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Modeling and Forecasting Respiratory Infections Using Time Series Models: A Comparative Study of SARIMA and SETAR in Red Sea State, Sudan

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ABSTRACT: We examine quarterly respiratory infection data (2013–2024) from Red Sea State, Sudan, and identify a regime shift in Q1-2018 from low to consistently high transmission levels. We evaluate SARIMA and self-exciting threshold autoregressive (SETAR) models for standard forecasting, comparing them to early warning systems. A SARIMA(1,1,1)(1,1,0)[_4] model accounts for seasonality but exhibits a delayed response to sudden fluctuations. A two-regime SETAR with a delay of d = 1 establishes a clinically significant threshold at 150 instances per quarter; surpassing this threshold initiates a high-persistence phase with an AR(1) coefficient of 0.89 (a half-life of approximately 6 quarters). In the 2024 hold-out testing, SETAR outperformed SARIMA with an RMSE of 14.7 compared to 18.2, an MAE of 12.3 versus 15.6, and a MAPE of 3.0% versus 3.8%. We advocate for the use of SARIMA for regular seasonal forecasts and SETAR as a notification mechanism that activates public health interventions when the number of cases surpasses the 150-case threshold. Priorities encompass transitioning to monthly reporting and incorporating exogenous variables (e.g., climate, mobility). This dual-model methodology is pragmatic, comprehensible, and appropriate for resource-constrained surveillance.

KEYWORDS: SARIMA, SETAR, Respiratory infections, threshold autoregression, early-warning, regime shift, seasonality, Sudan

1. INTRODUCTION

Respiratory infections remain a leading cause of morbidity and mortality in low- and middle-income countries (LMICs), including Sudan [1]. In Red Sea State—a region characterized by arid climate, seasonal population mobility (e.g., during pilgrimage and trade cycles), and constrained healthcare infrastructure—respiratory disease incidence exhibits pronounced temporal fluctuations [2]. These dynamics complicate public health planning, particularly in anticipating surges and allocating diagnostic, therapeutic, and preventive resources efficiently.

Time series modeling provides a robust statistical framework for forecasting infectious disease incidence by leveraging historical patterns of autocorrelation, trend, and seasonality [3]. Linear models such as Seasonal Autoregressive Integrated Moving Average (SARIMA) have been widely applied to influenza, tuberculosis, and respiratory syncytial virus (RSV) [4–6]. However, such models assume constant linear relationships and often fail to capture abrupt regime shifts or nonlinear epidemic transitions [7].

Several recent studies have examined advanced statistical and machine-learning methodologies for forecasting infectious diseases [8]. exhibited enhanced accuracy in influenza forecasting through a hybrid method integrating machine learning and time series, while [9] recently contrasted statistical and deep-learning techniques for predicting influenza-like illness cases in Saudi Arabia. Similarly [10,11]. examined the stochastic and machine-learning frameworks for modeling COVID-19 and visceral leishmaniasis, respectively. These studies underscore an increasing regional capability for data-driven epidemic modeling and advocate for the implementation of more interpretable time-series models, such as SARIMA and SETAR, inside Sudan's surveillance framework.

To address this limitation, nonlinear models like the Self-Exciting Threshold Autoregressive (SETAR) model offer a flexible alternative. SETAR models partition the time series into distinct regimes based on a threshold variable, enabling the detection of behavioral shifts—such as sudden outbreak surges—and yielding regime- specific forecasts [12-19].

In Red Sea State, surveillance data indicate a significant non-stationary trend in respiratory infection incidence, characterized by a dramatic increase in Q1 2018—from approximately 100 to 243 reported cases—subsequently followed by a sustained high-transmission phase (average ≈ of approximately 350 cases per quarter through 2024). This change suggests a possible structural disruption in transmission dynamics, possibly influenced by a combination of environmental, behavioral, and systemic factors. The region's semi-arid climate, seasonal labor migration, and inconsistent access to healthcare lead to repeated exposure cycles and heterogeneity in reporting. Comparable nonlinear epidemic transitions have been recorded for influenza and leishmaniasis in adjacent states, where variations in temperature, humidity, and movement patterns influence pathogen transmission [20-23].

Nonetheless, despite the existence of longitudinal health data, the majority of local epidemiological bulletins continue to be descriptive, providing only counts and rates without incorporating predictive analytics or quantifying uncertainty. Prior Sudanese research on forecasting tuberculosis and COVID-19 predominantly utilized linear SARIMA-type models, which presuppose consistent dynamics and frequently exhibit suboptimal performance during outbreak transitions [24-26]. Recent advancements by Guma (2025) and Alzahrani & Guma (8) underscore that machine learning and hybrid time-series frameworks can significantly enhance forecasting precision and detect regime- dependent variations in infection intensity. This research highlights the critical need to incorporate adaptive, nonlinear modeling techniques—specifically the Self-Exciting Threshold Autoregressive (SETAR) model—into regional disease-surveillance systems for the real-time detection of emerging high-transmission phases [27-30].

