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ISSN 2959-6130

Time Series Modeling and Forecasting of Breast Cancer Mortality among U.S. Women

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Abstract:
This study examines temporal mortality patterns among U.S. female breast cancer patients, addressing persistent health inequities across racial and ethnic groups through time series forecasting models. Using follow-up data from 4,024 cases via the U-BRITE platform, it systematically compared ARIMA, SARIMAX, ETS, and TBATS models. Results demonstrate that ARIMA and ETS achieved superior predictive accuracy with satisfactory residual diagnostics. SARIMAX, despite incorporating seasonal components and exogenous variables, failed to improve forecasts, while TBATS exhibited substantial prediction uncertainty. Analysis reveals elevated mortality risk during early post-diagnosis periods, suggesting systemic barriers in timely diagnosis and treatment. Based on identified high-risk windows, it proposes four intervention strategies: expanding screening coverage, enhancing medical support during peak-risk periods, establishing targeted programs for vulnerable populations, and reforming healthcare coverage systems. Methodologically, parsimonious models outperformed complex seasonal frameworks for monthly mortality data. Future research should integrate patient-level covariates and external factors to enhance predictive precision and inform evidence-based public health policy.

Keywords: Time Series forecasting; Exponential smoothing; Breast cancer mortality; Cancer mortality prediction; Autoregressive integrated moving average.

1. Introduction

Breast cancer ranks among the among the leading malignancies in women worldwide. It represents a major public health burden for American women [1]. It’s the second significant cancer after skin cancer. It’s also the second leading cause of cancer-related death [2].

According to epidemiological surveillance data from the National Cancer Institute (NCI), between 2018 and 2022, the age-adjusted incidence of female breast cancer in the United States was approximately 130.8

per 100,000 person-years. The mortality rate between 2019 and 2023 was about 19.2 per 100,000 person-years [3]. Projections for 2025 indicate approximately 310,720 new cases and 42,170 deaths from breast cancer among American women [4]. Ethnic disparities are particularly striking: among non-Hispanic black women and Hispanic women, breast cancer has become the leading cause of cancer death. Breast cancer mortality is approximately 38% higher among black women than white women, even though their incidence is slightly lower (-5%) [1]. Recent research shows that between 2004 and 2022, mortality among Black American women remained about 39% higher than white women. Among young women (20-39 years), the difference reached 104% [5]. These findings reveal that breast cancer is characterized not only by high incidence and mortality in the general population but also by profound health inequalities between ethnic groups.

The spread of screening such as mammography and therapeutic advances : surgery, radiotherapy, chemotherapy, targeted treatments, immunotherapy have significantly improved survival for American patients over recent decades [6]. Yet these advances don't benefit all populations equally. While early screening has increased early-stage diagnosis rates for some women, unequal healthcare access limits benefits for minorities and disadvantaged groups. Lifestyle factors (obesity, late motherhood, hormone replacement therapy) and socioeconomic barriers (inadequate insurance, treatment delays) contribute to persistent increases in incidence and mortality in certain subgroups [7]. Current research focuses on long-term trends in overall incidence and mortality. Little attention is paid to variations in death risk based on time elapsed since diagnosis. Applying time series methods to study mortality trends allows identification of high-risk time windows, optimization of medical resource allocation, and design of targeted intervention strategies.

This study focuses on two key questions: First, it examines how time series methods can accurately predict the temporal distribution of death risk among breast cancer patients. Second, it explores how these forecasts can be used to identify high-risk windows and inform the development of public health intervention strategies aimed at reducing mortality and health inequalities. By systematically comparing multiple-time series models, this research provides not only a methodological reference in cancer epidemiology but also proposes targeted, forecast-based intervention strategies. These are essential for reducing health gaps and improving the overall health level of the American female population.

2. Methodology

To accurately predict mortality trends among American women with breast cancer and identify high-risk time windows, this study adopts a multi-model comparison strategy. It systematically evaluates the predictive performance of four time series approaches: ARIMA, SARIMAX, ETS, and TBATS. Time series analysis is an important tool in predictive epidemiology. It captures temporal dynamics of disease progression and provides forward-looking insights into public health decision-making [8]. This chapter begins with a review of time series of methods applied to cancer epidemiology. This positions the methodological approach of this work precisely. It then describes the data source, preprocessing steps, model construction process, and evaluation criteria. This lays the foundation for the empirical analysis that follows.

2.1 Research Background and Study Approach

Time series analysis methods have a long-established history of application in medicine and public health. They have accumulated substantial experience particularly in forecasting epidemiological trends. Nevertheless, current research on breast cancer mortality most often relies on a single model. This lacks systematic comparison of different approaches. This study aims precisely to fill this gap through multi-model evaluation.

2.1.1 ARIMA model

The ARIMA model has become a standard tool due to its ability to effectively handle non-stationary time series. Zhang et al. applied it to forecast breast cancer incidence in China [8]. They demonstrated that this model captures trend fluctuations better than simple linear regression. Despite its strengths, ARIMA has notable limitations: it poorly handles data with marked seasonal components and does not allow integration of exogenous factors [9].

2.1.2 SARIMAX model

The SARIMAX model extends ARIMA by adding seasonal components and exogenous variables. This broadens its modeling capabilities. Liu et al.'s study confirmed that when exogenous variables are relevant, SARIMAX can significantly improve forecasting of chronic disease mortality [10]. That said, this model imposes strong requirements on data characteristics: in the absence of seasonality or when exogenous variables have low explanatory value, increased model complexity may harm forecast accuracy [11].

