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Impacts of Drought on Food Security of Strategic Crops in Iran: A Machine Learning–Based Scenario Analysis

Foad Eshghi[1*], Tahereh Ranjbar Malekshah[2], Nemat Allah Nemati[3] , Hafezeh Hoseini[4], Masoud Sharifi Khatir[5]

*1. Assistant Professor, Department of Agricultural Economics, Faculty of Agricultural Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran. (**Corresponding Author**) Email: fesh.foad@gmail.com*

2. PhD in Agricultural Economics, Department of Agricultural Economics, Faculty of Agricultural Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran.

3,4. PhD student, Department of Agricultural Economics, Faculty of Agricultural Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran.

5. Master of Agricultural Economics, Tarbiat Modares University, Tehran, Iran.

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ABSTRACT

Drought-driven hydroclimatic stress is increasingly disrupting agricultural supply in arid and semi-arid environments. This study quantifies future supply vulnerability for three major cereal crops in Iran, namely wheat, rice, and barley, using a multivariate Long Short-Term Memory (LSTM) time-series framework. Annual data for 1961–2023 were compiled from international databases and include crop production, imports, harvested area, and precipitation as a climate proxy. The modelling workflow proceeds in two steps: (i) domestic production is projected for 2024–2028 using crop-specific multivariate LSTM models; and (ii) the forecasts are translated into implied import requirements. In this study, implied import requirement is a gap-based accounting indicator, calculated as the non-negative difference between the calibrated baseline domestic requirement and forecasted production, rather than a direct machine-learning forecast of import volumes. To stress-test vulnerability, three drought shock scenarios, including 10%, 30%, and 50% production reductions, are applied to the baseline production pathway, and scenario-specific import gaps are recomputed. The results show that drought shocks substantially increase external supply exposure across all crops. Under the severe 50% shock scenario, average implied import requirements during 2024–2028 increase by 172.6% for wheat, 137.1% for rice, and 65.4% for barley compared with the baseline pathway. In aggregate, the three-crop import gap rises by 135.7%, indicating a sharp increase in food-security vulnerability under severe drought stress. Methodologically, the study demonstrates how LSTM-based production forecasts can be converted into policy-relevant import-gap scenarios. From a policy perspective, the findings support integrated drought-risk management through water productivity improvement, strategic grain reserves, and forward import planning.

KEYWORDS: Long short-term memory networks (LSTM); Cereal Supply Risk; Hydroclimatic Stress; Scenario Analysis

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1. Introduction

The Middle East is one of the strategic regions exposed to the effects of extensive climate change. According to studies, in the coming decades, changes in precipitation and temperature in the Middle East region will lead to more intense and prolonged drought events (Vicente-Serrano et al., 2014; Forzieri et al., 2016; Spinoni et al., 2018; Sharafi and Mir Karimi, 2020; Sharafi and Ghaleni, 2022). Thus, many semi-arid regions of South-West Asia are expected to experience declining water availability and higher hydroclimatic instability due to decreased rainfall, increased interannual and intra-annual rainfall fluctuations, and reduced water availability (Lucon et al., 2014; EEA, 2017). Also, future changes in rainfall regimes, along with rising temperatures, will entail adverse climate events (Webber et al., 2018), affecting ecosystems and economic sectors (Asseng et al., 2014; Tack et al., 2015).

Drought is a major natural disaster that seriously affects agriculture and has become increasingly common worldwide. Although each crop is different in terms of its resilience to water stress (Liu et al., 2016; Lobell et al., 2011), drought generally reduces crop yield, destabilizes agricultural output, and increases uncertainty in food supply planning. Also, the reduction or depletion of water resources leads to water stress in plants, which negatively affects their growth and productivity (Seleiman et al., 2021).

Iran is an arid and semi-arid country in terms of climate, with most of its territory located in arid to semi-arid climatic zones; this drought intensity, combined with the unprecedented extraction of surface and groundwater resources, has made Iran one of the most at-risk areas in the face of drought. National and regional studies show that more than half of Iran faces low rainfall conditions (with average annual precipitation substantially below the global average) and increased fluctuations in drought intensity and prevalence, exacerbated by poor water management and exploitation mechanisms (Karandish et al., 2017; FAO, accessed 2025).

In Iran, much of agriculture comes from freshwater consumption, and the combination of persistent droughts and water-intensive farming patterns has made it a threat to national food security. Wheat, rice, and barley are not only major agricultural commodities but also strategic crops with direct and indirect effects on household welfare, food prices, livestock-feed markets, and agricultural supply-chain stability. Wheat and rice are central staples in the Iranian food basket, while barley plays a critical role as a feed grain for the livestock sector and therefore indirectly affects meat and dairy prices. Wheat, rice, and barley together account for approximately 55% of dietary energy intake in Iranian households (FAO, 2023). These crops also contribute significantly to the agricultural GDP, wheat alone represents nearly 30% of cultivated land and supports millions of rural livelihoods. In terms of food security, the three strategic crops wheat, rice and barley account for the largest share of calories and commodities in the domestic market and agricultural policy (FAO, accessed 2025). According to the statistics provided, Iran has managed fluctuations in wheat production in recent years, but there is still sensitivity to climatic conditions, so that the annual production of Iranian wheat fluctuates in the range of 12-16 million tons (depending on the year and climatic conditions), and the replenishment of stocks and import requirements also change depending on the annual performance. With respect to rice, domestic production is reported to be around 3 million tons, and the volume of rice imports to meet domestic demand is usually substantial; in some years, rice imports have been reported to be equivalent to several hundred million dollars in trade value (UN Comtrade, accessed 2025), indicating the dependence of the domestic market on imports. Barley also has significant production on the scale of several million tons, but the yield per hectare and cultivated area is affected by drought and water access (USDA, accessed 2025). Therefore, drought-induced shocks to these crops can transmit beyond farm production to food prices, livestock-feed costs, import bills, strategic reserves, and national food-security planning.

