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Estimation of Quality Adjusted Life Year (QALY) for Different States of India During COVID-19

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Abstract

Covid-19 is an incessant pandemic which is widespread worldwide. Various epidemic models have been used for forecasting the covid-19 cases in India. In this paper we have tried to estimate quality adjusted life year (QALY) for the covid-19 infected patients from 26 March, 2020 till 28 May, 2020 in different states of India. A regression equation for time varying reproduction number has been defined using the basic Susceptible-Infective-Recovered (SIR) model, which is further used to obtain the utility function. The average QALY per month for each state has been computed on the basis of the proposed utility function. Various states are categorised as severe, moderate and controlled regions for the covid-19 pandemic based on QALY values.

Key words: QALY; Utilities; TSIR; Exponential regression; India; Covid-19.

1. Introduction

Pandemic has always attracted global attention due to widespread devastation caused to health of human beings as well as economy of a nation. Dazak *et al*. (2018) have estimated that around 1.67 million yet to be discovered viral species from key zoonotic families exist in mammal and bird hosts. More than 50 percent of these viral species have the potential to cause severe infections via transmission to humans. COVID-19 has a faster spread rate than its ancestors like SARS-COV and MERS-COV but lower mortality rate as stated by Giordano *et al.* (2020). In India covid-19 cases are widespread in all the states. The government had imposed a series of lockdown in five different phases across the country in order to further prevent the spread of virus through community transmission.

Researchers are using various mathematical models in order to study the crucial epidemiological properties of this epidemic. Akshaya *et al*. (2020) have stated how different forecasting techniques have played important roles in capturing the probability of infection and reproduction rate. Wu *et al.* (2020) have indicated that 86% of the infected individuals are expected to remain asymptomatic which are the main sole for spreading the infection under community transmission. Biswas *et al.* (2020) have stated on the basis of Euclidean network that an infected individual can infect another individual with distance (l), rate of infection (δ) and probability proportional to $l^{-\delta}$. In the early days of outbreak, government was keen on tracing contacts of persons who were closely related to the infected individuals.

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Those individuals were isolated in order to prevent the further spread of disease. Ghosh *et al.* (2020) analysed the case counts in India using standard epidemiological models and projected on the basis of crisis at present.

Ranjan (2020) reported that the early action of lockdown in India has a favourable effect in limiting the epidemic size. Deo *et al.* (2020) have estimated the reproduction number which was significantly reduced due to lockdown measures. Thus, lockdown not only prevented the rise in the number of cases but also created substantial economic loss to the weaker sections of the society. Chatterjee *et al.* (2020) have performed a review of the pandemic with the current evidence. They highlighted the key areas where research needs attention in order to create critical intelligence for the prevention of its spread. Ferguson *et al.* (2020) figures out South Korea, Taiwan and New Zealand among the few countries who have precisely managed to fight back against the virus.

In this paper we have tried to estimate QALY for the covid-19 infected patients from 26 March 2020 till 28 May 2020. We have estimated QALY by time series modelling of epidemiological model namely, Susceptible Infective Recovered (SIR) model with the exponential form. It enables us to estimate the utilities which in turn help us to compute the Quality Adjusted Life Year (QALY) per month for each state. This quality of life approach is first and foremost attempt in the time of pandemic which is carried over different states of India.

2. Methodology

2.1. Epidemic SIR model linked with exponential regression

Researchers have done a lot of manifold classifications based on SIR models during the covid-19 pandemic for different countries. Jewell *et al.* (2020) describes the underlying principles and value of projections in pandemic models. The early models relates to the region when virus had been circulating in a community. Meanwhile their projections were not robust and reliable. All these models have one thing in common that is the peak which is predicted on the basis of the number of infectives. Prakash *et al.* (2020) have replaced this peak as an artefact of plateau and described it with the help of persistence number. This peak acts as a plateau which grows flat and last for many weeks with no downward trend due to increase in the number of containment zones.

