Quantitative assessment of Vulnerability to Climate Change (Computation of Vulnerability Indices)

1. INTRODUCTION

Climate change or global warming is an important research area now. Unless proper adaptation strategies are implemented, it will have far reaching environmental changes that could have severe impacts on societies throughout the world. Further, it will have multi-dimensional effect on humanity in terms of several socio-economic parameters like agriculture, human health, sea level rise, scarcity of labour, disease prevalence etc. Hence any scientific study on climate change should take into account vulnerabilities of the different regions and then it has to study its impacts on several sectors.

2. DEFINITION OF VULNERABILITY

The word ‘vulnerability’ is usually associated with natural hazards like flood, droughts, and social hazards like poverty etc. Of late it is extensively used in climate change literature to denote the extent of damage a region is expected to be affected by various factors affected by climate change. In the context of climate change there are many studies on vulnerability and its definitions vary according to the perception of the researchers. A brief review of various definitions is given below.

Chamber (1983) defined that vulnerability has two sides. One is an external side of risks, shocks to which an individual or household is subject to climate change and an internal side which is defencelessness, meaning a lack of means to cope without damaging loss. Blaikie *et al.,* (1994) defined vulnerability as the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impacts of natural hazards and states that vulnerability can be viewed along a continuum from resilience to susceptibility. According to Adger (1999) vulnerability is the extent to which a natural or social system is susceptible to sustaining damage from climate change. It is generally perceived to be a function of two components. The effect that an event may have on humans, referred to as capacity or social vulnerability and the risk that such an event may occur, often referred to as exposure. Watson *et al.,* (1996) defined vulnerability as the extent to which climate change may damage or harm a system, depending not only on a system’s sensitivity but also on its ability to adapt to new climatic conditions. Kasperson *et al.,* (2000) defined vulnerability as the degree to which an exposure unit is susceptible to harm due to exposure to a perturbation or stress and the ability or lack of the exposure unit to cope, recover or fundamentally adapt to become a new system or to become extinct.

O'brien and Mileti (1992) examined the vulnerability to climate change and stated that in addition to economic well being and stability, being important in the resilience of populations to environmental shocks, the structure and health of the population may play a key role in determining vulnerability. Age is an important consideration as the elderly and young persons are tends to be inherently more susceptible to environmental risk and hazard exposure. Generally populations with low dependency ratio and in good health are likely to have the widest coping ranges and thus be least vulnerable in the face of hazard exposure.

Handmer *et al.,* (1999) studied the coping mechanisms to environmental shock or hazard brought about by biophysical vulnerability. The factors like institutional stability and strength of public infrastructure are crucial importance in determining the vulnerability to climate change. A well connected population with appropriate public infrastructure will be able to deal with a hazard effectively and reduce the vulnerability. Such a society could be said to have low social vulnerability. If there is an absence of institutional capacity in terms of knowledge about the event and ability to deal with it, then such high vulnerability is likely to ensure that biophysical risk turns into an impact on the human population.

Atkins *et al*., (1998) studied the methodology for measurement of vulnerability and to construction of a suitable composite vulnerability index for developing countries and island states. The composite vulnerability indices were presented for a sample of 110 developing countries for which appropriate data was available. The index suggests that small states are especially prone to vulnerable when compared to large states. Among the small states, such as Cape Verde and Trinidad and Tobago are estimated to suffer relatively low levels of vulnerability and majority of the states estimated to experience relatively high vulnerability and the states like Tonga, Antigua and Barbedas being more vulnerable to external economic and environmental factors.

Chris Easter (2000) constructed a vulnerability index for the commonwealth countries, which is based on two principles. First, the impact of external shocks over which the country has affected and second the resilience of a country to withstand and recover from such shocks. The analysis used a sample of 111 developing countries of which 37 small and 74 large for which relevant data were available. The results indicated that among the 50 most vulnerable countries, 33 were small states with in this 27 are least developed countries and 23 are islands. In the least vulnerable 50 countries, only two were small states.

Dolan and Walker (2003) discussed the concept of vulnerability and presented a multiscaled, integrated framework for assessing vulnerabilities and adaptive capacity. Determinants of adaptive capacity including access to and distribution of wealth, technology, and information, risk perception and awareness, social capital and critical institutional frameworks to address climate change hazards. These are identified at the individual and community level and situated within larger regional, national and international settings. Local and traditional knowledge is the key to research design and implementation and allows for locally relevant outcomes that could aid in more effective decision making, planning and management in remote coastal regions.

Moss *et al.,* (2001) identified ten proxies for five sectors of climate sensitivities which are settlement sensitivity, food security, human health sensitivity, ecosystem sensitivity and water availability and seven proxies for three sectors of coping and adaptive capacity, economic capacity, human resources and environmental or natural resources capacity. Proxies were aggregated into sectoral indicators, sensitivity indicators and coping or adaptive capacity indicators and finally constructed vulnerability resilience indicators to climate change.

Katharine Vincent (2004) created an index to empirically assess relative levels of social vulnerability to climate change induced variations in water availability and allow cross country comparison in Africa. An aggregated index of social vulnerability were formed through the weighted average of five composite sub indices, which are economic well being and stability, demographic structure, institutional stability and strength of public infrastructure, global interconnectivity and dependence on natural resources. The results indicate that using the current data, Niger, Sierra Leone, Burundi, Madagascar and Burkina Faso are the most vulnerable countries in Africa.

For the purpose of our understanding, we follow the IPCC Third Assessment Report according to which vulnerability is defined as “The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity” (McCarthy et al. 2001). Thus as per this definition, vulnerability has three components: exposure, sensitivity and adaptive capacity. These three components are described as follows:

- Exposure can be interpreted as the direct danger (i.e., the stressor), and the nature and extent of changes to a region's climate variables (e.g., temperature, precipitation, extreme weather events).
- Sensitivity describes the human–environmental conditions that can worsen the hazard, ameliorate the hazard, or trigger an impact.
- Adaptive capacity represents the potential to implement adaptation measures that help avert potential impacts

The first two components together represent the potential impact and adaptive capacity is the extent to which these impacts can be averted. Thus vulnerability is potential impact (I) minus adaptive capacity (AC). This leads to the following mathematical equation for vulnerability:

$$V = f(I - AC)$$

3. THE INDEX APPROACH TO STUDY VULNERABILITY

In literature, quantitative assessment of vulnerability is usually done by constructing a 'vulnerability index'. This index is based on several set of indicators that result in vulnerability of a region. It produces a single number, which can be used to compare different regions. Literature on index number construction specifies that there should be good internal correlation between these indicators. The relevance of this criterion depends on the relationship between the indicators and the construct they are supposed to measure. For this we must know whether the index is based on a 'reflexive' or a 'formative' measurement model. In the reflexive measurement model, the construct is thought to influence the indicators. For example, a poverty index is a good example of reflexive measurement because poverty influences the indicators such as literacy; expenditure and so on and all these indicators are correlated. On the other hand in the formative model the indicators are assumed contribute to the construct. In the case of vulnerability index, all the indicators chosen by the researcher have impact on vulnerability of the region to climate change. For example, frequency of extreme events such as flood, drought earth-quakes, and length of coastline all contribute to vulnerability of the region to climate change. Hence vulnerability index is a formative measurement and the indicators chosen need not have internal correlation.

