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CLASSIFICATION OF DISTRICTS OF ARUNACHAL PRADESH BASED ON VULNERABILITY TO FLOODS

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ABSTRACT

Assessment of vulnerability of Arunachal Pradesh to floods was carried out using Unequal Weights Index Method. The weights were assigned using two methods: Hazard/ Exposure/Adaptive Capacity/Vulnerability (HEAV) Mathematical Framework based on Analytical Hierarchy Process (AHP) and Iyengar & Sudarshan's method. UNDP's Human Development Index (HDI) was used to normalize the indicators for hazard, exposure, and adaptive capacity based on the functional relationship with vulnerability. Further, the districts of Arunachal Pradesh were classified based on the vulnerability indices using probability density function. Regularized incomplete beta function was used for this purpose. The study showed that, in terms of composite vulnerability, from both Iyengar & Sudarshan and HEAV framework, Changlang, Lower Subansiri and Tirap were the most vulnerable districts while Dibang Valley and Papumpare were the least vulnerable districts. The two unequal methods, namely, HEAV mathematical framework based on AHP and Iyengar and Sudarshan's method produced similar results. However, there were some differences in the indices due to difference in the assigned weights to indicators. Validation done by comparing state Govt. data, a global flood database and compilation of online news reports with results of the study (for both HEAV mathematical framework and Iyengar & Sudarshan's method) also proved to be quite matching and hence the results could be considered acceptable. However, since the AHP of assigning unequal weights was a subjective method and the weights were dependent on the decision maker, the Iyengar and Sudarshan's method was recommended.

Keywords: *Flood vulnerability, hazard, exposure, adaptive capacity, unequal weights.*

INTRODUCTION

The word 'vulnerability' is usually associated with natural hazards like flood, drought, and social hazards like poverty etc. The Intergovernmental Panel on Climate Change (IPCC, 1995), in its Second Assessment Report, defines vulnerability to climate change as "the extent to which climate change may damage or harm a system". Chamber (1983) described that vulnerability has two sides. One is an external side of risks, shocks to which an individual or household is subjected to a hazard and an internal side which is defenselessness, meaning a lack of means to cope without damaging loss. The vulnerability of a place on the earth surface to flood is a function of the region's exposure to the hazard (natural event) and the anthropogenic activities carried out within the catchment area, which impedes the free flow of water (UNESCO, 2012). Vulnerability is often reflected in the condition of the economic system as well as the socioeconomic characteristics of the population living in that system (Patnaik and Narayanan, 2009). Water resource systems are vulnerable to floods due to three main factors; hazard, exposure, and adaptive capacity. Hazard may be defined as a physical manifestation of flood posing threat to life, health, property or environment. Exposure can be understood as the values that are present at the location where floods can occur. Adaptive capacity is the ability of an entity – a country, a community, or an individual – to take action to cope better with current or potential adverse conditions brought about by hazards. Area that have high exposure and low coping capabilities would have the highest risk from a given flood event and those with low exposure and high coping abilities would have the lowest risk.

Many studies on quantitative assessment of vulnerability such as Schimmelpfennig and Yohe (1999), Pritchett et al. (2000), Downing et al. (2001), Moss et al. (2001), Kaly et al. (2002), and Luers et al. (2003) illustrated the composite index approach to measure vulnerability. For instance, Moss et al. (2000) in the Pacific Northwest Laboratory (PNL) used an index which is a composite of 16 variables selected from five sensitive sectors (settlement, food security, human health, ecosystem, and water) and three dimensions for coping capacity (economic, human resources, and environmental) to measure vulnerability to climate change for 38 countries. Roy and Thomas (2013) developed a methodology for the spatial vulnerability assessment of floods in the coastal regions of Bangladesh. Bahinipati (2014) adopted an integrated approach to assess vulnerability across the districts of Odisha, India and provided a better understanding of the adaptive capacity of households towards cyclone and flood. Ousmane et al. (2015) and Liu and Li (2015) also assessed the social vulnerability to flood in Medina Gounas. Kissi et al. (2015) carried out quantitative assessment of vulnerability to flood hazards in downstream area of Mono basin, south-eastern Togo of Yoto district. Letsie and Grab (2015) assessed social vulnerability of communities to natural hazards by

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applying a place-based social vulnerability index developed for the United States, to the Lesotho context.

For classificatory purposes, a simple ranking of the districts based on the indices would be enough. However, for a meaningful characterization of the different stages of vulnerability, suitable fractile classification from an assumed probability distribution is needed. This fractile classification will give more information and better understanding about the district. Iyengar and Sudarshan (1982) have used beta distribution for classification of regions based on multivariate data. Bhatacharjee and Wang (2011) also used beta distribution for classification of regions based on Facility Deprivation Index (FDI) and found it to be appropriate. Therefore, beta distribution is used in this study for the classification of districts.

India being the worst flood affected country next to Bangladesh, accounts one fifth of the global deaths by flood every year and on an average 30 million people are evacuated every year. The area vulnerable to flood is 40 Mha and average area affected by flood is 8 Mha. The northeast region of India, consisting of eight states covering a geographic area of 26.2 Mha and a population of 40 M, is characterized by large rural population (82%), low population density (148/km^2), large percentage of indigenous tribal communities (34–91%) and large area under forests (60%). The region has two main river basins (the Brahmaputra and the Barak), a large dependence of the population on natural resources, and poor infrastructure development. The region is also characterized by diverse climate regimes which are highly dependent on the southwest monsoon (June–September). Over 60% of the crop area is under rainfed agriculture, and so is highly vulnerable to climate variability and climate change (Ravindranath et al., 2011).

Arunachal Pradesh, due to its unique location in the fragile geo-environment of eastern Himalayan periphery and due to poor adaptive capacity, is very much vulnerable to water induced disasters like floods and landslides. In addition, the Siang River, which is the main contributor to Brahmaputra, and other north bank tributaries flow through Arunachal Pradesh making this state more vulnerable to floods. As such, vulnerability assessment of this state to flood is very important and has not been assessed so far.

