Sigma J Eng Nat Sci, Vol. 43, No. 4, pp. 1067–1074, August, 2025

Sigma Journal of Engineering and Natural Sciences
Web page info: https://sigma.yildiz.edu.tr
DOI: 10.14744/sigma.2025.00092

Research Article

On some aspects of advanced forecasting stochastic techniques with heteroscedastic disturbances for paddy seasonal dataset

O. Veerendra BABU[1], Khadar Babu SK[1,*]

[1]*Department of Mathematics, Vellore Institute of Technology, Vellore, Tamil Nadu, India-632014*

ARTICLE INFO

Article history
Received: 31 January 2024
Revised: 30 March 2024
Accepted: 26 July 2024

Keywords:
Auto Regressive Models (AR); Backscatter Values; FSARIMA; Mean Error; Time Series Perform Measures; Stationary Series

ABSTRACT

Timeseries data for model building plays a primary role in the analysis, prediction, and forecasting of feature values and explains the structure of the dataset, which is helpful for classification and forecasting problems. Usually, in time series modelling, the main objective is to collect data carefully and study rigorously the past data observations to develop an inherent structured model for prediction and forecasting. This model, which is used to generate future and forecasted time series data, The main focus is on seasonal time series data collected from the SCATSAT-1 Scatterometer data set. The present article shows that to develop first- and second order auto-regressive models, a fuzzy seasonal auto-regressive integrated moving averages model with heteroscedastic disturbances was developed for the forecasting and prediction of future datasets in a fuzzy environment. A fuzzy membership function was developed for the classification of the dataset using the inflexion point methodology. For model adequacy checking, we adopted measures such as mean absolute percent error, mean forecast error, mean squared error, and root mean squared error.

Cite this article as: Babu OV, Sk KB. On some aspects of advanced forecasting stochastic techniques with heteroscedastic disturbances for paddy seasonal dataset. Sigma J Eng Nat Sci 2025;43(4):1067–1074.

INTRODUCTION

India is one of the fastest-growing countries in the world, and it needs quality food to provide for every citizen. In Asia, rice is a stable food crop, and it is growing on 11% of the global crop land. Mostly, 3 billion people are depending on the rice crop, and it is a dominant food crop. The major food crops in India are paddy, wheat, and maize. Estimation and mapping of paddy, wheat, and maize crops is essential to managing the food requirements of the population in the world. The rice crop is becoming a significant agricultural crop due to its majority feeding people worldwide. In such a situation, there is a need to study and have erudite knowledge to cultivate rice crops with innovative growing methods to produce a significant output. Most of the population in the southern part of India depends on cultivating rice crops for all major seasons.

The rice crop has a 90–110-day crop cycle for short-term crops and 170-190 days for long-term crops. The rice crop stages are broadly classified into four stages: the puddling stage, the transplanting stage, the heading stage, and

***Corresponding author.**
*E-mail address: khadar.babu36@gmail.com, stat.veeru@gmail.com

This paper was recommended for publication in revised form by Regional Editor Ahmet Selim Dalkilic

Published by Yıldız Technical University Press, İstanbul, Turkey

the harvesting stage. Puddling is a non-vegetation stage, and rests are vegetation stages. The transplanting stage is a starting vegetation stage, and it grows approximately 14cm in height. The heading stage starts 45 days after transplanting a plant, and most of the panicles extract from the plant. This is a growing stage, and it may alter due to crop stress, low soil fertility, the availability of labour, and the climate conditions.

The development of the water using technology will help control crop stress at the heading stage. In a rice crop study, the identified bio-physical parameters are chlorophyll, LAI (leaf area index), FAPAR (fraction of cover), CWC, and biomass. This parameter indicates the healthy growth of the rice crop at the heading stage. The present article proposes to identify different rice crop growing stages using the normalized inflection method for satellite data.

Some promising results [1] in identifying paddy crop phenological parameters using dual-polarized SCATSAT-1 scatterometer data. This innovative approach improves crop monitoring techniques and agricultural management practices and provides valuable information to farmers and policymakers. The study revealed a significant impact of climate change on maize yield in China from 1979 to 2016, with heteroscedastic disturbances significantly affecting crop production [2].

Literature Review

A study on rice crops using quick SCATSAT-I scatterometer data with a temporal resolution of four days and a spectral resolution of 4.45km. They identified different rice crop growing stages during the monsoon season in 2004 in India [3]. Rice crop growing stages in the state of Telengana during the Karif season in 2004–2005. They performed experiments to observe and record rice crop behavior through different models [4]. Further study on the rice crop using a ground-based spectral index [5].

