



# Forecasting $CO_2$ Emission for Zimbabwe's Tourism Destination vibrancy: A Univariate Approach using Box-Jenkins ARIMA Model

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## Abstract

The study was based on understanding the effects of environmental and climate change on the attractiveness of Zimbabwe as a tourism destination, mainly focusing on levels of carbon dioxide ( $CO_2$ ) emission in the country. The drive for the research was that the modern tourist is now highly environmental sensitive especially when making a decision to travel or consume a tourism product or service. The study was initiated by a Box – Jenkins ARIMA (10, 1, 0) model to forecast future  $CO_2$  emission levels in the country. This was through using annual time series data on  $CO_2$  emissions in Zimbabwe from 1964 to 2014, to model and forecast  $CO_2$ . The results were then further investigated using a Qualitative research through in-depth interviews in order to understand the causes of the forecasted results. The initial result indicated that Zimbabwe  $CO_2$  emission data is I (1) using Diagnostic tests. The diagnostic tests further imply that the presented optimal model is indeed stable and acceptable. Finally the results from the model concluded that  $CO_2$  emissions in Zimbabwe is likely to increase in the next decade and thereby further exposing Zimbabwe to a plethora of climate related challenges. The research then further applied a QUAL to QUAN sequential mixed method. The qualitative research helped in discovering the causes of  $CO_2$  emission in Zimbabwe through in-depth interviews and the quantitative research helped in identifying the most dominant causes that need immediate attention. The likely causes of increased future emission of  $CO_2$  were said to be from: production of cement; mining of coal; smoke from public transport; informal mining of gold and burning of forests. The most dominant sources were then established to be: smoke from public transport and burning of forests. It therefore showed that the travel sector as a form of tourism results in increased emission of  $CO_2$ . The study then proposed five policy prescriptions for consideration by the government of Zimbabwe and other key stakeholders including those in the tourism sector.

**Keywords:** ARIMA Model,  $CO_2$  emissions, tourism destination, Zimbabwe



## Introduction

Globally, climate change has been found to be one of the most dominant determinants for tourism demand (UNWTO, 2009). For this study, climate change was analysed as the emission of Carbon Dioxide that is posing a threat to tourism development in Zimbabwe. This is because in the long-run there is a discovered link between carbon emission, tourism and economic development (Katircioglu et al., 2014). The Zimbabwean tourism industry has been reported to have faced a slump in tourists' arrivals and revenue inflows since year 2000 mainly due to the socio-economic and political upheavals transpiring in that country (Ndlovu & Heath, 2013; Chigora & Zvavahera, 2015; Chibaya, 2013), but with little effort to understand the environmental effect of climate change on tourism. To study tourism from a climate change perspective, there is need to focus on a particular location or geographical area (Moreno & Amelung, 2009; Becken, 2005). Geographically, the Zimbabwean case has not been theorised or conceptualised from a tourism and climate change point of view.

In general, climate change has been one of the top issues on international political agendas in recent years for global warming (IPCC, 2014). Global warming is one of the most gripping and complicated problems which is usually caused by greenhouse gas forming CO<sub>2</sub> emission in the atmosphere (Hossain et al, 2017). Existing studies indicated that more than two-thirds of greenhouse gas comes from fossil energy-related CO<sub>2</sub> emission (Wu et al, 2015). CO<sub>2</sub> is the most important greenhouse gas and is responsible for 58.8% of the greenhouse gases (World Bank, 2007). So forecasting the CO<sub>2</sub> emissions and analyzing its influence factors are critical in adjusting policies to the mitigate climate change (Wu et al, 2015). The top 3 countries at risk for climate change impacts, in order of their vulnerability are Haiti, Bangladesh and Zimbabwe (Maplecroft Report, 2011), justifying a re-visit of CO<sub>2</sub> emission from a Zimbabwean tourism perspective. Therefore, for this study, it was important to understand Zimbabwe's past CO<sub>2</sub> emission path with an aim to make a reliable prediction of its future emission. The study forecasted and modelled levels of CO<sub>2</sub> emission in Zimbabwe using ARIMA models.

## Literature review

### Climate change in Tourism

The issue of climate change has affected operations of Zimbabwe tourism industry and traditionally climate has been a key determinant for tourism (Becken & Hay, 2007). It is important to note that there is a positive correlation between climate and tourism (Moreno, 2010). From a CO<sub>2</sub> perspective, there are various environmental factors that affect tourism that can be viewed as global economic terrorism which include pollution, global warming and waste increase (Stefanica & Butnaru, 2015). However, predicting and modelling levels of Carbon Dioxide emission are still at a lower level in Africa and mainly in Zimbabwe. Tang (2015) made a research in the city of Heilongjiang, China investigating on the relationship between tourism and the environment by using coupling coordination degree model and information entropy weight. For this study ARIMA model was used in order to predict levels of CO<sub>2</sub> for assessing future performance of Zimbabwean tourism destination.

### Predicting Carbon Dioxide Levels using ARIMA model

In China, Sun (2009) studied CO<sub>2</sub> emission patterns for all 30 provinces based on ARIMA models and apparently found out that by 2010 CO<sub>2</sub> emission in China would be approximately 1990 mmt. Lotfalipour *et al* (2013) modeled and predicted CO<sub>2</sub> emissions in Iran based on Grey and ARIMA



models over the period 1965 to 2010 and apparently established that the amount of carbon dioxide emissions will reach up to 925.68 million tons in 2020 in Iran. Rahman & Hasan (2017), based on time series data of 44 years from 1972 to 2015 using ARIMA models; apparently revealed that the ARIMA (0, 2, 1) model is the optimal model for modeling and forecasting carbon dioxide in Bangladesh. In yet another Bangladesh study, Hossain et al (2017) modeled and forecasted carbon dioxide emissions in Bangladesh based on the Box-Jenkins ARIMA technique over the period 1972 to 2013 and apparently established that the ARIMA (12, 2, 12), ARIMA (8, 1, 3) and the ARIMA (5, 1, 5) are the best fit models for forecasting CO<sub>2</sub> emission from GFC, LFC and SFC rather the other methods of forecasting – HWNS and ANN models. Pruethsan (2017) examined CO<sub>2</sub> emissions in Thailand basing on the VARIMAX technique over the period 2000 to 2015 and apparently established that the VARIMAX (2, 1, 2) and VARIMAX (2, 1, 3) models are optimal models for modeling CO<sub>2</sub> emissions in Thailand. This study will make use of the generalized non-seasonal ARIMA technique in modeling and forecasting CO<sub>2</sub> emissions in Zimbabwe.