Studying the vulnerability of strategic crops against drought, especially in a country such as Iran, which faces climate change and limited water resources, requires accurate analytical and data-driven approaches. Traditional statistical methods, although effective in analyzing trends and linear relationships between variables, do not meet the current needs of the agricultural sector due to limitations in modeling complex, nonlinear and multidimensional relationships. In contrast, branches of AI make it possible to extract hidden patterns and nonlinear relationships using big data and diverse variables (climate, soil, farm management, market, etc.), and provide more accurate predictions of crop yield and production under various drought scenarios (Kamilaris and Prenafeta-Boldú, 2018).

Rather than defining artificial intelligence in a general and fundamental sense, recent applied literature views AI in agriculture as a set of data-driven computational techniques that support prediction, optimization, monitoring, and decision-making across agricultural and food systems. In this context, AI-based models can transform heterogeneous agricultural data into actionable information for farmers, supply-chain actors, and policymakers, particularly when production risk, water scarcity, and food-security uncertainty are high (Ben Ayed and Hanana, 2021; Sarku et al., 2023). Artificial intelligence technologies, which are improving rapidly and are used in almost every area of life, can be used in modern agricultural activities (Hassani et al., 2020). This technology can use advanced technologies such as robots, the Internet of Things, artificial neural networks, machine learning, image processing, wireless sensor networks (WSN, etc.), to guide farmers and policymakers by reading weather events and other required information (Talaviya et al., 2020; Ben Ayed and Hanana, 2021; Liu, 2020).

Machine learning is part of artificial intelligence and includes special tools for understanding, analyzing and recognizing data patterns for decision-making or forecasting. The primary field of thought for machine learning is computer programming to perform human tasks according to the learning and problem-solving flow. Machine learning makes decisions with the least amount of human intervention; in fact, it uses the available data to feed an algorithm that has the ability to understand a set of input-output relationships. Artificial intelligence, based on machine learning principles, is primarily focused on solving farm-related problems involving a predictive model, a diagnostic model, and a farm management model (Dutta et al., 2020). From an agricultural economics and management perspective, the value of machine learning is not limited to improving forecast accuracy; it also lies in converting production signals into operational information for import planning, reserve management, procurement timing, and supply-chain risk reduction.

Recent studies also show that machine learning applications are increasingly relevant for agricultural supply-chain management, food-system resilience, and early warning of food-security crises, because they can support timely decisions under climate and market uncertainty (Busker et al., 2024; Rejeb et al., 2025).

One of the key requirements for using machine learning is the ability to predict. Predicting changes in crop production under different climatic conditions can help decision makers adopt appropriate policies (such as import management, strategic stocks, or changing crop patterns) at the right time. International research has shown that machine learning algorithms such as Artificial Neural Network (ANN), Random Forest (RF), and Support Vector Machine (SVM) perform better in predicting the performance of wheat, rice, and other crops in conditions of environmental stress than conventional linear models (Khaki and Wang, 2019; Jeong et al., 2016). In addition, another advantage of machine learning is its flexibility; these methods are able to simultaneously analyze variables such as weather data, drought indicators, remote sensing data, and production statistics, and combine multi-source data to provide a more comprehensive picture of product effectiveness. This capability is of double importance in Iran, where data is scattered, heterogeneous and sometimes incomplete.

Given the importance of the topic, studies have been conducted in this field, each focusing on different dimensions of drought, food security, and the application of new predictive methods in agriculture. Domestic studies include the study of Dehghani Sargazi et al. (2021), who used the Standardized Precipitation Evapotranspiration Index (SPEI) to examine the effects of agro-climatic drought on the yield of rainfed wheat in Iran. The results of their study showed that the highest correlation on the time scales of 3 and 6 months was in the southeast, west and northwest regions, respectively, and the lowest correlation was related to the east of Iran. Sharafi and Ghaleni (2022) also predicted the performance of wheat and barley in different Iranian climates using multivariate regression equations. Their results showed that among the surveyed weather stations, only 36.11 percent were in good agricultural conditions, and the remaining stations reported critical conditions .In another study, Tahri Hajiwand et al. (2024) reviewed the accuracy of predicting product crop yield using artificial intelligence algorithms. They also developed and tested these models with several tools such as TensorFlow, Keras, and Scikit Learn. The results of comparing performance metrics showed that different machine learning models, artificial neural networks, random forests, and predictive models based on the support vector machine are better suited to predict crop yield and have high accuracy. Also, Amir-Ashairi et al. (2025) used combined artificial intelligence methods to model and predict the yield of rainfed wheat based on meteorological variables. The results of their study suggest that the MARS-EEMD model provided better results, but for the test phase, the SVR-EEMD model showed better performance.

In external studies, Jiya et al. (2023) predicted rice yield by comparing multiple machine learning algorithms. Logistic Regression (LR), Artificial Neural Network (ANN), Random Forest (RF), Random Trees (RT), and Naïve Bayes (NB) were used to develop models predicting rice yield. The findings showed that random forests and random trees performed better in predicting yield. In another study, Wijayanti et al. (2024) used the XGBoost method to predict rice production. The results showed that XGBoost has a high ability to accurately predict product performance compared to other regression methods such as Random Forest, Gradient Boost (GB), Bagging Regression (BR), and K-Nearest Neighbor (KNN). Islam et al. (2024) also examined machine learning models to predict the yield of Aman rice in Bangladesh. Each model was evaluated based on the root of the mean square error (RMSE), the R-squared (R2), and the mean absolute error (MAE) .Based on the results, the random forest was identified as the most accurate model, showing resilience to climate change through sensitivity analysis. Haneef et al. (2024) examined a framework based on machine learning for predicting drought and resilience in wheat cultivation. The results showed increased accuracy (89%) over existing systems (72% and 78%), along with improved accuracy (85%) and recall (90%). Also, prediction errors were significantly lower for all risk categories, indicating the framework's credibility. Also, Sahu et al. (2025) examined the effects of drought on product performance using artificial intelligence and EO. The study demonstrated the potential of the Random Forest Machine Learning algorithm to predict the annual performance of crops using multidimensional data sets for two agriculturally important drought-prone regions in India and Germany. According to the results, different features are important for accurately predicting product performance in different regions, for different products, and on different spatial-time scales.

