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## RE-EVALUATION OF WORLD POPULATION FIGURES: POLITICS AND FORECASTING MECHANICS

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**Abstract.** This paper forecasts the world population using the Autoregressive Integration Moving Average (ARIMA) for estimation and projection for short-range and long-term population sizes of the world, regions and sub-regions. The study provides evidence that growth and population explosion will continue in Sub-Saharan Africa, tending the need to aggressively promote pragmatic programmes that will balance population growth and sustainable economic growth in the region. The study argued that early projections took for granted the positive and negative implications of population growth on the social structure and offset the natural process, which might have implication(s) on survival rate. Given the obvious imbalance in population growth across continents and regions of the world, a more purposeful inter-regional and economic co-operation that supports and enhances population balancing and economic expansion among nations is highly recommended. In this regard, the United Nations should compel member states to vigorously and effectively implement domestic and international support programmes with this objective in view.

**Keywords:** ARMA/ARIMA; Population growth; Population projections; World population.

**JEL Classification:** J11, J18, C22

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### INTRODUCTION

The past two decades have seen renewed interest in population forecasting. This is not surprising given the importance of the subject matter in social and economic planning across all levels of human existence be it local, regional or international. Without gainsaying the fact, population remains a strong economic measuring and planning tool that impacts other associated resources and developmental elements. According to economists and other social experts, the attention given to population forecasting is driven by the dynamics in the world population from the second half of the 20th century, which widely contrasts with the century before. Early in the 20th century, the planet recorded a sluggish growth in human population expansion. While the changes in demographics were relatively small till the first half of the 20th century, the population growth expanded

unprecedentedly at the later end of the century (Shobande, 2018). There is wide consensus in literature that the world will experience population explosion in few decades from now with the African continent leading the pack with the highest growth rate (Dumont, 2018; Fernández-López de Pablo *et al.*, 2019; Marshall *et al.*, 2017).

Reports documented by the United Nations confirmed that the world population surged by nearly one billion in the last twelve years (United Nations, 2017). Further classification into regions indicates that the Asian continent accounts for three-fifth of the world population while North America and Oceania remain the least populated continents. In Asia, both China and India constitute sixty per cent of the population in the region; the countries also retained the largest population in the world for a long time (Satterthwaite, 2004). With the world population growth projected for 2030 and 2100, the African region will be met with 36 per cent and 256 per cent increase, respectively, largely overtaking both the world and Asian growth. By projection, Africa's population will equal Asian population in 2100 (United Nations, 2017).

With Asia being the largest potential candidate of population explosion, critical question arises as to whether an increase in population is a blessing or a curse. Furthermore, we are also interested in establishing if estimating future population accurately without error can possibly avert future socio-economic consequences through pragmatic policy prescriptions and execution. In addition, the notion of whether expected future population could be estimated to give precise predictions based on reliability of methodology or techniques applied is also considered in this paper. Further questions triggering curiosity on the subject matter are given some close attention – one of such questions is the place of the various theories developed over the last 300 years on population forecasting and the results, which have been disputed/questioned by remarkable events despite the volume of empirical facts backing the reported results.

This study estimates the potential future of world population. It probes whether political or instructional settings account for the disparities in estimates and figures presented among researchers in recent years, despite the power of Autoregressive Movement Average method and other advancement in econometric techniques.

The principal object of the study is to articulate the effects of population forecasting on demographic composition and social cost as well as the potential for future growth. The place of resource allocation and negotiation, political manoeuvring and social dynamics were all brought to fore in analysing the world population and proposing policy strategies for avoiding monitoring its trends.

Given its scope, this study is motivated to provide high-powered predictive evidence that corrects the avoidable errors that are common and documented in the body of research on this subject matter. However, these previous studies still provided support and background for the current study as this study looks forward to correcting those flaws noticed through the methodological approach innovated majorly for forecasting. The study then adopts Autoregressive Integration Moving Average (ARIMA) model as postulated by Box and Jenkins (1970) and Bartholomew (1971), for estimation and making projections for short-ranged and long-term population sizes for the world, regions and sub-regions. Contrary to the

economic and statistical model that investigates the variation in economic variables from a set of other variables, this approach relates its current values (population) to its past values and to the current and past random shocks. Therefore, the novelty of this study is based on the superiority of ARIMA methodological approach to predict the dynamic behaviour of the world population. We argue that previous studies relied heavily on the structural model and cared about heterogeneity, endogeneity and identified restriction imposed on the parameter of the ARIMA equation, which resorted to similar results documented so far. We claim that the forecast generated by ARIMA estimator was often policy effective compared to structural ones. In addition, we claim that the outcome of this study has the potential to reconcile the contemporary disagreements in population figures and serves as a policy instrument to stakeholders, as well as a point of reference for the academia.

The rest of the paper is organised as follows: Section II discusses the theoretical foundation and time series evidence of the study; Section III presents the theoretical framework and methodology, while Section IV concludes the paper with some policy implications of our findings.

## 1. LITERATURE REVIEW

The theoretical foundation of population forecasting began with the study of Thomas Robert Malthus, an English cleric and scholar in the field of political economics and demography. He was born in Rookery, near Dorking Surrey, England in 1766 and spent most of his career searching for the misery and blessings attached to population growth (Ross, 1999). Unlike early studies before him, Malthus saw the possibility that gluts (depressions) could exist and argued that position strongly. The essential argument presented in this essay is that population growth can and will outstrip food supply (Barrus, 2007). Malthus further argued that population would always tend to outrun resources and that improvement of humankind would be impossible without strict limits on reproduction.

Over the decades, Malthus's theory has been and remains the theory of population that attempts to explain the consequences of population forecasting of the law of nature (Notestein *et al.*, 1945; Ross, 1999). The main contribution of Malthus is that 'law of nature', which ordains that the effects of two unequal powers – the 'power in the earth to produce subsistence for man' and the 'power of population' – be kept equal by means of checks exerted upon the latter power (Hofmann, 2013). The concise formulation of the disparity of two powers, attributing to population a tendency to increase at a geometrical ratio and to subsist the capacity to increase at an arithmetical ratio, secured the pronouncement of a lasting impact. Malthus himself never ceased to consider it as fundamental to his theory (Hofmann, 2013; Notestein *et al.*, 1945; Ross, 1999).

The Malthus hypothetical conjure has continued to generate considerable volumes of literature overtime. Remarkably, the stream of studies has favoured experts' knowledge or judgment in population forecasting simulation based on their perception about uncertainties that result from future occurrence in determining the growth trends (Day, 2002). These set of studies argued that even when quantitative methods were applied to the estimation and the projection, expert knowledge still

played significantly crucial role in the conclusion about the future development of the population trends. Alders and Beer (2004) asserted that population size of the Dutch could be calculated by means of Monte Carlo simulation while making several assumptions about the mean and median of the probability distributions of the demographics. In this case, the variance of the distribution of these demographics (fertility, mortality and migration) largely determines the probability of the distribution of the future population size. In their study, the expert judgment is highly ranked above the analysis of errors of past forecasts and model-based estimates of forecast errors. They opined that judgment was more fundamental in the choice of variance selection even if the uncertainty evaluation was based on the time-series model or past errors (Alders & Beer, 2004). It means that it will be difficult to have precision in population prediction relying on the above-mentioned quantitative methods mostly when different years of extrapolation changes give pretty dissimilar projection results. Applying this methodology to the uncertain future fertility in the Netherlands, the study found that fertility had remained stable in the past few decades.

