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RESEARCH ARTICLE

Forecasting Number of Births in the Philippines Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

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ABSTRACT

The phenomenon of birth decline is a significant demographic challenge impacting nations worldwide which poses potential issues such as labor force shortages and an aging population. Lessening the negative effects necessitates the accurate projection of the number of births. Such projections are important in anticipating demand and allocating sufficient resources, as they provide a more actionable basis for planning and decision-making in areas such as health, social services, and education. Related studies focus only on forecasting birth rates and not on the actual number of births, which presents a research gap in the field. This study aims to address this gap by formulating a Seasonal Autoregressive Moving Average (SARIMA) model to forecast the number of births in the Philippines. Using the Box-Jenkins methodology, the SARIMA (2,1,2) (0,1,1) 12 was identified as the most suitable model based on the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and corrected AIC (AICc) scores among the potential models. The chosen model also obtained a 5.5% Mean Absolute Percentage Error (MAPE), indicating a highly accurate forecast. The SARIMA model effectively captured the seasonality of births, characterized by a peak from September to October. The forecast predicts a continued decline in birth numbers over the next five years, with an estimated 10.96% decrease from 2024 to 2028.

Keywords: Birth decline, box-jenkins method, forecasting, seasonal autoregressive integrated moving average, time series.

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1. Introduction

As today's generation is characterized by global demographic changes, a significant pattern emerges-a decline in birth rates that transcends borders and continents. The phenomenon raises fears of potential long-term problems in economies, societies, and overall population structure. This birth decline is influenced by a decrease in the average number of children born per woman, often falling below the replacement level needed to maintain a stable population over time. Demographic changes result in potential problems such as a shortage of the population belonging to the labor force, aging of the population, economic stagnation, and strain on the social welfare system.

A study [1] analyzing the top 49 most populous countries in the world in 2021 found that, over the past 70 years, each of these countries has experienced a decline in births. South Korea recorded 40.03 births per 1000 people in 1950. By 2021, the number had fallen to 5.58, resulting in an 86% decrease, making it the highest decline in birth rate among the lists. In fact, despite efforts of the government of South Korea to give incentives to people into parenthood, this low birthrate was recently considered a national emergency by politicians as concerns grow regarding the nation's economy, pension reserves, and security. Moreover, China, the nation with the largest population in the world in 2021, saw an 81% drop in its birth rate since 1950. It is evident that every country experienced a decrease in birth rates of at least 10%, except for the Democratic Republic of Congo, which saw a decline of less than 10% over the last seven decades.

The birth rate, measured by the crude birth rate (CBR), indicates the total number of live births per 1000 people in a population each year. Birth rate and fertility rate are both used to measure population growth, but the latter is more specific since it measures the average number of children that a woman will have over her childbearing years. A nation's fertility rate certainly affects the birth rate of the country, and a decline in fertility might also imply a decrease in the number of births.

In recent years, Southeast Asia has seen a significant decline in fertility rates. In 2023, Singapore recorded the lowest total fertility rate (TFR) in the region, at 0.97. A TFR below one is a demographic trend that has not been observed before in the history of Singapore. The effects of Singapore's low fertility rate are a growing challenge for its government. The serious addressed by the Minister in the Prime Minister's Office (PMO) Indranee Rajah include preserving dynamism, drawing in international businesses, and providing opportunities for the next generation [2].

Several factors have contributed to this declining trend, including the availability of family planning programs, along with higher levels of education for women and their involvement in the labor force, which has frequently led to a postponement of marriage and childbirth, which has decreased birth rates [3]. Another study [4] further highlighted the significant determinants influencing fertility rates, and these include women's education, urbanization, better hygiene, preventive healthcare measures, advancements in the economy that improve living conditions, and a decline in infant and child mortality rates. In developing nations, where high fertility rates and falling child mortality rates are major contributors to rapid population growth and elevated levels of poverty, the complex interactions between these variables assume even greater significance.

Replacement fertility is the total fertility rate at which women would have only enough children to sustain population levels [5]. If this level is maintained, each generation will replace itself. Moreover, an average of 2.1 births per woman is considered the replacement fertility rate. In the Philippines, the total fertility rate dropped from 2.7 in 2017 to 1.9 in 2022, indicating that the country is now below the replacement fertility level. A relevant study [6] finds five factors that are accountable for the fertility decline in the country for the past 50 years: (1) improving socioeconomic status, (2) changing marriage patterns, (3) increasing family planning use, (4) declining desired number of children, and (5) improving child survival. Moreover, the future of female fertility in the Philippines is anticipated to persist below replacement level, highlighting the importance of addressing the concern of population aging in the country. This study seeks to forecast the number of births in the Philippines which can guide policymakers to create evidence-based population policies that address challenges associated with the number of births in the country.

Lessening the negative effects necessitates the accurate projection of the number of births. Such projections are important in anticipating demand and allocating sufficient resources, as they provide a more actionable basis for planning and decision-making in areas such as health, social services, and education. However, related studies focus only on forecasting birth rates and not on the actual number of births, which presents a research gap in the field. This study aims to address this gap by formulating a Seasonal Autoregressive Moving Average (SARIMA) model to forecast the number of births in the Philippines. This approach provides a quantitative outlook for the next five years. Through this study, policymakers can leverage the forecasts to implement targeted strategies that align with the evolving demographic landscape of the Philippines.