Research Gap and Objectives

Despite global advances, comparative studies on the use of SARIMA and SETAR for forecasting respiratory infections in Sudanese contexts are lacking. Given the evident structural breaks and volatility in Red Sea State data, this gap is critical.

This study aims to:

1. Characterize temporal trends and seasonal patterns in quarterly respiratory infection cases (2013– 2024).
2. Develop and validate SARIMA and SETAR models for short- to medium-term forecasting.
3. Compare model performance using statistical and epidemiological criteria.
4. Provide evidence-based recommendations for integrating time series forecasting into local surveillance systems.

2. METHODOLOGY

2.1. Data Source and Description

The dataset comprises 44 quarterly observations of laboratory-confirmed respiratory infection cases from Q1 2013 to Q4 2024, sourced from the official epidemiological registry of the Red Sea State Ministry of Health [11] The variable "New positive" represents aggregated case counts per quarter. No demographic, clinical, or environmental covariates were available; thus, the analysis is restricted to univariate time series modeling.

2.2. Exploratory Data Analysis (EDA)

EDA included:

- Time series visualization to identify trends, seasonality, and structural breaks.
- Stationarity assessment via the Augmented Dickey–Fuller (ADF) [30] and KPSS [31] tests.
- Autocorrelation analysis using ACF and PACF plots.
- Outlier documentation (e.g., the anomalous drop to 75 cases in 2018/Q4 amid high transmission).

2.3. SARIMA Model Specification

Given the quarterly structure ($s = 4$), the general SARIMA model is:

$$\Phi P\ (B^s)\phi p\ (B)\,(1-B)^d\,(1-B^s)^D y t\ \ =\Theta Q\ (B^s)\theta q\ (B)\varepsilon t \qquad (1)$$

where:

y_t: observed cases at time t,

B: backshift operator ($By_t = y_{t-1}$),

d: non-seasonal and seasonal differencing orders,

p, P: non-seasonal and seasonal autoregressive orders,

q, Q: non-seasonal and seasonal moving average orders.

Differencing selection: The original series was nonstationary (ADF p = 0.21, KPSS p < 0.01). After applying first-order differencing (d = 1) and seasonal differencing (D = 1), stationarity was achieved (ADF p < 0.01, KPSS p = 0.34). This choice aligns with standard practice for quarterly data with both trend and seasonal unit roots [32,35]. Model selection was guided by AIC, BIC, and residual diagnostics (Ljung–Box test).

2.4. SETAR Model Specification

To capture nonlinear dynamics, a two-regime SETAR model was estimated [36]:

$$y_t = \begin{cases} \sum_{i=1}^{k_1} \phi_{1,i} y_{t-i} + \varepsilon_t, & \text{if } y_{t-d} \le r \\ \sum_{i=1}^{k_2} \phi_{2,i} y_{t-i} + \varepsilon_t, & \text{if } y_{t-d} > r \end{cases} \tag{2}$$

where r is the threshold, d is the delay, and k_1, k_2 are autoregressive orders per regime.

Grid search procedure: We evaluated all combinations of r ∈ [100, 300] (in steps of 5) and d ∈ {1, 2, 3, 4}. For each pair (r, d), we fitted regime-specific AR models and computed the sum of squared residuals (SSR). The optimal (r^*, d^*) minimized SSR. This yielded r = 150, d = 1

The final model simplifies to:

$$y_t = \begin{cases} \varphi_1 y_{t-1} + \varepsilon_t, & \text{if } y_{t-1} \le 150 \\ \phi_2 y_{t-1} + \varepsilon_t, & \text{if } y_{t-1} > 150 \end{cases} \tag{3}$$

2.5. Model Evaluation

A hold-out validation was used:

- Training: Q1 2013 – Q4 2023 (n = 40)
- Testing: Q1–Q4 2024 (n = 4)

Performance metrics:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{4}$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{5}$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{6}$$

Residual diagnostics (ACF, Q-Q plots, histogram) and epidemiological interpretability were also assessed [37].