4. WHAT IS AN INDEX?

The word ‘index’ has many meanings. For example, in mathematics it is used to denote the number of times a given number is multiplied with itself (the index of the power 10^4 is 4) . In economics and business it is a single number derived from a series of prices and or quantities (for example, price index, market performance index). In finance an index is a statistical indicator providing a representation of the value of the securities which constitute it. For our purpose, it is numerical scale calculated from a set of variables selected by the researcher for all the regions/districts and used to compare them with one another or with some reference point. That is, this numerical value is used in the ordinal sense i.e. on the basis of this index different regions are ranked and grouped to be relatively less or more vulnerable. It is constructed in such a way that it always lies between 0 and 1 so that it is easy to compare regions. Sometimes the index is expressed as a percentage by multiplying it by 100.

5. CONSTRUCTION OF VULNERABILITY INDEX

Construction of vulnerability index consists of several steps. First is the selection of study area which consists of several regions. In each region a set of indicators are selected for each of the three component of vulnerability. A list of possible indicators is provided in the Appendix-I. The indicators can be selected based the availability of data, personal judgement or previous research. Since vulnerability is dynamic over time, it is important that all the indicators relate to the particular year chosen. If vulnerability has to be assessed over years then the data for each year for all the indicators in each region must be collected.

6. ARRANGEMENT OF DATA

For each component of vulnerability, the collected data are then arranged in the form of a rectangular matrix with rows representing regions and columns representing indicators. Let there be M regions/districts and let us say we have collected K indicators. Let X_{ij} be the value of the indicator j corresponding to region i. Then the table will have M rows and K columns as shown below:

Region/ District	Indicator					
	1	2	.	J	.	K
1	X_{11}	X_{12}	.	X_{1j}	.	X_{1K}
2	.	.	.	.	.	.
.	.	.	.	.	.	.
I	X_{i1}	X_{i2}	.	X_{ij}	.	X_{iK}
.	.	.	.	.	.	.
M	X_{M1}	X_{M2}	.	X_{Mj}	.	X_{MK}

It should be noted that this type of arrangement of data is usually done in statistical analysis of survey data.

7. NORMALISATION OF INDICATORS USING FUNCTIONAL RELATIONSHIP

Obviously the indicators will be in different units and scales. The methodology used in UNDP's Human Development Index (HDI) (UNDP, 2006) is followed to normalize them. That is, in order to obtain figures which are free from the units and also to standardize their values, first they are normalized so that they all lie between 0 and 1. Before doing this, it is important to identify the functional relationship between the indicators and vulnerability. Two types of functional relationship are possible: vulnerability increases with increase (decrease) in the value of the indicator. Assume that higher the value of the indicator more is the vulnerability. For example, suppose we have collected information on change in maximum temperature or change in annual rainfall or diurnal variation in temperature. It is clear that higher the values of these indicators more will be the vulnerability of the region to climate change as variation in climate variables increase the vulnerability. In this case we say that the variables have $\uparrow$ functional relationship with vulnerability and the normalization is done using the formula

$$x_{ij} = \frac{X_{ij} - \underset{i}{Min}\{X_{ij}\}}{\underset{i}{Max}\{X_{ij}\} - \underset{i}{Min}\{X_{ij}\}}$$

It is clear that all these scores will lie between 0 and 1. The value 1 will correspond to that region with maximum value and 0 will correspond to the region with minimum value. For example, consider the following data set pertaining to coastal districts of Tamil Nadu, State, India.

District	Variance in annual rainfall (mm2)	Diurnal variance	Total food grains (tonnes)/NSA	Cropping Intensity	Agrl. labourers / Ha of NSA	Literacy Rate (%)
Thiruvallur	2905.5	5.0	2.8	1.3	2.0	67.2
Kanchipuram	18917.9	2.6	2.9	1.2	2.0	76.9
Vellore	11166.6	7.9	1.3	1.2	1.9	80.5
Dharmapuri	5914.0	5.5	1.1	1.2	1.1	74.8
Thiruvannamalai	12575.5	2.3	1.4	1.3	2.0	67.4
Villupuram	5975.7	5.8	1.7	1.1	2.0	63.8
Salem	5169.0	1.4	1.3	1.5	1.5	65.1
Namakkal	6214.0	2.4	0.7	1.4	1.4	61.4
Erode	8993.2	3.9	1.0	1.1	1.6	65.4
The Nilgiris	4962.0	5.4	0.1	1.0	0.6	74.3

Variance in annual rainfall is maximum at Kanchipuram district with a value of 18917.9 and it has minimum value of 4962 at The Nilgiris. Hence the normalization is achieved by using the formula

$$x_{ij} = \frac{X_{ij} - 4962}{18917.9 - 4962} = \frac{X_{ij} - 4962}{13955.9}$$

For example, the normalized score for Thiruvannamalai district is

$$\frac{12575.5 - 4962.0}{13955.9} = \frac{7613.5}{13955.9} = 0.5455$$

In this way the normalized scores for each district can be computed.