They used the max and min points in the derivative of the CIred edge to measure the dough grain, and middle booting of the point of the NDVI used. Mapping of biophysical parameters of agricultural crops using hyperspectral imagery [6]. The inflexion point methodology for classification of the crop stages, which are the puddling stage, transplanting stage, heading stage, and harvesting stage [7]. The previous study on paddy crops performed still in the in the reproductive stage using different remote sensing procedures, but the present study adopted inflection point methodology to differentiate different rice crop growing stages using backscatter scatterometer data and implemented different models with heteroscedastic disturbance. According to [8,9], they studied discontinuity with respect to the first derivative and hence the constant rates of increase and decrease of the data interpolated. Various Transform Approach to Fractional Integro-Differential Equations to the rice crop data [10-14].

According to [8], they studied discontinuity with respect to the first derivative and hence the constant rates of increase and decrease of the data interpolated. A procedure for finding pheonological dates on a time profile curve based on the maximum point of the vegetation index [15]. One of the difficult tasks in remote sensing is to detect the various seasonal vegetation trends of the different food crops. Two parametric Gaussian distributions are performed to identify the rice crop phenology [16,17,18] developed new technology for identifying crop type using decomposed components in this method, and they applied harmonic analysis to the time series data. [19,20,21] are studied the identification of different crop stages using SCATSAT-I Scaterometer data, and in 2020, they developed a procedure for a comparative study of NDVI (MODI) data on paddy crop growth. Additionally, the hypersoft set aspect of the method enables a more nuanced analysis of the data, taking into account the uncertainty and ambiguity inherent in passport quality assessment [22,23,].

Therefore, this study leads to a new part about a study on agriculture using different statistical models with this new kind of innovative satellite data analytical applications. One of the major objectives of the present research paper is to study and focus on effective methodology for rice crop phenological stages using backscatter scatterometer data and make the best possible FSARIMA model for statistical analysis of the dataset.

MATERIALS AND METHODS

Study Area

Rice phenology assessment and mapping were performed using experimental data from different areas in East Godavari and West Godavari Districts, which are located in the coastal areas of Andhra Pradesh, India. The study area is located between 800 21’40” E and 820 21’50” E longitude and 160 25’50” N to 180 90’0” N latitude. Godavari, Krishna, and Penna rivers are the main sources of the agricultural rice crop. The geographical territory of the east Godavari and west Godavari regions is 20,547 km2. The study areas are situated on the banks of the Godavari stream, which is full of fertile land. The most extreme farming area is involved by paddy crops in the study area due to the immense accessibility of water assets and prolific land (Fig. 1).

Auto Regression (AR) methodology is used for predicting and forecasting data at any stage in the rice crop. The data is divided into four stages:

i. Puddling stage,
ii. Transplanting stage,
iii. Heading stage, and
iv. Harvesting stage.

AR is primarily applied to the heading stage, aiming to increase crop output by estimating panicle growth. By accurately estimating panicle growth, farmers can make informed decisions on fertilizers, pesticides, and other inputs to maximize yield. AR also helps farmers understand factors influencing panicle growth, such as weather

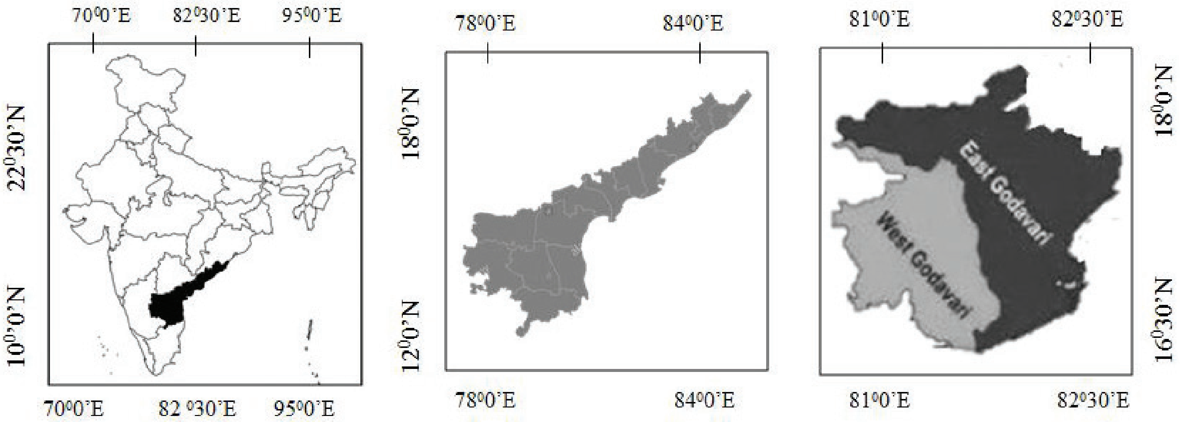

Figure 1. Study area.

conditions, soil quality, and irrigation practices. This information can be used to optimize crop management strategies and increase overall productivity. Overall, AR methodology is a valuable tool for maximizing crop yield and improving crop management strategies.