2.1.3 ETS model

The ETS model relies on exponential smoothing techniques, which assign different weights to past observations to generate forecasts. It flexibly adapts to various trends and seasonality patterns [12]. This approach has demonstrated effectiveness for short- and medium-term forecasting, notably in infectious disease surveillance in public health. Nonetheless, ETS is sensitive to extreme values. In

ISSN 2959-6130

certain cases, it may produce overly smooth forecasts [13].

2.1.4 TBATS model

The TBATS model was designed specifically for time series with multiple complex seasonal cycles. By combining various statistical techniques, it presents advantages in handling highly cyclical medical data . Nevertheless, parameter estimation remains complex, computational cost is high, and when seasonality is weak, its performance does not surpass that of simpler models. Second level headings are typed as part of the succeeding paragraph (like the subsection heading of this paragraph). Overall, research on breast cancer mortality forecasting presents three major limitations. First, model selection lacks systematic evaluation, making it difficult to identify the method best suited to the data under study. Second, most studies use aggregated annual or quarterly data and neglect high-frequency monthly data analysis, limiting the ability to identify short-term risk fluctuations. Third, predictive results often remain at the technical level and struggle to articulate with real health policy needs. The innovations of this study rest on three main points. First, systematically compare ARIMA, SARIMAX, ETS, and TBATS to provide robust methodological evaluation of breast cancer mortality forecasting. Second, monthly follow-up data to precisely describe temporal evolution of death risk and identify critical periods requiring particular attention. Third, forecast results to healthcare accessibility and health equity issues to propose operational recommendations and construct a complete pathway from technical analysis to practical application.

2.2 Data Source and Preprocessing

The data for this study comes from the U-BRITE platform, drawn from a clinical follow-up dataset comprising 4,024 cases of American women with breast cancer [14]. Before modeling, data preprocessing was performed. Patient survival status was first transformed into a binary variable (survival = 0, death = 1), and incomplete records were excluded. Next, the number of deaths was aggregated by follow-up month to construct a monthly time series of death counts. Using follow-up months rather than calendar months better reflects the dynamic process from diagnosis to death . For SARIMAX model construction, the average age of patients who died each month was calculated and integrated as an exogenous variable to evaluate the impact of age on prognosis [15]. The time series frequency was set to 12 to detect potential seasonal components. The data was split using a chronological approach: the last 24 months were used as the test sample to evaluate out-of-sample predictive performance, while earlier observations served as the training sample for parameter estimation .

2.3 Model Construction

After data preprocessing, this study selected four time series models for systematic comparison, following three principles: methodological diversity, increasing complexity, and suitability to data characteristics. The ARIMA model was chosen as the reference method, serving as a comparison standard for other approaches. An automated parameter selection algorithm based on the Akaike Information Criterion (AIC) was employed to identify the optimal parameter combination and avoid subjective bias [16]. The SARIMAX model, built on the ARIMA foundation, introduced seasonal components to explore potential cyclical patterns and integrated monthly average age as an exogenous variable to verify whether demographic information could improve forecast accuracy. The ETS model was used to flexibly combine three components—error, trend, and seasonality—through an automated model selection procedure that determines the optimal configuration among available specifications. The TBATS model was applied to evaluate the relevance of multi-seasonal modeling, being capable of capturing cyclical influence across multiple temporal scales. These four models, ranging from simplest to most complex, constitute a methodological gradient, and the forecast horizon was standardized 24 months. This multi-model comparison strategy not only identifies the best-performing method but also better reveals the structural characteristics of the time series.

2.4 Model Evaluation and Expected Performance

To comprehensively assess forecast accuracy, this study adopted four error metrics: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and symmetric mean absolute percentage error (sMAPE). These metrics measure forecast deviations from different angles and provide an overall performance evaluation. RMSE, by squaring errors then taking the root, gives stronger penalization to large errors. MAE, calculated as the simple average of absolute errors, offers a robust measure of overall error. MAPE expresses relative error as a percentage, facilitating comparisons across datasets, but can become unstable when actual values are close to zero. sMAPE corrects this problem by introducing summarization in the denominator. Beyond forecast errors, this study conducted residual diagnostics for all models, including graphical residual analysis, autocorrelation (ACF) and partial autocorrelation (PACF) functions, Q-Q normality plots, and the Ljung-Box test. If residuals pass these diagnostics, this indicates the model has properly extracted systematic information.

Based on data characteristics and modeling mechanisms, expectations for the four models are as follows. ARIMA, as the reference method, should exhibit stable performance . SARIMAX could improve forecasts if seasonality or age effects prove significant, but its results remain uncertain [17]. ETS is particularly suited to capturing short-term fluctuations but is sensitive to extreme values [13]. TBATS, conversely, might encounter parameter instability issues in the absence of marked seasonality [18]. ARIMA and ETS are expected to pass residual diagnostics, while SARIMAX and TBATS' performance will depend heavily on the structural complexity of the data. By combining multiple evaluation dimensions, this study does not simply identify the best-performing model but also seeks to reveal the underlying structural characteristics of the time series. These methodological findings will provide the foundation for empirical analyses in Chapter 3 and public policy recommendations in Chapter 4.

3. Analysis

This chapter presents the forecast results obtained by the four time series models applied to monthly breast cancer mortality data. The multidimensional evaluation identifies the best-performing forecasting method and analyzes the underlying reasons for observed differences between models. The analysis unfolds in five parts: description of temporal data characteristics, comparison of predictive performance across the four models, evaluation of forecast accuracy, residual diagnostics, and overall comparison with interpretation of results from a public health perspective.