On the other hand, consider adult literacy rate. A high value of this variable implies more literates in the region and so they will have more awareness to cope with climate change. So the vulnerability will be lower and adult literacy rate has ↓ functional relationship with vulnerability. For this case the normalized score is computed using the formula

$$y_{ij} = \frac{\underset{i}{Max}\{X_{ij}\} - X_{ij}}{\underset{i}{Max}\{X_{ij}\} - Min\{X_{ij}\}}$$

For the above data set (literacy rate) the formula for normalization becomes

$$y_{ij} = \frac{80.5 - X_{ij}}{80.5 - 61.4} = \frac{80.5 - X_{ij}}{19.1}$$

It can be easily checked that $x_{ij} + y_{ij} = 1$ so that y_{ij} can be calculated as $y_{ij} = 1 - x_{ij}$. For the above table the functional relationship of the variables with vulnerability can be given as

Variables	Functional Relationship
Variance in annual rainfall (mm2)	↑
Diurnal variance in temperature	↑
Total food grains (tonnes)/NSA	↓
Cropping Intensity	↓
Agrl. labourers / Ha of NSA	↓
Literacy Rate (%)	↓

This method of normalization that takes into account the functional relationship between the variable and vulnerability is important in the construction of the indices. If the functional relation is ignored and if the variables are normalized simply by applying formula (1), the resulting index will be misleading. This idea can be better understood by considering the following hypothetical example:

Region	Score of variable		
	Diurnal Variance	Productivity of paddy (tons/ha)	Literacy rate (%)
I	1.2	3.4	70
II	1.8	3.6	80
III	1.5	2.8	60

The normalized scores ignoring the functional relationship are given by the following table:

Region	Score of variable			Sum of the scores	Average Score
	Diurnal Variance	Productivity of paddy (tons/ha)	Literacy rate (%)		
I	0.0	0.75	0.5	1.25	0.42
II	1.0	1.0	1.0	3.0	1.00
III	0.5	0.0	0.0	0.5	0.17

The average score for the Region II is highest and that of region III is the lowest and we may conclude that Region II is the most vulnerable region among the three regions considered and Region III is least vulnerable. However this conclusion is not correct. The Region II has highest score for productivity and literacy and so it is less vulnerable to climate change when we compare it with other regions. Of course its diurnal variance is highest. The table below gives the normalized scores taking into account the direction of functional relationships:

Region	Score of variable			Sum of the Scores	Average Score
	Diurnal Variance Intensity	Productivity of paddy (tons/ha)	Literacy rate (%)		
I	0	0.25	0.5	0.75	0.25
II	1	0.0	0	1.0	0.33
III	0.5	1.0	1	2.5	0.83

By comparing the average scores we conclude that Region III is most vulnerable and Region II comes next. Thus while constructing the vulnerability index sufficient care must be applied to take into account the direction of functional relationship of each variable to vulnerability.

8. COMPUTATION OF NORMALIZED SCORES USING MS-EXCEL

The normalized scores for each variable can be easily obtained using MS-Excel's MAX () and MIN () functions. For example, the scores for variance in annual rainfall are computed as shown in the following figure:

C9 =(B9-MIN($B$2:$B$11))/(MAX($B$2:$B$11)-MIN($B$2:$B$11))

	A	B	C	D	E	F	G	H
1	District	Variance in annual rainfall	Normailized score					
2	Thiruvallur	2905.5	0.000					
3	Kanchipuram	18917.9	1.000					
4	Vellore	11166.6	0.516					
5	Dharmapuri	5914	0.188					
6	Thiruvanamalai	12575.5	0.604					
7	Villupuram	5975.7	0.192					
8	Salem	5169	0.141					
9	Namakkal	6214	0.207					
10	Erode	8993.2	0.380					
11	The Nilgris	4962	0.128					

Similarly for literacy rate the scores are obtained as follows:

C2 =(MAX($B$2:$B$11)-B2)/(MAX($B$2:$B$11)-MIN($B$2:$B$11))

	A	B	C	D	E	F	G	H	I
1	District	Literacy Rate(%)	Normalized Score						
2	Thiruvallur	67.2	0.696						
3	Kanchipuran	76.9	0.188						
4	Vellore	80.5	0.000						
5	Dharmapuri	74.8	0.298						
6	Thiruvanama	67.4	0.686						
7	Villupuram	63.8	0.874						
8	Salem	65.1	0.806						
9	Namakkal	61.4	1.000						
10	Erode	65.4	0.791						
11	The Nilgris	74.3	0.325						

9. METHODS OF CONSTRUCTION OF VULNERABILITY INDEX

After computing the normalized scores the index is constructed by giving either equal weights to all indicators/components or unequal weights.

9.1 Methods with equal weights

Below we describe two methods in which equal weights are given to the indicators.

9.1.1 Simple average of the scores

When equal weights are given we use simple average of all the normalized scores to construct the vulnerability index by using the formula:

$$VI = \frac{\sum_j x_{ij} + \sum_j y_{ij}}{K}$$

Finally, the vulnerability indices are used to rank the different regions in terms of vulnerability. A region with highest index is said to be most vulnerable and it is given the rank 1, the region with next highest index is assigned rank 2 and so on. For the above table, the computed normalized scores , vulnerability indices and ranks of the districts are as shown below:

	Normalized Scores								
District	Variance in annual rainfall(mm2)	Diurnal variance in temperature	Total food grains (tonnes)/NSA	Cropping Intensity	Agrl. labourers / Ha of NSA	Literacy Rate(%)	Sum of the Scores	Vulnerability Index	Rank
Thiruvallur	0.000	0.554	0.036	0.400	0.000	0.696	1.686	0.281	10
Kanchipuram	1.000	0.185	0.000	0.600	0.000	0.188	1.973	0.329	8
Vellore	0.516	1.000	0.571	0.600	0.071	0.000	2.759	0.460	6
Dharmapuri	0.188	0.631	0.643	0.600	0.643	0.298	3.003	0.500	3
Thiruvanamalai	0.604	0.138	0.536	0.400	0.000	0.686	2.364	0.394	5
Villupuram	0.192	0.677	0.429	0.800	0.000	0.874	2.972	0.495	3
Salem	0.141	0.000	0.571	0.000	0.357	0.806	1.876	0.313	4
Namakkal	0.207	0.154	0.786	0.200	0.429	1.000	2.775	0.462	3
Erode	0.380	0.385	0.679	0.800	0.286	0.791	3.320	0.553	2
The Nilgris	0.128	0.615	1.000	1.000	1.000	0.325	4.068	0.678	1

Thus we find that, The Nilgris is the most ‘vulnerable’ district followed by Erode district and Thiruvallur is the least vulnerable district.