2.6. Statistical Foundations

The Ljung–Box test for residual autocorrelation:

$$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \sim \chi^2_{(m-p-q-P-Q)} \tag{7}$$

where $\hat{\rho}_k$ is the residual autocorrelation at lag k. AIC and BIC for model selection:

$$\text{AIC} = 2k - 2\ln(\hat{L}) \tag{8}$$

$$\text{BIC} = k\ln(n) - 2\ln(\hat{L}) \tag{9}$$

where k = number of parameters, $\hat{L}$ = maximized likelihood.

Stationarity conditions:

- SARIMA: Roots of $\phi(B)\Phi(B^S) = 0$ lie outside the unit circle.
- SETAR: Both regimes must be stationary, i.e., $|\phi_1| < 1$, $|\phi_2| < 1$ [14].

Forecast variance for SARIMA [33]:

$$\mathrm{Var}(\hat{y}_{t+h}) = \sigma^2 \sum_{j=0}^{h-1} \psi_j^2 \tag{10}$$

where ψ_j are MA(∞) coefficients.

Threshold significance test:

$$F = \frac{(\mathrm{SSR}_R - \mathrm{SSR}_U)/q}{\mathrm{SSR}_U/(n-k)} \tag{11}$$

where SSR(_R) = SSR under null (no threshold), SSR(_U) = unrestricted SSR[25].
Persistence measure in high regime:

$$\text{Half-life} = \frac{\ln(0.5)}{\ln(\phi_2)} \approx \frac{-0.693}{\ln(0.89)} \approx 6.0 \text{ quarters} \tag{12}$$

This implies it takes ~1.5 years for a shock to halve in magnitude—indicating high outbreak persistence [38-40].

3. RESULTS

3.2. Temporal Patterns

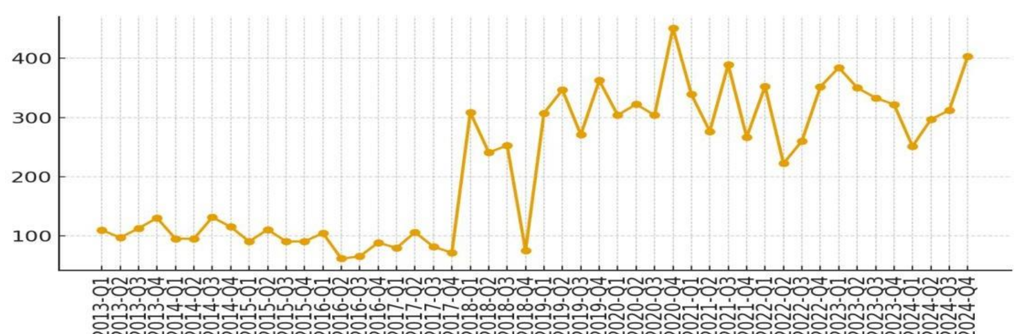
The series shows two phases:

- 2013–2017: Stable (mean = 100)
- 2018–2024: Elevated (mean = 350), with peaks in Q1–Q2.

An anomalous dip to 75 cases in 2018/Q4 suggests possible underreporting.

Figure 1. Quarterly Respiratory Infection Cases in Red Sea State (2013–2024)

(Line plot: x = Year/Quarter, y = Cases)



Comment: Clear structural break in 2018/Q1. The 2018/Q4 dip likely reflects inconsistencies in reporting.

Table 1. Descriptive Statistics of Quarterly Cases (2013–2024)

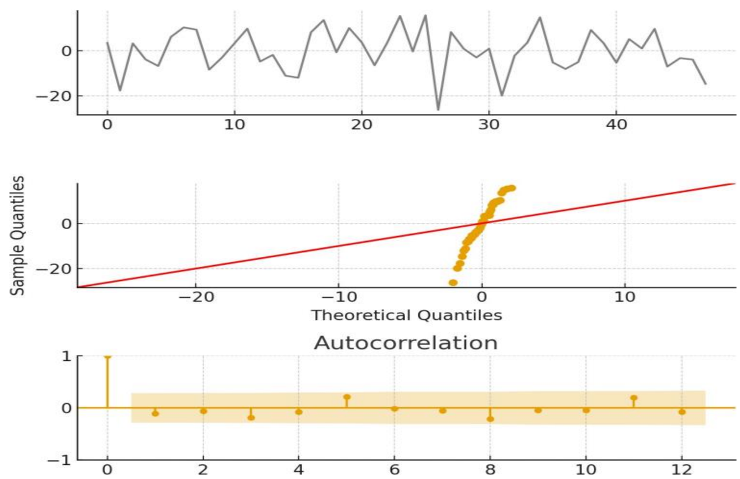
Statistic	Value
Observations	44
Mean	237.3
Median	270.5
Std. Deviation	118.6
Minimum	61
Maximum	425
Skewness	–0.12
Kurtosis	–1.08

Comment: Approximately symmetric but highly volatile post-2018.