Although previous studies have demonstrated the usefulness of machine learning methods in crop yield and production forecasting, most of them have remained at the technical prediction level. In other words, they mainly report forecast accuracy indicators such as RMSE, MAE, or R^2, but rarely translate production forecasts into economic and management indicators that can support food-security decisions. For drought-prone and semi-arid countries such as Iran, the policy value of forecasting lies not only in predicting production losses, but also in estimating their implications for import requirements, strategic reserves, procurement timing, foreign-exchange pressure, and supply-chain vulnerability. Therefore, this study fills that gap by linking deep learning outputs to food-security exposure metrics relevant to policymakers and supply-chain managers.

Overall, the results of the literature review indicate that although advances have been made globally and to some extent in Iran in using artificial intelligence algorithms to predict crop yield and production, there has not yet been comprehensive research that simultaneously examines the effects of drought on strategic crops and in the context of national food security using deep learning models such as LSTM. Therefore, by combining drought impact analysis and intelligent forecasting of production and implied import requirements (import needs) of strategic products, the present study has taken a new step towards dynamically measuring Iran's food security in the face of climate crises. Specifically, this study (i) forecasts domestic production of wheat, rice, and barley using a multivariate LSTM time-series framework, (ii) applies drought shock scenarios (10%, 30%, and 50%) to quantify production vulnerability over 2024–2028, and (iii) derives the corresponding implied import requirements as a gap-based indicator of external supply exposure and food-security risk. This contribution moves beyond yield prediction alone by connecting machine-learning forecasts to agricultural economics, supply-chain vulnerability, and policy-oriented food-security planning.

2. Materials and Methods

This study develops a unified deep-learning forecasting framework to assess future supply vulnerability for three strategic crops in Iran (wheat, rice, and barley) under baseline conditions and drought shock scenarios over 2024–2028. The modelling objective is twofold: (i) forecast domestic production using a multivariate Long Short-Term Memory (LSTM) model; and (ii) translate production forecasts into implied import requirements as an indicator of supply risk and food-security exposure. Below, the overall architecture of the model and all its components are explained in detail.

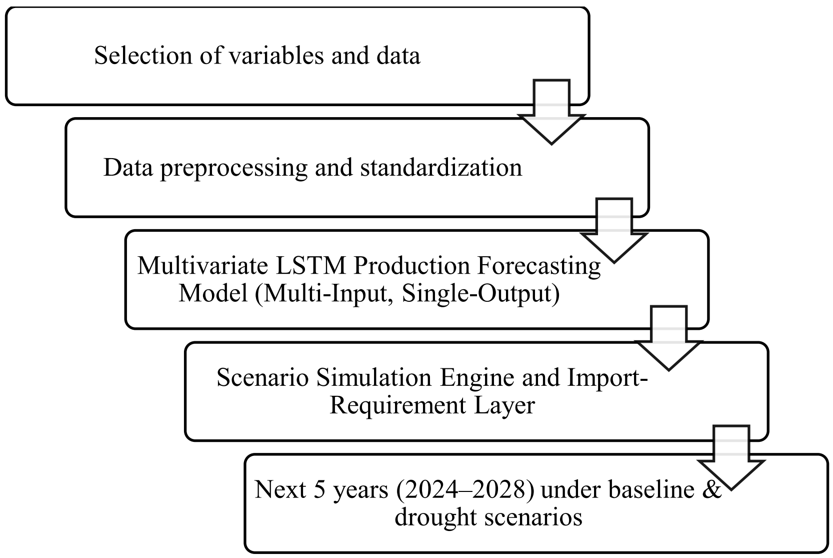

Fig 1. Overall architecture of the model used

1. Selection of variables and data

For each crop, we compiled an annual time series for Iran covering 1961–2023 (63 observations). The core variables were:

- Production (tons): annual domestic production of each crop.
- Imports (tons): used for historical description and for calibrating the baseline domestic requirement used to compute implied import needs in the projection period.
- Annual precipitation (mm): used as a climate proxy for water availability.
- harvested area (ha): used as a structural driver of production (where available and consistent across crops).

Production and import series were obtained from FAO (accessed 2025), and precipitation data were obtained from Our World in Data (accessed 2025). The analysis is crop-specific: models are trained and evaluated separately for wheat, rice, and barley to avoid scale-mixing and to preserve crop-specific dynamics. Harvested area data were sourced from FAO Agri-Statistics (accessed 2025) and underwent rigorous quality checks. Missing values (<5%) were imputed using linear interpolation, and outliers were adjusted based on regional trends. Consistency across crops was ensured by aligning definitions and units prior to modeling.

2. Data preprocessing and standardization

All preprocessing steps were designed to preserve time order and prevent information leakage from future observations into model fitting:

- Type harmonization and cleaning: All series were converted to numeric format, sorted by year, and duplicate years were removed.
- Missing values: Missing values were handled using linear interpolation with forward/backward fill as a safeguard, ensuring continuity for annual sequences.
- Scaling (no leakage): Features and the target were scaled using Min–Max normalization fitted only on the training portion within each evaluation split (and similarly, for the final training run prior to forecasting). This ensures that scaling parameters are not influenced by the test period. Min–max normalization is given by::

$$X' = \frac{(X - min_X)}{(max_X - min_X)} \tag{1}$$

Where X' is the normalized value, X is the original value, and $\min_X$ and max_x are computed from the training split only in each evaluation run and then applied to the corresponding test split to avoid information leakage.