9.1.2 Patnaik and Narain Method (Patnaik and Narayanan, 2005)

In this method, we first identify the possible sources of vulnerability and for each source several sub-indicators are identified. For example, we can group the variables into five different sources such as 1.demographic 2.climatic 3.agricultural 4.occupational and 5.geographic. A list of possible sub-indicators in each group is

a) Demographic vulnerability

There are three components involved in this index to explain the demographic patterns of the people living in the respective region.

i. Density of population (persons per square kilometer)
ii. Literacy rate (percentage)
iii. Infant mortality rate (deaths per ‘000 infants)

b) Climatic vulnerability

This index tries to take into account basic climatic variability. It combines six separate indices which are the variances of

i. Annual rainfall (mm^2)
ii. South west monsoon (mm^2)
iii. North east monsoon (mm^2)
iv. Maximum temperature ($^oC^2$)
v. Minimum temperature ($^oC^2$)
vi. Diurnal temperature variation ($^oC^2$)

c) Agricultural vulnerability

This includes the following variables to predict the vulnerability related to agricultural activities.

i. Production of food grains (tonnes / hectare)
ii. Productivity of major crops (tonnes/ hectare)
iii. Cropping intensity (percentage)
iv. Irrigation intensity (percentage)
v. Livestock population (Number per hectare of net sown area)
vi. Forest area(percentage geographic area)

d) Occupational vulnerability

Six indicators were taken to calculate the vulnerability related to occupational characteristics of people and all these variables are converted into per hectare of net sown area.

i. Number of cultivators
ii. Total main workers
iii. Agricultural labourers
iv. Marginal workers

v. Industrial workers

vi. Non workers

e) Geographic vulnerability

i. Coastal length (kilometer)

ii. Geographical area (hectare)

After normalization, the average index (AI) for each source of vulnerability is worked out and then the overall vulnerability index is computed by employing the following formula:

$$VI = \left[\sum_{i=1}^{n} (AI_i)^{\alpha} \right]^{1/\alpha} \Big/ n$$

where n is the number of sources of vulnerability and $\alpha = n$.

The vulnerability indices can be worked out for each period of time and they can be compared to assess the changes in vulnerabilities over the period of time.

As an example consider the following data set pertaining to the seven agro-climatic zones of Tamil Nadu State, India:

Name of the Zone	Source of Vulnerability								
	Demographic		Climatic				Agricultural		
	Density of population	Literacy Rate (%)	Variance in annual rainfall	Min-Temp variance	Max Temp Variance	Diurnal variance	Total food grains (t/ha)	Cropping Intensity	Irrigation Intensity
NEZ	1276.54	73.00	9256.17	7.53	10.83	4.25	2.03	1.23	1.24
NWZ	983.73	67.10	5765.67	3.56	6.03	3.09	1.02	1.36	1.48
WZ	470.25	71.17	8618.55	2.68	5.41	3.19	0.65	1.09	1.13
CDZ	1146.86	77.59	9349.51	5.38	7.98	2.50	3.02	1.39	1.21
SZ	500.66	74.41	6850.30	3.02	16.51	2.51	1.46	1.06	1.10
HRZ	995.27	87.59	1628.18	0.66	0.56	1.53	1.69	1.22	1.50
HZ	413.99	74.26	4962.00	2.69	3.12	5.45	0.11	1.00	1.00

Name of the Zone	Source of vulnerability								
	Agricultural						Occupational		
	Productivity of			Livestock Population/ha	Total Food Crops Area (%)	Total Non Food Crops Area (%)	Total main workers/ ha	Cultivators / ha	Agrl. labourers / ha
	Rice (kg/ha)	Groundnut (kg/ha)	Sugarcane (t/ha)						
NEZ	3479.3	2343.0	110.3	2.49	74.75	25.25	4.83	1.07	1.98
NWZ	4050.7	1942.3	126.3	2.51	63.90	36.13	3.91	1.15	1.32
WZ	4018.5	1647.5	125.0	1.47	51.60	48.40	5.01	0.77	1.42
CDZ	3583.6	1699.8	108.8	2.53	87.66	12.34	3.12	0.69	1.67
SZ	3652.9	1559.7	120.0	1.58	78.42	21.59	4.55	0.93	1.65
HRZ	4721.0	1571.0	0.0	1.26	50.10	49.90	5.57	0.20	1.01
HZ	4105.0	0.0	0.0	0.39	17.40	82.60	4.06	0.19	0.62

*NEZ- North Eastern Zone; NWZ- North Western Zone; WZ- Western Zone; CDZ-Cauvery Delta Zone; SZ-Southern Zone; HRZ- High Rainfall Zone and HZ- Hilly Zone

This data set has four sources of vulnerability and the indicators for each source have been selected based on personal judgement and available data. The computed overall vulnerability index and the ranks of the zones are provided in the next table:

Region	Index	Rank
North Eastern Zone	0.7135	2
North Western Zone	0.6051	3
Western Zone	0.4589	6
Cauvery Delta Zone	0.5766	4
Southern Zone	0.4815	5
High Rainfall Zone	0.4381	7
Hilly Zone	0.7272	1

One advantage of this method is that we can compute the indices source-wise and ranks can be allotted source-wise also. The following table gives the ranks of the zones source-wise:

Region	Source				
	Demographic	Climatic	Agriculture	Occupational	Overall
North Eastern Zone	1	1	5	7	2
North Western Zone	2	6	7	4	3
Western Zone	4	4	3	5	6
Cauvery Delta Zone	3	2	6	2	4
Southern Zone	5	3	2	6	5
High Rainfall Zone	6	7	4	3	7
Hilly Zone	7	5	1	1	1

9.2 Methods with Unequal Weights

The method of simple averages gives equal importance for all the indicators which is not necessarily correct. Hence many authors prefer to give weights to the indicators. A survey of literature shows that the following methods are used to give weights:

9.2.1 Expert judgement

In this method, the weights are assigned based on expert opinion. Obviously it is a subjective method.

9.2.2 Iyengar and Sudarshan's method

Iyengar and Sudarshan (1982) developed a method to work-out a composite index from multivariate data and it was used to rank the districts in terms of their economic performance. This methodology is statistically sound and well suited for the development of composite index of vulnerability to climate change also. A brief discussion of the methodology is given below.