The main goal of this study was to assign unequal weights to selected indicators for hazard, exposure, and adaptive capacity for estimation of vulnerability indices to floods, and to classify different districts of Arunachal Pradesh based on hazard, exposure, adaptive capacity and composite vulnerability indices.

Description of study area

The state of Arunachal Pradesh is situated between 26º 30' and 29º 28' N latitudes, and 91º 25' and 97º 24' E longitudes. It covers an area of 83,700 sq. km. The state is bounded by Tibet region of China in the north, Assam in the south, in the east by Myanmar and Nagaland, and in the west by Bhutan. The climate of Arunachal Pradesh is humid to per humid subtropical characterized by high rainfall and high humidity. However, temperate climate prevails at lower

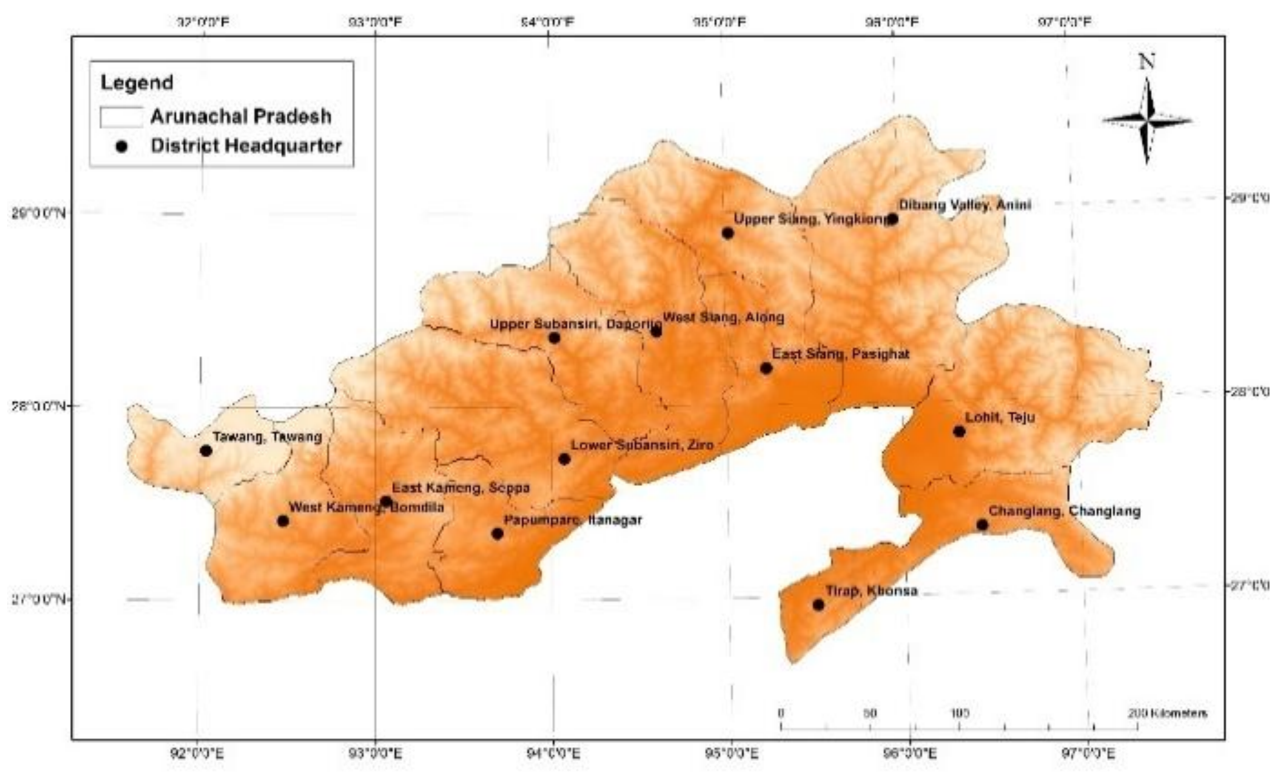

Fig. 1: The district map of Arunachal Pradesh.

Himalayan region. The greater Himalayan region is covered with perpetual snow. The average annual rainfall varies from 1,380 to 5,500 mm. The study area is presented in Fig. 1. The points shown in the figure are the centroids of each district labeled with the district names followed by its respective headquarters names. At present, there are 21 districts of Arunachal Pradesh but for this study, we have taken only 13 districts since our data period is 2004 and only 13 districts were there during this period. The latitude, longitude and elevation values for all the headquarters of 13 districts are shown in Table 1.

Table 1: District headquarters(HQ) of Arunachal Pradesh

Sl. No.	District	HQ	Latitude, °N	Longitude, °E	Altitude, m
1	Changlang	Changlang	27.12	95.71	580
2	Dibang Valley	Anini	28.79	95.89	1698
3	East Kameng	Seppa	27.32	93.00	363
4	East Siang	Pasighat	28.07	95.34	155
5	Lohit	Teju	27.92	96.17	244
6	Lower Subansiri	Ziro	27.56	93.80	1688
7	Papum Pare	Yupia (Itanagar)	27.07	93.59	440
8	Tawang	Tawang	27.59	91.87	2669
9	Tirap	Khonsa	27.19	95.47	1215
10	Upper Siang	Yingkiong	28.64	95.02	2500
11	Upper Subansiri	Daporijo	27.99	94.22	600
12	West Kameng	Bomdila	27.26	92.42	2217
13	West Siang	Along	27.98	94.70	619

Data and Methodology

Data acquisition

Values of different indicators of hazard, exposure and adaptive capacity were collected for 13 districts of Arunachal Pradesh from Directorate of Economics and Statistics, Government of Arunachal Pradesh, Itanagar for year 2004 and some census data were downloaded for year 2001 from http://www.censusindia.gov.in. The rainfall data used in this study were extracted from long period (1901–2010) daily gridded rainfall data set collected from India Meteorological Department (IMD) (Pai et al., 2014).

