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Time Series Modelling and Forecasting of Birth and Death Rates: A Case Study of Grimard Catholic Hospital, Dekina LGA, Nigeria

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Abstract
This study employs advanced time series modelling techniques to analyze and forecast monthly birth and death patterns recorded at Grimard Catholic Hospital, located in Dekina Local Government Area, Nigeria. Descriptive statistics reveal a stable trend in births with moderate seasonal variation, and a low, irregular pattern in mortality rates. Three univariate time series models: Seasonal-Trend decomposition using Loess (STL), AutoRegressive Integrated Moving Average (ARIMA), and Exponential Smoothing State Space (ETS), were applied to uncover temporal dynamics and project future values. Model performance was evaluated using Akaike- and Bayesian Information Criteria (AIC, BIC), alongside forecast accuracy metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Results show that ARIMA consistently outperformed both STL and ETS in forecasting births and deaths. The findings provide valuable insights for hospital resource planning and rural health policy development, emphasizing the critical role of statistical forecasting in informed healthcare decision-making.

Keywords: Forecasting, Birth and Death Rates, ARIMA Model, ETS Model, Public Health Planning

Introduction

Birth and death rates provide essential insights into a population's health and demographic conditions, reflecting both biological and social determinants as well as the quality and accessibility of healthcare services (World Health Organisation, 2018). High birth rates may indicate unmet family planning needs, while elevated death rates can reveal weaknesses in emergency care or chronic disease management. Monitoring these indicators over time is therefore crucial for guiding public health interventions and improving maternal and child health outcomes.vIn many developing countries, including Nigeria, healthcare institutions collect longitudinal data on births and maternal mortality, but these datasets are often underutilised due to limited analytical capacity and the absence of advanced statistical modelling. Grimard Catholic Hospital in Anyigba, Kogi State, a major maternity service provider in central Nigeria, has maintained comprehensive monthly records of births and maternal deaths from 2015 to 2024. This dataset presents an opportunity to apply sophisticated time series techniques capable of generating meaningful, evidence-based insights for health planning.

Time series analysis offers a powerful framework for identifying trends, seasonal patterns, and irregular fluctuations in longitudinal health data (Hyndman & Athanasopoulos, 2018). It is particularly suited to regularly spaced observations such as monthly hospital records. In this study, births and maternal deaths are treated as stochastic processes shaped by internal temporal dynamics—autocorrelation, trend, and seasonality—rather than external explanatory variables. Several established models can analyse such dynamics. The AutoRegressive Integrated Moving Average (ARIMA) and its seasonal extension (SARIMA) incorporate autoregressive, moving-average, and differencing components to address non-stationarity and cyclical variation (Box et al., 2015). Exponential smoothing models such as ETS (Error, Trend, Seasonality) are widely applied for short-term forecasting because of their simplicity and strong predictive performance (Hyndman & Athanasopoulos, 2018). STL decomposition provides a flexible method for isolating trend and seasonal structures. These models are particularly valuable in resource-limited settings because they are interpretable, computationally efficient, and effective for hospital-level planning.

Effective modelling requires identifying key components such as trend, seasonality, and random fluctuations, usually through transformations that ensure stationarity. Diagnostic tools, including differencing, decomposition, autocorrelation analysis, and the Augmented Dickey-Fuller (ADF) test, help validate model adequacy and suitability for forecasting. Empirical studies further demonstrate the usefulness of these methods in demographic and health research. Bravo and Coelho (2020) applied ARIMA to birth and mortality trends in Pakistan, while Le et al. (2014) used Generalised Additive Models to examine seasonal mortality among the elderly in Vietnam. In Nigeria, Ogundunmade et al. (2023) reported that ARIMA outperformed exponential smoothing and Holt-Winters methods for hospital datasets. More recently, Leger et al. (2025) emphasised the importance of flexible time series models capable of accommodating exogenous shocks such as pandemics.