The advantages of stochastic over deterministic techniques in population projection have made scholars desert the latter because stochastic methods are recognised to provide a rationally consistent and interpretable predictive distribution of interest (Li, Reuser, Kraus, & Alho, 2009). Torri and Vaupel (2012) transformed point predictions into stochastic forecast in the projection for life expectancy and population growth in Italy. The three steps carried out in point estimation were a forward projection to estimate the number of people still living, the number of births over the period and survivors at the beginning of next period, and the number of net migrations in each age group during the period. The study adopted Leslie Matrix putting into consideration fertility and mortality for sexes in each age group while net migration was assumed to be constant. In order to translate uncertain behaviour of the demographic variables that helps in providing stochastic forecast of the probability distribution of the population size, the study applied the Alho and Spencer (1985) scaled model for error to the baseline forecast errors and their empirical specifications proposed in year 2005 for robust estimation of the error term structure. The introduction of the stochastic terms in their model largely lent credence to subsequent projections contrary to the deterministic methodology in the previous studies on the demographic future of the country. Computing interval estimation, the study predicted a decline in population and unavoidable aging population in Italy for the forecast period. Li *et al.* (2009) also presented a stochastic forecast for the Chinese population. Contrary to experts' judgment to define fertility and mortality probabilistic intervals as applied by some research (Alders *et al.*, 2004), the study used probability distribution that was based on the time-series analysis. The study found that there was no glimpse of doubt that Chinese Population was aging rapidly.

Rayer (2007) responded to the large body of empirical debates on the assessment of the precision of the Mean Absolute Percent Error (MAPE). The study worked on comparative analyses of new methodologies now found in the growing body of research on population forecast. Both Median-APE and M-estimator were compared with MAPE. To answer this question of precision and bias, the study

confirmed that MAPE might have the tendency to go extreme when there were outliers. It therefore advocated that when there was presence of extreme outliers, MAPE could be avoided – a position that was very uncommon (Gorrostieta, Ombao, & Von Sachs, 2019). However, actually, MAPE does not necessarily overstate errors as criticized by other writers (Tayman & Swanson, 1999). In the population projection in the United States, they argued that there were no occasions when other measure of errors would lead to dissimilar assessment of the population projections. Rayer and Smith (2014) focused on making prediction interval for US population. They opined that since uncertainty usually resulted in any rapidly changing population, precision in projections was always difficult to make. Therefore, the study developed prediction interval estimates. The study argued that this empirically based prediction interval presented high accuracy of the population forecast. These two studies lent support to previous studies on the absolute percentage errors as Smith and Sincich (1988).

Simar and Wilson (2007) investigated the forecast accuracy of population projection made by the Australian Bureau of Statistics (ABS) in each decade between 1960s and 2000s. Using the adapted percentage error measure, it was shown that net international migration forecast errors largely contributed to the lack of precision in the population projection in Australia. In the Naïve model (Coshall & Charlesworth, 2011), the study found that corrected percentage error predicted about 6 per cent at ten-year forecast horizon for 1963, 1968 and 1970. When compared with the forecast by the Austrian Bureau of Statistics, it made the most inaccurate forecasts. The study however lends credence to the projections of the latter decades. Martin and Jim (1992) had also previously examined the source of forecast errors in the projections made by ABS and established a contrast with the rise in projection that had earlier been made with the increase in the forecast horizon where there tended to be accurate projections in the long than the short run.

## **2. DATA AND METHODOLOGY**

### **2.1. Data**

The data used for this study were sourced from the World Bank databank (World Development Indicator). Data between 1960 and 2016 were collected for the population of sub-regions, regions and the world population (World development Indicators, 2018). The grouping of countries into regions, therefore, followed the WDI classification. These data were checked for pre-estimation diagnostics before developing the ARMA processes and population projections for the available data. The projections were also compared with the past predictions.

### **2.2. Methodology**

Many reasons motivated the choice of ARIMA time series analysis estimation strategy, notably; it is widely considered superior in terms of forecasting accuracy as compared to an alternative structural model. Likewise, it allows researchers to investigate and predict the dynamics of univariate variables using an extrapolation mechanism to formulate strategies on the future behaviour. While using ARIMA,

the imposing restriction such as serious issues of endogeneity, heterogeneity and identification can be ignored with their consequences. Although it is sometimes difficult on empirical ground to make choice on appropriate modelling techniques to represent the real world situations, the performance of forecasting accuracy proven in past literature in such influential studies as (Lal, Jain, and Sinha, 1987; Carter & Narasimhan, 1996; Galavi & Brinkgreve, 2014) informed the adoption of Autoregressive Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA) for this study. This technique is based on Box-Jenkins time-series procedure proposed by Bartholomew (1971) that combines Autoregressive (AR) and Moving Average (MA). The Box-Jenkins procedure requires a reiterative process for estimating family of models and conducting a diagnostic test to choose the most appropriate one that fits the time-series data under consideration.

In this study, ARMA/ARIMA is developed and also examines the performance of the model using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) (Ben Amor, Boubaker, & Belkacem, 2018; Goto & Taniguchi, 2019). As postulated by Box and Jenkins in the second half of the 1970s (Zhang *et al.*, 2018), time series model had an autoregressive and moving average part (Gonçalves Mazzeu, Veiga, & Mariti, 2019). It means that Autoregressive (AR) and Moving Average (MA) are denoted as ARIMA ( $p, d, q$ ) where  $p$  signifies the order of autoregressive process,  $d$  indicates the order of differencing of the time-series data and  $q$  – the order of moving average process. As common to time-series analysis, the Box-Jenkins procedure requires the data to be mean reverting before estimation (Jebb & Tay, 2017; Xu, 2019), if time-series data are found to be mean reverting ( $d = 0$ ) or are made stationary by differencing in certain order as the case may be, ARMA/ARIMA model.

### 2.3. Model Specification

The authors' forecast model is stated as follows:

$$Y_t = \vartheta_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \varphi_3 Y_{t-3} + \dots + \varphi_p Y_{t-p} + \delta_1 \pi_{t-1} + \delta_2 \pi_{t-2} + \delta_3 \pi_{t-3} + \dots + \delta_q \pi_{t-q} + \varepsilon_t ;$$

$$Y_t = \vartheta_0 + \sum_{i=1}^p (\varphi_i Y_{t-i}) + \sum_{j=1}^q (\delta_j \pi_{t-j}) + \varepsilon_t ;$$

$$Y_t = \sum_{i=1}^p (\varphi_i Y_{t-i}) + \sum_{j=1}^q (\delta_j \pi_{t-j}) + \varepsilon_t ,$$

where  $Y_t$  is mean reverting series. Both  $p$  and  $q$  are orders of the lag for both Autoregressive and Moving Average.  $Y_{t-p}$  and  $\pi_{t-p}$  are the lag of the series and moving average till order of  $p$  and  $q$ , respectively.  $\varphi_1$  and  $\delta_j$  are a set of autoregressive and moving average parameters. If stationary  $Y_t$  follows an ARMA process, then  $Y_t$  is an ARIMA  $p, q$  or if  $Y_t$  is initially not stationary and it follows an ARIMA process after certain differencing then  $Y_t$  is an ARIMA  $p, d, q$ . The ARIMA procedure requires one to estimate a number of possible models and using information criterion to make selection for the most appropriate model. The selected model would then be used for forecasting (Brooks, 2019).

