

Comparative Analysis of Exponential, Logistic and Gompertz Models for Forecasting Afghanistan's Population up to 2050

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ABSTRACT

Good forecasts of population are vital to underpin economic planning, the formulation of public policy and sustainable development. Although many populations growth models have been utilized in demographic studies, limited research has systematically compared their predictive performance for Afghanistan using recent population data. The objective of this study is to forecast the population of Afghanistan up to 2050 by evaluating and comparing the performance of the Exponential, Logistic and Gompertz growth models. United Nations Department of Economic and Social Affairs (UN DESA), Population Division, World Population Prospects 2024 (Online Edition), annual population data 1990–2023. The data set was divided into a training set (1990–2013) and a testing set (2014–2023). The model parameters were estimated using the Nonlinear Least Squares (NLS) method. The model performance was evaluated using the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and the coefficient of determination (R^2). The results show that the Gompertz model gives the highest predictive accuracy in the testing dataset, outperforming both the Logistic and Exponential models for all evaluation metrics. The best model predicts Afghanistan's population will be about 83.24 million in 2050. Such findings could provide valuable evidence for demographic forecasting and can support policymakers in long-term planning, resource allocation, infrastructure development and sustainable development strategies in Afghanistan.

Keywords- Afghanistan Comparative, Analysis Exponential, Gompertz Model, Logistic Model, Population Forecasting.

I. INTRODUCTION

Population growth is one of the most important demographic indicators of economic development, social welfare, environmental sustainability and public policy planning. The government and policy makers need reliable population projections to plan for health, education, housing, employment, infrastructure expansion, food security and natural resources management (United Nations, 2024). The changes in fertility, mortality, migration and socio-economic factors affect the population dynamics, so the development of accurate forecasting approaches for sustainable development and evidence-based planning becomes increasingly important (Preston et al., 2001; United Nations, 2024).

Mathematical models of population growth have been widely used to describe population changes and predict future trends (Murray, 2002). Among these models, the Exponential, Logistic and Gompertz models are the most used deterministic models due to their computational simplicity and their ability to describe different population growth patterns (Murray, 2002; Akber et al., 2025). The Exponential model assumes that resources are unlimited and the growth rate is constant so it is appropriate for populations that are growing without constraints. But this assumption may result in unrealistic long-run forecasts, because it disregards environmental constraints. The Logistic model overcomes this shortcoming by including the notion of carrying capacity. The growth curve takes on the form of a S - shaped curve

which is symmetric. Conversely, the Gompertz model assumes an asymmetrical growth process in which the growth rate of the population is gradually reduced when the population reaches the maximum sustainable level (Gompertz, 1825; Murray, 2002). Differences in model assumptions can thus be important for the accuracy of forecasts in different demographic settings (Murray, 2002; Akber et al., 2025).

Previous theoretical studies have shown that the logistic and Gompertz models are flexible and appropriate for the description of population dynamics. In studies of generalized growth models, the Logistic and Gompertz equations have been shown to be special cases of more general population growth models. The relation between the Gompertz model and the θ -logistic model was established by Petroni et al. (2020) and Rodrigo and Zulkarnaen (2022) proposed a generalized population growth model with a time-dependent carrying capacity. These studies show that classical growth models are still useful, as they give interpretable parameters relating to the population growth rate and the limitations imposed by the environment.

The choice of Logistic and Gompertz models is very much related to the shape of population growth. Several studies have suggested the application of the Gompertz model for asymmetric growth patterns as it reaches the inflection point earlier and converges slowly to the carrying capacity. According to Pestana et al. (2023) and Dhar and Bhattacharya (n.d.), the Gompertz model is more flexible in case of gradual reduction of population growth over time. Similarly, studies conducted in uncertain environmental conditions have shown that both Logistic and Gompertz models may provide reliable population estimates under stochastic conditions (Samoletov and Vasiev, 2023).

