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A Hybrid Grey Bayesian Rolling Model for Forecasting Annual Rural Unemployment Rate in West Bengal

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SUMMARY

In this article, a reliable forecasting framework is developed for predicting the annual rural unemployment rate (UR) in West Bengal, India, where time series data are scarce and noisy. Accurate unemployment forecasts are crucial for targeted policymaking, especially in rural regions facing socio-economic vulnerabilities. The paper evaluates the performance of advanced grey system models in addressing data limitations and improving predictive accuracy. The study utilizes annual rural UR estimates for various age groups and gender from 2017–18 to 2023–24, derived from the Periodic Labour Force Survey (PLFS). Three forecasting models are developed: Grey Bayesian Model, Rolling Grey Model, and a hybrid Rolling Grey Bayesian Model. The models are compared against traditional moving averages using Relative Mean Absolute Percentage Error (RMAPE). Parameter estimation in the Bayesian models is implemented through MCMC simulations using WinBUGS. The results indicate that the Rolling Grey and Rolling Grey Bayesian models consistently outperform traditional and standalone grey models, with RMAPE values as low as 8.40%. These models show superior predictive capability, particularly for the 15–29 age group and female workforce categories. The dynamic updating mechanism of the rolling models effectively handles short time series and chaotic labour market data. This study demonstrates the novel integration of grey modelling with Bayesian inference and rolling mechanisms for rural labour market forecasting. It contributes a data-efficient, adaptive forecasting approach suited for regions with limited labour statistics, offering practical value for policymakers in developing economies.

Keywords: Unemployment rate; Grey systems; Rolling grey model; Bayesian grey model; Forecasting; PLFS.

1. INTRODUCTION

Unemployment in India, defined as the situation where individuals actively seeking work are unable to secure suitable employment, has become a critical issue contributing significantly to the economic slowdown. As a developing economy, India faces a unique unemployment landscape that presents challenges in both rural and urban areas (Nair 2020). High unemployment rates and stagnant economic growth are largely attributed to insufficient capital investment, which leads to the under-utilization of labour and human capital. This under-utilization results in diminished productivity across the economy and exacerbates critical societal issues such as poverty, malnutrition, and low per-capita income, highlighting the interconnectedness of these challenges within the Indian socio-economic context (Arora 2020). Unemployment is a complex phenomenon that significantly influences a country's economic activity and social framework. This complexity necessitates extensive research to devise effective solutions, as policymakers employ both fiscal and monetary tools to stimulate growth, which is often hampered by elevated unemployment rates (da Silva and de Araujo 2023). A well-established inverse relationship exists between economic growth and unemployment, indicating that a 1% reduction in unemployment can correspond to an approximate 3% increase in Gross National Product (GNP) (Mimi *et al.* 2022). Thus, rapid economic growth is central to policy objectives, emphasizing

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the necessity of investment programs to stimulate the economy and reduce unemployment (Dahal and Rai 2019).

Accurate prediction of the UR is important for the early recognition of socio-economic vulnerabilities, thereby aiding timely decision-making and targeted policy interventions (Chakraborty *et al.* 2012). The COVID-19 crisis has further highlighted the importance of robust forecasting methods, given the rapid contraction in economic activity and significant decline in labour market conditions (Nguyen 2021). Various time series models like moving averages, Holt's method, Holt-Winters Smoothing, and ARIMA have been employed for forecasting UR in different contexts, see for example (Claveria 2019; Syafwan *et al.* 2023) and references therein.

In India, estimates of annual rural URs are available at the state and national level from the PLFS conducted by the National Statistics Office (NSO), Government of India. However, these estimates are often delayed, and the available data is limited. At present, estimates of annual rural URs are available from 2017-18 to 2023-24. Traditional forecasting methods of predicting unemployment may not yield reliable forecasts due to violations of data requirement assumptions. The Grey model, proposed by Deng (1989), is well-suited for scenarios with limited data, as it requires minimal inputs to construct a forecasting model. Several studies have employed grey models in various contexts. El-Fouly *et al.* (2007) used improved grey predictor rolling models for wind power prediction. Akay and Atak (2007) applied grey prediction with a rolling mechanism for electricity demand forecasting. Meanwhile, Hsu and Wang (2007) applied a grey model with Bayesian analysis to forecast the output of integrated circuit industry. Li *et al.* (2020) employed a rolling grey model to forecast financial time series. Sinha and Sahu (2020) combined the rolling mechanism, grey model, and Bayesian estimation to forecast crop production in Uttarakhand state of India. Additionally, Ceylan (2021) utilized a grey rolling model optimized by particle swarm optimization to predict COVID-19 spread. Basak *et al.* (2023) applied grey model for prediction of quarterly urban URs in India at the state and national level based on PLFS data. Similarly, Pavithra *et al.* (2024) used grey model for forecasting of annual rural unemployment in West Bengal. This demonstrates that grey models, Bayesian techniques, and rolling mechanisms perform well in short time series. The rolling grey model and the Bayesian grey approach can enhance forecasting accuracy by continuously updating input data to address challenges arising from noisy and chaotic data. While Sinha and Sahu (2020) demonstrated the effectiveness of the rolling grey Bayesian framework for agricultural production forecasting, its application to labour market data, particularly, rural URs remain unexplored. Rural unemployment data differ fundamentally from agricultural production data in their volatility, sensitivity to economic shocks, and policy implications. Moreover, disaggregated analysis across different age groups and gender categories under both Usual Status and Current Weekly Status approaches has not been undertaken in prior studies. The present study fills this gap by adapting the hybrid rolling grey Bayesian framework to annual rural UR data from PLFS for West Bengal, covering different demographic categories, thereby offering a data-efficient, adaptive forecasting tool for labour market planning in data-scarce developing economies.

