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Age-Specific Mortality Rates in Nepal By Using Lee-Carter Model

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Abstract: *This study analyzes and forecasts age-specific mortality rates in Nepal using the Lee-Carter model. Using a dummy variable to account for the impact of the 2015 earthquake, this research presents a methodological adaptation of the Lee-Carter Model. The model is estimated through singular value decomposition and regression, and the mortality rates are forecasted to 2030. The results highlight gender specific mortality differences and an overall decline in mortality rates over time. While the study is limited by availability of only five years of data, the findings still provide valuable insights into Nepalese mortality trends. Datasets of larger time frames and region-specific data would further strengthen the model's predictive capabilities and provide quality insights.*

Keywords: *Mortality trend; Lee-carter model; Mortality forecasting; Gender-specific analysis*

1. Introduction

The subject of human mortality and its forecasting has always been a major concern for governments, policymakers, insurers, and other stakeholders. Mortality rates, which reflect the rate of deaths in a given population, are influenced by a number of factors, including socioeconomic conditions, healthcare quality, public health policies, and environmental changes [2].

In the context of Nepal, the country has made substantial progress in improving health outcomes over the past few decades, reflected in declining infant and maternal mortality rates and increasing life expectancy. However, Nepal continues to face numerous health challenges, including high rates of infectious diseases, malnutrition, and poor access to healthcare services in remote areas [7]. Furthermore, events such as 2015 earthquake lead to abrupt perturbations in mortality rates. Nepal's limited mortality data make modelling difficult, but the Lee-Carter Model effectively captures long-term trends even with sparse information.

2. Literature Review

Hong, et al. [5] discussed the importance of accurate mortality rate forecasting for insurance companies in the article titled "Forecasting mortality rates using hybrid Lee–Carter model, artificial neural network and random forest". Seventeen years of mortality data from 2000 to 2016 of Malaysia for both males and females were used as the dataset for this research. Mortality forecasting models such as the classical Lee-Carter (LC) model, LC-ARIMA (Auto Regressive Integrated Moving Average) model, and hybrid models combining LC with machine learning methods such as Random Forest (RF) and Artificial Neural Network (ANN) were used to compare and identify the best fitting model for the available data. The study recommends modeling mortality by gender, healthcare access, and country-specific socio-economic factors. It was recommended that the LC-ARIMA model was best fitted for countries with higher life expectancy and better healthcare systems due to consistent decrease in time trend k_t. The LC-ANN model was deemed more suitable for countries with less effective healthcare systems.

Gylys and Šiaulys [4] in the study Estimation of Uncertainty in Mortality Projections Using State-Space Lee-Carter Model addressed the limitations of the classical Lee-Carter stochastic mortality model by developing alternative models that incorporate state-space frameworks. The study utilized Lithuanian and Swedish mortality data for empirical illustrations, covering ages from 25 to 74, grouped in 5-year age groups for the periods 1959-2017 for Lithuania and 1900-2017 for Sweden. The findings of the research indicate that state-space models provide a better fit and more reasonable confidence intervals for projected mortality rates compared to the classical Lee-Carter model. The study demonstrates that the state-space model with Markovian regime-switching captures the effects of pandemics, such as the Spanish flu in Swedish data, more effectively. However, it is less effective in modeling prolonged but less sharp fluctuations in mortality trends, as observed in Lithuanian data.

Basellini et al. [1] in the paper Thirty Years on: A Review of the Lee-Carter Method for Forecasting Mortality provided analysis of the Lee-Carter (LC) method introduced in 1992 for mortality forecasting. The original LC method demonstrated robustness in capturing overall mortality trends but showed discrepancies when predicting specific age groups and subpopulations. Adjustments to the time index (k_t), such as those suggested by [2], and Rabbi and Mazzuco [9] aimed to better match observed mortality data. Their use of regression tree boosting and recurrent neural networks respectively improved the goodness-of-fit and reduced forecast errors. They suggest exploring methods to address the significant limitation of fixed age-specific parameters (b_x), possibly through techniques like parameter rotation used in the Gaussian approach.

3. Research Methodology

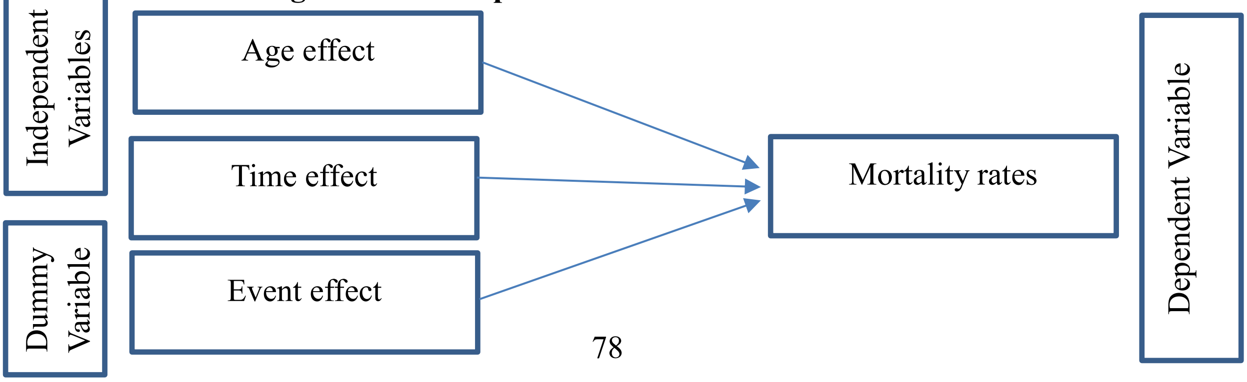
Theoretical Framework

The Lee-Carter model is a straightforward and powerful approach to capturing age-specific mortality rates over time. The model decomposes the logarithm of mortality rates into an age-specific component, a period component that captures temporal changes, and an interaction term. The age and interaction term are calculated as fixed and the time trend is forecasted into the future assuming the age and interaction term stay the same during the forecasted period. This decomposition enables a clear analysis of how mortality evolves across different age groups and time periods, making it a valuable tool for actuaries, demographers, and public health professionals [6]. Here, the proposed adaptation of classical Lee-Carter approach with a dummy variable allows for a simple and interpretable method with limited data.

