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Predicting the Welfare Cost of Premature Deaths Based on Unsafe Sanitation Risk using SutteARIMA and Comparison with Neural Network Time Series and Holt-Winters

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***Abstract*— Unhealthy and unsafe sanitation will make it easier for various diseases to attack the body. In addition, unsafe sanitation will also affect a country's economy, including declining welfare, tourism losses, and environmental losses due to the loss of productive land. The research aimed to estimate the welfare cost of premature deaths based on unsafe sanitation risks using the SutteARIMA, Neural Network Time Series, and Holt-Winters. The study analyzed estimates and projections of the welfare cost of premature deaths based on the risks of unsafe sanitation of BRICS countries (Brazil, Russia, Indonesia, China, and South Africa). The data in this research used secondary data. Secondary time series data was taken from the Environment Database of the OECD. Stat. (Mortality and welfare cost from exposure to environmental risks). The data on the study was based on variables: welfare cost of premature deaths, % GDP equivalent, risk: unsafe sanitation, age: all, sex: both, unit: percentage, and data from 2005 to 2019. The three forecasting methods (SutteARIMA, Neural Network Time Series, and Holt-Winters) were juxtaposed in fitting data to see the forecasting methods' reliability and accuracy. The accuracy of forecasting results was compared based on MAPE and MSE values. The results of the research showed that the SutteARIMA and NNAR(1,1) methods were best used to predict the welfare cost of premature deaths in view of unsafe sanitation risks for BRICS countries.**

***Keywords*—Forecasting; welfare cost; premature deaths; unsafe sanitation; SutteARIMA; NNAR; holt-winters.**

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I. INTRODUCTION

The environment and pollution are among the issues of concern for various countries. Environmental problems in Indonesia are increasing; of course, this problem needs a solution. If this problem is not solved, it will be a concern for human life in the future because the environment is the source of human life, such as air, water, food, and others.

The first environmental problem that needs to be sought is air, soil, and water pollution [1]. In order to get back to normal, this pollution problem takes millions of years. Air pollution that occurs today is caused by various gases and toxins resulting from burning fossil materials from various industries and factories. Except air pollution, industrial waste also provides soil pollution, which will damage nutrients nutrients in the soil, and of course, this pollution will have implications for plants that are the source of human life.

Furthermore, poor environmental conditions also certainly affect sanitation. Unhealthy and unsafe (bad) sanitation will make it easier for various diseases to attack the body, but conditions like this tend to be ignored by the community in the environment in the lower middle class. According to WHO [2], as many as 827,000 people die yearly in low- and middle-income countries from inadequate water, sanitation, and hygiene. These deaths represent 60% of the total deaths caused by diarrheal diseases. Of these 432,000 deaths were caused by poor sanitation.

Poor sanitation will certainly reduce human well-being, the economy, and social development. This is in line with the research by Van Minh and Hung [3] explained the fact that (1) as many as 45% of the global population (3.4 billion people) use safely managed sanitation services or, in other words, that as many as 55% are managed unsafely, (2) as many as 673 million still defecate in road sewers or in bushes (in the open), and (3) are estimated to be 10% of the world's population consuming food irrigated by wastewater.

In addition, several studies on economic costs and poor sanitation have been studied by experts in various developing countries. In 2006, inadequate sanitation resulted in India suffering economic losses of US$53.8 billion, equivalent to 6.4% of India's GDP [4]. Napitupulu and Hutton [5] said that poor sanitation and hygiene resulted in Indonesia losing about 2.3% of GDP or equivalent to US $ 6.3 billion. These losses are related to population welfare, tourist losses, and environmental losses due to the loss of productive land. Welfare cost of premature deaths is also an impact/risk caused by poor sanitation [6]. OECD said that the welfare cost of premature deaths in OECD countries amounted to 2.7% of their GDP while for BRIICS countries is triple the percentage. To see more about the development of welfare costs of premature deaths based on unsafe sanitation, it is necessary to forecast or project. This projection can be used as a consideration for the future economic improvement of the community. In addition, no research has discussed forecasting related to welfare costs of premature deaths based on unsafe sanitation.

SutteARIMA is used in this study based on the ability of this method to predict data in economics, business, and other fields. This can be seen from Ahmar and Boj [7], Ahmar et al. [8], Singh et al. [9], and Shih et.al. [10] research, which shows that the SutteARIMA method has more accurate prediction results when compared to other methods [7]–[9]. Based on this, researchers are interested in comparing the SutteARIMA method with other methods on other data, namely the estimation of welfare cost data. In addition, various authors have not studied predictions regarding Welfare Cost data.

II. MATERIAL AND METHODS

A. Data Source and Data Analysis

The study analyzed estimates and projections of the welfare cost of premature deaths based on the risks of unsafe sanitation. In this research, the word “welfare cost of premature deaths seen from unsafe sanitation risk” was shortened to *“welfare cost of unsafe sanitation*”. The data in this research used secondary data. Secondary time series data was taken from the Environment Database of the OECD. Stat. (Mortality and welfare cost from exposure to environmental risks). Based on OECD.Stat, data on mortality and DALYs from exposure to environmental risks are taken from GBD [11]. Welfare costs are calculated using a methodology adapted from OCDC [12].

