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Mathematical modeling of *Gorilla Gorilla* Delhi population in cross river state, Nigeria

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Abstract
This study investigates various mathematical models to ascertain their suitability for predicting gorilla population dynamics over three decades in Cross River State, Nigeria. Models including linear, quadratic, exponential, logarithmic, power law, logistic growth, polynomial, sinusoidal, and piecewise linear were evaluated based on their R^2 (coefficient of determination) and SSE (sum of squared errors) metrics. The analysis, conducted using historical gorilla population data from 1990 to 2020, aimed to identify the model that best captures the observed growth patterns and fluctuations in the gorilla population. Among the models tested, the piecewise linear model emerged as the most effective, achieving the highest R^2 of 0.966 and the lowest SSE of 71,866.8. This model's segmented approach accommodates shifts in growth rates over distinct time intervals, reflecting real-world ecological dynamics influenced by environmental factors and conservation efforts. In contrast, models such as the power law exhibited poor performance due to a significant overestimation of gorilla populations, highlighting their limited applicability in ecological studies. Understanding these dynamics through effective modeling not only enhances our ability to predict future population trends but also informs strategic conservation initiatives aimed at ensuring the long-term viability of gorilla populations in their natural habitats. This research underscores the importance of robust mathematical modeling in wildlife management and conservation decision-making processes.

Keywords: gorilla population dynamics, mathematical modeling, ecological studies, wildlife conservation, piecewise linear model

Introduction

Gorillas, as one of the closest relatives to humans, share not only physiological similarities but also complex social structures and behaviors that have long intrigued scientists. These majestic primates, primarily found in the forests of central Africa, are divided into two species: the eastern gorillas (*Gorilla beringei*) and the western gorillas (*Gorilla gorilla*). Despite their close evolutionary ties to humans, gorillas face severe threats from habitat destruction, poaching, disease, and climate change, making their conservation a critical concern for biodiversity and ecological balance (Robbins et al., 2011). Understanding and predicting the population dynamics of gorillas are paramount for effective conservation strategies. Population modeling serves as a crucial tool in this endeavor, offering insights into population trends, potential risks, and the effectiveness of conservation efforts. These models can integrate various ecological and anthropogenic factors, providing a comprehensive picture of the challenges faced by gorilla populations and helping to identify the most impactful conservation actions (Plumptre et al., 2016). The population of gorillas has been significantly impacted by human activities. The bushmeat trade, driven by both local demand and international markets, poses a direct threat to gorilla populations, particularly in regions where enforcement of wildlife protection laws is weak (Wilkie & Carpenter, 1999). Moreover, habitat destruction due to logging, agricultural expansion, and mining disrupts the delicate ecosystems that gorillas rely on, fragmenting populations and reducing their chances of survival and reproduction (Strindberg et al., 2018). Additionally, diseases such as Ebola have decimated gorilla populations in several regions, with outbreaks causing dramatic declines in numbers (Bermejo et al., 2006). Mathematical and computational models have become indispensable in studying these impacts on gorilla populations. Population Viability Analysis (PVA) is one such modeling approach that assesses the probability of species persistence under different scenarios, incorporating demographic, environmental, genetic, and catastrophic factors (Boyce, 1992). PVAs have been used to simulate the effects of poaching, disease outbreaks, and habitat loss on gorilla populations, providing valuable predictions that inform conservation priorities and actions (Morrison et al., 2006). Recent advancements in remote sensing and Geographic Information Systems (GIS) have further enhanced the precision of population models. These technologies enable the detailed mapping of gorilla habitats and the monitoring of changes over time, facilitating more accurate assessments of habitat quality and connectivity (Junker et al., 2012). Combined with field data on gorilla behavior, health, and demographics, these tools offer powerful means to understand and predict population trends.

