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Analysis of the evolution of infant mortality rates of children residing in the state of rio grande do sul, brazil

Análise da evolução das taxas de mortalidade de crianças com até um ano de idade residentes no estado do rio grande do sul

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Abstract:

Objective: This study aims to highlight the main characteristics and compare the evolution of infant mortality rates in the state of Rio Grande do Sul (RS) through the ARIMA and ARMA methodologies. Method The monthly infant mortality rates of the period of 2000 to 2017 were obtained from the Unified Health System (SUS) Department of Informatics (DATASUS). A descriptive analysis and time series modelling using the ARIMA and ARMA methodologies were carried out and discussed. Results: Cacique Doble, Alto Alegre, and São Valério do Sul were the cities of residence with the highest infant mortality rates for the state of RS in the period. Based on the residual analysis and the AIC and BIC penalizing criteria, a better quality of fit was observed in the ARMA(4,6) model. Conclusion Although the ARMA model presented better quality of fit, the accuracy measurements were lower in the SARIMA model. The proposed methodologies can guide the planning of preventive and educational policies aimed at the risk of a born alive dying during its first year of life.

Keywords: Infant mortality; Time series; ARIMA; ARMA; Forecasting.

Resumo:

Este estudo tem por objetivo destacar as principais características e comparar a evolução das taxas de mortalidade infantil no Estado do Rio Grande do Sul (RS) por meio das metodologias ARIMA e ARMA. Método: As taxas mensais de mortalidade infantil do período de 2000 a 2017 foram obtidas do Departamento de Informática do Sistema Único de Saúde (SUS) (DATASUS). Foi realizada e discutida uma análise descritiva e modelagem de séries temporais utilizando as metodologias ARIMA e ARMA. Resultados: Cacique Doble, Alto Alegre e São Valério do Sul foram as cidades de residência com as taxas de mortalidade infantil mais elevadas para o estado do RS no período. Com base na análise dos resíduos e nos critérios penalizadores de AIC e BIC, foi observada uma melhor qualidade de ajuste no modelo ARMA(4,6). Conclusão: Embora o modelo ARMA apresentasse melhor qualidade ajuste, as medidas de acuracidade foram inferiores no modelo SARIMA. As metodologias propostas podem orientar no planejamento de políticas preventivas e educativas voltadas ao risco de um nascido vivo morrer durante o seu primeiro ano de vida.

Palavras-chave: Mortalidade infantil; Séries temporais; ARIMA; ARMA; Previsão.

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INTRODUCTION

Infant mortality rates are some of the main indicators of the welfare of the population of a given region. It is a major health index and one of the main drivers behind the Sustainable Development Goals (SDGs) of the 2030 Agenda for Sustainable Development of the United Nations. Infant mortality is characterized by the number of deaths occurring from birth to 365 days after birth in a certain population [1]. Estimating the infant mortality coefficient has been encouraged by the growing interest in measuring infant death rates, not only as an indicator of health quality, but above all as a way to level the human development of a given population [2]. In this context, it is worth noting that infant mortality serves as an indicator of the living and health conditions of a certain group [3].

The causes attributed to infant deaths are directly related to socioeconomic issues such as poor housing and home conditions, little transportation infrastructure, and limited access to healthcare [4]. However, the model of social and economic development that prevailed in Brazil for decades centralized income, resources, and services favoring certain regions and social groups. Consequently, the country have a society marked by the principles of social inequality [2]. This management model has also driven the increase in infant deaths, a reflection of the existing limitations in health policies and living conditions of the population [5].

Considering the high infant mortality rate and the social and economic consequences of these deaths [5], it becomes pertinent to approach the topic using predictive methodologies in time series. The use of time series for the observation of regularly spaced events in time was developed by Box and Jenkins [6], from studies with emphasis on applications in the field of statistics, economics, engineering, and social sciences. Prediction models evaluate data by means of time series analysis and meet some assumptions by investigating the generating factor of the time series, making future forecasts for the series, describing the behavior of the series, and indicating the periodicity of the data.

Therefore, the aim of this study is to highlight the main characteristics of the infant mortality rates in the state of Rio Grande do Sul (RS) and compare the evolution of this time series using the ARIMA and ARMA methodologies. Predicting future infant mortality rates highlights the seriousness of the problem they represent. Thus, what is the appropriate methodology to establish the best prediction model for infant mortality rates in the RS state?