1.1. Statement of the Problem

The primary goal of this study is to use the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to forecast the number of births in the Philippines. The purpose of this paper is to address the following research questions:

1) Which SARIMA model is most appropriate for forecasting the number of births in the Philippines?
2) What is the projected number of births in the Philippines for the next five years based on the result of the SARIMA model?
3) What is the level of accuracy exhibited by the SARIMA model when utilized to forecast the number of births in the Philippines?
4) What are the possible implications of the projected number of births in the Philippines?

2. Literature Review

Southeast Asia's fertility rate has dropped from 5.5 in 1970 to barely 2.4 in 2015; if policymakers do nothing, this demographic shift could become severe. A report by the Economist Intelligence Unit [3] investigated the factors affecting the decline of birth rates in Southeast Asia, focusing on Thailand, Vietnam, and Malaysia. Five factors were discussed in this report, and the most significant factor in the decline of fertility rates was the implementation of family planning programs. Other factors that were examined in the report include rapid urbanization and migration, increased female education and labor force participation, families prioritizing 'quality' of life over 'quantity' of children, and lastly, biological infertility.

In Singapore, an all-time low record of 0.97 total fertility rate (TFR) was recorded in 2023. This is the second to the lowest TFR in the world, with South Korea topping the list at a TFR of 0.72. It is also reported that during the same year, there were only 30,500 resident births, or births that have at least one parent who is Singaporean or Permanent Resident (PR), compared to 35,330 births in 2019. Singapore's low birth rates and an aging population have led to a slowdown in workforce growth. It has been noted that, despite the influx of immigrants, Singapore lacks a sufficient local workforce to sustain continued robust economic growth [2]. In response to this issue, many solutions were proposed by the government to continue supporting Singaporeans in starting and raising families, such as elective egg freezing and additional paid parental leave.

Meanwhile, the same challenge is evident in Thailand, where record-low births and an ever-growing aging population may jeopardize the country's workforce and productivity. In 2022, there were 485,085 births recorded in the country, which is the lowest figure in 70 years. As stated by Thai Health Minister Cholnan Srikaew, these declining births have reached a critical breaking point since the workforce of about 39 million is outnumbered by the nationwide population of about 70 million. Some of the reasons for the decline in the number of births cited by

Sasiwimon Warunsiri Paweenat, an associate professor of economics at Thammasat University, are the improvement in quality and accessibility of the healthcare system, education, cost of living, changing attitudes, and maternity leave [7]. Moreover, Thai universities are also affected by the sharp decline in the number of births, and most of them are not able to meet their target number of enrollees. The current situation of Thai universities involves accepting fewer students compared to their annual capacity, as the number of students also starts to decline. This phenomenon had a negative impact on universities, leading to a decline in revenue and the dismissal of teachers. In the next five years, these struggling higher education institutions might lead to mergers or closures if they do not adapt to the situation [8].

Along with the birth decline of our neighboring countries, the Philippines is no exception. A decreasing trend in the number of registered live births in the country was observed from 2012 to 2017, with a noticeable 5.0% decrease in the last five years, from 1,790,367 births in 2012 to 1,700,618 recorded births in 2017 [9]. The declining births during this period may be influenced by several factors, including lifestyle changes, limited resources, and the use of family planning methods among married women. Moreover, the latest report by Philippine Statistics Authority [10] shows that the highest rate of decline was detected in 2021 with a decrease of 10.7% from 2020.

Likewise, the fertility rate in the Philippines was also found to be declining. Based on the survey report by Philippine Statistics Authority [11], the Philippines is now below the replacement fertility level of 2.1. The results have depicted that the total fertility rate decreased from 2.7 children per woman in 2017 to 1.9 children per woman in 2022. Factors such as family planning, education, the economy, and the use of contraceptives may have an impact on all these patterns.

The impact of this falling birth rate can be posed as a threat to the economy, and this might be one of the greatest challenges ever encountered by the global economy. There are several economic challenges that birth decline poses, and first on the list is labor shortage which is already evident in Japan and Germany [12]. As the working-age population is eventually decreasing, the economy's growth is also seen to be slowing down. Along with this consequence, this also means that there will be fewer consumers. The impact of this phenomenon decreases opportunities for domestic market growth and has been a significant factor in the economic challenges faced by Europe and certain regions in Latin America.

Moreover, Zhang [13] examined the consequences of falling birthrates in developed nations. The effects of low fertility were discussed along with how it influences various sectors in the economy. The findings of the study revealed that in the short run, low fertility rates have positive effects at both micro and macro levels. However, in the medium term, as the population ages and birth rates decline, there are concerns about social security having insufficient reserves to fulfill promised benefits, leading to growing gaps in coverage and increased costs.