The growth of rice yield is influenced by various parameters such as i) Chlorophyll content, ii) Canopy water content, and iii) Panicle brassbound. A model methodology is used to predict and forecast rice crop growth at the heading stage, incorporating data from weather conditions, soil fertility, and crop management practices. This allows for informed predictions about potential yield and real-time adjustments to optimize growth and maximize output. This predictive tool enables farmers to make strategic decisions to improve crop yield and overall agricultural productivity, ultimately leading to increased output.

Data Validations

Khadar Babu et al. [7] studied the normalized inflexion point approach for the classification of paddy crop phenological stages. The present paper shows how to extend the normalized transformation techniques into fuzzy normalized transformed techniques and fit a forecasting and predictive model for a rice crop phenological dataset. In fuzzy normalization, the concept was adopted by using the following standard variables:

$$\varphi_i = \frac{y_i - Min((y_i)}{Max\,(y_i) - Min\,(y_i)}, \text{for every i.}$$

and the fuzzy membership function was identified.

For the classification of phenological stages, we applied the inflection point approach and fit a forecasting model for a classified dataset. For model adequacy, check ME, MAE, RMSE, MPE, MAPE, SMAPE, and U_1.

At the stage of classification, the dataset can attain and touch heteroscedastic disturbances present or not in the rice crop data. If at any stage the heteroscedastic disturbance is present, we propose to apply the number of disturbances observed using ACF and PACF plots.

Homoscedastic Disturbances

The diagonal elements of the covariance matrix of ε are the same indicating that the variance of each ε_i is same and off-diagonal elements of the covariance matrix of ε are zero indicating that all disturbances are pairwise uncorrelated. This property of constancy of variance is termed as homoskedasticity and disturbances are called as homoscedastic disturbances [24,25].

i.e $Var\,(\varepsilon_i^2) = \sigma^2$, and $Cov\,(\varepsilon_i \varepsilon_j) = 0, i \neq j = 1,2,3, \dots, n.$

Heuristic Fsarima Algorithm

This section details the proposed FARIMA model and its selection processes, providing a detailed step-by-step guide as outlined in the following steps 1-10.

Step 1.

Adopting the absolute dataset with $|x_i|$. In the given dataset contains the negative values, hence we have taken the absolute values for the future studies.

Step 2.

Setting Fuzzy Normalized transform $y_i \in (0,1)$ and all values are rescaled by using the following formula

$$\varphi_i = \frac{y_i - Min((y_i)}{Max\,(y_i) - Min\,(y_i)}, \text{for every i.}$$

Step 3.

After fixing the fuzzy normalization in the current dataset, we initiated the model fit using an auto-regressive integrated moving average for seasonal normalized data with different orders (Fig. 2)

Step 4.

Making first order and second order derivative using the following derivatives $\left(\frac{\Delta y}{\Delta x}\right)$ and $\left(\frac{\Delta^2 y}{\Delta x^2}\right)$.

