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Assessing the suitability of different modeling techniques for meteorological forecasting on Chickpea wilt

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सार – 1 नवंबर, 1977 से 30 अप्रैल, 2022 के बीच हिसार जिले के लिए एकत्र किए गए दैनिक जलवायु डेटा का विश्लेषण किया गया है और इस अध्ययन में प्रस्तुत किया गया है। डेटा सेट को दो भागों में विभाजित किया गया था: प्रशिक्षण और परीक्षण डेटा। यह अध्ययन अधिकतम तापमान, न्यूनतम तापमान, सापेक्ष आर्द्रता (एम), सापेक्ष आर्द्रता (ई), तेज धूप के घंटे और वर्षा के लिए फिट किए गए एआरआईएमए, राज्य स्थान और मौसमी होल्ट-विंटर्स मॉडल के परिणाम प्रस्तुत करता है। मॉडल नवंबर 1977 से अप्रैल 2013 तक के डेटा पर प्रशिक्षित किए गए थे। शीर्ष चयनित एआरआईएमए मॉडल को मूल्यांकन मानदंडों के आधार पर चुना गया था, जैसे कि अकाइक सूचना मानदंड, मूल माध्य वर्ग त्रुटि, माध्य निरपेक्ष त्रुटि, माध्य निरपेक्ष प्रतिशत त्रुटि, इन-सैंपल एमएसई और महत्वपूर्ण गुणांकों की अधिकतम संख्या। स्टेट स्पेस मॉडल का चयन अकाइक सूचना मानदंड (AIC), बायेसियन सूचना मानदंड (BIC), रूट मीन स्क्वैयर्ड एरर (RMSE), मीन एब्सोल्यूट एरर (MAE), इन-सैंपल मीन स्क्वैयर्ड एरर (MSE) और मीन एब्सोल्यूट पर्सेंटेज एरर (MAPE) के न्यूनतम मानों के आधार पर किया गया था। मौसमी होल्ट-विंटर्स मॉडल को एडिटिव स्पेसिफिकेशन और 365 की अवधि के साथ फिट किया गया था। वैश्विक चना उत्पादन विभिन्न जैविक और अजैविक तनावों पर अत्यधिक निर्भर है। महत्वपूर्ण जैविक तनावों में से एक, फ्यूजेरियम विल्ट, चने की उत्पादकता को काफी हद तक सीमित कर देता है, जिससे कई देशों में 10 से 40% तक का आर्थिक नुकसान होता है और तापमान और आर्द्रता अनुकूल होने पर यह 100% तक बढ़ जाता है। मौसम का पूर्वानुमान पौधों की बीमारी के प्रबंधन में महत्वपूर्ण है क्योंकि यह मौसम की स्थिति रोगजनक विकास और प्रसार को कैसे प्रभावित करती है, इसका विश्लेषण करके रोग के प्रकोप की भविष्यवाणी करने में मदद करता है, जिससे किसानों को समय पर निवारक उपाय करने में मदद मिलती है।

ABSTRACT. The daily climate data collected for Hisar district between November 1, 1977 and April 30, 2022, has been analyzed and presented in this study. The data set was divided into two parts: training and testing data. This study presents the results of ARIMA, state space, and seasonal Holt-Winters models fitted for maximum temperature, minimum temperature, relative humidity (M), relative humidity (E), bright sunshine hours, and rainfall. The models were trained on data spanning from November 1977 to April 2013. The top selected ARIMA models were chosen based on evaluation criteria, such as the Akaike information criterion, root mean squared error, mean absolute error, mean absolute percentage error, in-sample MSE, and the maximum number of significant coefficients. The state space models were selected based on minimum values of the Akaike information criterion (AIC), Bayesian information criterion (BIC), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), in-sample Mean Squared Error (MSE), and Mean Absolute

PercentageError (MAPE). The seasonal Holt-Winters models were fitted with additive specifications and a period of 365. Global chickpea production is highly dependent on various biotic and abiotic stresses. One of the critical biotic stresses, *Fusarium* wilt, significantly limits chickpea productivity causing economic losses ranging from 10 to 40% in many countries and escalates to 100% when temperature and humidity are favourable. Weather forecasting is crucial in plant disease management as it helps to predict disease outbreaks by analyzing how weather conditions influence pathogen development and spread, allowing farmers to take timely preventative measures.

Key words – ARIMA, State space, Seasonal Holt-Winters, Time series data, Forecasting, Climate patterns.

1. Introduction

Weather forecasts is an application of Science and Technology to predict the state of atmosphere based on the data collected on temperature and precipitation. The attributes of weather make it inevitably difficult to predict weather phenomena with accuracy. It is crucial not only for disaster management, but also for other industries, like agriculture, etc. The search for an accurate forecasting tool thus takes on methodological significance. The availability and extraction of data, along with technological advancements, have revolutionized and changed meteorological forecasting. Sophisticated numerical models, machine learning algorithms, and artificial intelligence (AI) techniques have supplemented and, in some cases, supplanted traditional forecasting methods, which were based on empirical observations and statistical analysis (Carbonell *et al*., 2013). The goal of this study is to evaluate the applicability of different modelling approaches for meteorological forecasting.

Chickpea (*Cicer arietinum*) is an important *Rabi* pulse crop grown worldwide and plays a vital role for its nutritional value in the diets of millions of people, especially in developing countries, providing an essential source of protein, calcium, iron, phosphorus, and other minerals (Merga, B. & Haji, J. 2019) Approximately 12 million tonnes of chickpea are produced annually, with India contributing approximately 64%, followed by Australia holding 7% of the global share (ABARES 2021) The environmental factors, *viz*., atmospheric temperature, relative humidity, soil temperature, soil moisture and rainfall plays a vital role in prevalence of Fusarium wilt in chickpea (Merkuz and Getachew, 2012). Wilt disease sometimes escalates to 100% when the relative humidity is greater than 60% and the temperature ranges between 10 and 25 °C (Pande *et al.*, 2013).

Monitoring the weather parameters before cropping season or during the intercrop period helps in determining the efficiency of over wintering propagules in initiating the epidemics. For most plant diseases such as Fusarium wilt, the initial inoculum determines the severity and rate of epidemics which is governed by those overwintering propagules. Epidemiology deals with the population of pathogen on host under the influence of environment in a particular time, it is therefore essential to study the effects of all environmental factors, which involved in buildup of epidemic. For this purpose it is important to collect detailed information regarding the host, pathogen and environmental factors which may lead to development of epidemics. Understanding the epidemiology of chickpea wilt disease will enable us to precisely forecast its development, which will ultimately help the farmers to take up plant protection measures more accurately.

Hisar district, located in the state of Haryana, India, is an important agricultural region known for its production of crops such as wheat, cotton, chickpeaand mustard. The district's economy is heavily dependent on agriculture, which is highly sensitive to climate variability and weather conditions. Accurate weather forecasting is crucial for farmers in Hisar district to make informed decisions regarding crop management, irrigation scheduling, and pest control. Moreover, the district has experienced significant climate change in recent years, with increasing temperatures and changing precipitation patterns (Mishra *et al*., 2014a, 2014b). These changes have posed challenges to agricultural productivity and highlighted the need for reliable weather forecasting tools. By focusing on Hisar district, this study aims to provide insights into the effectiveness of different modeling approaches in capturing the unique climate characteristics of the region and supporting agricultural decision-makingespecially w.r.t. chickpea wilt.

