

Correction

Correction: Wang, M.; Li, T. Pest and Disease Prediction and Management for Sugarcane Using a Hybrid Autoregressive Integrated Moving Average—A Long Short-Term Memory Model. *Agriculture* 2025, 15, 500

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In the original publication [1], all references were not cited in correct order in Section “1. Introduction” for paragraph numbers 1, 2, 3, and 4. Now, 9 references in the main text were deleted, and reference 5 was replaced with another reference. The reference citations and reference list have been renumbered.

The paragraph numbers 1, 2, 3, and 4 in Section “1. Introduction” should read:

The challenges facing agricultural production are increasing with global climate change, the expansion of agricultural production and the increased complexity of pests and diseases. Accurate prediction and management of pests and diseases has become a key issue in ensuring food security and sustainable agricultural development. Sugarcane is one of the most important commercial crops globally, contributing significantly to the economies of major producing countries such as Brazil, India, China, and Thailand. According to the FAO, global sugarcane production exceeds 1.9 billion tons annually, and the industry supports millions of livelihoods. However, pests and diseases such as sugarcane borers, smut, and rust have led to substantial yield losses, often exceeding 20% in severely affected regions, translating into billions of dollars in economic losses. Thus, accurate prediction and management of sugarcane pests and diseases are critical for ensuring global food security, sustaining agricultural productivity, and protecting economic interests [1,2]. Traditional statistical models such as ARIMA are well-established for time series forecasting due to their ability to capture linear trends and seasonal variations. However, agricultural pest and disease data exhibit highly nonlinear and dynamic characteristics influenced by multiple exogenous variables such as temperature, humidity, and rainfall. These factors introduce complex dependencies that linear models alone fail to capture, leading to suboptimal predictions. Machine learning models, particularly deep learning-based approaches like Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in handling long-term dependencies and nonlinear data structures. By integrating ARIMA and LSTM into a hybrid framework, we can leverage ARIMA’s strength in linear trend detection and LSTM’s capability in nonlinear feature extraction, significantly enhancing predictive accuracy and robustness [3]. Consequently, there is a pressing requirement for more precise models that offer enhanced predictive capabilities to assist farmers and agricultural managers in addressing these issues [4].

In recent times, the advancement of big data and artificial intelligence (AI) technologies has led to notable advancements in the prediction of agricultural pests and diseases.



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Conventional time series forecasting techniques, including the autoregressive integrated moving average (ARIMA) model, have been extensively applied for forecasting agricultural yields as well as monitoring pests and diseases [3]. The ARIMA model is particularly effective in managing linear datasets and is well-suited for identifying long-term trends and seasonal variations in time series data [5]. However, due to the complexity and dynamics of agricultural production data, it is difficult for a single linear model to cope with the challenges of nonlinearity and long- and short-term dependencies. Therefore, scholars have begun to combine traditional statistical models with deep learning models to form hybrid models to improve prediction performance. Thus, hybrid models of big data and machine learning are gradually showing [6–8] strong advantages in agricultural pest and disease prediction. In particular, hybrid models combining ARIMA with Long Short-Term Memory (LSTM) neural networks excel in handling both linear and nonlinear data [9]. For example, ARIMA models are able to capture linear trends in time series, while LSTMs are able to effectively deal with nonlinear features and long- and short-term dependencies in serial data, thereby improving the accuracy of forecasts [1,10–12]. In research on agricultural pests and diseases, a variety of hybrid models have been applied to different crop and pest prediction scenarios. For example, Guo et al. [13]. In their prediction of the incidence of hepatitis B, verified that a model combining ARIMA and LSTM can effectively cope with seasonal fluctuations and substantially improve prediction accuracy. Similarly, Dhawan demonstrated the significant advantage of hybrid models in nonlinear data processing in a prediction study of sugarcane disease [14]. In addition, other studies have accurately predicted apple pests and diseases [15,16], cotton pests and diseases by fusing convolutional neural network (CNN) and LSTM models, which demonstrated the ability of hybrid models to incorporate a variety of data sources to further improve prediction accuracy [17,18].

In addition, in predicting agricultural pests and diseases, not only the data of the crop itself, but also external environmental factors such as weather and climate change need to be considered. Studies have shown that weather data have a significant impact on the occurrence of pests and diseases [1,19] introduced the Standardized Precipitation Evapotranspiration Index (SPEI) through an ARIMA-LSTM model in a drought prediction study in China and demonstrated that this hybrid model can effectively predict the impact of climate change on crop growth [20,21]. The combination of ARIMA with models such as support vector regression (SVR) and least squares support vector machine (LS-SVR) has also demonstrated high prediction accuracy in studies on the effects of climatic factors on pest and disease occurrence [10,22]. However, how to select appropriate models in specific agricultural scenarios and improve their prediction ability for complex pests and diseases remains an important challenge in current research [23].

This study presents an innovative hybrid ARIMA-LSTM model tailored for sugarcane pest and disease prediction, marking a significant advancement in agricultural forecasting. Unlike previous works that rely solely on either statistical or deep learning models, our approach systematically integrates the strengths of both methodologies. Moreover, we enhance prediction performance by incorporating exogenous climate variables, such as temperature and precipitation, into the modeling process. This hybrid framework not only improves forecasting accuracy but also provides actionable insights for precision agriculture, enabling farmers and policymakers to implement timely and effective disease control strategies. Our contribution lies in the novel fusion of time series statistical methods and deep learning techniques to develop a robust, data-driven decision-support tool for sustainable sugarcane production. In this study, we first modeled the linear characteristics of the pest and disease time series using the ARIMA model, and captured the potential nonlinear relationships and complex dynamics in the time series by LSTM [1,24]. In

addition, we further enhanced the predictive power of the model by introducing exogenous variables such as weather data [15,19]. The approach in this study echoes previous studies, for example, the model combining ARIMA and dynamic support vector machine (SVM) performed well in predicting the tree pest *Dendrolimus punctatus* [25], while in predicting, for example, cotton pests and apple diseases, the LSTM hybrid model also showed highlight predictive ability [19,26]. Suresh and Priya predicted sugarcane yields in India through an ARIMA model, and although the results showed its effectiveness in capturing linear trends, the performance of a single model was still limited when faced with the complex prediction of pest and disease [3,27]. By combining ARIMA and LSTM, the hybrid model proposed in this paper is not only capable of capturing linear and nonlinear variations in pest and disease time series, but also incorporates external environmental factors to enhance the robustness of forecasts [23,28].

The list of updated and rearranged references is as follows:

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The authors state that the scientific conclusions are unaffected. This correction was approved by the Academic Editor. The original publication has also been updated.

Reference

1. Wang, M.; Li, T. Pest and Disease Prediction and Management for Sugarcane Using a Hybrid Autoregressive Integrated Moving Average—A Long Short-Term Memory Model. *Agriculture* **2025**, *15*, 500. [[CrossRef](#)]

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