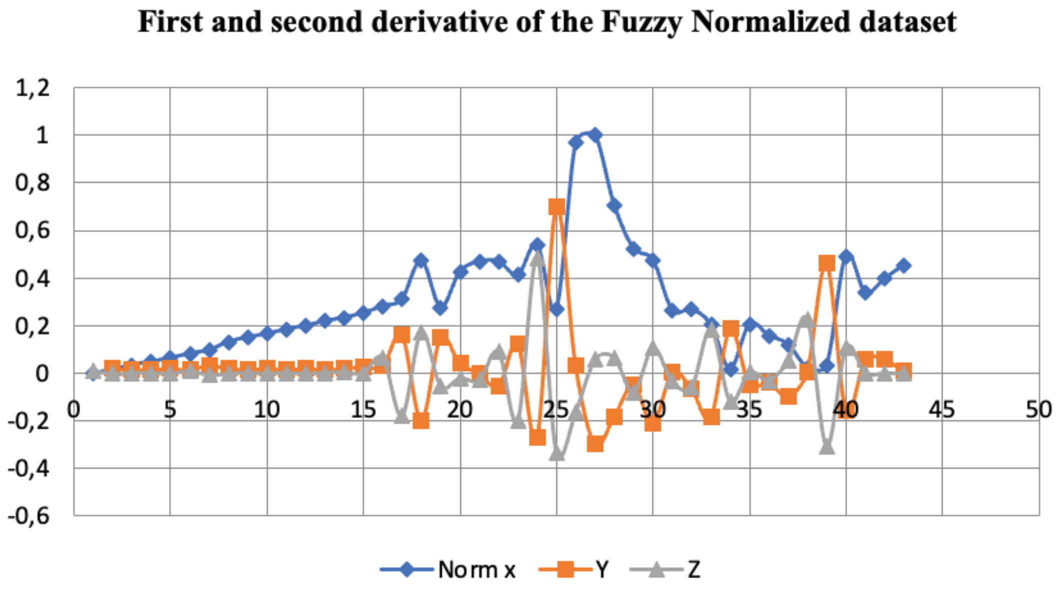

Figure 2. First and second derivative of the fuzzy normalized dataset.

Step 5.

Plotting the fuzzy normalized transformed data and identifying the most negatives are the inflexion points, which are assigned to classify different rice crop phenological stages of the dataset. In this study, the most negative has been detected and pointed out as an inflexion point (Fig. 3).

Step 6.

In this step, correlating values are removed as outliers in the dataset. The inflexion point is considered an outlier and removed or replaced by the mean value for better model accuracy if needed.

Step 7.

Classification of various stages Like Transplanting, Heading, and Harvesting stages.

In Figure 4, the time series plots show that sensors move more backscattered sensors at the heading stage, indicating that chlorophyll content appears at its maximum value on the 24th day of the crop period. In the second order auto-regressive model, chlorophyll content is almost just above the normal data.

Step 8.

Identify the Heteroscedastic disturbances are attained in the dataset.

Step 9.

Using the Fuzzy Normalized values, we need to build the model. By using ACF and PACF plots. The ACF and PACF of the Fuzzy normalized transformed data are plotted to determine if an AR (p) or MA (q) model is appropriated

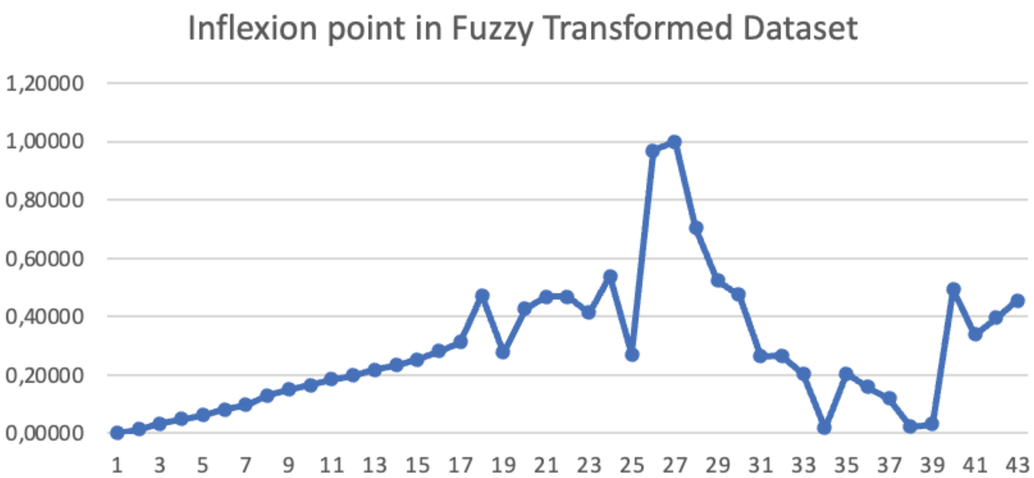

Figure 3. Inflexion points in fuzzy transformed dataset.