Different results have been obtained in empirical studies on the best performing population growth model. Welagedara et al. (2019) found that the Gompertz model was better than the Logistic model in forecasting Sri Lanka's population, showing lower RMSE, MAPD and SMAPE values. However, Terano (2018) reported that among several mathematical growth models applied to the Philippine population forecasting, the Logistic model was the one that gave the lowest MAPE. Our results indicate that the model performance depends on demographic features, data availability and evaluation criteria.

Additionally, diverse results have been obtained with models featuring unrestricted and restricted growth. Pflaumer (2012) stated that Exponential model usually overestimated the future population, because it assumes the continuous growth without limitations. The predictions made by the Logistic and Gompertz models were more similar to the demographic projections by the official institutions. Also, Lenak et al. (2026) and Mahkya et al. (2026) showed that Logistic models are generally more realistic for predicting population than Exponential

models since they consider environmental limits and carrying capacity.

Some studies have evaluated several mathematical models simultaneously. Idemudia and Ojo (2023) fitted seven population growth models to the Nigerian population data and concluded that the Exponential model is better than the Logistic and Gompertz models which also gave high R-square values, based on AIC, BIC and MSE criteria. The results show that one should take into account many statistical indicators, not only one performance measure, when trying to choose the best forecasting model.

Besides the researchers adapted classical growth models for the forecast accuracy improvement. Ayinde (2019) developed a numerical scheme for solving the Gompertz growth equation and showed its application in long term population prediction. Rocha (2016) combined the Allee effect with the Gompertz-Logistic model and demonstrated that population thresholds can affect long-term survival. Furthermore, Bradshaw and Herrando-Perez (2021) showed that Gompertz-Logistic models can capture density-dependent population feedback better than traditional Logistic models.

Besides demographic forecasting, the Logistic and Gompertz models have been successfully applied in many fields of science. Tattersall et al. (2021) showed that Gompertz models fit well to describe asymmetric growth patterns in scientific publications and Vieira et al. (2022) emphasized the need for accurate carrying capacity estimation to improve Logistic predictions. Further, Kabareh and Mageto (2017) showed that Logistic models can produce robust carrying capacity estimates even with irregular fluctuations in the datasets.

There is a lot of international research on mathematical population models, but few studies have looked at population forecasting in Afghanistan using deterministic growth approaches. Most of the existing studies have focused on statistical time-series forecasting methods. Haqbin and Khan (2024) assessed the Bayesian ARIMA and Bayesian Structural Time Series (BSTS) models for forecasting the population of Afghanistan and found that Bayesian ARIMA performed better. To the best of our knowledge, the most recent population projection study for Afghanistan is Haqbin and Khan (2024) which is available as a preprint at Research Square and has not been peer-reviewed yet. Therefore, comparisons to this study should be made with appropriate caution. It was included as a contextual benchmark as no recent peer reviewed study was available at the time of this research which specifically forecasted the population of Afghanistan. However, their study was on statistical forecasting techniques and did not consider classical mathematical growth models such as Exponential, Logistic and Gompertz models.

The comparison of the previous studies and the present research is summarized below.

Feature	Haqbin & Khan (2024)	Welagedara et al. (2019)	Idemudia & Ojo (2023)	Present Study
Study Area	Afghanistan	Sri Lanka	Nigeria	Afghanistan
Data Source	World Bank / Macrotrends	National population data	Nigerian population data	UN World Population Prospects 2024
Study Period	1950–2022	Historical population data	Historical population data	1990–2023
Models	Bayesian ARIMA, BSTS	Logistic and Gompertz	Seven mathematical growth models	Exponential, Logistic, Gompertz
Model Type	Statistical time-series models	Deterministic growth models	Deterministic growth models	Deterministic growth models
Parameter Estimation	Bayesian approach	Nonlinear fitting	Statistical optimization	Nonlinear least-squares optimization
Validation Metrics	Bayesian criteria	RMSE, MAPD, SMAPE	R ² , AIC, BIC, MSE	RMSE, MAE, MAPE, R ²
Forecast Horizon	Annual population forecast	Population forecasting	Population forecasting	Forecast up to 2050
Best Model	Bayesian ARIMA	Gompertz	Exponential	Gompertz

Comparison shows that the previous studies have mostly used either statistical time series models or individual mathematical growth models. However, very few studies have compared Exponential, Logistic and Gompertz models on the same data set, same criteria of validation and population data of Afghanistan. Thus, a complete evaluation of deterministic growth models is still needed.