In the context of developing countries like the Philippines, [14] considered it as both an opportunity and a challenge. PopCom viewed it as a positive step in accelerating socioeconomic progress by improving the quality and capacity of the country's resources in different sectors. At the household level, a lower fertility rate allows personal development for individuals and couples. However, Vietnam [15] and India [16], [17] are concerned about the effects of birth decline, as it will have a significant effect on economic growth and population aging.

Most of the related studies explore the application of ARIMA models in forecasting birth rates internationally. Studies in Tamil Nadu, India [18], and Ghana [19] employed ARIMA models to project future birth rates, with results suggesting a declining trend. Additionally, a study in Ghana [20] compared the seasonal SARIMA model with Holt-Winters seasonal methods, concluding that SARIMA models were superior in forecasting monthly birth rates. To select the best model, AIC, BIC, and AICc were used in the studies and the lowest scores will be selected as the best model [18]–[20].

The examined studies were beneficial to the researchers by presenting evidence that SARIMA is a valuable method for projecting future birth rates in the Philippines. Employing a suitable methodology, this research aimed to conduct a comprehensive performance review, addressing the critical aspects of birth rate dynamics.

3. Methodology

3.1. Research Design

Fig. 1 shows the entire process of finding the best SARIMA model. The first step in creating a SARIMA model is data collection and preparation, which includes obtaining historical time series data and cleaning the data before analysis. The dataset is then plotted to analyze its behavior. To prevent overfitting, the data is then divided into two sets: the training set and the testing set. Next, the data's stationarity is assessed; if it is, the process moves on to the next step; if not, the proper sequence of differencing must be used to bring the data into stationarity.

The next phase involves determining the appropriate autoregressive (AR) and moving average (MA) orders, considering that the data has already achieved stationarity. This is done by analyzing the differenced time series' partial autocorrelation function (PACF) and autocorrelation function (ACF). After that, the model is fitted to the stationary data using techniques like Akaike Information Criterion (AIC), corrected Akaike Information Criterion (AICc), and Bayesian Information Criterion (BIC) to estimate the model parameters. After the model is estimated, the next step is to run diagnostic tests, like the invertibility and Ljung-Box tests, to evaluate the predictive ability of the chosen SARIMA model. Choosing the best SARIMA model to use is the next step after performing diagnostic tests. Statistical measures such as root mean squared error (RMSE) and mean absolute percentage error (MAPE) are used in this assessment. The final phase is forecasting, in which future values of the time series data are predicted using the verified model.

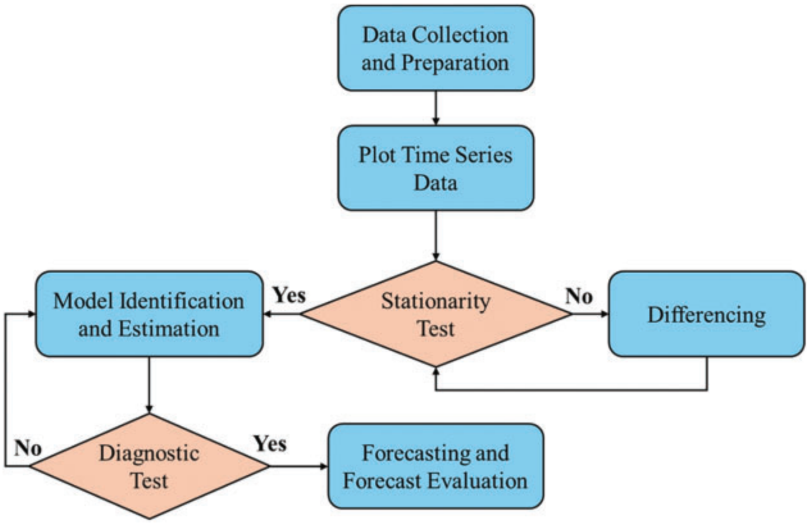

Fig. 1. Box-Jenkins methodology.

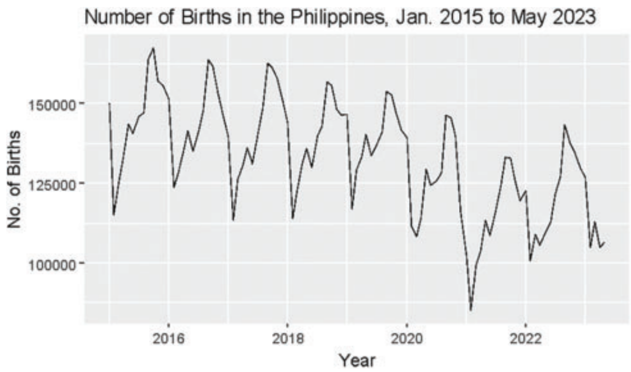

Fig. 2. Plot of number of births in the Philippines (Jan. 2015–May 2023).

3.2. Data Collection

The researchers gathered the data from the Philippine Statistics Authority Data Archive - psada.psa.gov.ph. The PSA Data Archive (PSADA) functions as the systematic repository of PSA's data collection and generation of statistics. The researchers obtained 101 observations from PSA's vital statistics report, covering the period from January 2015 to May 2023. Then, Microsoft Excel was used to arrange the data taken from PSADA. Following that, the R programming language was used to export the data to RStudio.