### **Research objectives**

- To project CO<sub>2</sub> emission levels in Zimbabwe for the next decade;
- To outline factors leading to CO<sub>2</sub> emission in Zimbabwe; and
- To discuss the effect of CO<sub>2</sub> emission on tourism growth in Zimbabwe.

### **Statement of problem**

Globally, emission of carbon dioxide is projected to increase (Lee et al., 2001). In this view, various sectors of the economy will continue to be negatively impacted in their operations especially the tourism sector which is the main cause of concern for this study. The current tourist is highly environmental sensitive to an extent of only patronising destinations that respects and preserves the environment. This is supported by Butler (2000) who stated that quality of the environment is becoming the most dominant determinant of tourism demand compared to infrastructure, price and marketing. Even with little research and records of the past levels of CO<sub>2</sub> emission and its effect in Zimbabwe, the intention of this study was to predict levels of CO<sub>2</sub> for the next decade in Zimbabwe. As postulated by Dubois et al. (2011) it is possible to reduce emissions in the tourism sector by 2050. For this study, the main aim was to alert tourism destination managers and policy makers on the future levels of CO<sub>2</sub> emission and understand the causes so as to create policies and other proactive mechanisms for a sustainable tourism development. This is because the tourism industry has been regarded as the least prepared industry to work on the challenges and chances of climate change compared to other industries (Scott, 2011).

### **Research methodology**

#### **ARIMA Models**

ARIMA models are often considered as delivering more accurate forecasts than econometric techniques (Song *et al*, 2003b). ARIMA models outperform multivariate models in forecasting performance (du Preez & Witt, 2003). Overall performance of ARIMA models is superior to that of the naïve models and smoothing techniques (Goh & Law, 2002). ARIMA models were developed by Box and Jenkins in the 1970s and their approach of identification, estimation and diagnostics is based on the principle of parsimony (Asteriou & Hall, 2007).



The general form of the ARIMA (p, d, q) can be represented by a backward shift operator as:

$$\phi(B)(1 - B)^d CZ_t = \theta(B)\mu_t \dots \dots \dots [1]$$

Where the autoregressive (AR) and moving average (MA) characteristic operators are:

$$\phi(B) = (1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p) \dots \dots \dots [2]$$

$$\theta(B) = (1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q) \dots \dots \dots [3]$$

and

$$(1 - B)^d CZ_t = \Delta^d CZ_t \dots \dots \dots [4]$$

Where  $\phi$  is the parameter estimate of the autoregressive component,  $\theta$  is the parameter estimate of the moving average component,  $\Delta$  is the difference operator, d is the difference, B is the backshift operator and  $\mu_t$  is the disturbance term.

### The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018i). A further QUAL to QUAN sequential mixed methods was applied. A qualitative research helped to obtain data to understand the general causes of increased CO<sub>2</sub> emission. A quantitative research was then used to further come up with the most dominant causes of CO<sub>2</sub> emission in Zimbabwe.

### In-depth Interviews

Qualitative research was achieved using in-depth interviews on n=8 participants who were selected using a purposive judgmental sampling method. The basis was on the expertise in tourism and environment management, years of experience and academic excellence. The profiles for interview participants is as shown in Table 1.1 below.

**Table 1. Profiles for interviews**

SECTOR	n	POSTION	DURATION	DATE
Ministry of Environment	3	Climate Change Scientists	45 minutes each	18/09/18
Zimbabwe Tourism Authority	1	Destination Marketing Officer	1 hour 11 minutes	11/10/ 18
Zimbabwe Parks & Wildlife Authority	1	Consumptive Tourism Officer	55 minutes	13/12/18
Midlands State University	1	Tourism Lecturer	1 hour 06 minutes	8/11/18
Ministry of Tourism & Hospitality	2	Principal Officers	50 minutes each	14/01/19



## Surveys

For a quantitative research, 56 respondents were engaged through a stratified random sampling in three main sectors of the tourism industry which are accommodation (18), travel (16) and resorts (22). A further convenience sampling was done to distribute survey questionnaires to those who were available across the three sectors when the research was done.

## Data Collection

The study was initially based on 50 observations of annual total CO<sub>2</sub> emissions (CZ) in Zimbabwe (i.e 1964-2014). These were sourced from the World Bank online database, which is a reliable source of various macroeconomic data for all countries in the world. Hence, the research had to prefer this source on the basis of its credibility and recognition. Secondly, qualitative data was collected using in-depth interviews and lastly survey questionnaires were used to collect quantitative data.

## Data Analysis

The study analysed the CO<sub>2</sub> prediction data using Stationarity Tests: Graphical Analysis and descriptive statistics. For the qualitative data, the study applied a content analysis so as to establish themes. Quantitative data was turned from frequencies to percentages which were then tabulated.