In this study, estimating ARIMA model for population projection follows sequential procedures from identifying the order of integration of the population

(world and regions) to forecasting. Mean reversion (stationarity) is a fundamental assumption in the development of ARIMA as most time-series estimation. Since population is perceived to maintain trend over time period, differencing may be required (Raman, Sathianandan, Sharma, & Mohanty, 2017). The study used Augmented Dickey-Fuller test, Philip-Perron test of stationarity alongside Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) that indicate stationarity/non-stationarity through rapid/weak dampening in the spikes (Anderson, Deistler, & Dufour, 2019; Petrova, 2019).

The second step in ARIMA model is to identify the suitable model. This is done by determining how far the current observation correlates with previous past observations and disturbances/shocks (Beare, 2018; Corberán-Vallet, Bermúdez, & Vercher, 2011), i.e., identifying the orders of  $p$  and/or  $q$  in the model using the ACF and PACF of the plotted stationary population figures. AR( $p$ ) model is selected when PACF spikes cut off after lag  $p$  but ACF has exponential decay to zero (Alsharif, Younes, & Kim, 2019). MA( $q$ ) model is selected if ACF cut off after lag  $q$  when PACF has an exponential decay to zero and ARMA ( $p, q$ ) is selected when ACF and PACF spikes cut off at a specific  $p$  and  $q$  (Astill, Harvey, Leybourne, Sollis, & Robert Taylor, 2018; Bratu, 2012; Zhang *et al.*, 2018). After identification is complete, and since more than one model might be feasible, diagnostic check is carried out on the estimated models and the most suitable one is selected for forecast.

### 3. EMPIRICAL RESULTS

In this section, we present the results of our estimated baseline model. The empirical results start by summarising the population of each continent and the world.

**Table 1.** Descriptive Statistics Population

	EAS, B	SSF, B	SAS, B	NAC, B	MEA, B	LCN, B	ECS, B	WLD, B
<b>Mean</b>	1.727211	0.531799	1.115901	0.277078	0.247923	0.428383	0.813549	5.141843
<b>Maximum</b>	2.296786	1.033106	1.766383	0.359479	0.436721	0.637664	0.911995	7.442136
<b>Minimum</b>	1.042017	0.228526	0.571857	0.198624	0.105489	0.220434	0.667246	3.034193
<b>Std. Dev.</b>	0.392209	0.236202	0.371897	0.048049	0.100970	0.127552	0.068604	1.336201
<b>Observations</b>	57	57	57	57	57	57	57	57

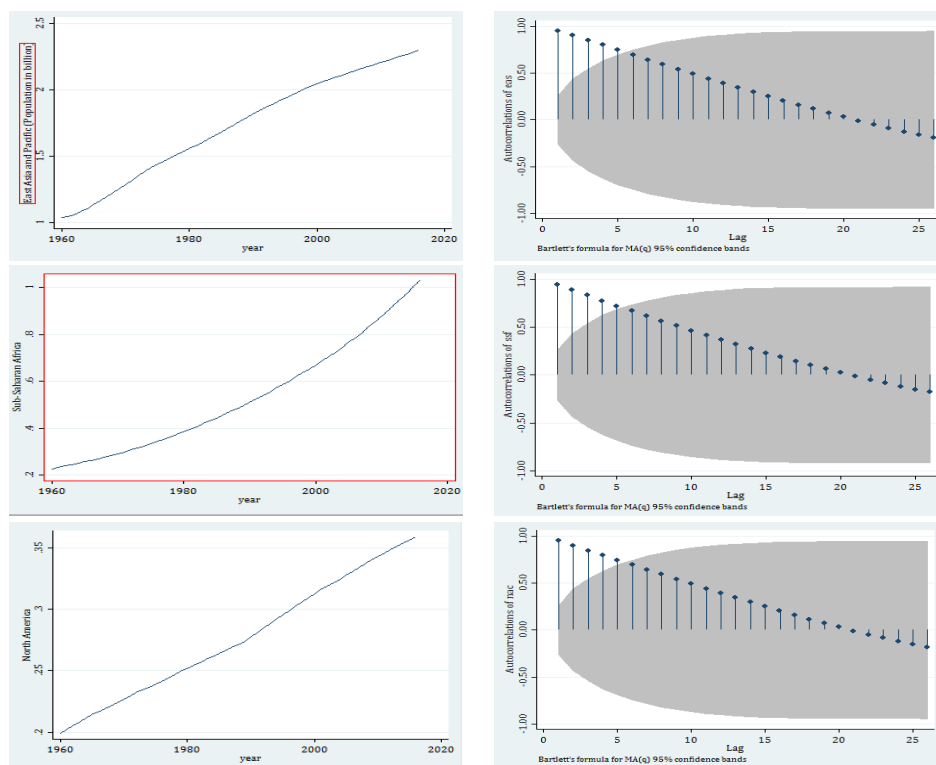
Source: The authors' calculation

Table 1 shows the summary statistics of the population of all the continents and the world. The descriptive statistics are expressed in billion population. From 1960, the average of population of East Asia and Pacific region is approximately 1.73 billion while the maximum and minimum are 2.30 and 1.04 billion, respectively. The standard deviation is approximately 0.39 billion. This indicates that the population does not deviate widely from its mean over the period of 57 years. The population of sub-Sub Saharan Africa shows an average of 0.53 billion. The

maximum (1.03 billion) and the minimum (0.23 billion) reveal that the region exhibited fast growth over the years with fairly high variability.