SIR models encapsulate the number of susceptibles to the number of infectives, further to the number of recovered and death cases for a disease. It is also known as the compartmental model in epidemiology. Wu *et al.* (2020) have defined variants of SIR models for policy decisions in China. As human to human transmission occurs there is high rise in the number of infectives. It is deducible that the susceptibles are more likely to get infected and people in the infected stage are either likely to enter the stage of recovered cases or death. The infectious period determined by Ma (2020) states that it is exponentially distributed with mean $(1/\gamma)$. Also, Wallinga *et al.* (2006) have introduced a nonparametric method to develop reproduction number from exponential growth rate.

The flow of individuals from susceptible to infective to recover as well as to death cases have been monitored with the help of system of non-linear differential equations, which are defined as:

$$\frac{\delta S}{\delta t} = -\frac{\beta IS}{N} \tag{1}$$
$$\frac{\delta I}{\delta t} = \frac{\beta IS}{N} - \gamma I \tag{2}$$
$$\frac{\delta R}{\delta t} = \gamma I \tag{3}$$

$$R_0 = \frac{\beta}{\gamma} \tag{4}$$

where $S = S(t)$ is the total number of confirmed cases in a particular state, $I = I(t)$ is the number of active positive cases, $R = R(t)$ denotes the number of recovered individuals. β is the transmission rate, $\gamma$is the recovery rate. The reproduction number (R_0) can be rewritten as the ratio of transmission rate to recovery rate as given in equation (4). When the disease is transmitted from one to person to another under the assumption that the whole population is vulnerable to the exposure of infection, this rate has a steady increase. The individuals are not vaccinated because the infection erupted for the first time with no way to control the spread. This number reproduces itself in the case of communicable infection. When $R_0 > 1$ then the situation of epidemic results and if $0 < R_0 < 1$ then the infection will eventually die out soon.

2.2. Regression equation for time varying reproduction number (R_t)

We redefine reproduction number (R_t) as a function of t in order to depict the time dependency of the SIR model for the study of disease progression. Under the assumption, $S+I+R = N$ which is the total population for a state. The initial conditions are defined as $S(t) \geq 0$, $I(0)=0$, $R(0)=0$ converge to an equilibrium.

Using equations (1) to (4) we can redefine β and R_t as:

$$\beta = \left(\frac{\delta I}{\delta t} + \frac{\delta R}{\delta t}\right)\frac{N}{IS} \tag{5}$$

$$R_t = \left(\frac{\acute{I}+\acute{R}}{\acute{R}}\right)\frac{N}{S} = \left(\frac{\Delta I(t)}{\Delta R(t)} - 1\right)\frac{N}{S} = \frac{CN}{S} \tag{6}$$

where $\acute{I}, \acute{R}$ are the partial derivates of infective and recovered cases respectively (Derivation is given in appendix), and $C = \left(\frac{\Delta I(t)}{\Delta R(t)} - 1\right)$ is calculated as the ratio of change in number of infectives to change in number of recovered cases. The values of R_t follows exponential distribution (observed on the basis of AIC values). Thus, we can link the parameters obtained from the above equation (6) to the exponential form by means of link function:

$$R_t = Ae^{\alpha t} \tag{7}$$

where $A = \frac{CN}{S}$ and α is the parameter of the exponential model.

2.3. Utility function

In economic theory, utility is defined as a production function of demand and supply. It is differentiated with respect to time in order to get the preference value for a consumer at a point of time. Borrowing the same concept into health preference for different states of India, we define utility as a function of confirmed, recovered cases and R_t. The production function for utility is defined in a multiplicative form as:

$$U_t = kA_tB_t \tag{8}$$

where $A_t = \frac{1}{S(t)}$, $B_t = R_t$ and the constant k gives the ratio of estimated coefficient of variable C to the number of active infective cases.

Then the utilities for different states can be estimated by:

$$U(t) = \frac{Estimated\ coefficient\ of\ variable\ C * R_t}{Estimated\ coefficient\ of\ active\ cases * S(t)} \tag{9}$$

The state-wise utility values are calculated using equation (9). These are further multiplied with the average length of stay in hospitals in order to get the QALY values over a period of 3 months.