## Tests

### Diagnostic Tests & Model Evaluation - Stationarity Tests: Graphical Analysis

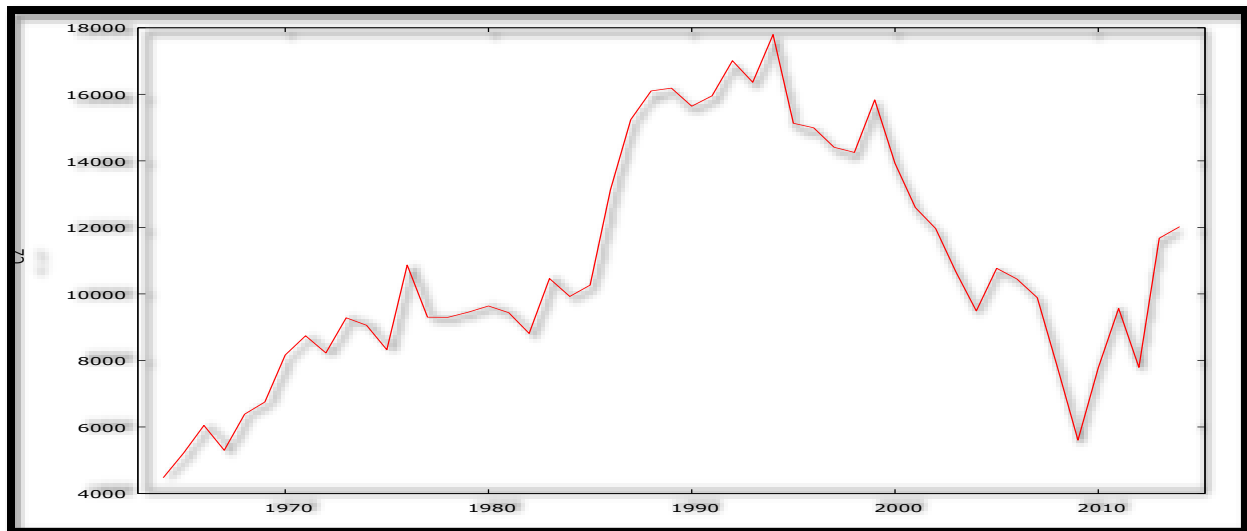


Figure 1. The Correlogram in Levels Source: Research Tests (2019)

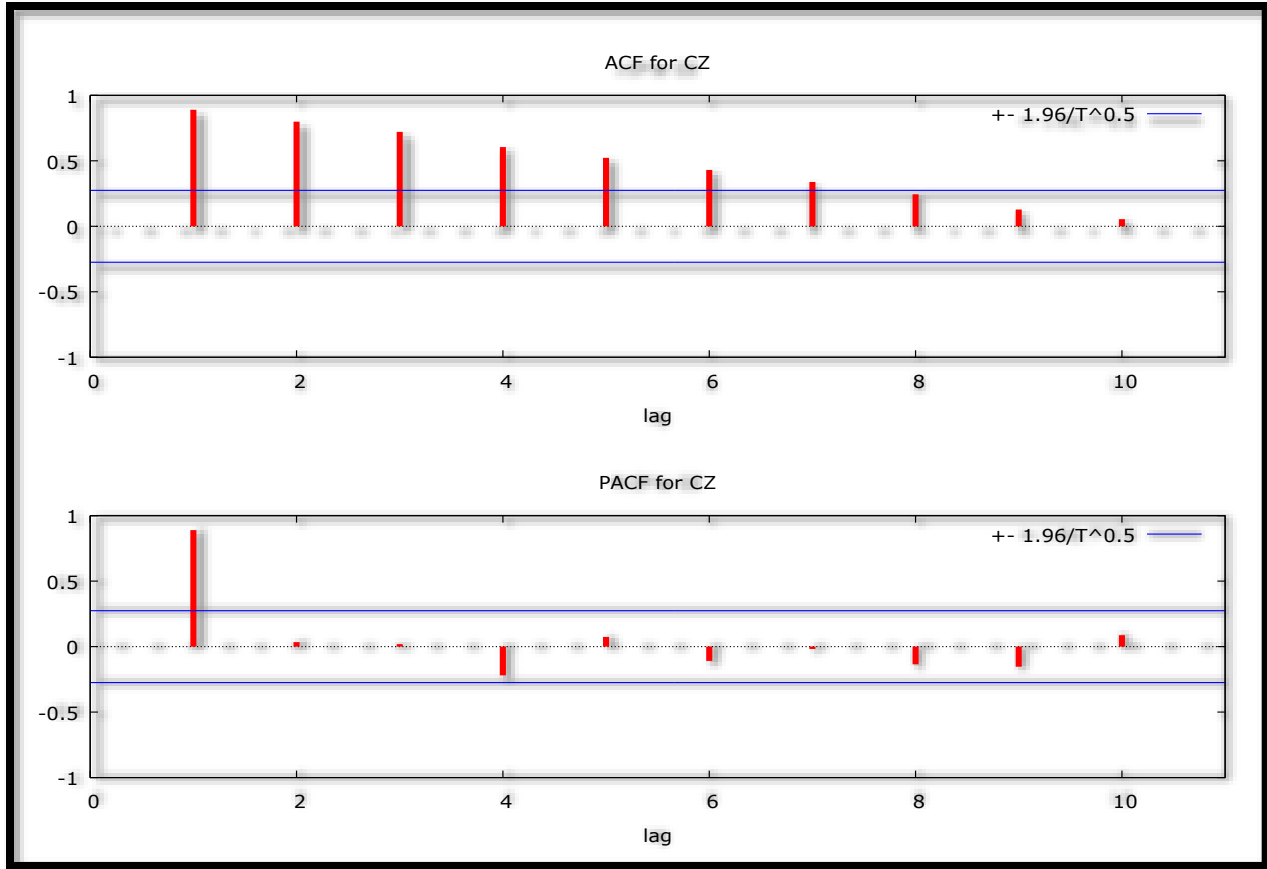


Figure 2. The ADF Test Source: Research Tests (2019)

Table 2. Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
CZ	-2.005191	0.2838	-3.568308	@1%	Not stationary
			-2.921175	@5%	Not stationary
			-2.598551	@10%	Not stationary

Table 3. Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
CZ	-1.749217	0.7141	-4.152511	@1%	Not stationary
			-3.502373	@5%	Not stationary
			-3.180699	@10%	Not stationary

Table 4. Without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
CZ	0.137846	0.7216	-2.612033	@1%	Not stationary
			-1.947520	@5%	Not stationary
			-1.612650	@10%	Not stationary

\*\*\*Figures 1 and 2 and tables 1 – 3 indicate that the CZ series is not I (0), its mean and variance change over time.

