dld. The precipitation and temperature data used to calculate the drought indicators are freely accessible through the Indian Meteorological Department (Pai et al., 2014) at https://www.imdpune.gov.in/cmpg/Griddata/Rainfall_25_NetCDF.html. The monthly Niño 3.4 index from NOAA Physical Sciences Laboratory's HadISST1.1 data set (Rayner et al., 2003) can be accessed at: https://psl.noaa.gov/data/timeseries/month/Nino34/.

The ECMWF SEAS5 data set (Johnson et al., 2019) can be accessed from the operational archives of the MARS catalogue: https://www.ecmwf.int/en/forecasts/dataset/operational-archive.

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