Conceptual Framework

A conceptual framework is a graphical depiction of the research problem that directs the investigation. In descriptive research, a suggested model can be used to identify or explore categories, while in qualitative research, it can be used to provide a working hypothesis or set of research questions. The conceptual framework is depicted in Figure 3.1.

Figure 3.1 Conceptual Framework of the Research



Data

Numerical data of age specific mortality rate is gathered from the World Health Organization (WHO), Regional Health Observatory- South East Asia. The data is categorized into male, female and both sexes and divided into 19 different age groups across five years.

Model Specification for Data Analysis

The required regression model can be represented as follows:

$$\log_e(m_{x,t}) = a_x + b_x k_t + e_{x,t} \tag{3.1}$$

where,

$m_{x,t}$ is the central mortality rate at age x in year t

a_x describes the general shape of mortality at age x

b_x measures the change in the rates in response to an underlying time trend in the level of mortality

k_t reflects the effect of the time trend on mortality at time t, and

$e_{x,t}$ are independently distributed random variables with means of zero and some variance to be estimated.

To obtain unique estimates of the parameters, the constraints are:

$$\sum b_x = 1 \text{ and } \sum k_t = 0 \tag{3.2}$$

The original approach of Lee and Carter first estimated the a_x as the time-averaged logarithms of mortality at each age x.

If $\hat{m}_{x,t}$ is the maximum likelihood estimate (MLE) of $m_{x,t}$, then:

$$\hat{a}_x = \frac{1}{n}\sum \ln(\hat{m}_{x,t}) \tag{3.3}$$

is MLE of a_x where $\hat{m}_{x,t}$ is the number of deaths of individuals aged x at time t divided by population of the same aged individuals at same time t.

Then, singular value decomposition of the matrix of centered age profiles of mortality $\log_e(m_{x,t}) - a_x$ is used to estimate the b_x and k_t .

The input to the model is a matrix of age specific mortality rates ordered monotonically by time, usually with ages in columns and years in rows.

The model uses singular value decomposition (SVD) to find:

A univariate time series vector that captures 80–90% of the mortality trend (k_t),

A vector that describes the relative mortality at each age (b_x).

Good (1969) stated that if Z is an m x n matrix, then there exists a factorization of the form

$$\text{SVD}(Z) = U\sum V^T \tag{3.4}$$

where U is an m x m orthogonal matrix. $\sum$ is an m x n matrix with non-negative numbers on the diagonal. V^T is the conjugate transpose of the n x n orthogonal matrix V.

In matrix form,

$$U = \begin{bmatrix} u_{1,1} & \cdots & u_{1,m} \\ \vdots & \ddots & \vdots \\ u_{m,1} & \cdots & u_{m,m'} \end{bmatrix}, \sum = \begin{bmatrix} \sigma_{1,1} & \cdots & \sigma_{1,n} \\ \vdots & \ddots & \vdots \\ \sigma_{m,1} & \cdots & \sigma_{m,n'} \end{bmatrix}, V^T = \begin{bmatrix} v_{1,1} & \cdots & v_{1,n} \\ \vdots & \ddots & \vdots \\ v_{n,1} & \cdots & v_{n,n'} \end{bmatrix}$$

The diagonal entries of $\sum$ are the singular values of Z. The singular values are the square roots of the eigenvalues used in obtaining matrix U, and is listed in descending order which is uniquely determined by Z matrix.

The columns of U are in decreasing order of importance. The first column gives more information of primary characteristics in data than the second than the third and so on. The columns of V^T are in decreasing order of importance. The first column gives more information of primary time trend in data than the second than the third and so on. The singular values are in descending order and they provide the variation of data that is explained by the first columns of U and V^T.

Here, the entries of Z matrix are the values of the matrix $\log_e(m_{x,t}) - a_x$.

$$Z = \log_e(m_{x,t}) - a_x = b_x\, k_t \tag{3.5}$$

$$\text{SVD}(Z) = U\Sigma V^T = \sigma_1 U_{x,1} V_{t,1} + \cdots + \sigma_r U_{x,r} V_{t,r} = \Sigma_{i=0}^{r} \sigma_i U_{x,i} V_{t,i} \tag{3.6}$$

where r is rank of matrix Z.

Lee-Carter model uses only rank 1.

$$\hat{Z}_{x,t} = \sigma_1 U_{x,1} V_{t,1} = \hat{b}_x \hat{k}_t \tag{3.7}$$

$\hat{b}_x$ is the first column of matrix U.

$\hat{k}_t$ is the multiplication of first singular value of matrix and first column of matrix V.

In order to measure the proportion of variation explained by the first columns of matrices U and V, the square of first singular value is divided by the sum of squares of all the singular values.

$$\text{Percentage of variation explained} = \frac{\sigma_1^2}{\Sigma_i \sigma_i^2} \tag{3.8}$$

In order to fulfill the imposed limitations of the LC model on $\hat{b}_x$ and $\hat{k}_t$ mentioned in (3.2), the values are adjusted as follows:

$$\hat{b}_x = \frac{1}{\Sigma_x u_{x,1}} \left(u_{1,1}\; u_{2,1} \ldots u_{x,1}\right)^T \tag{3.9}$$

$$\hat{k}_t = \Sigma_x u_{x,1} \times \sigma_1 \times (v_{1,1}\; v_{2,1} \ldots v_{t,1}) \tag{3.10}$$