Despite this evidence, there is a lack of localised research using advanced time series methods on hospital-level maternal health data in Nigeria. Although institutions like Grimard Catholic Hospital possess rich time-stamped records, they often lack the analytical frameworks required to extract strategic insights. This study therefore aims to model and forecast monthly births and maternal deaths using a 10-year dataset (2015–2024), assess temporal patterns, and determine the most accurate forecasting approach among STL, ARIMA, and ETS models. The study examines historical patterns, develops suitable models, and evaluates their performance based on accuracy, residual behaviour, and predictive reliability. The remainder of this paper is structured as follows: Section 2 outlines the methodological approach employed in the study. Section 3 describes the dataset and its characteristics. Section 4 presents the data analysis and model diagnostics. Section 5 discusses the results and their implications, while Section 6 concludes the study with key findings and recommendations.

Methods and Materials

This study employs analytical time series methods to model and forecast monthly birth and death rates recorded at Grimard Catholic Hospital, Anyigba, covering the period from January 2015 to December 2024. The dataset consists of 120 monthly observations for each variable. Prior to modeling, data cleaning was performed to identify and address missing values and outliers, while preprocessing ensured temporal regularity using R Statistical Software (R Core Team, 2023).

Let $\{\}_{t=1}$ represent the monthly time series data, where Y_t denotes either the birth rate or death rate recorded at time t, with $T = 120$. Each series $\{\}$ is assumed to follow a stochastic process governed by time-dependent dynamics. To assess the suitability for modeling, the stationarity of each series was evaluated using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979). A time series Y_t is considered stationary if its mean, variance, and autocovariance remain constant over time. The ADF test estimates the following regression:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-1} + \varepsilon_t \tag{1}$$

where Δ denotes first difference, α is a constant, βt is the trend, and ε_t is white noise. Test hypothesis $H_0 : \gamma = 0$ indicates non-stationarity.

Autoregressive Integrated Moving Average (ARIMA) Model

Upon verifying stationarity, the Autoregressive Integrated Moving Average (ARIMA) model was applied (Box et al., 2015). An ARIMA(p, d, q) model is given by:

$$\Phi(B)(1-B)^d Y_t = \Theta(B)\varepsilon_t \tag{2}$$

where B is the backward shift operator $(BY_t = Y_{t-1})$, $\Phi(B) = 1 - \phi_1 B - \ldots - \phi_p B^p$ is the autoregressive (AR)

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component, and $\Theta(B)=1+\theta_1 B+...+\theta_q B^q$ is the moving average (MA) component. The differencing order d ensures stationarity. Model identification was performed using autocorrelation (ACF) and partial autocorrelation (PACF) plots, and parameters were estimated via maximum likelihood.

Exponential Smoothing State Space (ETS) Model

In parallel, the Exponential Smoothing State Space (ETS) model was employed (Hyndman & Athanasopoulos, 2021). The ETS framework captures error, trend, and seasonal components within a state space structure. The general ETS(A,A,A) model is defined as:

$$Y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t \tag{3}$$

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t \tag{4}$$

$$b_t = b_{t-1} + \beta\varepsilon_t \tag{5}$$

$$s_t = s_{t-m} + \gamma\varepsilon_t \tag{6}$$

where ℓ_t represents the level, b_t the trend, s_t the seasonal component, m the seasonal period, and $\alpha\beta, \gamma$ are smoothing parameters estimated by minimizing the sum of squared errors.

Seasonal-Trend Decomposition Using Loess (STL)

The trend, seasonal, and irregular components of the series were also extracted and examined using the Seasonal and Trend decomposition using Loess (STL) method (Cleveland et al., 1990). The observed series is expressed as follows by the STL decomposition:

$$Y_t = T_t + S_t + R_t \tag{7}$$

where T_t denotes the long-term trend, S_t represents the periodic seasonal pattern, and R_t is the remainder or random component. The Loess smoothing technique allows for flexible modeling of both trend and seasonal variations, making STL suitable for non-linear and non-stationary series.

Model Evaluation and Forecast Accuracy

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), which are defined as follows, were minimised in order to aid model selection:

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

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

where $\hat{L}$ is the maximized likelihood, k the number of parameters, and n the number of observations (Shumway & Stoffer, 2017).

Two common metrics were used to assess forecasting performance: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are given by:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \quad (10$$

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$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \tag{11}$$

All computations, including decomposition, model fitting, diagnostics, and visualization, were performed using R (version 4.5.0) and key packages such as forecast, tseries, and ggplot2 (Cleveland et al., 1990; Hyndman & Athanasopoulos, 2021; R Core Team, 2023). This analytical framework supports robust and reproducible modeling of vital health statistics.