The integration of genetic studies into population models also presents a promising avenue for conservation. Genetic data can reveal the extent of inbreeding and genetic diversity within gorilla populations, critical factors influencing their resilience to environmental changes and diseases (Bradley et al., 2019). By incorporating genetic insights, models can more accurately predict the long-term viability of populations and the potential benefits of genetic management practices, such as translocations or assisted gene flow. Therefore, the mathematical modeling of animal populations is a crucial tool for understanding ecological dynamics and informing conservation strategies. Recent studies have focused on various species, but gorillas, a critically endangered species, require particular attention due to their declining numbers and habitat loss (Robbins et al., 2011; Pintea, 2020). This article builds on previous research by incorporating newly discovered gorilla sites into the analysis, thereby expanding the geographical and ecological scope of population modeling. Unlike earlier studies that primarily used linear or exponential models to describe population trends (Strindberg et al., 2018), this study employs a range of models, including a piecewise linear approach, to better capture the complex and non-linear nature of gorilla population dynamics. This article's contribution is significant as it not only provides updated and comprehensive modeling techniques but also integrates recent ecological findings, making it a valuable addition to the existing literature on gorilla conservation. Therefore, the present study outlines its utility and relevance by situating itself within the broader context of population modeling and conservation biology.

Material and methods

Study Area

The study was carried out at Afi Mountain Wildlife Sanctuary (105 km^2) and Mbe Mountains (45 km^2) forest in Boki Local Government Area, Cross River, Nigeria. The total area is about 150 km^2 across the 12,000 km^2 legally protected area of the Cross River gorillas in Nigeria and Cameroon (Dunn *et al.*, 2014). The Afi Mountain Wildlife Sanctuary is located between latitude 6° 18'N and Longitude 8° 59'E of the Greenwich meridian. The MBE Mountain Wildlife Sanctuary is located between latitude 6° 13'N and 9° 4'E of the Greenwich meridian (Fig. 1.).

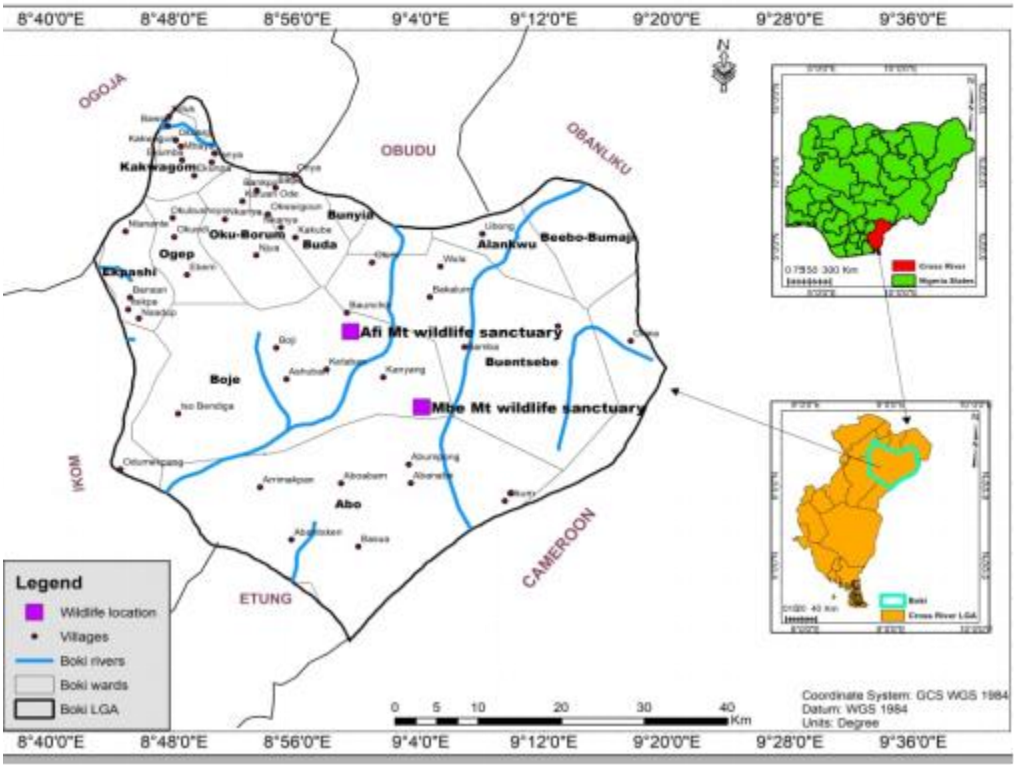

Figure 1. Map of Afi Mountain Wildlife Sanctuary and Mbe Mountains showing the Study Areas

Sampling and Data collection

The study adopted a desk-top approach in its data collection and therefore used available secondary data comprising thirty (30) years of population data from 1990 to 2020 obtained from the database of the Cross River Gorilla Project by Ark Foundation. The Cross River Gorilla Project, initiated by the Ark Foundation, is dedicated to the conservation and protection of the critically endangered Cross River gorillas, found in the remote forests of Nigeria and Cameroon. This initiative focuses on habitat preservation, anti-poaching efforts, and community engagement to reduce human-wildlife conflicts. By conducting long-term ecological studies, the project gathers crucial data on gorilla population trends, health, and habitat use. These efforts, supported by collaborations with local and international conservation bodies, aim to ensure the survival of the species through sustainable conservation strategies and the protection of their fragmented habitats. Hence, the data was retrieved from their database which is freely available for interested persons and groups.