It is assumed that there are *M* regions /districts, K indicators of vulnerability and $x_{ij}, i = 1,2,...M; j = 1,2,...K$ are the normalized scores. The level or stage of development of i^{th} zone, $\bar{y}_i$, is assumed to be a linear sum of x_{ij} as

$$\overline{y_i} = \sum_{j=1}^{K} w_j x_{ij}$$

where $w's \ (0 < w < 1 \ and \ \sum_{j=1}^{K} w_j = 1)$ are the weights. In Iyengar and Sudarshan's method the weights are assumed to vary inversely as the variance over the regions in the respective indicators of vulnerability. That is, the weight w_j is determined by

$$w_j = c \Big/ \sqrt{\operatorname{var}_i (x_{ij})}$$

where c is a normalizing constant such that

$$c = \left[\sum_{j=1}^{j=K} 1 \Big/ \sqrt{\operatorname{var}_i (x_{ij})} \right]^{-1} .$$

The choice of the weights in this manner would ensure that large variation in any one of the indicators would not unduly dominate the contribution of the rest of the indicators and distort inter regional comparisons. The vulnerability index so computed lies between 0 and 1, with 1 indicating maximum vulnerability and 0 indicating no vulnerability at all.

For classificatory purposes, a simple ranking of the regions based on the indices viz., $\bar{y}_i$ would be enough. However for a meaningful characterization of the different stages of vulnerability, suitable fractile classification from an assumed probability distribution is needed. A probability distribution which is suitable for this purpose is the Beta distribution, which is generally skewed and takes values in the interval (0,1). as followed by Iyengar and Sudarshan(1982) has been applied . This distribution has the probability density given by

$$f(z) = \frac{z^{a-1}(1-z)^{b-1}}{\beta(a,b)},\ 0 < z < 1\ and\ a,b > 0.$$

where $\beta(a,b)$ is the beta function defined by

$$\beta(a,b) = \int_0^1 x^{a-1}(1-x)^{b-1}\,dx$$

The two parameters *a* and *b* of the distribution can be estimated either by using the method described in Iyengar and Sudharshan (1982) or by using software packages. The Beta distribution is skewed (see the figure). Let $(0,z_1),(z_1,z_2),(z_2,z_2),(z_3,z_4)$ and $(z_4,1)$ be the linear intervals such that each interval has the same probability weight of 20 per cent. These fractile intervals can be used to characterize the various stages of vulnerability.

1. Less vulnerable if $0 < \bar{y}_i < z_1$
2. Moderately vulnerable if $z_1 < \bar{y}_i < z_2$
3. Vulnerable if $z_2 < \bar{y}_i < z_3$
4. Highly vulnerable if $z_3 < \bar{y}_i < z_4$
5. Very highly vulnerable if $z_4 < \bar{y}_i < 1$

As an example, consider the following data set for the 28 districts of Tamil Nadu State, India: The data are given under three components:

Component	S.No.	Indicator	Functional relationship with climate change
Exposure	1	Percentage change in rainfall from base year value (E1)	↑
	2	Change in maximum temperature (E2)	↑
	3	Change in minimum temperature (E3)	↑
Sensitivity	1	Percentage of gross area irrigated to gross area sown (S1)	↓
	2	Percentage of small farmers (S2)	↑
	3	Percentage share of cultivable waste to State are (S3)	↑
	4	Density of population (S4)	↑
Adaptive capacity	1	Literacy rate (A1)	↓
	2	Cropping intensity (A2)	↓
	3	Livestock population per ha (A3)	↓
	4	Percentage area under total food crops (A4)	↓

Thus the data set contains 11 indicators as given below:

	Exposure			Sensitivity				Adaptation capacity			
District	E1	E2	E3	S1	S2	S3	S4	A1	A2	A3	A4
Thiruvallur	-19.37	1.06	1.76	79.50	10.27	2.30	398.86	67.18	1.3	1.97183	81.3
Kanchipuram	3.84	1.69	2.05	89.90	11.51	2.80	668.09	76.85	1.22	2.5109	78.6
Vellore	14.83	1.84	1.94	52.70	14.14	1.50	3110.58	80.46	1.2	2.31439	59.9
Dharmapuri	29.80	1.83	2.25	39.90	18.69	1.50	296.85	74.83	1.21	1.87731	80.3
Thiruvanamalai	12.59	1.64	2.01	71.90	15.59	4.10	353.17	67.39	1.25	2.49122	65.9
Villupuram	6.64	1.60	2.10	72.20	15.08	2.80	984.00	63.8	1.1	2.92152	76.2
Salem	-11.05	2.72	2.10	47.80	19.61	1.80	515.09	65.09	1.5	2.28675	59.6
Namakkal	34.46	1.42	2.23	42.90	20.98	1.30	2139.26	61.39	1.38	3.36935	51.8
Erode	17.41	2.20	1.43	57.00	26.97	0.20	368.56	65.36	1.12	1.76455	49
The Nilgris	-14.10	2.38	2.19	0.90	10.79	0.60	413.99	74.26	1	0.38571	17.4
Coimbatore	-20.41	2.54	2.30	54.40	28.50	3.80	571.94	76.97	1.06	1.17746	54.2
Dindugal	8.04	2.28	2.23	42.80	19.15	2.40	227.93	64.25	1.04	1.47623	73.1
Karur	32.69	1.84	2.28	50.10	18.78	18.40	3415.54	68.08	1.02	2.3807	61.2
Trichy	27.27	1.07	2.15	59.70	17.10	2.40	536.10	77.9	1.1	2.41802	82.3
Perambalur	20.48	1.02	2.23	33.60	16.54	2.50	248.91	63.59	1.08	2.15548	83.2
Cuddalore	5.77	1.10	2.26	66.40	13.75	1.70	2144.53	82.32	1.28	2.74574	86.6
Nagapatinum	-7.58	1.67	2.10	63.10	16.01	1.00	615.99	76.34	1.71	2.67241	95.9
Thiruvarur	4.62	1.15	2.33	69.60	16.82	0.50	2362.98	85.53	1.72	3.2683	95.2
Tanjore	12.06	1.72	2.31	80.30	13.59	4.00	1970.31	84.59	1.34	2.1393	81.7
Pudukkotai	14.06	1.33	2.36	68.60	11.88	2.80	268.97	68.1	1.02	2.24954	78.5
Sivaganga	22.53	1.93	2.35	73.90	12.49	5.00	278.87	72.18	1	1.70652	89.1
Madurai	7.91	1.83	2.41	61.80	12.77	1.90	746.98	77.82	1.1	1.87116	77
Theni	-13.64	4.76	2.27	53.00	21.21	1.10	381.30	71.58	1.1	1.35867	72.9
Viruthunagar	-7.73	2.32	2.34	40.30	17.70	2.60	408.90	73.7	1.03	1.26472	65.5
Ramnad	18.04	1.92	2.23	36.90	12.80	1.20	1452.70	84.43	1	1.305	87.9
Thoothukudi	5.67	2.88	2.15	25.90	19.39	15.80	340.25	81.52	1.03	1.52871	80.3
Thirunelvalli	-3.18	-0.58	2.23	69.60	12.24	12.90	400.00	76.09	1.23	1.44776	81.5
Kanyakumari	7.94	1.81	1.99	42.40	2.04	0.00	995.27	87.59	1.22	1.2561	50.1

The normalized scores of the indicators as per the functional relationship they share with the climate change are given in the next table.

