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Projection of age specific death rate and life expectancy of Uttar Pradesh (India) using MCMC technique in Bayesian procedure

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Abstract

In this paper we have projected the Life expectancy and Age Specific Death Rate of Uttar Pradesh using Monte Carlo Marcov chain technique in Bayesian procedure. Parameters are estimated in 95% confidence interval in Bayesian framework. Non-informative prior distribution has been used by us for running the model.

Keywords: Bayesian methodology, Life expectancy, Age Specific Death Rate, R software.

Introduction

We have used Bayesian approach for analyzing our data using WinBUGS and R statistical computational software. In the MCMC simulation some difficult integrals arises which can be easily tackled by WinBUGS software. Its flexibility allows us to manipulate difficult integrals.

Uttar Pradesh is very populous state of India, so it becomes very necessary to project the Age specific death rate and Life expectancy for the policy makers and Government to fulfill the health requirement and to provide good medicinal facility for the increasing population.

Life expectancy tells that for how many year a person will survive in future. Age Specific death rates gives idea that how many people are dying in the various age groups due to various causes.

Congdon P[1]., Dyson T. et al[2], Gelman A. et al[3], Gilks et al[4], Gill J[5] all suggested the idea of analyzing the observed data using MCMC technique in Bayesian process. Rahul et al[6], Rahul, Pandey G.S. et al[7], Rahul, Singh G.P. et al[8] gave the idea how to project the population of India and its States using Bayesian procedure in WinBUGS by using suitable model. Registrar General of India, 2006[9], reported the future values of population of India and its States. Spiegelhalter et al[10] suggested how to run different programs in WinBUGS by giving suitable examples.

Objective: Our aim is to observe past and future trend in Age specific Death Rate and Life expectancy at birth in U.P., India. Age Specific Death Rates (ASDR) data are collected from various S.R.S. reports starting 1971 to 2010. We will obtain life table survival ratio "lx" using these data for the year 2010. Our aim is to obtain Age Specific Death Rates for each age group separately and Life Expectancy for the period 2011 to 2051 in Bayesian frame work. We will obtain life table survival ratio "lx" using these data for the year 2010. Using time series data of ASDRs we have computed Brass's Logit parameters "α" and "β" and "lx" for males and females separately and then projected values will be used to estimate the Life Expectancy at birth and Age specific Death Rates for future.

Methodology

Bayesian Methods: Use of Bayesian methodology in the field of data analysis is somewhat new. This methodology has found enormous support in the last two decades from the people belonging to various disciplines. A Bayesian approach to a problem starts with the formulation of probability model that is thought to describe adequately the underlying mechanism of the system based on the past study and the sample collection process. The next step in the process is to devise appropriate prior distributions to the parameters of the model, the unobserved quantities of ultimate interest, which are intended to capture the beliefs about the situation on the basis of past experiences before seeing the data. After observing the data, Baye's rule is applied to obtain the posterior distributions, for these unobserved quantities of ultimate interest/parameters, which are their conditional probability distributions given the observed data. The principle may simply may be expressed symbolically as follows –

$$P(\eta / x) = \frac{P(\eta)\, x\, P(\eta / \theta)}{P(x)}$$

$$= \frac{prior\ x\, likelihood}{M\arg inal}$$

$$= \frac{P(\eta)\, x\, P(x/\eta)}{\int P(\eta)\, x\, P(x/\eta) d\theta} \tag{1}$$

Here**,** η shows unobserved values of parameters, P(η) represents prior distribution for the parameter η. P(x/ η) shows the probability distribution for x for given prior distribution and is popularly known as likelihood function of x, and P(η/x) is known as the posterior distribution of parameters of interest. Once the posterior distribution of η is calculated then we will be able to estimates the parameter η.