The use of time series analysis as a method for researching data trends is growing in popularity. Then, to get there, we employ machine learning and error-free deep learning. Even when the weather is only slightly off, farmers never the less suffer a great deal from the weather's unpredictable character. Time series modelling is widely used to increase the veracity of weather forecasts. Sunlight, humidity, and temperature are all crucial for the growth and development of plants. The dew point temperature and relative humidity can be used to determine the amount of moisture in the air (Shrestha, 2019). In addition, plants require other conditions, like the proper temperature and adequate sunlight. According to Easterling *et al*. (2000), preliminary findings from this study indicate that there may be a narrower maximum-minimum temperature difference, which could have detrimental effects on agriculture. Between 1950 and 2008, there were significant regional variations in temperature and humidity, among other climatic parameters (Mishra *et al.*, 2014a, 2014b). Mishra *et al*. (2014b) state that throughout the previous few decades, precipitation has declined, temperatures have climbed over most of India, and as a result, so have the frequency of droughts and soil moisture for agricultural development. Utilizing state-of-the-art technology and analytical techniques, meteorologists and climate scientists work to produce forecasts that address long-term climate patterns in addition to short-term changes. A number of modelling techniques, from the conventional to the cutting edge, have been developed in this pursuit.

Despite the advancements in weather forecasting techniques, there remains a gap in the literature regarding the comprehensive evaluation and comparison of different modeling approaches for meteorological forecasting in specific regions. While numerous studies have applied various forecasting methods to weather data, few have conducted a thorough assessment of multiple techniques using a wide range of evaluation criteria and focusing on a particular district. Moreover, the majority of existing studies have focused on short-term forecasting, leaving room for exploration of long-term forecasting performance (Mishra *et al*., 2020; Mohammed *et al*., 2021; Yonar *et al*., 2022).

This study aims to address this gap by conducting a comprehensive evaluation of three prominent modeling techniques - ARIMA, state space, and seasonal Holt-Winters models - for meteorological forecasting in Hisar district for chickpea wilt disease. By utilizing a long-term daily climate dataset spanning over 30 years and employing a rigorous evaluation framework, this study provides a detailed comparison of the models' performance in capturing the unique climate characteristics of the region. The study also explores the strengths and weaknesses of each modeling approach and their suitability for different meteorological variables. By addressing this gap, the study contributes to the existing body of knowledge on weather forecasting and offers valuable insights for researchers, meteorologists and decision-makers in Hisar district and similar agricultural regions.

In this study, we investigate these modelling approaches in detail with the aim of addressing the following important questions:

(*i*) Which modelling approaches perform better in forecasting of the weather?

(*ii*) How well do various modelling approaches meet the requirements as evaluated based on various criteria, including AIC, BIC, RMSE, MAE, MAPE and in-sample MSE for weather forecasting?

(*iii*) What is the strength and weakness of the models selected in the study?

(*iv*) Do the selected models react to the nature of the data?

(*v*) Is there any model that fits all?

Three different modelling approaches were used in this extensive study, which covered 44 years from November 1977 to April 2022, to forecast meteorological variables such as maximum temperature, minimum temperature, relative humidity (M), relative humidity (E), bright sun shine hours, and rainfall. The modelling approaches used were ARIMA, state space, and seasonal Holt-Winters models. A comprehensive analysis utilising a number of metrics, including AIC, BIC, RMSE, MAE, MAPE, and in-sample MSE, was conducted to evaluate these models. This study highlights the value of carefully weighing different modelling strategies and assessing each one's effectiveness to highlight the role that model selection plays in meteorological forecasting. The dynamic nature of weather events makes it difficult to predict weather patterns with any degree of accuracy. Precise weather forecasting has implications for disaster management, agriculture and other businesses, in addition to every day preparation. Thus, the search for robust forecasting methods is important from a methodological perspective. The study is divided into different sections: data and methodology of the study, the findings and discussion and followed by conclusions.

2. Methodology

Location of the study : Haryana state is located in NW India, contributed tremendously to the success of the Green Revolution in India. The data pertains tothe Agrometeorology observatory in Chaudhary Charan Singh Haryana Agricultural University Hisar located in Haryana State. The district Hisar lies at the 29° 5'5"N latitude and 75° 45'55"E longitudes. The climate of Haryana is strongly influenced by north-westerly cold and south-westerly monsoon winds.

ARIMA Model : Autoregressive Integrated Moving Average (ARIMA) models are a class of statistical models used for analyzing and forecasting time series data. ARIMA models are composed of three key components: autoregressive (AR), differencing (I) and moving average (MA) (Box *et al*., 2015).

The AR component represents the relationship between an observation and a certain number of lagged observations. It captures the idea that the current value of a time series can be predicted based on its past values. The AR (p) model is defined as:

$$y\_t = \varphi\_1\ y\_\{t-1\} + \varphi\_2\ y\_\{t-2\} + \ldots + \varphi\_p y\_\{t-p\} + \varepsilon\_t$$

where y_t is the value of the time series at time t, $\varphi_1, \varphi_2, \ldots, \varphi_p$ are the autoregressive coefficients and ε_t is the error term.

The *I* component refers to the degree of differencing required to make the time series stationary. Differencing involves computing the differences between consecutive observations to remove the trend and stabilize the mean of the time series. The first-order differencing is defined as:

$$y't = y_t - y_{t-1}$$

where y'_t is the differenced series.

The MA component represents the relationship between an observation and a residual error from a moving average model applied to lagged observations. The MA (q) model is defined as:

$$y_t = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q}$$

where $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients.

ARIMA models combine these three components to capture the complex patterns in the data. The ARIMA (p,d,q) model is defined as:

$$(1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p)(1 - B)^d y_t = (1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q)\varepsilon_t$$

Where B is the backshift operator and d is the degree of differencing.

The selection of the appropriate ARIMA model involves identifying the values of p, d and q that best fit the data. This is typically done through the examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as well as the use of information criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) (Mishra *et al*., 2020; Mohammed *et al*., 2021).

State Space Models (SSMs) : State space models (SSMs) are a flexible class of models that represent a time series as a system of equations consisting of an observation equation and a state equation (Durbin & Koopman, 2012). The observation equation describes the relationship between the observed data and the unobserved state variables, while the state equation describes the evolution of the state variables over time.

The general form of a state space model is given by:

Observation equation : $y_t = Z_t\alpha + \varepsilon_t$

State equation: $\alpha_{t+1} = T_t\alpha_t + R_t\eta_t$

Where y_t is the observed time series, α_t is the state vector, Z_t is the observation matrix, T_t is the transition matrix, R_t is the selection matrix, ε_t is the observation error and η_t is the state error. The errors ε_t and η_t are assumed to be independent and normally distributed with mean zero and covariance matrices H_t and Q_t, respectively.

State space models can accommodate a wide range of specifications, including trend, seasonal and irregular components. The most common types of state space models are the local level model, the local linear trend model and the basic structural model (BSM) (Yadav *et al*., 2022).

The local level model is the simplest form of a state space model, where the observation equation is given by:

$$y_t = \mu_t + \varepsilon_t$$

and the state equation is given by:

$$\mu_{t+1} = \mu_t + \eta_t$$

where μ_t is the level component, representing the underlying mean of the time series.

The local linear trend model extends the local level model by incorporating a slope component to capture the trend in the data. The observation equation remains the same, while the state equation becomes:

$$\mu_{t+1} = \mu_t + v_t + \eta_t$$

$$v_{t+1} = v_t + \xi_t$$

where v_t is the slope component, representing the rate of change in the level.

The basic structural model (BSM) further extends the local linear trend model by including a seasonal component. The observation equation is given by:

$$y_t = \mu_t + \gamma_t + \varepsilon_t$$

and the state equations are given by:

$$\mu_{t+1} = \mu_t + v_t + \eta_t$$

$$v_{t+1} = v_t + \xi_t$$

$$\gamma_{t+1} = -\gamma_t - \gamma_{t-1} - \ldots - \gamma_{t-s+2} + \omega_t$$

where γ_t is the seasonal component with a period of s and ω_t is the seasonal error term.

State space models are typically estimated using the Kalman filter, which recursively updates the estimates of the state variables as new observations become available (Durbin & Koopman, 2012). The Kalman filter also provides a way to compute the likelihood function, which can be used for parameter estimation and model selection.

Seasonal Holt-Winters models : Seasonal Holt-Winters models, also known as triple exponential smoothing, are an extension of the classical Holt-Winters exponential smoothing method that incorporates seasonality (Hyndman *et al*., 2008). These models are particularly useful for forecasting time series with recurring seasonal patterns.