3. Data

The study includes data for the daily number of cases from different states of India. The daily case counts for the covid-19 infected patients from 26 March, 2020 till 28 May, 2020 has been obtained from the websites of Ministry of Health and Family Welfare (MOHFW, Government of India), Covid19India organisation, worldometer India tracker. Among the 28 states and 8 union territories, we have included 20 states and 5 union territories in our dataset. The remaining states and union territories have been excluded due to non-availability of data records for the duration of 3 months (March-May). The count for a daily case was accumulated on a weekly basis. These were further aggregated on monthly basis. The Table 4 for different values of R_t is given in appendix which has been taken from COVID-19 India organisation data operations group. The data for different states with total number of confirmed, active, recovered and death cases is presented below in Table 1.

Table 1: State wise data of COVID-19 cases as on 28 May 2020

State	Confirmed	Recovered	Deaths	Active
Andhra Pradesh	8929	4307	106	4516
Bihar	7808	5631	51	2126
Chandigarh	406	316	6	84
Chhattisgarh	2255	1421	11	823
Delhi	59746	33013	2175	24558
Gujarat	27317	19357	1664	6296
Haryana	10709	5557	161	4991
Himachal Pradesh	702	419	7	263
Jammu and Kashmir	5956	3382	82	2492
Jharkhand	2089	1406	11	672
Karnataka	9150	5618	138	3390
Kerala	3173	1659	22	1490
Ladakh	837	134	1	702
Madhya Pradesh	11903	9015	515	2373
Maharashtra	132075	65744	6170	60147
Manipur	841	250	1	591
Odisha	5303	3720	21	1562
Puducherry	383	149	8	226
Punjab	4074	2700	99	1275

Rajasthan	14997	11652	349	2996
Tamil Nadu	59377	32754	757	25866
Telangana	7802	3731	210	3861
Uttar Pradesh	17731	10995	550	6186
Uttarakhand	2344	1500	27	802
West Bengal	13945	8297	555	5093

4. Implementation and Results

Ma *et al*. (2014) have used exponential curve at the time of onset but as the spread increases it tries to flatten out in due course of time. Ghosh and Mondal (2020) have identified the number of corona positive cases in the month of March by extrapolation of exponential growth model. They have used low time axis values on the basis of sigmoid function whose growth is saturated with an assumption of 10^4 or 10^5 values in different states. In the early month of March till late May there is a deviation in the number of cases from exponential growth to non-exponential growth. Prakash *et al.* (2020) have indicated that the number of daily new cases increases as the number of cumulative infections. Ma (2020) in the initial growth phase of cumulative number of cases has derived a linear relationship with time by using a log linear scale. Since an epidemic grows exponentially in an initial phase. Guerrero (2020) forecasted the spread of virus by using logistic and SIR model combination. Giordano *et al*. (2020) have defined eight stages of an infection and called the model as SIDARTHE.

Assuming that the entire population across all the states have equal likely chance of being susceptible to infection, the best distributional fit to the reproduction number (R_t) in all the states is determined on the basis of Akaike Information Criterion (AIC) values using the fitdistrplus package in the *R* programming language as shown below in Table 2.

Table 2: Potential form of distributions with AIC values

Distribution	Log Likelihood	AIC
Normal	–46.36955	88.7391
Exponential	–31.01179	60.02358
Log Logistic	–46.01647	88.0329
Log Normal	–39.34114	74.68229
Weibull	–45.80388	87.60776
Gamma	–41.745	79.4915

The model having least AIC value is the best model. From Table 2, we can choose the distribution on the basis of least AIC value and maximum log likelihood value. Regardless of their random movement within the population, exponential distribution best fit the data. The model equation (7) indicates that

$$R_t \sim Exponential(9.397762).$$

After taking logarithm of the equation (7) and running the regression we get:

$$logR_t = -1.80 + .0813\ logN - 0.268\ logC - 0.150\ logS + 9.3977\mathrm{t} + \varepsilon \tag{10}$$

where ε is the random error component which follows normal distribution.