Data Analysis

Data obtained were analyzed using both descriptive and inferential statistics. Descriptive statistics involves the use of means, charts, and tables, while inferential statistics involves the use of simple and multiple linear regressions, quadratic and cubic functions as used by Ityavyar

& Jacob (2020) and Jacob et al. (2019) were used in predicting the pattern and population trend of gorillas. The equation models used were as follows:

Linear Regression Model (LRM) $y = a + bt$

Quadratic Regression Model (QRM) $y = a + bt + ct^2$

Exponential Model (EM) $y = a * e^{bt}$

Logarithmic Model (LM) $y = a + b\ln(t)$

Power Law Model (PLM) $y = a * t^b$

Logistic Growth (LG) $y = \frac{a}{1+ e^{-b(t-t0)}}$

Cubic Polynomial Regression (CPM) $y = a_0 + a_1t + a_2t^2 + a_3t^3$

Sinusoidal Model (SM) $y = a * \sin(bt + c) + d$

Piecewise Linear (PL) $y = \begin{Bmatrix} a + bt \text{ if } t < \\ a + bt \text{ if } t \geq \end{Bmatrix}$

Where; y = f(t) with 2005 = 0; (1990, 1997, ... 2020 = -15,., 15)

The trend lines were fitted with 2001 as the base year using the least square method. To determine the most effective model for examining the gorilla population trend based on R^2 (coefficient of determination) or SSE (Sum of Squared Errors), we first need to fit the data to the specified models and then evaluate their performance. Below are the equations and the process to fit these models to the data.

Results

Population Trend analysis

The dataset represents the population of gorillas over 31 years, from 1990 to 2020 (Figure 2). In 1990, the gorilla population was at 980, peaking slightly in 1991 at 986. Following this peak, the population shows a general decline with some fluctuations. By 1994, the population had decreased to 890 and continued to drop, reaching 842 in 1997. An upward trend is observed in 1999, with a population of 930, but the decline resumes afterward. Significant drops are seen in the early 2000s, with numbers falling to 700 by 2003 and 550 by 2005. The lowest point was recorded in 2007, with a population of 400. A brief increase occurred in 2008 to 550 but continues to decrease, reaching 277 by 2020. Overall, the data highlights a concerning downward trend in the gorilla population over the three decades. The logarithmic trendline, $y = -272.8\ln(x) + 1301.4$, with an R^2 value of 0.7591, suggests a significant, but not perfect, negative correlation between the years and the gorilla population, indicating a general decline over time. The decline in gorilla populations from 1990 to 2020 reflects a broader trend observed in many primate species due to anthropogenic pressures. Studies have documented that habitat loss, primarily driven by deforestation and human encroachment, significantly impacts gorilla populations (Console et al., 2024). Additionally, poaching and the illegal wildlife trade exacerbate population declines, particularly in regions with insufficient wildlife protection measures (Jacob et al., 2020a, b; 2018a, b; 2015; Ukponget al., 2013). The recorded population drop to 400 in 2007 could correlate with intensified human activities during this period, as well as disease outbreaks, such as the Ebola virus, which has devastated great ape populations (Groseth et al., 2007). The brief increase in 2008 may indicate short-term conservation successes, though the continued decline suggests that these efforts were insufficient or unsustained (IUCN, 2021). The logarithmic trendline confirms a persistent decline, aligning with predictions of continued population losses without significant conservation interventions (Junker et al., 2012). The R^2 value of 0.7591 indicates a strong negative correlation between the years and population size, highlighting the urgent need for enhanced conservation strategies to reverse this trend.