To address this research gap, this study tries to compare the performance of Exponential, Logistic and Gompertz population growth models in forecasting population of Afghanistan. Analysis was performed using annual population data (1990–2023) from the UN World Population Prospects 2024. The data set was divided into a training period (1990–2013) for estimating the parameters and a testing period (2014–2023) for the purpose of validating the model. Parameters were estimated by nonlinear least-squares optimization using Python. The model performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and coefficient of determination (R²).

The novelty of this study is to provide a systematic comparison of three classical deterministic models of population growth for Afghanistan, based on a unified dataset and evaluation framework. The findings are expected to be helpful in identifying the most suitable

mathematical model of growth for long-term population projection and provide useful evidence for demographic analysis, development planning and policy making in Afghanistan.

II. METHODS AND MATERIALS

In the present study a quantitative comparative modelling approach was applied to assess and compare the performance of three deterministic population growth models; the Exponential, Logistic and Gompertz models. The aim was to find out which model best fitted the pattern of past population growth in Afghanistan and gave the best long-term forecasts. The analysis includes parameter estimation, fitting a model, validation against independent observations and comparison based on statistical accuracy indicators.

2.1 Data Source and Data Partitioning

Annual population estimates of Afghanistan from 1990 to 2023 were downloaded from the United Nations Department of Economic and Social Affairs (UN DESA), Population Division, World Population Prospects 2024 (Online Edition). The dataset consisted of annual mid-year population estimates. Which was used to calibrate the model, validate the model and forecast into the future.

Table 1. Annual Population of Afghanistan (1990–2023)

Year	Population	Year	Population	Year	Population
1990	12,045,660	2002	21,378,117	2014	32,792,523
1991	12,238,879	2003	22,733,049	2015	33,831,763.5
1992	13,278,973.5	2004	23,560,653.5	2016	34,700,612
1993	14,943,172	2005	24,404,567	2017	35,688,934.5
1994	16,250,794.5	2006	25,424,094.5	2018	36,743,039
1995	17,065,835.5	2007	25,909,852	2019	37,856,121
1996	17,763,266	2008	26,482,622	2020	39,068,979

1997	18,452,091.5	2009	27,466,100.5	2021	40,000,412
1998	19,159,995.5	2010	28,284,088.5	2022	40,578,842
1999	19,887,784.5	2011	29,347,708	2023	41,454,761
2000	20,130,327	2012	30,560,034	—	—
2001	20,284,307	2013	31,622,704	—	—

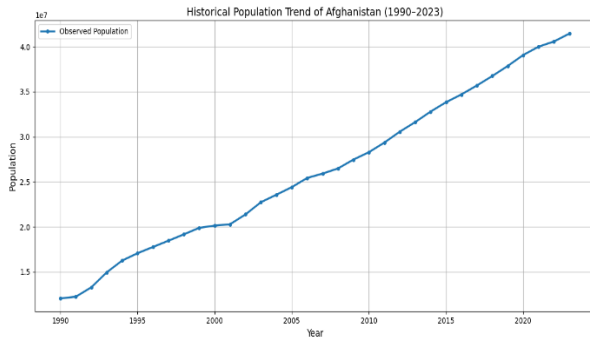


Figure 1. Historical population trend of Afghanistan from 1990 to 2023.

The data were split into two subsets. Parameter estimation was performed using data from 1990 to 2013 as training dataset, while model evaluation was performed using data from 2014 to 2023 as independent testing dataset. Using this method, the forecasting capability of each model was tested on new observations and the risk of overfitting was reduced.

2.2 Models of Mathematical Growth

In this study, the Gompertz, exponential and logistic models of deterministic population growth were assessed.