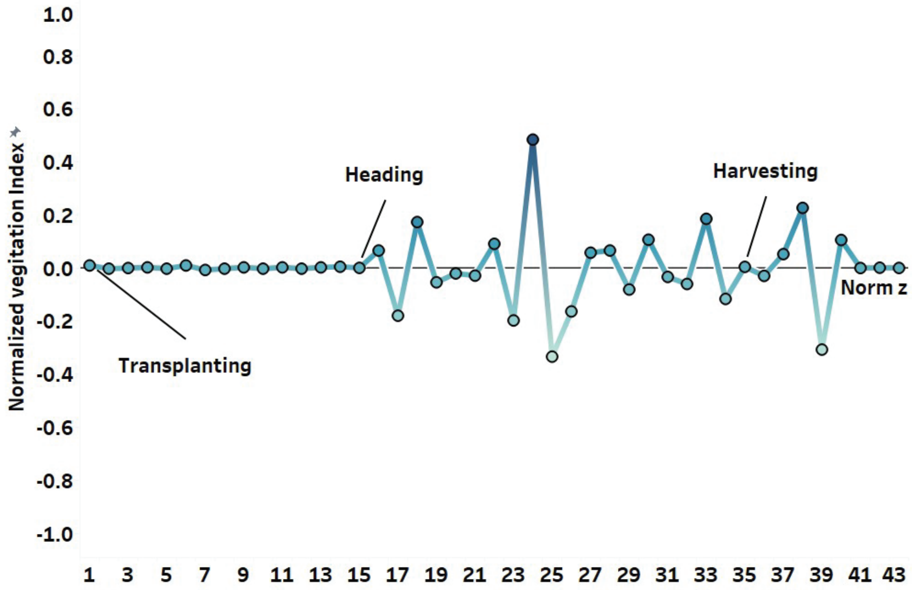

Figure 4. Second iteration of the data.

Table 1. ACF and PACF values for the fuzzy normalized transformation values of rice crop dataset

Correlogram		Alpha	0.05	Correlogram		Alpha	0.05
Lags	ACF	Lower	Upper	Lags	PACF	Lower	Upper
1	0.718422	-0.29889	0.298892	1	0.718422	-0.29889	0.298892
2	0.569599	-0.42609	0.426092	2	0.110501	-0.29889	0.298892
3	0.457685	-0.48941	0.489412	3	0.029927	-0.29889	0.298892
4	0.316031	-0.52626	0.526262	4	-0.10152	-0.29889	0.298892
5	0.21913	-0.54295	0.542951	5	-0.02048	-0.29889	0.298892
6	0.139989	-0.5508	0.550796	6	-0.02337	-0.29889	0.298892
7	-0.01242	-0.55396	0.553965	7	-0.20199	-0.29889	0.298892
8	-0.04362	-0.55399	0.55399	8	0.070337	-0.29889	0.298892
9	-0.07394	-0.5543	0.554297	9	-0.00079	-0.29889	0.298892
10	-0.15134	-0.55518	0.555177	10	-0.111	-0.29889	0.298892

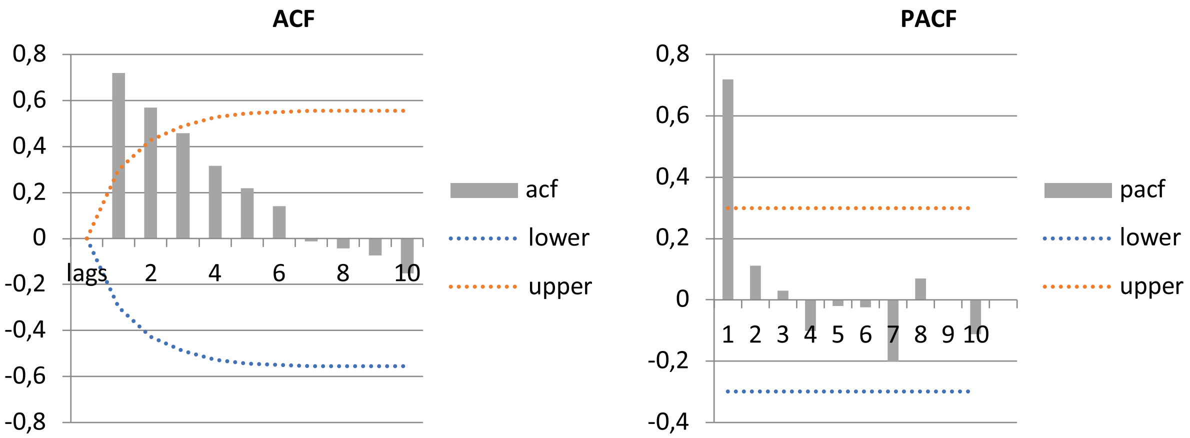

Figure 5. ACF and PACF plot for the fuzzy normalized transformation values of rice crop dataset.