A simple linear regression model with a dummy variable is used for analyzing the time trend. This can be expressed as:

$$k_t = \gamma_0 + \gamma_1 t + \delta D_t + \nu_t \tag{3.11}$$

where, γ_0 is the intercept term

γ_1 is the slope parameter

D_t is a dummy variable for catastrophic events which impact mortality rates

δ is the coefficient for the dummy variable, capturing the effect of the catastrophic event

ν_t is the error term for the time trend

Integrating the time trend component into the Lee-Carter model:

$$\log_e(m_{x,t}) = a_x + b_x(\gamma_0 + \gamma_1 t + \delta D_t + \nu_t) + e_{x,t} \tag{3.12}$$

4. Results and Discussions

Data Visualization

Figure 4.1 Age Specific Mortality Rates for Both Sexes

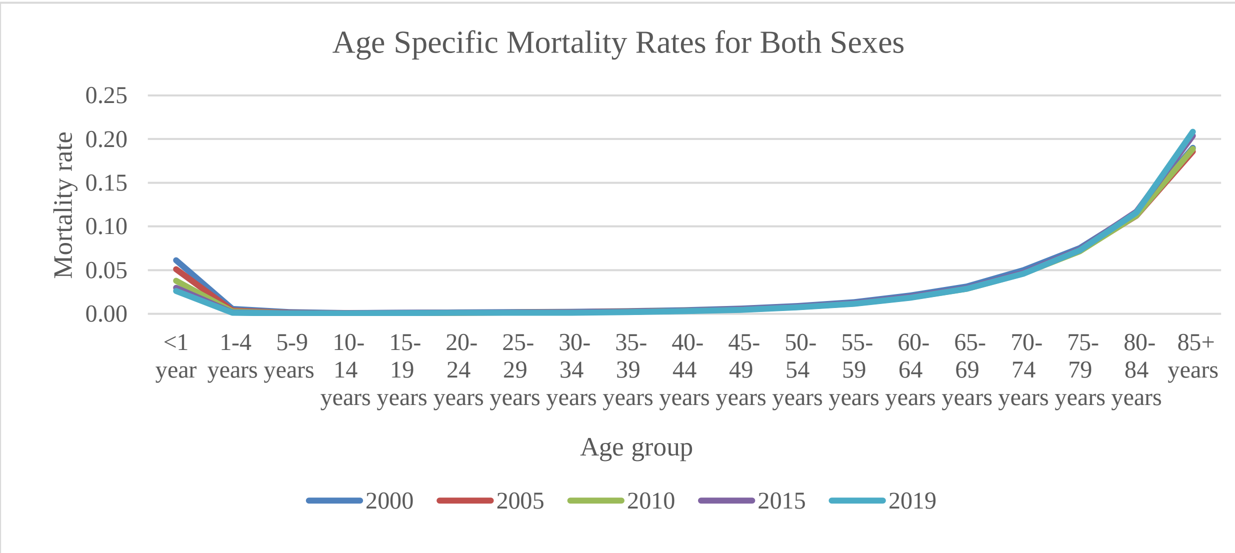
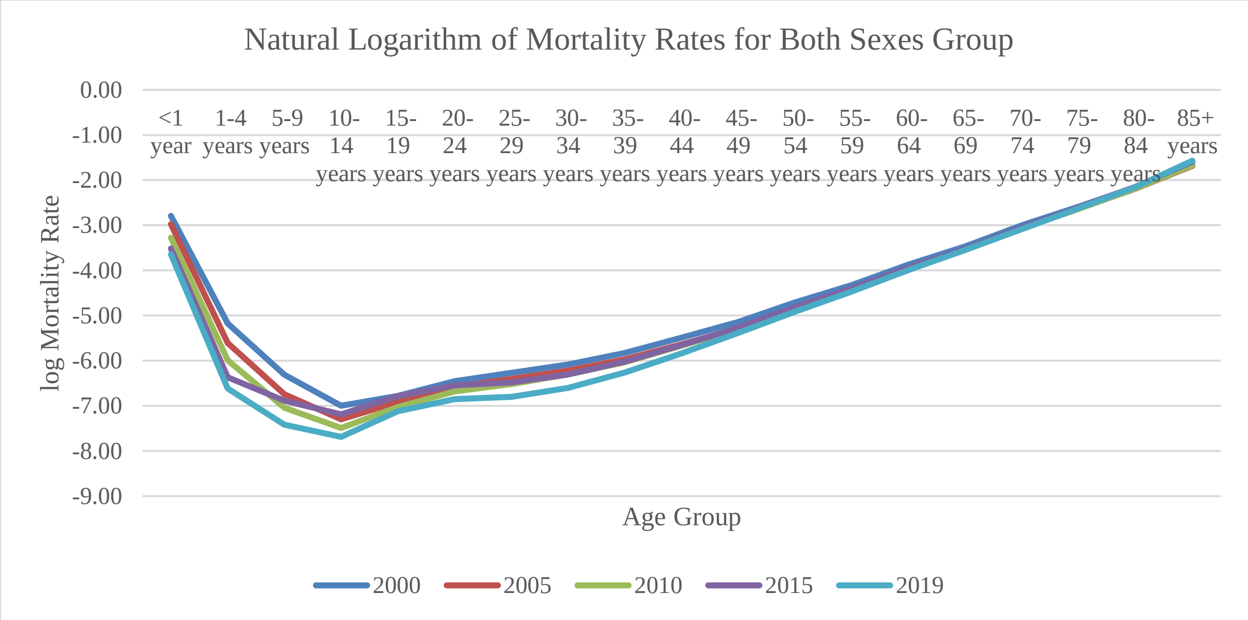


Figure 4.1 shows the age-specific mortality rates for both sexes across five selected years. The overall pattern observed is a U-shaped curve, indicating higher mortality rates at the youngest (<1 year) and oldest (85+ years) age groups, with exponential increase in mortality from age group 30 years and above. It can also be observed that mortality for ages <1 year and 1-4 years is decreasing consistently over the years.