2.2.1 Model of Exponential Growth

The exponential model assumes that, in the absence of environmental constraints, population growth is continuous and occurs at a constant proportional rate. The governing differential equation is

$$\frac{dP(t)}{dt} = rP(t) \quad (1)$$

whose analytical solution is

$$P(t) = P_0 e^{rt} \quad (2)$$

where $P(t)$ denotes the population at time t , P_0 is the initial population and r is the intrinsic growth rate (Murray, 2002).

2.2.2 Logistic Growth Model

The Logistic model is an extension of the exponential model with the addition of the carrying capacity that limits the growth of the population due to environmental constraints. The model reads

$$\frac{dP(t)}{dt} = rP(t) \left(1 - \frac{P(t)}{K} \right) \quad (3)$$

and has the analytical solution

$$P(t) = \frac{K}{1 + Ae^{-rt}} \quad (4)$$

where K denotes the carrying capacity, r is the intrinsic growth rate and

$$A = \frac{K - P_0}{P_0} \quad (5)$$

The Logistic model yields a symmetric sigmoidal growth curve (Verhulst, 1838).

2.2.3 Growth Model: Gompertz

The Gompertz model assumes the relative growth rate decreases in a logarithmic fashion as the population approaches carrying capacity. It is expressed as:

$$\frac{dP(t)}{dt} = rP(t) \ln \left(\frac{K}{P(t)} \right) \quad (6)$$

and its analytical solution is

$$P(t) = Ke^{(-Ae^{-rt})} \quad (7)$$

with

$$A = \ln \left(\frac{K}{P_0} \right) \quad (8)$$

The Gompertz model produces an asymmetrical sigmoidal growth curve, unlike the Logistic model and is therefore particularly appropriate for long-term demographic forecasting (Gompertz, 1825).

2.3 Initial Parameter Estimates

The initial parameters were obtained from the training data set (1990-2013). The initial population (P_0) was set according to the first observation of the training dataset.

The carrying capacity (K) for the Logistic and Gompertz models was fixed at 400 million. This value was adopted based on previous studies of population projection (Akber et al., 2025). Here K was treated as a fixed parameter and not estimated, because the main objective was to compare the forecasting performance of models under the same carrying-capacity assumption. The other parameters, growth rate (r) and constant parameter (A), were estimated through nonlinear optimization using the training data.

2.4 Parameter Optimization

The model parameters were optimized using the Nonlinear Least Squares (NLS) method implemented in Python using the SciPy optimization library.

During optimization, only unknown parameters were adjusted, while P_0 and K remained fixed. The optimal parameters were obtained by minimizing the residual sum of squares (RSS):

$$RSS = \sum_{i=1}^n (P_i - \hat{P}_i)^2 \quad (9)$$

where P_i is the observed population and $\hat{P}_i$ is the predicted population. The optimization procedure was performed using the least-squares algorithm provided by the SciPy library (Virtanen et al., 2020).

2.5 Model Performance Evaluation

Each model has been trained and tested with the data. Five statistical indicators were employed:

The Mean Squared Error (MSE) is defined as

$$MSE = \frac{1}{n} \sum_{i=1}^n (P_i - \hat{P}_i)^2 \quad (10)$$

The Root Mean Square Error (RMSE) is

$$RMSE = \sqrt{MSE} \quad (11)$$

The Mean Absolute Error (MAE) is

$$MAE = \frac{1}{n} \sum_{i=1}^n |P_i - \hat{P}_i| \quad (12)$$

The Mean Absolute Percentage Error (MAPE) is

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{P_i - \hat{P}_i}{P_i} \right| \quad (13)$$

and the coefficient of determination is computed as

$$R^2 = 1 - \frac{\sum (P_i - \hat{P}_i)^2}{\sum (P_i - \bar{P})^2} \quad (14)$$

The smaller the values of MSE, RMSE, MAE and MAPE, the better the predictive accuracy and the larger the R^2 values, the better the agreement between the observed and predicted population values.