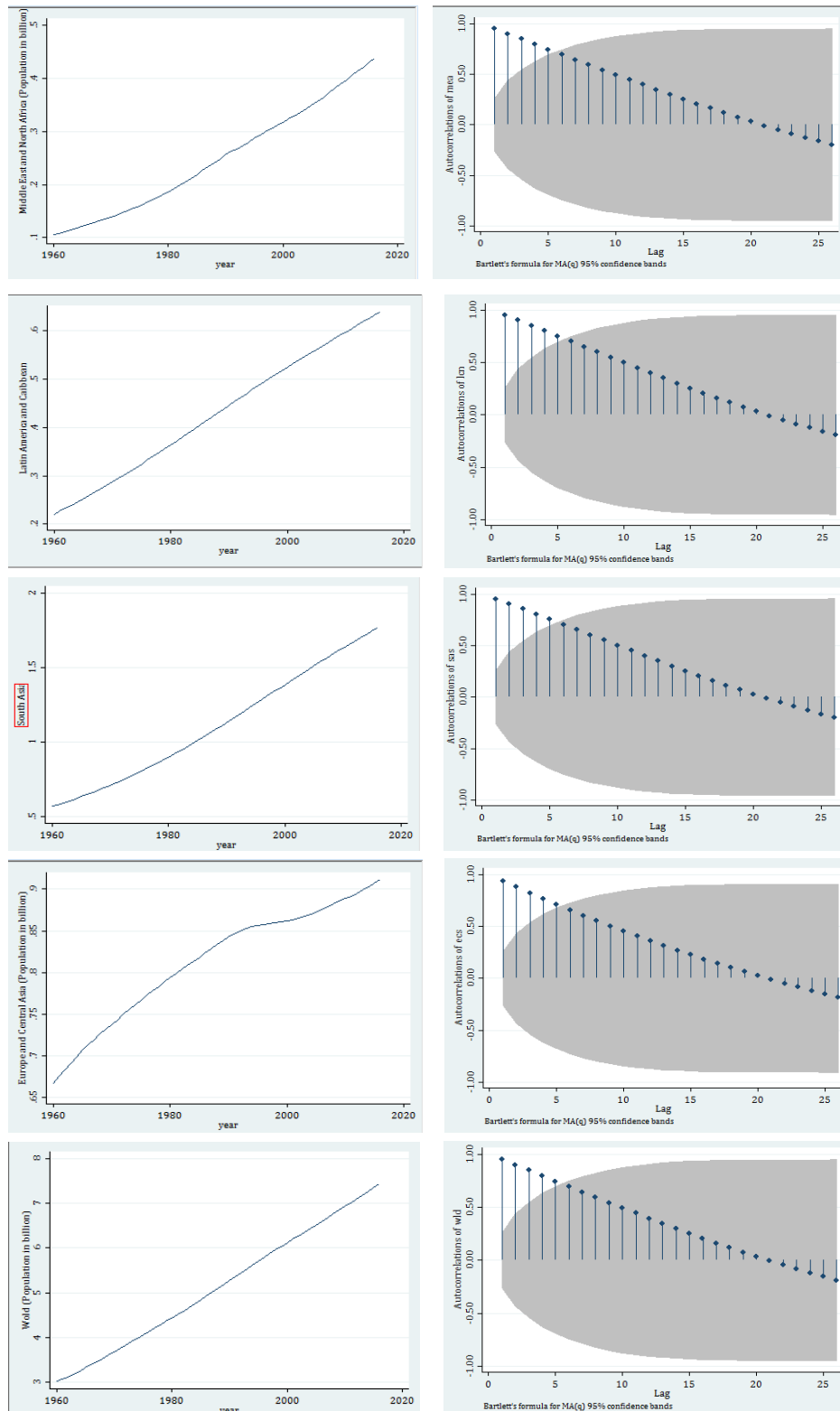
South Asia with an average population of 1.12 billion since 1960 indicates that the population has increased steadily within the period under consideration deviating only by 0.37 billion. North America has maintained a fairly low growth within 57 years. The population has minimum of 0.2 billion and maximum of 0.36 billion having an average and standard deviation of 0.28 billion and 0.04 billion. The population in the region has a relatively low variability. The Middle East and North Africa's population has minimum of 0.11 billion and maximum of 0.43 billion with an average population of 0.25 billion within the years considered. Latin America and the Caribbean shows fairly low variability. Europe and Central Asia deviated fairly simply away from its average while the world population doubled itself within the periods.

The analysis continues by conducting the pre-diagnostic test of stationarity to investigate the mean reversion using autocorrelation function (ACF) plots. ACF usually shows the dependence and cross-correlation of data in different period and is used to find repeating patterns. Examining these tests on the original time-series data for the current study, the plots are trendy and autocorrelation function plots show significantly high magnitude spikes, a slow dampening indicating that the series are not stationary at level, Fig.1 and Fig.2. This signifies the need for differencing as shown in the Fig.3.



**Fig. 1.** Level Population and Autocorrelation Plots (East Asia and Pacific, Sub-Saharan Africa and North America).





**Fig. 2.** Level Population and Autocorrelation Plots (Middle East and North Africa, Latin America and Caribbean, South Asia, Europe and Central Asia, World).

### 3.1. Unit Root Tests

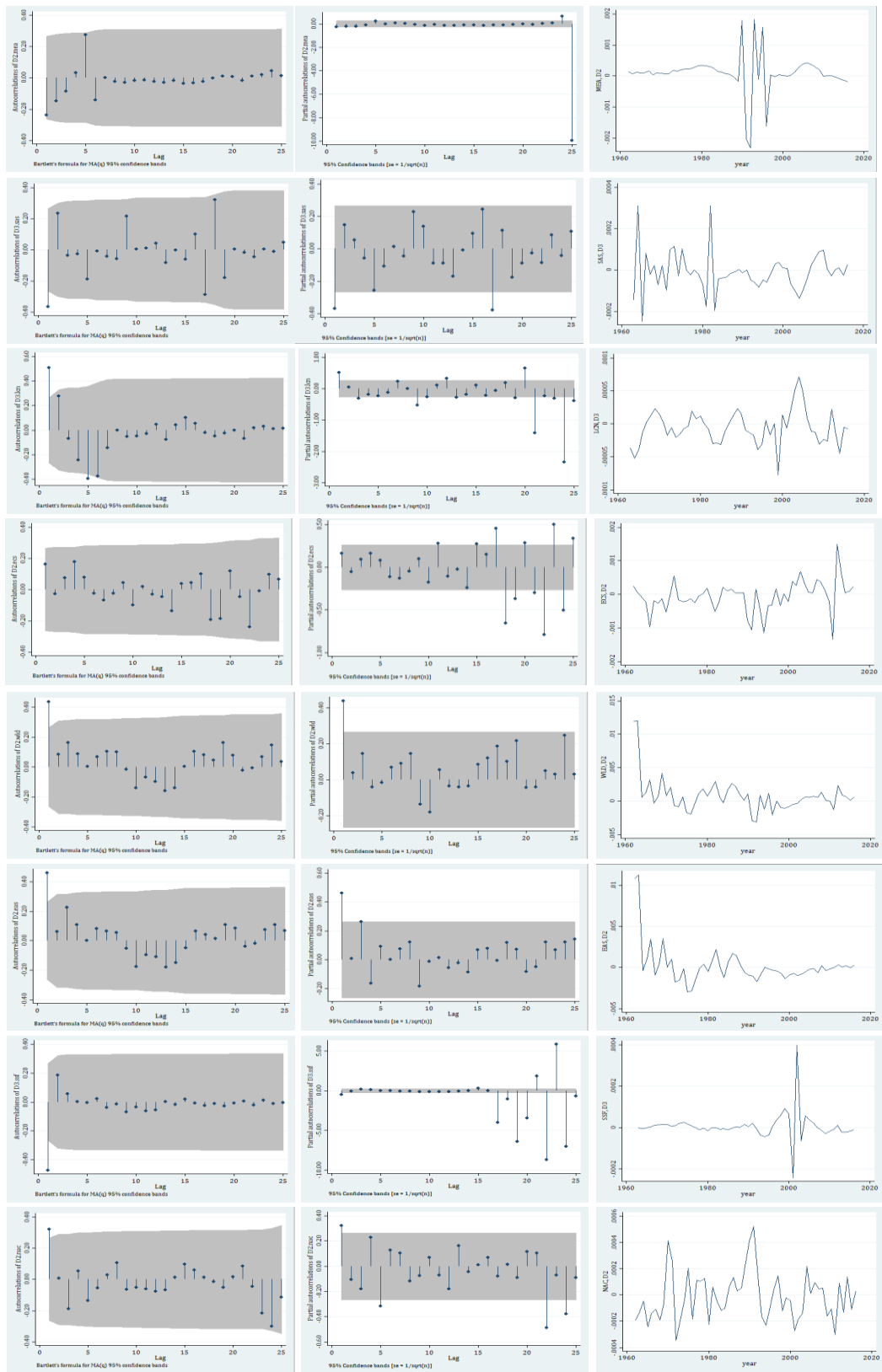
The trendy time plots and the weak dampening of the spikes in the autocorrelation plots confirm the need for differencing. Another test of stationarity adopted in the study is the Augmented Dickey-Fuller (ADF) test of unit root. The test hypothesized the presence of unit root in the data series. The test indicates the presence of unit root in the data series, i.e., we fail to reject the null hypothesis when the original data are subjected to the stationarity test. Investigating the order of integration for each of the regions, it shows that East Asia has I(2); becomes mean reverting at second order differencing. Sub-Saharan Africa has I(3); at the third order differencing. South-Asia has I(3); at the third order differencing. North America has I(2); at the second order differencing. Middle East and North Africa have I(2); at the second order differencing. Latin America and the Caribbean has I(3); at the third order differencing. Europe and Central Asia have I(2); at the second order differencing. The world has I(2); at the second order differencing. Fitting the ARIMA ( $p, d, q$ ) models, the  $d$  is specified as the order provided by the ADF test.