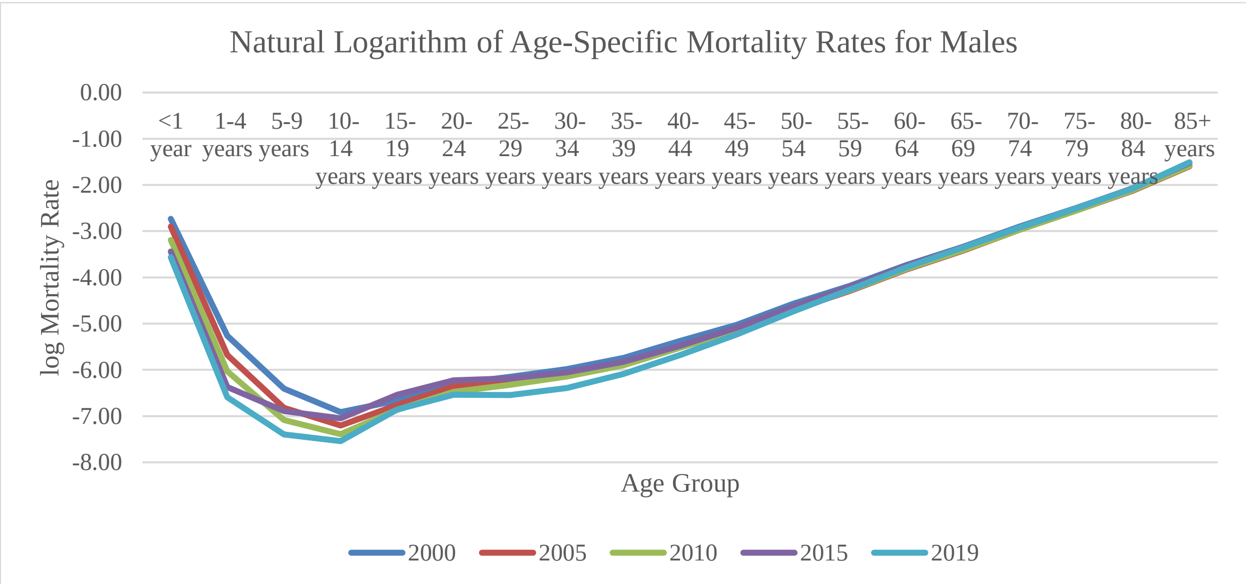
Figure 4.2 Natural Logarithm of Age Specific Mortality Rates for Both Sexes Group



The natural logarithm of mortality rates was considered on the Y-axis on the same data. Figure 4.2 shows the significant hump on the log of mortality data from age group 10-14 years to 30-34 years. This is due to the behavioral tendencies of humans during this age to take high risks. Also, they are likely to be involved in regular jobs which directly or indirectly impact their mortality. The other most prominent observation in Figure 4.2 is the crossing of mortality rates of year 2015 due to occurrence of a major earthquake.

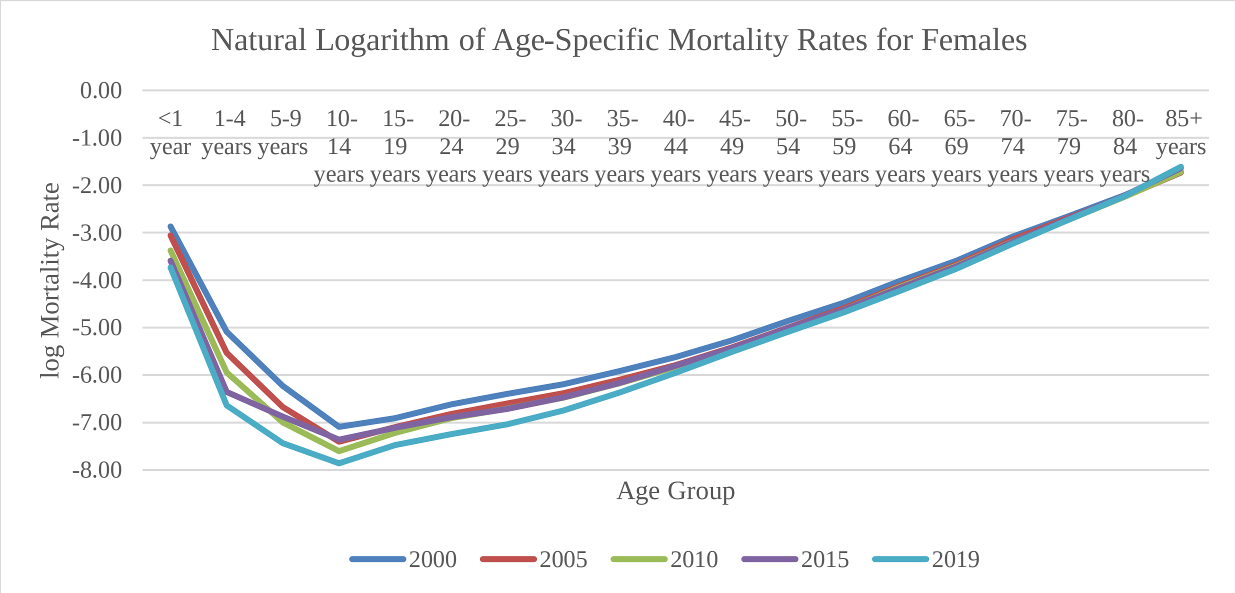
Figure 4.3 highlights the greater size of hump in the male mortality data. Also, the log of mortality rates for age groups 10-14 years to 30-34 years is the highest in 2015 highlighting the larger impact of earthquake on mortality of males.