Time series analysis using ARIMA methodology was already used to forecast infant mortality rates in India [7] and China [8]. There are also studies that use ARIMA to analyze neonatal mortality (when the death occurs before reaching 28 days of age) [9,10] and under-five mortality [11]. To the best of our knowledge, there are currently no studies that compare the performance of ARIMA and ARMA methodologies when forecasting infant mortality rates in the state of RS, Brazil.

The quality of fit of the ARMA modeling was shown to be higher than other methodologies in the study by Palm and Bayer [12] that analyzed the stored energy rates in Southern Brazil in the period of 2009 to 2015. This conclusion was also obtained in the study of Bayer, Tondolo and Müller[13] when analyzing a database related to a tire manufacturing process, as well as in the analysis of relative humidity data in the cities of Brasília, Manaus, and Santa Maria. Melchior et al. [14] analyze the mortality rates due to occupational accidents of the three states in the southern region of Brazil and also found the quality of fit of ARMA model to be better. However, there are no studies that used such modeling for fitted infant mortality rates.

We found out that when fitting infant mortality rates of the state of RS the quality of fit of the ARMA model was superior. The RS infant mortality rate is lower than the national average but is still far from rates presented by high-income world economies. This work highlights infant mortality indicators with the purpose of encouraging the development of health policies and actions with emphasis on prenatal care, childbirth, and protection of children's health.

METHODS

The information related to the infant mortality of Brazilians were obtained by consulting the records of official bodies such as Brazil's Unified Health System (SUS) IT Department DATASUS - – Departamento de Informática do SUS (http://datasus.saude.gov.br/). For the time series analysis, we used the monthly records of infant mortality from January 2000 to June 2017, for fitting, and from July to December 2017, to evaluate the quality of the models. The proposed methodology was implemented using language R.

To compare the prediction models, ARIMA modeling was performed according to the methodological steps proposed by Box and Jenkins [6] and ARMA modeling was performed according to Rocha and Cribari-Neto [15] builds on the work of Ferrari and Cribari-Neto [16]. In addition, the Augmented Dickey Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were performed to verify the stationarity condition and identify the model for the time series analyzed.

The ARIMA methodology was proposed by Box-Jenkins [6] and is mainly used in time series forecasting. This method assumes normality and highlights the analysis of the properties of the time series. The ARIMA(p,d,q) model, which characterizes the Box-Jenkins model, consists of expressions identified as the order (p) of the autoregressive part (AR), with an order of differentiation model (d) and an order (q) for moving averages (MA) [17].

Seasonality is another feature that can be added to the ARIMA models and represents the peaks that recur periodically in the time series [18]. Models with seasonal components are called Seasonal Autoregressive Integrated Moving Average (SARIMA) (p,d,q)(P, D, Q)s whereas "s" represents the order of seasonality.

However, to use the ARIMA methodology, it is first necessary to ensure that the estimated parameters are significant over time. Therefore, the basic assumption of the time series stationarity must be met [18]. When the time series does not exhibit such behavior, transformations may be applied, and the order of integration (I) considered corresponds to the number of differences necessary to make the nonstationary series stationary [19]. Once the stationarity is verified and the differences are applied, if necessary, the best predictor model is chosen by analyzing the Autocorrelation Function (FAC) and Partial Autocorrelation Function (FACP). So, to assist in deciding the number of parameters that should be introduced in the model the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are used to assist in deciding the number of parameters that should be introduced in the model [20].

In addition, alternative criteria were also considered to identify the best fit among the competing models. The most commonly used accuracy measures are: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root-Mean-Square Error (RMSE) [21].

The ARMA methodology is based on the beta () distribution, which is used to model random variables of interest distributed over a range delimited by two known scalar values a and b, where $a<b$. Scalars a and b usually assume values 0 and 1, as when modeling percentages and rates [22]. The transformation of (y - a)/(b - a), is recommended by Cribari-Neto and Zeileis [23] , to model a variable on a standard unit interval. Whether in the ARIMA models or the model parameters of ARMA, it is relevant to clarify that both are estimated via maximum likelihood [24].

RESULTS

In this section is presented a descriptive analysis of the infant mortality rates registered in the state of RS. Table 1 shows the descriptive analysis of infant mortality rates per 1,000 live births in RS Brazil, from 2000 to 2017.