Model: Linear regression is used to estimate the future trend in Brass's log it parameters

$$Y = a + b * t \tag{2}$$

Where t is the time, a is intercept and b represents the slope. We have used non informative prior for all unknown parameter of the model. Non-informative providing limited information and we do not have idea of specific nature of their probability distribution. Some more ideas are suggested in WinBUGS manual by Spiegel halter, Thomas, Best, and Gilks.

Tools: Bayesian approach faces serious computational difficulties due to likely involvement of complicated mathematical expressions in the posterior distributions. Many of these have been suitably addressed with greater ease using Markov Chain Monte Carlo methods. The Markov Chain Monte Carlo (MCMC) method is an iterative tool. The term "Monte Carlo method" refers to simulation processes, using random numbers. This method is commonly used to evaluate, iteratively, approximate value of some of the complex integrals involving expectation of a function of a random variable. The evaluation is made by generating large independent simulated samples from the (complex) distribution of the random variable, and taking the average of the function values obtained on these sample points. The freely available software WinBUGS (Bayesian inference Using Gibbs Sampling for Windows) helps us in finding the estimates of parameters by using MCMC process. In this process, we need to run a number of chains for each parameter for a long time. When the chains have run sufficiently large number of iterations and have reached to the stationary distribution then the samples obtained by further running of the chains are supposed to be drawn randomly from the posterior distribution of the parameter. WinBUGS provides a number of inbuilt diagnostics to assess the convergence of the chains. In practice, one should use multiple diagnostics on a single chain and WinBUGS allows multiple chains for each parameter to run simultaneously. A few of the diagnostics available with the WinBUGS and used in this study are briefly described below. Running multiple chains is a way to check the convergence of MCMC simulations. WinBUGS provides a running trace plot of the chains of updates for the parameters. When different chains do not provide sufficient mixing of chains even after a long run, it indicates lack of convergence of the chains. Another diagnostic available with WinBUGS is due to Brooks-Gelman-Rubin (bgr). It calculates the modified form of Gelman-Rubin convergence statistic; see Brooks and Gelman. It provides a plot of the statistic in which the width of the central 80% interval of the pooled runs is green, the average width of the 80% intervals within the individual runs is blue, and their ratio R^2 (= pooled / within) is red. For plotting purposes the pooled and within interval widths are normalized to have an overall maximum of one. Brooks and Gelman emphasize that one should be concerned both with convergence of R to 1, and with convergence of both the pooled and within interval widths to stability. WinBUGS also provides smoothed density plots of the chains. When the chains approach to stationarity, then the density plot shall take a normal shape. A lack of normality or multimodality is also an indication of the absence of convergence of the chain. Auto correlation is another diagnostic available. If the chains converge to the stationary distribution then the auto correlation shall decrease with the increase in lags. It also provides us a basis to assess the convergence of the chain. A detailed discussion on the diagnostics can be found in Gill.

Once we are convinced that chains have been converged through the diagnostics, we will need to run the simulation for a further number of iterations to obtain samples that can be used for posterior inference. The more samples we save, the more accurate will be our posterior estimates. Once we have run enough updates and are satisfied with the history of chains, we discard the previous samples. We obtain the summary statistics only from the samples generated afterwards.

Software: We will use very popular and freely available statistical software R. It is available at free of cost. It works as S-PLUS. But S-plus is commercial software and comes at high prices. R runs on various platforms like Windows, Linux etc. It is little bit slowly in comparison to S –Plus. R reads data in csv and txt format.

WinBUGS: It is a statistical software for Bayesian analysis using Markov chain Monte Carlo (MCMC) methods. It has developed a scripting language BUGS (Bayesian Inference Using Gibbs Sampling) for the implementation of WinBUGS. WinBUGS may be called through package, R2WinBUGS.

R: R is freely available open source software on internet. It is now gaining popularity among students and teachers. It has many features of S+ software but it lags little bit in graphics and speed. In our work we have called WinBUGS several times as per required and combining the results we got the result of α, β and lx values for male and female separately in R we will get the required results.