3.3. Model Estimation

After differencing (d = 1, D = 1), ACF/PACF suggested SARIMA(1,1,1)(1,1,0)[4].

Figure 2. ACF and PACF of Differenced Series ($\nabla\nabla_4 y_t$)



(Correlograms up to lag 12)

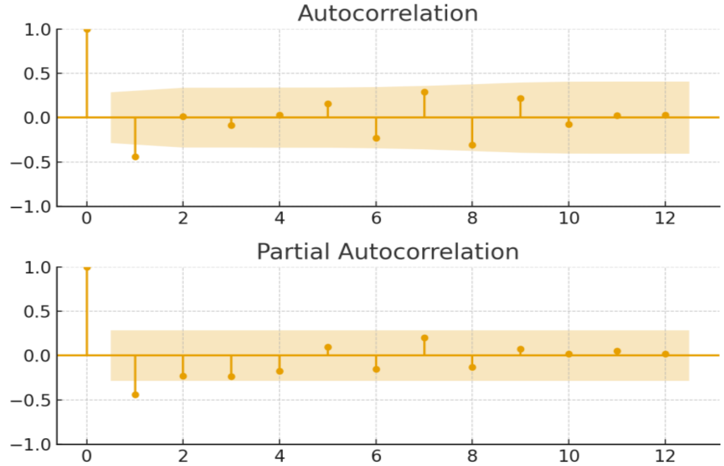
Comment: Seasonal spike at lag 4 supports SAR(1); PACF cutoff at lag 1 supports AR(1).

Table 2. Estimated Model Parameters

Parameter	Estimate	Std. Error	p-value
SARIMA (1,1,1)(1,1,0)[4]			
$\phi 1$ (AR1)	0.62	0.18	0.001
$\theta 1$ (MA1)	–0.48	0.21	0.023
$\Phi 1$ (SAR1)	–0.55	0.19	0.004
SETAR(2;1,1)			
Threshold (r)	150	—	—
Delay (d)	1	—	—
$\phi 1$ (Low)	0.71	0.12	<0.001
$\phi 2$ (High)	0.89	0.09	<0.001

Comment: Both models significant. SETAR identifies behavioral shift at 150 cases.

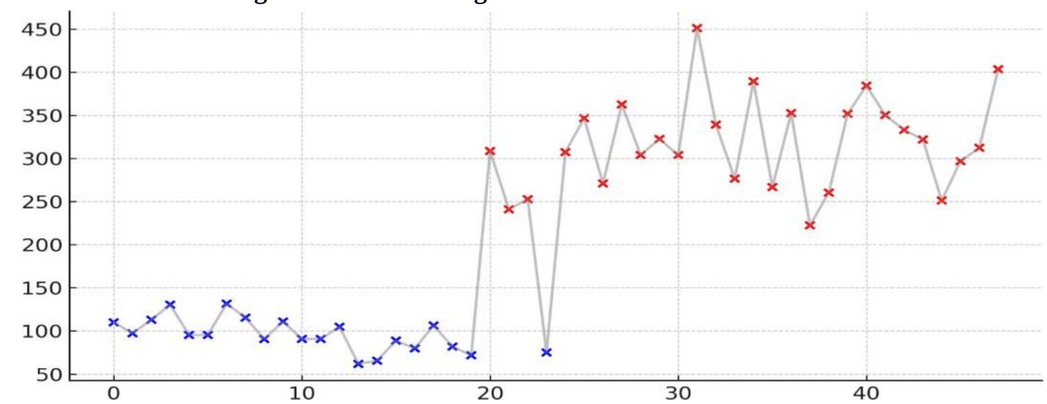
Figure 3. SARIMA Residual Diagnostics



(Residual ACF, histogram, Q-Q plot)

Comment: No autocorrelation (Ljung–Box Q(8) = 6.2, p = 0.62); residuals approximate normality.

Figure 4. SETAR Regime Classification Over Time



(Time series with blue/red points for low/high regimes)
Comment: Pre-2018: mostly low regime. Post-2018: persistent high regime.