3.3. Data Processing

In forecasting time series, splitting the data is essential for resolving the overfitting problem and facilitating model assessment. The training set consists of 80% of the sample data, while the testing set comprises the remaining 20%. The model was trained using the training set, and predictions were generated for each item in the test set.

3.4. Model Identification

If the time series exhibits non-stationarity, differencing can help stabilize the mean of a time series by subtracting the current observation and previous observations of the series. Stationarity tests such as Augmented Dickey-Fuller (ADF) Test, Philipps Perron Unit Root (PP) Test, and Kwiatkowski-Philipps-Schmidt-Shinn (KPSS) Test were used to test the stationarity. After making the data stationary, the potential models for the SARIMA were identified by observing the plots of the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF).

3.5. Model Estimation

The model parameters of the potential SARIMA models were estimated using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and corrected Akaike Information Criterion (AICc). The lowest AIC, BIC, and AICc will be selected as the most suitable model to forecast the time series data.

3.6. Diagnostic Checking

In assessing whether a model has effectively captured the information present in the dataset, residuals can serve as a valuable tool. Analyzing residuals can help determine how well the model fits the observed data and, if necessary, assist in making necessary adjustments to the model. In this research, Invertibility and Ljung-Box tests were applied.

3.7. Forecasting Evaluation

The researchers used a rolling origin approach to evaluate the model generated by SARIMA. Accuracy in forecasting is assessed by comparing existing data with forecasts generated by the model for known periods. The forecast error, which is the variance between actual and predicted values, indicates the model's accuracy. A lower forecast error signifies a more accurate model. Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used to measure the forecasting accuracy in this study.

4. Results and Discussion

4.1. Plotting Time Series

Fig. 2 depicts a time series graph illustrating the monthly birth count from January 2015 to May 2023, consisting of 101 observations. Upon visual examination of the data,

Fig. 3. Data partition of number of births in the Philippines (Jan. 2015–May 2023).

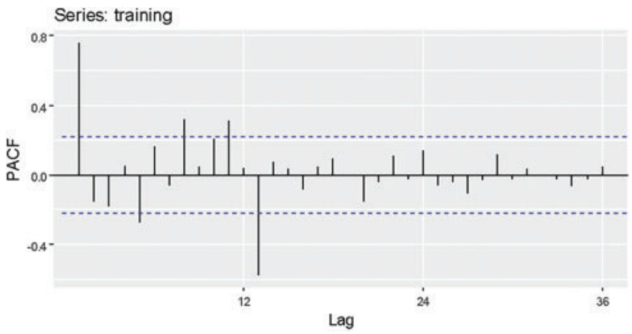

Fig. 4. PACF plot of number of births training set time series.

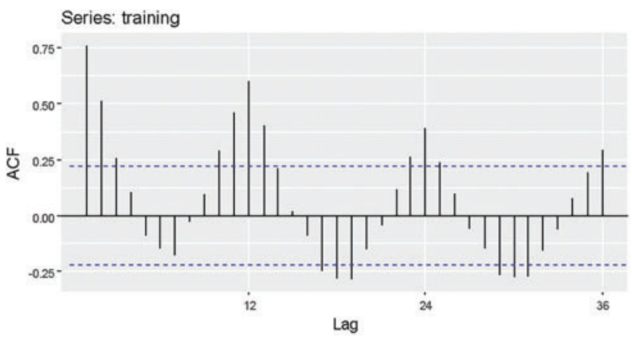

Fig. 5. ACF plot of number of births training set time series.

there is a gradually decreasing trend and a seasonal pattern appears evident, with the highest number of births occurring in September and October, while February consistently has the lowest number of births.

4.2. *Data Partition*

As shown in Fig. 3, the datasets were divided into training set and testing set. The training set, comprising 80% of the entire dataset, was utilized for model development and parameter estimation, while the remaining 20% is the testing set, used to evaluate the predictive performance and accuracy of the developed model.

4.3. *Stationarity Test*

The PACF plot of the training set of time series data is displayed in Fig. 4. Significant lags are present at lags 1, 5, 8, 11, and 13, suggesting that these lags are correlated, which could indicate non-stationarity in the data.

TABLE I: Stationarity Test for Training Set Data

Stationarity test	p-value	Decision rule
ADF	0.01	Reject H_O, data is stationary
PP	0.01	Reject H_O, data is stationary
KPSS	0.01251	Reject H_O, data is non-stationary

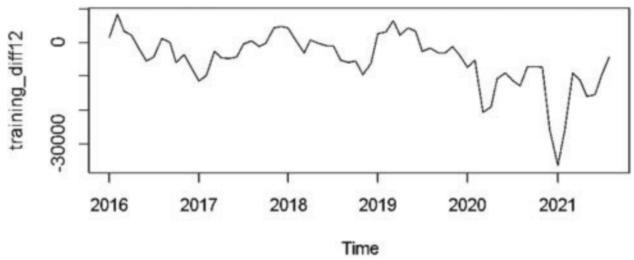

Fig. 6. Plot of number of births after first seasonal differencing.