R code to estimate the life expectancy at birth and ASDR

```
Survival<-read.table("lx2010.csv",header=T,sep=",")
##lxF is life table survival ratio for female
## lxM life table survival ratio for male
## AxM and AxF are the array to hold the data for male and female separately
## alpha.F, beta.F, alpha.M, beta.M are Brass's logit parameters
```

```
lxF<-Survival$F.2010
lxM<-Survival$M.2010
AxM<-AxF<-NULL
for (i in 1:length(lxF)){AxF[i]<-.5*log((1-lxF[i])/lxF[i])}
for (i in 1:length(lxF)){lxF11[i,]<-
1/(1+exp(2*alpha.F[1,]+2*beta.F[1,]*AxF[i]))}
for (i in 1:length(lxF)){lxF16[i,]<-
1/(1+exp(2*alpha.F[2,]+2*beta.F[2,]*AxF[i]))}
for (i in 1:length(lxF)){lxF21[i,]<-
1/(1+exp(2*alpha.F[3,]+2*beta.F[3,]*AxF[i]))}
for (i in 1:length(lxF)){lxF26[i,]<-
1/(1+exp(2*alpha.F[4,]+2*beta.F[4,]*AxF[i]))}
for (i in 1:length(lxF)){lxF31[i,]<-
1/(1+exp(2*alpha.F[5,]+2*beta.F[5,]*AxF[i]))}
for (i in 1:length(lxF)){lxF36[i,]<-
1/(1+exp(2*alpha.F[6,]+2*beta.F[6,]*AxF[i]))}
for (i in 1:length(lxF)){lxF41[i,]<-
1/(1+exp(2*alpha.F[7,]+2*beta.F[7,]*AxF[i]))}
for (i in 1:length(lxF)){lxF46[i,]<-
1/(1+exp(2*alpha.F[8,]+2*beta.F[8,]*AxF[i]))}
lxM51<-lxM46<-lxM41<-lxM36<-lxM31<-lxM26<-lxM21<-
lxM16<-lxM11<-array(0,c(SIZE+1,ITER))
for (i in 1:length(lxM)){lxM11[i,]<-
1/(1+exp(2*Alpha.M[1,]+2*beta.M[1,]*AxM[i]))}
for (i in 1:length(lxM)){lxM16[i,]<-
1/(1+exp(2*Alpha.M[2,]+2*beta.M[2,]*AxM[i]))}
for (i in 1:length(lxM)){lxM21[i,]<-
1/(1+exp(2*Alpha.M[3,]+2*beta.M[3,]*AxM[i]))}
for (i in 1:length(lxM)){lxM26[i,]<-
1/(1+exp(2*alpha.M[4,]+2*beta.M[4,]*AxM[i]))}
for (i in 1:length(lxM)){lxM31[i,]<-
1/(1+exp(2*alpha.M[5,]+2*beta.M[5,]*AxM[i]))}
for (i in 1:length(lxM)){lxM36[i,]<-
1/(1+exp(2*alpha.M[6,]+2*beta.M[6,]*AxM[i]))}
for (i in 1:length(lxM)){lxM41[i,]<-
1/(1+exp(2*alpha.M[7,]+2*beta.M[7,]*AxM[i]))}
for (i in 1:length(lxM)){lxM46[i,]<-
1/(1+exp(2*alpha.M[8,]+2*beta.M[8,]*AxM[i]))}
for (i in 1:length(lxM)){lxM51[i,]<-
1/(1+exp(2*alpha.M[9,]+2*beta.M[9,]*AxM[i]))}
for (i in 1:length(lxF)){lxF51[i,]<-
1/(1+exp(2*alpha.F[9,]+2*beta.F[9,]*AxF[i]))}
e0MFORE<-array(0,c(BASEANDSTEPS,ITER))
for (i in 1:ITER){e0MFORE[1,i]<-sum(lxM11[,i]*5)}
for (i in 1:ITER){e0MFORE[2,i]<-sum(lxM16[,i]*5)}
for (i in 1:ITER){e0MFORE[3,i]<-sum(lxM21[,i]*5)}
for (i in 1:ITER){e0MFORE[4,i]<-sum(lxM26[,i]*5)}
for (i in 1:ITER){e0MFORE[5,i]<-sum(lxM31[,i]*5)}
for (i in 1:ITER){e0MFORE[6,i]<-sum(lxM36[,i]*5)}
for (i in 1:ITER){e0MFORE[7,i]<-sum(lxM41[,i]*5)}
for (i in 1:ITER){e0MFORE[8,i]<-sum(lxM46[,i]*5)}
for (i in 1:ITER){e0MFORE[9,i]<-sum(lxM51[,i]*5)}
## e0FFORE, e0MFORE, projected values of life expectancy of
Female and Male population seprately
e0FFORE<-array(0,c(BASEANDSTEPS,ITER))
for (i in 1:ITER){e0FFORE[1,i]<-sum(lxF11[,i]*5)}
for (i in 1:ITER){e0FFORE[2,i]<-sum(lxF16[,i]*5)}
for (i in 1:ITER){e0FFORE[3,i]<-sum(lxF21[,i]*5)}
for (i in 1:ITER){e0FFORE[4,i]<-sum(lxF26[,i]*5)}
for (i in 1:ITER){e0FFORE[5,i]<-sum(lxF31[,i]*5)}
for (i in 1:ITER){e0FFORE[6,i]<-sum(lxF36[,i]*5)}
for (i in 1:ITER){e0FFORE[7,i]<-sum(lxF41[,i]*5)}
for (i in 1:ITER){e0FFORE[8,i]<-sum(lxF46[,i]*5)}
for (i in 1:ITER){e0FFORE[9,i]<-sum(lxF51[,i]*5)}
```