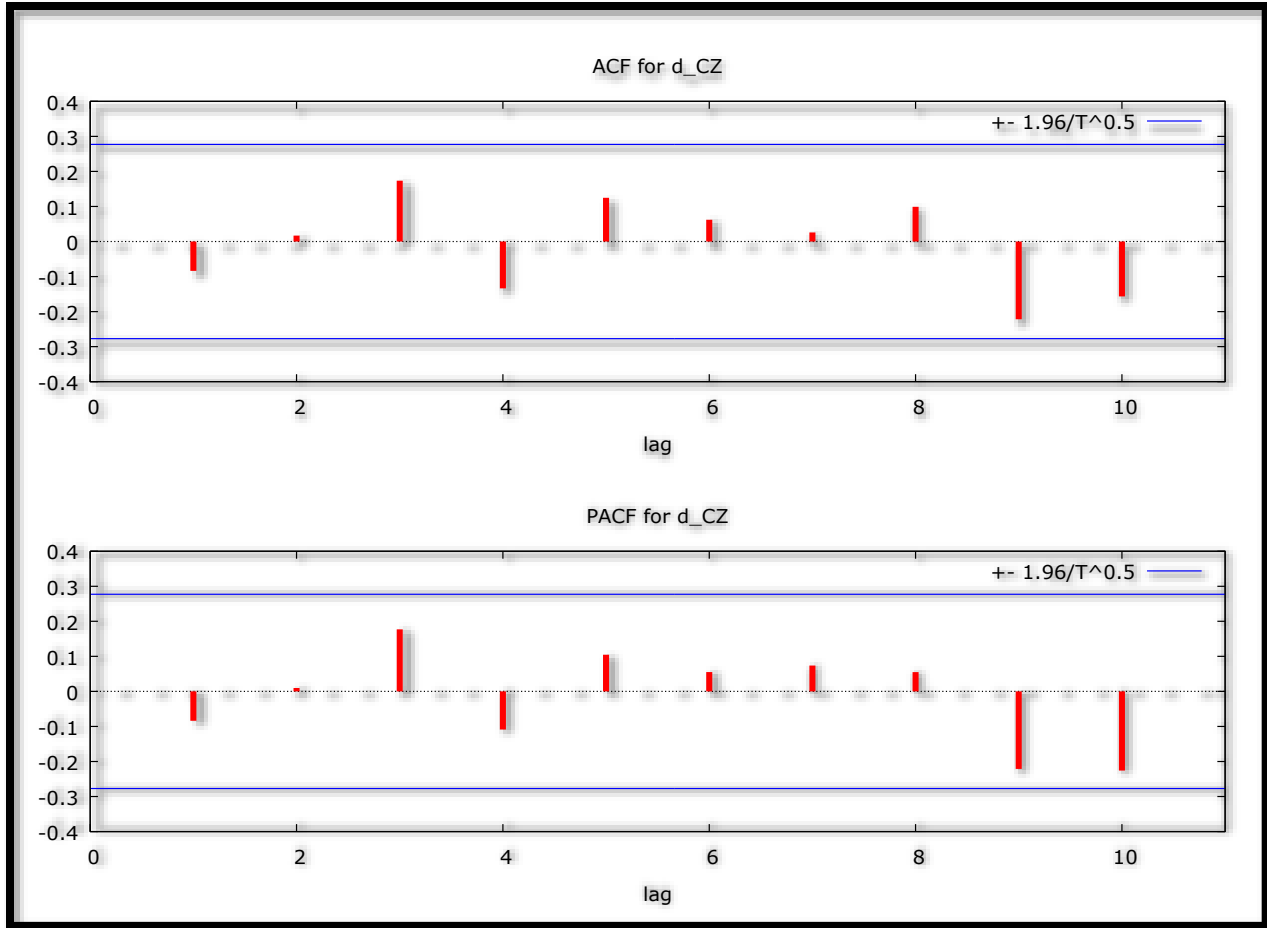


Figure 3. The Correlogram (at 1<sup>st</sup> Differences) Source: Research Tests (2019)

Table 5. 1<sup>st</sup> Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
CZ	-7.469542	0.0000	-3.571310	@1%	Stationary
			-2.922449	@5%	Stationary
			-2.599224	@10%	Stationary

Table 6 1<sup>st</sup> Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
CZ	-7.519718	0.0000	-4.156734	@1%	Stationary
			-3.504330	@5%	Stationary
			-3.181826	@10%	Stationary

Table 7 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
CZ	-7.465169	0.0000	-2.613010	@1%	Stationary
			-1.947665	@5%	Stationary
			-1.612573	@10%	Stationary

\*\*\*Figure 3 and tables 5 – 7 indicate that CZ series became stationary after taking first differences. Thus the CZ series is an I (1) variable.