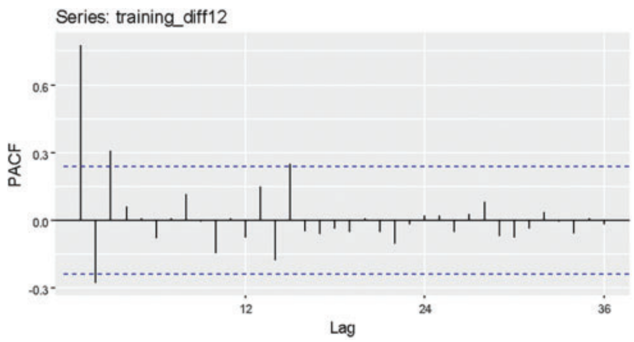

Fig. 7. PACF (First order seasonal differencing).

From the ACF plot depicted in Fig. 5, it is observed that notable lags occur at intervals of 12, indicating a clear seasonal pattern in the data. Additionally, the presence of lags outside the confidence interval implies that the data may exhibit significant autocorrelation, which could indicate non-stationarity. Thus, it may be advisable to perform a seasonal differencing.

Table I shows the results of the Augmented Dickey-Fuller (ADF) test, Phillips-Perron Unit Root (PP) Test, and Kwiatkowski-Phillips-Schmidt-Shinn (KPSS) test for the training set data. The ADF and PP test results indicate that the data is stationary [21], [22], however, the KPSS tells us that the data is non-stationary [23]. To address this, a first-order seasonal difference will be applied to the data.

4.4. *First-Order Seasonal Difference*

Fig. 6 illustrates the plot of the time series after the first-order seasonal differencing. This transformation results in a smoother pattern, compared to the original plot. However, there is a notable downward spike observed in the year 2021. Hence, it is imperative to subject the time series to further stationary tests to conduct a comprehensive analysis of the data.

Following first-order seasonal differencing, the PACF plot of the time series is displayed in Fig. 7. Significantly, there are spikes showing correlations between these observations at lags 1, 2, 3, and 15. The time series may contain non-stationarity, based on this pattern.

The ACF plot of the number of births time series after first-order seasonal differencing presented in Fig. 8 shows a gradual and slow decline in ACF values as the lag

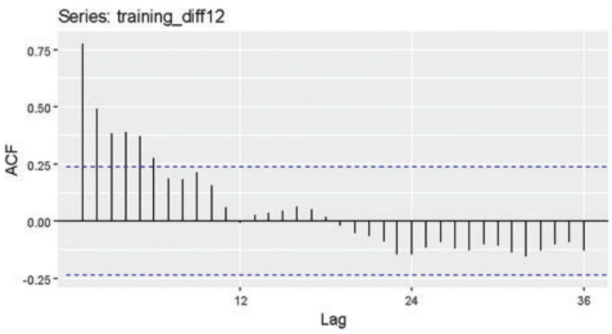

Fig. 8. ACF (First order seasonal differencing).

TABLE II: STATIONARITY TEST AFTER FIRST-ORDER SEASONAL DIFFERENCE

Stationarity test	p-value	Decision rule
ADF	0.4253	Accept H_O, data is non-stationary
PP	0.05068	Accept H_O, data is non-stationary
KPSS	0.01	Reject H_O, data is non-stationary

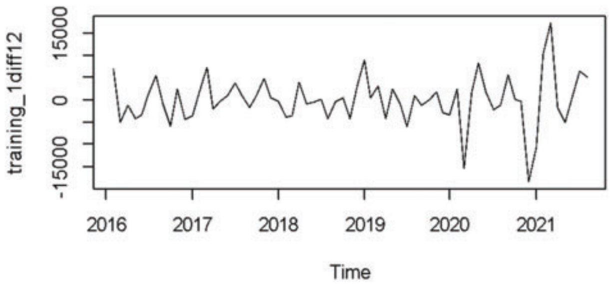

Fig. 9. Plot of number of births after first non-seasonal differencing.

increases. This observation strongly suggests that there is still non-stationarity in the data.

Table II reveals the results of the stationarity tests after the first-order seasonal difference. All the tests revealed that the data is still stationary, so another first-order non-seasonal difference will be applied to the data.

4.5. *First-Order Non-Seasonal Difference*

Fig. 9 displays the plot after first-order non-seasonal differencing. There is no noticeable trend or seasonality in the plot, suggesting that the data may be stationary.

The PACF plot in Fig. 10 displays significant lags in orders 2 and 14. It is assumed that the differenced time series is already stationary since most of the plot's lags fall within the confidence interval.

With significant lags in orders 2 and 3, the ACF plot from Fig. 11 shows that most lags are now within the confidence interval. Hence, based on the ACF plot, the differenced time series is stationary.

Table III shows the test results from the ADF, PP, and KPSS tests. The results reveal that the time series is now stationary after performing first-order non-seasonal differencing.

4.6. *Model Identification*

4.6.1. *Non-Seasonal AR and MA Component*

Firstly, the PACF plot offers insights into the potential values for the AR component of the model. In our case, the examination of this plot suggests that lags 2 and 14

Fig. 10. PACF (First order non-seasonal differencing).