2. MATERIALS AND METHODS

2.1 Data description

The study utilizes annual rural UR estimates of West Bengal in both usual status (ps+ss) and current weekly status (CWS) for various age groups and gender from 2017-18 to 2023-24, derived from the PLFS annual reports conducted by the NSO, Government of India. Under the usual status (ps+ss) approach, a person is classified as employed if engaged in any work activity either as their principal or subsidiary occupation. This means that even if someone is not employed in their principal activity, they are still counted as employed under the usual status (ps+ss) framework, provided they carried out some economic activity in a subsidiary capacity for at least 30 days within the 365 days prior to the survey date. The principal activity (ps) status refers to the economic activity on which a person spent the majority of their time during the preceding 365 days, determined by the major time criterion, whereas subsidiary activity (ss) status, on the other hand, captures any additional economic activity pursued for 30 or more days during the same reference period. The UR derived from the usual status approach is well-suited for examining long-term employment patterns and structural trends in the labour market. In contrast, CWS approach offers a snapshot of unemployment over a short, seven-day reference window within the survey period. Under CWS approach, a person is classified as unemployed if they did not work even for a single hour during the preceding seven days, despite being available for or actively seeking work for at least one hour. Consequently, the UR based on CWS is more appropriate for assessing the immediate state of the labour market or measuring the effects of recent economic developments. The usual status-based UR tends to be more stable and consistent, reflecting a person's broader labour market engagement over an extended period, whereas the CWS-based UR is inherently more sensitive to short-term variations such as seasonal shifts or sudden economic disruptions.

2.2 Moving average

The simple moving average, introduced by G.U. Yule in 1909, is defined as the mathematical average of recent actual values. Consequently, the forecast for any time period, t becomes the average of the actual data from the selected preceding periods. The mathematical formula for the moving average model is as follows,

$$M_t = \frac{Y_t + Y_{t-1} + ... + Y_{t-n+1}}{n},$$

where M_t is the moving average for time period t, Y_t is the actual value at time period t, and n represents the number of time periods considered in the moving average. The forecast at time period ($t+1$), is given by, $F_{t+1} = M_t$. A moving average of order n is denoted as MA (n).

2.3 Grey model

Grey model of first order and one variable, referred to as GM (1,1), is widely applied in time series forecasting with a limited number of data points. Minimum four observations are required to fit a grey model. Here, a new data series is generated from original data series by accumulated generating operation (AGO) as follows,

Original data series: $\mathbf{y}^{(0)} = (y_1^{(0)}, y_2^{(0)}, \ldots, y_n^{(0)})$

New data series: $\mathbf{y}^{(1)} = (y_1^{(1)}, y_2^{(1)}, \ldots, y_n^{(1)})$

$y_1^{(1)} = y_1^{(0)}$ and $y_t^{(1)} = \sum_{i=1}^{t} y_i^{(0)}$; $t = 2,\ldots,n$.

Then, $\mathbf{y}^{(1)}$ is approximated as a first order differential equation,

$$\frac{d\mathbf{y}^{(1)}}{dt} + \beta \mathbf{y}^{(1)} = \alpha \tag{1}$$

where, β and α are the developing coefficient and control variable respectively. The parameters of grey differential equation in (1), *i.e.*, $\boldsymbol{\theta} = (\alpha, \beta)'$ are estimated by ordinary least squares as follows,

$$\boldsymbol{\theta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

where, $\mathbf{X} = [-\mathbf{z}\ \mathbf{1}_{n-1}]$,

$\mathbf{z} = (z_2, z_3, ..., z_n)'$,

$z_t = \delta y_t^{(1)} + (1-\delta) y_{t-1}^{(1)}$, $t = 2,3,...,n$,

$\mathbf{1}_{n-1}$ is the unit vector of length n-1 and

$\mathbf{y} = (y_2^{(0)}, y_3^{(0)}, ..., y_n^{(0)})$.

Here, δ is the adjustment coefficient which may vary from 0 to 1. From the Grey differential equation, the solution of $y_t^{(1)}$ at time ($t+1$) is given by

$$y_{t+1}^{(p)} = \left[y_1^{(0)} - \frac{\beta}{\alpha} \right] e^{-\alpha t} + \frac{\beta}{\alpha}.$$

The predicted value of the original data sequence at time ($t+1$) is given by

$$y_{t+1}^{(p)} = \left[y_1^{(0)} - \frac{\beta}{\alpha} \right] e^{-\alpha t}(1 - e^{\alpha}) \tag{2}$$