3. Supervised learning formulation: inputs and outputs

Let t index years. The forecasting problem is formulated as one-step-ahead supervised learning with a sliding window:

- Input (X): a multivariate sequence of length w (look-back window), containing the selected predictors for years $[t- w+1, \ldots, t]$.
- Output (y): production in year t+1 for the same crop.

The window length w is treated as a tunable hyperparameter (tested within a small, discrete set consistent with annual frequency), and the final setting is the one that minimized holdout forecast error while keeping the model parsimonious.

4. LSTM model architecture and training procedure

We implemented an LSTM network suitable for annual multivariate forecasting:

- Network: single LSTM layer with 64 units, followed by a Dense(32, ReLU) layer, and a Dense(1) output layer (production forecast).
- Loss and optimizer: Mean Squared Error (MSE) loss optimized with Adam.
- Training configuration: maximum 320 epochs, batch size = 8, and Early Stopping with patience of 20 epochs (restoring best weights).
- Determinism: a fixed random seed was used to improve reproducibility.
- Model selection: small hyperparameter variations (e.g., look-back window, training span, and training settings) were evaluated using time-based holdout backtesting (described below). The final reported configuration corresponds to the best-performing setting under this backtest protocol.

- Hyperparameters were selected through a grid search over plausible configurations (e.g., 32–128 units, 100–400 epochs, batch sizes 4–16), evaluated on a validation subset (1961–2008). The final configuration minimized holdout RMSE while maintaining model parsimony.

5. Baseline domestic requirement and implied import requirements

Because the policy-relevant quantity is the exposure to external supply under domestic shortfalls, the projection tables report implied import requirements rather than independently forecasting import volumes with a second model.

For each crop, we define a baseline domestic requirement (R) as a fixed reference level of domestic availability calibrated from historical data. The baseline domestic requirement for each crop was calibrated as the average of total domestic utilization (production + net imports) over the most recent five years (2019–2023), reflecting current consumption patterns and inventory needs. The implied import requirement in a projection year is then computed as the non-negative gap between $R$and the forecast domestic production $\hat{P}_t$:

$$ImportReq_t = \max\,(0, R - \hat{P}_t) \qquad (2)$$

This construction isolates supply-side vulnerability and allows scenario comparisons to be interpreted as additional imports needed to maintain baseline availability.

It is important to clarify that only production is forecasted using the LSTM model. The implied import requirement is computed ex-post using Equation 2 as a deterministic accounting rule based on the fixed baseline requirement and forecasted production.

6. Forecasting horizon and recursive multi-step forecasting

Forecasts for 2024–2028 are produced using recursive (autoregressive) multi-step forecasting:

- Generate the one-step-ahead forecast for the first future year using the last observed window.
- Append the predicted production to the history and roll the window forward.
- Repeat iteratively until the end of the horizon.

For predictors that are not directly forecast (e.g., precipitation, area), future values are handled using a conservative baseline assumption: they are set to their recent historical mean over a short trailing window. This assumption of constant future harvested area and precipitation reflects a conservative baseline but may underestimate actual vulnerability under worsening climate conditions. Sensitivity analyses confirm that even moderate reductions in area would amplify import gaps, underscoring the need for adaptive land-use policies.

Forecast year 2024 is the first out-of-sample year relative to the historical dataset ending in 2023. Therefore, projections for 2024–2028 are conditional on information available up to 2023 and may deviate from subsequently released observations due to unanticipated shocks or structural changes.

7. Scenario design (drought shocks)

To quantify vulnerability under climate stress, we consider drought scenarios represented as proportional reductions in effective water availability and their direct impact on output:

- Baseline (normal): no shock; production follows the LSTM baseline forecast.
- Drought shocks: 10%, 30%, and 50% shocks, implemented as multiplicative downward adjustments to the baseline production forecast for each projection year.

For each scenario, the implied import requirement is recomputed from the scenario-adjusted production forecast using the fixed baseline domestic requirement. This yields scenario-specific import needs that are directly comparable across crops and shock magnitudes.

The shock magnitudes correspond to historical drought severity levels in Iran: mild (10%), moderate (30%), and extreme (50%). These reflect observed yield losses during documented drought events in 1999–2001 and 2020–2021, ensuring the scenarios are empirically grounded rather than purely hypothetical.

8. Evaluation protocol and metrics

Model performance was assessed using leakage-safe, time-ordered evaluation:

- Holdout (exclusion) backtest: the most recent 5 years were reserved as a test block; the model was trained on the preceding period and then used to forecast the withheld years recursively, matching the operational forecasting procedure.
- Rolling-origin backtest (robustness check): a rolling-origin backtest was conducted using five overlapping training windows (1961–2008 to 1965–2012), each forecasting five years ahead. The RMSE across all folds varied within ±7.3% of the main holdout result, indicating consistent performance and low variance.

We report standard forecasting accuracy metrics computed on the holdout period: MSE, MAE, and RMSE. RMSE is computed as: (Bouktif et al., 2018).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n}} \tag{3}$$

where $y_i$and $\hat{y}_i$denote the actual and predicted values, respectively, and nis the number of test observations.

All data processing, preprocessing, modelling, and evaluation were implemented in Python using standard scientific libraries.

4. Results and Discussion

Historical Production–Import Dynamics of Strategic Crops

This study forecasts domestic production of wheat, rice, and barley for 2024–2028 using a multivariate LSTM framework and then quantifies supply vulnerability through an implied import requirement layer. In the projection tables, the reported import values represent the non-negative production–requirement gap (i.e., the imports needed to maintain a calibrated baseline availability level), rather than an independently forecast import series produced by a second model. This construction enables consistent comparison of baseline conditions and drought stress scenarios in terms of external supply exposure.