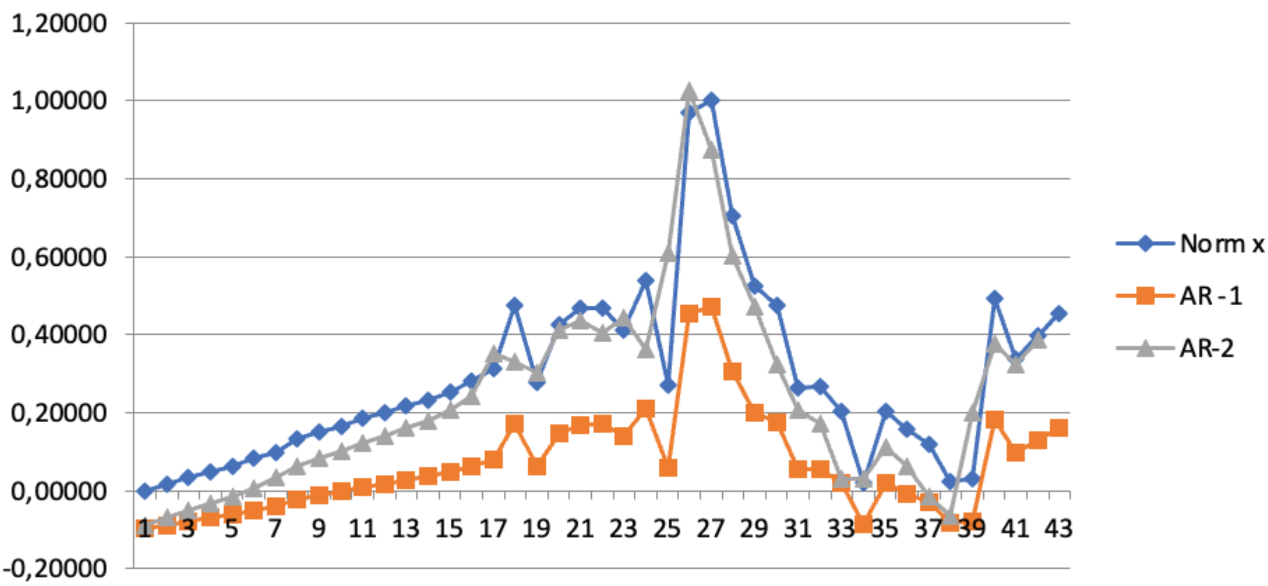

Figure 6. Forecasted value for the dataset by AR(1) and AR(2) values.

and to identify potential candidate models. The values are noted in Table 1, and Figure 5 shows that the ACF and PACF plots for the identifying the AR models.

Step 10.

Using various PEM (Performance Error Measures) for analysis the error measures for the forecasting values has been derived from the AR models and make the best model for forecasting and prediction.

The AR(1) and AR(2) models are effective for predicting and forecasting data in rice crop backscatter datasets, and can identify missing points in data. The paper demonstrates that standard statistical measures can be used to assess the fitness of these models in model fitting

Table 2. Error statistics of AR1 and AR2

Error statistics	AR1	AR2
ME	0.222681132	0.04999487
MSE	0.059384215	0.01040026
RMSE	0.243688766	0.10198168
MAE	0.222681132	0.08292661
MPE	1.384128354	0.41657533
MAPE	1.384128354	0.79408127
SMAPE	1.45438258	0.65787887
U1	0.46821951	0.14272539
U2	0.99385658	0.65028093