Figure 4.3 Natural Logarithm of Age Specific Mortality Rates for Males



There is no significant hump present in age group 10-14 years to 30-34 years in Figure 4.4. This means females are lesser involved in risky activities during that age. However, the impact of earthquake is prominent in female's mortality data as well, but the impact is lower than that of males. This is because the mortality rates in 2015 for none of the age groups exceed mortality rates of 2000 in females unlike in males which was observed in Figure 4.3.

Figure 4.4 Natural Logarithm of Age Specific Mortality Rates for Females



Descriptive Statistics

Descriptive statistics are essential in quantitative research because they allow us to grasp the major features of a dataset without the need for complicated models. In this study, we used descriptive statistics such as mean, median and standard deviation to draw key information from the dataset.

Table 4.1 Descriptive Statistics of Mortality Rates for Both Sexes

Year	Mean	Median	Standard Deviation	Minimum	Maximum	Count
2000	0.0313	0.0059	0.0498	0.0009	0.1901	19
2005	0.0294	0.0051	0.0484	0.0007	0.1859	19
2010	0.0287	0.0050	0.0488	0.0006	0.1888	19
2015	0.0296	0.0052	0.0520	0.0008	0.2038	19
2019	0.0290	0.0046	0.0529	0.0005	0.2084	19

Table 4.1 presents descriptive statistics of the mortality rates across years. The mean mortality rates across all ages seem to consistently decrease over the years from 2000 to 2010. However, due to earthquakes and aftershocks of large magnitudes that occurred in 2015, the average mortality seems to have risen on that particular year. The median of all years lies in age-group 45-49 years and seems to be consistently improving over time except for year 2015. The standard deviation of mortality rates has increased over time except for the year 2010. Similarly, the minimum mortality across all years lie in age-group 10-14 years while the maximum of all years lies in age group 85+ years which was expected.

Lee-Carter Model

Maximum Likelihood Estimation

From equation (3.3), $\hat{a}_x$ was calculated as average of log mortality rates for each age group.

Figure 4.5 Line Graph of $\hat{a}_x$ Across Age Groups and Sex

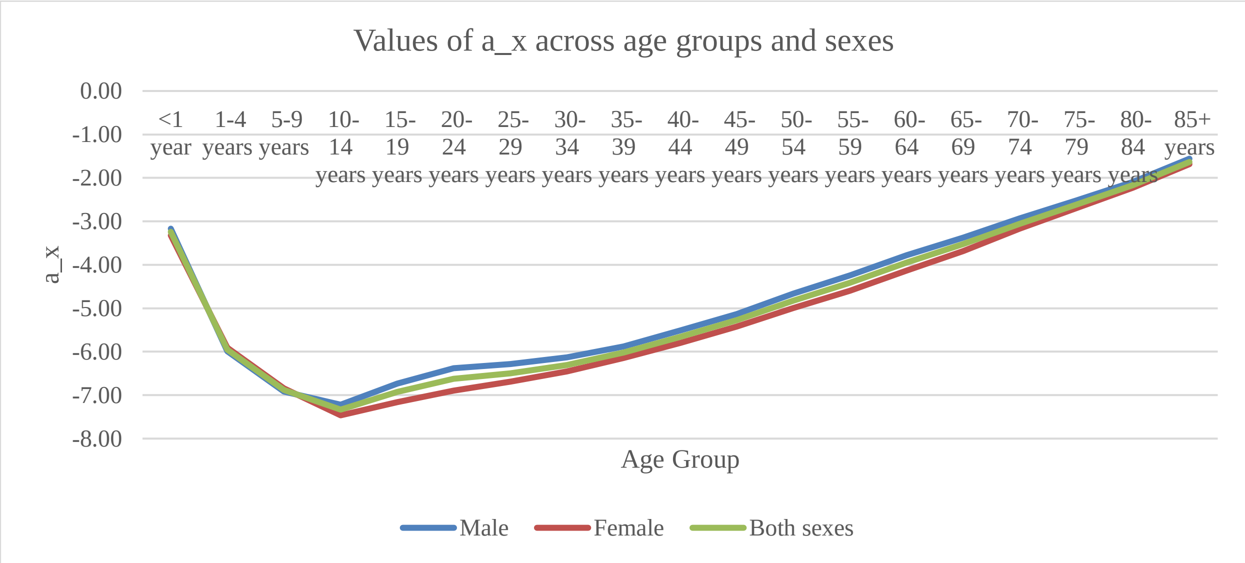


Figure 4.5 shows the average trend of log of mortality rates for males, females and sexes. There is no distinct difference in a_x values for males and females in earlier age groups but the gap starts to widen after 5-9 age group. The values of a_x for males seem to distinctively higher than that of females. The peculiar hump from 10-14 years age group to 30-34 years age group is absent in a_x for females. As the age-group advances, the males show consistently higher a_x than females, however, both are linearly increasing in a_x.

Singular Value Decomposition

Applying equation (3.5) and (3.6) onto the male mortality data, female mortality data, and both sexes mortality data, matrices U, $\sum$ and V were calculated for all sex groups. According to equation (3.8), the proportion of variation is calculated and is presented in Table 4.2.