Trend analysis of these rainfall data was then carried out for the whole 100 years and two sets of 30 years (1971–2000 and 1981–2010). The Mann-Kendall (MK) (Mann, 1945) test was used in this study for detection of rainfall trend. MK test was a statistical yes/ no type hypothesis testing procedure and, therefore, another index, Sen slope (Sen, 1968) was used to quantify the magnitude of such trend. Being non-parametric, Sen slope also enjoys the same advantages mentioned earlier for the MK test. The “Arc Trend” ArcGIS toolbar developed by Bandyopadhyay et al. (2011) was used for this purpose. The Sen slope values were directly used as indicators. However, yes/ no results of MK test with significance levels 1%, 5%, and 10% were converted to numeric indicators following Table 2.

Table 2: Conversion of MK test result to numeric indicator

Sl. No.	MK test result			Value of indicator
	1% level of significance	5% level of significance	10% level of significance	
1	Y-	Y-	Y-	-3
2	N	Y-	Y-	-2
3	N	N	Y-	-1
4	N	N	N	0
5	N	N	Y+	1
6	N	Y+	Y+	2
7	Y+	Y+	Y+	3

Selection of indicators and their functional relationship with vulnerability

From the available district-wise data of the state, the indicators for each component of vulnerability were selected based on the definition given by IPCC on its Third Assessment Report (McCarthy et al., 2001), where they considered vulnerability to result from the interaction of three broad components, namely, hazard, exposure, and adaptive capacity. For assessing vulnerability to flood, indicators were selected separately for hazard, exposure and adaptive capacity in terms of their impact to vulnerability (Table 3). After finalizing the indicators, functional relationships of the indicators with the vulnerability to flood (for Iyengar and Sudarshan’s method) and between the indicators and component (for HEAV mathematical framework) were set up.

For Iyengar and Sudarshan’s method, the relationships were set up based on how the indicators were affecting the vulnerability to flood. Two types of functional relationship were possible: increase in the value of the indicator increased the vulnerability or decreased the vulnerability. For example, if we take rainfall, it is clear that higher the value of this indicator, more will be the vulnerability of that district to flood and we can say there is increasing functional relationship with vulnerability which is shown by ↑ in Table 3. On the other hand, more land area means all of it may not get submerged and people can take refuge there, leading to decreasing relationship with vulnerability to flood, which is shown by ↓ in Table 3. For HEAV mathematical framework, the relationship was between the indicator and the component (hazard, exposure and adaptive capacity) of vulnerability and is also shown in Table 3.

Table 3: Functional relationship between the indicators and vulnerability

Component	Sl. No.	Indicators	Notation	Functional Relationship (Iyengar and Sudarshan's method)	Functional Relationship (HEAV mathematical framework)
Hazard	1	Elevation (m)	(H1)	↓	↓
	2	Rainfall (mm)	(H2)	↑	↑
	3	Rainfall trend for 30 years	(H3)	↑	↑
	4	Slope of rainfall trend for 30 years	(H4)	↑	↑
	5	Rainfall trend of 100 years	(H5)	↑	↑
	6	Slope of rainfall trend for 100 years	(H6)	↑	↑
Exposure	7	Total population	(E1)	↑	↑
	8	% of agricultural land to total land	(E2)	↑	↑
	9	% of rain-fed land	(E3)	↑	↑
	10	% of workforce in agriculture	(E4)	↑	↑
	11	% of rural population	(E5)	↑	↑
	12	Cereal/rice yield (metric tonnes/ha)	(E6)	↑	↑
	13	Total population of livestock and poultry	(E7)	↑	↑
	14	Consumption of fertilizer	(E8)	↑	↑
Adaptive Capacity	15	Land area (sq. km)	(A1)	↓	↑
	16	% of literacy rate	(A2)	↓	↑
	17	% of literacy rate of people aged 15 to 24	(A3)	↓	↑
	18	% or urban population	(A4)	↓	↑
	19	% of household electrified	(A5)	↓	↑
	20	% of female population	(A6)	↓	↑
	21	% of students enrolled in primary education	(A7)	↓	↑
	22	% of students enrolled in secondary education	(A8)	↓	↑
	23	% of students enrolled in tertiary education	(A9)	↓	↑
	24	% of population with access to drinking water	(A10)	↓	↑
	25	% of non-worker population	(A11)	↑	↓

Arrangement of indicators

For each component of vulnerability, the collected data were then arranged in the form of a rectangular matrix with rows representing districts and columns representing indicators. Let there be *M* districts and let us say we have collected *K* indicators. For *M* number of districts and *K* number of indicators, X_{ij} will be the value of the indicator *j* corresponding to district *i* and the matrix table will have *M* rows and *K* columns (i=1,2,3,…,M and j=1,2,3,…,K).

Normalization of indicators using functional relationship

The methodology used in UNDP's Human Development Index (HDI) (UNDP, 2006) was followed to normalize the indicators. Normalization was done based on the functional relationship which had already been set (Table 3).

For Iyengar and Sudarshan's method, if the variables had increasing functional relationship with vulnerability then normalization was done using equation:

$$x_{ij} = \frac{X_{ij} - \text{Min}\{X_{ij}\}}{\text{Max}\{X_{ij}\} - \text{Min}\{X_{ij}\}} \qquad (1)$$

And if the variables had decreasing functional relationship with vulnerability then normalization was done using:

$$x_{ij} = \frac{\text{Max}\{X_{ij}\} - X_{ij}}{\text{Max}\{X_{ij}\} - \text{Min}\{X_{ij}\}} \qquad (2)$$

where ,x_{ij} is the normalized value of indicator, X_{ij} is the raw value of indicator.

For HEAV mathematical framework, if the indicators were positively associated with the corresponding component then normalization was done using Eq. (1) and if the indicators were negatively associated with the corresponding component then Eq. (2) was used for normalization.

The normalized values for indicators of hazard and exposure were given same for both the methods (Iyengar and Sudarshan's method and HEAV mathematical framework) since they had same functional relationship. However, the functional relationship for adaptive capacity for the two methods were different and therefore, the normalized values of indicators for both the methods were different.

Methods of Construction of Vulnerability Indices (VIs) using Unequal Weights

The method of simple averages gives equal importance for all the indicators which are not necessarily correct. A survey of literature (Gbetibouo and Ringler, 2009; Swain and

Swain, 2011; Parekh et al., 2015) showed that the following two methods could be used to give unequal weights:

1. Expert Judgement
2. Iyengar and Sudarshan's Method

Expert Judgement

In this method, the weights were assigned based on expert opinion and it was a subjective method. Hazard/ Exposure/ Adaptive Capacity/ Vulnerability (HEAV) Mathematical Framework based on Analytical Hierarchy Process (AHP) was a type of expert judgement method.