Data Description and Structure

This study makes use of a longitudinal dataset that includes monthly birth and death records from January 2015 to December 2024 from Grimard Catholic Hospital in Anyigba, Kogi State, Nigeria. The dataset, which was taken from hospital registries, offers a thorough description of the outcomes for mothers and newborns over a ten-year period. Births and deaths are the two main categories into which the data are divided after being methodically arranged by calendar month and year.

Table 1 summarizes the monthly counts for each category across the ten-year period. It includes both annual totals and a cumulative aggregate to facilitate the identification of trends and temporal comparisons. This rich time series supports the investigation of seasonal effects, inter-annual

Table 1: Monthly Birth and Death Records from Grimard Catholic Hospital, Anyigba (2015–2024)

Month	Case	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Total
January	Birth	49	35	38	25	30	20	18	24	21	15	275
	Death	0	1	0	0	1	0	1	0	2	0	5
February	Birth	37	31	24	37	25	12	17	26	24	13	506
	Death	0	2	0	1	1	0	0	1	0	0	6
March	Birth	57	41	43	37	33	24	22	28	30	17	283
	Death	0	0	0	0	0	1	1	1	0	0	3
April	Birth	40	42	45	45	35	28	29	15	21	18	318
	Death	1	0	1	2	1	1	0	0	1	1	8
May	Birth	58	53	38	35	32	26	36	31	25	27	335
	Death	0	0	0	0	0	1	1	0	0	2	4
June	Birth	62	28	41	26	30	26	19	23	13	21	298
	Death	0	0	2	2	0	1	1	1	0	0	9
July	Birth	42	38	27	21	34	16	29	26	26	17	276
	Death	0	1	0	2	0	0	1	0	0	0	4
August	Birth	40	30	33	27	29	14	16	15	17	13	234
	Death	1	0	0	0	2	0	0	0	1	0	4
September	Birth	36	41	29	25	30	15	20	25	18	19	258
	Death	0	0	0	0	0	0	1	0	1	0	2
October	Birth	38	34	33	38	25	25	30	28	16	22	289
	Death	2	1	0	0	0	0	1	0	0	1	5
November	Birth	46	33	26	22	30	25	14	25	18	16	255
	Death	1	0	0	0	1	1	0	1	1	1	6
December	Birth	26	28	34	27	23	26	25	21	17	16	243
	Death	1	0	2	1	0	1	0	2	0	2	9
Total	Birth	531	434	465	365	356	257	275	281	251	214	3570
Total	Death	10	8	4	6	6	5	7	6	6	7	63

Variability, and long-term dynamics in birth and death outcomes within the hospital setting.

Exploratory and Main Data Analysis

An Exploratory Data Analysis (EDA) was carried out to comprehend the underlying structure and temporal dynamics of the monthly birth and death records from Grimard Catholic Hospital (2015–2024). In the dataset shown in Table 1, this initial stage sought to characterise the distributional features, evaluate variability, find seasonal patterns, and spot possible anomalies.

While summary statistics were calculated to quantify measures of central tendency and dispersion, time series visualisation offered insights into overall movement and temporal changes for both birth and death series. Decomposition techniques were used to further examine seasonal and trend components. Additionally, the dataset was checked for outliers and missing values, and it was determined that the data integrity was sufficient for time series modelling.

Descriptive Summary Statistics

Key descriptive statistics were calculated to summarize the monthly birth and death records over the ten-year period. These include totals, annual and monthly averages, measures of dispersion (standard deviation), and extreme values. The results, summarized in Table 2, provide a foundational understanding prior to model-based forecasting.

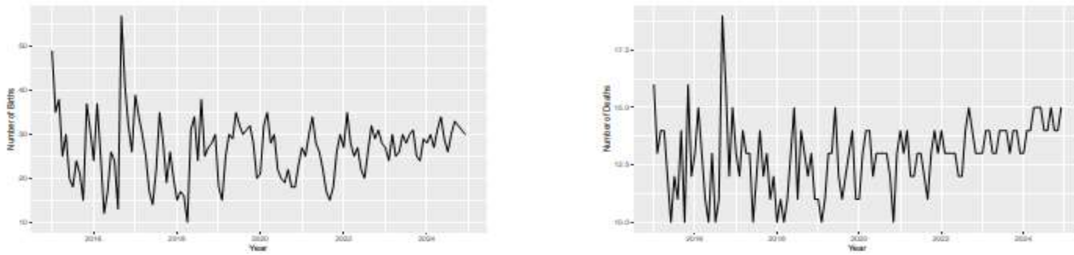
Table 2: Descriptive Summary of Monthly Birth and Death Records (2015–2024)