The value of coefficient of determination for the above model is 0.9075. This implies that 90.75% of the total variation in the number of reproduction number which varies by time is explained by the set of confirmed, recovered and active cases. Then we differentiate the model equation in order to get the utilities for each state. This analytic model (in equation 10) serves to be better choice for estimation of quality of life for covid-19 patients. It eliminates the drawback of solving the differential equations again and again along with differentiating the likelihood function.

5. Quality Adjusted Life Year (QALY)

Quality Adjusted Life Year (QALY) is a metric used by health economists to evaluate new and innovative healthcare treatment for any particular disease. It is an important measurement of health outcome which gives the quality adjusted life years for an individual or group of individuals. Drummond *et al.* (1997) have introduced the quality of life which can be quantified by using the concept of utility. Whitehead and Ali (2010) have combined the effects of health care interventions on mortality as well as morbidity. Their definition of QALY goes around a single index termed as common currency enabling comparison across different disease areas which can further be extended to different states. Thus, QALY is a summary measure which incorporates the impact on quantity as well as quality of life.

QALD (Quality Adjusted Life Days) for childbirth and maternity service in India have also been estimated by Grover *et al*. (2019). These QALDs are estimated for different quintiles which are classified on the basis of usual monthly per capita expenditure. Deo and Grover (2020) have defined utility as a function of longitudinal covariate which is significantly associated with a disease progression. In this paper we estimate QALY by linking the utility function with the conventional epidemiological models. On the basis of utility function and average length of stay in hospital (ALOS) QALY's for different states can be estimated by:

$$QALY = Utility * Averagelengthofstayinhospital \tag{11}$$

ALOS in the hospital has been accumulated from a weekly data base. Using the datasets of total confirmed cases, recovered cases, deaths and active cases given in Table 1, we have estimated QALY for the corona virus affected patients for various states as given in Table 3 below:

Table 3: QALY's based on different states of India

State	R_t	U_t	ALOS	Q_M
Andhra Pradesh	0.15	2.215	13.17	0.317
Bihar	0.12	4.115	8.04	0.360
Chandigarh	0.06	5.415	13.54	0.797
Chhattisgarh	0.11	3.070	5.856	0.295
Delhi	0.13	2.726	12.646	0.375
Gujarat	0.13	4.861	10.21	0.539
Haryana	0.08	2.404	9.582	0.250
Himachal Pradesh	0.08	2.990	6.81	0.221
Jammu and Kashmir	0.13	2.678	13.01	0.379
Jharkhand	0.17	3.483	1.16	0.44
Karnataka	0.09	3.024	15.22	0.500

Kerala	0.07	2.386	10.26	0.66
Ladakh	0.01	1.336	25.77	0.374
Madhya Pradesh	0.16	5.620	8.23	0.503
Maharashtra	0.13	2.460	13.7	0.366
Manipur	0.06	1.594	2.26	0.39
Odisha	0.11	3.804	13.22	0.547
Puducherry	0.06	1.899	9.1	0.88
Punjab	0.11	3.580	16.55	0.644
Rajasthan	0.12	5.608	11.09	0.676
Tamil Nadu	0.17	2.572	10.74	0.300
Telangana	0.12	2.264	10.91	0.268
Uttar Pradesh	0.11	3.211	13.48	0.471
Uttarakhand	0.08	3.274	9.7	0.345
West Bengal	0.13	3.068	10.05	0.335

There is a huge variation in QALY per month (Q_M) values across different states of India. It indicates that few states are on the verge of better quality of life with QALY value closer to 1 than other states which are in worse condition with QALY value close to 0. QALY provides a better tool to policy makers for identifying how preventive measures implemented in various states have impacted differently. They help us to conclude on those states of India whose QALY value is close to 1 thus, indicating adequate lockdown and preventive measures which were taken timely in order to curb the virus. Thus the disease progression and QALY variation will help the policy makers to initiate new frameworks for states with lower quality of life for corona virus affected regions. One way of representation through QALY is done by means of classifying the states with values greater than 0.5 or less than it.