Determination of weights using Analytic Hierarchy Process (AHP)

The AHP is a multi-criteria decision making method developed by Saaty (1980) and it uses hierarchical structures to represent a problem and then develop priorities for alternatives based on the consistency of the judgments given by the experts or users.

On the basis of a pair wise comparison weighting scale, the vulnerability domains and indicators were prioritized. This common scale for assigning of weight was the Saaty Rating scale (Table 4). Using AHP pair wise comparison, the weights of the indicators was assigned and a weight matrix was generated. The weight matrix for hazard, exposure, adaptive capacity and composite vulnerability are given in Table 5, 6, 7 and 8, respectively.

Table 4: The Saaty rating scale

Intensity of importance	Definition	Explanation
1	Equal Importance	Two factors contribute equally to the objective.
3	Somewhat more important	Experience and judgment slightly favor one over the other.
5	Much more important	Experience and judgment strongly favor one over the other.
7	Very much more important	Experience and judgment very strongly favor one over the other. Its importance is demonstrated in practice.
9	Absolutely more important	The evidence favoring one over the other is of the highest possible validity.
2,4,6,8	Intermediate values	When compromise is needed.

The n^{th} roots for all indicators were summed and the eigenvector corresponding to each indicator was calculated by dividing each value of n^{th} root of product by its total.

The Consistency Index for a matrix was calculated as below:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{3}$$

Where, λ_{max} is the maximum eigen value and n is the number of indicators. To estimate λ_{max}, each component of the new vector was divided by the corresponding eigenvector element. The mean of these values gave λ_{max}. The Consistency Ratio (CR) to measure how consistent the judgment was then made. The CI for the different size of weight matrix is available in the Saaty's (1980) book. CR could be obtained as follows:

$$CR = CI/CI_{table} \tag{4}$$

The CRs for all the component of each state are given in Table 9.

Determination of VIs

HEAV methodology (grossly based on HVAR methodology of Assaf, 2010) was used in this study for quantitative assessment of vulnerability for floods to changing climate in north-east India. Vulnerability, as a function of weighted indicators of hazard, exposure, and adaptive capacity, was determined.

Vulnerability was assessed by three criteria, such as hazard, exposure, and adaptive capacity as follows (IPCC, 2001):

Vulnerability = *f* (Hazard, Exposure, Adaptive Capacity)

$$V = [H \times (E - A)] \tag{5}$$

Vulnerability in a particular location can be obtained as below:

$$V(l) = \{wh_c \times H_c(l)\} \times [\{we_c \times E_c(l)\} - wac \times Acl \tag{6}$$

where,

$V(l)$ is VI at location l, $H_c(l)$ is commensurate composite indicator of hazard at location l and wh_c is its corresponding weight, $E_c(l)$ is commensurate composite indicator of exposure at location $l$and we_c is its corresponding weight; $A_c(l)$ is commensurate composite indicator of adaptive capacity at location l and wa_c is its corresponding weight.

To construct the commensurate composite indicator different weights was assigned to different indicators under hazard, exposure, and adaptive capacity as below:

$$H_c(l) = \sum_{k=1}^{NH} wh_k \times H_k(l) \tag{7}$$

$$E_c(l) = \sum_{k=1}^{NE} we_k \times E_k(l) \quad (8)$$

$$A_c(l) = \sum_{k=1}^{NA} wa_k \times A_k(l) \quad (9)$$

where,

$H_k(l)$ is k^{th} commensurated indicator of hazard at location l and wh_k is its corresponding weight, $E_k(l)$ is k^{th} commensurated indicator of exposure at location l and we_k is its corresponding weight, $A_k(l)$ is k^{th} commensurated indicator of adaptive capacity at location l and wa_k is its corresponding weight.

Iyengar and Sudarshan's Method

Determination of unequal weights

Iyengar and Sudarshan (1982) assumed that the weights vary inversely to the standard deviation of the respective indicators of vulnerability and this method was used to find the weights of the indicators. Hence the weight, w_j, is determined by:

$$w_j = \frac{c}{\sqrt{V_j}} \quad (10)$$

where, $V_j = \mathrm{Var}(x_i)$ over all the districts for j^{th} indicator and c is a normalizing constant that can be obtained as:

$$c = \left[\sum_{j=1}^{K} \frac{1}{\sqrt{V_j}}\right]^{-1} \quad (11)$$

The choice of the weights in this manner ensured that large variation in any one of the indicators did not unduly dominate the contribution of the rest of the indicators and thereby distort the inter-district comparisons (Iyengar and Sudarshan, 1982).

Determination of VIs

Iyengar and Sudarshan (1982) developed a method to work out a composite index from multivariate data for Andhra Pradesh and Karnataka to rank the districts in terms of their economic performance. This method was statistically sound and well suited for the development of composite index of vulnerability. The VI of i^{th} zone $(\bar{y}_i)$ was assumed to be a linear sum of weighted x_{ij} as given below:

$$\bar{y}_i = \sum_{j=1}^{K} w_j\, x_{ij} \quad (12)$$

where, w_j $(0 < w_j < 1$ and $\sum_{j=1}^{K} w_j = 1)$ are the weights calculated using Eq. 10. The $\mathrm{VI}(\bar{y}_i)$ so computed lied between 0 and 1, with 1 indicating maximum vulnerability and 0 indicating minimum vulnerability.

Classification of districts based on VIs

For classification of the districts based on the VIs, the beta probability distribution, which was generally skewed and takes values in the interval (0,1) was applied. This distribution was also used by Iyengar and Sudarshan (1982) in their study. This distribution has the probability density as given below:

$$f(x) = \frac{1}{\beta(a,b)} x^{a-1}(1-x)^{b-1}, 0 < x < 1 \; and \; a, b > 0 \quad (13)$$

= 0, otherwise

$$\text{with, } \beta(a,b) = \int_0^1 x^{a-1}(1-x)^{b-1} \quad (14)$$

where, x is the realization variable of the beta function whose value lies between 0 and 1, a and b are two positive shape parameters that appear as exponents of the random variable and control the shape of the distribution.