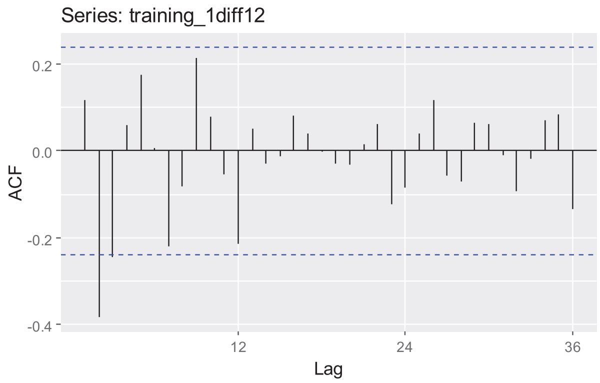

Fig. 11. ACF (First order non-seasonal differencing).

TABLE III: STATIONARITY TEST AFTER FIRST-ORDER NON-SEASONAL DIFFERENCE

Stationarity test	p-value	Decision rule
ADF	0.01	Reject H_O, data is stationary
PP	0.01	Reject H_O, data is stationary
KPSS	0.1	Accept H_O, data is stationary

indicate potential values for the AR component. It is also important to note that given the monthly frequency of observations, lags greater than 12 are considered non-significant, thus, we will only have lag 2 as our value for the AR component.

Moreover, following the first-order non-seasonal differencing, the data has already attained stationarity. Therefore, for the integrated process or (d) model, we will employ a value of 1.

Furthermore, the ACF plot assists in identifying the possible values for the MA model. In this context, the possible values for the MA component are lags 2 and 3, as observed from the ACF plot.

4.6.2. *Seasonal AR and MA Component*

After the data has attained stationarity after the first seasonal differencing, the value of seasonal d is assigned to 1. For the seasonal p and q values, orders at lags 12 and 24 must be observed. In the ACF plot in Fig. 13, a strong decay on lags 12 and 24 is shown. Therefore, a Seasonal Moving Average (SMA) 1 model must be considered. Moreover, the PACF in Fig. 12 also shows a decay on lags 12 and 24, implying that a Seasonal Autoregressive (SAR) 1 must also be considered.

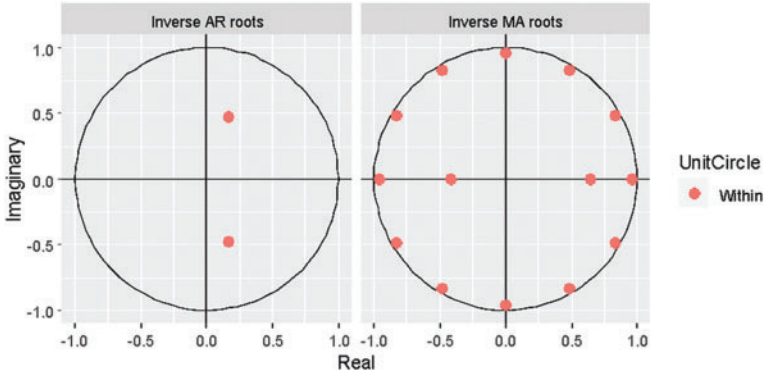

Fig. 12. Inverse roots of ARMA structure.