2.4 Bayesian grey model

In Bayesian grey model, the parameters of grey differential equation in (1), *i.e.*, $\boldsymbol{\theta} = (\alpha, \beta)'$ are estimated using Bayesian method of estimation. In Bayesian methods, the parameters of a model may be simulated directly via methods for exploration of posterior distributions. Among the various computational approaches available, the Markov Chain Monte Carlo (MCMC) method is the most widely employed. It estimates posterior distributions by iteratively drawing random samples from the full conditional distribution of each parameter, conditioned on both the remaining parameters and the observed data. A posterior probability is determined by integrating prior knowledge with sample information through the application of Bayes' theorem, with the resulting distribution reflecting the relative precision of both sources of information. The overarching goal of Bayesian analysis is to construct a probabilistic model that captures the relationship between the parameters of interest and the observable variables, and subsequently derive the conditional probability distribution of those parameters given the available data. In grey model, the observations consist of original data sequence except the first observation in the vector, $\boldsymbol{y}$ and the predictor variable is given by the matrix $\mathbf{X}$. Here, the parameters to be estimated are $\boldsymbol{\theta}$ and the error variance of the fitted model, σ^2. Let, the distribution of $\boldsymbol{y}$, given the parameters $\boldsymbol{\theta}$, σ^2 and predictors $\mathbf{X}$, is a normal distribution with mean $\mathbf{X\theta}$ and variance $\sigma^2\boldsymbol{I}$. The prior distribution for the joint parameter vector $\boldsymbol{\theta} = (\alpha, \beta)'$ and error variance $\sigma^2$is a non-informative (diffuse) Jeffrey s-type prior, specified as: $p(\boldsymbol{\theta}, \sigma^2) \propto 1/\sigma^2$. This implies a flat (uniform) prior on $\boldsymbol{\theta}$ and a scale-invariant prior on σ^2, which is a standard non-informative prior choice in Bayesian linear regression when no strong prior knowledge is available. Given the parameters of GM(1, 1) model and the limited availability of historical unemployment data in India, non-informative priors are deliberately chosen to allow the data to dominate the posterior inference. Thus, the posterior distribution of $\boldsymbol{\theta}$ given σ^2 is $\boldsymbol{\theta}|\sigma^2, \boldsymbol{y} \sim N\left(\left(\mathbf{X'X}\right)^{-1}\mathbf{X'y}, \sigma^2\left(\mathbf{X'X}\right)^{-1}\right)$ and the marginal posterior distribution of σ^2 is $\sigma^2|\boldsymbol{y}$~Inverse $\chi^2(n - 3, s^2)$. After estimating the parameters, $\boldsymbol{\theta} = (\alpha, \beta)'$ using Bayesian technique, the predicted value of original data series at time (t+1) is obtained by substituting the estimated parameters in equation (2) as given below,

$$y_{t+1}^{(p)} = \left[y_1^{(0)} - \frac{b}{\mathrm{a}}\right]e^{-\mathrm{a}t}(1 - e^{\mathrm{a}}),$$

where, a and b are Bayesian parameter estimates of α and β respectively.

2.5 Rolling mechanism for grey and Bayesian grey model

When dealing with chaotic and noisy data, the grey model which is developed based on all the observations may lead to error accumulation. In such situations, a rolling mechanism may be applied, wherein the input data is progressively updated with each iteration of the grey prediction process by discarding older observations. The underlying purpose of this mechanism is to ensure that, at every step, the data feeding into the subsequent iteration consists exclusively of the most recent and relevant information available. The rolling grey or rolling Bayesian grey model applies this technique using a rolling window of the latest data points, removing older data in each loop. This technique helps to eliminate the error accumulation and focus more on the current state of the data. To be more specific, the length of rolling window considered in this study is five. Thus, the first roll contains time series $\left\{y_1^{(0)}, y_2^{(0)}, y_3^{(0)}, y_4^{(0)}, y_5^{(0)}\right\}$ which is used to forecast sixth data $y_6^{(0)}$. After the actual sixth data appear, next roll $\left\{y_2^{(0)}, y_3^{(0)}, y_4^{(0)}, y_5^{(0)}, y_6^{(0)}\right\}$ is used to forecast $y_7^{(0)}$. The process is repeated till the time series reaches the end.

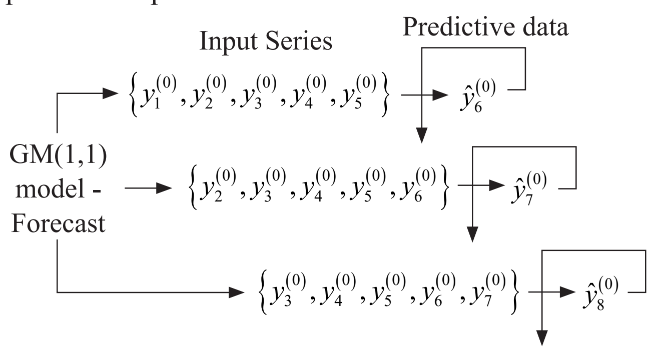

Fig. 1. Five order rolling grey model

2.6 Forecasting accuracy evaluation

Different competing models used in the study are evaluated using Relative Mean absolute percentage error (RMAPE) criterion, defined as

$$RMAPE = \frac{1}{n-1}\sum_{i=2}^{n}\frac{\left|y_i^{(0)} - y_i^{(p)}\right|}{y_i^{(0)}} X\,100\%$$

where, $y_i^{(0)}$ and $y_i^{(p)}$ denote the actual and predicted values of annual rural URs respectively.

3. RESULTS AND DISCUSSION

The descriptive statistics of the annual rural UR estimates in both usual status and CWS in West Bengal for various age groups and gender are presented in Table 1. The results in Table 1 reveal that annual rural UR is higher in the age group 15-29 years. The median annual rural UR in this age group are 11.20, 5.60 and 10.40 for male, female and person respectively. The female annual URs in the rural areas in both usual status and CWS are lower than males for all the age groups but having more variability than males except for15 years and above age group in CWS. The estimates of annual UR in CWS are higher than in usual status which indicates that unemployment in short term period is higher than that of long-term period. Also, the variability of URs in CWS is more than 37% which is quite higher than in usual status. These findings suggest that younger individuals, particularly those aged 15-29 years, face the higher unemployment in rural areas, with high variability over the years.