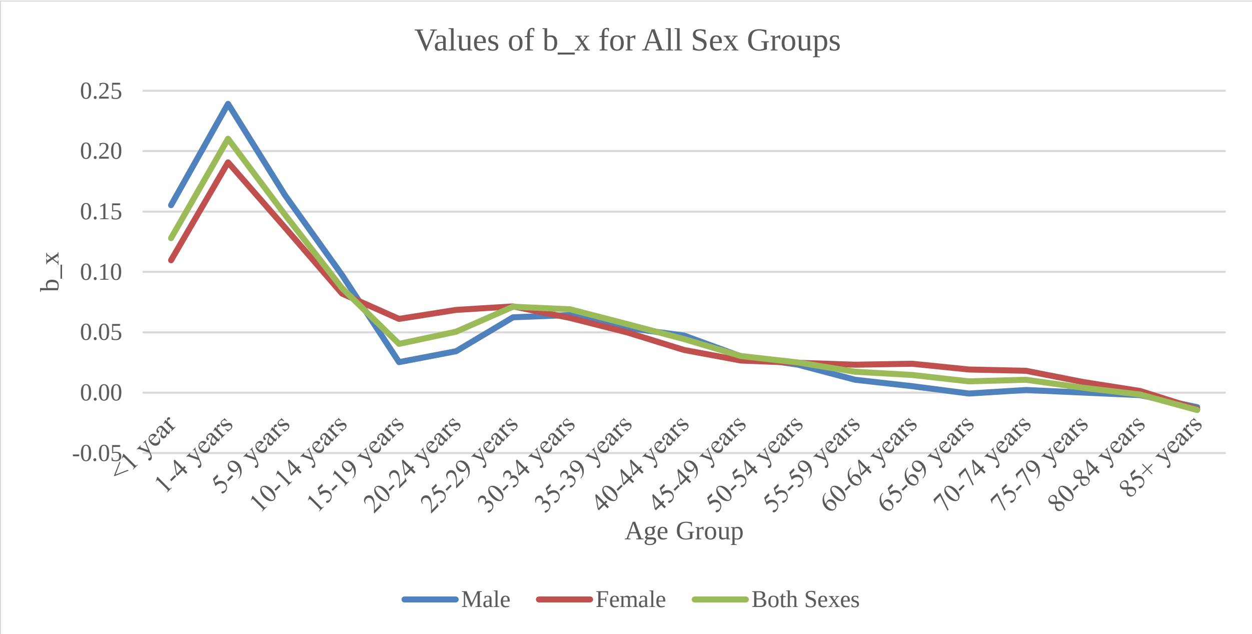
Table 4.2 Proportion of Variation Explained by First Singular Values

Group	Proportion of variation explained
Males	85%
Females	94%
Both sexes	91%

The proportion of variation explained are high numbers all exceeding 80%. Hence, considering single vector from SVD is sufficient. The data for females is better explained than males, meaning that males data has irregularities in mortality trend than that of females. The values of b_x and k_t are calculated according to equation (3.7) The values of b_x represent the mortality sensitivity age groups with respect to time.

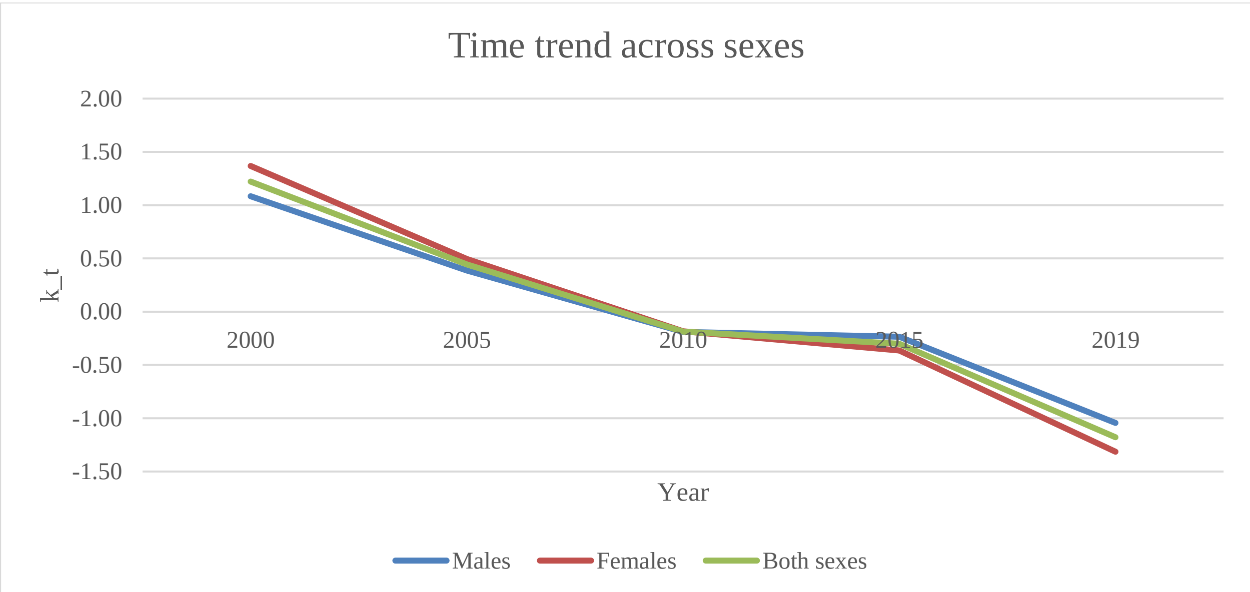
Figure 4.6 shows the trend of $\hat{b}_x$ across all age groups and sexes. It shows that mortality sensitivity is highest at age group 1-4 years and starts to decline onwards. It means over the years; the mortality of age group 1-4 years has improved the most. Since male mortality was higher than females in that age-group, better improvements can be observed in male data than female data. However, a bump in sensitivity is seen from 10-14 years age group to 30-34 years age group in males showing improvements in mortality is less significant across these age groups. The same bump is lacking in females because there was no hike in mortality for females in the same age group, and thus the improvement was linear with other age-groups. After 50-54 years age group, female mortality sensitivity over time, or in other words, its improvement, is seen to be greater than males. Overall, the values of $\hat{b}_x$ starts to decline with age, showing that with increase in age, the sensitivity of mortality improvement also declines. This is because at higher ages, the mortality is high due to natural ageing and is difficult to improve.

Figure 4.6 Line Graph of $\hat{b}_x$ for Males, Females, And Both Sexes



From Figure 4.7, a linear decline in $\hat{k}_t$ can be observed across all groups except for the year 2015. The graph illustrates that the overall trend of mortality is decreasing with time, except for year 2015. The linear decrease in values of $\hat{k}_t$ is consistent with the analysis of Lee and Carter which was done on the US mortality data [6].