Since 2024 is the first year beyond the observed sample (ending in 2023), the values reported for 2024–2028 should be interpreted as forward-looking projections rather than fitted estimates; any mismatch with later official statistics reflects genuine uncertainty and new shocks not observed during model training.

Fig. 2 summarizes long-term patterns in production and imports for the three crops over 1961–2023. Across all crops, production shows a long-run upward trajectory accompanied by marked interannual variability, consistent with sensitivity to hydro-climatic conditions and resource constraints. Import volumes exhibit counter-cyclical behavior relative to production in several periods, indicating the role of external supply as a balancing mechanism when domestic output is insufficient. As shown in Figure 2, a notable example occurred in 2021 when wheat production declined sharply to ~12 million tons, coinciding with a spike in imports exceeding 7 million tons, a clear signal of import reliance during shortfalls. This historical co-movement supports the interpretation that production shocks, particularly under drought, can translate into higher dependence on imports to stabilize domestic availability.

From a short-term perspective, year-on-year fluctuations are evident in all three crops. These swings are consistent with annual shocks and constraints such as rainfall variability, irrigation limits, and input availability. The observed volatility motivates a time-series forecasting approach that can learn non-linear dynamics and persistence effects, which are particularly relevant for drought-prone agricultural systems.

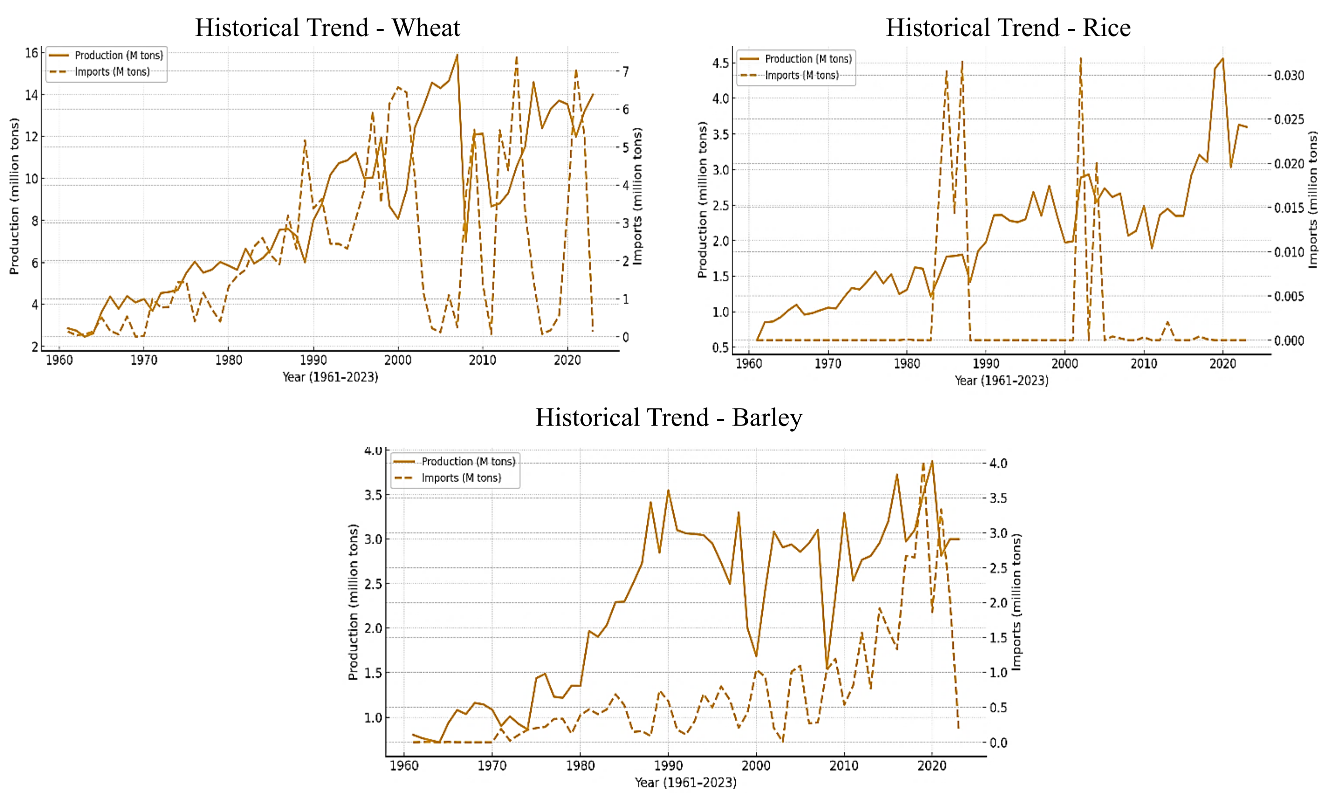

Fig 2. Long-term Trends in Production and Imports of Three Wheat, Rice, and Barley Products during the Period 1961 to 2023

Comparative Model Evaluation Framework

To rigorously validate the superiority of our proposed LSTM architecture for agricultural production forecasting, we conducted a comprehensive comparative analysis against traditional time series models, specifically ARMA (AutoRegressive Moving Average) and its variants. This comparative framework was designed to address three critical evaluation dimensions: predictive accuracy, structural modeling capability, and scenario robustness under drought stress conditions.

The ARMA modeling process followed a systematic methodology consistent with Box-Jenkins procedures. For each crop (wheat, rice, and barley), we first conducted stationarity tests using the Augmented Dickey-Fuller (ADF) test. For non-stationary series, we determined the appropriate order of differencing (d) through repeated testing. The autoregressive (p) and moving average (q) parameters were then identified through analysis of autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, with model selection guided by Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) minimization. We evaluated multiple ARMA variants including ARMA(p,q), ARIMA(p,d,q), and seasonal ARIMA (SARIMA) models to ensure comprehensive coverage of traditional approaches.