**Table 2.** Unit Root Tests

Variables	Level			Differencing		
	Order	Test Stat.	MacKinnon Appr. $P$ -val.	Order	Test Stat.	MacKinnon Appr. $P$ -val.
East Asia and Pacific (EAS)	I(0)	2.364	1.0000	I(2)	-5.940***	0.0000
Sub-Saharan Africa (SSA)	I(0)	19	1.0000	I(3)	-11.938***	0.0000
South Asia (SAS)	I(0)	8.771	1.0000	I(3)	-10.717***	0.0000
North America (NAC)	I(0)	-0.781	0.9672	I(2)	-5.220***	0.0000
Middle East and North Africa (MEA)	I(0)	11.591	1.0000	I(2)	-9.174***	0.0000
Latin America and Caribbean (LCN)	I(0)	-1.394	0.8628	I(3)	-4.159***	0.0008
Europe and Central Asia (ECS)	I(0)	16.146	-	I(2)	-6.120***	0.0000
World (WLD)	I(0)	6.946	1.0000	I(2)	-5.925***	0.0000

Note: Robust standard error in parentheses. \* $P < 0.1$ ; \*\* $P < 0.05$ ; \*\*\* $P < 0.001$

Source: The authors' calculation



**Fig. 3.** Differenced Population and Autocorrelation Plots (Middle East and North Africa, South Asia, Latin America and Caribbean, Europe and Central Asia, World, East Asia and Pacific, Sub-Saharan Africa, North America).

### 3.2. Model Identification

Based on graphical ACF and PACF function in the Fig. 3, the following ARIMA processes are generated. The order of  $p$  and  $q$  are chosen as explained in the Method (Section III). For example, Fig. 3. depicts that the spikes in both ACF and PACF plots cut at lag 1 for EAS. These possible models presented in Table 3.

**Table 3.** Possible ARIMA Models

	AR ( $p, d$ )	MA( $d, q$ )	ARIMA( $p, d, q$ )
East Asia and Pacific (EAS)	AR (1, 2)	MA(2, 1)	ARIMA(1, 2, 1)
Sub-Saharan Africa (SSA)	AR (1, 3)	MA(3, 1)	ARIMA(1, 3, 1)
South Asia (SAS)	AR (1, 3)	MA(3, 1)	ARIMA(1, 3, 1)
North America (NAC)	AR (5, 2)	MA(2, 1)	ARIMA(5, 2, 1)
Middle East and North Africa (MEA)	AR (1, 2)	MA(2, 1/5)	ARIMA(1, 2, 1/5)
Latin America and Caribbean (LCN)	AR (1/5, 3)	MA(3, 1)	ARIMA(1/5/6, 2, 1)
Europe and Central Asia (ECS)	AR (0, 2)	MA(2, 11)	ARIMA(0, 2, 11)
World (WLD)	AR (1, 2)	MA(2, 1)	ARIMA(1, 2, 1)

**Table 4.** Model Estimation

	Coefficients				Information Criteria			
	$\phi_1$	$\delta_1$	Constant	$\sigma$	Log Likelihood	RMSE	BIC	AIC
EAS								
AR(1)	0.694*** (0.0744)	–	0.000632 (0.00133)	0.00197*** (0.000116)	264.1703	0.001973	–516.318	–522.340
MA(1)	–	0.802*** (0.0974)	0.000259 (0.000569)	0.00185*** (0.000126)	267.4116	0.001864	–522.801	–528.8232
ARMA(1,1)	0.832*** (0.118)	–0.180 (0.328)	0.000984 (0.00189)	0.00197*** (0.000120)	264.1728	0.001969	–512.316	–520.3456
SSA								
AR(1)	–0.465*** (0.0604)	–	7.04e-06 (5.93e-06)	6.00e-05*** (3.44e-06)	448.1733	0.00006	–884.379	–890.346
MA(1)	–	–0.376** (0.150)	7.21e-06 (6.86e-06)	6.16e-05*** (6.11e-06)	446.8153	0.000062	–881.663	–887.6306
ARMA(1,1)	–0.417 (0.298)	–0.0620 (0.391)	7.06e-06 (7.28e-06)	6.00e-05*** (5.49e-06)	448.2134	0.00006	–880.470	–888.4269
SAS								
AR(1)	–0.374*** (0.108)	–	–0.000011 (0.000010)	0.000089*** (0.000008)	427.1143	0.000089	–842.261	–848.2287
MA(1)	–	–0.278** (0.108)	–0.000011 (0.000010)	0.000091*** (0.000008)	425.9705	0.000091	–839.974	–845.941
ARMA(1,1)	–0.670** (0.286)	0.330 (0.365)	–0.0000106 (0.0000111)	0.0000879*** (7.51e-06)	427.6145	0.000088	–839.273	–847.2289
NAC								
AR(5)	–0.138 (0.150)	–	–0.0000116 (0.0000246)	0.000180*** (0.0000175)	396.0568	0.000180	–780.091	–786.1135
MA(1)	–	0.288** (0.146)	–0.0000133 (0.000032)	0.0001729*** (0.0000179)	398.3673	0.000173	–784.713	–790.7345
ARMA(5,1)	–0.199 (0.140)	0.322** (0.152)	–0.000011 (0.000027)	0.0001694*** (0.0000174)	399.366	0.000169	–782.702	–790.732
ECS								
MA(11)	–	0.106 (0.209)	–0.0000544 (0.0000708)	0.0004556 (0.0000395)	–	–	–	–
WLD								
AR(1)	0.642*** (0.0653)	–	0.0011717 (0.0010161)	0.0021761 (0.0001349)	258.8515	0.002176	–505.680	–511.7029

EAS	Coefficients				Information Criteria			
	$\phi_1$	$\delta_1$	Constant	$\sigma$	Log Likelihood	RMSE	BIC	AIC
MA(1)	–	0.5636*** (0.130)	0.00089 (0.000613)	0.0022132 (0.000162)	257.9995	0.00221	–503.977	–509.999
ARMA(1,1)	0.798*** (0.123)	–0.191 (0.292)	(0.0014583 (0.0013668)	0.0021681 (0.0001416)	258.9626	0.002168	–501.895	–509.9252