2.6 Model Selection and Prediction

The three models were compared based on their performance indicators on the training and testing datasets. The model with the lowest prediction errors and highest R^2 value was considered to be the most suitable forecasting model.

Subsequently, the selected model was used to produce Afghanistan's population projections from 2024 to 2050, based on the optimized parameters from the training data set.

III. FINDINGS

3.1 Estimates of model parameters

The Exponential, Logistic and Gompertz models were fitted using the training dataset (1990-2013). The initial population (P_0) was set to the observed population in 1990 and the carrying capacity (K) for the Logistic and Gompertz models was set to 400 million. The other parameters were estimated by non-linear least-squares optimization.

Table 2. Estimated parameters of the Exponential, Logistic and Gompertz population growth models From training dataset (1990–2013).

Model	Parameter	Estimated Value
Exponential	P_0	12,045,660
	r	0.044161
Logistic	K	400,000,000
	A	28.499548
	r	0.039545
Gompertz	K	400,000,000
	A	3.412190
	r	0.012941

The estimated parameters suggest differences in the growth behaviour of the models. The Exponential model produced the highest intrinsic growth rate, whereas the Logistic and Gompertz models included the constraint of carrying capacity and showed bounded population growth.

3.2 Model Fitting Results

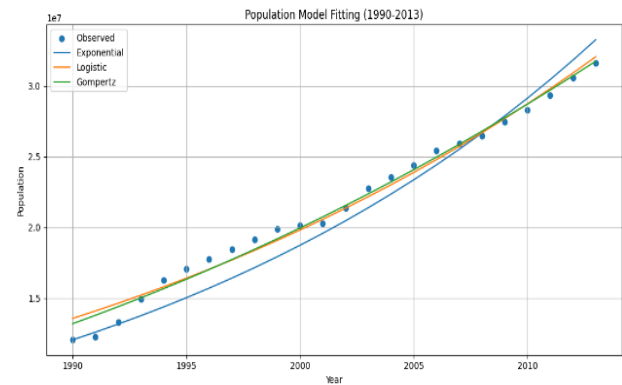


Figure 2. Population growth curves of the Exponential, Logistic and Gompertz models fitted by the training dataset (1990–2013).

Figure 1 shows the fitted curves of the three models. All models were consistent with the overall historical population trend during the training period. But the fitting patterns were different. The Exponential model deviated from the observed values towards the end of the training period while the Logistic and Gompertz models were more in line with the observed population data.

3.3 Performance of Training Dataset

Table 3. Population growth models performance on the training dataset (1990–2013).

Model	MSE	RMS E	MAE	MA PE (%)	R^2
Exponential	1.7009×10^{12}	1,304,199	1,130,412	5.504	0.9469
Logistic	5.4060×10^{11}	735,253	599,752	3.469	0.9831
Gompertz	3.8535×10^{11}	620,764	502,624	2.930	0.9880

Among all the models evaluated, the Gompertz model had the lowest values for MSE, RMSE, MAE and MAPE and the highest value for R^2 (0.9880). The Logistic model showed the second-best fitting performance. The Exponential model produced higher fitting errors.

3.4 Forecast Performance on Testing Dataset

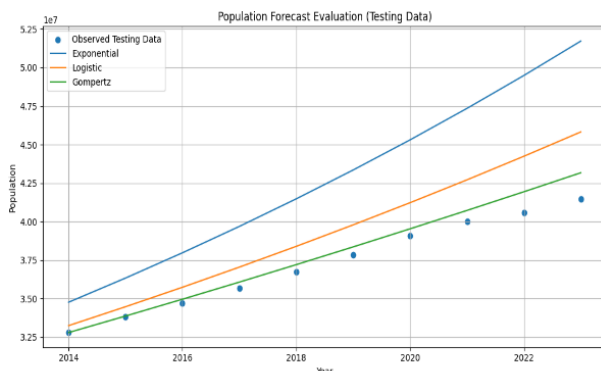


Figure 3. Forecasting performance of the Exponential, Logistic and Gompertz models for the testing period (2014-2023).