Statistic	**Births**	**Deaths**
Total (2015–2024)	3,570	63
Mean per year	357.0	6.3
Mean per month	29.75	0.53
Maximum monthly count	62 (Jun 2015)	2 (multiple months)
Minimum monthly count	12 (Feb 2020)	0 (several months)
Standard deviation	10.87	0.71
Median monthly count	29	0
Zero-death months	–	91 out of 120

Table 2 presents descriptive statistics for monthly births and deaths recorded between 2015 and 2024. Births averaged 29.75 per month, with a peak of 62 and a minimum of 12. Deaths were rare, averaging 0.53 monthly, with 91 out of 120 months recording zero deaths. The data suggest relatively stable birth trends and infrequent mortality over the ten-year period.

Time Series Visualization

Figure 1 displays monthly time series plots of births and deaths that show long-term mobility, temporal variability, and possible cyclic behaviour. Compared to the deaths series, which is still scant and has little change over the course of the observation period, the births data shows comparatively significant seasonal trends.



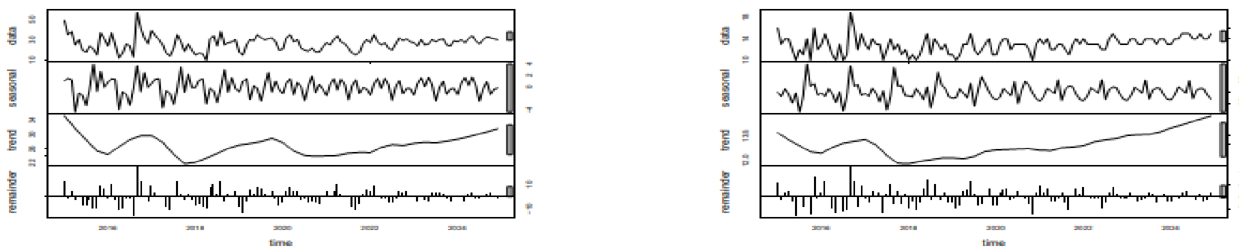
(a): Births (b): Deaths

Figure 1: Monthly Births and Deaths at Grimard Catholic Hospital (2015–2024)

Figure 1 displays the monthly trends in births and deaths at Grimard Catholic Hospital from 2015 to 2024. Panel (a) shows consistent birth fluctuations with periodic peaks, while panel (b) reveals sparse and irregular death occurrences. The contrasting patterns highlight stable birth rates over time and low mortality, with most months recording zero or very few deaths throughout the study period.

Seasonal-Trend Decomposition

To further investigate structural components in the series, a Seasonal-Trend Decomposition using Loess (STL) was applied. As shown in Figure 2, the decomposition effectively separates the trend, seasonal, and residual components. The birth series displays pronounced seasonality and a mild declining trend, whereas the death series lacks a consistent seasonal pattern.



(a): Births (b): Deaths

Figure 2: STL Decomposition of Birth and Death Series

Figure 2 illustrates the STL decomposition of the monthly birth and death series. Panel (a) reveals a strong seasonal pattern and noticeable trend in the birth data, indicating periodic fluctuations over time. In contrast, panel (b) shows minimal seasonality and a flat trend in the death series, reflecting the sparse and irregular nature of mortality events throughout the observation period.

Forecasting Models and Comparative Evaluation

This section describes the modelling and forecasting of monthly births and deaths at Grimard Catholic Hospital, Anyigba, using three univariate forecasting techniques: Seasonal-Trend Decomposition via Loess (STL), AutoRegressive Integrated Moving Average (ARIMA), and Exponential Smoothing State Space (ETS). The Augmented Dickey–Fuller (ADF) test is used to assess series stationarity before model estimate, forecasting, and comparative evaluation based on information requirements and prediction accuracy measurements.

Stationarity Assessment

The ADF test was used to assess each time series' stationarity prior to model estimation. The birth and death series are both stationary at the 1% significance level, according to the results shown in Table 3. This suggests that whereas the death series attained stationarity upon first differencing, the birth series did not require additional differencing.