Table 1. Descriptive statistics of annual rural UR in usual status for 15-29 and 15-59 years age group

Statistics	15-29 Years			15-59 Years		
	Male	Female	Person	Male	Female	Person
Minimum	5.90	3.60	5.20	1.90	1.10	1.70
Maximum	15.10	8.60	13.70	5.40	2.70	4.80
Mean	10.84	6.13	10.40	3.87	1.80	3.39
Median	11.20	5.60	9.89	4.20	1.80	3.50
CV	27.40	29.69	25.10	32.04	32.22	30.38

Table 2. Descriptive statistics of annual rural UR in usual status for 15 years and above, and all age group

Statistics	15 Years and above			All age group		
	Male	Female	Person	Male	Female	Person
Minimum	1.70	1.10	1.50	1.70	1.10	1.50
Maximum	4.80	2.80	4.40	4.80	2.80	4.40
Mean	3.46	1.77	3.07	3.50	1.76	3.11
Median	3.70	1.70	3.20	3.70	1.70	3.20
CV	32.37	33.90	31.27	31.71	34.09	30.87

Table 3. Descriptive statistics of annual rural UR in CWS for 15 years and above, and all age group

Statistics	15 Years and above			All age group		
	Male	Female	Person	Male	Female	Person
Minimum	2.80	2.20	2.60	2.80	2.20	2.60
Maximum	10.40	6.70	9.50	10.40	6.70	9.50
Mean	6.53	4.63	6.55	7.12	4.63	6.57
Median	7.20	4.70	6.80	7.40	4.70	6.80
CV	40.89	39.54	40.10	37.38	39.54	39.64

In the present study, MA (2) and MA (3) is fitted to forecast the annual rural URs in West Bengal for various categories of age group and gender. In MA (2) and MA (3), averages of actual annual rural URs from the previous two and three years are calculated respectively. In grey Bayesian model, Bayesian parameter estimation is carried out using WinBUGS (Windows Bayesian Inference Using Gibbs Sampling) version 1.4. The model is specified using the Win BUGS model language with a normal likelihood for the response vector $\boldsymbol{y}$ and a non-informative prior $p(\boldsymbol{\theta}, \sigma^2) \propto 1/\sigma^2$. A total of 5,000 Markov Chain Monte Carlo (MCMC) iterations are run, with the first 1,000 discarded as burn-in to allow the chain to converge to the stationary distribution before samples are collected. Every iteration after burn-in is retained (thinning interval = 1), as the chain exhibited good mixing with no significant autocorrelation in the retained samples. Finally, 4,000 posterior draws are used for estimation. The convergence of the MCMC chains is assessed using the following standard diagnostic tools within WinBUGS 1.4. The trace plots for parameters α and β are examined for all 18 demographic categories. The chains showed satisfactory stationarity and good mixing after the burn-in period, with no apparent trends or drifts. The marginal posterior distribution density plots of parameter α and β, depicted in Figure 2 to Figure 5, exhibited smooth, approximately normal-shaped densities across all categories, indicating well-behaved and converged chains. Multiple chains are run and the Gelman-Rubin Rstatistic is computed. For all parameters and all demographic groups, R values are less than 1.05, confirming satisfactory convergence.

The parameter estimates of α and β are nothing but posterior means of Bayesian parameter estimates, *i.e.*, a and b respectively, which are presented in Table 4 and 5. These estimates are substituted in equation (2) and predicted values are obtained. In the rolling grey model, the values of δ varied from 0.30 to 0.80 for a fixed order of 5, and the final selections were made based on the lowest RMAPE for each group. For 15-29 males, 15-29 females, 15-29 persons, 15 years and above males, 15 years and above females, all males, and all females, the rolling grey model of order 5 with δ=0.70 was selected. For 15-59 females, δ=0.40 was chosen, while for 15-59

Table 4. Parameter estimates of Bayesian grey, rolling grey and rolling grey Bayesian models for prediction of annual rural UR in usual status

Category	Bayesian Grey		Roll	Rolling Grey		Rolling Grey Bayesian	
	a	b		a	b	a	b
15-29 Male	14.84	0.10	Roll 1	12.04	0.01	12.00	-0.01
			Roll 2	18.57	-0.22	18.54	0.22
			Roll 3	14.76	-0.16	14.71	0.15
15-29 Female	6.04	-0.01	Roll 1	6.56	-0.01	6.55	-0.01
			Roll 2	9.94	-0.21	9.93	0.21
			Roll 3	5.89	0.02	5.84	-0.03
15-29 Person	13.36	0.08	Roll 1	11.14	-0.01	11.11	2.63
			Roll 2	17.08	-0.23	17.05	0.23
			Roll 3	13.04	-0.14	12.98	0.14
15-59 Male	5.80	0.13	Roll 1	4.74	-0.02	4.73	0.02
			Roll 2	7.09	-0.25	7.08	0.24
			Roll 3	6.08	-0.23	6.06	0.23
15-59 Female	1.95	0.02	Roll 1	2.19	-0.06	2.18	0.06
			Roll 2	3.68	-0.34	3.68	0.34
			Roll 3	0.89	0.13	0.87	-0.13
15-59 Person	5.20	0.12	Roll 1	4.38	-0.05	4.37	0.04
			Roll 2	6.30	-0.26	6.29	0.26
			Roll 3	4.67	-0.18	4.65	0.17
Above 15 Male	5.22	0.13	Roll 1	4.30	-0.03	4.29	0.03
			Roll 2	6.17	-0.24	6.16	0.24
			Roll 3	5.26	-0.23	5.25	0.22
Above 15 Female	1.95	0.03	Roll 1	2.19	-0.08	2.18	0.07
			Roll 2	3.42	-0.33	3.14	0.32
			Roll 3	0.99	0.11	0.97	-0.12
Above 15 Person	4.82	0.13	Roll 1	4.02	-0.05	4.01	0.05
			Roll 2	5.82	-0.27	5.81	0.27
			Roll 3	4.37	-0.19	4.35	0.19
All Male	5.59	0.14	Roll 1	4.62	-0.05	4.62	0.05
			Roll 2	6.24	-0.24	6.23	0.24
			Roll 3	5.18	-0.22	5.17	0.21
All Female	1.95	0.03	Roll 1	2.19	-0.08	2.18	0.07
			Roll 2	3.42	-0.33	3.41	0.32
			Roll 3	0.99	0.11	0.97	-0.12
All Person	4.99	0.13	Roll 1	4.25	-0.06	4.24	0.06
			Roll 2	5.87	-0.27	5.86	0.27
			Roll 3	4.28	-0.18	4.26	0.18