The data on the study was based on variables: welfare cost of premature deaths, % GDP *equivalent, risk: unsafe sanitation*, age: all, sex: both, unit: percentage, and data from 2005 to 2019. Based on Institute for Health Metrics and Evaluation, unsafe sanitation in the research was defined based on the type of main toilet used by households [13]. This methodology has been exploited on a limited basis by BRICS countries (Brazil, Russia, Indonesia, China, and South Africa). This research would provide a deeper insight into the projections of welfare costs. To obtain forecasting results, software R was used for data analysis using SutteForecastR packages and forecasts. The use of this software facilitates the data analysis process.

B. Autoregressive Integrate Moving Average (ARIMA)

Box and Gwilym Jenkins in 1976, first introduced the ARIMA model, so this method is commonly known as ARIMA Box-Jenkins. The ARIMA model consists of two aspects of the process; they are the Autoregressive (AR) process and the Moving Average (MA) process, so in general, the ARIMA model is notated as ARIMA(p,d,q), with p stating the order of the AR Process, q stating the order of the MA process, and d stating differencing [14]–[16].

1) The Autoregressive (AR) process: The Autoregressive model is a model that describes the relationship between a Y depend on variable and an independent variable which was the Y value at the previous time [17]. The general form of an Autoregressive order p, AR(p) process is based on Wei [18], as in Equation (1).

$$\begin{aligned} Z_t &= \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \ldots + \varphi_p Z_{t-p} + a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in R, t \in Z \\ Z_t &= \varphi_1 B Z_t + \varphi_2 B^2 Z_t + \ldots + \varphi_p B^p Z_t + a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in R, t \in Z \\ (1 - \varphi_1 B + \varphi_2 B^2 + \ldots + \varphi_p B^p) Z_t &= a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in \mathrm{R}, t \in \mathrm{Z} \end{aligned} \tag{1}$$

This equation can be simplified into $\varphi_P(B) Z_t = a_t$, where $\varphi_P(B) = 1 - \varphi_1 B + \varphi_2 B^2 + \ldots + \varphi_p B^p$. AR(p) It is also commonly denoted as ARIMA(p,0,0).

2) *The Moving Average (MA) Process:* The Moving Average model was a model which described the dependence of Y depend on variables on consecutive previous time error values [19]. The general form of a moving average process order q stated MA(q) is in reference to Wei [18]:

$$\begin{aligned} Z_t &= a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-1}, a_t \sim \mathrm{WN}(0,\sigma^2), \theta_i \in R, t \in Z \\ Z_t &= a_t - \theta_1 B a_t - \theta_2 B^2 a_t - \ldots - \theta_q B^q a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \theta_i \in R, t \in Z \\ Z_t &= (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \theta_i \in R, t \in Z \end{aligned} \tag{2}$$

or

$$Z_t = \theta_Q(B) a_t, a_t \sim \mathit{WN}(0,\sigma^2), \theta_i \in R, t \in Z \tag{3}$$

with:

$$\theta_Q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \tag{4}$$

3) Autoregresive Moving Average or ARMA(p, q)

Z_t process is said to follow ARMA's autoregressive moving average mix model(*p,q*) if it met [18]:

$$\begin{aligned} Z_t &= \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \ldots + \varphi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \ldots - \theta_q a_{t-1}, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in R, t \in Z \\ Z_t &= \varphi_1 B Z_t + \varphi_2 B^2 Z_t + \ldots + \varphi_p B^p Z_t + a_t - \theta_1 B a_t - \theta_2 B^2 a_t - \ldots - \theta_q B^q a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in R, t \in Z \\ (1 - \varphi_1 B + \varphi_2 B^2 + \ldots + \varphi_p B^p) Z_t &= (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in R, t \in Z \\ \varphi_P(B) Z_t &= \theta_Q(B) a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \varphi_i \in R, t \in Z \end{aligned} \tag{5}$$

with:

$$\varphi_{\mathrm{P}}(B) = 1 - \varphi_1 B + \varphi_2 B^2 + \ldots + \varphi_p B^p \tag{6}$$

and

$$\theta_Q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q \tag{7}$$

The three ARIMA models described earlier are stationary processes. Zt process was said to follow a non-stationary ARIMA model on average if there was a d order (d > 1) or in general, this model is referred to as ARIMA(p,d,q) with d as differencing. As for the mathematical model [20]:

$$(1-B)^d Z_t = a_t, a_t \sim \mathrm{WN}(0,\sigma^2), d, t \in \mathrm{Z} \tag{8}$$

$$\varphi_P(B)(1-B)^d Z_t = \theta_Q(B)a_t, a_t \sim \mathrm{WN}(0,\sigma^2), \theta_i, \varphi_i \in \mathrm{R}, d, t \in \mathrm{Z} \tag{9}$$

In forecasting, ARIMA Box and Jenkins have four stages: model identification, parameter estimation, diagnostic checking, and forecasting [21][22].