Analysis: Table-1 and Table-2 given below are the projected value of the estimates of Age Specific Death Rate of females and males in Uttar Pradesh in 95% confidence interval. Table-3 represents the projected value of life expectancy at birth.

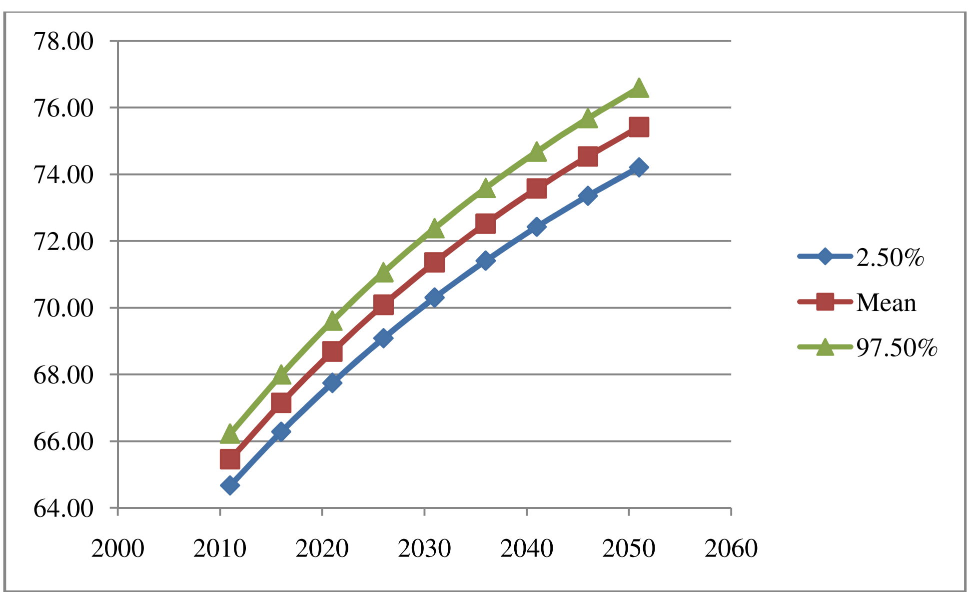

Figure-1: Life expectancy of Males at birth, U.P.