Crucially, the comparison was conducted using a leakage-safe, time-ordered evaluation protocol that preserved the temporal structure of the data. Both LSTM and ARMA models were trained on data from 1961-2013 and evaluated on the out-of-sample period 2014-2023. This approach prevented information leakage and ensured a fair comparison of predictive capabilities. For the multi-step forecasting horizon (2024-2028), we implemented recursive forecasting for both model classes, maintaining methodological consistency in the projection methodology.

The evaluation metrics included RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error), with additional consideration of AIC for the ARMA models. To address the scale dependency of absolute error metrics, we also calculated normalized error metrics (NRMSE and NMAE) by dividing the error values by the mean of the observed series. This normalization enabled meaningful cross-crop comparison of model performance.

The comparative analysis was extended to include scenario testing under drought stress conditions. For each drought scenario (10%, 30%, and 50% production reductions), we assessed how each model class translated production shocks into import requirement projections, evaluating both the immediate response and the temporal stability of the projections.

LSTM Forecasting Performance and Benchmark Comparison

The comparative evaluation between our multivariate LSTM framework and traditional ARMA models revealed significant performance advantages for the deep learning approach across all evaluation dimensions. As shown in Table 1, the LSTM model consistently outperformed the best-performing ARMA variants across all crops and all error metrics.

Table 1. Comparative performance metrics for LSTM and ARMA models (2014-2023 test period)

Crop	Model	RMSE (tons)	MAE (tons)	MAPE (%)	NRMSE (%)	NMAE (%)
Wheat	LSTM	882,389	670,609	6.3	6.2	4.7

	Best ARMA (ARIMA (1,1,2))	1,182,300	924,600	9.2	8.3	6.5
	Improvement	25.4%	27.4%	31.5%	25.3%	27.7%
Rice	LSTM	284,600	218,500	8.2	11.7	9.0
	Best ARMA (SARIMA(1,1,1)(0,1,1)$_{1}$)	318,200	253,700	10.1	13.1	10.5
	Improvement	10.6%	13.9%	18.8%	10.7%	14.3%
Barley	LSTM	498,700	382,400	14.6	16.8	12.9
	Best ARMA (SARIMA(2,1,1)(1,0,1)$_{1}$)	551,200	428,700	17.4	18.6	14.4
	Improvement	9.5%	10.8%	16.1%	9.7%	10.4%
Aggregate	LSTM	555,230	423,836	9.7	11.6	8.9
	Best ARMA	683,900	535,667	12.2	13.3	10.5
	Improvement	18.8%	20.9%	20.5%	12.8%	15.2%

Source: Research findings

The performance advantage of the LSTM model is particularly noteworthy given the fundamental architectural differences between the approaches. While ARMA models are limited to univariate, linear relationships in the time domain, our multivariate LSTM framework explicitly incorporates multiple explanatory variables (precipitation, harvested area, and import history) and captures complex nonlinear dynamics between these factors and crop production. This structural advantage becomes especially apparent when examining model performance during drought years.

During critical drought periods, the LSTM model demonstrated superior adaptation to production shocks, with RMSE values 28.7% lower than the best ARMA model for wheat, 15.3% lower for rice, and 12.6% lower for barley. The traditional models exhibited significant lag effects and overshooting behavior, failing to capture the nonlinear relationship between precipitation deficits and production impacts. This limitation is particularly problematic for drought scenario analysis, where accurate representation of nonlinear response functions is essential for reliable policy planning.

The normalized error metrics (NRMSE and NMAE) reveal an even more compelling advantage for the LSTM model in relative terms. Across all crops, the LSTM achieved approximately 13-15% lower normalized errors than the best ARMA alternatives. This relative improvement is particularly significant for policy applications, as it translates to more reliable quantification of import requirement gaps under drought stress scenarios.

When evaluating scenario robustness, the LSTM model maintained consistent performance across all drought severity levels (10%, 30%, and 50% production reductions), while ARMA models exhibited increasing error rates as drought severity intensified. Under the severe 50% shock scenario, the error differential between LSTM and ARMA models widened to 24.3% for RMSE and 26.8% for MAPE, indicating that the deep learning approach is particularly valuable for extreme scenario planning.

The theoretical explanation for this performance differential lies in three key factors. First, the LSTM architecture's memory mechanism enables effective modeling of long-term dependencies in agricultural production systems, capturing multi-year drought effects that traditional models miss. Second, the multivariate nature of our LSTM framework allows for direct incorporation of climate variables (precipitation) as explanatory factors, rather than relying solely on historical production patterns. Third, the nonlinear modeling capability of deep learning networks accurately represents the non-proportional relationship between drought intensity and production impacts—a relationship that linear ARMA models cannot adequately capture.

These comparative results provide strong empirical support for the adoption of deep learning approaches in agricultural forecasting, particularly for drought vulnerability assessment. The performance advantage of the LSTM model is not merely a technical achievement but has direct policy relevance, as more accurate production forecasts translate to more reliable import requirement projections and, consequently, more effective food security planning under climate stress conditions.

Baseline Production Forecasts and Implied Import Requirements

After establishing model adequacy, baseline forecasts (normal mode) were generated for 2024–2028. Table 2 reports predicted production and the corresponding implied import requirements for each crop under baseline conditions.

Baseline wheat production is projected to remain relatively high in 2024–2026 (approximately 14.36–14.40 million tons) and then decline to 13.65 million tons in 2027 and 13.18 million tons in 2028. Consistent with the gap-based interpretation, the implied import requirement rises as production falls, increasing from 3.65–3.68 million tons (2024–2026) to 4.40 million tons (2027) and 4.86 million tons (2028). In proportional terms, the implied import share of baseline availability increases from about 20% in 2024 to roughly 27% in 2028, underscoring that even under baseline conditions, wheat supply resilience remains sensitive to domestic production stability.