males, all persons, 15 years and above persons, and all persons, δ=0.60 was deemed appropriate. In the context of the Current Weekly Status (CWS), δ=0.40 was selected for 15 years and above females and all females, while δ=0.80 was chosen for 15 years and above males, all males, and all persons. The Bayesian parameter estimation is combined with the 5-order rolling grey model with a δ value, which is refereed as rolling grey Bayesian model and implemented at three rolls to forecast the annual rural URs of West Bengal. The estimated parameter values obtained during each roll demonstrate stability and are presented in Table 4 and 5. Following this, the parameter estimates obtained from each roll are substituted in equation (2) to obtain the predicted values.

Table 5. Parameter estimates of Bayesian grey, rolling grey and rolling grey Bayesian models for prediction of annual rural UR in CWS

Category	Bayesian Grey		Roll	Rolling Grey		Rolling Grey Bayesian	
	a	b		a	b	a	b
Above 15 Male	11.05	0.16	Roll 1	8.90	-0.04	8.89	0.03
			Roll 2	13.21	-0.28	13.19	0.28
			Roll 3	11.36	-0.29	11.32	0.29
Above 15 Female	8.74	0.22	Roll 1	9.39	-0.25	9.38	0.25
			Roll 2	8.61	-0.30	8.86	0.31
			Roll 3	4.51	-0.11	4.50	0.11
Above 15 Person	10.52	0.17	Roll 1	8.87	-0.07	8.85	0.07
			Roll 2	12.22	-0.29	12.20	0.29
			Roll 3	9.85	-0.27	9.82	0.27
All Male	11.17	0.17	Roll 1	9.09	-0.04	9.08	0.04
			Roll 2	13.27	-0.28	13.24	0.28
			Roll 3	11.29	-0.29	11.25	0.28
All Female	8.74	0.22	Roll 1	9.39	-0.25	9.38	0.25
			Roll 2	8.61	-0.30	8.60	0.30
			Roll 3	4.51	-0.11	4.50	0.11
All Person	10.57	0.18	Roll 1	8.97	-0.07	8.85	0.07
			Roll 2	12.24	-0.29	12.23	0.29
			Roll 3	9.78	-0.27	9.74	0.26