Table-1(a): Projected ASDR for females, Uttar Pradesh from 2011 to 2051.

Age/Year	2011			2016			2021		
	2.5%	Mean	97.5%5	2.5%	Mean	97.5%	2.5%	Mean	97.5%
0	17.247	18.867	20.569	13.442	14.986	16.616	10.455	11.879	13.404
5	1.435	1.550	1.671	1.170	1.286	1.408	0.950	1.061	1.182
10	0.785	0.847	0.912	0.642	0.705	0.771	0.522	0.583	0.649
15	1.358	1.465	1.575	1.114	1.222	1.336	0.909	1.014	1.127
20	2.042	2.199	2.363	1.681	1.842	2.011	1.378	1.536	1.704
25	2.235	2.405	2.581	1.851	2.025	2.207	1.524	1.696	1.879
30	2.472	2.656	2.847	2.059	2.248	2.447	1.702	1.892	2.093
35	2.966	3.182	3.406	2.059	2.709	2.944	2.065	2.292	2.531
40	2.489	2.667	2.852	2.096	2.283	2.479	1.751	1.941	2.141
45	4.594	4.916	5.250	3.895	4.234	4.592	3.276	3.622	3.989
50	7.824	8.347	8.901	6.699	7.263	7.855	5.691	6.274	6.891
55	8.332	8.866	9.432	7.227	7.806	8.421	6.210	6.821	7.470
60	17.647	18.705	19.828	15.555	16.741	17.991	13.595	14.864	16.211
65	25.953	27.383	28.885	23.423	25.067	26.787	20.949	22.758	24.658
70	47.662	49.954	52.313	44.373	47.069	49.881	40.905	44.006	47.255
75	70.951	73.807	76.640	68.324	71.770	75.260	65.315	69.356	73.510
80	89.995	93.026	95.981	89.081	92.793	96.438	87.667	92.175	96.589

Table-1(b): Projected ASDR for females, Uttar Pradesh from 2011 to 2051.

Age/Year	2026			2031			2036		
	2.5%	Mean	97.%5	2.5%	Mean	97.5%	2.5%	Mean	97.5%
0	8.123	9.402	10.798	6.292	7.432	8.690	4.865	5.869	6.989
5	0.766	0.873	0.989	0.616	0.715	0.825	0.494	0.584	0.685
10	0.423	0.481	0.545	0.341	0.395	0.455	0.274	0.324	0.379
15	0.738	0.838	0.948	0.596	0.690	0.795	0.480	0.567	0.664
20	1.122	1.274	1.439	0.910	1.053	1.210	0.736	0.867	1.015
25	1.248	1.413	1.593	1.016	1.173	1.346	0.825	0.971	1.133
30	1.401	1.584	1.783	1.146	1.321	1.512	0.934	1.097	1.279
35	1.708	1.929	2.166	1.404	1.616	1.847	1.150	1.349	1.568
40	1.455	1.641	1.840	1.203	1.382	1.576	0.990	1.158	1.344
45	2.739	3.081	3.448	2.276	2.608	2.968	1.884	2.198	2.545
50	4.802	5.387	6.016	4.029	4.600	5.224	3.365	3.910	4.517
55	5.300	5.921	6.589	4.492	5.109	5.783	3.784	4.386	5.048
60	11.780	13.102	14.514	10.134	11.476	12.916	8.661	9.994	11.439
65	18.565	20.504	22.553	16.322	18.344	20.508	14.245	16.307	18.542
70	37.384	40.833	44.486	33.862	37.619	41.602	30.433	34.423	38.684
75	61.880	66.602	71.474	58.181	63.560	69.073	54.344	60.283	66.484
80	85.899	91.167	96.434	83.694	89.777	95.892	81.030	88.012	95.047

Table-1(c): Projected ASDR for females, Uttar Pradesh from 2011 to 2051.