Table 1. Descriptive measures of infant mortality rates per 1,000 live births in the state of RS, from 2000 to 2017

Descriptive Statistics	Rio Grande do Sul		
	Infant mortality rates	Infant deaths	Live births per month
Average	12.70	153.4	12,090
Median	12.11	142.5	11,981
Standard deviation	2.52	39.62	1,163.75
Coefficient of variation (%)	0.20	0.2582	0.0963
Minimum	6.79	84	9,514
Maximum	20.01	278	15,915

The highest monthly number of infant deaths in RS in the period from 2000 to 2017 occurred in July 2000, with 278 deaths. In that month, the infant mortality rate was 18.66 deaths per 1,000 live births and there were 14,902 births. Among these deaths, 146 (53%) were male, 124 (45%) were aged between 3 hours and 4 months, and 214 (77%) had white skin. The state capital, Porto Alegre, was the municipality of residence with the highest number of infant deaths, 35 (13%), while the city of Pelotas ranked second with 17 (6%) cases. As for the place of occurrence of the death, the hospital was cited in 210 (76%) cases.

With respect to the monthly infant mortality rate in the state of RS, the highest rate recorded for the period from 2000 to 2017 occurred in June 2002 with 20.01 deaths per 1,000 live births (245 infant deaths recorded out of 12,246 births). Among these deaths, 140

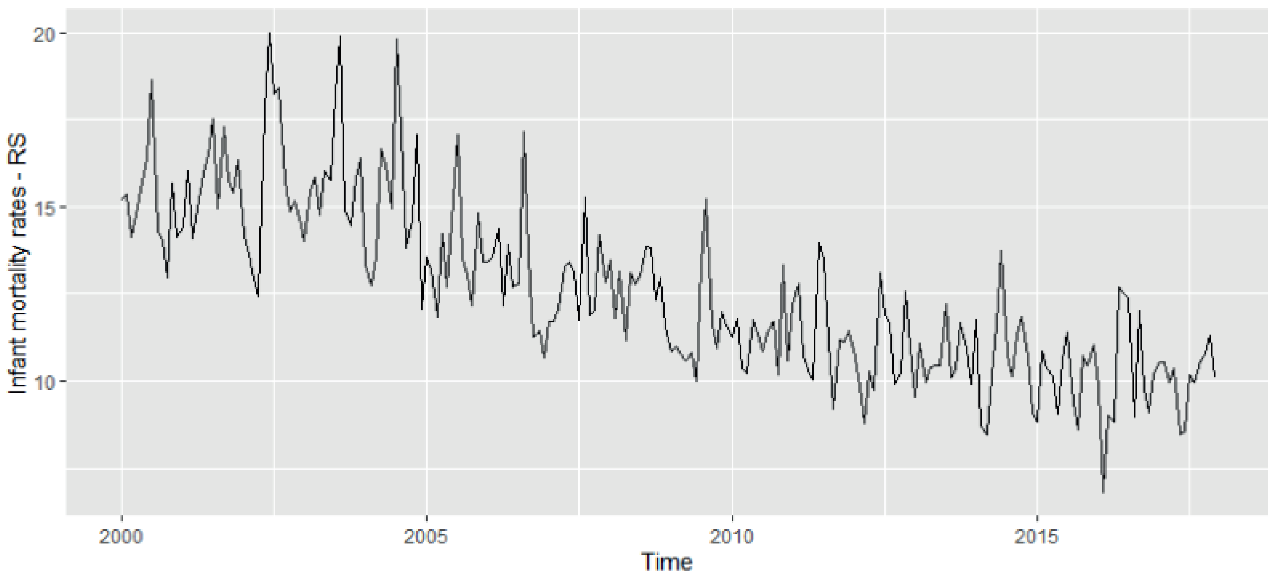
(57%) were male and 116 (47%) were aged between 01 day and 5 months, but there were 129 (53%) cases in which the age of the victims was ignored. As for race or color, 194 (79%) were white. The hospital was the main place of occurrence of infant death with 201 (82%) situations.

The lowest number of infant deaths and the lowest monthly infant mortality rate in RS in period from 2000 to 2017 occurred in February 2016 with 6.79 deaths per 1,000 live births (84 infant deaths recorded out of 12,371 births). Among these 84 deaths, 53 (63%) were male, 72 (86%) were white, and in 34 (40%) situations the victim was between 3 hours and 2 months old. In 80 (95%) cases the place of occurrence of the infant death was the hospital. As for the municipality of residence, Porto Alegre was mentioned in 13 (15%) cases, followed by Novo Hamburgo with 7 (8%) cases.