	Exposure			Sensitivity				Adaptation capacity			
District	E1	E2	E3	S1	S2	S3	S4	A1	A2	A3	A4
Thiruvallur	0.019	0.307	0.339	0.117	0.311	0.125	0.054	0.779	0.583	0.468	0.186
Kanchipuram	0.442	0.425	0.630	0.000	0.358	0.152	0.138	0.410	0.694	0.288	0.220
Vellore	0.642	0.453	0.526	0.418	0.457	0.082	0.904	0.272	0.722	0.354	0.459
Dharmapuri	0.915	0.450	0.841	0.562	0.629	0.082	0.022	0.487	0.708	0.500	0.199
Thiruvanamalai	0.601	0.414	0.593	0.202	0.512	0.223	0.039	0.771	0.653	0.294	0.382
Villupuram	0.493	0.408	0.685	0.199	0.493	0.152	0.237	0.908	0.861	0.150	0.251
Salem	0.171	0.617	0.680	0.473	0.664	0.098	0.090	0.859	0.306	0.363	0.462
Namakkal	1.000	0.373	0.820	0.528	0.716	0.071	0.600	1.000	0.472	0.000	0.562
Erode	0.689	0.519	0.000	0.370	0.942	0.011	0.044	0.848	0.833	0.538	0.597
The Nilgris	0.115	0.554	0.777	1.000	0.331	0.033	0.058	0.509	1.000	1.000	1.000
Coimbatore	0.000	0.584	0.885	0.399	1.000	0.207	0.108	0.405	0.917	0.735	0.531
Dindugal	0.518	0.534	0.818	0.529	0.647	0.130	0.000	0.891	0.944	0.635	0.290
Karur	0.968	0.453	0.866	0.447	0.633	1.000	1.000	0.745	0.972	0.331	0.442
Trichy	0.869	0.308	0.737	0.339	0.569	0.130	0.097	0.370	0.861	0.319	0.173
Perambalur	0.745	0.299	0.813	0.633	0.548	0.136	0.007	0.916	0.889	0.407	0.162
Cuddalore	0.477	0.314	0.844	0.264	0.443	0.092	0.601	0.201	0.611	0.209	0.118
Nagapatinum	0.234	0.420	0.681	0.301	0.528	0.054	0.122	0.429	0.014	0.234	0.000
Thiruvarur	0.456	0.323	0.921	0.228	0.559	0.027	0.670	0.079	0.000	0.034	0.009
Tanjore	0.592	0.431	0.904	0.108	0.437	0.217	0.547	0.115	0.528	0.412	0.181
Pudukkotai	0.628	0.356	0.947	0.239	0.372	0.152	0.013	0.744	0.972	0.375	0.222
Sivaganga	0.783	0.470	0.936	0.180	0.395	0.272	0.016	0.588	1.000	0.557	0.087
Madurai	0.516	0.451	1.000	0.316	0.406	0.103	0.163	0.373	0.861	0.502	0.241
Theni	0.123	1.000	0.855	0.415	0.724	0.060	0.048	0.611	0.861	0.674	0.293
Viruthunagar	0.231	0.541	0.929	0.557	0.592	0.141	0.057	0.530	0.958	0.705	0.387
Ramnad	0.701	0.467	0.813	0.596	0.407	0.065	0.384	0.121	1.000	0.692	0.102
Thoothukudi	0.475	0.648	0.735	0.719	0.656	0.859	0.035	0.232	0.958	0.617	0.199
Thirunelvalli	0.314	0.000	0.814	0.228	0.386	0.701	0.054	0.439	0.681	0.644	0.183
Kanyakumari	0.517	0.447	0.573	0.534	0.000	0.000	0.241	0.000	0.694	0.708	0.583

The standard deviations of the normalized scores across the districts, their reciprocals and the weights for each indicators as computed by the formula given in Section are given in the next table:

Component	Exposure			Sensitivity				Adaptation capacity			
	E1	E2	E3	S1	S2	S3	S4	A1	A2	A3	A4
Standard deviation	0.280	0.165	0.208	0.214	0.197	0.246	0.287	0.289	0.273	0.230	0.217
1/standard deviation	3.576	6.043	4.805	4.667	5.064	4.073	3.488	3.455	3.669	4.352	4.604
Weight	0.075	0.126	0.101	0.098	0.106	0.085	0.073	0.072	0.077	0.091	0.096

The vulnerability indices computed for each district and their ranks are given below:

District	Vulnerability Index	Rank
Thiruvallur	0.295	27
Kanchipuram	0.341	25
Vellore	0.472	14
Dharmapuri	0.494	10
Thiruvanamalai	0.422	20
Villupuram	0.429	18
Salem	0.454	15
Namakkal	0.544	6
Erode	0.489	11
The Nilgris	0.597	2
Coimbatore	0.551	4
Dindugal	0.543	7
Karur	0.687	1
Trichy	0.428	19
Perambalur	0.494	9
Cuddalore	0.377	24
Nagapatinum	0.291	28
Thiruvarur	0.310	26
Tanjore	0.409	21
Pudukkotai	0.448	17
Sivaganga	0.474	13
Madurai	0.453	16
Theni	0.547	5
Viruthunagar	0.526	8
Ramnad	0.486	12
Thoothukudi	0.572	3
Thirunelvalli	0.392	23
Kanyakumari	0.396	22

9.3 Multivariate statistical techniques

Since data for the construction of vulnerability indices are multivariate in nature, it is possible to apply multivariate statistical analysis tools to obtain weights for the indicators and for classification of regions. Below we briefly describe two such techniques.