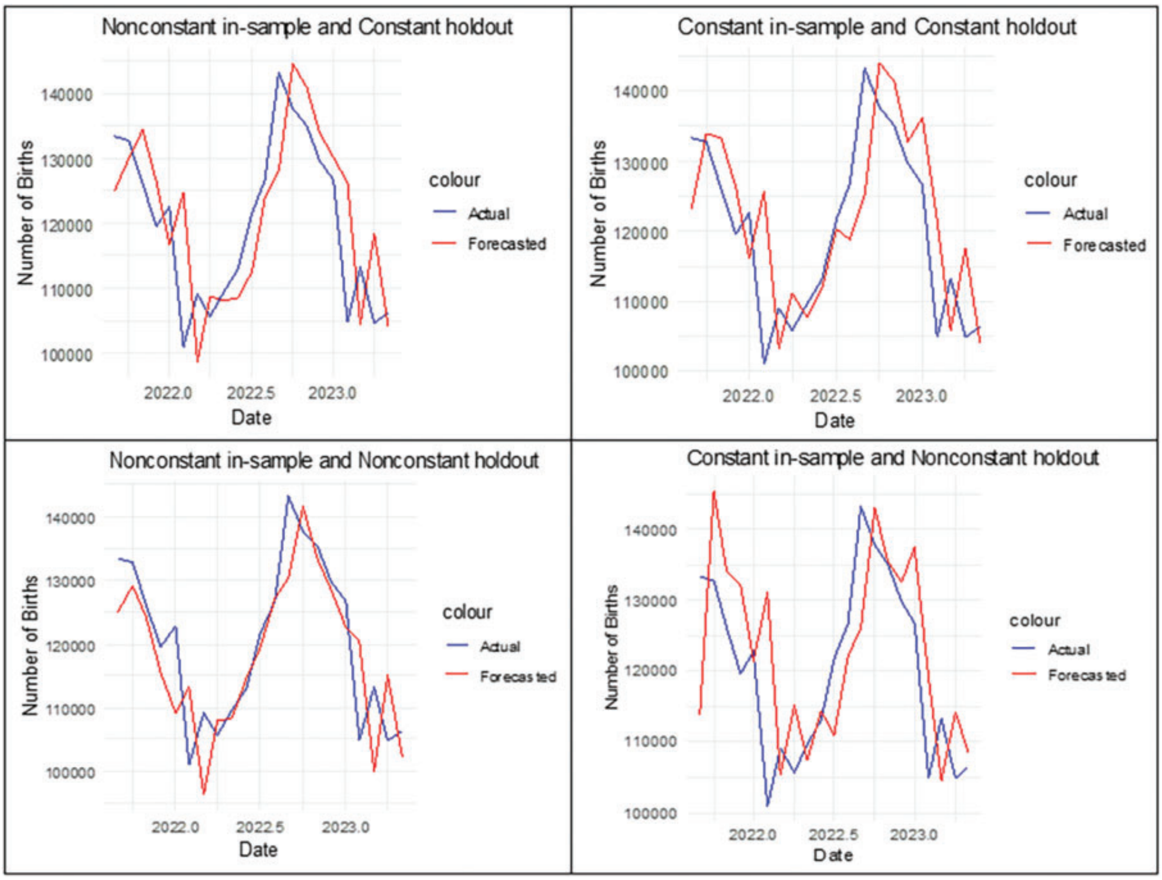

Fig. 13. Rolling origin forecast of number of births time series.

4.7. Model Estimation

TABLE IV: POTENTIAL SARIMA MODELS

SARIMA Model	AIC	BIC	AICC
$(2,1,2)(1,1,0)_{12}$	1327.02	1340.25	1328.42
$(2,1,2)(1,1,1)_{12}$	1325.13	1340.56	1327.03
$(2,1,2)(0,1,1)_{12}$	1323.25	1336.47	1324.65
$(2,1,3)(1,1,0)_{12}$	1328.83	1344.26	1330.72
$(2,1,3)(1,1,1)_{12}$	1326.64	1344.27	1329.12
$(2,1,3)(0,1,1)_{12}$	1324.77	1340.20	1326.67

Note: Table IV presents the candidate SARIMA models. Among these models, SARIMA $(2, 1, 2)\,(0, 1, 1)_{12}$ exhibits the lowest AIC, BIC, and AICC scores at 1323.25, 1336.47, and 1324.65, respectively. Hence, it suggests that SARIMA $(2, 1, 2)\,(0, 1, 1)_{12}$ stands as the most suitable model for forecasting the time series based on the evaluation metrics.

4.8. Diagnostic Checking

4.8.1. Invertibility

As seen in Fig. 12, all inverse roots of the SARIMA model $(2, 1, 2)\,(0, 1, 1)_{12}$ fall inside the unit circle, indicating that ARMA structure is invertible. This invertibility property implies that the SARIMA model $(2, 1, 2)\,(0, 1, 1)_{12}$ is a good model for forecasting.

4.8.2. Ljung-Box Test

Table V displays that the p-value of both the training set and testing set is greater than 0.05. This suggests that there is insufficient evidence to reject the null hypothesis of no autocorrelation in the residuals, based on the Ljung-Box Test [24]. Moreover, this indicates that the selected SARIMA model is significantly appropriate, and forecasting can already be performed.

TABLE V: Ljung-Box Test for the Residuals of SARIMA $(2,1,2)(0,1,1)_{12}$ Model

	Training set	Testing set
p-value	0.5355	0.8166

TABLE VI: Error Measures for Rolling Origin Forecast

Rolling origin forecast	MAPE	RMSE
Nonconstant in-sample and constant holdout	6.635754%	10,001.96
Constant in-sample and constant holdout	6.324309%	9,760.93
Nonconstant in-sample and nonconstant holdout	5.594820%	8,046.20
Constant in-sample and nonconstant holdout	7.218636%	11,408.41

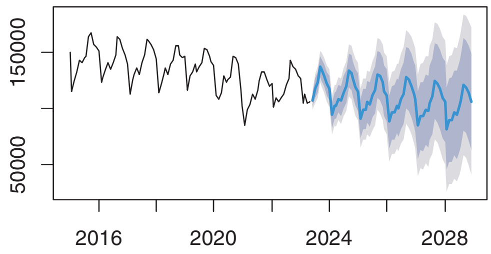

Fig. 14. Sample forecast of number of births based on SARIMA $(2,1,2)(0,1,1)_{12}$.

4.9. *Forecasting Evaluation*

Fig. 13 shows the plots of rolling origin forecasts with different combinations: (1) nonconstant in-sample and constant holdout, (2) constant in-sample and constant holdout, (3) nonconstant in-sample and nonconstant holdout, and (4) constant in-sample and nonconstant holdout. From these forecasts, the lowest MAPE and RMSE will be chosen as the rolling origin forecast.