Age/Year		2041		2046			2051		
	2.5%	Mean	97.5%	2.5%	Mean	97.5%	2.5%	Mean	97.5%
0	3.761	4.631	5.617	2.903	3.653	5.617	3.653	2.880	3.615
5	0.395	0.476	0.568	0.315	0.387	0.568	0.387	0.314	0.389
10	0.219	0.264	0.315	0.175	0.215	0.315	0.215	0.175	0.217
15	0.386	0.464	0.553	0.309	0.379	0.553	0.379	0.309	0.381
20	0.594	0.713	0.849	0.477	0.584	0.849	0.584	0.478	0.588
25	0.668	0.801	0.951	0.539	0.659	0.951	0.659	0.541	0.665
30	0.760	0.909	1.078	0.616	0.751	1.078	0.751	0.619	0.760
35	0.939	1.122	1.328	0.765	0.931	1.328	0.931	0.771	0.944
40	0.811	0.968	1.143	0.664	0.806	1.143	0.806	0.670	0.819
45	1.553	1.846	2.176	1.275	1.545	2.176	1.545	1.290	1.576
50	2.797	3.310	3.893	2.314	2.793	3.893	2.793	2.350	2.861
55	3.176	3.749	4.389	2.650	3.192	4.389	3.192	2.709	3.285
60	7.364	8.659	10.089	6.236	7.470	10.089	7.470	6.420	7.747
65	12.349	14.413	16.674	10.654	12.674	16.674	12.674	11.094	13.293
70	27.167	31.300	35.786	24.080	28.293	35.786	28.293	25.439	30.123
75	50.354	56.831	63.669	46.311	53.264	63.669	53.264	49.642	57.470
80	77.965	85.893	93.904	74.646	83.443	93.904	83.443	80.692	90.630

Table-2(a): Projected ASDR of Male population, Uttar Pradesh 2011 to 2051.

Age/Year	2011			2016			2021		
	2.5%	Mean	97.%5	2.5%	Mean	97.5%	2.5%	Mean	97.5%
0	17.247	18.867	20.569	13.442	14.986	16.616	10.455	11.879	13.404
5	1.435	1.550	1.671	1.170	1.286	1.408	0.950	1.061	1.182
10	0.785	0.847	0.912	0.642	0.705	0.771	0.522	0.583	0.649
15	1.358	1.465	1.575	1.114	1.222	1.336	0.909	1.014	1.127
20	2.042	2.199	2.363	1.681	1.842	2.011	1.378	1.536	1.704
25	2.235	2.405	2.581	1.851	2.025	2.207	1.524	1.696	1.879
30	2.472	2.656	2.847	2.059	2.248	2.447	1.702	1.892	2.093
35	2.966	3.182	3.406	2.059	2.709	2.944	2.065	2.292	2.531
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45	4.594	4.916	5.250	3.895	4.234	4.592	3.276	3.622	3.989
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55	8.332	8.866	9.432	7.227	7.806	8.421	6.210	6.821	7.470
60	17.647	18.705	19.828	15.555	16.741	17.991	13.595	14.864	16.211
65	25.953	27.383	28.885	23.423	25.067	26.787	20.949	22.758	24.658
70	47.662	49.954	52.313	44.373	47.069	49.881	40.905	44.006	47.255
75	70.951	73.807	76.640	68.324	71.770	75.260	65.315	69.356	73.510
80	89.995	93.026	95.981	89.081	92.793	96.438	87.667	92.175	96.589

Table-2(b): Projected ASDR of Male population, Uttar Pradesh 2011 to 2051.