Based on the VIs for all the districts, the estimated values of a and b could be obtained using the method of maximum likelihood (Johnson and Kotz, 1970) as below:

$$a = m_1\left[\frac{m_1(1-m_1)}{m_2} - 1\right] \quad (15)$$

$$b = (1-m_1)\left[\frac{m_1(1-m_1)}{m_2} - 1\right] \quad (16)$$

where, m_1 is the mean of all VIs and m_2 is the variance of all VIs.

Five equal intervals were made and $(0, z_1)$, (z_1, z_2), (z_2, z_3), (z_3, z_4) and $(z_4, 1)$ were the linear intervals such that each interval had the same probability weight of 20 percent. These fractile intervals could be used to characterize the various levels of vulnerability as:

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

The values of z_1, z_2, z_3, and z_4 could be calculated using regularized incomplete beta function calculator. In this study the online calculator developed by Casio Computer Co. Ltd.(http://keisan.casio.com/exec/system/1180573395) was used.

RESULTS AND DISCUSSION

Normalization of indicators

Hazard

The maximum and minimum values (Table 10) were used for normalizing all the indicator values. For hazard component, taking elevation of the district headquarters indicator as an example, the maximum value is 2,669 m (Tawang) and minimum value is 155 m (East Siang) above mean sea level. These two values were used in either of the two Eqs. 1 or 2 for normalizing the indicators depending on their functional relationship shown in Table 3. In case of elevation of the district headquarters indicator, the more is the value, the less would be the vulnerability to flood, as most of the district population is normally concentrated near the district headquarters. Hence it has a decreasing functional relationship with vulnerability. Therefore, Eq. 2 is used to normalize this indicator. The same procedure is followed for other remaining hazard indicators also. As an example, the map of normalized rainfall indicator is shown in Fig. 2. From the map it can be seen that Changlang has the lowest normalized rainfall value of 0.00 and Papumpare has the highest value of 1.00.

Exposure

For exposure component, taking total population as an example, we can see from Table 10 that Lohit has

Table 5 Weight matrix for hazard component

	Elevation	Rainfall	Rainfall Trend (30 years)	Slope of rainfall trend (30 years)	Rainfall Trend (100 years)	Slope of rainfall trend (100 years)
Elevation	1	1/7	1/3	1/3	1/3	1/3
Rainfall	7	1	7	5	7	5
Rainfall Trend (30 years)	3	1/7	1	1/3	1	1/3
Slope of rainfall trend (30 years)	3	1/5	3	1	3	1
Rainfall Trend (100 years)	3	1/7	1	1/4	1	1/3
Slope of rainfall trend (100 years)	3	1/5	3	1	3	1

Table 6 Weight matrix for exposure component

	Total population	% of agricultural land to total	% of rain-fed land	% of workforce in agriculture	% of rural population	Cereal yield	Total population of livestock and poultry	Consumption of fertilizer (in metric ton)
Total population	1	1/5	1	1/5	1/9	1/3	1/3	1/3
% of agricultural land to total	5	1	3	1	1/5	3	7	5
% of rain-fed land	1	1/3	1	1/3	1/3	3	3	3
% of workforce in agriculture	5	1	3	1	1	3	7	7
% of rural population	9	5	3	1	1	5	7	7
Cereal yield	3	1/3	1/3	1/3	0.2	1	5	3
Total population of livestock and poultry	3	1/7	1/3	1/7	1/7	0.2	1	1
Consumption of fertilizer	3	0.2	1/3	1/7	1/7	1/3	1	1

Table 7 Weight matrix for adaptive capacity component

	Land area (Sq.Km)	Literacy rate (%)	Literacy rate of people aged 15 to 24	% of urban population	% of household electrified	% of female population	% of students enrolled in primary education	% of students enrolled in secondary level	% of students enrolled in tertiary level	Access to drinking water	% w p
Land area	1	1/7	1/7	1/5	3	1/3	1/3	1/7	1/7	1/5	
Literacy rate	7	1	1	3	9	3	1	1	1	3	
Literacy rate of people aged 15 to 24	7	1	1	3	7	3	1	1	1	3	
% of urban population	5	1/3	1/3	1	5	3	1/3	1/3	1/3	1/3	
% of household electrified	1/3	1/9	1/7	0.2	1	1/3	1/9	1/9	1/9	1/3	
% of female population	3	1/3	1/3	1/3	3	1	1/5	1/5	1/3	1	
% of students enrolled in primary education	9	1	1	3	9	5	1	3	5	1	
% of students enrolled in secondary level	7	1	1	3	9	5	1/3	1	3	1	
% of students enrolled in tertiary level	7	1	1	3	9	3	0.2	1/3	1	1	
Access to drinking water	5	1/3	1/3	3	3	1	1	1	1	1	
% of non-worker population	5	1/3	1/3	7	5	3	1/5	1/5	1/5	1/5	

Table 8 Weight matrix for composite vulnerability

	Hazard	Exposure	Adaptive Capacity
Hazard	1	3	5
Exposure	1/3	1	3
Adaptive Capacity	1/5	1/5	1

Table 9 The consistency ratios of the AHP weight matrix

Sl. No.	State	Hazard	Exposure	Adaptive Capacity	Composite Vulnerability
1	Arunachal Pradesh	0.05	0.09	0.10	0.03

maximum population with 1,43,527 and Upper Siang has the lowest with 33,363. By definition of exposure it can be defined that more densely populated area may be considered more exposed to flood. This is because even if the magnitude of the flood is low, a more densely populated area would mean a larger number of people exposed to the hazard as compared to a less densely populated area resulting in more vulnerability. Therefore, for this indicator, there will be increasing functional relationship with the vulnerability. And hence, Eq. 1 was used to normalize this indicator using the maximum and minimum values. Similarly, the other indicators of this component were also normalized taking their respective maximum and minimum values and considering their functional relationships with vulnerability. As an example, the map of normalized rural population is shown in Fig. 3. The map shows that Papumpare has the lowest normalized rural population and Upper Siang has the highest.