3.1 Data Characteristics and Time Series Analysis

Fig. 1 illustrates the monthly time series of death counts constructed from 4,024 cases of American women with breast cancer from the U-BRITE platform, along with its autocorrelation characteristics. The series covers approximately ten months of follow-up, with the horizontal axis representing months since diagnosis and the vertical axis showing the number of deaths. Overall, the trend shows a gradual increase in death counts during the first months of follow-up (months 1 to 2), reaching a peak between the 2nd and 4th months (approximately 10 to 15 deaths per month), before progressively declining to lower levels during the intermediate and late periods (months 5 to 10). This rise-and-fall curve pattern reflects the temporal distribution of death risk among breast cancer patients. Risk is relatively high in the early stage after diagnosis, which may be related to late diagnoses, low treatment tolerance, or the presence of complications [15].

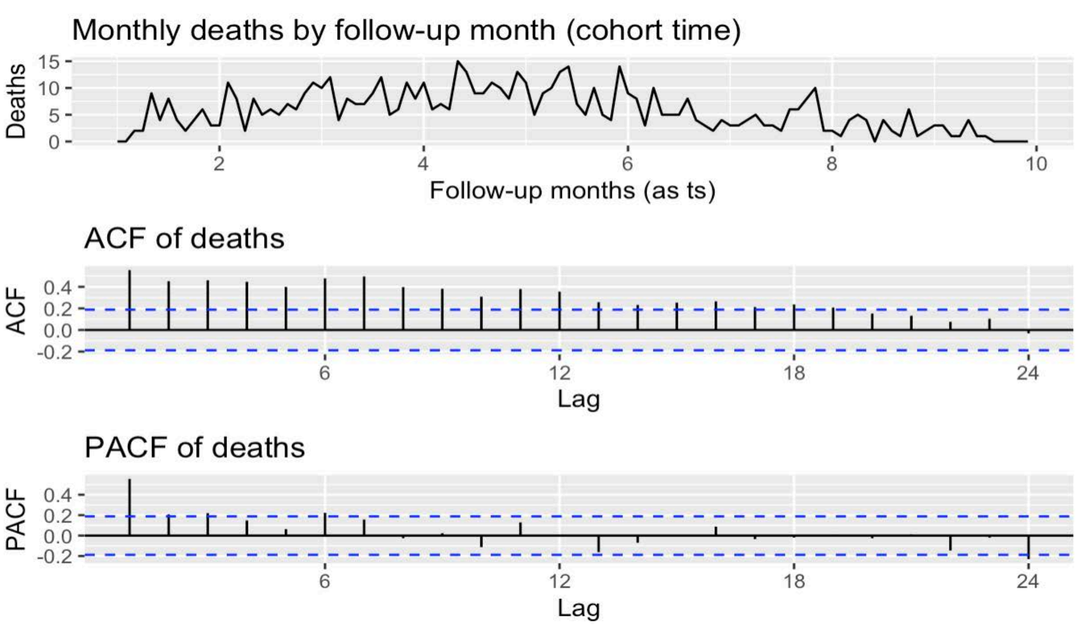

Fig. 1 Time Series of Monthly Deaths and Autocorrelation Analysis

The series exhibits notable variability but does not display a marked seasonal pattern. The autocorrelation function (ACF) plot indicates that most autocorrelation coefficients at different lags fall within the 95% confidence interval, with only a few lags slightly exceeding the boundaries. This suggests weak autocorrelation in the series. The partial autocorrelation function (PACF) plot shows similar characteristics. This result suggests the data primarily consists of a trend and random fluctuations, without significant 12-month periodicity. This constitutes an important foundation for interpreting the model performances presented later.

3.2 Comparison of Forecast Results from Four

ISSN 2959-6130

Models

Fig. 2 presents the forecast results obtained by the four models—ARIMA, SARIMAX, ETS, and TBATS—on the test sample (the last 24 months), along with their 95% confidence intervals. The solid purple line represents the observed historical mortality data from the training sample, while the colored curves and shaded areas indicate the predicted values from each model and their confidence intervals, respectively.