Table VI shows the values of the error measures for the rolling origin forecast including the MAPE and RMSE. Among all the forecasts, the rolling origin forecast with nonconstant in-sample and nonconstant holdout holds the lowest value of MAPE with 5.49582% and RMSE of 8,046.201. The value of MAPE signifies that, on average, the forecasted values deviate by 5.49582% from the actual values. As per the criterion [25], a MAPE value below 10% indicates a highly accurate forecast. Moreover, the MAPE value of the SARIMA $(2,1,2)(0,1,1)_{12}$ model suggests a satisfactory fit. This observation highlights how well the model captures the patterns in the dataset, resulting in forecasts that closely align with the actual values.

4.10. *Sample Forecast*

A line graph illustrating the sample forecast of the number of births is shown in Fig. 14. The actual number of births is represented in black, while the projected birth count for the next five years, based on SARIMA $(2,1,2)(0,1,1)_{12}$ is displayed in blue. The forecast suggests a gradual decline in the number of births, following a seasonal pattern.

The data from Table VII indicates a downward trend in the birth count over the next five years. Births are projected to decrease from 1,380,329 in 2024 to 1,229,035 in 2028, representing a 10.96% decline. This supports the findings of Masha *et al.* [19], which indicate a negative relationship between birth rate and time.

TABLE VII: Forecasted Number of Births per Year (2024–2028)

Year	Forecasted
2024	1,380,329
2025	1,342,499
2026	1,304,676
2027	1,266,857
2027	1,229,035

5. Summary of Findings

The objective of this research is to develop a Seasonal Autoregressive Integrated Moving Average (SARIMA) model based on the historical birth data in the Philippines from January 2015 to May 2023 to forecast the number of births in the Philippines for the next five years. After transforming the data into stationary, the plots of the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF) were evaluated to identify potential SARIMA models. There were six potential SARIMA model candidates, but SARIMA $(2,1,2)(0,1,1)_{12}$ was the most suitable according to different criteria. The chosen model obtained the lowest Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Corrected Akaike Information Criterion (AICC) among the other models, with a mean absolute percentage error (MAPE) of 5.5%, and a Root Mean Square (RMSE) of 8,046.2. Thus, SARIMA $(2,1,2)(0,1,1)_{12}$ was the model utilized to forecast the data for the next five years, revealing that the number of births in the Philippines might experience a 10.96% decline from 2024 to 2028.

6. Conclusions

Consistent with the findings of Aryee *et al*. [20], which suggest that SARIMA models can optimally predict birth rates, our analysis confirms that the SARIMA model is a useful tool for representing the number of births. It provides valuable insights for demographic planning in the Philippines, particularly because it captures the seasonal pattern of the dataset. The forecast captured the seasonality of births with peaks every September and October and troughs every February. This information can be utilized to anticipate demand and allocate sufficient resources, particularly in the healthcare sector, as suggested by the study of Aryee *et al*. [20]. Aside from the SARIMA model, the researchers have also utilized Rolling Origin in the test forecast, which is an effective approach especially when dealing with time series. The Rolling Origin forecast with nonconstant in-sample and nonconstant holdout is selected among the other forecasts since it obtained the least error measures. Moreover, the results of this paper hold significant relevance to policymakers, healthcare providers, economic planners, and insurance companies. By understanding the population dynamics and anticipating shifts in demand for maternity care services, this research equips decision-makers with essential data to formulate policies.

To conclude, fewer births will certainly affect the demographic aspect of a nation. The projected decline in the number of births in the Philippines indicates varied effects on various aspects. As mentioned by the report of Locus [14], while it may lessen the pressure on resources and contribute to improved living standards, it also helps personal development opportunities for families, resulting in enhanced financial stability through increased savings. However, the forecasted birth decline does not always suggest a positive indicator for the economy. The demographic shift could also impose challenges such as labor force shortages and an aging population. If the sharp drop in the number of births continues, it may also affect the number of enrollees in schools and universities, just like what Thailand has experienced [8]. We need to learn from the countries that are currently facing this demographic challenge, like South Korea, Singapore, and Japan [2], [12]. These countries have already taken measures to increase their fertility rate by giving support to those who wish to raise a family. Although the numbers are far from the countries mentioned, the government should still prepare for the consequences that this phenomenon holds. Overall, the forecasted number of births serves as a valuable tool for policymakers, offering insights and guiding the development of strategies to address the evolving needs of the population.

7. Implications

The implications of the forecasted decline in births include potential impacts on various sectors such as the economy, labor force, education system, and social welfare. By understanding and anticipating these demographic shifts, decision-makers can develop targeted strategies to mitigate challenges and adapt to the evolving population dynamics. The research findings provide valuable information for policymakers, healthcare providers, economic planners, and other stakeholders to make informed decisions and plan for the changing demographic landscape in the Philippines.

8. Recommendations

The findings of the study could have been improved if more data points had been used since more observations in a time series would have produced more precise results. The focus of this study is to predict the number of births, however, it would also be useful to analyze other parameters that could influence the birth decline, such as social structure, economic prosperity, and urbanization within the country. Moreover, to enhance forecasting accuracy, alternative models like neural networks, deep neural networks, and causal models could be explored by future researchers.

Conflict of Interest

Authors declare that they do not have any conflict of interest.

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