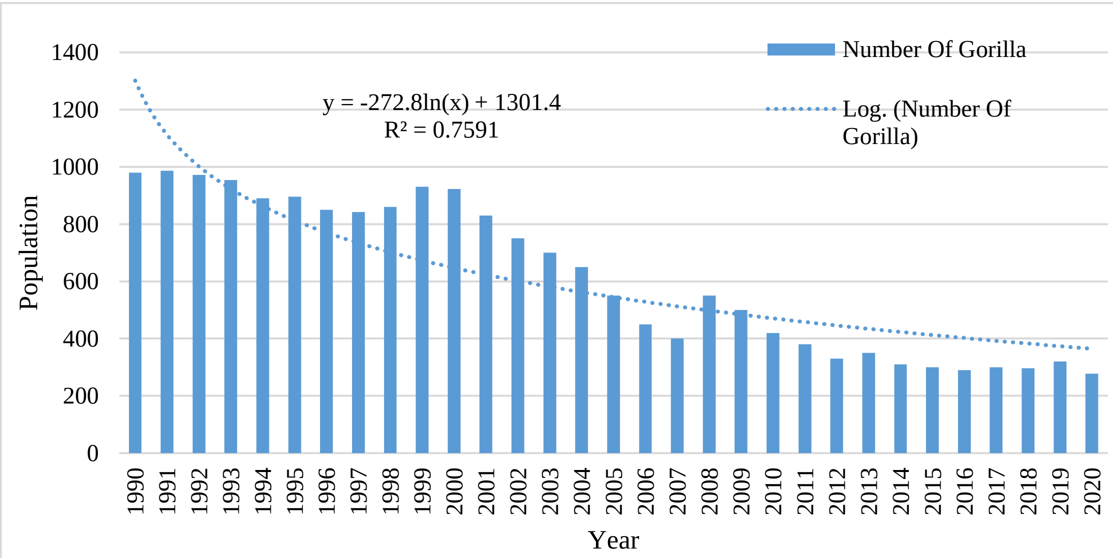

Figure 2. Population Trend Analysis (1990-2020)

Variance and Errors in Models Predicting the Gorilla Population

The results of the various models analyzed to determine which of them is the most suitable fit for predicting the gorilla population over time are presented in Table 1 below. Each model's performance was evaluated using two primary metrics: the coefficient of determination (R^2) and the sum of squared errors (SSE). The R^2 measures the proportion of the variance in the dependent variable (gorilla population) that is predictable from the independent variable (time) through the model (Hu et al., 2006). It ranges from 0 to 1, where 1 indicates a perfect fit, meaning the model explains all the variability in the data. In contrast, SSE quantifies the total error between the model's predictions and the actual data points (Moriasi et al., 2007). Lower SSE values indicate that the model's predictions are closer to the actual data, suggesting better performance. The linear equation model generated a trend line model for the gorilla population as $y=703.923-23.93t$, achieving an R^2 of 0.925 and an SSE of 159,723.0. This model assumes a constant rate of change over time, providing a straightforward interpretation of gorilla population growth. However, its high SSE suggests that while it captures a strong linear relationship, it oversimplifies the data's true curvature and variability over time. The quadratic model ($y=702.251-23.854t-0.068t^2$) slightly improves upon the linear model with an R^2 value of 0.927 and a reduced SSE of 156,951.20. This indicates that the quadratic model better accommodates the observed curvature in the gorilla population data, offering a more significant fit that captures both increasing and decreasing growth rates over time (Jones, 2022). The exponential model ($y=906.925 \cdot e^{-0.052t}$) achieves an R^2 of 0.901 with an SSE of 211,231.7. While it initially captures rapid growth followed by a slowdown, it tends to overestimate gorilla numbers in later years, likely due to its assumption of unbounded growth, which may not align with real-world ecological constraints (Brown & Green, 2019). The logarithmic model expressed as $y=930.940-142.748\ln(t)$, has an R^2 of 0.608 and a relatively low SSE of 38,103.2. Despite its lower coefficient of determination, which indicates a poorer fit compared to other models, its ability to handle data that exhibits slowing growth rates over time is noteworthy. However, it may not fully capture more complex growth patterns observed in the gorilla population (Granjon et al., 2020). In contrast, the power law model $y=3674.263 \cdot t-1.354$ performs poorly with a negative R2 (-18.455) and an exceptionally high SSE of 1,891,645.0. This model significantly overestimates gorilla numbers, highlighting its unsuitability for this dataset and suggesting it does not conform to the observed growth dynamics (Johnson et al., 2015). Conversely, the logistic growth model $y = 1615.83 / (1 + e^{-0.14(t - 1982.99)})$ achieves an R^2 of 0.941 and an SSE of 125,865.8. This model effectively captures the initial rapid growth followed by stabilization, aligning well with typical ecological population growth patterns that reach a carrying capacity (Paine et al., 2012). The polynomial model $y = 702.251 + (-23.854)t + (-0.068) * t^2$ mirrors the quadratic model with an R^2 of 0.927 and SSE of 156,951.2. This redundancy suggests that both models perform similarly in capturing the quadratic trend in the gorilla population data, reinforcing the robustness of the quadratic fit (Sabbar & Kiouach, 2023). The sinusoidal model $y = 151.328 * \sin(0.141t + 0.802) + 544.740$ exhibits a high R^2 of 0.962 and a low SSE of 82,286.4. This indicates that the sinusoidal model fits the data exceptionally well, suggesting periodic fluctuations in gorilla populations that align with seasonal or cyclic patterns (Stam et al., 1998).