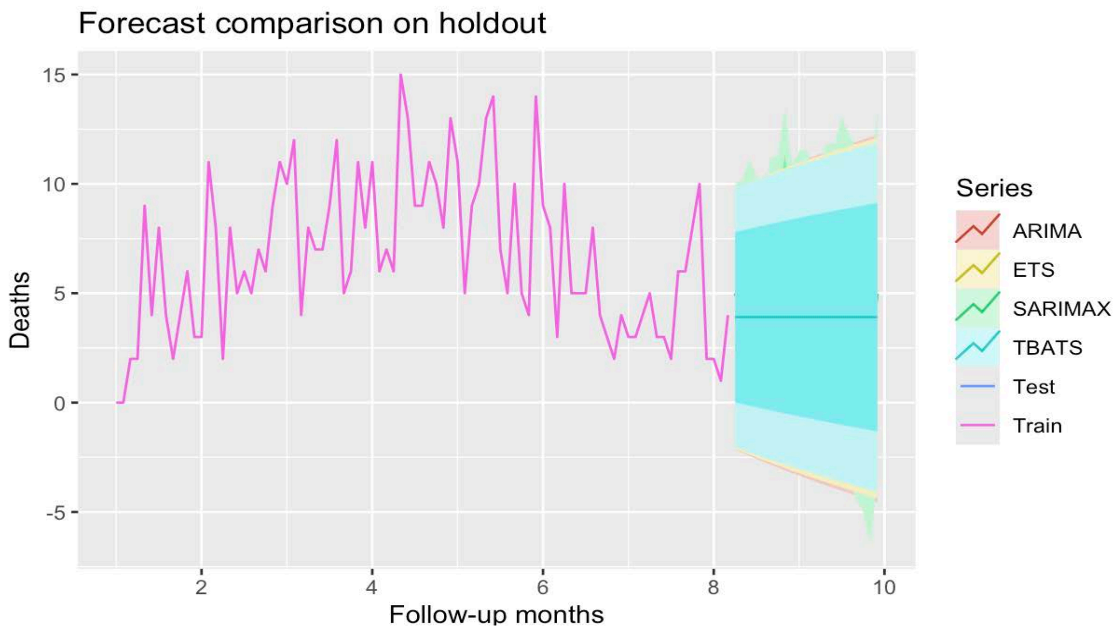

Fig. 2 Comparison of Forecast Results from Four Time Series Models

Regarding forecast trajectories, the ARIMA and ETS models produce relatively smooth and close curves with relatively narrow confidence intervals. This reflects higher predictive accuracy and lower uncertainty. These two models successfully capture the declining trend in death counts. In contrast, the TBATS model exhibits the widest confidence intervals, revealing maximum predictive uncertainty. This finding aligns with the anticipated analysis from Section 2.4: in the absence of marked multiple seasonality in the data, the complexity of TBATS's modeling mechanism can lead to parameter estimation instability. The SARIMAX model, meanwhile, presents confidence intervals of intermediate width, but its predicted values deviate more substantially from observed values, indicating overall less satisfactory predictive performance.

3.3 Model Forecast Accuracy Evaluation

Table 1 presents the forecast error metrics for the four models on the test sample. Regarding absolute error metrics, RMSE and MAE, the ARIMA model achieves the best results (RMSE = 2.681; MAE = 2.344), followed very closely by the ETS model with nearly equivalent performance (RMSE = 2.702; MAE = 2.358). The gap between the two is only approximately 0.02, demonstrating that their predictive capabilities are virtually identical on this dataset. The TBATS model records slightly higher errors but remaining within an acceptable range (RMSE = 2.733; MAE = 2.380). In contrast, the SARIMAX model displays the worst results across all metrics, with RMSE reaching 3.241, approximately 21% higher than the best model. This indicates that adding seasonal components and the exogenous variable (average age) did not improve forecasts but instead increased biases.

Table 1. Comparison of Forecast Results from Four Models

Model	RMSE	MAE	MAPE	sMAPE
ARIMA	2.681122	2.343624	134.2518	102.9294
ETS	2.701847	2.358272	135.4729	103.0249
TBATS	2.732754	2.379950	137.2801	103.1633
SARIMAX	3.241364	2.768310	185.6000	108.5689

Regarding relative error metrics, MAPE and sMAPE, MAPE values are generally high (all exceeding 100%) due to the low number of deaths observed in certain months. To mitigate this issue, sMAPE, through its symmetrized formulation, provides a more robust measure of relative error. The model ranking according to sMAPE is identical to that observed for absolute errors: ARIMA is lowest (102.9%), followed by ETS (103.0%), then TBATS (103.2%), while SARIMAX remains highest (108.6%). Combining all four metrics, ARIMA and ETS emerge as the most accurate models with nearly equivalent performance. This confirms the hypothesis formulated in Section 2.4: when series characteristics are relatively simple, parsimonious and efficient models often outperform more complex ones. SARIMAX's poor performance can be explained by three main reasons. First, the ACF/PACF analysis had already shown the absence of marked seasonality, reducing the value of seasonal components. Second, variations in monthly average age of deceased patients are probably small, thus limiting the explanatory value of the exogenous variable. Third, adding additional parameters led to overfitting, deteriorating out-of-sample generalization capability [19].

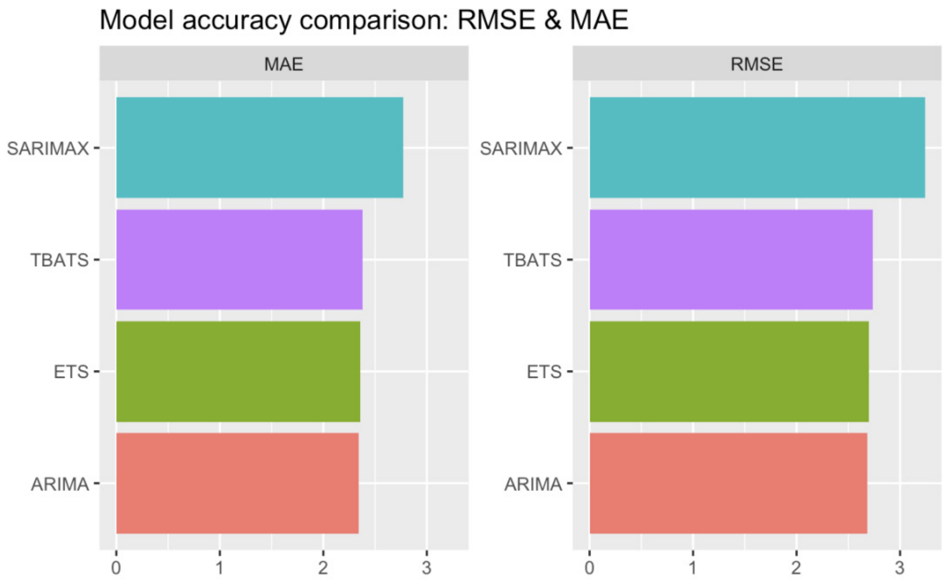

Fig. 3 Bar Chart Comparison of MAE and RMSE

Fig. 3 illustrates, in bar chart form, the comparison of RMSE and MAE for the four models, visually confirming the results from Table 1. Both charts display consistent rankings: ARIMA and ETS present the lowest and closest errors, TBATS shows intermediate errors, and SARIMAX exhibits markedly higher errors. This visualization clearly highlights the performance differences between models. Fig. 4 presents the comparison of results obtained with MAPE and sMAPE. Although MAPE values are generally high due to its sensitivity to small values, sMAPE, through its symmetrized formulation, provides a more reliable measure of relative error. The ranking of the four models according to these relative metrics is strictly identical to that observed for absolute errors: ARIMA and ETS display the best performance on both percentage measures, while SARIMAX sits markedly above the other models.