C. α-Sutte Indicator

Like the Box-Jenkins ARIMA method, the α-Sutte Indicator method also used previous data in its forecasting [23]. The α-the moving average approach developed Sutte Indicator. This approach was used to look at previous and future data trends. The α-Sutte Indicator used the previous four data (Z_{t-1},Z_{t-2},Z_{t-3}, and Z_{t-4}) to forecast data [24], [25]. The mathematical formula of α-Sutte Indicator is shown in equation (10) [23][26].

$$Z_t = \frac{\gamma\left(\frac{\Delta x}{\frac{\gamma+\delta}{2}}\right)+\beta\left(\frac{\Delta y}{\frac{\beta+\gamma}{2}}\right)+\alpha\left(\frac{\Delta z}{\frac{\alpha+\beta}{2}}\right)}{3} \tag{10}$$

where:

$$\begin{aligned} \delta &= Z_{t-4} \\ \gamma &= Z_{t-3} \\ \beta &= Z_{t-2} \\ \alpha &= Z_{t-1} \\ \Delta x &= \gamma - \delta = Z_{t-3} - Z_{t-4} \\ \Delta y &= \beta - \gamma = Z_{t-2} - Z_{t-3} \\ \Delta z &= \alpha - \beta = Z_{t-1} - Z_{t-2} \end{aligned}$$

Z_t = data at *t* time

Z_{t-k} = data at $(t-k)$ time

D. SutteARIMA

SutteARIMA is one of the new methods of forecasting time series. This method is a combination of the α-Sutte Indicator and ARIMA Box-Jenkins methods. SutteARIMA was developed by Ansari Saleh Ahmar and Eva Boj del Val in 2019 [7]–[9]. The following is described by the SutteARIMA method mathematically. The mathematical formula of α-Sutte Indicator can be simplified as follows:

$$\begin{aligned} Z_t &= \frac{\gamma\left(\frac{\Delta x}{\frac{\gamma+\delta}{2}}\right)+\beta\left(\frac{\Delta y}{\frac{\beta+\gamma}{2}}\right)+\alpha\left(\frac{\Delta z}{\frac{\alpha+\beta}{2}}\right)}{3} \\ Z_t &= \frac{\frac{\gamma\Delta x}{\frac{\gamma+\delta}{2}}+\frac{\beta\Delta y}{\frac{\beta+\gamma}{2}}+\frac{\alpha\Delta z}{\frac{\alpha+\beta}{2}}}{3} \\ Z_t &= \frac{\gamma\Delta x}{\frac{3\gamma+3\delta}{2}}+\frac{\beta\Delta y}{\frac{3\beta+3\gamma}{2}}+\frac{\alpha\Delta z}{\frac{3\alpha+3\beta}{2}} \\ Z_t &= \frac{2\gamma\Delta x}{3\gamma+3\delta}+\frac{2\beta\Delta y}{3\beta+3\gamma}+\frac{2\alpha\Delta z}{3\alpha+3\beta} \\ Z_t &= \gamma\frac{2\Delta x}{3\gamma+3\delta}+\beta\frac{2\Delta y}{3\beta+3\gamma}+\alpha\frac{2\Delta z}{3\alpha+3\beta} \end{aligned} \tag{11}$$

and the formula for ARIMA(p,d,q):

$$\phi_p(B)Z_t = \theta_q(B)a_t, a_t \sim WN(0,\sigma^2), \phi_p, \theta_q \in \mathrm{R}, t \in \mathrm{Z}. \tag{12}$$

with $\varphi_p(B) = (1-\varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_p B^p)$ (for AR(p)) and $\theta_q(B) = (1-\theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q)$ (for MA(q)) Equation (12) can be further elaborated and obtained:

$$\begin{aligned} (1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p)Z_t &= (1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q)a_t \\ Z_t-\phi_1 BZ_t-\phi_2 B^2 Z_t-\ldots-\phi_p B^p Z_t &= a_t-\theta_1 Ba_t - \theta_2 B^2 a_t-\ldots-\theta_q B^q a_t \end{aligned} \tag{13}$$

The backward shift operator equation $B^p Z_t$ can be changed to Z_{t-p}. If equation (13) is changed according to the backward shift operator equation, then we get:

$$\begin{aligned} Z_t-\phi_1 Z_{t-1}-\phi_2 Z_{t-2}-\ldots-\phi_p Z_{t-p} &= a_t-\theta_1 a_{t-1} - \theta_2 a_{t-2}-\ldots-\theta_q a_{t-q} \\ Z_t = \phi_1 Z_{t-1}+\phi_2 Z_{t-2}+\ldots+\phi_p Z_{t-p} &+ a_t-\theta_1 a_{t-1} - \theta_2 a_{t-2}-\ldots-\theta_q a_{t-q} \end{aligned} \tag{14}$$