The seasonal Holt-Winters model consists of three smoothing equations : the level equation, the trend equation, and the seasonal equation. The model can be formulated in two ways: additive and multiplicative, depending on whether the seasonal component is added or multiplied to the level and trend components.

The additive seasonal Holt-Winters model is given by:

Level : $\ell_t = \alpha[y_t - s_{t-m}] + (1-\alpha)[\ell_{t-1} + b_{t-1}]$

Trend : $b_t = \beta[\ell_t - \ell_{t-1}] + (1-\beta)\, b_{t-1}$

Seasonal : $s_t = \gamma(y_t - \ell_t) + (1-\gamma)\, s_{t-m}$

Forecast : $\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t-m+h_m^+}$

where ℓ_t is the level component, b_t is the trend component, s_t is the seasonal component with a period of m, α, β and γ are the smoothing parameters for the level, trend and seasonal components, respectively and $h_m^+ = [(h-1) \bmod m] + 1$.

The multiplicative seasonal Holt-Winters model is given by:

Level : $\ell_t = \alpha[y_t / s_{t-m}] + (1-\alpha)[\ell_{t-1} + b_{t-1}]$

Trend : $b_t = \beta[\ell_t - \ell_{t-1}] + (1-\beta)\, b_{t-1}$

Seasonal : $s_t = \gamma(y_t / \ell_t) + (1-\gamma)\, s_{t-m}$

Forecast : $\hat{y}_{t+h|t} = (\ell_t + hb_t)\, s_{t-m+h_m^+}$

The selection of the appropriate seasonal Holt-Winters model (additive or multiplicative) depends on the characteristics of the time series and therelationship between the seasonal variation and the level of the series. The smoothing parameters (α, β and γ) can be estimated by minimizing the sum of squared errors or using maximum likelihood estimation (Hyndman *et al*., 2008).

Daily climate data collected for Hisar district between November 1, 1977 and April 30, 2022 & chickpea wilt disease incidence (during cropping season) was used in this study. The dataset was divided into two parts: training data and testing data. A chronological split was employed to ensure that the models were trained on historical data and tested on future data, mimicking a real-world forecasting scenario (Mishra *et al*., 2020; Yadav *et al*., 2022).

The data from November 1, 1977 to April 30, 2013 (80% or 6,524 observations) were used as the training dataset, while the data from May 1, 2013 to April 30, 2022 (20% or 1,631 observations) were used as the testing dataset. This chronological split allows for the assessment of the models' performance in forecasting future values based on historical patterns and trends (Mishra *et al*., 2020; Yadav *et al*., 2022).

The models were fitted to the training data, and their performance was evaluated using various metrics such as AIC, BIC, RMSE, MAE, MAPE and in-sample MSE.

The use of a chronological split, as opposed to a random split, is particularly important in time series forecasting because it preserves the temporal structure of the data (Box *et al*., 2015; Hyndman & Athanasopoulos, 2018). Random splitting may lead to the inclusion of future observations in the training set, which can result in overly optimistic performance estimates and may not reflect the true forecasting ability of the models (Hyndman & Athanasopoulos, 2018).

By using a chronological split, the study ensures that the models are evaluated on their ability to forecast future values based solely on past observations, providing a more realistic assessment of their performance (Mishra *et al*., 2020; Yadav *et al*., 2022). This approach is consistent with the common practice in time series forecasting and allows for a fair comparison of the different modeling techniques (ARIMA, state space, and seasonal Holt-Winters) used in the study (Box *et al*., 2015; Durbin & Koopman, 2012; Hyndman *et al*., 2008).

For the ARIMA models, the appropriate orders of p, d, and q were determined using the ACF and PACF plots, as well as the AIC and BIC values. The selected models were then used to forecast the testing data, and their performance was compared using the evaluation metrics.

The state space models were specified based on the characteristics of the time series and the presence of trend and seasonal components. The local level, local linear trend, and basic structural models were fitted to the data, and their parameters were estimated using the Kalman filter. The best-performing models were selected based on the evaluation metrics.

The seasonal Holt-Winters models were applied with both additive and multiplicative specifications and the smoothing parameters were estimated by minimizing the sum of squared errors. The performance of the models was assessed using the evaluation metrics, and the best-performing specification was selected for each meteorological variable.

The choice of ARIMA, state space, and seasonal Holt-Winters models for this study was based on several factors. First, these techniques have been widely used in the field of time series forecasting and have proven to be effective in capturing various patterns and characteristics of time series data (Box *et al*., 2015; Durbin & Koopman, 2012; Hyndman *et al*., 2008). Second, these methods are capable of handling different types of time series, including those with trend, seasonality, and irregular components, which are common in meteorological data (Mishra *et al*., 2020; Yadav *et al*., 2022).

ARIMA models were selected for their ability to capture the autocorrelation structure of the time series and their flexibility in modeling both stationary and non-stationary data (Box *et al*., 2015). These models have been successfully applied in various fields, including meteorology, hydrology, and environmental sciences (Mishra *et al*. 2024; Yadav *et al*., 2024; Ray *et al*. 2023a; Ray *et al*. 2023b; Mishra *et al*. 2023a; Mishra *et al*. 2023b; Mishra *et al*. 2023c; Mishra *et al*., 2020; Mohammed *et al*., 2021; Yonar *et al*., 2022; Raghav *et al*., 2022).

State space models were chosen for their ability to provide a flexible and unified framework for modeling time series data (Durbin & Koopman, 2012). These models can accommodate a wide range of specifications, including trend, seasonal, and irregular components, and can be easily extended to incorporate exogenous variables or interventions (Yadav *et al*., 2022). Moreover, state space models have been shown to outperform other methods in terms of forecasting accuracy and computational efficiency (Yadav *et al*., 2022).

Seasonal Holt-Winters models were selected for their ability to capture the seasonal patterns in the time series data (Hyndman *et al*., 2008). These models are particularly useful for forecasting time series with recurring seasonal patterns, such as those observed in meteorological variables (Mishra *et al*., 2021). The seasonal Holt-Winters models have been successfully applied in various domains, including energy, tourism, and retail (Hyndman *et al*., 2008).

Other techniques, such as artificial neural networks (ANNs) and deep learning methods, were not considered in this study due to their higher complexity and computational requirements.

While advanced machine learning techniques, such as deep learning and ensemble methods, have demonstrated promising results in handling complex systems (Al khatib *et al*., 2023) and capturing intricate, unseen non-linear patterns (Al khatib, 2023), they often necessitate substantial amounts of data and extensive hyperparameter tuning to achieve optimal performance. Conversely, the selected time series forecasting techniques, namely ARIMA, state space, and seasonal Holt-Winters models, offer a more straightforward implementation and interpretation process. These models have been proven to deliver accurate forecasts with a lower computational burden (Box *et al*., 2015; Durbin & Koopman, 2012; Hyndman *et al*., 2008), making them an attractive choice for many forecasting applications. The relative simplicity and effectiveness of these techniques make them valuable tools for practitioners and researchers seeking reliable and efficient forecasting solutions.