For the stratified analysis by municipality (based on the municipality of residence of the mother), the sum of all deaths was performed, as well as the sum of all births in the period from 2000 to 2017. In this case, the municipality of Cacique Doble presented the highest infant mortality rate for the state of RS, of 28.19 deaths per 1,000 live births (1,135 births and 32 deaths), followed by Alto Alegre with 27.78 deaths per 1,000 live births (288 births and 8 deaths) and São Valério do Sul with 26.75 deaths per 1,000 live births (785 births and 21 deaths). The capital Porto Alegre had a rate of 11.3 deaths per 1,000 live births (348,053 births and 3,932 deaths), while the state average is 12.73 deaths per 1,000 live births.

To better understand the behavior of the variables analyzed, Figure 1 depicts the original series of the monthly infant mortality rates per 1,000 live births for the state of RS. It is possible to observe the behavior of the infant mortality rates during the 216 months considered. It is noteworthy that the series did not present evidence of stationarity.

Figure 1. Estimates for infant mortality rates in representative world regions in 2017.



After the graphic analysis of the original series, the first stage of the Box-Jenkins methodology is performed, the analysis of ACF and PACF.

The key values of the ADF and KPSS unit roots tests for series stationarity in level are -2.036 and 3.745 respectively, with p-value 0.563.

In the infant mortality series analyzed, the hypothesis of existence of unit root was not rejected, since both tests converge their results, thus, it was opted for the first-order difference of the series, making it stationary. The stationarity of the differenced time series is confirmed by ADF and KPSS tests at 1% significance level.

Determining the p and q orders of the models is a fundamental step in fitting ARIMA and ARMA time series models [22]. From this perspective, model selection considered an exhaustive computational search aimed at minimizing AIC and BIC.

In the sequence, Table 2 shows the diagnostic analysis of the SARIMA and ARMA models selected for the state of RS, Brazil.

Table 2. SARIMA and ARMA models fitted for infant mortality rates per 1,000 live births in the state of RS, Brazil.

Model	Estimates	p-value	AIC	BIC
$SARIMA(1,1,1)(1,0,1)_{12}$	$\Phi_1 = 0.180$ $\theta_1 = -0.923$ $\Phi_{12} = 0.923$ $\theta_{12} = 0.762$	0.017 < 0.001 < 0.001 < 0.001	741.71	758.42
$\beta ARMA(4,6)$	$\Phi_4 = 0.282$ $\theta_6 = 0.119$	0.0000 0.0246	-129.6316	-116.2432

Four competing models were fitted to the data series. The AIC and BIC were used to identify the ones with the best fit to the series of infant mortality rates in the state of RS, Brazil, which are presented in Table 2. According to this criteria, the best model for the series was ARMA(4, 6) as it had the lowest AIC and BIC. Subsequently, the fitted models were verified to ensure they met all the white noise assumptions.