Adaptive Capacity

For adaptive capacity component, taking literacy rate as an

Table 10: Maximum and minimum values of the indicators

Sl. No.	Indicator	Maximum	Minimum
Hazard			
1	H1	2669 (Tawang)	153(East Siang)
2	H2	3451.92 (Papumpare)	1367.67 (Changlang)
3	H3	1 (West Kameng)	-3 (Dibang Valley, East Siang, Lower Subansiri, Upper Siang, West Siang)
4	H4	0.11 (Tawang)	-0.21(Upper Siang)
5	H5	0 (Changlang, Dibang Valley, East Siang, Tawang, Upper Siang, West Kameng, West Siang)	-3 (Lohit, Lower Subansiri, Tirap, Upper Subansiri)
6	H6	0.01 (West Siang)	-0.02 (Lohit)
Exposure			
7	E1	143527 (Lohit)	33363 (Upper Siang)
8	E2	5.82 (Changlang)	0.53 (Upper Siang)
9	E3	4.61 (Tirap)	0.05 (Upper Siang)
10	E4	37.17 (Tirap)	9.78 (Papumpare)
11	E5	100 (Upper Siang)	0.84 (Papumpare)
12	E6	2.07 (East Siang)	0.84 (Papumpare)
13	E7	362329 (East Siang)	51774 (Tawang)
14	E8	116.98 (West Kameng)	24.03 (Papumpare)
Adaptive Capacity			
15	A1	13029 (Dibang Valley)	2172 (Tawang)
16	A2	69.32 (Papumpare)	40.64 (East Kameng)
17	A3	81.65 (West Siang)	57.81 (Tirap)
18	A4	50.15 (Papumpare)	0 (Upper Siang)
19	A5	86.15 (Papumpare)	29.03 (East Kameng)
20	A6	49.63 (East Kameng)	42.97 (West Kameng)
21	A7	26.79 (Lower Subansiri)	9.45 (Lohit)
22	A8	3.67 (Lower Subansiri)	9.45 (Lohit)
23	A9	1.92 (Dibang Valley)	0.62 (Tirap)
24	A10	100 (Upper Siang)	86.83 (Papumpare)
25	A11	63.83(Papumpare)	44.18 (Tawang)

example, from Table 10 it can be seen that Papumpare has the highest literacy rate with 69.32% and East Kameng has the least literacy rate with 40.64%. A high value of this variable implies more literates in the district and so they will have more awareness to cope with flood. So the vulnerability will be lower and literacy rate has decreasing functional relationship with vulnerability. Therefore, Eq. 2 was used for normalizing this indicator using its maximum and minimum values. The other indicators of this component were also normalized following the same procedure. An example map of normalized land area is shown in Fig. 4. The map shows that Tawang district has the lowest and Dibang Valley has the highest land area.

Assigning of weights

Iyengar and Sudershan

Weights for indicators of hazard component were calculated from the normalized hazard indicators. The resulting assigned weights were 0.17, 0.15, 0.16, 0.21, 0.12, and 0.20 for elevation of district headquarters, rainfall, rainfall trend for 30 years, slope of rainfall trend for 30 years, rainfall trend for 100 years, and slope of rainfall trend for 100 years, respectively.

For indicators of exposure component, the weights assigned were 0.12, 0.10, 0.13, 0.13, 0.15, 0.15, 0.12, and 0.11 for total population, percentage of agricultural land, percentage of rain-fed land, percentage of workforce in agriculture, percentage of rural population, cereal yield, total population of livestock and poultry, and consumption of fertilizer, respectively.

For indicators of adaptive capacity component, the assigned weights were 0.09, 0.09, 0.08, 0.11, 0.10, 0.09, 0.09, 0.08, 0.07, 0.09, and 0.10 for land area, percentage of literacy rate, percentage of literacy rate of people aged 15 to 24, percentage of urban population, percentage of household electrified, percentage of female population, total students enrolled in primary education, total students enrolled in secondary education, total students enrolled in tertiary education, percentage of population with access to drinking water, and percentage of non-worker population, respectively.

HEAV mathematical framework

Weights for indicators of hazard component were calculated from the normalized hazard indicators. The resulting assigned weights were 0.04, 0.52, 0.07, 0.15, 0.07 and 0.15 for elevation of district headquarters, rainfall, rainfall trend for 30 years, slope of rainfall trend for 30 years, rainfall trend for 100 years, and slope of rainfall trend for 100 years, respectively.

For indicators of exposure component, the weights assigned were 0.03, 0.18, 0.09, 0.23, 0.32, 0.08, 0.03 and 0.04 for total population, percentage of agricultural land, percentage of rain-fed land, percentage of workforce in agriculture, percentage of rural population, cereal yield, total population of livestock and poultry, and consumption of fertilizer, respectively.

For indicators of adaptive capacity component, the assigned weights were 0.02, 0.15, 0.14, 0.05, 0.01, 0.04, 0.19, 0.15, 0.11, 0.09 and 0.05 for land area, percentage of literacy rate, percentage of literacy rate of people aged 15 to 24, percentage of urban population, percentage of household electrified, percentage of female population, total students enrolled in primary education, total students enrolled in secondary education, total students enrolled in tertiary education, percentage of population with access to drinking water, and percentage of non-worker population, respectively.

Construction of VIs

Based on the weights assigned, the vulnerability indices were calculated. The different components of vulnerability (hazard, exposure and adaptive capacity) were analyzed separately considering indicators belonging to that component only, and the districts were ranked depending on their relative vulnerability. In addition, for Iyengar and Sudarshan, a composite VI was computed by aggregating all the indicators of the three components together and for HEAV mathematical framework, composite VIs was computed by aggregating the indices of each component. Computing the vulnerability separately for each component in this way help us understand how each district performs differently with respect to different components of vulnerability, i.e., some districts may have a higher rank on the hazard component but a lower rank on the exposure component and/ or on adaptive capacity component and vice versa (Sharma and Patwardhan, 2008). This will ultimately help us identify priority component for remedial measures for districts that rank high in the composite VI.