From November 1, 1977 to April 30, 2022, the MAX Temperature in Hisar district has increased during the period from (8 °C) to (45.6 °C). Average MAX Temperature in Hisar district was (26.19 °C). Kurtosis value was (-0.26) and the value of skewness was (0.37) which is close to 0.5 indicating the distributions is mesokurtic. The minimum Temperature in Hisar district has increased during the period from (-3.5 °C) to (30.5 °C). Average minimum Temperature in Hisar district was (9.53 °C). Kurtosis value was (-0.30) and the value of skewness was (0.45) which is close to 0.5 indicating the distributions is mesokurtic. The Relative Humidity (M) in Hisar district has increased during the period from (11%) to (100%). Average Relative Humidity (M) in Hisar district was (85.47%). Kurtosis value was (2.47) indicating that the distribution is flat and has thin tails (Platykurtic distributions) and the value of skewness was (-1.58), the negative skew refers to a longer or fatter tail on the left side of the distribution. The Relative Humidity (E) in Hisar district has increased during the period from (4%) to (100%). Average Relative Humidity (E) in Hisar district was (41.47%). Kurtosis value was (0.37) indicating the distributions is mesokurtic. The value of skewness was (0.83), indicating there is an opportunity of rising in Relative Humidity (E) in Hisar district. The Bright Sun Shine Hours in Hisar district has increased during the period from (0 h) to (74.80 h). Average Bright Sun Shine Hours in Hisar district was (7.23 h). Kurtosis

TABLE 1

Descriptive statistics for MAX Temperature, MIN Temperature, Relative Humidity (M), Relative Humidity (E), Bright Sun Shine Hours and Rainfall between November 1, 1977 and April 30, 2022 with No.of Susceptible wilt

	MAX Temperature	MIN Temperature	Relative Humidity (M)	Relative Humidity (E)	Bright Sun Shine Hours	Rainfall	No. of susceptible Chickpea genotype
Length	8155	8155	8155	8155	8155	8155	42
Mean	26.19	9.53	85.47	41.47	7.23	0.36	1448.95
STD	6.58	5.45	13.70	18.23	2.93	2.38	933.35
Mini	8	-3.5	11	4	0	0	86
max	45.6	30.50	100	100	74.80	58.20	3436
kurtosis	-0.26	-0.30	2.44	0.37	34.75	164.17	-0.93
skew	0.37	0.45	-1.58	0.83	0.53	11.14	0.37
Median	25.4	9	90	38	8.1	0	1302

TABLE 2

ARIMA Model fitted for MAX Temperature, MIN Temperature, Relative Humidity (M), Relative Humidity (E), Bright Sun Shine Hours and Rainfall for training data set (1977-11-01 to 2013-04-30)

	MODEL	Akaike Information Criterion (AIC)	Bayesian Information Criterion (BIC)	MAE	RMSE	MAPE	in-sample MSE
MAX Temperature	ARIMA (6,0,4)	27885.451	27966.850	1.476	2.047	6.152	4.189
MIN Temperature	ARIMA (4,0,3)	30067.543	30128.592	1.811	2.419	-	5.853
Relative Humidity (M)	ARIMA (4,0,1)	46580.051	46627.534	6.055	8.585	8.350	73.697
Relative Humidity (E)	ARIMA (4,0,1)	49653.015	49700.498	7.633	10.864	21.319	118.036
Bright Sun Shine Hours	ARIMA (3,1,3)	29787.646	29835.128	1.600	2.372	-	5.625
Rainfall	ARIMA (0,0,2)	30143.0692	30170.1967	0.6650	2.4449	-	5.9777

TABLE 3

State Space Models fitted for MAX Temperature, MIN Temperature, Relative Humidity (M), Relative Humidity (E), Bright Sun Shine Hours and Rainfall for training data set (1977-11-01 to 2013-04-30)

	Component	Value	Std.Err	t-stat	Prob	Akaike Information Criterion (AIC)	Bayesian Information Criterion (BIC)	MAE	RMSE	MAPE	in-sample MSE
MAX Temperature	level	29.82	2.374	12.56	0.0000	28488.504	28780.184	1.531	2.135	6.407	4.557
MIN Temperature	level	15.44	3.000	5.147	2.7225e-07	30939.531	31231.210	1.892	2.595	-	6.736
Relative Humidity (M)	level	74.85	6.228	12.02	0.0000	46800.954	47092.633	6.023	8.727	8.131	76.154
Relative Humidity (E)	level	28.70	10.51	2.730	0.0064	50082.834	50374.513	7.829	11.250	20.916	126.573
Bright Sun Shine Hours	level	7.004	1.567	4.470	7.9659e-06	30531.966	30823.645	1.682	2.514	-	6.322
Rainfall	level	0.3685	0.0304	12.13	0.00	30500.5800	30792.2594	0.7399	2.4264	-	5.8872

TABLE 4

Seasonal Holt-Winters models fitted for MAX Temperature, MIN Temperature, Relative Humidity (M), Relative Humidity (E), Bright Sun Shine Hours and Rainfall for training data set (1977-11-01 to 2013-04-30)

Model parameters			Specifications Additive, Period = 365			
Parameter type		Value	MAE	RMSE	MAPE	in-sample MSE
MAX Temperature	Smoothing level	0.7968	1.892	2.549	7.784	6.498
	Smoothing growth	4.9520e-04				
	Smoothing seasonal	1.0000				
MIN Temperature	Smoothing level	0.8324	2.308	3.046	-	9.278
	Smoothing growth	9.9043e-05				
	Smoothing seasonal	1.0000				
Relative Humidity (M)	Smoothing level	0.3243	7.373	10.211	9.803	104.257
	Smoothing growth	1.9177e-06				
	Smoothing seasonal	0.3734				
Relative Humidity (E)	Smoothing level	0.5645	9.704	13.250	26.852	175.560
	Smoothing growth	3.3134e-06				
	Smoothing seasonal	0.4866				
Bright Sun Shine Hours	Smoothing level	0.2523	1.979	2.796	-	7.816
	Smoothing growth	5.3929e-05				
	Smoothing seasonal	0.2503				
Rainfall	Smoothing level	0.0036	0.7889	2.8322	-	8.0216
	Smoothing growth	2.4595e-04				
	Smoothing seasonal	0.3122				

value was (34.75) indicating the data follows a Leptokurtic distribution which shows heavy tails on either side, which means there are outliers in the data. The value of skewness was (0.53), indicating there is an opportunity of rising in Bright Sun Shine Hours in Hisar district. The Rainfall in Hisar district has increased during the period from (0 mm) to (58.2 mm). Average Rainfall in Hisar district was (0.36 mm). Kurtosis value was (164.17) indicating the data follows a Leptokurtic distribution which shows heavy tails on either side, which means there are outliers in the data. The value of skewness was (11.14), indicating there is an opportunity of rising in Rainfall in Hisar district (Table 1). The positive skewness value of number of susceptible wilt showing it is continuous to increase due to high temperature.

The top selected ARIMA models are shown in (Table 2). These models were chosen based on several evaluation criteria, including the Akaike information criterion, root mean squared error, mean absolute error, mean absolute percentage error, in-sample MSE, and the maximum number of significant coefficients. These criteria were used to assess the fit and predictive performance of the models, in order to identify the most suitable models for the data.

(Table 3) presents the parameter estimates of the state space models. The best-fit model on the training dataset (covering the period 1977-11-01 to 2013-04-30) was determined based on the minimum values of the Akaike information criterion (AIC), Bayesian information criterion (BIC), root mean squared error (RMSE), mean absolute error (MAE), in-sample MSE, and mean absolute percentage error (MAPE). This model was deemed to be the most suitable for all the time series data.

(Table 4) presents the parameter estimates of the Seasonal Holt-Winters models. The best-fit model on the training dataset (covering the period 1977-11-01 to 2013-04-30) was determined based on the minimum values of the Akaike information criterion (AIC), Bayesian information criterion (BIC), root mean squared error (RMSE), mean absolute error (MAE), in-sample MSE, and mean absolute percentage error (MAPE). This model was deemed to be the most suitable for all the time series data. The comparison between (Table 2), (Table 3) and (Table 4) reveals that the ARIMA models outperformed the state space models and the Seasonal Holt-Winters models on the training datasets for all-time series, as the ARIMA models had minimum values for most of the evaluation criteria. This suggests that the ARIMA models were able to fit the training data well and make accurate predictions for disease forecasting.

(Table 5) presents a comparison between the best ARIMA models, the best state space models, and the best Seasonal Holt-Winters models on the testing dataset, based on the lowest values of RMSE, MAE, and MAPE.