**Table 8. Evaluation of ARIMA models (without a constant)**

Model	AIC	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	869.8551	0.99133	161.04	1087.1	1365.9	10.872
ARIMA (1, 1, 2)	871.1907	0.99081	142.87	1074.8	1356.4	10.763
ARIMA (1, 1, 3)	871.2578	0.9609	140.49	1054	1329.1	10.51
ARIMA (1, 1, 4)	872.6742	0.95039	142.16	1068	1319.9	10.654
ARIMA (1, 1, 5)	873.2939	0.93835	134.65	1048.4	1299.3	10.361
ARIMA (1, 1, 6)	873.0851	0.90775	121.9	1061.8	1264	10.454
ARIMA (1, 1, 7)	874.6292	0.90602	119.27	1058.9	1258	10.447
ARIMA (1, 1, 8)	876.4193	0.90689	103.93	1013.2	1253.2	10.075
ARIMA (1, 1, 9)	874.4816	0.83869	169.2	989.71	1199.5	9.8827
ARIMA (2, 1, 1)	871.3721	0.99426	143.19	1077	1359.1	10.798
ARIMA (3, 1, 1)	870.5238	0.9471	141.25	1055.5	1318.6	10.501
ARIMA (4, 1, 1)	872.4014	0.94497	144.83	1059.9	1316.8	10.554
ARIMA (5, 1, 1)	873.6944	0.9424	134.49	1052	1306.5	10.474
ARIMA (6, 1, 1)	875.6356	0.94274	133.37	1053.6	1305.7	10.491
ARIMA (7, 1, 1)	877.3871	0.93991	127.05	1042.3	1302.2	10.365
ARIMA (8, 1, 1)	878.9795	0.93428	120.62	1043.8	1296.3	10.377
ARIMA (9, 1, 1)	875.4254	0.86309	190.44	1004.8	1214.9	9.9499
ARIMA (10, 1, 1)	874.8942	0.83033	183.66	972.5	1178.1	9.6186
ARIMA (1, 1, 0)	867.8565	0.99117	161.18	1087.1	1365.9	10.869
ARIMA (2, 1, 0)	869.8465	0.9924	159.97	1087.3	1365.8	10.884
ARIMA (3, 1, 0)	869.8407	0.96586	139	1068.2	1337.4	10.616
ARIMA (4, 1, 0)	870.8640	0.95053	145.88	1069.3	1323.4	10.648
ARIMA (5, 1, 0)	871.9627	0.9431	140.7	1051.3	1310.3	10.474
ARIMA (6, 1, 0)	873.7435	0.94342	137.16	1056.1	1307.2	10.518
ARIMA (7, 1, 0)	875.3987	0.94021	127.88	1042.5	1302.4	10.368
ARIMA (8, 1, 0)	877.3098	0.93782	122.84	1041.9	1301.1	10.361
ARIMA (9, 1, 0)	875.7533	0.90471	155	1030.5	1248.6	10.263
ARIMA (10, 1, 0)	873.0141	<b>0.82809</b>	188.09	969.28	1179.9	9.5717
ARIMA (0, 1, 1)	867.8696	0.99134	160.9	1086.5	1366.1	10.862
ARIMA (0, 1, 2)	869.7324	0.99267	158.67	1087	1364.1	10.912
ARIMA (0, 1, 3)	870.5006	0.9738	141.8	1065.4	1346.8	10.608
ARIMA (0, 1, 4)	870.683	0.9501	141.68	1069.8	1319.9	10.673
ARIMA (0, 1, 5)	872.5577	0.95157	147.24	1046.4	1318.9	10.432
ARIMA (0, 1, 6)	871.6655	0.90469	132.36	1065.7	1270.7	10.483
ARIMA (0, 1, 7)	872.6441	0.90725	117.92	1056.2	1258.5	10.424
ARIMA (0, 1, 9)	873.9379	0.86342	132.81	996.82	1219	9.9488
ARIMA (0, 1, 10)	874.1122	0.83964	144.8	982.3	1196.4	9.8068

A model with a lower AIC value is better than the one with a higher AIC value (Nyoni, 2018n). Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018i). The study will consider Theil's U in order to choose the best model. Therefore, for forecasting annual total CO<sub>2</sub> in Zimbabwe, the ARIMA (10, 1, 0) model is carefully selected.





## Residual & Stability Tests

### ADF Tests of the Residuals of the ARIMA (10, 1, 0)

Table 9 Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R <sub>t</sub>	-5.967035	0.0000	-3.610453	@1%	Stationary
			-2.938987	@5%	Stationary
			-2.607932	@10%	Stationary

Table 10. Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R <sub>t</sub>	-5.993480	0.0001	-4.211868	@1%	Stationary
			-3.529758	@5%	Stationary
			-3.196411	@10%	Stationary

Table 11. Without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R <sub>t</sub>	-5.947905	0.0000	-2.625606	@1%	Stationary
			-1.949609	@5%	Stationary
			-1.611593	@10%	Stationary

\*\*\*Tables 9 – 11 demonstrate that the residuals of the ARIMA (10, 1, 0) model are stationary.

### Stability Test of the ARIMA (10, 1, 0)

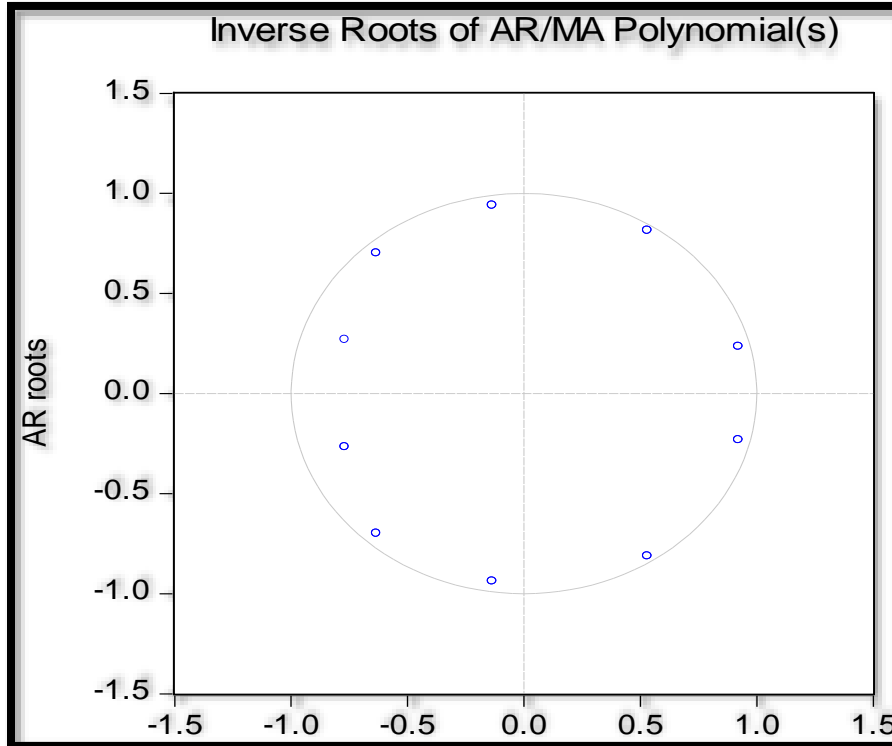


Figure 4. Stability Test of the ARIMA (10, 1, 0) Source: Research Tests (2019)



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen best model, the ARIMA (10, 1, 0) model is indeed stable and acceptable.