Iyengar and Sudershan

Using the weights assigned and the normalized indicators in Eq.10, vulnerability indices and ranks for the 13 districts were calculated based on indicators of hazard, exposure and adaptive capacity components, as well as, composite VI. The VIs and ranks calculated considering all indicators are shown in Table 11.

When only hazard component is considered, East Kameng is the most vulnerable district followed by West Kameng, and Dibang Valley is the least vulnerable district followed by Upper Subansiri. This may be because the district headquarters of East Kameng is situated in lower elevation areas and receive high amount of rainfall and West Kameng has maximum rainfall trend in both 30 years and 100 years; whereas, district headquarters of Dibang Valley has least received rainfall with significant negative trend of rainfall for 30 years and Upper Subansiri has significant negative trend in both rainfall trend for 30 years and 100 years.

It can be seen from Table 11 that, when only exposure component is considered, Changlang ranks 1st followed by East Siang, and Upper Subansiri is the least vulnerable district followed by Papumpare. This can be attributed to the higher percentage of agricultural land in Changlang and East Siang and Papumpare having the minimum values of many indicators of exposure component (four out of eight).

For the same reason, Upper Siang also ranks third lowest in terms of exposure.

When only adaptive capacity is considered, Tirap ranks first followed by Tawang while Papumpare ranks last. This may be because Tirap and Tawang have very low values for adaptive capacity indicators, e.g., land area, percentage of literate people ages 15 to 24, and students enrolled in tertiary education; whereas, Papumpare, a small district in which capital of Arunachal Pradesh Itanagar is situated, has highest literacy rate, highest percentage of urban population, and highest percentage of household electrified.

Table 11: Vulnerability indices and ranks for hazard, exposure, adaptive capacity, and composite vulnerability from I&S Method

Districts	Hazard		Exposure		Adaptive Capacity		Composite vulnerability	
	VI	Rank	VI	Rank	VI	Rank	VI	Rank
Changlang	0.63	3	0.71	1	0.68	3	0.68	1
Dibang Valley	0.31	13	0.35	10	0.43	10	0.38	12
East Kameng	0.67	1	0.41	7	0.58	6	0.54	6
East Siang	0.61	4	0.67	2	0.41	11	0.54	7
Lohit	0.44	10	0.56	4	0.68	4	0.59	3
Lower Subansiri	0.43	11	0.53	5	0.38	12	0.44	10
Papumpare	0.55	7	0.29	12	0.35	13	0.37	13
Tawang	0.61	5	0.40	9	0.69	2	0.57	4
Tirap	0.49	9	0.57	3	0.69	1	0.61	2
Upper Siang	0.53	8	0.31	11	0.54	7	0.46	6
Upper Subansiri	0.43	12	0.27	13	0.51	8	0.41	11
West Kameng	0.65	2	0.41	8	0.61	5	0.55	5
West Siang	0.59	6	0.48	6	0.44	9	0.49	8

For calculating the composite VI, all the normalized indicators of hazard, exposure and adaptive capacity components were considered together. The composite vulnerability indices and ranks for the 13 districts of Arunachal Pradesh are also shown in Table 11. In terms of composite VI Changlang ranks first while Papumpare ranks last followed by Dibang Valley.

HEAV mathematical framework

The vulnerability values and ranks were calculated based on indicators of hazard, exposure and adaptive capacity components, as well as, composite VIs. The VIs and ranks are shown in Table 12. When only hazard component is considered, Papumpare is the most vulnerable district followed by East Kameng, and Dibang Valley is the least vulnerable district, followed by Changlang. When only exposure component is considered, Changlang is most vulnerable, followed by Tirap, and Papumpare is the least vulnerable district followed by Upper Subansiri. When only adaptive capacity is considered, Papumpare comes first followed by East Siang while Tirap is the least, followed by Upper Subansiri.

For calculating the composite VIs Eq. 6 was used. All the normalized indicators of hazard, exposure and adaptive capacity components were considered together. The composite vulnerability indices and ranks for the 13 districts of Arunachal Pradesh are also shown in Table 12. In terms of composite VIs, Tirap is most vulnerable with a value of 1, while Papumpare is the least with a value of 0.

Table 12: Vulnerability indices and ranks for hazard, exposure, adaptive capacity and composite vulnerability index from HEAV framework

Districts	Hazard		Exposure		Adaptive Capacity		Composite vulnerability	
	VI	Rank	VI	Rank	VI	Rank	VI	Rank
Changlang	0.35	12	0.82	1	0.27	10	0.90	3
Dibang Valley	0.20	13	0.44	10	0.60	5	0.30	12
East Kameng	0.71	2	0.51	7	0.40	8	0.89	4
East Siang	0.64	4	0.62	4	0.68	2	0.83	5
Lohit	0.51	8	0.52	6	0.25	11	0.81	6
Lower Subansiri	0.66	3	0.64	3	0.64	4	0.92	2
Papumpare	0.72	1	0.22	13	0.76	1	0.00	13
Tawang	0.43	9	0.47	9	0.21	12	0.67	8
Tirap	0.42	11	0.75	2	0.20	13	1.00	1
Upper Siang	0.58	7	0.54	5	0.48	6	0.78	7
Upper Subansiri	0.63	5	0.37	12	0.47	7	0.51	11
West Kameng	0.42	10	0.43	11	0.38	9	0.52	10
West Siang	0.62	6	0.50	8	0.65	3	0.60	9

Classification of districts

To classify the districts of Arunachal Pradesh based on composite VIs, VIs were further graduated using beta distribution based on the estimated parameters of *a* and *b*. The values, thus calculated from Eqs. 15 and 16 are presented in Table 13. With these, the values of z_1, z_2, z_3 and z_4 were calculated using the beta distribution online calculator developed by Casio Computer Co. Ltd. (http://keisan.casio.com/exec/system/1180573395) and the resulting 20 percent cut-off points are also shown in Table 13. Based on these calculations, the districts of Arunachal Pradesh were finally classified into five clusters (Very less, less, moderate, high, and very high) depending on the levels of composite VIs.