ISSN 2959-6130

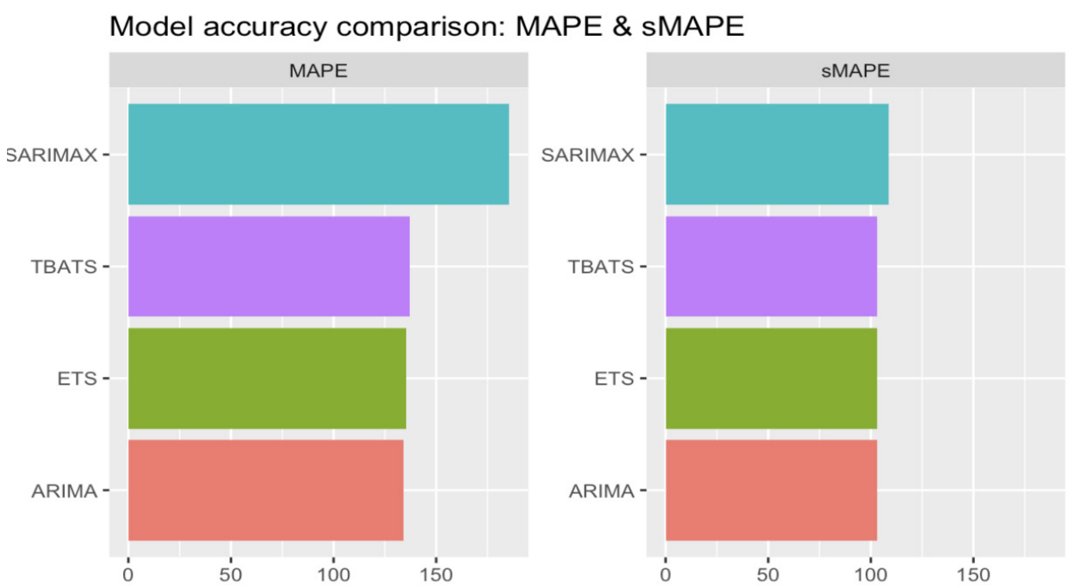

Fig. 4 Bar Chart Comparison of RMSE and MAE

3.4 Overall Comparison of Accuracy across Four Models

To systematically compare the predictive performance of the four models, Table 2 consolidates the four-error metrics from Table 1 and calculates for each model the average ranking as well as the relative error increase.

Table 2. Comprehensive Comparison of Forecast Accuracy across Four Models

	ARIMA	ETS	TBATS	SARIMAX
RMSE	2.681	2.702	2.733	3.241
MAE	2.344	2.358	2.389	2.768
MAPE(%)	134.3	135.5	137.3	185.6
sMAPE(%)	102.9	103.0	103.2	108.6
Error Increase Relative to Optimal Model(%)	0	+ 0.8	+ 1.9	+ 20.9

The overall comparison highlights that ARIMA and ETS models clearly outperform the others in terms of predictive accuracy. ARIMA obtains an average rank of 1.25, placing first on three of the four metrics. ETS displays an average rank of 1.75, with performance very close to ARIMA's—the RMSE gap between the two models is only 0.8%. This "two-model consistency" considerably strengthens the credibility of forecast results and indicates that two distinct modeling mechanisms lead to highly convergent conclusions on this dataset. The TBATS model ranks third on average, with a relative RMSE increase of only 1.9% compared to the best-performing model, which remains acceptable. Despite this, given its much higher complexity compared to ARIMA and ETS, such a small gap does not justify using a more sophisticated modeling approach. The SARIMAX model ranks last across all metrics, with a relative RMSE increase reaching 20.9% compared to the optimal model. This shows that for this dataset, adding seasonal components and an exogenous variable did not improve forecast accuracy but instead significantly deteriorated it. Connected to the ACF/PACF analysis results from Section 3.1, the absence of marked seasonality in the data confirms the hypothesis stated in Section 2.4: when data characteristics do not match model assumptions, increasing complexity can lead to overfitting. Based on this overall comparison of predictive accuracy, ARIMA and ETS emerge as the most suitable models for this study's data.

3.5 Model Residual Diagnostics

After the overall evaluation of forecast accuracy, this section conducts residual diagnostics to verify the adequacy of model fit. Residual diagnostics constitute an essential step in assessing whether a model has sufficiently extracted the systematic information contained in the time series. Fig. 5 presents the residual diagnostic results for the ARI-

MA model. The residuals fluctuate randomly around zero, without systematic trend or clustering of anomalies. The ACF and PACF plots show that most lags fall within the 95% confidence interval, with only a few points slightly exceeding the bounds. This indicates that the residual series generally satisfies the white noise assumption. The Q-Q plot reveals that residuals approximately follow a normal distribution, with only slight deviations in the distribution tales. These results suggest that the ARIMA model has correctly extracted the systematic information from the time series and presents good fit.