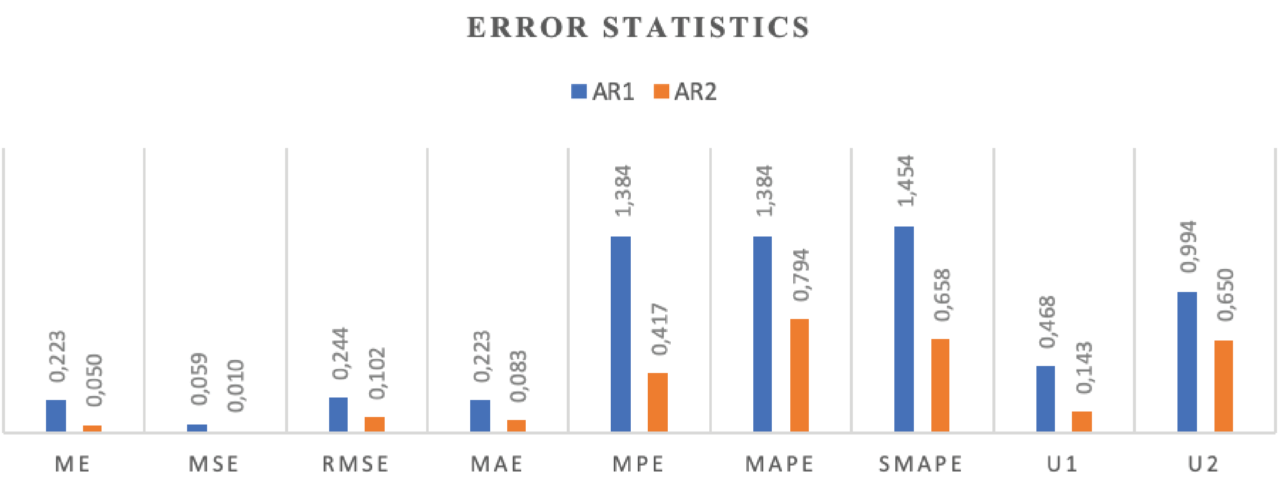

Figure 7. Error statistics of models.

technology. In Figure 6. Shows that the forecasted value through AR(1) and AR(2) models. It shows that the AR(2) values are closely near to the actual values.

The study uses MAPE to select the best forecasting model with minimal error for method accuracy. The MAPE for AR (1) is 1.384, indicating the best fit for rice crop data. AR (2) has a smaller MAPE of 0.794. Futuristic auto-regressive first and second order models are also feasible for locating missing observations and obtaining future predictions and forecasting scenarios.

The fitted models are ideal for backscatter data sets, with MPE and MAE accuracy measures close to zero. First and second-order auto-regressive models are the best fit for backscattered time series data. The model produces MPE=1.384 for AR (1) and 0.4165 for AR (2), and MAE = 0.222 for AR (1) and 0.0829 for AR (2). Both accuracy measures are approaching zero, indicating no bias. And figure 7, shows that the error statistics of Auto regressive Models.

CONCLUSION

AR(1) and AR(2) were developed for prediction and forecasting the future dataset. The main results, ME, MSE, MAPE, MPE, RMSE, U1, and U2, are obtained and are under consideration for the model building. The model-building concept adopted future normalization techniques to transform data into structured series. For classification, the inflexion point methodology is best and shows the best linear auto-regressive models for orders I and II. Continuous monitoring systems have been found to be a more accurate method for identifying different rice crop growing stages for the Kharif season. The classification of these stages is 15 days, 20 days, and 8 days for transplanting, heading, and harvesting stages, respectively. This aligns with ground truth observation, yielding transplanting, heading, and harvesting times of 15, 18, and 10 days. The findings suggest that continuous monitoring systems can accurately track and predict rice crop growth stages, enabling farmers to optimize their cultivation practices.

By better understanding the needs of different crops and their responses to various conditions, farmers can optimize their resources and increase yields. This research could also lead to the development of new technologies and innovations that could revolutionize the way crops are grown and harvested. Ultimately, this could lead to a more sustainable and productive agricultural sector, ensuring food security for future generations.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

REFERENCES

[1] Palakuru M, Yarrakula K, Chaube NR, Sk KB, Rao YS. Identification of paddy crop phenological parameters using dual polarized SCATSAT-1 (ISRO, India) scatterometer data. Environ Sci Pollut Res 2019;26:1565−1575. [CrossRef]

[2] Wu JZ, Zhang J, Ge ZM, Xing LW, Han SQ, Chen SHEN, et al. Impact of climate change on maize yield in China from 1979 to 2016. J Integr Agric 2021;20:289−299. [CrossRef]

[3] Oza SR, Panigrahy S, Parihar JS. Concurrent use of active and passive microwave remote sensing data for monitoring of rice crop. Int J Appl Earth Obs Geoinform 2008;10:296−304. [CrossRef]

[4] Raj HK, Kushwaha HS. Effect of planting dates and soil water regimes on growth and yield of upland rice. Oryza 2008;45:129−132.