If we define:

$$\begin{aligned} \delta &= Z_{t-4} \\ \gamma &= Z_{t-3} \\ \beta &= Z_{t-2}\alpha = Z_{t-1} \end{aligned} \tag{15}$$

and we substitute equation (15) to the equation (14), obtained:

$$\begin{aligned} Z_t = \phi_1\alpha+\phi_2\beta+\phi_3\gamma+\phi_4\delta+\ldots+\phi_p Z_{t-p} \\ + a_t-\theta_1 a_{t-1}-\theta_2 a_{t-2}-\ldots-\theta_q a_{t-q} \end{aligned} \tag{16}$$

In the last stage (combination of formulas), we do the addition process between equations (11) and (16), so that we obtained:

$$\begin{aligned} 2Z_t &= \phi_1\alpha+\phi_2\beta+\phi_3\gamma+\phi_4\delta+\ldots+\phi_p Z_{t-p}+ \\ &\quad a_t-\theta_1 a_{t-1}-\theta_2 a_{t-2}-\ldots-\theta_q a_{t-q}+ \\ &\quad \gamma\frac{2\Delta x}{3\gamma+3\delta}+\beta\frac{2\Delta y}{3\beta+3\gamma}+\alpha\frac{2\Delta z}{3\alpha+3\beta} \\ Z_t &= \alpha\left(\frac{\phi_1}{2}+\frac{\Delta z}{3\alpha+3\beta}\right)+\beta\left(\frac{\phi_3}{2}+\frac{\Delta y}{3\beta+3\gamma}\right)+\gamma\left(\frac{\phi_3}{2}+\frac{\Delta x}{3\gamma+3\delta}\right)+ \\ &\quad \frac{\phi_4\delta}{2}+\ldots+\frac{\phi_p Z_{t-p}}{2}+\frac{a_t}{2}-\frac{\theta_1 a_{t-1}}{2}-\frac{\theta_2 a_{t-2}}{2}-\ldots-\frac{\theta_q a_{t-q}}{2} \end{aligned} \tag{17}$$

Equation (17) is the final formula of SutteARIMA.

E. Measures for the Comparison of Methods to Evaluate the Forecast Accuracy

To see the accuracy level of SutteARIMA, it can be compared to other forecasting methods, namely Holt-Winters and Neural Network Autoregression (NNETAR). To evaluate the accuracy of forecasting models, an error evaluation method was widely used in previous literature and selected as an evaluation metric, MAPE. The smaller the MAPE value, the higher the forecasting accuracy [27], [28]

III. Results and Discussion

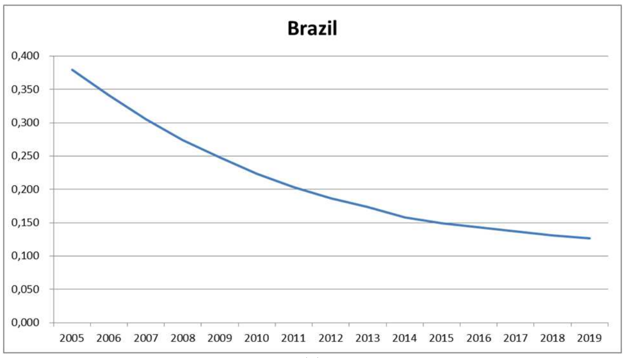
From the summary of data statistics presented in Table I, it was seen that the highest average *welfare cost of unsafe sanitation* was in India at 3.966% of GDP followed by South Africa (1.650%), Indonesia (1.214%), Brazil (0.212%), and Russia (0.013%). Table I also showed that skewness from

Brazil, Russia, Indonesia, China, and South Africa was positive, meaning that most data distribution was at a low value, in other words, the welfare cost of premature was in a low category.

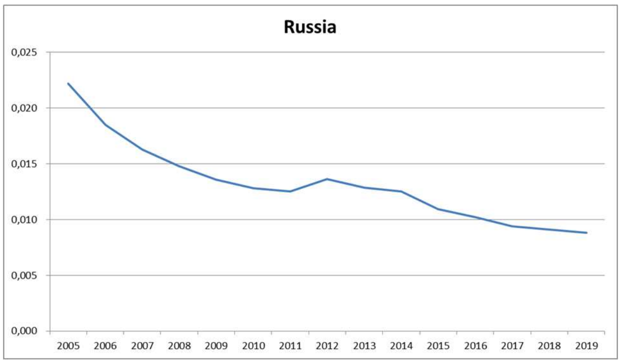
TABLE I
DESCRIPTIVE ANALYSIS OF BRICS WELFARE COST OF UNSAFE SANITATION DATA

	Brazil	Russia	Indonesia	China	South Africa
Mean	0.212	0.013	1.214	0.032	1.650
Median	0.187	0.013	1.109	0.024	1.617
Standard Deviation	0.081	0.004	0.434	0.019	0.453
Kurtosis	-0.373	1.373	-1.060	1.357	-1.402
Skewness	0.864	1.108	0.487	1.427	0.122
Range	0.252	0.013	1.330	0.065	1.316
Minimum	0.127	0.009	0.665	0.014	1.028
Maximum	0.379	0.022	1.996	0.079	2.344
Count	15	15	15	15	15