Classification I: *QALY* values > 0.5

States: Chandigarh, Gujarat, Karnataka, Kerela, Madhya Pradesh, Odisha, Puducherry, Punjab, Rajasthan

Classification II: *QALY* values < 0.5

States: Andhra Pradesh, Bihar, Chhattisgarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Ladakh, Maharashtra, Manipur, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand, West Bengal

Thus from the above classification we can observe that there are 16 states which needs more preventive measures and strict lockdown guidelines in order to get better QALY values. While classification I indicates that these states also need to follow continued guidelines under covid-19 since their QALY values are not so much closer to one.

6. Discussion

India is a densely populated country with restricted infrastructure for healthcare systems in order to tackle a pandemic. With due demands of hospital beds, the state and central government are working towards creation of new corona isolation wards, medical equipment like ventilators, testing kits, personal protective equipment (PPE) kits, sanitizers, masks *etc*. Ranjan (2020) clearly states that the immediate action of lockdown imposed by the Indian government proved to be fruitful in early spread of infection as compared worldwide.

Salman and Salem (2020) have also listed the age group and immunity developed due to BCG vaccination which has favoured lower mortality rate in India. Also the testing rate is lower in India as compared to other countries which under estimates our number of positive cases. Testing of samples was done in India with restrictions. It majorly targets those individuals which show severe symptoms of prolonged high fever, acute respiratory syndrome patients, people travelling from high risk countries with their immediate contacts, symptomatic health care workers/professionals. People with mild to moderate symptoms are advised for home quarantine with few general medications of fever, multivitamins, cough syrups, immunity booster food etc.

Ferguson *et al*. (2020) reveals that if all the countries adopt social distancing, testing and isolation of infected cases then the global death would cut down by 1.9 million by the end of 2020. Mair (2020) has stated how the different economic situations will change due to corona virus. In order to prioritise the protection of livelihoods we have to respond towards the pandemic with extreme combinations. The vaccination introduced for this infection need to be made by keeping in mind about its cost effectiveness for our population. Grover and Aggarwal (2020) have proposed cost effectiveness analysis on the basis of health outcome DALY. Shankar *et al.* (2020) have stated the mitigation strategy on how to closely monitor the effective reproduction number below one which is useful to prevent the spread.

States which lie in severe category further require lockdown measures as well as strict adherence to the guidelines of prevention to covid-19. For allay of our estimation procedures we have limited our models by considering homogenous distribution of population across all the states. It fails to capture the variations in population density for rural as well as urban India. Due to non-availability of data based on age, gender, occupation, travel history etc we could not resort to stratification on the basis of different predictors. Mandal *et al*. (2020) have stated that the probability of an infected air traveller coming back to India as the final destination which further import the risk in Delhi, followed by Mumbai, Kolkata, Bengaluru, Chennai, Hyderabad, Kochi. Menon (2020) highlights the differences among the states in terms of population density. Mumbai has higher population density with closer contacts in terms of transmission from one person to another than in comparison to spare populated Arunachal Pradesh.

The city of Maharashtra, Mumbai appears similar to epicentre Wuhan in China due to high call in the number of COVID-19 cases but the slum area Dharavi has placed an extraordinary example of combating with the virus. Due to excessive testing and following the guidelines for the prevention under covid-19 there has been speedy decline in the number of deaths and active cases. Masih (2020) list Kerala as the first state in the country to report a corona virus case. They had maximum influx of students returning from China as a carrier. But their health infrastructure followed district monitoring, risk communication, and engagement of health professionals with aggressive testing.

Singhal (2020) has listed the laboratory parameters such as white blood cell count, lymphocyte count, platelet count, procalcitonin etc which can be assessed for the estimation of quality of life when the virus hits the body. The scope of estimation for QALY can further be extended for patients who are elderly with underlying co-morbidities such as hypertension, diabetes, cardiovascular disease etc in order to study the variations with adverse outcomes.