TABLE 5

RMSE, MAE and MAPE for testing data set (2013-05-01 to 2022-04-30 or 1631 observations)

	ARIMA Models			State Space Models			The Seasonal Holt-Winters models		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
MAX Temperature	2.0513	1.5247	6.56	2.1454	1.559	6.71	2.4357	1.8603	7.95
MIN Temperature	2.4334	1.8808	30.032	2.6009	1.9393	29.73	2.8563	2.2058	33.61
Relative Humidity (M)	8.26	5.94	7.46	8.45	5.75	7.14	9	6.49	8.05
Relative Humidity (E)	10.64	7.78	16.44	11.13	8.07	16.89	12.28	9.35	20.26
Bright Sun Shine Hours	2.344	1.81	-	2.5246	1.8954	-	2.7093	2.0954	-
Rainfall	1.6578	0.6541	-	1.6889	0.676	-	1.9247	0.7473	-

TABLE 6

Forecasting from 01-05-2022 to 15-05-2022 using best forecasting models for MAX Temperature, MIN Temperature, Relative Humidity (M), Relative Humidity (E), Bright Sun Shine Hours and Rainfall

Day	MAX Temperature	MIN Temperature	Relative Humidity (M)	Relative Humidity (E)	Bright Sun Shine Hours	Rainfall
2022-05-01	36.27252	19.36631	60.73727	22.06919	7.617534	0.304668
2022-05-02	30.78198	17.26388	65.49211	35.42409	7.923903	0.304666
2022-05-03	30.56198	13.83812	78.9696	37.36564	7.909538	0.304667
2022-05-04	28.7759	12.07032	83.75834	36.60512	7.253911	0.304667
2022-05-05	28.99401	11.65567	84.14759	33.69769	7.994461	0.304667
2022-05-06	28.46426	12.75567	87.19973	36.59393	7.536779	0.304667
2022-05-07	26.29718	14.91809	82.04528	41.24115	4.32974	0.304667
2022-05-08	27.54832	15.54328	83.00792	65.05045	4.001364	1.500999
2022-05-09	23.24091	11.70074	90.08463	53.43904	3.865136	0.861298
2022-05-10	24.8028	12.23895	93.47965	51.48433	5.524162	0.229384
2022-05-11	24.56987	11.29509	94.27622	45.3928	4.661742	0.278587
2022-05-12	25.82683	10.58293	94.75571	39.90797	6.776208	0.31355
2022-05-13	25.96296	9.75018	95.87267	44.00372	7.188675	0.305098
2022-05-14	26.06307	9.505876	97.78636	41.03003	7.077499	0.30401
2022-05-15	25.68105	8.8968	96.91505	39.6458	6.475179	0.304736

The results show that the ARIMA model outperformed the state space model and Seasonal Holt-Winters models in predicting MAX Temperature, MIN Temperature, Relative Humidity (E), Bright Sun Shine Hours and Rainfall (Kour *et al.*, 2011). The prediction accuracy of the ARIMA model was found to be very high, as all the values of the accuracy criteria (AIC, BIC, RMSE, MAE, and MAPE) were lower than the values of the corresponding criteria for the state space model and Seasonal Holt-Winters models. According to (Al khatib, *et al*., 2021) using anew forecasting method did not guarantee more robust forecasts than traditional ones in all cases, there are more factors that have effects on the accuracy of forecasting models including frequency of the data, complexity of data, number of observations, the seasonality in time series, cyclic variations of time series, stationarity of time series, trending behaviour of time series, the long of out-sample forecast and randomness of the data (Mishra *et al.*, 2023). However, it should be noted that the ARIMA model may suffer from overfitting issues, as it has good performance on the training dataset but may not generalize well to other data, such as the testing set. In contrast, the state space model was found to be better than the ARIMA model in predicting Relative Humidity (M) due to the presence of some outliers in the data. The state space model is capable of flexibly capturing the complex, non-linear nature of the data series with different specifications, structural breaks, shifts, time-varying parameters, missing data, and stationarity is not required. The state space model is also suitable for dynamic time series models that include unobserved components, while the ARIMA model requires stationary data and may require differencing to remove trend and seasonal effects. The model that performs better on the testing dataset is generally considered to be the better model. This is because the testing dataset is used to evaluate how well a model generalizes to new data, which is more important than how well it fits the training data. However, it's important to note that there are many factors that can affect model performance, and it's possible for a model to perform poorly on both the training and testing datasets, for example the Seasonal Holt-Winters models in this

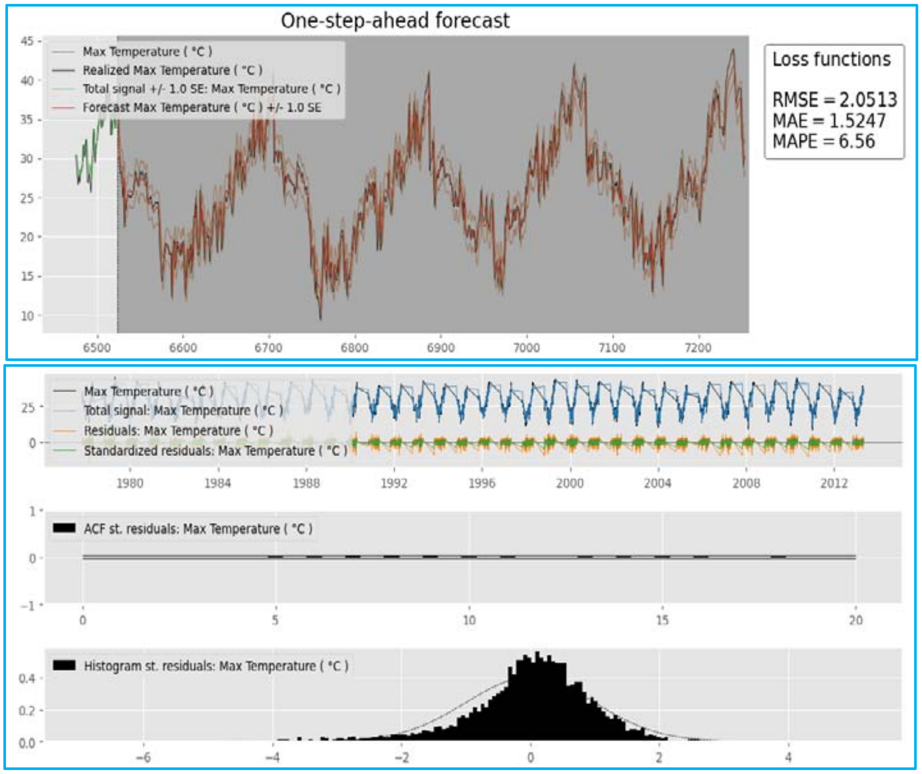

Fig. 1. Actual and forecast values for MAX Temperature with (Total Signal-Residuals diagnostics) during the period 01-05-2022 to 15-05-2022 using ARIMA models