## Findings and discussions

**Table 12 Descriptive Statistics**

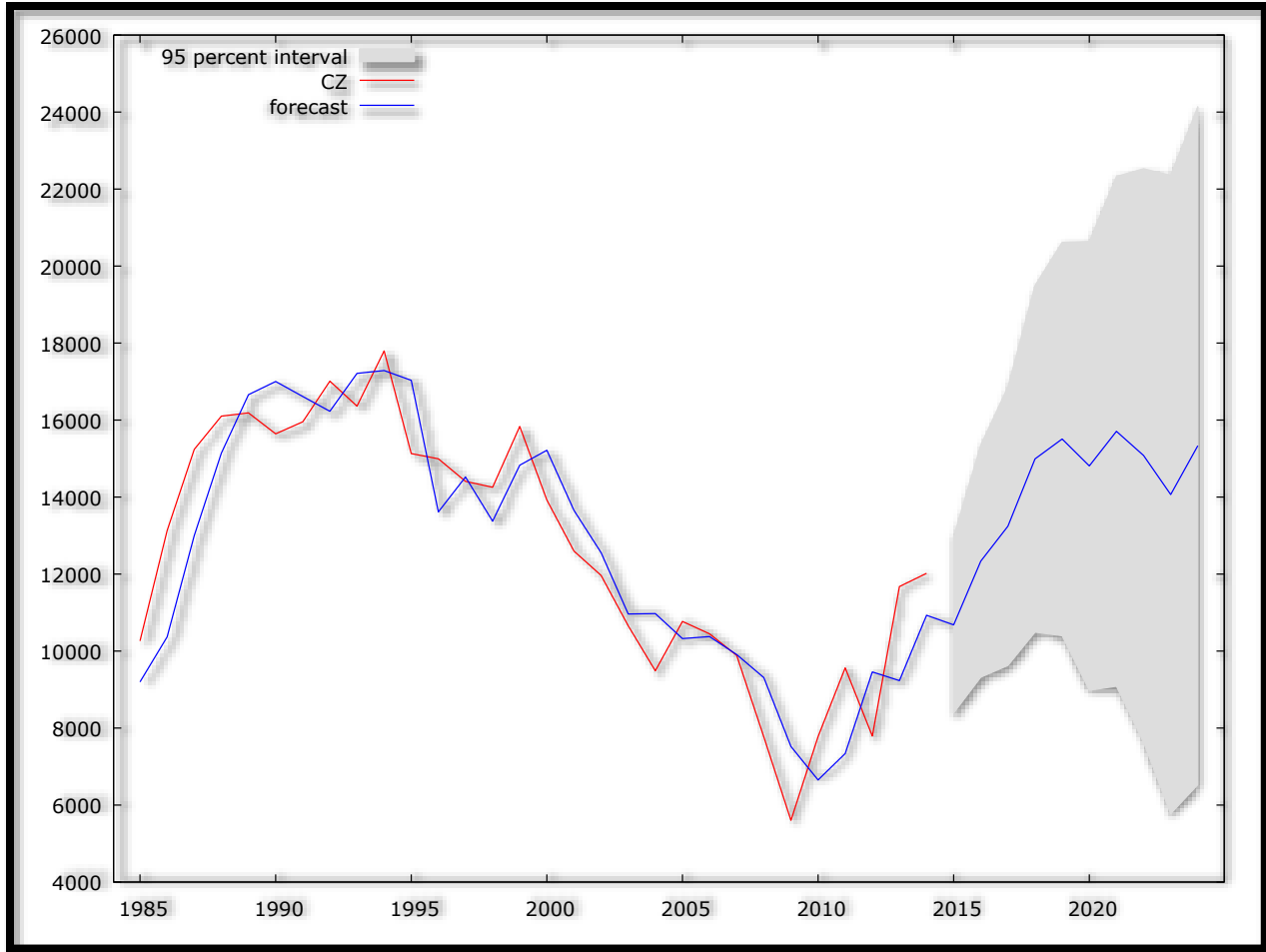
Description	Statistic
Mean	10851
Median	9923
Minimum	4474
Maximum	17796
Standard deviation	3511.1
Skewness	0.25921
Excess kurtosis	-0.9083

The mean is positive, i.e. 10851. The minimum carbon dioxide emission is 4474 and the maximum carbon dioxide emission is 17796. Skewness is 0.25921 and the most crucial thing about it is that it is positive, showing that it is positively skewed and non-symmetric. Kurtosis is -0.9083; indicating that the carbon dioxide emission series is not normally distributed.