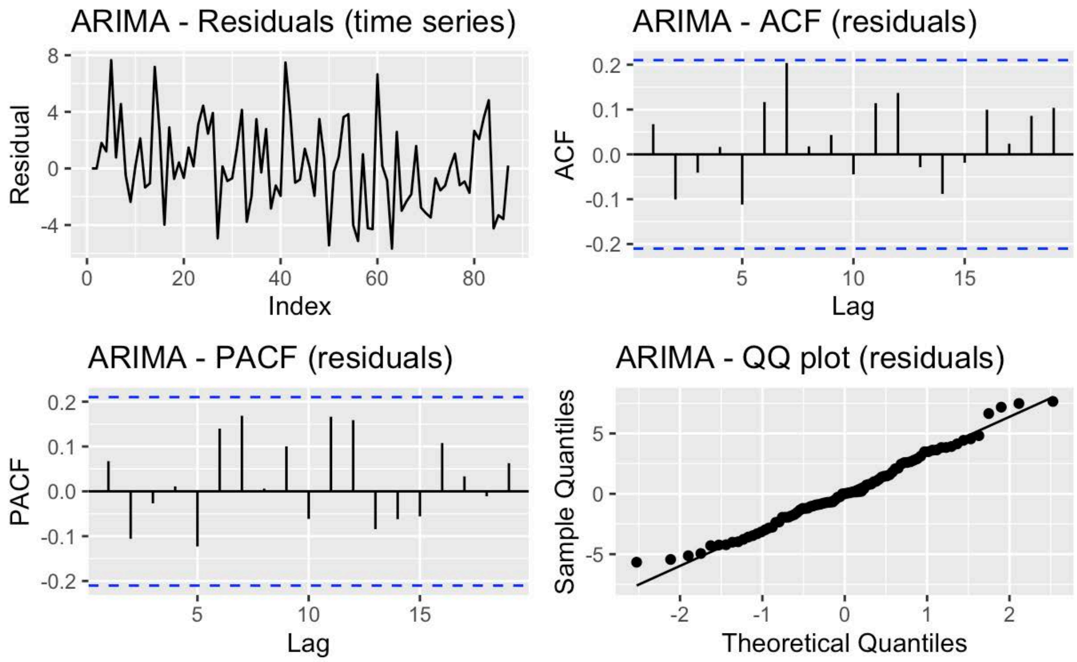

Fig. 5 ARIMA Model Residual Diagnostic Results

The SARIMAX model (Fig. 6) shows residual characteristics similar to ARIMA: residuals generally behave as white noise, the ACF and PACF reveal no significant correlations, and the Q-Q plot confirms approximate normality. Although residual diagnostics validate statistical adequacy, forecast accuracy results show that introducing exogenous variables and seasonal components did not bring effective improvement but instead increased model complexity.

ISSN 2959-6130

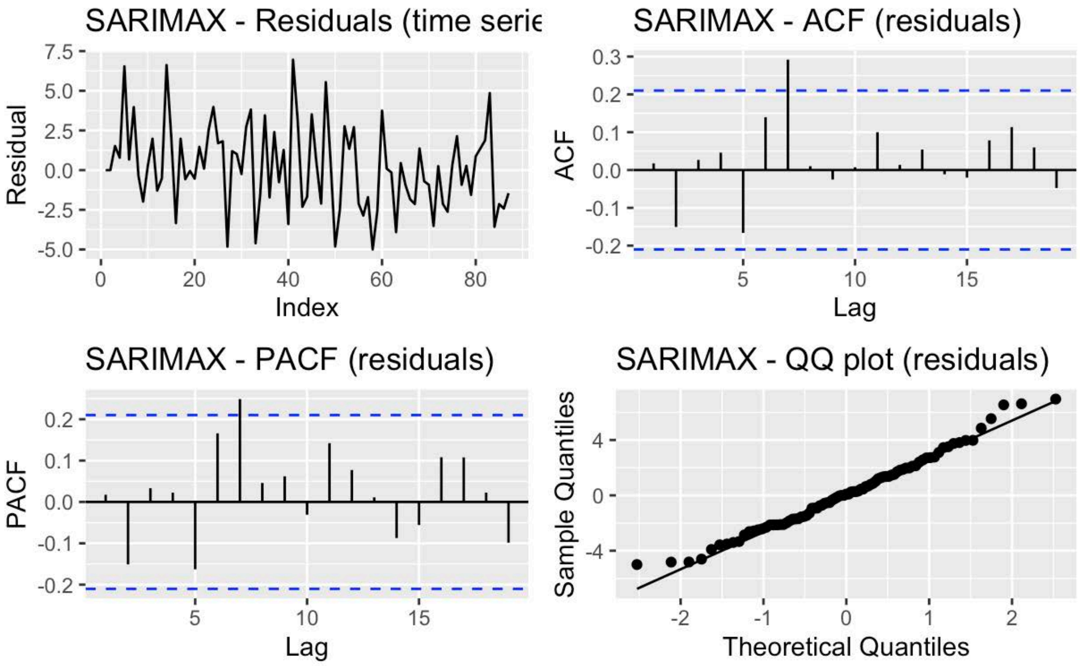

Fig. 6 SARIMA Model Residual Diagnostic Results

The ETS model (Fig. 7) also presents excellent residual performance: residuals oscillate around zero without apparent bias, and all diagnostics confirm statistical assumptions. This shows that the exponential smoothing mechanism successfully captures the temporal characteristics of the data.