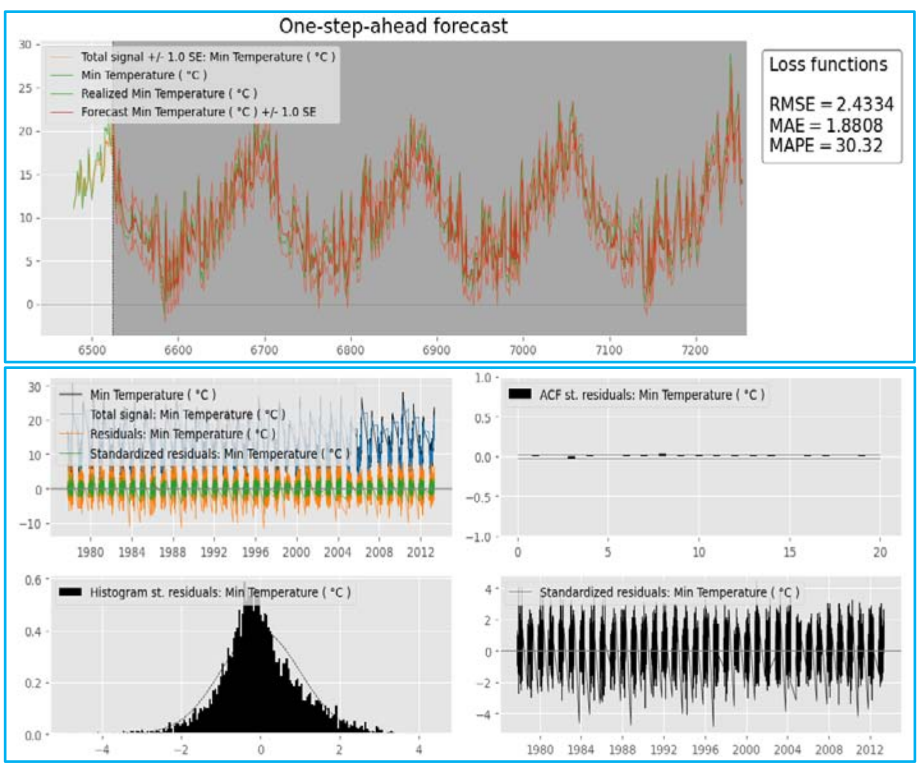

Fig. 2. Actual and forecast values for MIN Temperature with (Total Signal - Residuals diagnostics) during the period 01-05-2022 to 15-05-2022 using ARIMA models

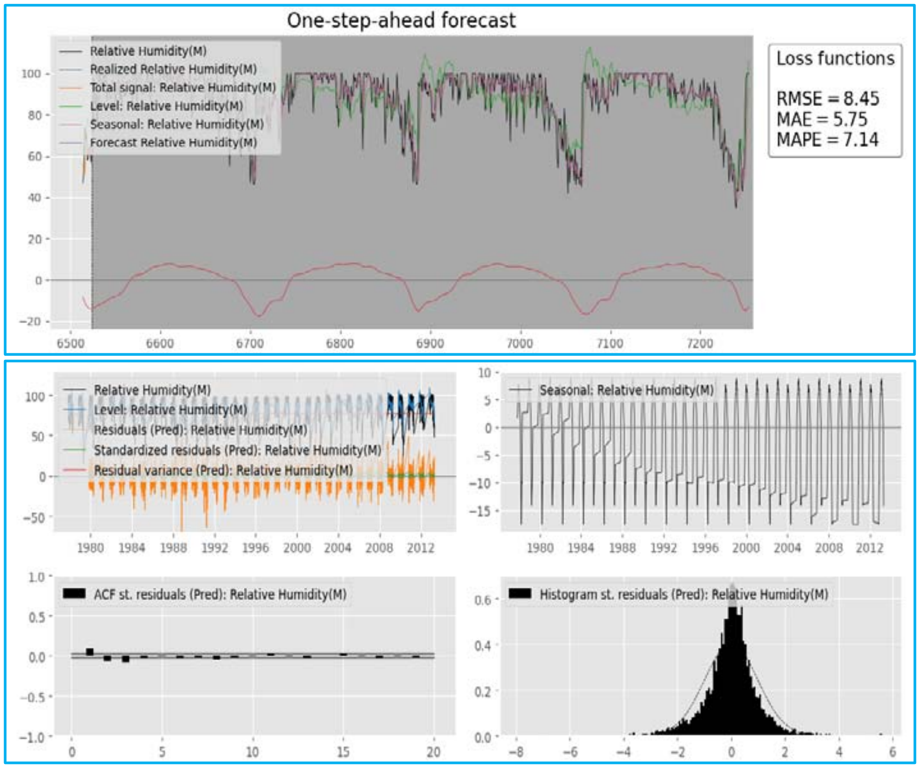

Fig. 3. Actual and forecast values for Relative Humidity (M) with (Total Signal - level- seasonal- Residuals diagnostics) during the period 01-05-2022 to 15-05-2022 using State Space model

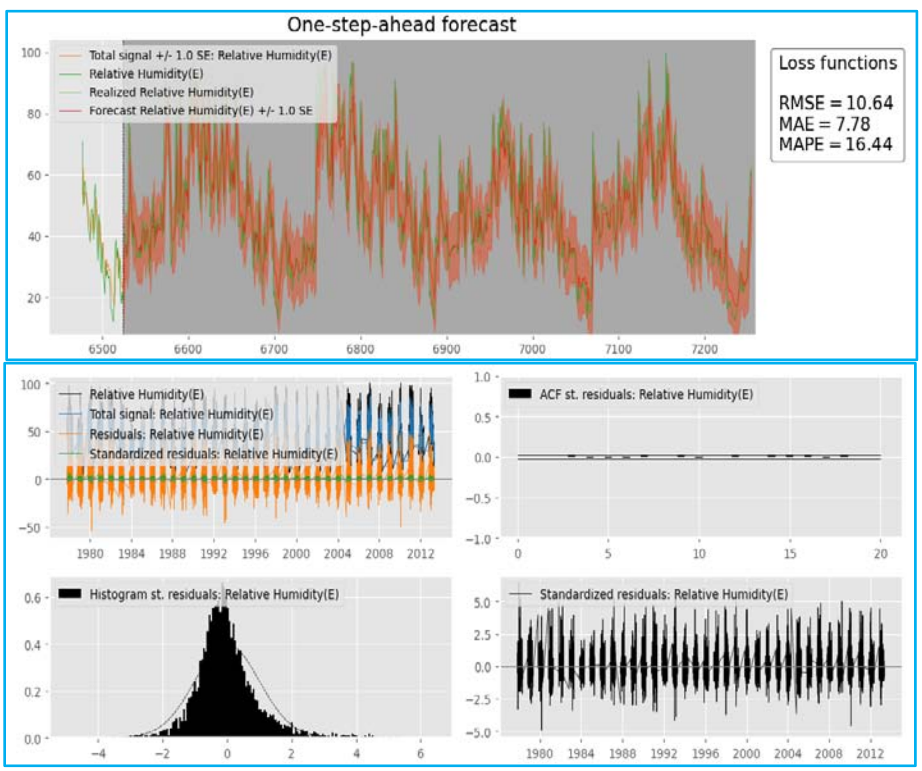

Fig. 4. Actual and forecast values for Relative Humidity (E)with (Total Signal - Residuals diagnostics) during the period 01-05-2022 to 15-05-2022 using ARIMA model

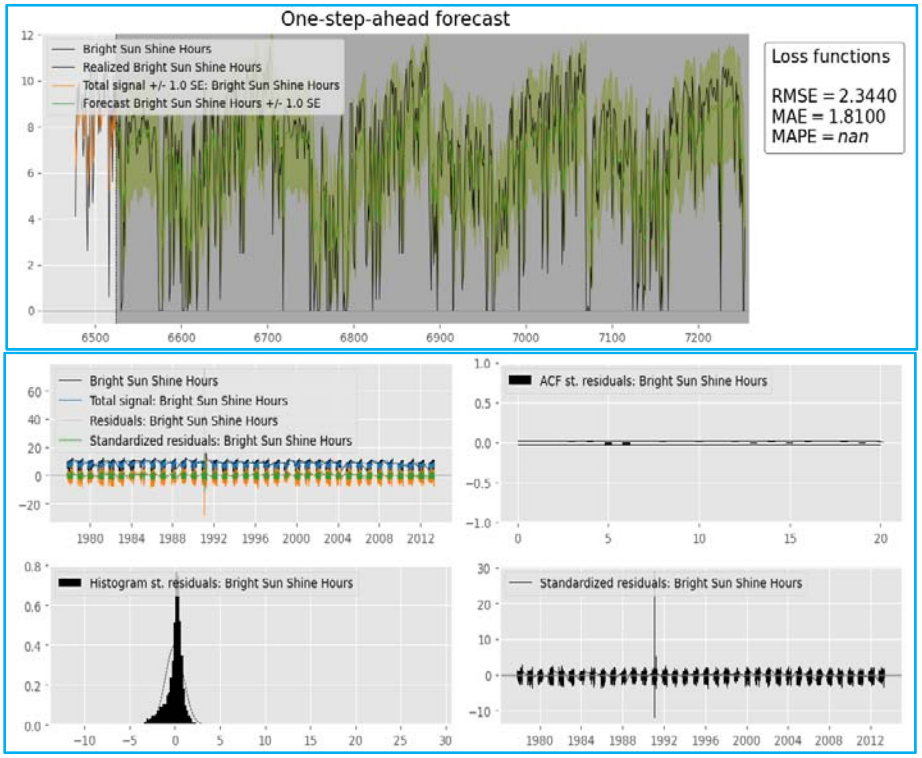

Fig. 5. Actual and forecast values for Bright Sun Shine Hourswith (Total Signal - Residuals diagnostics) during the period 01-05-2022 to 15-05-2022 using ARIMA model

study. Overall, the results of state space models were close to results of ARIMA models, which highlight the importance of considering multiple modeling approaches and evaluating their performance on both training and testing data to identify the most suitable models for a given dataset.