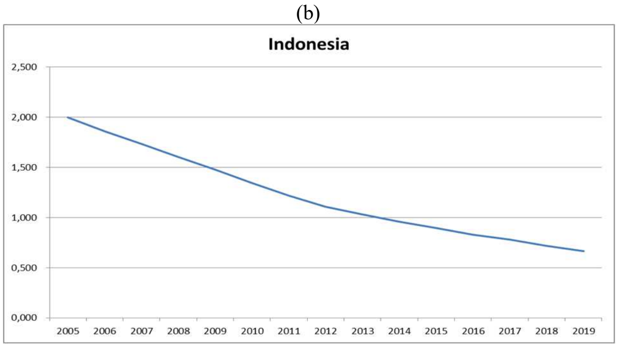
The time series plot (Figure 1a-1e) illustrated that *welfare cost of unsafe sanitation* from Russia and China are below 1% of GDP and had decreased every year, as were Brazil, Indonesia, and South Africa, which also experienced a decline every year. This meant that the community's economic level would be better, and the country's economic burden would be reduced to deal with the risks of unsafe sanitation.



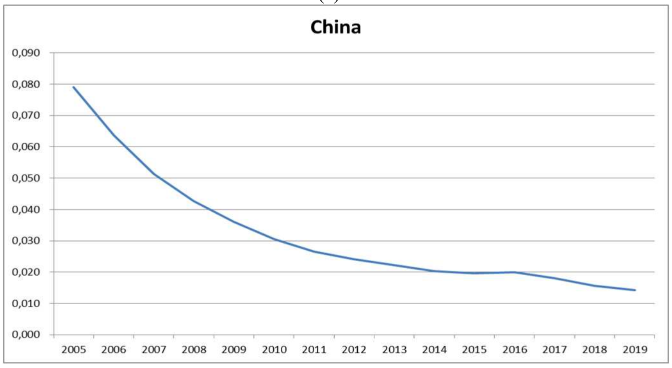
(a)



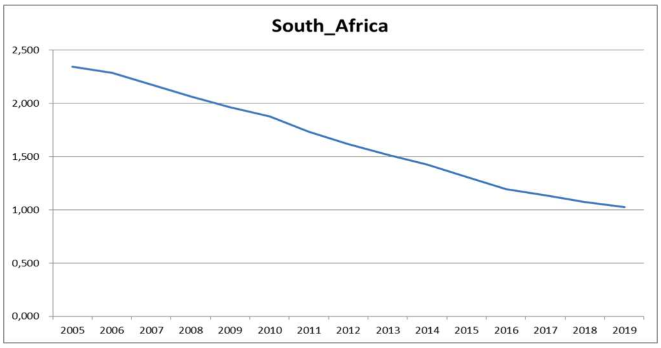
(b)



(c)



(d)



(e)

Fig. 1 The time series plot of welfare cost of unsafe sanitation of Brazil (a), Russia (b), Indonesia (c), China (d), and South Africa (e).

In Figure 1, it also indicates that the country of India experienced an increase in 2007 and 2008 experienced a sharp increase from the previous year (2006), and then felt sharply also after 2008 and was a country that experienced a drastic decline when compared to other countries which meant that the economic cost of society gradually became good. This is in line with the opinion Van Minh and Hung [3] that sanitation improvement will bring many benefits, both directly and indirectly, especially in the economic field, which include: (1) savings in health care costs; (2) more job opportunities due to longer life and reduced working days caused by illness; and (3) non-health benefits such as time. Moreover, these results also support the UN Global Goals on Sustainable Development to eradicate poverty and a just and sustainable world by 2030 [29].

Short-term forecasts for the *welfare cost of unsafe sanitation* were important for making strategic decisions regarding the country's economic conditions for the future. Therefore, it became very important to look at fluctuations in the welfare cost of unsafe sanitation in BRICS countries. The study applied ARIMA, SutteARIMA, and Holt-Winters forecasting models to forecast the *welfare cost of unsafe sanitation* in Brazil, Russia, India, Indonesia, China, and South Africa. The results of the forecasting data fitting for the ARIMA, SutteARIMA, and Holt-Winters methods in BRICS countries are presented in Table II. Table II shows the average value of the percentage of error (MAPE) of each forecasting method used. Table II shows that the MAPE value for SutteARIMA was lower than other forecasting methods for BIS (Brazil, Indonesia, and South Africa) and NNAR(1,1) for Russia and China. Indonesia and South Africa) and NNAR(1,1) for Russia and China.