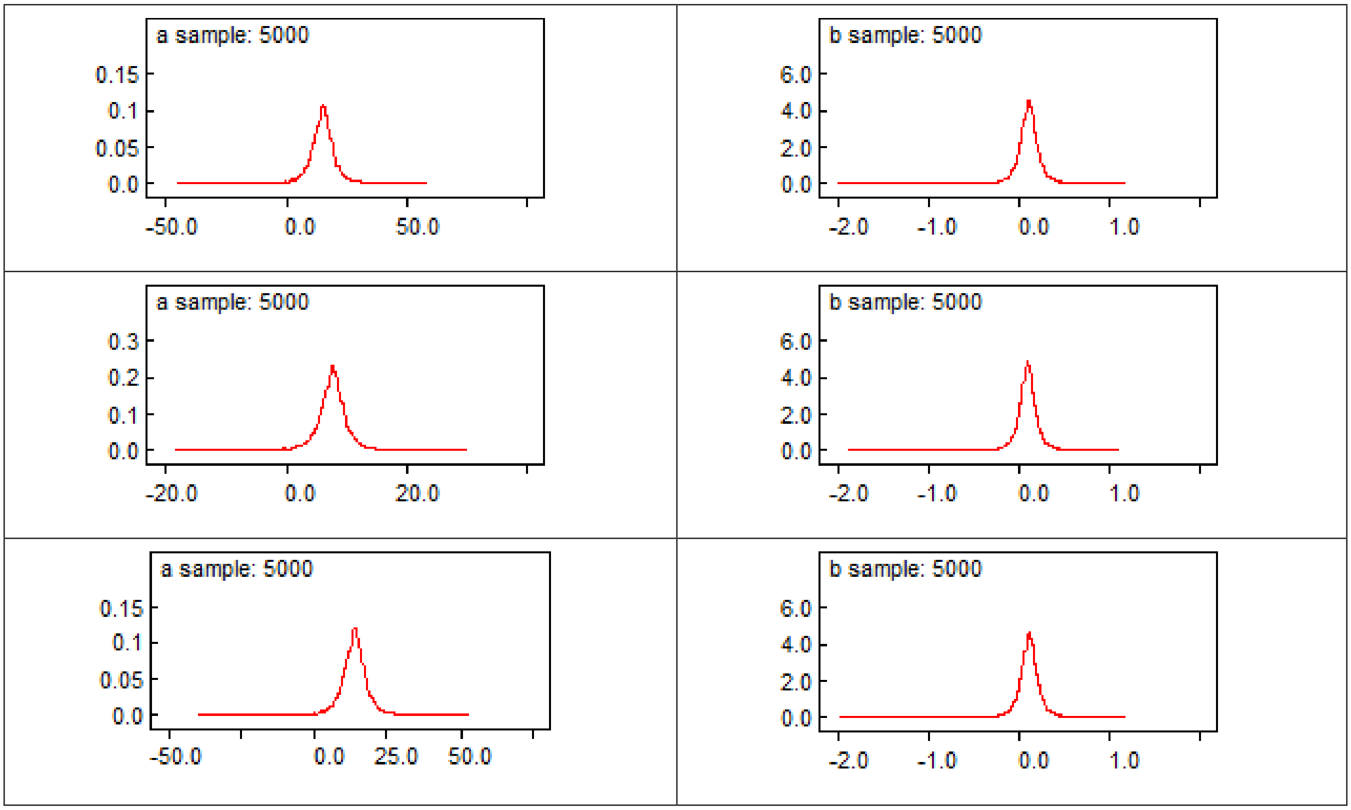

Fig. 2. Kernel density plots of Bayesian parameter estimates, a and b for annual rural UR in usual status for 15-29 years male, female and person

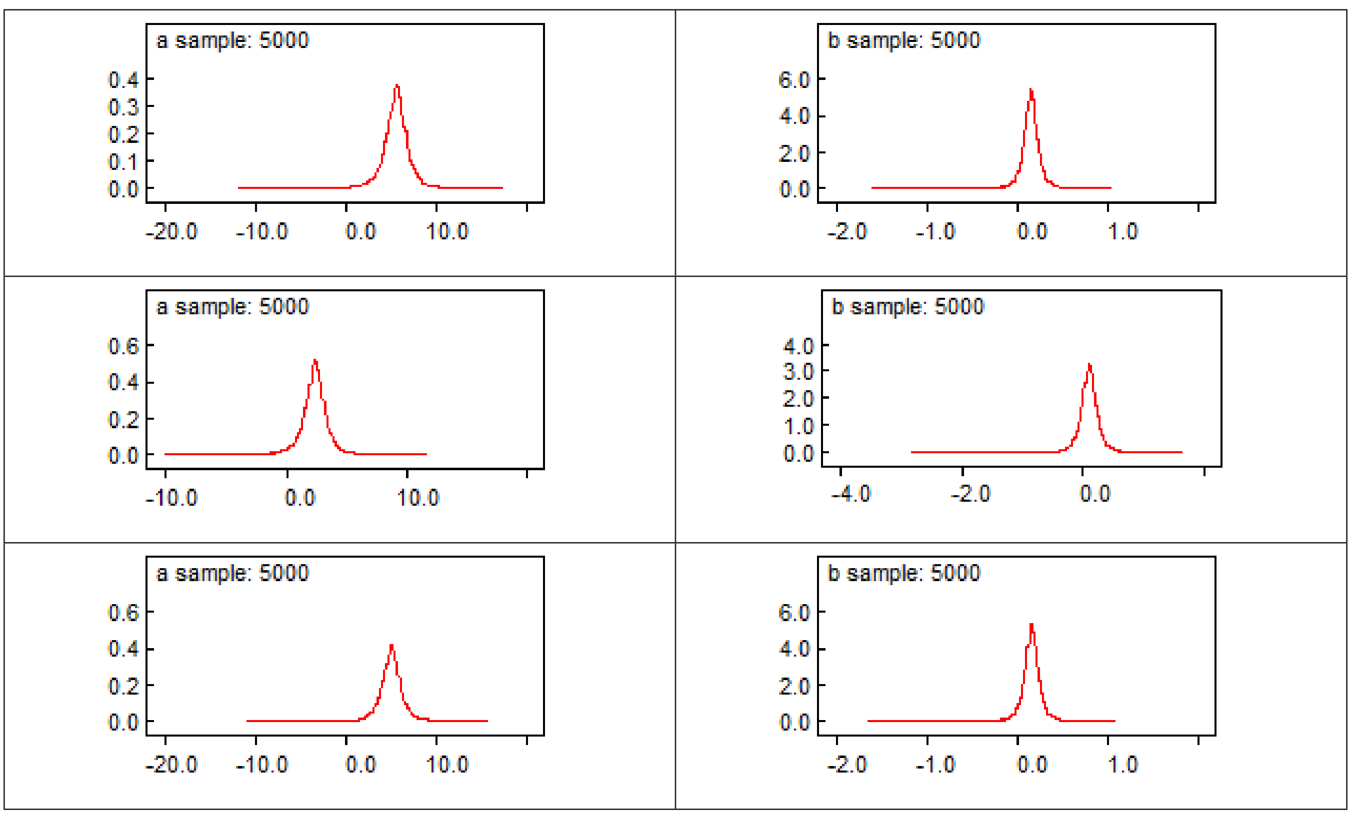

Fig. 3. Kernel density plots of Bayesian parameter estimates, a and b for annual rural UR in usual status for all age male, female and person