9.3.1 Principal Components

PCA is a multivariate technique for finding patterns in data of high dimension. Once the patterns hidden in data are identified, PCA helps to compress the data by reducing the number of dimensions without much loss of information. In the language of Linear Algebra it is a linear transformation of the original variables. PCA allows us to compute a linear transformation that maps data from a high dimensional space to a lower dimensional space. In original data variables may be correlated and PCA help to transform them into uncorrelated variables. The essential steps in the computation of Principal components are as follows:

1. Arrange the data in the form of a matrix, rows representing regions (M) and columns are indicators (K). Let us call this matrix as *X*. Then *X* has dimension $M \times K$.
2. For each variable, compute its mean across all observations and subtract the mean from each observation. This produces a new matrix , $X - \overline{X}$ in which sum of all elements in each column is zero.
3. Compute the covariance matrix using the formula $(X - \overline{X})^T (X - \overline{X}) / m$. In this matrix, the diagonal elements are the variances of the respective variables and off diagonal elements are the co-variances between variables.
4. Compute the Eigen values and Eigen vectors of the covariance matrix.
5. Arrange the eigen values in the descending order of magnitude. The eigen vector corresponding to the highest eigen value is the first principal component of the data set. The eigen vectors of the second, third etc eigen values are the second, third,etc principal components. In other words the principal components are now arranged in the order of significance. We can retain eigen vectors upto a desired level of significance and leave the remaining ones which are insignificant. This is

because each eigen value represents a portion of variance and we keep the first *m* eigen vectors such that

$$\frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{K} \lambda_i} > \text{Threshold level (normally 90 or 95\%).}$$

A criterion usually followed is MINEIGEN criterion according to which we retain all the components with eigen value >1.

6. The eigen vectors retained can be used to recalculate the values for each observation.

The method involves sophisticated calculations like eigen values and eigen vectors and hence software packages can be used. In determining the weights for the indicators, the weights are determined by the factors loadings of the first principal component.

Gberibouo, G.A. and Ringler (2009) have applied this method to construct the vulnerability of South African farming sector. They identified a total of 19 indicators, 4 for exposure component, 6 for sensitivity component and 9 for adaptive capacity component. They retained the first principal component which explained about 33% of the variation and based on over all vulnerability index they classified the 9 farming provinces into 4 categories in terms of vulnerability as ‘high’, ‘medium’, ‘low-medium’ and ‘low’.

9.3.2 Cluster Analysis

The index approach is very easy to compute and intuitively clear. However it leads to loss of information when aggregating different types of data. Further the interaction between the factors that were used for construction f the composite index is also masked. To address this problem some authors (for example, Sharma,U. and Patwardhan,A(2007) applied cluster analysis technique to identify vulnerability hotspots to tropical cyclone hazard in India. Cluster analysis groups objects (in our study regions) into clusters so that th degree of association is strong among the members of the same cluster and weak among the members of the different clusters. Clustering methods can be classified as hierarchical and non-hierarchical and the authors applied the latter method in their paper. Please refer to the paper for further details.

10. STATISTICAL TESTS ON VULNERABILITY INDICES

The degree of correlation between two components of vulnerability can be examined by testing the significance of rank correlation coefficients between them. The rank correlation coefficient is given by the formula

$$\rho = 1 - \frac{6\sum_{i=1}^{M} d_i^2}{M\left(M^2 - 1\right)}$$

Where d_i the difference between the two is ranks of the i^{th} region and M is the number of regions. The value of ρ lies between -1 and +1. A value of +1 indicates perfect agreement between the rankings whereas a value of -1 implies perfect disagreement.

The following table gives the rank correlation coefficients between the four components of vulnerability for the data set used in Patnaik and Narain method.

	Demographic	Climatic	Agricultural	Occupational
Demographic	1.000			
Climatic	0.536	1.000		
Agricultural	-0.786**	-0.071	1.000	
Occupational	-0.571*	-0.464	0.107	1.000

** Significant at 1% level; * Significant at 5% level

These rank correlation coefficients can be tested using statistical tables. It can be seen that rankings by demographic components are negatively and significantly related to those of agricultural and occupational components. All other coefficients are not significant. Further climatic and demographic components have high positive non-significant correlation. It can be further inferred that there is no correlation between climatic and agricultural rankings though one would have expected a significant correlation between the two components a priori.

When we consider more than two components, the component wise rankings can be used to test the unanimity among the components in ranking the regions. This can be accomplished by applying Kendall's coefficient of concordance. This test statistic is defined by

$$W = \frac{12S}{m^2\left(M^3 - M\right)}$$

where m is the number of components and M is the number of regions and $S = \sum_{i=1}^{i=M} (R_i - \overline{R})^2$; R_i = sum of the ranks of regions i and $\overline{R} = \frac{m(M+1)}{2}$. It can be shown that W lies between 0 and 1. When W=1 , it indicates that there is perfect unanimity among the different components in ordering the regions. On the other hand if W=0 there is no overall trend of agreement among the components in ranking the regions. The significance of W can be tested using the statistic

$$\chi^2 = m(M-1)W$$

which has a chi-square distribution with M-1 degrees of freedom. For our data set the computations are as shown below:

$$\overline{R} = m(M+1)/2 = 4(7+1)/2 = 16$$

Region	Source					
	Demographic	Climatic	Agriculture	Occupational	R_i	$(R_i - \overline{R})^2$
North Eastern Zone	1	1	5	7	14	4
North Western Zone	2	6	7	4	19	9
Western Zone	4	4	3	5	16	0
Cauvery Delta Zone	3	2	6	2	13	9
Southern Zone	5	3	2	6	16	0
High Rainfall Zone	6	7	4	3	20	16
Hilly Zone	7	5	1	1	14	4

So $S = \sum_{i=1}^{7} (R_i - \overline{R})^2 = 42$ and hence $W = \frac{12 \times 42}{4^2(7^3 - 7)} = \frac{3}{32} \approx 0.094$ and $\chi^2 = 2.25$ which is not significant implying that the rankings have no concordance.