These epidemic also teach us lessons how to build a stronger healthcare infrastructure with good investment and community engagement.

7. Conclusions

Azad and Poonia (2020) have listed short term forecasts for the infection spread across the Indian states. On the similar lines, Ghosh *et al*. (2020) have divided the states into three different zones based on daily infection rate (*DIR*) as severe, moderate and controlled. We have considered exponential regression alongwith SIR model on the dataset of different states and the analysis done by Ghosh *et al*. (2020) goes in conjunction with each other, thus fitting the scenario of infections precisely and robustly. We further establish a link between the states in terms of DIR and Q_M.

States with an increasing trend in DIR such as Maharashtra ($Q_M = 0.36$); Delhi ($Q_M = 0.37$); Bihar ($Q_M = 0.36$); Andhra Pradesh ($Q_M = 0.31$); Uttar Pradesh ($Q_M = 0.47$); Haryana ($Q_M = 0.25$); Tamil Nadu ($Q_M = 0.30$); West Bengal ($Q_M = 0.33$); Chattisgarh ($Q_M = 0.29$); Himachal Pradesh ($Q_M = 0.22$); Jammu and Kashmir ($Q_M = 0.37$); Jharkhand ($Q_M = 0.44$); Ladakh ($Q_M = 0.37$); Manipur ($Q_M = 0.39$); Telangana ($Q_M = 0.26$); Uttarakhand ($Q_M = 0.34$); Thus all the above states are densely populated with high *DIR* values and lower $QALY$ values (less than 0.5). They belong to the category of severe states affected by covid-19.

States with decreasing trend in DIR and non-increasing growth in active cases such as Gujarat ($Q_M = 0.53$); Madhya Pradesh ($Q_M = 0.50$); Karnataka ($Q_M = 0.5$); Odisha ($Q_M = 0.54$); These states are termed as moderate regions.

States with decreasing trend in *DIR* and decreasing growth in active cases such as Kerala (Q_M =0.66); Chandigarh ($Q_M = 0.79$); Rajasthan ($Q_M = 0.67$); Punjab ($Q_M = 0.64$); Puducherry ($Q_M = 0.88$); and higher *QALY* values (greater than 0.5) will lie under controlled regions against covid-19.

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APPENDIX

1. Formulation of R_t

Using the identity from numerical analysis which links the difference operator in finite differences as:

$$(1+\delta)^n = 1+\Delta \tag{12}$$

$$\delta = \frac{\Delta}{n} + \frac{\frac{1}{n}\left(\frac{1}{n}-1\right)\Delta^2}{2!} + \frac{\frac{1}{n}\left(\frac{1}{n}-1\right)\left(\frac{1}{n}-2\right)\Delta^3}{3!} + \cdots \tag{13}$$

Substituting the above identity in equation (6) for single term and ignoring higher order difference operators, we get

$$\delta I = \frac{\Delta}{n} I.$$

The equation (6) can be rewritten as:

$$R_t = \left(\frac{\left\{\frac{I(t+1)-I(t)}{\Delta t}\right\} + \left\{\frac{R(t+1)-R(t)}{\Delta t}\right\}}{\left\{\frac{R(t+1)-R(t)}{\Delta t}\right\}} \right) \frac{N}{S} \tag{14}$$

$$= \left(\frac{\Delta I(t) + \Delta R(t)}{\Delta R(t)} \right) \frac{N}{S}$$

$$= \left(\frac{\Delta I(t)}{\Delta R(t)} - 1 \right) \frac{N}{S} = \frac{CN}{S}$$

2. Formulation of the utility function

The utility function has been defined as the production function of susceptible, recovered and R_t.

$$U_t = f(S, R, R_t) \tag{15}$$

The marginal utility from equation (6) and (7) is obtained as :

$$\frac{\delta R_t}{\delta t} = \frac{CN}{S} e^{\alpha t} \alpha$$

$$\frac{\delta R}{\delta t} = \frac{-N(I+R)}{R_t S t^2} + \frac{N(I+R)}{St} \frac{(-1)}{R_t^2} \frac{\delta R_t}{\delta t}$$

Thus we can conclude that,

$$U_t \propto \frac{1}{S}, U_t \propto R_t \tag{16}$$

3. R_t values for different states of India

The values of R_t were accessed from covid-19 India 2020 tracker with different time points *i.e.*, t = 7, 14, 21,...., 70 days are presented below in Table 4.