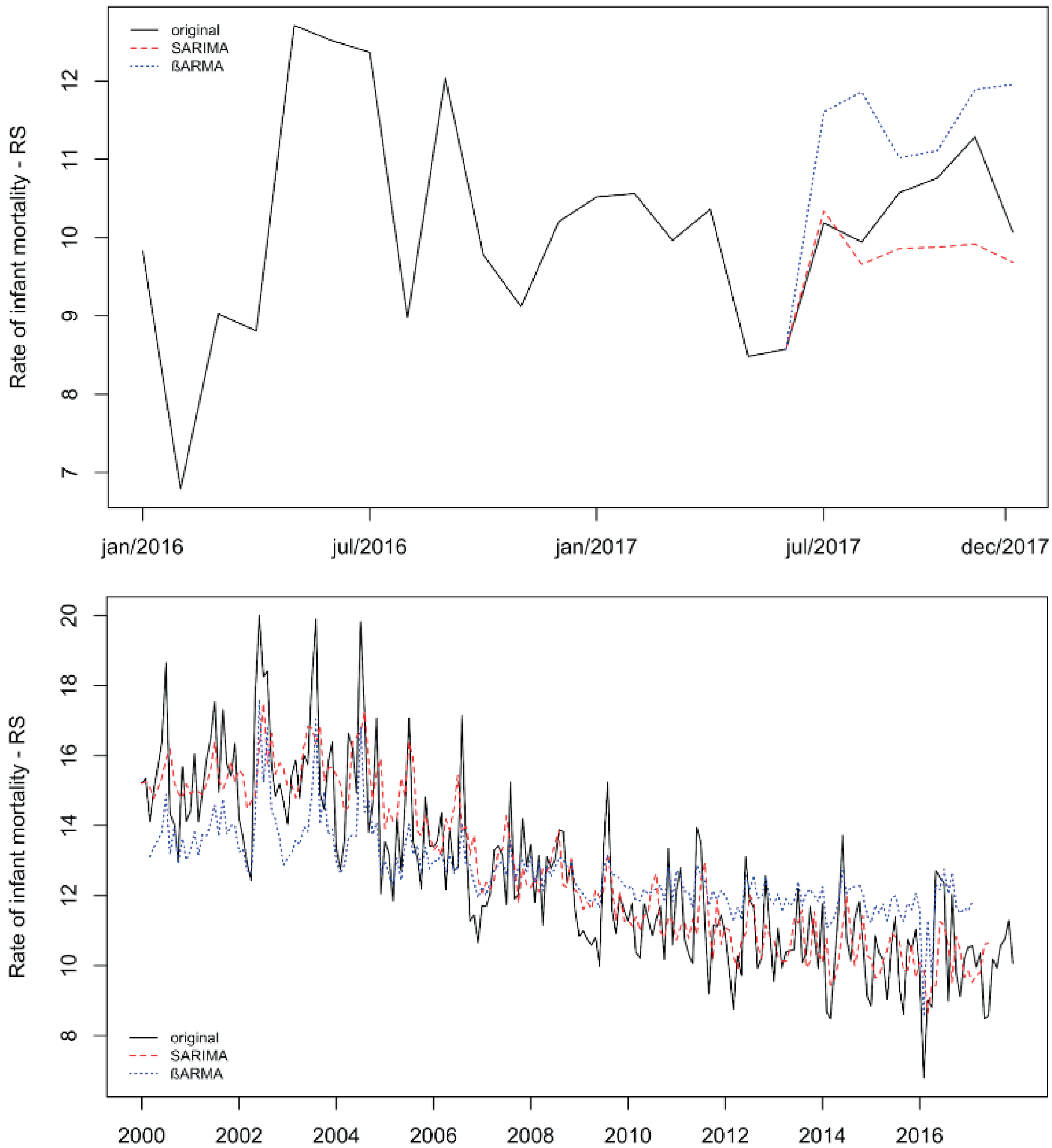
The forecasting was performed for six values (or six months) after 210th observation (referring to June 2017). Table 3 shows a comparison between the original values and the forecasts of SARIMA and ARMA models. For each period, we highlighted the forecasts that were closer to the original series in boldface.

Table 3. Results of forecasts of infant mortality rates in the state of RS, Brazil, based on out-sample forecast for July–December 2017.

Period	Observed value	SARIMA forecast	βARMA forecast
Jul/2017	10.186335	**10.341512**	11.60439
Aug/2017	9.943425	**9.661384**	11.86188
Sep/2017	10.573882	9.859713	**11.01921**
Oct/2017	10.760808	9.877287	**11.10782**
Nov/2017	11.287988	9.916187	**11.89055**
Dec/2017	10.070404	**9.685453**	11.95435

Figure 2 illustrates both the out-sample forecast, as well as the predicted values within the sample and the actual values for the period. The SARIMA and ARMA model predictions from July to December 2017 in the state of RS Brazil were similar. Each of the models presented closer results on three out of the six forecasted values, however while most of the SARIMA values were lower than the observed values, the values predicted by ARMA were all higher than the observed values. The closer result was presented by SARIMA in July 2017, where it was off by only 0.156. Overall, both models yielded accurate forecasts for the series.

Figure 2. Comparison of out-sample forecasts and predicted values within the sample of SARIMA and ARMA for infant mortality rates per 1,000 live births in the state of RS, Brazil.



The models were compared based on the actual and predicted values. This was done by analyzing the RMSE, MAE, and MAPE. The RMSE for SARIMA is 1.371, while for ARMA it is 1.286 (6% lower). The MAE is 1.093 for SARIMA and 1.103 for ARMA (1% higher). Lastly, the MAPE is 8.861 for SARIMA and 10.783 for ARMA (22% higher).

The ARMA methodology presented the best fit since it exhibits the lowest AIC and BIC values. However, when analyzing the accuracy measures it is noticeable through the percentage values (%) that the values assigned to the MAE and MAPE accuracy measures are higher when considering the predicted values for the ARMA model. The RMSE was the only accuracy measure where the ARMA model presented better results than the SARIMA model.