Figure 2 illustrates the comparison between the observed and predicted population values during the testing period. The Gompertz model matched the observed population trend better than the other models. The Logistic model showed moderate deviations while the Exponential model provided larger differences particularly in the later years. Performance on Test Dataset

Table 4. Evaluation of population growth models on testing dataset (2014–2023).

Model	MSE	RMS E	MAE	MAPE (%)	R ²
Exponential	3.6768×10^{13}	6,063,652	5,477,098	14.259	-3.5536
Logistic	5.4616×10^{12}	2,337,002	1,998,567	5.156	0.3236
Gompertz	6.2427×10^{11}	790,106	591,943	1.503	0.9227

The Gompertz model with the lowest RMSE (790,106), MAE (591,943) and MAPE (1.503%) values and the highest R² value (0.9227) presented the best performance for forecasting in the testing dataset. The Logistic model was less accurate in forecasting, the Exponential model exhibited the largest errors and a negative R² value. 3.6 forecasting future population using the Gompertz model Based on the performance of the testing, the Gompertz model was chosen for future population forecasting. The population of Afghanistan from 2024 to 2050 was estimated using the optimized parameters obtained from the training dataset.

Table 5. Afghanistan population projection with Gompertz model (2024-2050).

Year	Predicted Population	Year	Predicted Population	Year	Predicted Population
2024	44,429,034	2033	56,571,378	2042	70,143,951
2025	45,702,327	2034	58,012,159	2043	71,731,787
2026	46,995,034	2035	59,470,399	2044	73,334,457
2027	48,306,977	2036	60,945,838	2045	74,951,637
2028	49,637,970	2037	62,438,204	2046	76,582,998
2029	50,987,813	2038	63,947,219	2047	78,228,205
2030	52,356,297	2039	65,472,598	2048	79,886,920
2031	53,743,207	2040	67,014,047	2049	81,558,799
2032	55,148,312	2041	68,571,266	2050	83,243,496

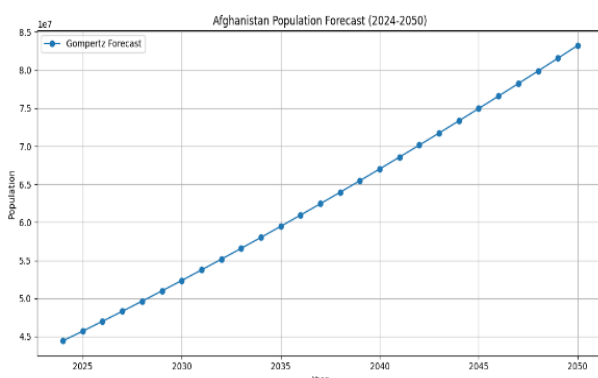


Fig. 4. Afghanistan population prediction by Gompertz model (2024-2050).

The forecast results suggest approximately that the population of Afghanistan will grow from about 44.43 million in 2024 to 83.24 million in 2050.

IV. DISCUSSION

The primary objective of this research was to find out the most suitable deterministic growth model for the population projection of Afghanistan by contrasting the Exponential, Logistic and Gompertz models in a combined calibration and validation framework. The results demonstrate that model selection has a strong effect on long-term population forecasts, even if all models are calibrated on the same historical data set. Of all the models evaluated, the Gompertz model provided the best predictive accuracy throughout and is suggested to provide the most realistic picture of the dynamics of the population in Afghanistan.

The better performance of the Gompertz model can be explained by the asymmetric sigmoid growth structure. Unlike the Exponential model which assumes unrestricted population growth and the Logistic model which assumes symmetric growth around the carrying

capacity, the Gompertz model allows the population growth rate to decline gradually over time. This behavior is more consistent with actual demographic systems, where population growth is affected by slow changes in fertility, mortality, migration, socioeconomic development and resource availability. Therefore, the Gompertz model was better able to capture the observed population trajectory of Afghanistan.