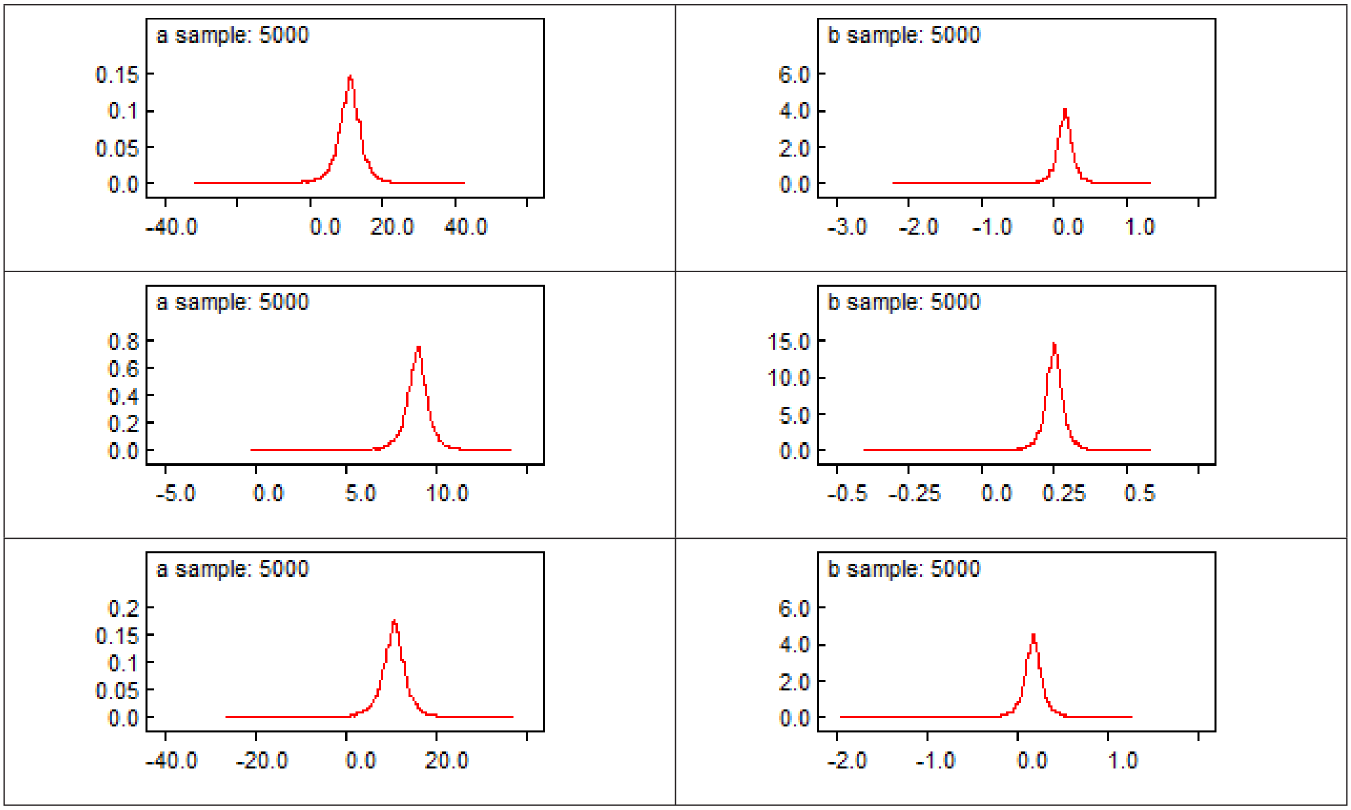

Fig. 4. Kernel density plots of Bayesian parameter estimates, a and b for annual rural UR in CWS for 15 years and above male, female and person