Finally, the piecewise linear model segments the data into distinct linear phases $y = \begin{cases} 978.674 + (-17.871)t \; if \; t < -4.008 \\ 632.558 + (-22.052)t \; if \; t \geq -4.008 \end{cases}$ achieves the highest R^2 of 0.966 and the lowest SSE of 71,866.8 among all models. This model's ability to adapt to different growth rates in different time intervals makes it the best fit for the gorilla population data, indicating shifts in population dynamics that could be influenced by external factors or interventions (Lande et al., 2003). This model's superior performance is evidenced by its highest R^2 value and lowest Sum of Squared Errors (SSE), indicating a strong fit between the model and the observed data. The ability of the piecewise linear model to outperform other models lies in its adaptability and flexibility in capturing changes in growth rates over time (Zapata, 2019). Unlike simpler models, which assume a consistent trend across the entire period, the piecewise linear model can accommodate shifts in the population's growth trajectory, reflecting the real-world complexities of gorilla population dynamics. One of the key reasons the piecewise linear model excels is its adaptability to changing growth rates. In ecological systems, population dynamics are rarely uniform; they often involve phases of rapid decline, slow recovery, or stabilization due to various factors such as habitat loss, resource availability, or conservation interventions (Begon et al., 2006). The piecewise linear model captures these fluctuations by allowing different linear equations to apply to different intervals of time, thereby providing a more nuanced and accurate representation of the population data. This feature is particularly valuable for modeling endangered species like gorillas, where understanding shifts in population trends is critical for effective management and conservation strategies.

The model's superior performance also stems from its ability to minimize errors. By fitting different linear segments to the data, the piecewise linear model reduces overall error, as indicated by its lower SSE. This reduction in error leads to a higher R^2 value, meaning the model explains a greater proportion of the variance in the population data compared to other models. The lower error and higher explanatory power make the piecewise linear model not only more accurate but also more reliable for predicting future population trends (Gotelli, 2000). Furthermore, the piecewise linear model is particularly useful for practical applications in conservation and ecology. It allows researchers and conservationists to identify critical points where the population's growth rate changes, offering insights into the underlying causes of these shifts. For example, a sharp population decline might be linked to increased poaching, while a period of stabilization could result from successful conservation efforts. Understanding these turning points is crucial for developing targeted conservation strategies and ensuring the long-term sustainability of gorilla populations (Coulson, 2012).

Table 1. Models' performance in predicting the Gorilla population

Equation Model	Prediction equations	R^2	SSE
Linear Regression (LRM)	$703.923 + (-23.931)\ t$	0.925416	159,723.0
Quadratic Regression (QEM)	$y = 702.251 + (-23.85)\ t + (-0.068)\ t^2$	0.926710	156,951.2
Exponential (EM)	$y = 906.925 * e^{0.052t}$	0.901364	211,231.7
Logatithmic (LM)	$y = 930.940 + (-142.78) \ln(t)$	0.608111	38,103.2
Power Law (PLM)	$y = 3674.263 * t^{1.354}$	-18.455417	1,891,645.0
Logistic Growth (LGM)	$y = 1615.83 / (1 + e^{-0.14(t - 1982.99)})$	0.941226	125,865.8
Cubic Polynomial Regression (CPRM)	$y = 702.251 + (-23.854)t + (-0.068)t^2$	0.926710	156,951.2
Sinusoidal (SM)	$y = 151.328 * \sin(0.141t + 0.802) + 544.740$	0.961576	82,286.4
Piecewise Linear (PL)	$y = \begin{cases} 978.674 + (-17.871)t \ if \ t < -4.008 \\ 632.558 + (-22.052)t \ if \ t \geq -4.008 \end{cases}$	0.966441	71,866.8