According to the results presented in (Table 6), the Max Temperature is expected to reach 25.68 °C on15-05-2022 with a negative growth rate of -24.68% during the period 01-05-2022 to 15-05-2022. The Min Temperature is expected to reach 8.8968 °C on15-05-2022with anegative growth rate of -54.06% during the period 01-05-2022 to 15-05-2022. The Relative Humidity (M) is expected to reach 96.91% on 15-05-2022 with a positive growth rate of 0.59% during the same period. The Relative Humidity (E) is expected to reach 39.64% on15-05-2022 with a positive growth rate of 0.79% during the same period. The Bright Sun Shine Hours is expected to reach 6.47 hours on -05-15-05-2022 with a negative growth rate of -14.99% during the same period. The rainfall is forecasted to reach 0.3047 mm on 15-05-2022 and remain constant throughout the same period.

3. Forecasting

After developing the top models, forecasting was conducted for MAX Temperature, MIN Temperature, Relative Humidity (M), Relative Humidity (E), Bright Sun Shine Hours and Rainfall. The most important for chickpea wilt disease is Temperature, R.H. & sunshine hours. The residuals of the chosen models were found to be stationary and white noise for all-time series, indicating that the models were able to capture the underlying patterns and trends in the data. Using the best-fit models, predicted values were generated for the period from 01-05-2022 to 15-05-2022 and are presented in the figures (Fig. 1 to Fig. 6). The figures show that the predicted values and forecasted lines are generally close to the actual values, demonstrating the effectiveness of the selected models. The forecast results suggest that there will be a decrease in MAX Temperature, MIN Temperature, and The Bright Sun Shine Hours (Fig. 1, Fig. 2 and Fig. 5). However, the forecast suggests that there will be an increase in The Relative Humidity (M) and The Relative Humidity (E) (Fig. 3 and Fig. 4). There will be no change in rainfall during the same period (Fig. 6).

4. Conclusions

In this study, three different types of models, namely ARIMA, state space and seasonal Holt-Winters models were used to forecast the maximum temperature, minimum temperature, relative humidity (M), relative

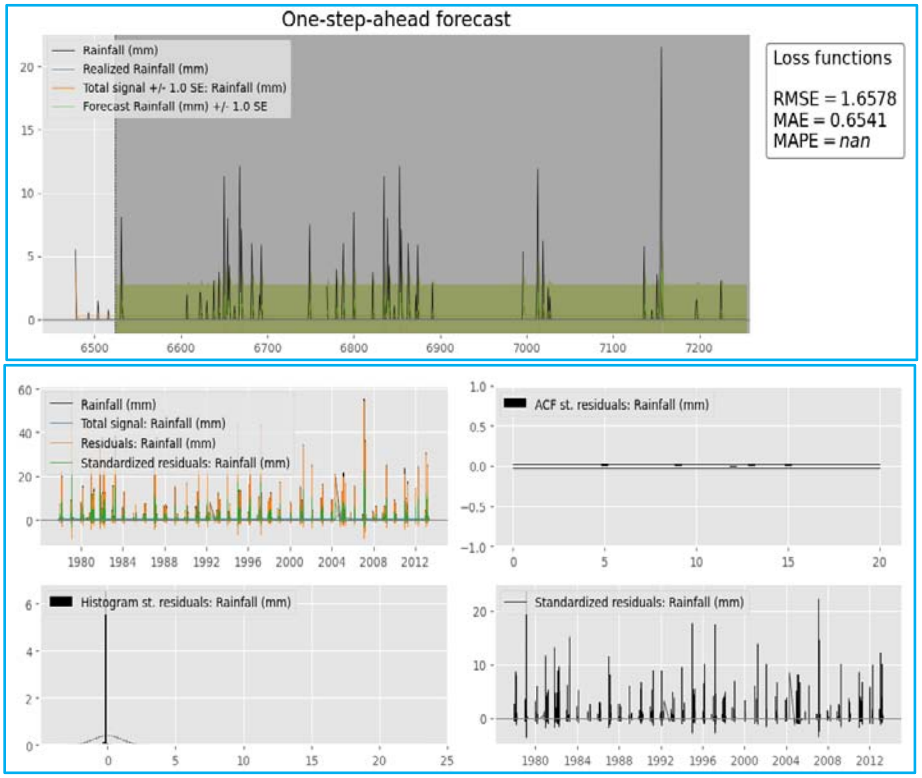

Fig. 6. Actual and forecast values for Rainfallwith (Total Signal -Residuals diagnostics) during the period 01-05-2022 to 15-05-2022 using ARIMA model

humidity (E), bright sun shine hours, and rainfall for a period of 30 years from November 1977 to April 2013. The models were evaluated based on various criteria, including AIC, BIC, RMSE, MAE, MAPE and in-sample MSE. The top selected ARIMA models. The state space models were selected based on the minimum values of AIC, BIC, RMSE, MAE, in-sample MSE and MAPE and the best-fit model was found to be suitable for all the time series data. Finally, seasonal Holt-Winters models werealso fitted, and the models' parameters were evaluated based on MAE, RMSE, MAPE and in-sample MSE. The comparison presented in this study revealed that the ARIMA model was the top-performing model in predicting MAX Temperature, MIN Temperature, Relative Humidity (E), Bright Sun Shine Hours, and Rainfallfor prediction of wilt disease in chickpea. The accuracy of the ARIMA model was exceptional, with lower values for all evaluation criteria compared to the state space model and Seasonal Holt-Winters models. However, it's important to mention that the ARIMA model may suffer from overfitting issues and may not generalize well to other datasets. On the other hand, the state space model demonstrated its strength in predicting Relative Humidity (M), where the ARIMA model struggled due to outliers in the data. The state space model's flexibility in capturing the complex, non-linear nature of data series, and its ability to handle dynamic time series models makes it a suitable alternative to the ARIMA model. It is worth noting that there is no one-size-fits-all solution when it comes to modeling, and it's essential to consider various modeling approaches and evaluate their performance on both training and testing datasets. Overall, the study underscores the importance of careful consideration and evaluation of different models to identify the most suitable approach for a given dataset. The results show that the models with the best-fit parameters were able to forecast the different meteorological variables accurately. Overall, this study provides valuable insights into the prediction of meteorological variables and demonstrates the usefulness of different modeling techniques in this contextwhich will be helpful directly or indirectly in management of plant disease like Fusarium wilt of chickpea.

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References

AL Khatib AMG, Yonar H, Abotaleb M, Mishra P, Yonar A, Karakaya K, Badr A, Dhaka V., 2021, “Modeling and forecasting of egg production in India using time series models”, *Eurasian J. Vet. Sci.*, **37**, 4, 265-273.doi:https://doi.org/10.15312/EurasianJVetSci.2021.352.

Al khatib, A. M. G., 2023, "The complexity of financial development and economic growth nexus in Syria : A nonlinear modelling approach with artificial neural networks and NARDL model", *Heliyon*, **9**, 10, 1-18. https://doi.org/10.1016/j.heliyon.2023.e20265.