Regarding the predictive efficacy of the selected models, Figure 2 shows that there is a similar degree of proximity between the original data and the values predicted by the SARIMA and ARMA, models in the RS series. However, the data within the sample shows different degrees of proximity among the two models. While the SARIMA correctly captures the seasonality and the downward trend of the series, the ARMA model misses both series' characteristics.

After fitting the best prediction models for infant mortality rates in the state of RS, Brazil, a residual analysis was performed. This was done using portmanteau tests from the work of Ljung and Box, Dufour and Roy, and Scher to verify the existence of the first m autocorrelations in the residuals. All tests presented $p > 0.05$.

In addition, Shapiro and Wilk, Kolmogorov–Smirnov and Jarque and Bera normality tests were performed. All tests indicate normality of residuals for the fitted ARIMA and ARMA models for the time series at a 1% nominal level.

DISCUSSION

The infant mortality rate (under one year of age) is a very important indicator because it measures the life expectancy at birth. In addition, these indicators have historically been used to assess the health, education, and living conditions of population. The infant mortality represent highly undesirable events, because these death occur very early in life and are in general avoidable [1].

A country's infant mortality rates reflect its economic and social development. In this context, infant deaths from infectious diseases are important indicators of poverty, while malnutrition, lack of basic sanitation and primary care deficiencies are causes of diarrhea infant mortality. Moreover, there is the influence of socioeconomic indicators that can dramatically amplify the risks of infant deaths in a given population [4].

It should also be considered that maternal exposure to various direct or indirect risks decreases the chances of child survival, since prenatal health and obstetric care are affected [25]. Therefore, mothers who does not have access to clear water, electricity, and basic health care are subject to mortality risks due to poor health conditions, sharing these risks with their children [26].

A major social challenge is to reduce the infant deaths from disadvantaged classes with strategic health-related interventions [27]. For these strategies to be efficient, it is first necessary to know the causes of infant mortality to select the most appropriate strategies for reducing these deaths 26. The causes of infant mortality are associated with determinants at the individual, household, and community levels. The economic and social characteristics of the neighborhood where the child lives can drastically affect the conditions and behaviors linked to child health[1].

Moreover, in Brazil, increased income is directly associated with better health conditions, which means that, in general, infant deaths are concentrated in poorer regions[25] with marked infant malnutrition, lower living conditions, basic sanitation, and public health. The level of education and maternal monthly income, in addition to alcoholism and smoking, are factors that directly influence infant mortality, increasing the risk of death [27].

Thus, improvement in the quality of health systems, valorization of national data, and the dissemination of policies to encourage gestational monitoring are fundamental to the preservation of children's lives [2]. It is worth noting that many of the deaths may be preventable, especially by improving the organization, quality, and access to health services [5]. Therefore, it is important to identify the deaths that could have been prevented by adequate maternal and child health care [3].

CONCLUSION

The infant mortality coefficient was indicated by municipality of residence of the mother, in addition to the vulnerability characteristics of infants, mothers, and childbirth for the state of RS, Brazil. Thus, this study presented a comparative analysis of the application of ARIMA and ARMA models for the prediction of infant mortality rates in the state of RS, Brazil. This is the first application to examine the prediction ability of these time series models for infant mortality rates in the state of RS, Brazil.

When comparing the SARIMA and ARMA models it was observed a better performance in fitting the ARMA model in the time horizon of 6 months, because the model

ARMA(4,6) obtained the lowest AIC and BIC. In this sense the result is expected since ARMA is a model specifically suited for continuous time series. However, the difference of the forecasted and the original values were very close for both models, therefore they obtained a similar forecasting performance. Moreover, the analysis of the residues of the chosen models also confirms the superiority of the ARMA methodology in describing the behavior of infant mortality rates in the state of RS, Brazil. In this context, since there are very few applications of ARMA, the results point to an empirical indication that the application of such a model proved to be positive both in terms of the quality of the fit and in terms of the results for time series predictions of the type proportions or rates with limited intervals. Therefore, the ARMA methodology is appropriate to establish the best prediction model for infant mortality rates in the RS state.

Considering the growing number of research using the ARIMA 17 and ARMA 14,24 methodologies, it is suggested their use in the analysis of infant mortality in other states of Brazil. Moreover, it is highly encouraged to carry out studies comparing the methodologies for predicting fetal mortality rates, which have social and human impacts similar of those of infant mortality. Finally, it is concluded that the proposed methodologies can contribute to guide the planning of preventive and educational policies aimed at the risk of a live birth dying during its first year of life.

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