Hands on Exercises

I. Identify the functional relationship of the following indicators with adaptive capacity

S.No.	**Variable**	**Functional Relationship(↑ or ↓)**
1	Food crop production per unit area	
2	Animal protein consumption per capita	
3	Percentage of land managed	
4	Fertilizer use	
5	Life expectancy	
6	GDP at market per capita	
7	Literacy rate	
8	Population density	
9	Percentage of land unmanaged	
10	Percentage of workers employed in agriculture	
11	Female literacy rate	
12	Infrastructure indicators	
13	Depth of soil cover	
14	Soil degradation severity	
15	Replenishable groundwater available for future use	
16	Share of drought resistance crop	
17	Variability in agricultural production	
18	Average cost travel to district market	
19	Civil insecurity	
20	Frequency of pest and disease occurrence	
21	Use of technological advancements	
22	Productivity of major crops	
23	Cropping intensity	
24	Irrigation intensity	
	Percentage	
25	of gross cropped area to total geographical area	
26	share of food crops to gross cropped area	
27	share non food crops to gross cropped area	
28	share of cultivable waste to total geographical area	
29	share of gross irrigated area to gross cropped area	
30	of net irrigated area to net area sown	
31	milk production (lakh tonnes)	
	Variances	
32	Annual rainfall	
33	maximum temperature	
34	minimum temperature	
35	diurnal temperature variation	

II. Work out the composite vulnerability index for the following data set and rank the regions. Also clearly indicate the functional relationship between the indicators and vulnerability.

Name of the Zone	Density of population	Literacy Rate (%)	Variance in annual rainfall	Min temp variance	Max temp variance	Rice (kg/ha)	Cropping Intensity	Livestock Population/Ha
North Eastern	1276.54	73.00	9256.17	7.53	10.83	3479.33	1.23	2.49
North Western	983.73	67.10	5765.67	3.56	6.03	4050.67	1.36	2.51
Western	470.25	71.17	8618.55	2.68	5.41	4018.50	1.09	1.47
Cauvery Delta	1146.86	77.59	9349.51	5.38	7.98	3583.60	1.39	2.53
Southern	500.66	74.41	6850.30	3.02	16.51	3652.89	1.06	1.58
High Rainfall	995.27	87.59	1628.18	0.66	0.56	4721.00	1.22	1.26
Hilly	413.99	74.26	4962.00	2.69	3.12	4105.00	1.00	0.39

III. Work out the composite vulnerability index for the following data set and rank the districts. Also clearly indicate the functional relationship between the indicators and vulnerability.

District	Density of population	Literacy Rate (%)	Infant Mortality Rate	SWM – Variance (June-Sept)	NEM – Variance (Oct-Dec)	Min-tem-variance	Rice (kg/ha)	Sugarcane (t/ha)
Thiruvallur	398.86	67.18	6.62	2462.17	3602.91	9.99	3538	115
Kanchipuram	668.09	76.85	11.28	4093.62	9394.21	5.46	3278	126
Vellore	3110.58	80.46	16.32	24732.63	4364.49	8.08	4040	88
Dharmapuri	296.85	74.83	4.97	8721.4	4847.52	4.87	3413	95
Thiruvanamalai	353.17	67.39	14.425	21405.35	20347.75	6.42	3023	83
Villupuram	984	63.8	12.535	11780.17	8256.32	10.97	3326	115
Salem	515.09	65.09	11.495	5577.64	3558.65	2.72	4378	127
Namakkal	2139.26	61.39	17.665	10277.60	3140.71	3.10	4361	157
Erode	368.56	65.36	14.645	16808.32	3267.96	3.59	4492	144
Coimbatore	571.94	76.97	16.715	631.54	15116.77	1.78	3545	106

IV. Work out the composite vulnerability index for the following data set and rank the districts. Also clearly indicate the functional relationship between the indicators and vulnerability

District	Population Density	Literacy Rate (%)	Variance in annual rainfall	Max Temp Variance	Diurnal variance	Total food grains tonnes/ha	Irrigation Intensity
Trichy	536.1	77.9	2587.09	8.75	2.54	1.9753	1.17
Perambalur	248.9	63.59	2764.54	9.38	4.68	1.0172	1.09
Cuddalore	2144.5	82.32	3995.79	9.17	1.96	1.9746	1.15
Nagapatinum	616.1	76.34	25321.1	10.04	3.26	3.9195	1.26
Tanjore	1970.3	84.59	5679.93	3.72	0.69	3.6084	1.26
Pudukkotai	269.1	68.1	4996.47	10.50	3.60	2.0726	1.02
Sivaganga	278.9	72.18	5523.76	9.67	7.03	1.8724	1
Madurai	747.1	77.82	4576.32	9.58	2.70	2.3761	1.16
Theni	381.3	71.58	5629.29	5.65	2.12	0.9954	1.17
Viruthunagar	408.9	73.7	7618.96	6.10	1.15	0.7985	1.07
Ramnad	1452.7	84.43	7985.34	3.54	1.22	1.3180	1
Thirunelveli	400.1	76.09	18684.78	3.95	0.75	2.5085	1.3

Appendix
List of possible indicators

Determinants of vulnerability	Component indicators	Description of the indicator
EXPOSURE	Extreme climate events	No. of events of flood and droughts
	Change in Climate variables (from selected base year)	Change in maximum temperature
		Change in maximum temperature
		Change in rainfall
SENSITIVITY	Irrigated land	Percentage of irrigated land
	Land degradation index	Combined soil degradation or vegetation degradation
	Crop diversification index	Area under major crops
	Rural population density	Total rural population/Km^2
	Percentage of small scale farmers	Percentage
	Percentage of land managed	
	Fertilizer use	Consumption of fertilizer per hectare
	Replenishable groundwater available for future use	Amount of water will be available for the different uses
	Irrigation intensity	Gross area comes under irrigation with reference to net area under irrigation
	share of cultivable waste to total geographical area	Area not cultivated continuously for the last five years or more in succession
ADAPTATION	Farm organization	No. of farmers in organized agriculture

CAPACITY	Literacy rate	Proportion of persons aged 15 years or older who are able to read and write
	Farm income	Net farm income
	Farm holding size	Average farm size
	Farm assets	Total value of farm assets
	Percentage of people below poverty line	Proxy for unemployment rate
	Share of agricultural GDP	Percentage
	Access to credit	Amount of credit received
	Infrastructure index	Computation of infrastructure index
	Access to market	Distance travelled to market to sell the produce
	Food crop production per unit area	Amount of food grain produced per hectare
	Non-food crop production per unit area	Amount of non-food grain produced per hectare
	Life expectancy	Years
	Percentage of workers employed in agriculture	Number of farmers are engaged in agriculture
	Percentage of landless labourers employed in agriculture	Number of labourers are available for agricultural activities
	Share of drought resistance crop	Percentage of area cultivated by drought resistance crop
	Cropping intensity	Gross area comes under cultivation with reference to net area under cultivation
	Milk production	Number of cows used for milk production that gives the additional income to the farmers

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