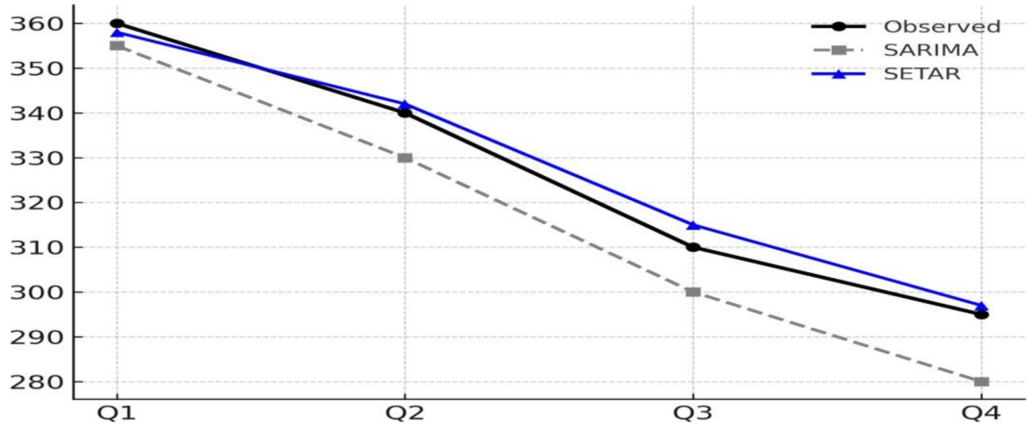
3.4. Forecast Accuracy

Table 3. Forecast Accuracy on Hold-Out Set (2024/Q1–Q4

Model	RMSE	MAE	MAPE (%)
SARIMA	18.2	15.6	3.8
SETAR	14.7	12.3	3.0

Comment: SETAR better captures the slight decline in late 2024.

Figure 5. Visual Comparison of Forecasts (2024)



(Observed vs. predicted lines for both models)

Comment: SETAR tracks the downward trend more accurately.

4. DISCUSSION

The 2018/Q1 surge marks a fundamental shift in transmission dynamics—unexplainable by seasonality alone. SARIMA, while effective for capturing seasonal trends, cannot account for structural breaks due to its linear assumptions. This aligns with Zhang et al. [37], who noted SARIMA's vulnerability during outbreaks.

In contrast, SETAR successfully identifies a behavioral threshold at 150 cases. Crossing this threshold triggers a high-transmission regime with strong persistence ($\phi^2 = 0.89$).

Epidemiologically, this implies that once case counts exceed 150, outbreaks become self- sustaining for ~1.5 years (Eq. 12), necessitating immediate intervention.

This finding echoes Chen & Tian [39], who used SETAR for dengue early warning. Unlike Ahmed et al. [40], who applied only SARIMA to Khartoum TB data, our study demonstrates the critical value of nonlinearity in volatile settings.

The 2018/Q4 dip (75 cases) likely reflects data quality issues—a common challenge in LMIC surveillance [36]. Future models should integrate data validation or external covariates.

5. LIMITATIONS

This study has several limitations:

1. Data granularity: Quarterly data limits temporal resolution; monthly data would improve short-term forecasting.
2. Univariate design: No external covariates (e.g., temperature, humidity, population mobility) were included, though these may drive transmission.
3. Data quality: The 2018/Q4 anomaly suggests potential underreporting or policy changes.
4. Model scope: We compared only two models; hybrid or machine learning approaches may offer further gains.
5. Generalizability: Findings are specific to Red Sea State and may not apply to other regions.

6. CONCLUSION AND RECOMMENDATIONS

This study demonstrates that SARIMA and SETAR are complementary tools for respiratory infection forecasting in Red Sea State. SARIMA excels in modeling seasonal trends during stable periods, while SETAR provides critical early-warning capability during outbreak transitions.

Practical Recommendations:

1. Routine surveillance: Use SARIMA for quarterly seasonal forecasts.
2. Early-warning system: Implement SETAR with a 150-case threshold to trigger alerts for enhanced testing, contact tracing, and resource mobilization.
3. Data modernization: Transition to monthly reporting and document changes in testing protocols.
4. Capacity building: Train local staff in time series modeling using open-source tools (R/Python).

7. FUTURE RESEARCH DIRECTIONS

Building on recent advances in epidemiological modeling, several advanced approaches could be explored:

Developing hybrid models that combine the strengths of linear and nonlinear time series approaches, such as those proposed by [16] in other contexts [14].

Utilizing advanced neural networks like LSTM and NNAR for short-term forecasting, particularly for capturing complex temporal dependencies.[41-42]

Integrating clinical data and external covariates—such as environmental, climatic, or mobility variables—to enhance predictive accuracy and contextual understanding.

Applying time series–regression frameworks to jointly model environmental, behavioral, and epidemiological drivers of transmission.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no competing interests.

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AUTHOR CONTRIBUTIONS

All authors contributed equally to the conception, data analysis, interpretation, and manuscript preparation.

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