Age/Year	2026			2031			2036		
	2.5%	Mean	97.%5	2.5%	Mean	97.5%	2.5%	Mean	97.5%
0	8.123	9.402	10.798	6.292	7.432	8.690	4.865	5.869	6.989
5	0.766	0.873	0.989	0.616	0.715	0.825	0.494	0.584	0.685
10	0.423	0.481	0.545	0.341	0.395	0.455	0.274	0.324	0.379
15	0.738	0.838	0.948	0.596	0.690	0.795	0.480	0.567	0.664
20	1.122	1.274	1.439	0.910	1.053	1.210	0.736	0.867	1.015
25	1.248	1.413	1.593	1.016	1.173	1.346	0.825	0.971	1.133
30	1.401	1.584	1.783	1.146	1.321	1.512	0.934	1.097	1.279
35	1.708	1.929	2.166	1.404	1.616	1.847	1.150	1.349	1.568
40	1.455	1.641	1.840	1.203	1.382	1.576	0.990	1.158	1.344
45	2.739	3.081	3.448	2.276	2.608	2.968	1.884	2.198	2.545
50	4.802	5.387	6.016	4.029	4.600	5.224	3.365	3.910	4.517
55	5.300	5.921	6.589	4.492	5.109	5.783	3.784	4.386	5.048
60	11.780	13.102	14.514	10.134	11.476	12.916	8.661	9.994	11.439
65	18.565	20.504	22.553	16.322	18.344	20.508	14.245	16.307	18.542
70	37.384	40.833	44.486	33.862	37.619	41.602	30.433	34.423	38.684
75	61.880	66.602	71.474	58.181	63.560	69.073	54.344	60.283	66.484
80	85.899	91.167	96.434	83.694	89.777	95.892	81.030	88.012	95.047

Table-2(c): Projected ASDR of Male population, Uttar Pradesh 2011 to 2051.

Age/Year	2041			2046			2051		
	2.5%	Mean	97.%5	2.5%	Mean	97.5%	2.5%	Mean	97.5%
0	3.761	4.631	5.617	2.903	3.653	5.617	3.653	2.880	3.615
5	0.395	0.476	0.568	0.315	0.387	0.568	0.387	0.314	0.389
10	0.219	0.264	0.315	0.175	0.215	0.315	0.215	0.175	0.217
15	0.386	0.464	0.553	0.309	0.379	0.553	0.379	0.309	0.381
20	0.594	0.713	0.849	0.477	0.584	0.849	0.584	0.478	0.588
25	0.668	0.801	0.951	0.539	0.659	0.951	0.659	0.541	0.665
30	0.760	0.909	1.078	0.616	0.751	1.078	0.751	0.619	0.760
35	0.939	1.122	1.328	0.765	0.931	1.328	0.931	0.771	0.944
40	0.811	0.968	1.143	0.664	0.806	1.143	0.806	0.670	0.819
45	1.553	1.846	2.176	1.275	1.545	2.176	1.545	1.290	1.576
50	2.797	3.310	3.893	2.314	2.793	3.893	2.793	2.350	2.861
55	3.176	3.749	4.389	2.650	3.192	4.389	3.192	2.709	3.285
60	7.364	8.659	10.089	6.236	7.470	10.089	7.470	6.420	7.747
65	12.349	14.413	16.674	10.654	12.674	16.674	12.674	11.094	13.293
70	27.167	31.300	35.786	24.080	28.293	35.786	28.293	25.439	30.123
75	50.354	56.831	63.669	46.311	53.264	63.669	53.264	49.642	57.470
80	77.965	85.893	93.904	74.646	83.443	93.904	83.443	80.692	90.630

Table-3: Life expectancy at birth in for Males, U.P.

Males			
Year	2.50%	Mean	97.50%
2011	64.68	65.46	66.23
2016	66.28	67.15	68.00
2021	67.75	68.68	69.61
2026	69.09	70.08	71.07
2031	70.30	71.36	72.38
2036	71.41	72.52	73.59
2041	72.42	73.57	74.68
2046	73.36	74.53	75.68
2051	74.21	75.41	76.59

Table-4: Life expectancy at birth for Females in U.P.