Table 13: Estimated beta distribution parameters and the fractile values

	a	b	z_1	z_2	z_3	z_4
Iyengar and Sudarshan's method	3.81	13.31	0.43	0.48	0.53	0.59
HEAV mathematical framework	.15	0.56	0.39	0.65	0.83	0.95

Iyengar and Sudarshan's method

Fig. 5 presents the district classification map based on indices of adaptive capacity component. In terms of composite vulnerability, Changlang and Tirap have the highest VIs and lie in the zone of very high vulnerability followed by Lohit, East Siang, East Kameng, West Kameng and Tawang which lie in the high vulnerability zone. This is because they are low on adaptive capacity indicators with moderate on exposure indicators. Dibang Valley, Papumpare and Upper Subansiri are least vulnerable to flood followed by West Siang in the moderate vulnerability zone.

HEAV mathematical framework

For HEAV framework, based on the levels of vulnerability for composite index, the districts are classified and are shown in Fig. 6. It is observed that, Tirap has the highest VI and lie in the zone of very high vulnerability, followed by Changlang, East Kameng and Lower Subansiri lying in the high vulnerability zone. This is because the adaptive capacity indicators of these districts were low and the exposure indicators were high. Dibang valley and Papumpare are least vulnerable followed by Upper Subansiri, West Kameng and West Siang in the moderate vulnerability zone. Their adaptive capacity values were high while the exposure indicators were low.

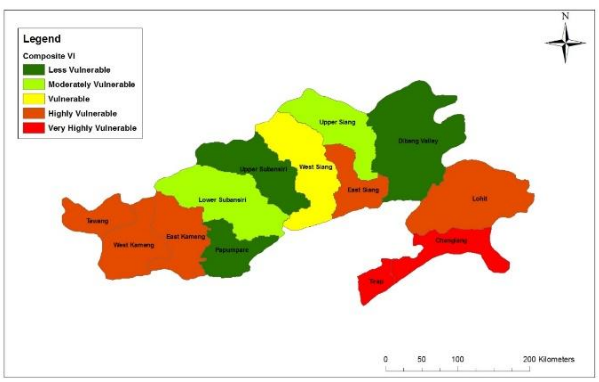

Fig. 5. Classified map of Arunachal Pradesh in terms of composite vulnerability to flood as per Iyenger&Sudarshan method.

Validation

Few data available with the state government of Arunachal Pradesh, a global flood inventory (Adhikari et al., 2010), and some online compilation of various media reports for different years have been collected and analysed for validation. In this study, Changlang and Tirap have been identified as the districts which are very highly vulnerable to flood followed by Lohit, East Siang, East Kameng, West Kameng and Tawang. And as per the report of 2010 given by Directorate of Disaster Management of Arunachal Pradesh (Govt. of Arunachal Pradesh, 2010), Lohit, Changlang, East Siang, East Kameng, Dibang Valley, and Upper Siang have been worst affected by flood. This report and our result are quite similar except for Dibang Valley which has been identified as less vulnerable district in our study. This may be because by 2010 the socio-economic condition of this particular district has changed. An online report for 16 July 2004 (ReliefWeb, 2004), which is a compilation of reports from Relief and Rehabilitation department, Govt. of Arunachal Pradesh and various media reports, also shows that East Kameng, East Siang, Lower Dibang Valley, Lohit, and Changlang have been worst affected by flood. A global flood database (Adhikari et al., 2010) have listed Lohit, East Siang, East Kameng, and Upper Siang as flood affected districts with high fatality rate in 2000, 2004, and 2005. In another report given by Govt. of Arunachal Pradesh (2014), Changlang, Lohit and East Siang have been identified as the highly vulnerable districts. All these reports support the result of our study and hence been well validated.

CONCLUSION

The study showed that, East Kameng, Papumpare and West Kameng were the most vulnerable districts while Changlang, Dibang Valley, Lower Subansiri and Upper Subansiri were less vulnerable to flood in terms of hazard component. Changlang, East Siang and Tirap were found to be the most vulnerable districts and Papumpare and Upper Subansiri the least vulnerable districts in terms of exposure

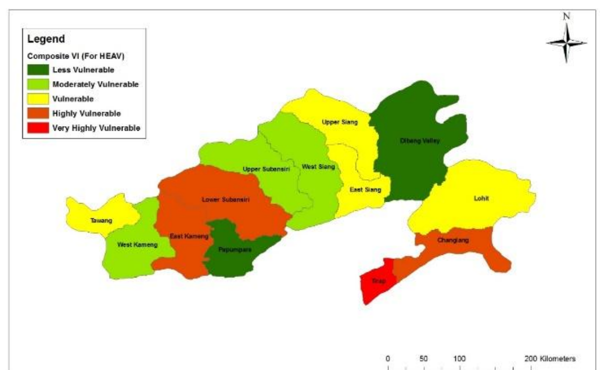

Fig. 6. Classified map of Arunachal Pradesh in terms of composite vulnerability to flood as per HEAV Framework.

component. Tawang, Tirap and Upper Subansiri were found to be the most vulnerable districts and East Siang, Lower Subansiri and Papumpare were the least vulnerable districts to flood in terms of adaptive capacity. In terms of composite vulnerability, from both Iyengar & Sudarshan and HEAV framework, it was found that Changlang, Lower Subansiri and Tirap were the most vulnerable districts while Dibang Valley and Papumpare were the least vulnerable districts. A point to be noted here is that districts that emerge as very highly vulnerable when the components are considered separately may not necessarily mean that the same district will be highly vulnerable when all the components are considered together, i.e., composite vulnerability. For example, Papumpare is not in very highly vulnerable zone even if it is very highly vulnerable in terms of hazard components due to its less vulnerability from adaptive capacity component.

The two unequal methods, namely, HEAV mathematical framework based on AHP and Iyengar and Sudarshan's method produced similar results. However, there were some differences in the indices due to difference in the assigned weights to indicators. Validation done by comparing state Govt. data, a global flood database and compilation of online news reports with results of the study (for both HEAV mathematical framework and Iyengar and Sudarshan's method) also proved to be quite matching and hence the results could be considered acceptable. However, since the AHP of assigning unequal weights was a subjective method and the weights were dependent on the decision maker, the Iyengar and Sudarshan's method was recommended.

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