**Table 13. Results Presentation<sup>1</sup>**

ARIMA (10, 1, 0) Model:				
$\Delta CZ_{t-1} = -0.142\Delta CZ_{t-1} - 0.004\Delta CZ_{t-2} + 0.298\Delta CZ_{t-3} - 0.01\Delta CZ_{t-4} + 0.144\Delta CZ_{t-5} + 0.104\Delta CZ_{t-6} + 0.196\Delta CZ_{t-7} + 0.047\Delta CZ_{t-8} - 0.331\Delta CZ_{t-9} - 0.353\Delta CZ_{t-10} \dots \dots \dots [5]$				
Variable	Coefficient	Std. Error	z	p-value
AR (1)	-0.141612	0.132928	-1.065	0.2867
AR (2)	-0.00365788	0.136977	-0.02656	0.9788
AR (3)	0.297553	0.143514	2.073	0.0381**
AR (4)	-0.0298537	0.147844	-0.2019	0.84
AR (5)	0.144370	0.152063	0.9494	0.3424
AR (6)	0.103555	0.150378	0.6886	0.4911
AR (7)	0.195623	0.169512	1.154	0.2485
AR (8)	0.0473247	0.162867	0.2906	0.7714
AR (9)	-0.330984	0.166577	-1.987	0.0469**
AR (10)	-0.352667	0.177066	-1.992	0.0464**

<sup>1</sup> The \*, \*\* and \*\*\* means significant at 10%, 5% and 1% levels of significance; respectively.



**Figure 5.** Forecast Graph Research Findings (2019)

**Table 13 Predicted Total Population**

Year	Prediction	Std. Error	95% Confidence Interval
2015	10680.13	1167.443	8391.98 - 12968.27
2016	12335.83	1538.560	9320.31 - 15351.35
2017	13242.90	1846.669	9623.50 - 16862.31
2018	14992.51	2297.311	10489.86 - 19495.15
2019	15508.19	2607.538	10397.51 - 20618.87
2020	14809.21	2974.056	8980.16 - 20638.25
2021	15707.86	3378.130	9086.85 - 22328.88
2022	15080.32	3800.467	7631.54 - 22529.10
2023	14065.93	4230.393	5774.51 - 22357.35
2024	15333.72	4492.610	6528.36 - 24139.07



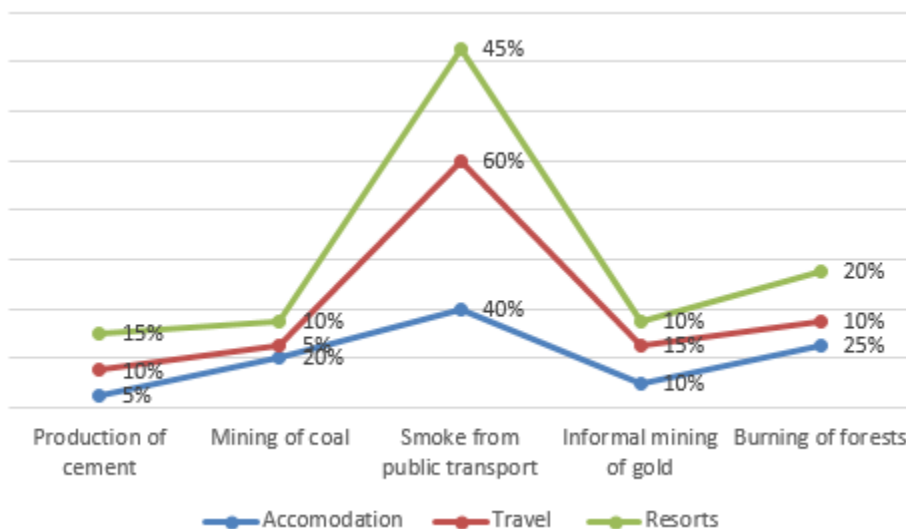
Figure 5 (with a forecast range from 2015 – 2024) and Table 13, clearly show that Zimbabwe annual total CO<sub>2</sub> emission is likely to rise over the next decade. With a 95% confidence interval of 6528.36 kt to 24139.07 kt and a projected annual total CO<sub>2</sub> emission of 15333.72kt by 2024, the chosen ARIMA (10, 1, 0) model is apparently sending warning signals to Environmental Economists in Zimbabwe on the need to take action in light of climate change and global warming.

### Results from in-depth interviews

A further in-depth interview was conducted in order to understand the general causes of increased CO<sub>2</sub> emission. This was because results from the ARIMA Tests indicated that in the next decade emission of CO<sub>2</sub> is going to increase in the Zimbabwe. Since the aim of the study was to advise the government and various environment and tourism stakeholders on the emission levels of CO<sub>2</sub>, the results became a concern to understand the causes of increased emission levels. The results from in-depth interview informed that the main causes are as follows:

- Production of cement;
- Mining of coal;
- Smoke from public transport;
- Informal mining of gold; and
- Burning of forests.

### Results from surveys



**Figure 6.** Responses on the cause of CO<sub>2</sub> emission tourism sector Sources: Research Findings (2019)

The presentation in Figure 6 above shows that all the sectors concluded that the most common source of carbon dioxide emission in Zimbabwe is the smoke from public transport that is Accommodation (40%); Travel (60%); and Resorts (45%). These responses might be due to the fact that most of the public transport are not using green energy and some are not maintained to an extent of producing more Carbon Dioxide. This was also supported other authors (Peeters & Dubois, 2010; Nepal, 2008) who announced that the travel segment of the tourism industry is the main source of most emission especially from the air transport.



## Conclusion

The study shows that the ARIMA (10, 1, 0) model is not only stable but also the most suitable model to forecast annual total CO<sub>2</sub> in Zimbabwe for the next 10 years. The model predicts that by 2024, Zimbabwe's annual total CO<sub>2</sub> emission will be approximately, 15 000 kt. This is a warning signal to Environmental Economists in Zimbabwe, particularly with regard to climate change and global warming. The results of this study are invaluable for the government of Zimbabwe, especially when it comes to medium-term and long-term planning. Also from a tourism perspective, the study shows that the travel sector is the most contributor of CO<sub>2</sub> emission from the public transport that produce smoke into the atmosphere.

## Recommendations

- There is need for reduction in consumption of fossil fuels in Zimbabwe.
- There is need to develop and or acquire more effective energy saving technologies.
- The use of renewable energies in Zimbabwe is also highly recommended.
- There is also need to strive to continuously educate the Zimbabwean society on the essence of lowering pollution levels.
- The government of Zimbabwe ought to reduce pollution by implementing policy actions such as increasing tax on the polluting companies, especially those that use fossil fuels in their production activities.