Table 3: ADF Test for Stationarity

Series	**ADF Statistic**	**Lag Order**	***p*-value**
Births	−6.52	4	< 0.01
Deaths	−5.17	4	< 0.01

The null hypothesis of a unit root is rejected since both ADF statistics are significantly negative (−6.52 for births and −5.17 for deaths), with corresponding *p*-values below 0.01. The series are therefore appropriate for ARIMA and related time series modelling.

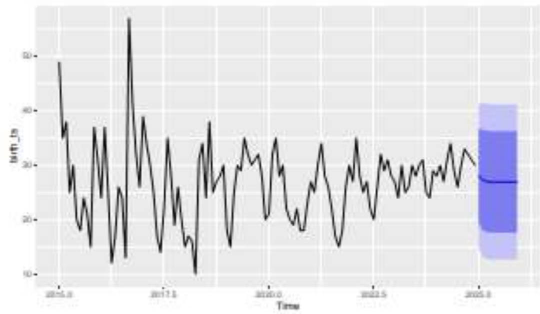
Model Estimation and Forecasting

The observed monthly data was used to estimate three models: ARIMA, State Learning Technique (SLT), and Exponential Smoothing State Space (ETS). The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to assist the model selection process; lower values suggest a better trade-off between model fit and parsimony.

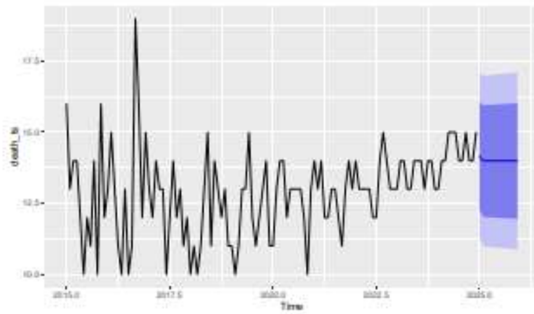
Table 4: Model Fit Comparison Using AIC and BIC for Birth and Death Series

Series	**Model**	**AIC**	**BIC**
Births	ARIMA(1,0,0)	801.34	809.70
	ETS(M,N,N)	1052.79	1061.15
	SLT(Optimal)	789.41	797.65
Deaths	ARIMA(0,1,2)	437.64	445.97
	ETS(A,N,N)	675.51	683.88
	SLT(Optimal)	421.36	429.70

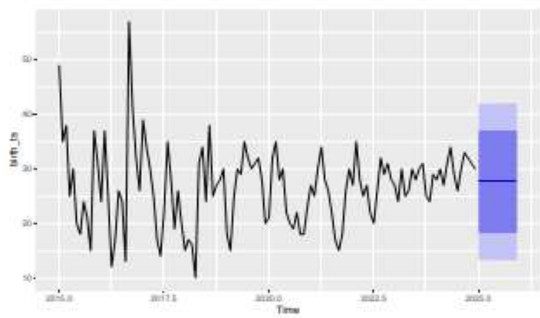
The model selection findings are summarised in Table 4. The ARIMA and SLT models produce significantly lower AIC and BIC values than the ETS model for both the birth and death series, indicating better fit and efficiency. The SLT model had the lowest information criteria values out of all of them, indicating that it had the best predictive power.