Note: Robust standard error in parentheses. \* $P < 0.1$ ; \*\* $P < 0.05$ ; \*\*\* $P < 0.001$

Source: The authors' calculation

**Table 5. Model Estimation**

MEA	Coefficients					Information Criteria			
	$\phi_1$	$\delta_1$	$\delta_2$	Constant	$\Sigma$	Log Likelihood	RMSE	BIC	AIC
AR(1)	–0.233*** (0.058)	–	–	0.000089 (0.000082)	0.0006193*** (0.0000316)	328.2106	0.000619	–644.399	–650.4212
MA(1)	–	–0.400*** (0.091)	–	0.0000913 (0.0000595)	0.0006052 (0.0000292)	329.4197	0.000605	–652.839	–646.81
ARMA(1,1/5)	0.1167 (0.428)	–0.463 (0.485)	0.225 (0.162)	0.000084 (0.000093)	0.000584*** (0.000052)	331.1901	0.000584	–642.343	–652.3803
LCN	$\phi_1$	$\phi_2$	$\delta_2$	Constant	$\Sigma$				
AR(1/5)	0.431*** (0.0915)	–0.327** (0.137)		–5.42e–06 (3.86e–06)	0.0000205*** (1.38e–06)	505.8269	0.000021	–995.697	–1003.654
MA(1)	–	–	0.367*** (0.089)	–6.18e–06 (4.30e–06)	0.0000231*** (1.75e–06)	499.7145	0.000023	–987.462	–993.429
ARMA(1/5,1)	0.501** (0.227)	–0.318** (0.134)	–0.104 (0.248)	–5.42e–06 (3.82e–06)	0.0000204*** (1.40e–06)	506.005	0.000021	–992.065	–1002.01

Note: Robust standard error in parentheses. \* $P < 0.1$ ; \*\* $P < 0.05$ ; \*\*\* $P < 0.001$

Source: The authors' calculation

**Table 6. Adopted Model**

Region	Model
East Asia and Pacific (EAS)	MA(1)
Sub-Saharan Africa (SSA)	AR(1)
South Asia (SAS)	AR(1)
North America (NAC)	AR(5), MA(1)
Middle East and North Africa (MEA)	MA(1)
Latin America and Caribbean (LCN)	AR(1/5)
Europe and Central Asia (ECS)	–
World (WLD)	AR(1)

Source: The authors' calculation

### 3.3. Model Selection

Table 4 shows the estimation of the possible model as identified by the autocorrelation function and partial autocorrelation function in the Fig. 3. The stationary (differenced) data are estimated according to the identification of number of lags for autoregressive and Moving Average using the Root Mean Squared Errors (RMSE) along the Information Criterion; Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

These information criteria are very well used in practice to examine the model selection and performance. Cross-checking these values, lag 1 of the Moving Average MA(1) shows reliable RMSE and Information Criterion for Eastern Asia and Pacific (EAS). This indicates that the East Asia Population follows the ARIMA process. The immediate past disturbance to the population figures would significantly affect the current population figures. MA(1) better predicts and projects future population for the region. The magnitude of the spike (after differenced) of lag 1 of the Partial autocorrelation is estimated to be 0.8. East Asian population is said to respond spectacularly to the instantaneous past shocks in the population.

For Sub-Saharan Africa, the selection criteria indicate that the ARIMA process AR(1) is well suitable for the region. The immediate past population explains the current population. This is plausible for an ever-growing populated region of Sub-Saharan Africa. The magnitude of the spike of the autocorrelation for differenced variable matches the coefficient (-0.465) reported in the regression. RMSE and information criteria establish that AR(1) would forecast well enough than MA(1).

The model predicted for South Asia (SAS) also follows ARIMA process of AR(1). Although ARMA(1,1) as predicted by RMSE nicely fits tight enough with AR(1), the coefficients are not significant. SAS model will perform very well with AR(1), i.e., the past population determines the current population size. The magnitude of the spike of the first lag of the autocorrelation function is -0.37 for the first differenced data. Both AR(5) and MA(1) would be estimated for North America. This is because the information criteria and the RMSE could not agree on the model. When one of the information criteria agrees with RMSE, the choice of appropriate model is clear and the most favoured one is considered. In any case, both models are used in forecasting and compared with previous projections for the region.

The Middle East and North Africa are predicted to follow MA(1) ARIMA process. The past disturbance in the population is indicated to affect the current population size and is predicted to fit pattern of population growth in the region. As observed for South Asian region, the ARIMA(1,1) shows a better RMSE and lower information criteria. The model cannot be used because the coefficients are insignificant in the model. Therefore, the MA(1) is used for projecting population size in the region. The magnitude of the lag one spike of the partial autocorrelation for differenced data is -0.356. Latin America and the Caribbean is predicted to follow AR(1/5). Both the first and fifth lags of the population in region are shown to affect the current population in region. This model is chosen ahead of MA(1) because while examining the ARIMA(1/5,1), the coefficient became insignificant.

The current world population tends to respond well to the past year population changes than its disturbance. There is no absolute conclusion using both information criteria, but the behaviour of the population seems to respond well to past immediate changes than to past immediate shocks. RMSE is smaller while the autoregressive coefficient was still significant after estimating ARIMA(1,1). Europe and Central Asia could not identify any ARIMA process after differencing the population figures. Therefore, no projection would be made for these regions. The cross-examination of the model shows that a certain pattern is similarly followed by different regions. Eastern Asia and Pacific, and the Middle East and North Africa are predicted to follow MA(1) process. Sub-Saharan Africa and South Asia follow the AR(1) process.

Table 7 shows N-period ahead forecast for different horizons. The developed models in the previous tables are used to project the future population size and growth for the regions and the world. With STATA simple commands, the minimum Root Mean Square Error models project the following.