## References

- Asteriou, D. & Hall, S. G. (2007). *Applied Econometrics: a modern approach*, Revised Edition, *Palgrave MacMillan*, New York.
- Becken, S. (2005). Harmonizing climate change adaptation and mitigation: The case of tourist resorts in Fiji. *Global Environmental Change*, 15(4), 381–393.
- Becken, S. & Hay, J. E. (2007). *Tourism and climate change: risks and opportunities*. Clevedon, Buffalo, Toronto: *Channel View Publications*.
- Butler, R.W. (2000). Tourism and the environment: A geographical perspective. *Tourism Geographies*, 2(3), 337-358.
- Chibaya, T. (2013). From 'Zimbabwe Africa's Paradise to Zimbabwe A World of Wonders': Benefits and Challenges of Rebranding Zimbabwe as A Tourist Destination. *Developing Country Studies*, 13(5), 84-91
- Chigora, F. & Zvavahera, P. (2015). Strategic Management and Branding Panacea for Surviving in Volatile Environments: Case of Zimbabwe Tourism Industry. *Business and Management Horizons*, 3(2), 24-33.
- Du Preez, J. & Witt, S. F. (2003). Univariate and multivariate time series forecasting: An application to tourism demand, *International Journal of Forecasting*, 19, 435 – 451.
- Dubois, G., Peeters, P., Ceron, J.P. & Gössling, S., (2011). The future tourism mobility of the world population: Emission growth versus climate policy. *Transportation Research Part A: Policy and Practice*, 45(10), 1031-1042.



- Goh, C. & Law, R. (2002). Modeling and forecasting tourism demand for arrivals with stochastic non-stationary seasonality and intervention, *Tourism Management*, 23, 499 – 510.
- Hossain, A., Islam, M. A., Kamruzzaman, M., Khalek, M. A. & Ali, M. A. (2017). Forecasting carbon dioxide emissions in Bangladesh using Box-Jenkins ARIMA models, *Department of Statistics, University of Rajshahi*.
- IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC.
- Katircioglu, S.T., Feridun, M. & Kilinc, C. (2014) .Induced energy consumption and CO<sub>2</sub> emissions: The case of Cyprus. *Renew. Sustain. Energy Review*, 29, 634–640.
- Lee, J. J., Lukachko, S. P., Waitz, I. A. & Schafer, A. (2001). Historical and future trends in aircraft performance, cost, and emissions, *Annual Review of Environment and Resources*, 26,167–200.
- Lotfalipour, M. R., Falahi, M. A. & Bastam, M (2013). Prediction of CO<sub>2</sub> emissions in Iran using Grey and ARIMA models, *International Journal of Energy Economics and Policy*, 3 (3), 229 – 237.
- Maplecroft Report (2011). The top ten countries at risk for climate change impacts, Available online at <http://earthsky.org>
- Moreno, A. (2010). Climate change and tourism: Impacts and vulnerability of coastal Europe. Netherlands: Universitaire Pers Maastricht.
- Moreno, A. & Amelung, B. (2009). Climate change and tourist comfort on Europe's beaches in summer: A reassessment. *Coastal Management*, 37(6), 550–568.
- Ndlovu, J. & Heath, E. (2013). Re-branding of Zimbabwe to enhance sustainable tourism development: Panacea or Villain. *Academic Journals*, 1(12), 947-955.
- Nepal, S.K. (2008).Tourism-induced rural energy consumption in the Annapurna regional of Nepal. *Tourism Management* 29, 89–100.
- Nyoni, T. (2018l). Modeling Forecasting Naira / USD Exchange Rate in Nigeria: a Box – Jenkins ARIMA approach, *University of Munich Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88622.
- Nyoni, T. (2018n). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis, *Dimorian Review*, 5 (6), 16 – 40.
- Nyoni, T. (2018i). Box – Jenkins ARIMA Approach to Predicting net FDI inflows in Zimbabwe, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 87737.
- Peeters, P. & Dubois, G. (2010). Tourism travel under climate change mitigation constraints. *J. Transp. Geogr.* 13,131–140.
- Pruethsan, S. (2017). VARIMAX model to forecast the emission of carbon dioxide from energy consumption in rubber and petroleum industries sectors in Thailand, *Journal of Ecological Engineering*, 18 (3), 112 – 117.
- Scott, D. (2011). Why sustainable tourism must address climate change. *Journal of Sustainable Tourism*, 19(1), 17 - 34.



Song, H., Witt, S. F. & Jensen, T. C. (2003b). Tourism forecasting: accuracy of alternative econometric models, *International Journal of Forecasting*, 19, 123 – 141.

Stefănica, M. & Butnaru, G.I. (2015). Research on Tourists' Perception of the Relationship between Tourism and Environment. *Procedia Economics and Finance*, 20, 595-600.

Sun, X. (2009). Analyze China's CO<sub>2</sub> emission pattern and forecast its future emission, Masters Thesis, *Nicholas School of Environment*, Duke University.

Tang, C.F. & Tan, B.W. (2015). The impact of energy consumption, income and foreign direct investment on carbon dioxide emissions in Vietnam. *Energy*, 79, 447-454

UNWTO (ed.). (2009). From Davos to Copenhagen and Beyond: Advancing Tourism's Response to Climate Change. Madrid: UNWTO background paper.

World Bank (2007). Growth and CO<sub>2</sub> emissions: how do different countries fare, Environment Department, *World Bank*, Washington DC.

Wu, L., Liu, S., Liu, D., Fang, Z. & Xu, H. (2015). Modeling and forecasting CO<sub>2</sub> emissions in the BRICS (Brazil, Russia, India, China and South Africa) countries using a novel multi-variable grey model, *Energy*, 79, 489 – 495.