TABLE II
RESULTS FROM FITTING DATA OF WELFARE COST OF UNSAFE SANITATION IN THE BRIC COUNTRIES (IN % OF GDP)

MAPE

Year	Actual	NNAR(1,1)	APE	Holt-Winters	APE	SutteARIMA	APE
Brazil							
2013	0,1734794	0,1767602	1,891	0,1711273	1,356	0,17104255	**1,405**
2014	0,1578301	0,1700074	7,715	0,1550920	1,735	0,16065525	**1,790**
2015	0,1490128	0,1658247	11,282	0,1390567	6,681	0,14920605	**0,130**
2016	0,1435286	0,1633132	13,784	0,1230214	14,288	0,14236750	**0,809**
2017	0,1367670	0,1618344	18,329	0,1069861	21,775	0,13794295	**0,860**
2018	0,1313277	0,1609739	22,574	0,0909508	30,745	0,13342775	**1,599**
2019	0,1269887	0,1604766	26,371	0,0749155	41,006	0,12908845	**1,653**
MAPE			14,564		16,798		**1,178**
Russia							
2013	0,01285526	0,01318123	**2,536**	0,01473715	14,639	0,01419479	10,420
2014	0,01250842	0,01305881	**4,400**	0,01585333	26,741	0,01437686	14,937
2015	0,01092056	0,01302868	**19,304**	0,01696951	55,390	0,01475200	35,085
2016	0,01020045	0,01302152	**27,656**	0,01808569	77,303	0,01407547	37,989
2017	0,00938820	0,01301982	**38,683**	0,01920187	104,532	0,01428151	52,122
2018	0,00908916	0,01301943	**43,241**	0,02031805	123,542	0,01436073	57,998
2019	0,00882433	0,01301933	**47,539**	0,02143423	142,899	0,01496697	69,610
MAPE			**26,194**		77,864		39,737
Indonesia							
2013	1,0287220	1,0339087	0,504	0,9762072	5,105	0,98746845	**4,010**
2014	0,9561172	0,9872646	3,258	0,8557900	10,493	0,89246520	**6,657**
2015	0,8935973	0,9612859	7,575	0,7353728	17,706	0,80113195	**10,348**
2016	0,8281561	0,9477433	14,440	0,6149556	25,744	0,71357050	**13,836**
2017	0,7792289	0,9409397	20,753	0,4945384	36,535	0,61997125	**20,438**
2018	0,7166271	0,9375869	30,833	0,3741212	47,794	0,53595575	**25,211**
2019	0,6652942	0,9359505	40,682	0,2537040	61,866	0,44142195	**33,650**
MAPE			16,864		29,320		**16,307**
China							
2013	0,02229171	0,02267446	**1,717**	0,02178235	2,285	0,02179325	2,236
2014	0,02031202	0,02175240	**7,091**	0,01938338	4,572	0,02147710	5,736
2015	0,01966367	0,02119929	**7,809**	0,01698441	13,625	0,02137686	8,712
2016	0,01993219	0,02087159	**4,713**	0,01458544	26,825	0,02242460	12,504
2017	0,01812268	0,02067888	**14,105**	0,01218647	32,756	0,02444984	34,913
2018	0,01562034	0,02056606	**31,662**	0,00978750	37,341	0,02552099	63,383
2019	0,01429536	0,02050019	**43,405**	0,00738853	48,315	0,02630541	84,014
MAPE			**15,786**		23,674		30,214

Year	Actual	NNAR(1,1)	APE	Holt-Winters	APE	SutteARIMA	APE
South Africa							
2013	1,516820	1,518704	0,124	1,4970448	1,304	1,50872910	**0,533**
2014	1,427502	1,446839	1,355	1,3772695	3,519	1,40528020	**1,557**
2015	1,309026	1,400346	6,976	1,2574943	3,937	1,31698585	**0,608**
2016	1,195841	1,372947	14,810	1,1377191	4,860	1,20571350	**0,826**
2017	1,135177	1,357753	19,607	1,0179438	10,327	1,09530680	**3,512**
2018	1,072341	1,349625	25,858	0,8981686	16,242	1,01762480	**5,103**
2019	1,027596	1,345361	30,923	0,7783933	24,251	0,94298610	**8,234**
MAPE			14,236		9,206		**2,910**

MSE

Year	Actual	NNAR(1,1)	SE	Holt-Winters	SE	SutteARIMA	SE
Brazil							
2013	0,1734794	0,17676	1,08E-05	0,1711273	5,53E-06	0,17104255	**5,94E-06**
2014	0,1578301	0,170007	1,48E-04	0,1550920	7,50E-06	0,16065525	**7,98E-06**
2015	0,1490128	0,165825	2,83E-04	0,1390567	9,91E-05	0,14920605	**3,73E-08**
2016	0,1435286	0,163313	3,91E-04	0,1230214	4,21E-04	0,14236750	**1,35E-06**
2017	0,1367670	0,161834	6,28E-04	0,1069861	8,87E-04	0,13794295	**1,38E-06**
2018	0,1313277	0,160974	8,79E-04	0,0909508	1,63E-03	0,13342775	**4,41E-06**
2019	0,1269887	0,160477	1,12E-03	0,0749155	2,71E-03	0,12908845	**4,41E-06**
MSE			4,95E-04		8,23E-04		**3,64E-06**