**Table 7.** Population Forecast

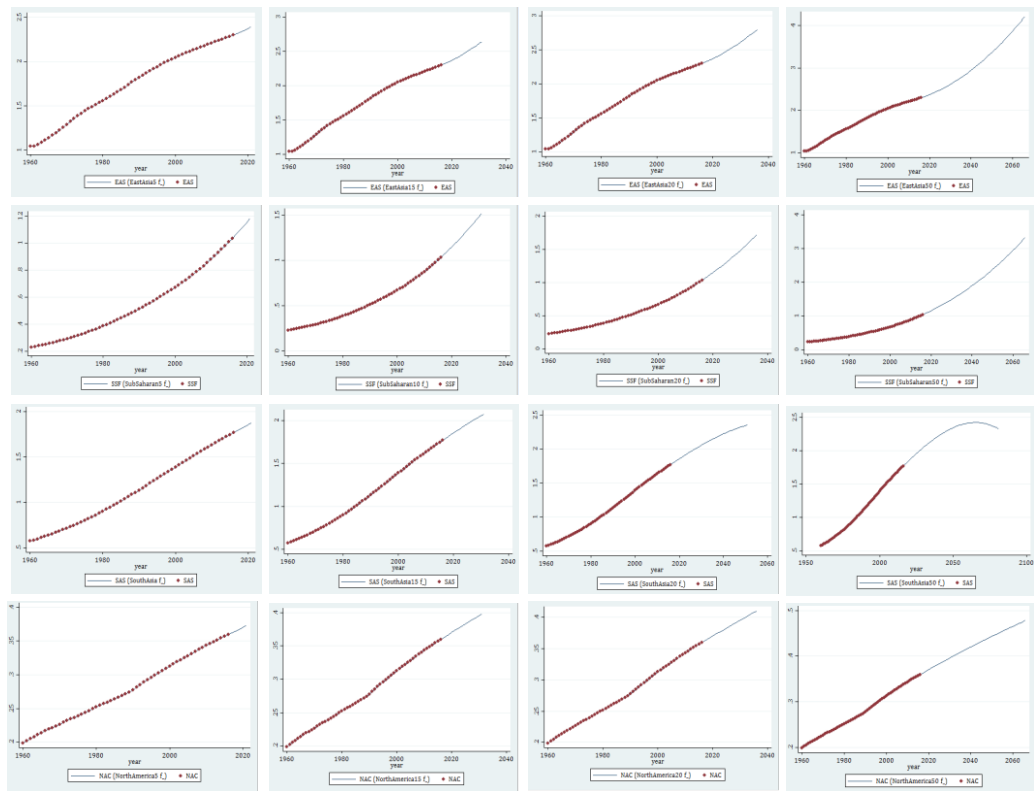
Region	Horizon			
	5 yrs Forecast, B	15 yrs Forecast, B	20 yrs Forecast, B	50 yrs Forecast, B
East Asia and Pacific (EAS)	2.389237	2.640884	2.800081	4.222494
Sub-Saharan Africa (SSA)	1.179962	1.522337	1.719617	3.324022
South Asia (SAS)	1.874431	2.071634	2.352047	2.323049
North America (NAC)	0.372604	0.397983	0.410237	0.477669
Middle East and North Africa (MEA)	0.477691	0.566480	0.614299	0.949157
Latin America and Caribbean (LCN)	0.668630	0.719115	0.7372009	0.703056
Europe and Central Asia (ECS)	–	–	–	–
World (WLD)	7.891292	8.874831	9.410457	–

Source: The authors' calculation using STATA

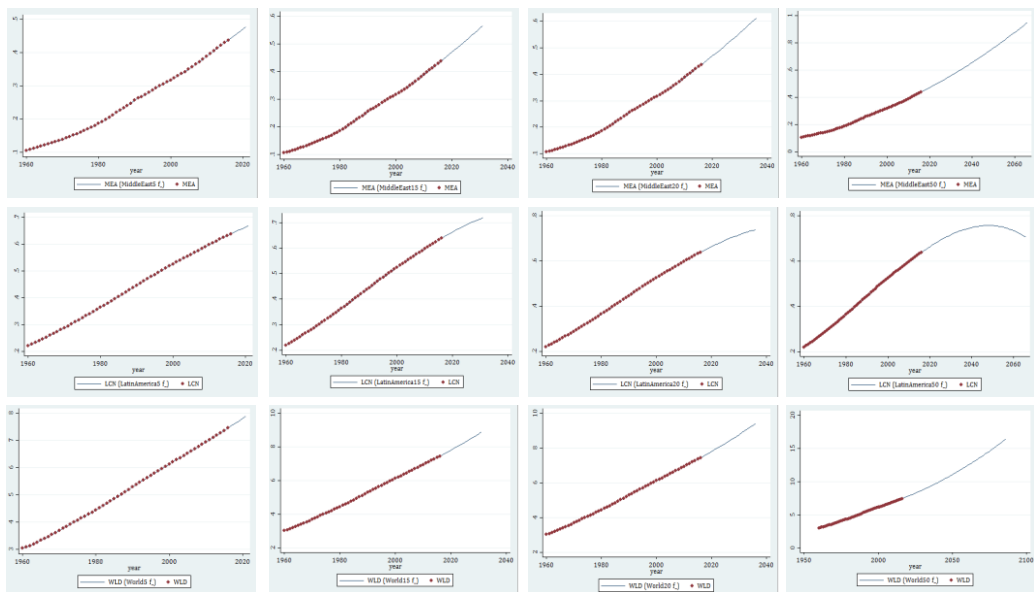
**Table 8.** Population Growth

Region	Horizon/ Growth rate (2016/100)			
	5 yrs	15 yrs	20 yrs	50 yrs
East Asia and Pacific (EAS)	4.03 %	14.98 %	21.91 %	83.84 %
Sub-Saharan Africa (SSA)	14.21 %	47.36 %	66.45 %	221.75 %
South Asia (SAS)	6.12 %	17.28 %	33.16 %	31.51 %
North America (NAC)	3.65 %	10.71 %	14.12 %	32.88 %
Middle East and North Africa (MEA)	9.38 %	29.71 %	40.66 %	117.34 %
Latin America and Caribbean (LCN)	4.86 %	12.77 %	15.61 %	10.25 %
Europe and Central Asia (ECS)	–	–	–	–
World (WLD)	6.04 %	19.25 %	26.45 %	–

Source: The authors' calculation using Excel



**Fig. 4.** Out-of-Sample Forecast: 5yrs, 15yrs, 20yrs & 50 yrs (East Asia and Pacific, Sub-Saharan Africa, South Asia, North America).



**Fig. 5.** Out-of-Sample Forecast: 5yrs, 15yrs, 20yrs & 50 yrs (Middle East and North Africa, Europe and Central Asia, Latin America and Caribbean, World).



The forecast table reveals the snapshot of population projections for different years. East Asia and Pacific is projected to add up to approximately 2.4 billion population in 2021, 2.6 billion in 2031, 2.8 billion in 2036 and 4.2 billion in 2066. The population increase in this region would be fairly stable over the next fifty years. The 50-year projection suggests the region would add approximately 84 % to its population over the period of fifty years.

Sub-Saharan Africa is projected to increase by approximately 222 % in the next fifty years. This accounts for the largest growth amongst the entire regions. The 5-year forecast indicates the population size of SSA would add up to approximately 1.2 billion in 2021; 15-year forecast indicates population size of 1.5 billion in 2031. By 2036, the population size of SSA would have increased more than half of its current population size. The 50-year forecast shows that the continent would have multiplied itself two times by 2066. South Asia maintained a stable level of growth but a decline in growth in the 50-year forecast. The region is projected to increase by approximately 6 % in 2021, 17 % in 2031, and 33 % in 2031 but there will be a decline in growth in 2066. As would be seen in the graphical growth path in the next sub-section, the population is projected to experience a decline in population for some period in the mid of the twenty-first century. The population projected dropped from 2.35 billion to 2.32 billion between 2036 and 2066.

The projection of the population of North America is fairly stable within the horizons. The population is forecast to increase by 3.7 % in the next five years, 19.7 % in 15 years, 14.2 % in 20 years and 32.8 % in 50 years. The size of the continent is projected to be 410 million in 2036 and 478 million in 2066. The Middle East and North Africa are projected to double their current number in the next fifty years. Its current size is forecast to grow by 9.38 % in 2021, 29.7 % in 2031, 40.66 % in 2036 and more than 100 % fifty years from now. Its population size would move from 437 million in 2016 to approximately 949 million in 2066 making the second projected fastest growing population in the world.