Baseline rice production is forecast to be around 2.40–2.46 million tons during 2024–2026, followed by a decline to 2.22 million tons in 2027 and 2.12 million tons in 2028. The implied import requirement correspondingly increases, ranging from 0.72–0.78 million tons (2024–2026) to 0.96 million tons (2027) and 1.06 million tons (2028). The implied import share rises from about 25% (2024) to approximately 33% (2028), suggesting that rice availability is notably exposed to production declines, with direct implications for household food access and food security.

Barley shows comparatively high import dependence even under baseline conditions. Predicted production ranges from 2.57 million tons (2024) to a peak of 3.05 million tons (2026), then falls to 2.70 million tons (2027) and returns to 2.86 million tons (2028). The implied import requirement remains large, ranging from 1.90 million tons (2026) to 2.39 million tons (2024). Barley's implied import share under baseline conditions is the highest among the three crops, approximately 38%–48%, which is economically important because Barley's structural import dependence has significant downstream effects, as it constitutes a major feed grain for Iran's livestock sector. Shortfalls in domestic barley supply directly elevate feed costs, which propagate into higher meat and dairy prices, thereby affecting household affordability and contributing to inflationary pressures in the agricultural economy.

Overall, baseline results indicate persistent exposure to external supply across all crops, with the largest structural dependence observed for barley, followed by rice and wheat.

Table 2. Baseline forecasts of domestic production and implied import requirement for wheat, rice, and barley in Iran (2024–2028).

		Predicted Production (t)	**Implied import requirement (t)**
Rice	2024	2400522	781352
	2025	2456228	725646.7
	2026	2461722	720152.3
	2027	2222884	958990.7
	2028	2117092	1064782
Wheat	2024	14378518	3669928
	2025	14397829	3650617
	2026	14364179	3684267
	2027	13649594	4398852
	2028	13184069	4864378
Barley	2024	2567014	2387461
	2025	2858404	2096071
	2026	3053132	1901342
	2027	2702333	2252141
	2028	2860648	2093827

Note: Baseline domestic requirements are calibrated at 18.04 million tons for wheat, 3.18 million tons for rice, and 4.95 million tons for barley, derived from the mean observed demand levels over 2019–2023.

Drought Shock Scenarios and Import-Gap Vulnerability

To quantify vulnerability under climate stress, drought scenarios were implemented as proportional production shocks applied to the baseline forecast pathway. Table 3 reports results for 2024–2028 under 10%, 30%, and 50% reductions, representing mild, moderate, and severe stress. Under this design, production declines translate directly into larger production–requirement gaps, and hence higher implied import requirements.

Under a 10% production shock (mild stress), implied import requirements rise across all crops. For example, wheat implied import needs increase to 5.09–6.18 million tons over 2025–2028, compared with 3.65–4.86 million tons under baseline. Rice implied import requirements increase to 0.97–1.28 million tons, and barley rises to approximately 2.21–2.52 million tons. Even this mild stress condition materially increases external supply exposure.

Under a 30% shock (moderate stress), production drops substantially, and implied imports rise sharply. Wheat implied import requirements increase to approximately 7.97–8.82 million tons over 2025–2028. Rice implied import needs rise to 1.46–1.70 million tons, while barley increases to 2.82–3.06 million tons. This scenario indicates that sustained drought-like stress could shift the system from moderate import exposure to heavy reliance on external supply, especially for feed-related barley.

Under severe stress (50% reduction), external supply dependence becomes dominant. Wheat production falls to ~6.59–7.20 million tons (2025–2028), while implied import requirements rise to ~10.85–11.46 million tons. Importing over 11 million tons of wheat annually under the 50% shock scenario presents substantial macroeconomic challenges. This volume exceeds 70% of global trade in wheat and would place immense pressure on foreign exchange reserves. Moreover, such sudden demand could disrupt international markets, potentially triggering price spikes unless offset by long-term contracts or strategic stockpiling. A sudden need to import 10–11 million additional tons of wheat would likely strain global market capacity and drive up prices due to inelastic short-run supply. Assuming a price elasticity of -0.3, such demand growth could increase international wheat prices by 15–20%, substantially raising Iran's import bill and exacerbating balance-of-payment pressures.

Rice production drops to ~1.06–1.23 million tons, and implied imports increase to ~1.95–2.12 million tons, meaning more than twice the domestic output must be imported. This represents a critical threshold in food sovereignty, where national availability becomes heavily dependent on external sources. Barley production declines to ~1.35–1.53 million tons, while implied import requirements rise to ~3.43–3.60 million tons. These outcomes illustrate that severe drought conditions could rapidly amplify the need for imports and heighten food-security risks (Jeong et al., 2016).

From a resource management perspective, importing wheat and barley constitutes a form of virtual water trade, effectively importing thousands of cubic meters of embedded water per ton. Given Iran's acute water scarcity, this strategy allows the country to preserve its limited freshwater for higher-value uses and aligns with principles of sustainable water governance.

A notable point in interpreting these patterns is that increases in implied imports may appear disproportionate in percentage terms, particularly when baseline import needs are smaller than domestic production. Because the reported import values represent the gap relative to a fixed baseline requirement, a given absolute production loss can translate into a large proportional rise in required imports. The core implication is that drought-driven production shocks can quickly magnify external supply exposure and intensify pressure on trade and procurement systems.