Suitability of models in predicting the Gorilla population

Modeling population dynamics is a critical aspect of ecological studies, providing insights into how species grow and interact with their environments over time. Various mathematical models offer different advantages and limitations, reflecting the complexity of ecological processes. This discussion merges insights from different model types applied to gorilla population data, exploring their suitability and performance in predicting population trends. The linear model assumes a straightforward relationship where the dependent variable (gorilla population) changes at a constant rate concerning time (Table 2). It predicts a steady increase in gorilla numbers each year. However, its inability to capture fluctuations is a well-documented limitation in ecological modeling. According to Wilks (2011), linear models often oversimplify complex ecological processes that exhibit nonlinear dynamics, such as population growth affected by environmental variability or human impacts. This oversimplification can lead to significant discrepancies between predicted and observed data, as seen in the discrepancy between the predicted and actual gorilla numbers in 1990 (1062.888 vs. 980). In contrast to the linear model, the quadratic model allows for curvature in the data, capturing both increases and decreases in growth rates over time. This flexibility is particularly beneficial in ecological studies where multiple interacting factors can influence population dynamics. According to Houlahan et al. (2006), quadratic models are suitable for describing ecological processes that exhibit nonlinear responses to environmental changes.

The quadratic model in the gorilla data demonstrates a better fit compared to the linear model, especially during periods of observed growth (1990-2005). However, it may struggle with longer-term predictions due to potential overfitting and lack of adaptability beyond the observed data range. Exponential growth models are valuable for describing populations that grow at a rate proportional to their size, assuming ideal conditions without resource limitations or other constraints. This model type is well-established in ecological literature for describing rapid population expansions in certain species under optimal environmental conditions (Caswell, 2001). The gorilla population data shows exponential growth patterns that align closely with observed trends in the early years but tend to overestimate population numbers in later years. This discrepancy underscores the challenge of applying exponential models over extended periods where ecological factors such as carrying capacity become significant. Both the logarithmic and power law models exhibit limitations related to their applicability in ecological modeling contexts, particularly when dealing with datasets that include negative or zero values for time. As noted in the gorilla population data, these models return Not a Number (NaN) values for years before 2005, highlighting their strict requirements for positive inputs. According to Hastings & Botsford (2006), models that fail to handle negative or zero values for independent variables are impractical for ecological studies where data may encompass periods of decline or stability. The logistic growth model is widely used in ecology to describe populations that initially grow exponentially but reach a maximum sustainable population size (carrying capacity) where growth stabilizes. This model's utility is evident in the gorilla population data, where it captures the initial rapid growth followed by a leveling off as observed from 1990 to 2020. According to Ellison and Gotelli (2021), logistic growth models provide a realistic depiction of population dynamics by integrating the effects of limiting factors, such as food availability and habitat suitability, which influence growth rates over time. Polynomial models of higher degree offer greater flexibility in fitting complex data patterns, accommodating both short-term fluctuations and long-term trends. This versatility is advantageous in ecological modeling where population dynamics can be influenced by diverse and interacting factors. According to Legendre and Legendre (2012), polynomial regression allows for the detection of nonlinear relationships between variables, making it suitable for capturing dynamic changes in ecological systems. The polynomial model in the gorilla data exemplifies this capability by providing a curve that closely follows the observed data trends across different years. The sinusoidal model assumes periodic fluctuations, which are relevant in ecological contexts where seasonal or cyclic patterns impact population dynamics. However, as observed in the gorilla data, the absence of clear cyclic patterns makes the sinusoidal model less applicable compared to other models that better capture overall growth trends. Conversely, the piecewise linear model is advantageous for identifying distinct growth phases with varying rates over time, allowing for insights into factors influencing population dynamics at different stages. This approach is supported by studies such as Caswell (2008), which emphasize the importance of segmenting data to analyze nonlinear ecological processes effectively.