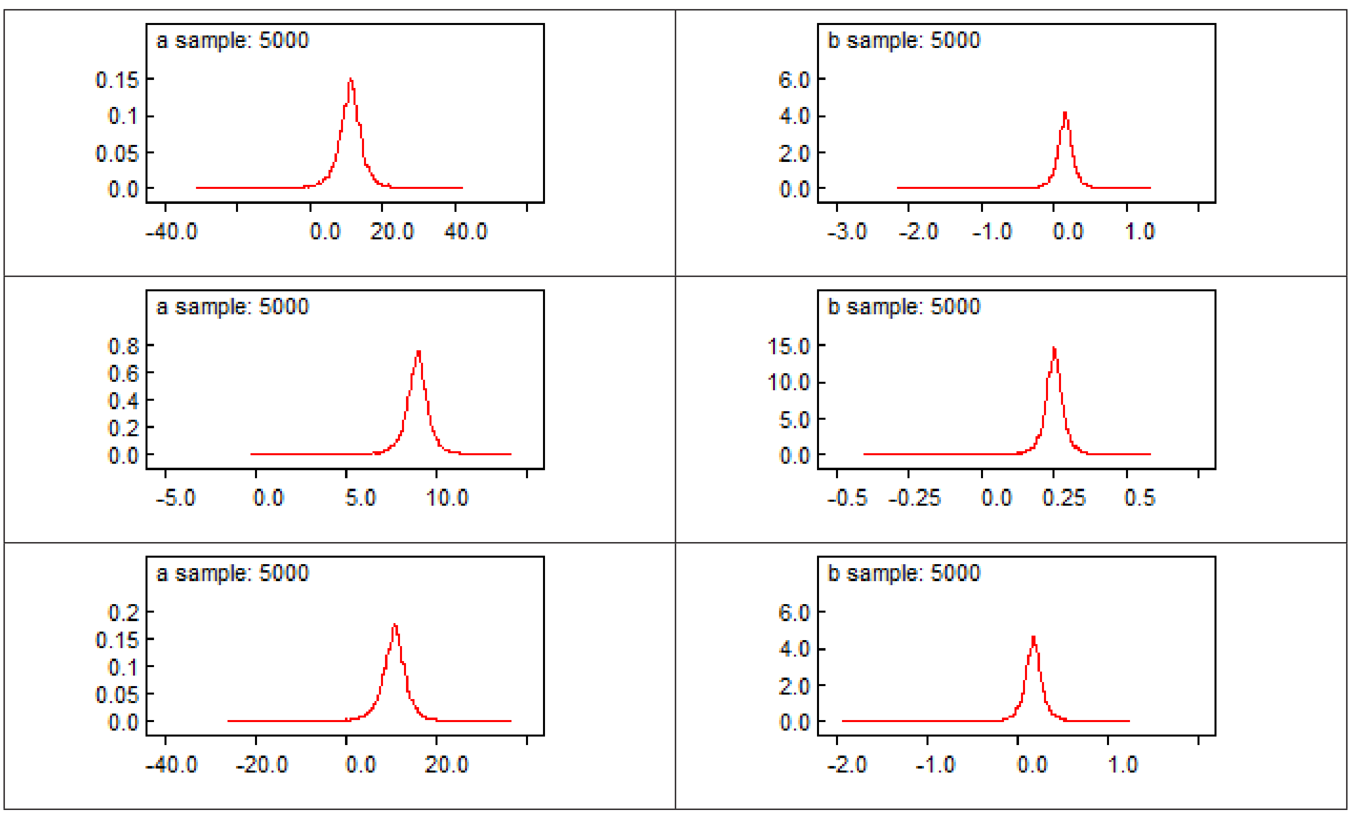

Fig. 5. Kernel density plots of Bayesian parameter estimates, a and b for annual rural UR in CWS for all age male, female and person

The best fitted model is determined for each category of age group and gender on the basis of minimum RMAPE values. The RMAPE values for all the models corresponding to URs of different categories of age group and gender are shown in Table 6.

Table 6. RMAPE values of different models

Category	MA2	MA3	Bayesian Grey	Rolling Grey	Rolling Grey Bayesian
15-29 Male	36.59	30.14	21.21	15.35	15.60
15-29 Female	42.11	41.20	27.20	19.18	19.18
15-29 Person	35.30	31.63	21.90	15.60	16.27
15-59 Male	50.41	41.51	20.89	14.40	13.99
15-59 Female	45.59	43.91	30.59	19.68	19.39
15-59 Person	37.40	25.26	19.14	13.94	13.87
Above 15 Male	50.81	37.14	20.55	13.84	13.84
Above 15 Female	45.83	45.09	30.80	19.98	20.56
Above 15 Person	43.90	31.20	20.02	14.26	14.26
All Male	50.43	36.47	18.54	13.61	13.61
All Female	45.83	45.09	30.80	19.98	20.56
All Person	48.01	34.61	19.54	14.24	14.58
Above 15 Male CWS	76.92	59.06	30.22	17.76	18.21
Above 15 Female CWS	55.44	37.22	12.57	8.40	8.40
Above 15 Person CWS	74.11	54.85	25.30	16.72	16.74
All Male CWS	75.99	58.16	27.69	17.84	18.02
All Female CWS	55.44	37.22	12.57	8.64	8.64
All Person CWS	73.07	53.97	23.07	16.88	16.95

The results in Table 6 reveal that rolling grey and rolling grey Bayesian models outperformed the grey Bayesian and moving average models in terms of RMAPE values. Consequently, either the rolling grey or rolling grey Bayesian model is the best performing model to forecast annual rural URs. Finally, the forecasted values of annual rural URs in both usual status and CWS for various age groups and gender are obtained for the year 2024-25 which are presented in Table 7.

Table 7. Forecasted annual rural UR in usual status and CWS in West Bengal for the year 2024-25

Category	Best fitted model	Forecast
15-29 Male	Rolling grey	6.13
15-29 Female	Rolling grey Bayesian	6.56
15-29 Person	Rolling grey	5.93
15-59 Male	Rolling grey Bayesian	1.68
15-59 Female	Rolling grey Bayesian	2.19
15-59 Person	Rolling grey Bayesian	1.76
Above 15 Male	Rolling grey Bayesian	1.56
Above 15 Female	Rolling grey	2.15
Above 15 Person	Rolling grey Bayesian	1.47
All Male	Rolling grey Bayesian	1.62
All Female	Rolling grey	2.15
All Person	Rolling grey	1.55
Above 15 Male CWS	Rolling grey	2.26
Above 15 Female CWS	Rolling grey Bayesian	2.36
Above 15 Person CWS	Rolling grey	2.14
All Male CWS	Rolling grey	2.30
All Female CWS	Rolling grey Bayesian	2.36
All Person CWS	Rolling grey	2.18

4. CONCLUSIONS

The study highlights the efficacy of grey-based models, particularly the rolling grey, Bayesian grey and rolling grey Bayesian models, in forecasting annual rural URs of West Bengal. Unlike traditional forecasting models like moving averages, which require extensive data and often fail in the presence of noise or irregularities, the grey models proved highly adaptable to the limited and chaotic data available for annual rural UR. The integration of Bayesian methods further enhanced the model's predictive capabilities by allowing for continuous data updates and improved accuracy, making it a suitable tool for handling uncertain and incomplete datasets. The results of this study show that the rolling grey and Bayesian rolling grey models provide significantly more accurate predictions of annual rural URs, particularly for younger age groups (15-29 years), where unemployment is most prevalent. By consistently outperforming other methods, these models offer a reliable mechanism for policymakers to predict unemployment rates and make timely interventions. The findings also underline the need for tailored, data-efficient approaches in unemployment forecasting, especially in developing regions where the availability of reliable data is often a challenge. These forecasts can inform targeted strategies to reduce unemployment, foster greater economic stability and address socio-economic issues like poverty and malnutrition in rural areas.

Conflicts of interest/Competing interests The authors declare that there is no conflict of interest related to this article.

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