Population forecast for Latin America and the Caribbean indicates that the region will experience a stable growth for next twenty years but a decline in population thereafter. The 5-year projected population size for the region increased from 638 million in 2016 to 668 million in 2021 and 737 million in 2036. In 50 years, the population size nose-dived to 703 million with only 10.3 % growth from now. The world population exhibits a gradual growth rate within the forecast horizons.

The global population is projected to grow by 6 % in the next five years with population size of 7.9 billion as compared to 7.4 billion in 2016. Twenty years from now, the model reveals that population would have grown to 9.4 billion, an addition of 26.5 % change. No forecast is made for Europe and Central Asia. The four different horizon population forecasts reveal that all regions would experience positive growth for the next twenty years given the current level of fertility and mortality rate. As shown in Fig. 4 there was a similar pattern of growth during the course of twenty year – forecast for all the regions, the regions diverge over the next 30 years of forecast. Sub-Saharan Africa rose faster than others (Middle East, East Asia and North America) from the mid-2030s. These three other regions also exhibited an upward change in the growth path, but it was gradual. North America

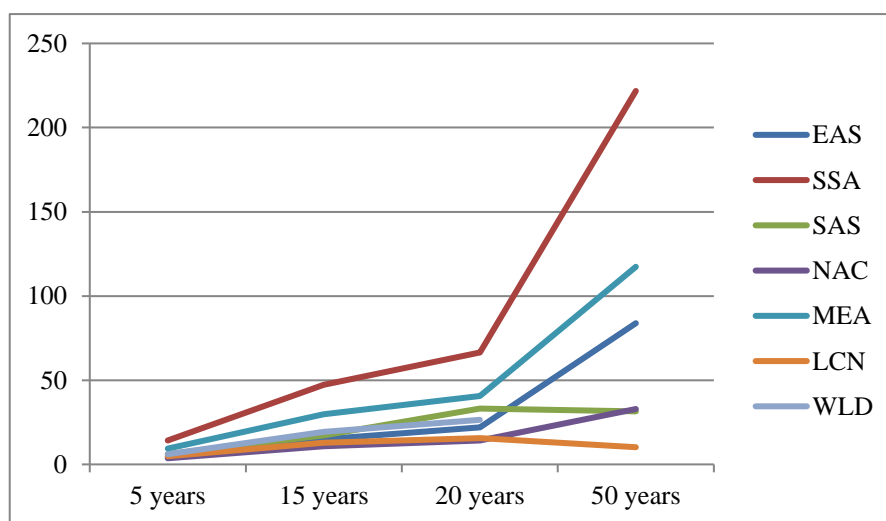
was the least in those regions changing the course of growth while converging with declining growth of South Asia. Both Latin America and South Asia indicate a declining growth rate after twenty years of growth and seem to maintain a constant growth after some periods.

### 3.4. Comparison of the Results and Evaluation of the Models

The adopted models used in projection did well in the estimation of the future population size of all the regions considered. Based on the assumption on the previous and current demographics, the projections showed that there would be an upward trend in population growth over the next twenty years.

These results support many research findings on the population path for these periods. 2017 Revision: World Population Prospects (United Nation, 2017) had once projected a continuous increase in human inhabitants on the planet for the projected periods. Consistent with the previous studies, the forecast growth in the world population in the next 50 years is expected to take place in Africa followed by the Asian continent. This substantial growth would be more pronounced in 50 years with Africa adding twice of its current size and significantly increasing its global share of the world population. There is therefore no contradiction when the United Nation (2017) projected Africa's fertility decline at some points in the century. Africa is predominantly youth getting to adult age. The maturity of the larger share of the people in this age bracket will cause them to reproduce themselves in the course of the years. The United Nations once revealed that these young people would mature to adulthood in future when they start bearing children.

As revealed by the empirical body of literature, sub-continent of Asia would experience a fertility decline over the course of some periods in the century. In the current study as shown in Fig. 6. South Asia would experience a decline in growth starting from the mid-2030s. This corroborates the expected fertility and overall population decline in the population size of Asia. Invariably, the region would experience the expected decrease in its current share of the global population.



**Fig. 6.** Population growth path.

The study also supports the increase at a decreasing rate of the global population growth. Fig 6. shows that the world population growth is relatively flat over the forecast periods, barely rising as observed for some regions. This result is in congruence with the expected growth predicted for the global population in literature. The size is projected to increase but increasing at a decreasing rate. The study guesses that counter-balance effects among the population of the regions might be an important factor for stabilizing the global population growth. Both Latin America and the Caribbean, and South Asia are forecast to decline between 2036 and 2066, while Sub-Saharan Africa, East Asia and North America show an increase within the periods. This finding is consistent with the literature. These models are perceived to perform pretty well in the projection of the future population size and the growth rate as the estimated results are consistent with recently estimated projections in literature. No projection could be made for European and Central Asia because of identification and estimation problem.

## CONCLUSION

The world population transition remains a serious contemporary issue at the forefront of sustainable development. This paper focused on projecting the world population figures for the period of 1960–2016. The findings of the study show various projections and population growth expected across different regions of the world. One main motivation is that the projections of the future population are fundamental in the process of drafting and implementing the global development policies especially in the regions that are expected to experience higher growth in the future. Thus, this projection remains policy instruments for crafting and addressing policy questions when nations meet at regional, international or global meetings. Even though the 2030 Agenda for Sustainable Development favours international migration as a pathway to even economic and social development and labour market rebalancing to improve world's labour productivity, the actualization of those highlighted goals in the programme still stand a test of time. This programme undermines the claimed adverse effect of cross-border migration and it is believed to engender a higher living standard in the less developed countries through their remittances.

Approaches to curtailing the population growth in some of the identified regions have been advocated for and are perceived to begin to take different outlook in the global and regional areas of the world. Several studies and the current one have provided foresight on the growth pattern of the human inhabitants across regions and continents signalling the need for a proactive step in helping the identified fast-growing regions, such as Sub-Saharan Africa. This must be done to ensure the balancing of their population growth with a sustainable level of economic growth.

It is essentially fundamental to address certain important questions on causes of the divergent economic development we see today and how developmental programmes can be used to combat the negative economic impacts of the high population projected for most developing regions in the world. Sub-Saharan Africa, often prone to migration, is established to exhibit large population until the end of

the century. This might pose a big immigration threat to developed and currently emerging economies in the near future. Likewise, East Asia (where a large portion of world inhabitants lives now) and the Middle East countries are forecast to increase more rapidly in fifty years. It may be plausible to say that reliability on migration for global development, as anticipated by the United Nations, is too simplistic to engender any appreciably needed level of development to combat an adverse effect of global population surge. The population projection as revealed in the study is not isolated inferences in the body of literature and its impact on the economic life of the inhabitants should be taken more seriously in achieving a balanced global society. To achieve a more appreciable and visible result in the drive towards population management, large-scale inter-regional cooperation and economic support that enhance simultaneous movement in population growth and economic expansion among nations should be promoted. The United Nations should rise beyond statistical projections and coordinate member nations for effective implementation of its various domestic and international support programmes. All should be done to co-opt the understanding and cooperation of all member states towards implementing this agenda.

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