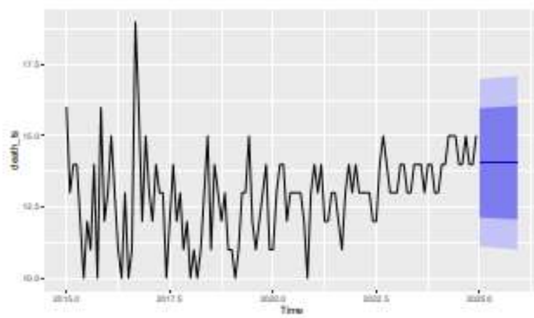
(a) ARIMA Births Forecasts



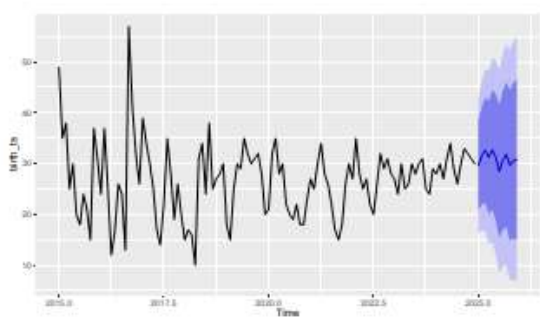
(b) ARIMA Deaths Forecasts



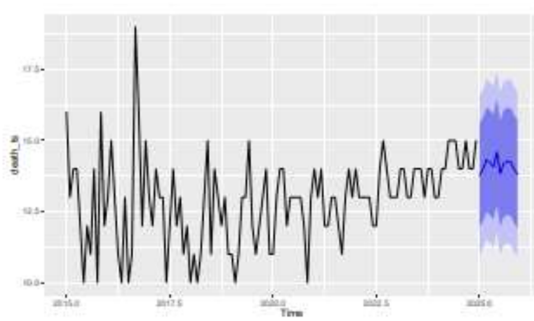
(c) ETS Births Forecasts



(d) ETS Deaths Forecasts



(e) SLT Births Forecasts



(f) SLT Deaths Forecasts

Figure 3: Comparative Forecasts of Births and Deaths Using ARIMA, ETS, and SLT Models

The birth and death predictions from the three models are contrasted in Figure 3. SLT adjusts to nonlinear patterns with smaller confidence intervals, ETS generates smoother level-based projections, and ARIMA successfully captures short-term variations for the birth series. All models show low and erratic counts for the death series, but SLT produces more consistent and adaptable forecasts. Overall, ARIMA and SLT perform better than ETS, with SLT exhibiting the best trade-off between predicted accuracy and flexibility for both series.

Model Evaluation

Information criteria (AIC and BIC) and forecast accuracy measures (RMSE and MAE) were used to evaluate the models' comparative performance. In terms of model fit, ARIMA and SLT beat ETS, with SLT marginally exceeding ARIMA, as seen in Table 4. These findings demonstrate the superior flexibility of SLT for capturing nonlinear temporal patterns in hospital birth and death data, as well as the relative efficiency of ARIMA for linear dynamics.

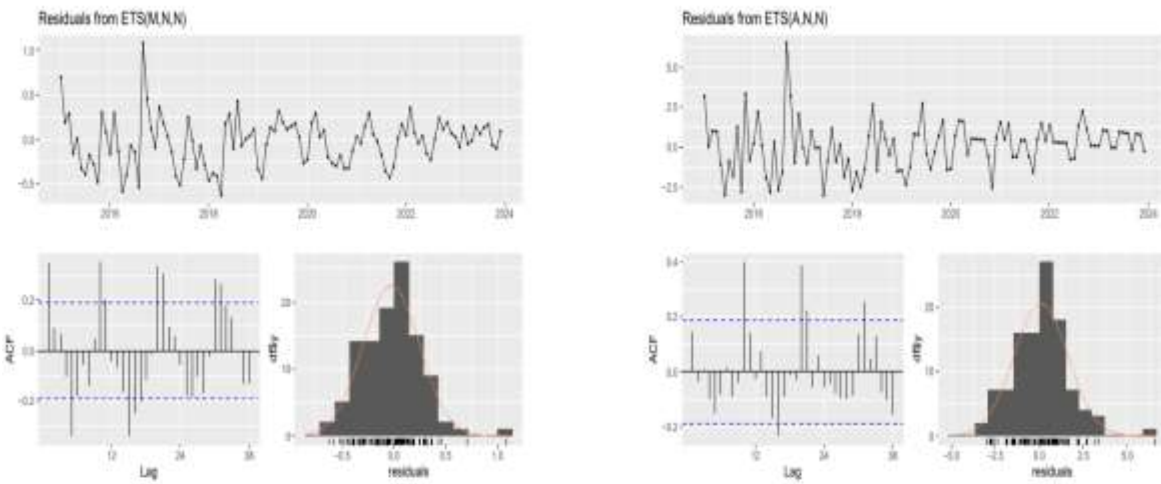
Table 5: Forecast Accuracy Metrics (2024 Test Set)

Metric	Births	Deaths
RMSE	4.19	1.27
MAE	3.63	1.14

Using the 2024 test set, Table 5 shows the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) for births and deaths. Forecasts for deaths are more accurate than those for births, as indicated by the lower error numbers for deaths (RMSE = 1.27, MAE = 1.14).