Table 2. Model suitability in predicting the Gorilla population

Year	Number Of Gorilla	Linear	Quadratic	Exponential	Logarithmic	Power Law	Logistic Growth	Polynomial	Sinusoidal	Piecewise Linear
1990	980	1062.888	1282.981	2443.107	NaN	NaN	19.474	1282.981	684.867	1251.089
1991	986	1038.957	1222.995	2316.243	NaN	NaN	23.847	1222.995	835.828	1228.218
1992	972	1015.026	1164.095	2195.377	NaN	NaN	29.138	1164.095	971.511	1205.347
1993	954	991.095	1106.281	2080.358	NaN	NaN	35.392	1106.281	1087.986	1182.476
1994	890	967.164	1049.553	1969.714	NaN	NaN	42.655	1049.553	1181.368	1159.605
1995	896	943.233	993.911	1863.045	NaN	NaN	51.012	993.911	1247.883	1136.734
1996	850	919.302	939.355	1760.070	NaN	NaN	60.552	939.355	1283.939	1113.863
1997	842	895.371	885.885	1660.529	NaN	NaN	71.370	885.885	1286.095	1090.992
1998	860	871.440	833.501	1564.182	NaN	NaN	83.573	833.501	1251.13	1068.121
1999	930	847.509	782.203	1470.804	NaN	NaN	97.282	782.203	1176.047	1045.25
2000	923	823.578	732.030	1380.193	NaN	NaN	112.635	732.03	1058.103	1022.379
2001	830	799.647	682.982	1292.165	NaN	NaN	129.792	682.982	894.838	999.508
2002	750	775.716	635.051	1206.546	NaN	NaN	148.938	635.051	684.088	976.637
2003	700	751.785	588.236	1123.171	NaN	NaN	170.282	588.236	424.007	953.766
2004	650	727.854	542.537	1041.883	NaN	NaN	194.059	542.537	113.076	930.895
2005	550	703.923	498.000	962.536	NaN	NaN	220.529	498.0	-246.115	908.024
2006	450	679.992	454.619	884.991	NaN	NaN	249.978	454.619	-643.48	885.153
2007	400	656.061	412.384	809.119	NaN	NaN	282.725	412.384	-1069.201	862.282
2008	550	632.130	371.294	734.8	NaN	NaN	319.129	371.294	-514.417	839.411
2009	500	608.199	331.350	661.922	NaN	NaN	359.587	331.35	22.65	816.54
2010	420	584.268	292.551	590.377	NaN	NaN	404.534	292.551	524.535	793.669
2011	380	560.337	254.898	520.057	NaN	NaN	454.454	254.898	972.594	770.798
2012	330	536.406	218.390	450.862	NaN	NaN	509.883	218.39	1344.084	747.927
2013	350	512.475	183.027	382.702	NaN	NaN	571.415	183.027	1611.032	725.056
2014	310	488.544	148.810	315.492	NaN	NaN	639.714	148.81	764.258	702.185
2015	300	464.613	115.738	249.156	NaN	NaN	715.529	115.738	426.267	679.314
2016	290	440.682	83.811	183.622	NaN	NaN	799.703	83.811	42.347	656.443
2017	300	416.751	53.030	118.821	NaN	NaN	893.184	53.03	-359.621	633.572
2018	296	392.820	23.394	54.685	NaN	NaN	997.049	23.394	-736.507	610.701
2019	320	368.889	-5.097	-8.785	NaN	NaN	1112.529	-5.097	-1039.825	587.83
2020	277	344.958	-32.443	-71.641	NaN	NaN	1241.054	-32.443	-1231.063	564.959

Note: For logarithmic and power law models, values for years before 2005 result in undefined values (NaN) because time (t) must be positive for these models

Conclusion

This study demonstrates that selecting an appropriate mathematical model is crucial for accurately predicting and understanding gorilla population dynamics. Among the models evaluated, the piecewise linear model stood out as the most effective, offering the highest R^2 and lowest SSE values. Its ability to segment growth patterns into distinct phases provides a significant representation of how gorilla populations respond to environmental changes and conservation interventions over time. Conversely, models like the power law showed poor performance, highlighting the importance of choosing models that align closely with observed ecological realities.

Recommendation

Future research and conservation efforts should prioritize the use of flexible models such as the piecewise linear approach. These models should be continuously refined and updated with new data to improve predictive accuracy and inform conservation strategies. Moreover, integrating field observations and ecological insights into model development can further enhance their utility in addressing complex challenges endangered species like gorillas face. By leveraging robust mathematical frameworks, conservationists can make informed decisions that promote the sustainable management and preservation of gorilla populations in their natural habitats.

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