Figure 4.7 Line Graph of $\hat{k}_t$ for Males, Females, And Both Sexes



Results of Regression Analysis

A linear model is to be fitted on the values of $\hat{k}_t$ for forecasting of mortality. Since the data is available only for 5 years, a simple linear regression is fitted. Fitting any other complex time-series model could raise the question of overfitting the model in this case.

Equation (3.11) uses a simple linear regression model with a dummy variable to model the data. The summary statistics of the linear regression are presented in the Tables 4.3 to 4.7 respectively.

Table 4.3 Regression Statistics

	Males	**Females**	**Both sexes**
Multiple R	0.9957	0.9971	0.9967
Adjusted R Square	0.9829	0.9884	0.9870
Standard Error	0.1034	0.1080	0.1020

From Table 4.3, it can be observed that Multiple R greater than 0.95 for all groups suggesting extremely strong linear relationship between the dependent and independent variables. Adjusted R Square of 0.9829 for males means that around 98% of the variability in dependent variable for males is explained by the independent variables. The value of standard error for the males is 0.1034, which means the average variation of the observed values from the fitted model is 0.1034. Similarly, Adjusted R Square for females and both sexes group shows approximately 99% of the variability in dependent variable is explained by the independent variables. The value of standard error for the females and both sexes group shows the average variation of the observed values from the fitted model is 0.1080 for females and 0.1020 for both sex group.

Table 4.4 ANOVA Result

	Males	**Females**	**Both sexes**
F-Statistic	116.1986	170.8454	152.6698
Significance of F	0.0085	0.0058	0.0065

Table 4.4 shows that F-Statistic and significance of F for males, females and both sexes. The F-statistic for males, females and both sexes group is 116.1986, 170.8454 and 152.6698 respectively and the significance of F is 0.0085, 0.0058 and 0.0065 respectively. The significance of F for all groups is less than 0.01. This suggests that the value of adjusted R Square is appropriate at 99% confidence level for males, females and both sexes group.

Table 4.5 Coefficients of Regression for Males

	Coefficients	**Standard Error**	**t stat**	**P value**
γ_0 **(Intercept)**	222.3928			
γ_1**(Year)**	-0.1107	0.0074	-15.0331	0.0044
δ **(Dummy Variable)**	0.4272	0.1251	3.4153	0.0761

From Table 4.5, the value of γ_1 is -0.1107 which means for each year passed, the value of k_t decreases by 0.1107. The value of standard error is 0.0074 which means that the average deviation of observed values from fitted line is 0.0074. The t stat value is -15.0331 and the p-value is 0.0044 which is less than 0.01 which means that the value of γ_1 is statistically significant at 99% confidence level. The value of δ is 0.4272 which means if any event occurs that triggers the dummy variable, the value of k_t for the year increases by 0.4272. The standard error is 0.1251 meaning that the average deviation of observed values from fitted line is 0.1251. The t stat is 3.4153 and the p-value is 0.0761 which is less than 0.10.

This means that the value of γ_1 is statistically significant at 90% confidence level. The results of the mathematical model suggest that ordinary least square model with dummy variable is a good fit for male k_t at 90% confidence level.

Hence the equation for k_t for males is

$$k_t = 222.3928 - 0.1107 * Year + 0.4272 * Dummy + \nu_t \quad (4.1)$$

Similar analysis is done for values in Table 4.6 and the results of the mathematical model suggest that ordinary least square model with dummy variable is a good fit for k_t at 90% confidence level.

The equation for k_t for females is

$$k_t = 279.7112 - 0.1392 * Year + 0.4492 * Dummy + \nu_t \quad (4.2)$$

Table 4.6 Coefficients of Regression for Females

	Coefficients	Standard Error	t stat	P value
γ_0 (Intercept)	279.7112			
γ_1(Year)	-0.1392	0.0077	-18.0954	0.0030
δ (Dummy Variable)	0.4492	0.1307	3.4378	0.07519

Likewise, the results of the mathematical model in Table 4.7 suggest that ordinary least square model with dummy variable is a good fit for k_t at 90% confidence level.

The equation for k_t for both sexes is

$$k_t = 250.6755 - 0.1248 * Year + 0.4366 * Dummy + \nu_t \quad (4.3)$$

Table 4.7 Coefficients of Regression for Both Sexes

	Coefficients	Standard Error	t stat	P value
γ_0 (Intercept)	250.6755			
γ_1(Year)	-0.1248	0.0073	-17.6130	0.0034
δ (Dummy Variable)	0.4366	0.1235	3.5360	0.0715

Mortality Forecasting

After fitting the Lee-Carter Model into the data, now the mortality rates are to be predicted for future years. First of all, the values of k_t are to be estimated from the linear model for required years. The values of forecasted k_t allows for calculation of mortality rates in future times. Table 4.8 summarizes the values of k_t for years 2021, 2025 and 2030 for males, females and both sexes.

Table 4.8 Values of Predicted k_t for All Sexes

Year	Dummy	k_t for Males	k_t for Females	k_t for Both Sexes
2021	1	-0.8981	-1.1999	-1.0481
2025	0	-1.7680	-2.2060	-1.9838
2030	0	-2.3215	-2.9021	-2.6077

The values of k_t from Table 4.8 provide a base for forecasting the mortality values in the years. According to Worldometer info, COVID caused deaths of nearly 9,000 Nepalese in year 2021, which is very close to the number of death due to earthquake in 2015. Hence, the dummy variable is 1 for year 2021. Overall, the k_t values are decreasing linearly over time. This means continuous mortality improvement is expected in Nepal.