Residual Diagnostics

To make sure that the fitted models accurately represented the key dynamics of the data, residual diagnostic checks were used to further evaluate the model's appropriateness. Standardised residuals, autocorrelation functions (ACF), and normality behaviour are shown in diagnostic plots for the ETS and ARIMA models in Figures 4 and 5. Residuals should ideally be homoscedastic, uncorrelated, white noise-like, and centred around zero.



(a): Births

(b): Deaths

Figure 4: Residual Diagnostics for ETS Models

The residual diagnostic plots for the ETS models of births and deaths are displayed in Figure 4. The residual variance stays roughly constant, indicating model stability and appropriate error dispersion over time, and the residuals are randomly distributed with no obvious patterns or systematic autocorrelation, confirming that the ETS models sufficiently captured the level and trend components of both series.

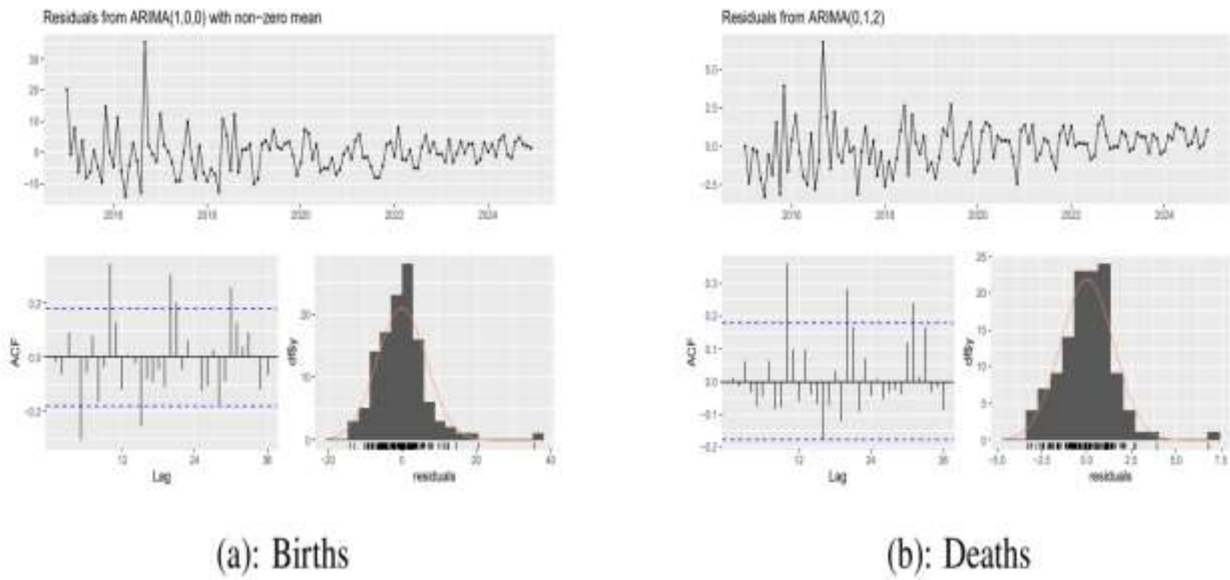


Figure 5: Residual Diagnostics for ARIMA Models

The residual diagnostics for the ARIMA models are shown in Figure 5. The plots show that there is no discernible trend or considerable autocorrelation, and the residuals are randomly distributed around zero, indicating that the ARIMA models were successful in capturing the temporal structure of both the birth and death series.
The residuals also display homoscedasticity, implying consistent variance across the forecast horizon. These results collectively affirm the adequacy and reliability of the ARIMA and ETS models for short-term forecasting, with ARIMA exhibiting slightly better residual behavior and overall performance.

Discussion

Monthly birth and death records from Grimard Catholic Hospital in Anyigba from 2015 to 2024 were analysed, and the results show that the two series have different temporal behaviours and modelling traits. According to descriptive statistics, the monthly birth rate is continuously high, averaging about 29.75 births, with moderate variation during the observation period. This consistency suggests a steady reproductive tendency among the hospital's clientele. On the other hand, deaths are rare, occurring in more than 75% of the months. The death series' exceptional sparsity restricts the ability to identify systematic temporal features and creates difficulties for conventional time series modelling.