Females			
Year	2.50%	Mean	97.50%
2011	66.46	67.52	68.56
2016	68.74	69.88	71.00
2021	70.79	72.01	73.20
2026	72.65	73.91	75.13
2031	74.31	75.61	76.85
2036	75.80	77.12	78.37
2041	77.14	78.47	79.72
2046	78.35	79.68	80.92
2051	79.44	80.75	81.98

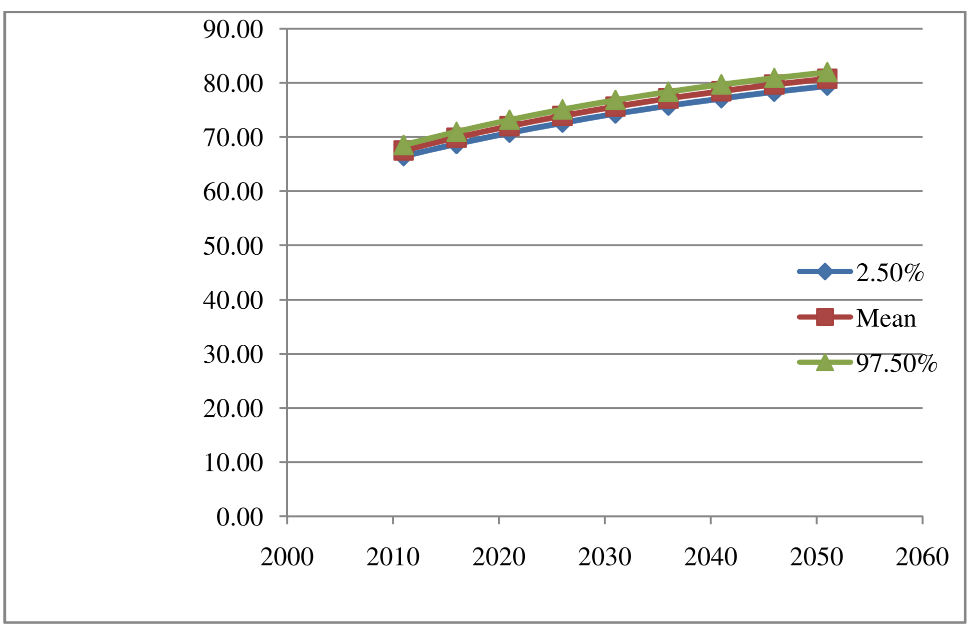

Figure-2: Life expectancy of females at birth, U.P.

Results and discussion

We have obtained the result with the help of MCMC technique in Bayesian procedure and above mentioned Tables- 1 to 4 shows the required result in 95% confidence interval. We can say that in early age and in the later ages are high. ASDR will fall with the passage of time and Life expectancy for both sexes will increase.

Conclusion

We have adopted Bayesian data analysis procedure to estimate our parameters and we have used WinBUGS and R (freely available software) to implement our model. Data obtained from different SRS reports of Age specific Death rate of U.P. was used to estimate α, β for male and female population separately then projected in 95% confidence interval by Bayesian procedure. Then we estimated life table survival ratio for both the sexes and were used to project the life expectancy at birth for both sexes along with ASDR in 95% confidence interval. The estimated values of the parameters of proposed model are shown in Table-1, Table-2, Table-3 and Table-4. The result shows that Age specific death rate for Females in Table-1, and ASDR for Males are shown in Table-2. Life expectancy at birth for Males are shown in Table-3 and for females in Table-4. ASDR will be higher in the older age group and will fall down very slowly in the future. Life expectancy for male population will increase with the passage of time and expected to reach maximum up to 76.59 years. Life expectancy of females will be higher as compared to the male population.

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