Figure 4.8 Natural Logarithm of Predicted Mortality Rates $m_{x,t}$ for Males

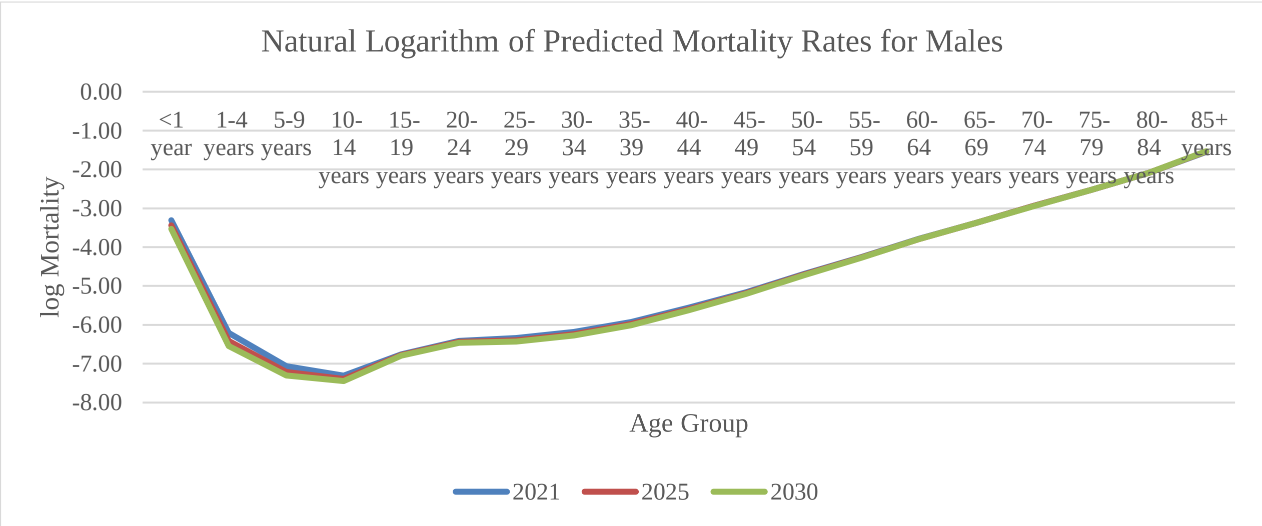


Figure 4.8 illustrates the trend of log of predicted mortality rates over the years across all age groups for males. The consistent improvement in mortality can be observed along with the U-shaped curve of mortality rates and a peculiar hump at age groups from 10 years to 34 years. However, the gap between the line of 2021 and 2025 seem to be higher than that between other years because 2021 was expected to have greater mortality rates due to COVID-19.

Figure 4.9 Natural Logarithm of Predicted Mortality Rates $m_{x,t}$ for Females

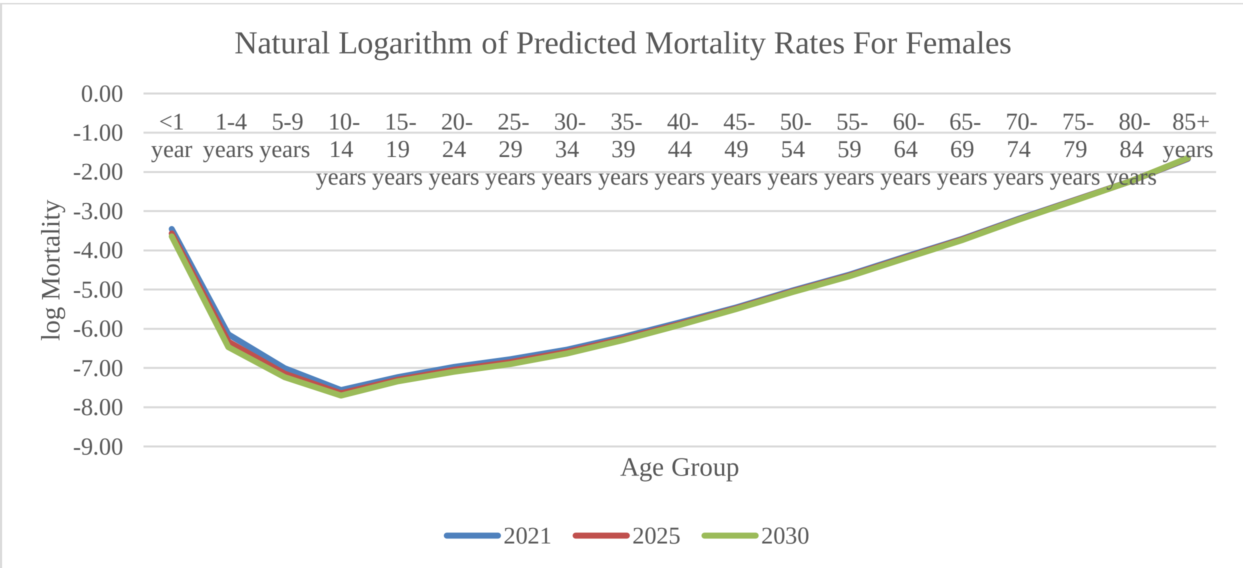


Figure 4.9 illustrates the trend of log of mortality rates over the years across all age groups of females. Similar to that of males, there seems to be continuous improvement in mortality for females across the years. However, the hump in mortality is not significant in Figure 4.11 compared to Figure 4.10 which is consistent with the observed data.

5. Conclusion

This study shows the significant decline in mortality rates among younger age groups, moderate improvement in middle age groups, and limited improvements in elderly populations, with greater improvements in females compared to males. This paper contributes by applying the Lee-Carter model to Nepalese mortality rates, accounting for the catastrophic events. This study also highlights that even with only 5 years of age-specific mortality data, the Lee-Carter model can be applied with reliable accuracy. However, age-specific datasets of larger time frames would enhance the forecasting accuracy and would allow the use of complex models to fit the time trend. Also, region-specific datasets would allow for more precise modelling of local mortality patterns, setting region-specific parameters, a comparative study of trends across regions, and ultimately support interventions for improvement in mortality rates of Nepal.

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