Russia							
Year	**Actual**	**NNAR(1,1)**	**SE**	**Holt-Winters**	**SE**	**SutteARIMA**	**SE**
2013	0,012855260	0,013181	**1,06E-07**	0,01473715	3,54E-06	0,014194787	1,79E-06
2014	0,012508420	0,013059	**3,03E-07**	0,01585333	1,12E-05	0,014376861	3,49E-06
2015	0,010920560	0,013029	**4,44E-06**	0,01696951	3,66E-05	0,014751999	1,47E-05
2016	0,010200450	0,013022	**7,96E-06**	0,01808569	6,22E-05	0,014075474	1,50E-05
2017	0,009388195	0,013020	**1,32E-05**	0,01920187	9,63E-05	0,014281510	2,39E-05
2018	0,009089161	0,013019	**1,54E-05**	0,02031805	1,26E-04	0,014360726	2,78E-05
2019	0,008824331	0,013019	**1,76E-05**	0,02143423	1,59E-04	0,014966975	3,77E-05
	MSE		**8,44E-06**		7,07E-05		1,78E-05

Indonesia							
Year	**Actual**	**NNAR(1,1)**	**SE**	**Holt-Winters**	**SE**	**SutteARIMA**	**SE**
2013	1,0287220	1,033909	2,69E-05	0,9762072	2,76E-03	0,98746845	**1,70E-03**
2014	0,9561172	0,987265	9,70E-04	0,8557900	1,01E-02	0,89246520	**4,05E-03**
2015	0,8935973	0,961286	4,58E-03	0,7353728	2,50E-02	0,80113195	**8,55E-03**
2016	0,8281561	0,947743	1,43E-02	0,6149556	4,55E-02	0,71357050	**1,31E-02**
2017	0,7792289	0,940940	2,62E-02	0,4945384	8,10E-02	0,61997125	**2,54E-02**
2018	0,7166271	0,937587	4,88E-02	0,3741212	1,17E-01	0,53595575	**3,26E-02**
2019	0,6652942	0,935951	7,33E-02	0,2537040	1,69E-01	0,44142195	**5,01E-02**
	MSE		2,40E-02		6,44E-02		**1,94E-02**

China							
Year	**Actual**	**NNAR(1,1)**	**SE**	**Holt-Winters**	**SE**	**SutteARIMA**	**SE**
2013	0,02229171	0,022674	**1,46E-07**	0,02178235	2,59E-07	0,021793250	2,48E-07
2014	0,02031202	0,021752	**2,07E-06**	0,01938338	8,62E-07	0,021477100	1,36E-06
2015	0,01966367	0,021199	**2,36E-06**	0,01698441	7,18E-06	0,021376855	2,94E-06
2016	0,01993219	0,020872	**8,82E-07**	0,01458544	2,86E-05	0,022424600	6,21E-06
2017	0,01812268	0,020679	**6,53E-06**	0,01218647	3,52E-05	0,024449835	4,00E-05
2018	0,01562034	0,020566	**2,45E-05**	0,00978750	3,40E-05	0,025520985	9,80E-05
2019	0,01429536	0,020500	**3,85E-05**	0,00738853	4,77E-05	0,026305405	1,44E-04
	MSE		**1,07E-05**		2,20E-05		4,19E-05

South Africa							
Year	**Actual**	**NNAR(1,1)**	**SE**	**Holt-Winters**	**SE**	**SutteARIMA**	**SE**
2013	1,516820	1,518704	3,55E-06	1,4970448	3,91E-04	1,50872910	**6,55E-05**
2014	1,427502	1,446839	3,74E-04	1,3772695	2,52E-03	1,40528020	**4,94E-04**
2015	1,309026	1,400346	8,34E-03	1,2574943	2,66E-03	1,31698585	**6,34E-05**
2016	1,195841	1,372947	3,14E-02	1,1377191	3,38E-03	1,20571350	**9,75E-05**
2017	1,135177	1,357753	4,95E-02	1,0179438	1,37E-02	1,09530680	**1,59E-03**
2018	1,072341	1,349625	7,69E-02	0,8981686	3,03E-02	1,01762480	**2,99E-03**
2019	1,027596	1,345361	1,01E-01	0,7783933	6,21E-02	0,94298610	**7,16E-03**
	MSE		3,82E-02		1,64E-02		**1,78E-03**

A complete comparison of MAPE and MSE of each forecasting method can be seen in Table II. This is in line with the study results obtained by Thoplan [30], which said that the MAPE and MASE values of NNAR were compared to Holt-Winters and ARIMA. Similarly, the average value of square error (MSE) was in line with MAPE values, and it was SutteARIMA lower for BIS (Brazil, Indonesia, South Africa).