The worse performance of the exponential model confirms the fact that the assumption of a constant growth rate is not appropriate for long-term demographic forecasts. Although the Exponential model adequately accounts for the early stages of population growth, it does not take into account environmental limitations and demographic changes that become more prominent as time goes on. In the same way, although the Logistic model improved forecasting accuracy by including a carrying capacity, the assumption of symmetric population growth was a limitation in explaining the slower decline in growth rate found in the Afghan population.

The results are generally consistent with previous studies reporting the Gompertz model's superior performance in long-term demographic forecasting. Welagedara et al. (2019) found that the Gompertz model was more accurate than the Logistic model in predicting Sri Lankan population data. Pflaumer (2012) also reported that Gompertz-based forecasts were closer to official demographic forecasts than unrestricted growth models. However, Terano (2018) found that the Logistic model was more suitable for the population data of the Philippines. These variations indicate that the model's performance depends on the country-specific demographic characteristics, the period of the observation and the evaluation criteria used. Thus, no population model can be optimal in all cases, which underlines the need for assessing models using data specific to each country.

The expected growth in the population of Afghanistan from about 44.43 million in 2024 to 83.24 million in 2050 has a major impact on the national development planning. Continued population growth will likely increase demand for education, health care services, job opportunities, housing, transportation, food security, water resources and energy infrastructure. Therefore, reliable long-term population forecasts can provide useful quantitative evidence to the policymakers in designing sustainable development strategies and allocating public resources efficiently.

The encouraging results notwithstanding, some limitations should be noted. The carrying capacity was assumed constant throughout the analysis, whereas the demographic capacity may change due to technological progress, economic development, environmental conditions, migration and public policy. Moreover, the models were constructed using only historical population data and did not explicitly incorporate demographic drivers such as fertility, mortality, migration, age

structure, or socioeconomic variables. Therefore, the forecasts should be viewed as projections of past growth trends rather than accurate predictions of future population size.

V. CONCLUSION

In this research, the exponential, logistic and Gompertz growth models were used to compare and find the most appropriate mathematical model to predict the population of Afghanistan using the annual population data of 1990-2023. We systematically evaluated the predictive performance of the three classical deterministic growth models using a common parameter estimation procedure and an independent training-testing validation framework.

The results indicated that the Gompertz model provided the best forecasting accuracy which was consistently better than the Exponential and Logistic models. The asymmetric growth structure enabled it to represent the population dynamics of Afghanistan more realistically and therefore it was the most suitable model for long-term population forecasting. According to the optimized Gompertz model, the population of Afghanistan will increase from around 44.43 million in 2024 to around 83.24 million in 2050.

The main contribution of the present study is the first systematic comparative evaluation of the Exponential, Logistic and Gompertz models for Afghanistan, based on a unified dataset, identical parameter estimation procedures and independent validation data. The results provide practical evidence for the choice of an appropriate mathematical growth model and can assist government agencies and policy makers in demographic planning, infrastructure development, education, health care, employment and sustainable resource management.

The results should be interpreted, however, within the framework of the assumptions of the models adopted. Future studies should include demographic and socioeconomic determinants, explore uncertainty with confidence and prediction intervals, perform sensitivity analyses on key model parameters and compare classical growth models with advanced statistical and machine learning methods to enhance the reliability of long-term population forecasts for Afghanistan.

AUTHORS CONTRIBUTIONS

Said Rahman Danish conceived the study, designed the methodology, contributed to the development of the research methodology, collected and processed the population data, performed the mathematical modelling and statistical analysis, interpreted the results and prepared the original manuscript.

Abdul Wakil Bidar contributed to the development of the research methodology, reviewed the mathematical

modelling approach and provided scientific feedback during the preparation of the manuscript.

Naqibullah Darwish involved in data analysis validation, result review and critical revision of the manuscript for quality and clarity.

All authors have read and approved the manuscript in its final form.

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Funding was not provided for the manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The population data used in this study were obtained from the United Nations Department of Economic and Social Affairs (UN DESA), Population Division, World Population Prospects 2024 database and can be freely accessed at:

All The data generated and (analysed) during the present study is available in the corresponding public source and is available from the corresponding author upon reasonable request.

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