These disparate dynamics are further highlighted by time series visualisation and Seasonal-Trend Decomposition using Loess (STL). The birth series shows distinct and frequent seasonal variations, with noticeable peaks usually around the middle of the year, indicating cyclical environmental or demographic impacts. Over the course of the decade, a slight negative trend may also be seen, suggesting a possible slow drop in birth rates. On the other hand, the death series appears as an erratic sequence with intermittent nonzero counts and lacks obvious seasonal or trend components. This pattern illustrates how mortality occurrences in the hospital dataset are low-frequency and intrinsically stochastic.

The Augmented Dickey–Fuller (ADF) test was used to assess the stationarity of the two series. The birth series is stationary in its level form, according to the results, whereas the death series only becomes stationary after first differencing. This implies that whereas the death process has a more random walk-like pattern and requires alteration prior to model estimate, the birth process oscillates around a stable mean.

Both series were modelled and forecasted using three univariate forecasting frameworks: Seasonal-Trend decomposition via Loess (STL), AutoRegressive Integrated Moving Average (ARIMA), and Exponential Smoothing State Space (ETS). Based on model selection and accuracy criteria, ARIMA models outperformed the others. In keeping with the stationary nature of the series, the ARIMA(1,0,0) specification for births successfully captured short-run autocorrelation without differencing. The ARIMA(0,1,2) model, which accommodates the irregular post-differenced structure with little overparameterization, offered the best match for deaths.

Model selection, guided by the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), consistently favored ARIMA over ETS models. Forecast accuracy metrics, Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), reinforced this conclusion, indicating that ARIMA yielded lower forecast errors and greater predictive precision. Although ETS models (ETS(M,N,N) for births and ETS(A,N,N) for deaths) captured general level dynamics, their relatively higher error statistics and information criteria values point to reduced forecasting efficiency. STL-based forecasts, while useful for decomposing structural components, were less responsive to short-term fluctuations and exhibited wider uncertainty bounds.

These results are further supported by a visual comparison of forecast trajectories. Birth ARIMA forecasts have small confidence intervals and dependable projections because they closely match past seasonal peaks. Despite the inherent challenge of modelling sparse and low-count data, ARIMA(0,1,2) offers more accurate and reliable predictions for deaths than STL or ETS.

The suitability of the fitted models is validated by residual diagnostic tests. Both the ARIMA and ETS models' standardised residuals show randomness, no autocorrelation, and constant variance, suggesting that the models accurately represent the fundamental structure of the data without systematic bias. These findings confirm the accuracy of the projections produced and the statistical robustness of the modelling procedure.

For both the birth and death series in this investigation, the results show that ARIMA models offer the most precise, economical, and reliable forecasts. While the irregular pattern of death occurrences poses more modelling issues but can still be successfully handled with suitable differencing and ARIMA specification, the comparatively stable and structured form of the birth data makes it well suited for traditional time series modelling. For short-term forecasting of hospital-based birth and death records, the ARIMA framework turns out to be the best option overall.

Conclusion

In order to model and predict monthly births and deaths at Grimard Catholic Hospital in Anyigba during a ten-year period (2015–2024), this study used a thorough time series technique. In addition to extremely rare and irregular death events, descriptive analysis showed consistent and somewhat seasonal birth trends. The use of three forecasting models—STL, ARIMA, and ETS—made it easier to compare and evaluate the predictive ability of each approach.

ARIMA models outperformed both ETS and STL in terms of fit and forecast accuracy, making them the most successful forecasting tools. The ARIMA(1,0,0) and ARIMA(0,1,2) models for births and deaths, respectively, showed good diagnostic validity and accurately represented the temporal structure of the series.

Recommendations

The importance of data-driven forecasting in hospital administration and public health planning is shown by this study. While the low and erratic mortality rates show little stress but call for ongoing observation, the stable birth trends suggest that resources like personnel, supplies, and bed space should be in line with predicted mid-year peaks. In order to improve long-term prediction, especially when incorporating external influences like policy changes or epidemics, future research may investigate sophisticated models like SARIMA, Bayesian approaches, or machine learning techniques. ARIMA proved successful for short-term forecasting. All things considered, the results offer a useful framework for resource optimisation and evidence-based decision-making in healthcare organisations.

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