Al khatib, A. M. G., Alshaib, B. M., & Kanaan, A. M., 2023, "The Interaction Between Financial Development and Economic Growth: A Novel Application of Transfer Entropy and Nonlinear Approach in Algeria", *Sage Open*, **13**, 4, https://doi.org/10.1177/21582440231217871.

Box, G. E., Jenkins, G. M., Reinsel, G. C. & Ljung, G. M., 2015, Time series analysis : Forecasting and control. John Wiley & Sons.

Carbonell, L. T., Mastrapa, G. C., Rodriguez, Y. F., Escudero, L. A., Gacita, M. S., Morlot, A. B., ... & Rivas, S. P., 2013, "Assessment of the Weather Research and Forecasting model implementation in Cuba addressed to diagnostic air quality modeling", *Atmospheric Pollution Research*, **4**, 1, 64-74. https://doi.org/10.5094/APR.2013.007.

Durbin, J., & Koopman, S. J., 2012, "Time series analysis by state space methods", Oxford University Press.

Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R., & Mearns, L. O., 2000, "Climate extremes: observations, modeling, and impacts", *Science*, **289**, 5487, 2068-2074.

Hyndman, R. J., & Athanasopoulos, G., 2018, "Forecasting: principles and practice", (2nd ed.). OTexts. Chapter 7 : Exponential smoothing.

Hyndman, R. J., Koehler, A. B., Ord, J. K., & Snyder, R. D., 2008, "Forecasting with exponential smoothing : The state space approach", Springer Science & Business Media.

Kaur, L., Gill, K. K., Kingra, P. K., Sandhu, J. S., &Sirari, A. 2011. "Correlation between weather variables and Ascochyta blight disease of chickpea", *Journal of Agrometeorology*, **13**, 2, 145-149.

Merga, B., & Haji, J., 2019, "Economic importance of chickpea: Production, value, and world trade", *Cogent Food & Agriculture*, **5**, 1, 1615718. https://doi.org/10.1080/23311932.2019.1615718.

Mishra, P., Al Khatib, A. M. G., Lal, P., Anwar, A., Nganvongpanit, K., Abotaleb, M., ... and Punyapornwithaya, V., 2023a, "An Overview of Pulses Production in India: Retrospect and Prospects of the Future Food with an Application of Hybrid Models", *National Academy Science Letters*, **46**, 5, 1-8. https://doi.org/10.1007/s40009-023-01267-2.

Mishra, P., Al Khatib, A. M. G., Sardar, I., Mohammed, J., Karakaya, K., Dash, A., ... & Dubey, A., 2021, "Modeling and forecasting of sugarcane production in India", *Sugar Tech*, **23**, 6, 1317-1324.

Mishra, P., Al Khatib, A. M. G., Sardar, I., Mohammed, J., Ray, M., Manish, K., ... & Rono, K., 2020, "Modelling and forecasting of COVID-19 in India", *Journal of Infectious Diseases and Epidemiology*, **6**, 5, 1-11.doi: 10.23937/2474-3658/1510162.

Mishra, P., Al Khatib, A.M.G., Lal, P., *et al*., 2023, "An Overview of Pulses Production in India: Retrospect and Prospects of the Future Food with an Application of Hybrid Models", *Natl. Acad. Sci. Lett*. https://doi.org/10.1007/s40009-023-01267-2.

Mishra, P., Al khatib, A.M.G., Mohamad Alshaib, B., *et al*., "Forecasting Potato Production in Major South Asian Countries : a Comparative Study of Machine Learning and Time Series Models", *Potato Res*., (2023c). https://doi.org/10.1007/s11540-023-09683-z.

Mishra, P., Al Khatib, A.M.G., Yadav, S., *et al*.,2024, "Modeling and forecasting rainfall patterns in India: a time series analysis with XGBoost algorithm", *Environ. Earth Sci*., **83**, 163. https://doi.org/10.1007/s12665-024-11481-w.

Mishra, P., Alakkari, K. M., Lama, A., Ray, S., Singh, M., Shoko, C., ... & Karakaya, K., 2023b, "Modeling and Forecasting of Sugarcane Production in South Asian Countries", *Current Applied Science And Technology*, **23**, 1, 1-15. doi : https://doi.org/10.55003/cast.2022.01.23.002.

Mishra, V., D. Kumar, A. R. Ganguly, J. Sanjay, M. Mujumdar, R. Krishnan, and R. D. Shah., 2014a, "Reliability of regional and global climate models to simulate precipitation extremes over India", *J. Geophys. Res. Atmospheres*.

Mishra, V., Shah, R., & Thrasher, B., 2014b, "Soil moisture droughts under the retrospective and projected climate in India", *Journal of Hydrometeorology*, **15**, 6, 2267-2292.141006071153004, doi:10.1175/JHM-D-13-0177.1.

Mohammed, J., Al Khatib, A. M. G., Mishra, P., Adjei, P., Singh, P. K., Priya, S. K., & Das, S. S., 2021, "Modeling and forecasting of Covid-19 from the context of Ghana", *African Review of Economics and Finance*, **13**, 2, 124-141.

Pande, S., Sharma, M., &Guvvala, G., 2013, "An updated review of biology, pathogenicity, epidemiology and management of wilt disease of pigeonpea (Cajanuscajan (L.) Millsp.)", *Journal of Food Legumes*, **26**, 1-2, 1-14.

Raghav, Y. S., Mishra, P., Alakkari, K. M., Singh, M., Al Khatib, A. M. G., &Balloo, R., 2022, "Modelling and forecasting of pulses production in south asian countries and its role in nutritional security", *Legume Research-An International Journal*, **45**, 4, 454-461.

Rahman, U. H., Ray, S., Al Khatib, A. M. G., Lal, P., Mishra, P.,Fatih, C., ...& Alakkari, K. 2022. "State of art of SARIMA model in second wave on covid-19 in India", *International Journal of Agricultural & Statistical Sciences*, **18**, 1, 141-152.

Ray, S., Al Khatib, A.M.G., Kumari, B., Biswas, T., Nuta, A.C. and Mishra, P., 2023a, "Forecasting cash crop production with statistical and neural network model", *J. Crop and Weed*, **19**, 1, 194-201. https://doi.org/10.22271/09746315.2023.v19.i1.1679.

Ray, S., Mishra, P., Ayad, H., Kumari, P., Sharma, R., Kumari, B., Al Khatib, A.M.G., T amang, A. & Biswas, T., 2023b, "Prediction of Fruit Production in India: An Econometric Approach", *Journal of Horticultural Research*, **31**, 1, 25-34. https://doi.org/10.2478/johr-2023-0005.

Shrestha, A. K., Thapa, A., & Gautam, H., 2019, "Solar Radiation, Air Temperature, Relative Humidity, and Dew Point Study : Damak, Jhapa, Nepal", *International Journal of Photoenergy*.

Yadav, S., Al khatib, A. M. G., Alshaib, B. M., Ranjan, S., Kumari, B., Alkader, N. A., ... & Kapoor, P., 2024, "Decoding Potato Power: A Global Forecast of Production with Machine Learning and State-of-the-Art Techniques", *Potato Research*, 1-22.https://doi.org/10.1007/s11540-024-09705-4.

Yadav, S., Mishra, P., Kumari, B., Shah, I. A., Karakaya, K., Shrivastri, S., ...& Al Khatib, A. M. G., 2022, "Modelling and Forecasting of Maize Production in South Asian Countries", *Economic Affairs*, **67**, 4, 519-531. doi: https://doi.org/10.46852/0424-2513.4.2022.18.

Yonar, H., Yonar, A., Mishra, P., Abotaleb, M., Al Khatib, A. M. G., Makarovskikh, T., & Cam, M., 2022, "Modeling and forecasting of milk production in different breeds in Turkey", *The Indian Journal of Animal Sciences*, **92**, 1, 246-253.