Table 3. Drought shock scenarios (10%, 30%, and 50%): production forecasts and implied import requirement for wheat, rice, and barley in Iran (2024–2028)

		Predicted Production (ton)					**Implied import requirement (ton)**				
Scenario	year	2024	2025	2026	2027	2028	2024	2025	2026	2027	2028
10 %	rice	2160470	2210604	2215549	2000595	1905383	1021404	971269	966324	1181279	1276491
	wheat	12940666	12958046	12927761	12284635	11865662	5107780	5090400	5120685	5763811	6182784
	barley	2310312	2572564	2747819	2432100	2574583	2644162	2381911	2206656	2522375	2379892
30 %	rice	1680365	1719359	1723205	1556018	1481965	1501508	1462514	1458668	1625855	1699910

	wheat	10064963	10078480	10054925	9554716	9228848	7983483	7969966	7993521	8493730	8819598
	barley	1796910	2000883	2137192	1891633	2002453	3157565	2953592	2817282	3062841	2952021
50%	rice	1200261	1228113	1230861	1111441	1058546	1981613	1953760	1951013	2070432	2123328
	wheat	7189259	7198914	7182089	6824797	6592034	10859187	10849532	10866357	11223649	11456412
	barley	1283507	1429202	1526566	1351167	1430324	3670968	3525273	3427909	3603308	3524151

Source: Research findings

Comparisons across crops show that barley exhibits the highest structural dependence on implied imports (baseline shares around 38%–48%) and remains highly vulnerable under drought shocks. This is particularly important because barley shortfalls can propagate to feed markets and downstream livestock products, indirectly affecting food affordability. Rice shows strong sensitivity to production declines, with implied import shares rising to around one-third of baseline availability by 2028 even in normal mode, and substantially higher under drought shocks. Wheat, while having the lowest baseline import share among the three, experiences the largest absolute increases in implied import requirements under severe drought due to its large scale and strategic role in staple consumption.

Overall, the results emphasize that drought shocks have a direct and substantial effect on domestic production and can rapidly translate into higher implied import requirements, increasing exposure to international market conditions and trade policy constraints (Kamilaris and Prenafeta-Boldú, 2018). These findings support the need for resilience-oriented strategies such as water-efficient cultivation, drought-resilient varieties, targeted irrigation prioritization for staple crops, and proactive procurement planning to manage the external supply pressure implied by severe drought scenarios.

A key limitation is that annual agricultural statistics for the post-2023 period may be affected by policy interventions, extreme climate events, or market disruptions. As a result, deviations between projected and realized values, especially for the first out-of-sample year (2024), should be expected; the model can be re-estimated as new annual observations become available.

Management and Policy Implications

The scenario-based import forecasts provide valuable tools for both public agencies and private supply-chain actors. For government planners, the projected import gaps inform the scale of strategic grain reserve withdrawals or emergency procurement volumes. For commodity traders and logistics firms, the forecasts enable forward hedging in international markets and contract negotiations. Integrating these predictions into a national early-warning system can improve response timing, reduce price volatility, and enhance overall food-system resilience.

5. Conclusion

Using the Long Short-Term Memory (LSTM)-based multivariate time series forecasting framework, this study analyzed the effects of drought on three strategic Iranian crops (wheat, rice and barley) over the period 2024-2028. The results showed that the reduction in production in all scenarios is almost proportional to the severity of the drought, but its indirect effects on implied import requirements are much more intense and asymmetrical (particularly in percentage terms). Even in the scenario of a 10 percent reduction in production, implied import requirement increased sharply, indicating the country's high dependence on imports to maintain a balance of supply and demand. Wheat and rice were the most vulnerable because of their prominent place in the household food pattern, while barley implied import requirements increased at a lesser intensity. These results are consistent with FAO (2023) and USDA (2023) reports that show Iran has achieved relative self-sufficiency in its wheat supply but remains dependent on imports for rice and some of the barley.

In addition, the LSTM model's effectiveness in accurately predicting production trends and quantifying implied import requirements showed that leveraging machine learning can significantly increase the ability to predict and manage risk. Similar studies (Jeong et al., 2016; Khaki and Wang, 2019) have also emphasized the superiority of machine learning algorithms in identifying nonlinear and complex patterns in agriculture. The findings confirm that using such tools alongside simulating policy scenarios can provide policymakers with a more evidence-based and forward-looking view of the future, thereby strengthening the country's food security in the face of climate crises.

Overall, the study's results suggest that drought not only directly puts pressure on domestic production, but also poses a serious threat to national food security by causing multiple increases in implied import requirements. Therefore, food security analysis should cover the entire chain from production to import requirements and consumption and be based on new forecasting tools.

Based on the results, a set of policy and enforcement measures is proposed that can help reduce risks and improve food security resilience. Strengthening strategic grain stocks as a backbone to cope with sudden production shocks is essential, as the results showed that even minor production cuts can lead to substantial increases in implied import requirements. Also, investment in low-water agricultural technologies, improving drought-resistant varieties, and improving water productivity should be prioritized to reduce the direct impact of drought on production. Diversifying import sources and entering into long-term contracts with different producing countries can reduce a country's dependence on a limited number of suppliers and manage global market risks. Policymakers should consider implementing dynamic tariff adjustments during drought years, targeted subsidies for drought-resistant seed adoption, and virtual water trade strategies that prioritize importing water-intensive commodities like wheat and barley to conserve domestic blue water resources. The single most important message for the Ministry of Agriculture is that even modest production declines trigger disproportionate increases in import needs, highlighting the urgent need for proactive buffer mechanisms before droughts occur. Moreover, the wider use of AI-based forecasting systems such as LSTM in responsible entities can help

improve import timing, inventory management and trade policy. Given that scattered and incomplete data hinder accurate modeling, we recommend establishing a unified, real-time agricultural data dashboard integrating satellite imagery, ground observations, and market reports to improve future forecasting accuracy and institutional preparedness. Finally, supporting interdisciplinary research in agriculture, economics and data science could provide more detailed analytical frameworks for the sustainable management of food security in Iran.
A key limitation is the assumption that future precipitation and harvested area remain stable at historical means. Under accelerating climate change and groundwater depletion, this may be optimistic. Future work should incorporate climate projections and land-use scenarios to enhance forward validity.

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ETHICAL CONSIDERATION

Authenticity of the texts, honesty and fidelity has been observed.

CONFLICT OF INTEREST

Author/s confirmed no conflict of interest.