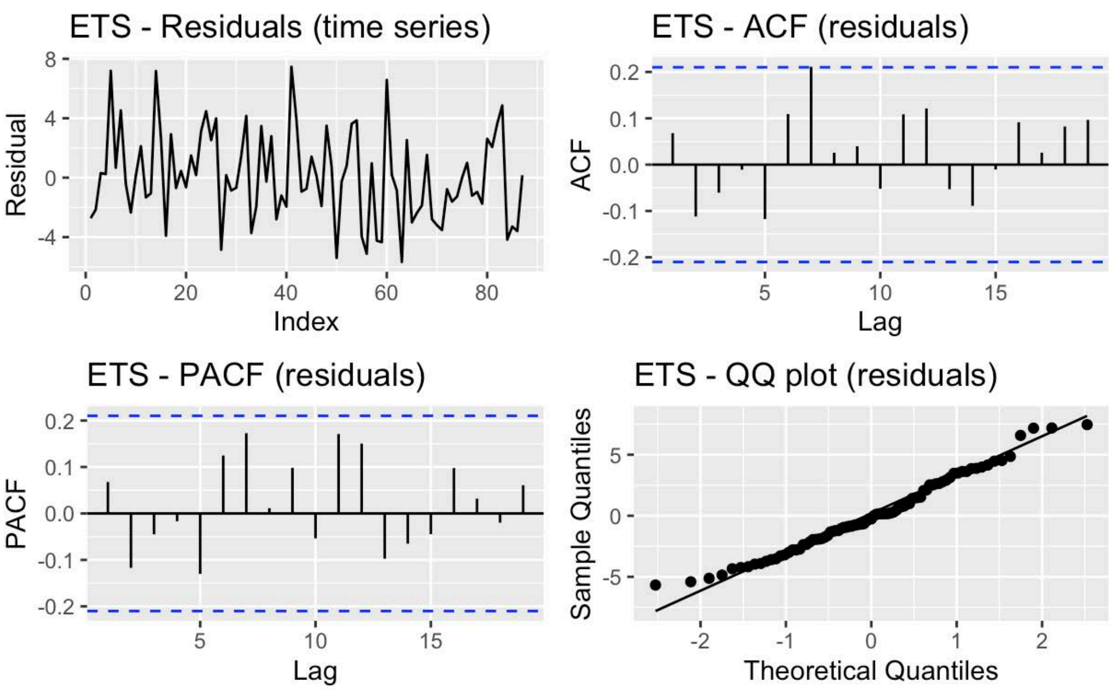

Fig.7 ETS Model Residual Diagnostic Results

The TBATS model (Fig. 8) displays residual distribution generally similar to other models, satisfying the main diagnostic tests. Nevertheless, given the wider width of its forecast intervals, these results indicate that TBATS's capacity for modeling complex seasonality's could not be effectively exploited in this dataset.

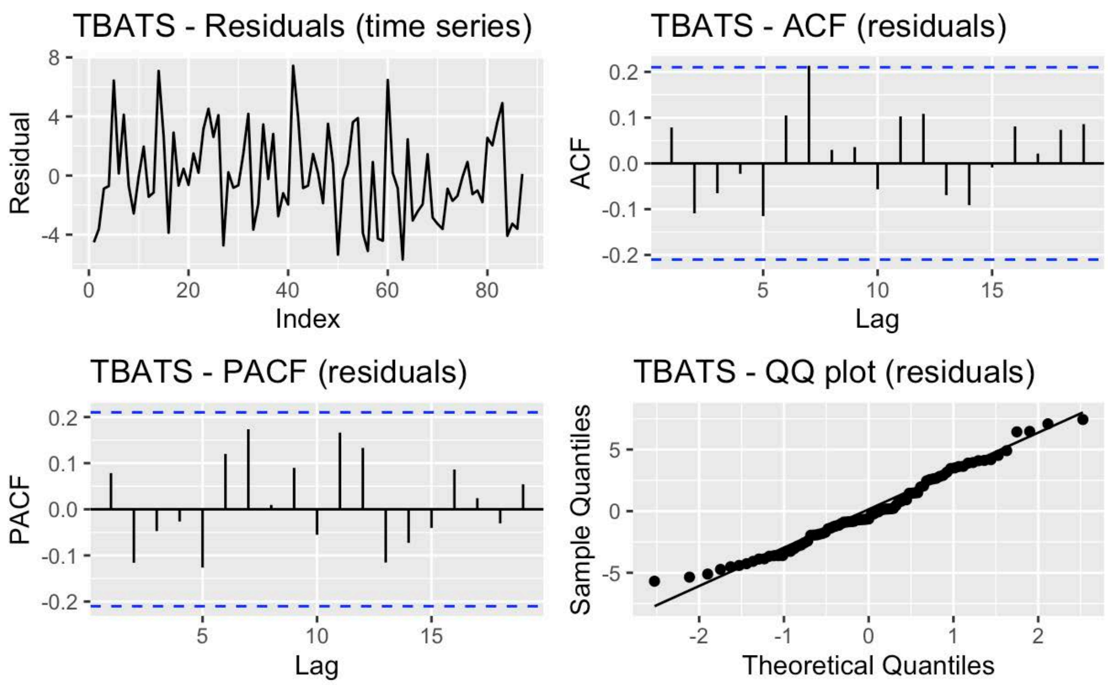

Fig. 8 TBATS Model Residual Diagnostic Results

Table 3 presents the Ljung-Box test results for the four models. At lag 24, all p-values exceed 0.05 (ARIMA: 0.5850; SARIMAX: 0.5908; ETS: 0.6062; TBATS: 0.6473), which does not allow rejection of the null hypothesis that residuals are white noise. This result proves that the fit of each model is statistically satisfactory: they successfully extracted systematic information from the series, with remaining residuals corresponding to random noise [20].