[5] He Z, Li S, Wang Y, Dai L, Lin S. Monitoring rice phenology based on backscattering characteristics of multi-temporal RADARSAT-2 datasets. Remote Sensing 2018;10:420−429. [CrossRef]

[6] Santra P, Moharana PC, Kumar M, Soni ML, Pandey CB, Chaudhari SK, et al. Crop production and economic loss due to wind erosion in hot arid ecosystem of India. Aeolian Res 2017;28:71−82. [CrossRef]

[7] Babu KSK, Chesneau C, Anthonysamy V. Rice crop growth analysis using Auto Regressive Models. J Prob Stat Sci 2023;21:50−59. [CrossRef]

[8] Park J, Tateishi R, Matsuoka M. A proposal of the Temporal Window Operation (TWO) method to remove high-frequency noises in AVHRR NDVI time series data. J Japan Soc Photogrammetry Remote Sensing 1999;38:36−47. [CrossRef]

[9] Kumar P, Prasad RK, Gupta DK, Mishra VN, Vishwakarma AK, Yadav RP, et al. Estimation of winter wheat crop growth parameters using time series Sentinel-1A SAR data. Geocarto Int 2018;33:942−956. [CrossRef]

[10] Gunasekar T, Thiravidarani J, Mahdal M, Raghavendran P, Venkatesan A, Elangovan M. Study of Non-Linear Impulsive Neutral Fuzzy Delay Differential Equations with Non-Local conditions. Mathematics 2023;11:3734. [CrossRef]

[11] Gunasekar Th, Raghavendran P, Santra SS, Sajid M. Analyzing existence, uniqueness, and stability of

neutral fractional Volterra-Fredholm integro-differential equations. J Math Comput Sci-JM 2024;33:390–407. [CrossRef]
[12] Gunasekar T, Raghavendran P. The Mohand Transform Approach to Fractional Integro-Differential Equations. J Comput Anal Appl 2024;33:58–371. [CrossRef]
[13] Gunasekar T, Thiravidarani J, Mahdal M, Raghavendran P, Venkatesan A, Elangovan M. Study of Non-Linear Impulsive Neutral Fuzzy Delay Differential Equations with Non-Local Conditions. Mathematics 2023;11:3734. [CrossRef]
[14] Raghavendran P, Gunasekar Th, Balasundaram H, Santra SS, Majumder D, Baleanu D. Solving fractional integro-differential equations by Aboodh transform. J Math Comput Sci-JM 2024;32:229–240. [CrossRef]
[15] Zhang X, Friedl MA, Strahler AH, Hodges JCF, Gao F, Reed BC. Monitoring vegetation phenology using MODIS. Remote Sens Environ 2003;84:471–475. [CrossRef]
[16] Kotani A, Hiyama T, Ohta T, Hanamura M, Kambatuku JR, Awala K, Iilima M. Impact of rice cultivation on evapotranspiration in small seasonal wetlands of north-central Namibia. Hydrol Res Lett 2017;11:134–140. [CrossRef]
[17] Akiyama T, Kawamura K, Fukuo A, Chen ZZ. Sustainable grassland management using GIS, GPS and remote sensing data in Inner Mongolia. In: Uchida S, Youqi C, Saito G, editors. Application on remote sensing technology for the management of agricultural resources. Beijing: China Agricultural Scientech Press; 2002. p. 13–19.
[18] Xiao X, Boles S, Frolking S, Salas W, Moore III B, He L, et al. Observation of flooding and rice transplanting of paddy rice field at the site to landscape scales in China using VEGETATION sensor data. Int J Remote Sens 2002;23:3009–3022. [CrossRef]
[19] Palakuru M, Adamala S, Bachina HB. Modeling yield and backscatter using satellite derived biophysical variables of rice crop based on Artificial Neural Networks. J Agrometeorol 2020;22:41–47. [CrossRef]
[20] Khadar Babu SK, Chesneau C, Anthonysamy V, Ravichandaran S, Shakila CV. Efficacy of the rice crop growth using different smoothing methods. J Appl Anal Comput 2022;12:2593–2599. [CrossRef]
[21] Anthonysamy V, Babu K, Chesneau C. Heuristics approach for the Holt-Winters multiplicative method with new initial values. Model Assoc Stat Appl 2023;18:165–170. [CrossRef]
[22] Saeed M, Wahab A, Ali J, Bonyah E. A robust algorithmic framework for the evaluation of international cricket batters in ODI format based on q-rung linguistic neutrosophic quantification. Heliyon 2023;9. [CrossRef]
[23] Sakamoto T, Yokozawa M, Toritani H, Shibayama M, Ishitsuka N, Ohno H. A crop phenology detection method using time-series MODIS data. Remote Sens Environ 2005;96:366–374. [CrossRef]
[24] Şengül S, Bekiryazici Z, Merdan M. Wong-Zakai approximation for stochastic models of smoking. Sigma: J Eng Nat Sci 2023;41:958–968. [CrossRef]
[25] Şekerci AZ, Aydın N. A stochastic model for facility locations using the priority of fuzzy AHP. Sigma J Eng Nat Sci 2022;40:649–662. [CrossRef]