Table 4: The values of R_t

State	R_1	R_2	R_3	R_4	R_5
Andhra Pradesh	0.188	0.245	0.245	0.08	0.145
Bihar	0.107	0.115	0.12	0.072	0.137
Chandigarh	0.068	0.092	0.079	0.012	0.053
Chhattisgarh	0.165	0.188	0.047	0.103	0.104
Delhi	0.134	0.154	0.22	0.107	0.131
Gujarat	0.132	0.152	0.106	0.165	0.144
Haryana	0.06	0.063	0.119	0.081	0.076

Himachal Pradesh	0.024	0.057	0.178	0.088	0.087
Jammu and Kashmir	0.127	0.229	0.128	0.1006	0.135
Jharkhand	0.148	0.167	0.189	0.222	0.245
Karnataka	0.171	0.146	0.07	0.055	0.084
Kerala	0.15	0.139	0.057	0.02	0.058
Ladakh	0.002	0.0039	0.006	0.015	0.011
Madhya Pradesh	0.197	0.258	0.182	0.136	0.162
Maharashtra	0.179	0.1387	0.15	0.127	0.130
Manipur	0.055	0.0619	0.064	0.075	0.080
Odisha	0.043	0.062	0.227	0.094	0.112
Puducherry	0.056	0.0727	0.147	0.029	0.061
Punjab	0.284	0.111	0.082	0.09	0.077
Rajasthan	0.12	0.125	0.166	0.138	0.122
Tamil Nadu	0.26	0.297	0.244	0.08	0.149
Telangana	0.309	0.146	0.158	0.076	0.103
Uttar Pradesh	0.096	0.115	0.146	0.09	0.115
Uttarakhand	0.059	0.084	0.145	0.05	0.082
West Bengal	0.145	0.192	0.143	0.113	0.123
State	**R_6**	**R_7**	**R_8**	**R_9**	**R_{10}**
Andhra Pradesh	0.156	0.178	0.117	0.189	0.120
Bihar	0.145	0.131	0.118	0.107	0.099
Chandigarh	0.137	0.128	0.119	0.114	0.112
Chhattisgarh	0.053	0.062	0.065	0.062	0.060
Delhi	0.104	0.094	0.085	0.080	0.085
Gujarat	0.131	0.121	0.112	0.105	0.099
Haryana	0.144	0.134	0.123	0.114	0.106
Himachal Pradesh	0.076	0.073	0.071	0.067	0.064
Jammu and Kashmir	0.087	0.075	0.070	0.067	0.071
Jharkhand	0.135	0.121	0.110	0.102	0.096
Karnataka	0.199	0.187	0.146	0.122	0.118
Kerala	0.084	0.076	0.071	0.068	0.068
Ladakh	0.058	0.051	0.045	0.042	0.041
Madhya Pradesh	0.011	0.017	0.020	0.021	0.021
Maharashtra	0.162	0.145	0.130	0.120	0.111
Manipur	0.130	0.124	0.115	0.109	0.104
Odisha	0.076	0.054	0.048	0.032	0.018
Puducherry	0.112	0.104	0.104	0.105	0.102
Punjab	0.061	0.054	0.051	0.051	0.055
Rajasthan	0.077	0.089	0.088	0.082	0.075
Tamil Nadu	0.122	0.110	0.101	0.094	0.088
Telangana	0.149	0.139	0.134	0.126	0.118
Uttar Pradesh	0.103	0.090	0.080	0.074	0.069
Uttarakhand	0.115	0.106	0.097	0.090	0.085
West Bengal	0.082	0.073	0.066	0.062	0.070