Table 3. Ljung-box Test Results

Model	LjungBox -X^2	df	p-value
ARIMA	21.904	24	0.5850
SARIMAX	21.806	24	0.5908
ETS	21.548	24	0.6062
TBATS	20.854	24	0.6473

The convergence of residual diagnostic results highlights an essential phenomenon: all models achieve sufficient fit on the training sample, but their differences manifest in terms of generalization capability. ARIMA and ETS, through their simple structure and limited number of parameters, avoid overfitting and display good performance on the test sample. In contrast, SARIMAX and TBATS, while effective in fitting the training sample, lose their advantage in out-of-sample forecasting and even suffer negative effects due to their complexity. This finding reaffirms the importance of "model parsimony" in time series forecasting.

3.6 Integrated Comparison and Interpretation of Results

Combining predictive accuracy and residual diagnostic results, this study reaches the following main findings: ARIMA and ETS models offer the best performance, and these are equivalent (with an RMSE gap of only 0.8%). The TBATS model sits in an intermediate position, while SARIMAX presents the worst results. This finding confirms the expectations formulated in Section 2.4 and reveals that breast cancer mortality data primarily consists of a trend and random fluctuations, without significant seasonality or complex cyclical patterns. The superiority of ARIMA and ETS stems from the simplicity and efficiency of their mechanisms. ARIMA eliminates non-stationarity through differencing and captures trend fluctuations via autoregressive and moving average component. ETS, meanwhile, assigns higher weight to recent observations through exponential smoothing, which aligns well with the characteristic of higher death risk at the beginning of

ISSN 2959-6130

follow-up [12]. SARIMAX's poor performance results from the absence of 12-month annual periodicity in the data and the low explanatory value of the exogenous variable. The increase in parameter count led to overfitting [19]. As for TBATS, although its errors remain controlled, its confidence intervals are the widest. Its mechanism for modeling complex seasonality brought no additional advantage in a series with simple structure . The forecast results reveal the phenomenon of high death risk in early follow-up, which holds major importance for public health policy. This may reflect late diagnoses, low treatment tolerance, or barriers to healthcare accessibility. These problems are particularly pronounced among ethnic minorities and low-income populations [21]. Consequently, public health interventions should concentrate resources on the early screening phase before diagnosis, as well as the first months following it. This means expanding screening coverage, strengthening medical support, and improving treatment accessibility to reduce early mortality risk.

4. Recommendations

This chapter answers the research questions, proposes public health intervention strategies.

4.1 Results

Regarding the first research question (how to use time series methods to accurately predict the temporal distribution characteristics of death risk), empirical results demonstrate that ARIMA and ETS models are most suitable for forecasting, with RMSE differing by only 0.8%. This reveals that the data primarily consists of trend and random fluctuations (see Table 1, Figure 1). SARIMAX performed worst due to lack of seasonality in the data (RMSE 21% higher), confirming that model selection should be based on data characteristics rather than blindly pursuing complexity . Regarding the second research question (how to identify high-risk time windows and propose intervention strategies), the forecasting models successfully identified a death risk peak during months 2-4 of follow-up (approximately 10-15 deaths/month). This pattern relates to factors such as late-stage diagnosis and poor treatment tolerance, which may be more severe among ethnic minorities and low-income women. Strategies to reduce early follow-up mortality must simultaneously address health equity issues.

4.2 Public Health Intervention Strategies Based on Forecast Results

Based on early follow-up mortality risks identified by forecasting models, this study proposes four interventions. First, expand mammography screening with full insurance coverage and culturally adapted outreach for minorities. Second, optimize resource allocation during the critical 2–4-month post-diagnosis period through fast-track services and patient navigation. Third, provide vulnerable groups with targeted prevention programs, financial support, and culturally competent care. Fourth, reform healthcare systems by expanding coverage, reducing costs, and establishing value-based payment models. These measures aim to reduce mortality and health disparities.

5. Conclusion

Through systematic evaluation of ARIMA, SARIMAX, ETS, and TBATS forecasting approaches, this investigation established the superiority of ARIMA and ETS models for predicting breast cancer mortality among American women. The identification of elevated death risk during early follow-up months (2-4) provides empirical foundation for optimizing healthcare resource distribution and developing timely intervention protocols. The contribution of predictive modeling extends beyond technical precision to addressing fundamental inequities in population health. Elevated early-stage mortality reflects systemic barriers including limited healthcare access, socioeconomic disparities, and structural discrimination, challenges that disproportionately affect Black, Hispanic, and economically disadvantaged women. Consequently, reducing breast cancer deaths requires comprehensive reform spanning social welfare systems, employment policies, gender equity initiatives, and racial justice frameworks, rather than relying solely on clinical advancements. The four intervention strategies proposed—strengthening early screening programs, enhancing initial treatment support, establishing equity-focused mechanisms, and reforming insurance coverage systems—constitute an integrated policy architecture. Effective reduction of female breast cancer mortality and advancement of health equity depend on coordinated implementation of these measures, translating forecasting insights into targeted public health action. Subsequent investigations should deepen understanding of inequality mechanisms, assess intervention effectiveness, and generate evidence supporting the development of more equitable and efficient healthcare delivery systems.

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