Table III shows that the SutteARIMA method had a better level of accuracy than the NNAR(1,1) and Holt-Winters methods in Brazil, Indonesia, and South Africa, and differently for Russia and China, the NNAR(1,1) method was more accurate. This was because China's welfare cost of unsafe sanitation in 2014-2016 and Russia in 2010-2011 and 2013-2014 were of fixed value (unchanged). Based on Table II, the forecasting of the next three periods would be used for forecasting methods that had an accuracy rate from each country, it was the SutteARIMA method for Brazil, Russia, Indonesia, and South Africa, while the Holt-winters method was used for China.

TABLE III
FORECASTING ACCURACY RATE ON DATA FITTINGS

Brazil			
	NNAR(1,1)	Holt-Winters	SutteARIMA
MAPE	14.564	16.798	1.178
MSE	4.95×10^{-4}	8.23×10^{-4}	3.64×10^{-6}
Russia			
Actual	NNAR(1,1)	Holt-Winters	SutteARIMA
MAPE	26.194	77.864	39.737
MSE	8.44×10^{-6}	7.07×10^{-5}	1.78×10^{-5}
Indonesia			
Actual	NNAR(1,1)	Holt-Winters	SutteARIMA
MAPE	16.864	29.320	16.307
MSE	2.40×10^{-2}	0.85579	1.94×10^{-2}
China			
Actual	NNAR(1,1)	Holt-Winters	SutteARIMA
MAPE	15.786	23.674	30.214
MSE	1.07×10^{-5}	2.20×10^{-5}	4.19×10^{-5}
South Africa			
Actual	NNAR(1,1)	Holt-Winters	SutteARIMA
MAPE	14.236	9.206	2.910
MSE	3.82×10^{-2}	1.64×10^{-2}	1.78×10^{-3}

The results of forecasting three upcoming periods (Year 2020-2022) were presented in Table IV. Table IV shows that the forecasting results for Brazil are decreasing slowly, as is the case for Russia, Indonesia, and South Africa, which is around 0.0005, in contrast to China, which is stagnant at 0.014.

Based on Table IV shows that in 2020-2022, the welfare cost of premature deaths seen from the risk of unsafe sanitation for BRICS countries was below 1% of GDP, and the value of the welfare cost had decreased. SutteARIMA forecasts the estimated value of welfare costs of premature deaths in view of unsafe sanitation risks in 2020-2022 for Brazil: 0.12159085%; 0,11663228%; 0.11183158% of GDP; Indonesia was: 0.61301223%; 0,55982835%; 0.50971437% of GDP; South Africa was: 0.97295459%; 0,92029194%; 0.87091249% of GDP. In comparison, NNAR(1.1) forecasted for Russia was: 0.00849886%; 0,00818285%; 0.00787554% of GDP; and for China: 0.01446956%; 0,01459298%; 0.01468052% of GDP.

TABLE IV
RESULTS OF FORECASTING THE WELFARE COST OF UNSAFE SANITATION IN BRICS COUNTRIES (IN % OF GDP)

Brazil	
	SutteARIMA
2020	0.12159085
2021	0.11663228
2022	0.11183158
Russia	
	NNAR(1,1)
2020	0.00849886
2021	0.00818285
2022	0.00787554
Indonesia	
	SutteARIMA
2020	0.61301223
2021	0.55982835
2022	0.50971437
China	
	NNAR(1,1)
2020	0.01446956
2021	0.01459298
2022	0.01468052
South Africa	
	SutteARIMA
2020	0.97295459
2021	0.92029194
2022	0.87091249

IV. CONCLUSION

As per data from 2013 to 2019, it was obtained that the SutteARIMA and NNAR (1,1) methods were best used to predict the welfare cost of premature deaths in view of unsafe sanitation risks for BRICS countries. Based on this, we proposed two different methods for predicting the welfare cost of premature deaths in view of the risk of unsafe sanitation in Brazil, Russia, Indonesia, China, and South Africa. The first is the neural network time series method, the NNAR(1,1) model could be used to predict in Russia and China. The second is SutteARIMA could be used to predict in Brazil, Indonesia, and South Africa.

The results showed that the SutteARIMA and NNAR(1,1) models were most appropriate for forecasting the welfare cost of premature deaths in view of unsafe sanitation risks for BRICS countries, and it could simultaneously provide input and information for policymakers as a consideration in policy-making/decisions because this decision-making would certainly have an impact in the future. Furthermore, this approach could be compared with other methods, such as the indicator α-Sutte, NNAR, Theta, time series linear model (TSLM), or other forecasting methods.

Although the proposed SutteARIMA model was superior in forecasting accuracy, some issues still need to be investigated further. For example, many other factors influencing the welfare cost of premature deaths might not be considered in the research. Further research may be necessary to test similar and other time series data to see how accurate sutteARIMA forecasting results are.

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