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" Assessment And Spatial Analysis Of Agricultural Vulnerability To Climate Change In Maharashtra: A District-Level Perspective"

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Abstract
This study investigates the district-wise exposure index to climate change in Maharashtra, India, spanning the period from 1980 to 2020. Utilizing exposure scores, Palghar emerges as the most exposed district, while Latur exhibits the lowest exposure. Vulnerability classification, employing the Beta distribution and fractile method, categorizes districts into least vulnerable, moderately vulnerable, vulnerable, highly vulnerable, and most vulnerable. Spatial mapping using Q-GIS illustrates the varying degrees of vulnerability across districts. This comprehensive assessment provides valuable insights into the vulnerability landscape of Maharashtra's districts, offering a foundation for informed climate policies, agricultural practices, and disaster preparedness initiatives.

Key words: *Climate change, Exposure, Agriculture, Performance indicator.*

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I. Introduction

Numerous studies on socioeconomic vulnerability to climate change employ diverse methodologies and indicators. Regional assessments often follow the IPCC approach, with modifications for local contexts. Brenkert and Malone (2005) used the Vulnerability-Resilience Indicator Prototype, adapted for Indian dietary customs and freshwater data, finding nine states somewhat resilient. Das (2013) examined regional vulnerability in Indian agriculture, producing a Socio-Economic Vulnerability Index based on indicators like irrigation strength and poverty.

Malakar and Mishra (2016) focused on city-level vulnerability, categorizing indicators into infrastructure, technology, finance, social, and space. Senapati and Gupta (2017) studied Mumbai's fishing communities, revealing vulnerability due to resource limitations. Ayanlade et al. (2018) explored rainfall variability in African agro-climatic zones, while Rao (2019) assessed agrarian vulnerability in Maharashtra. Krishnan et al. (2019) developed a socio-economic vulnerability index, and Carpena (2019) found drought impacting household nutrition. Singh (2020) studied farmers' perceptions in Bundelkhand. Balaganesh et al. (2020) mapped drought-related climate change in Tamil Nadu, revealing varying vulnerability across districts.

II. Materials And Methods

Data sources

Time series data on crop acreage, production, productivity, gross cropped area, and economic indicators are sourced from government publications, including the Statistical Abstract of Maharashtra State, Epitomes of Agriculture in Maharashtra, and Socio-economic Review. District-level daily average rainfall data spanning 40 years (1980 to 2021) is collected from 'Solar Radiation Data (SoDa)3 - Solar energy services for professionals' online web services.

The choice of vulnerability indicators

Exposure indicators

Trends in *kharif ,rabi and zaid* rainfall
Trends in *kharif ,rabi and zaid* relative humidity
Trends in *kharif ,rabi and zaid* maximum temperature.
Trends in *kharif ,rabi and zaid* minimum temperature.

Arrangement of data

Data for sector-wise and composite vulnerability, with M districts and K indicators, are organized in a rectangular matrix. Each row represents a region, and each column represents an indicator, denoted as Xij for the value of indicator j in region i.

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}

Normalisation of indicators / variables

The methodology developed by Anand and Sen (1994) for calculation of Human Development Index and used by UNDPs for preparation of Human Development Index report (HDI) for the year 2006 was used to normalise the indicators. The normalised indicators were laid in between 0 to 1. Formulae to normalise the variable having positive and negative functional relationship with vulnerability are as follows:

For positive functional relation

$$Y_{ij} = \frac{X_{ij} - Min\ (X_{ij})}{max(\ X_{ij}) - min\ (X_{ij})}$$

For negative functional relation

$$Y_{ij} = \frac{Max(X_{ij}) -\ (X_{ij})}{max(\ X_{ij}) - min\ (X_{ij})}$$

The value 1 corresponds to that region with maximum vulnerability and 0 correspond to the region with minimum vulnerability.

Construction of Vulnerability Index (Unequal Weight)

After normalising the indicators, the weights are assumed to vary inversely as the variance over the regions/districts in the respective indicators of vulnerability. That is, the weight w_j is determined by

$$w_j = c \Big/ \sqrt{\underset{i}{\mathrm{var}}\left(x_{ij}\right)}$$

Where c is a normalizing constant such that

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

The vulnerability index so computed was laid between 0 and 1. A value of one indicated maximum vulnerability and zero indicated no vulnerability at all.

Aggregation of component indices

Potential Impact (PI_i) = Exposure $_i$

Ranking of districts

The calculated vulnerability indices were used to rank the different districts in terms of vulnerability. A district with highest index is said to be most vulnerable and it was given the rank 1, the district with next highest index was assigned rank 2 and so on.

Classification of districts

For classificatory purpose, a simple ranking of the districts based on their respective index would be enough. However for a meaningful characterization of different stages of vulnerability, suitable fractile classification from an assumed distribution is needed (Palanisami *et al*. 2009). Beta distribution, a continuous probability distribution is suitable for this purpose. It is generally skewed and takes values in the interval (0, 1), parameterized by two shape parameters, denoted by α and β (Iyengar and Sudarshan 1982).

Mapping of Districts:

With the help of Q-GIS, spatial data for each of the variables was processed to create a set of single-factor maps. Based on the map, The vulnerability of each area will be assessed and locate several high risk areas to low risk areas (1 to 0). Identifying the risks in each case and associating them with a specific region will be useful for decision makers.

III. Results And Discussion

District wise exposure index in Maharashtra

Exposure scores calculated from 1980 to 2020 indicate Palghar with the highest (0.5657) and Latur with the lowest (0.2936) exposure in Maharashtra. Thane, Raigad, Sindhudurg, and Nashik are most vulnerable due to increased kharif rainfall, relative humidity, and temperatures, mainly in the coastal region. Conversely, districts like Amaravati, Gadchiroli, Yavatmal, and others in central Maharashtra and Vidarbha exhibit lower exposure due to consistent climatic conditions.

Table 3.1.1: District wise exposure index in Maharashtra

S.No	Districts	Exposure Index
1.	Palghar	0.5657
2.	Nashik	0.5377
3.	Thane	0.5244
4.	Raigad	0.5187
5.	Sindhudurg	0.5032

Classification of Districts into most vulnerable to least vulnerable district as per the magnitude of exposure index.

Meaningful characterization of different stages of vulnerability, suitable fractile classification (Palanisami *et al*. 2009) method is used. Beta distribution, a continuous probability distribution is suitable for this purpose. It is generally skewed and takes values in the interval (0, 1), parameterized by two shape parameters, denoted by α and β (Iyengar and Sudarshan 1982). Hence, its value is near to zero the districts viz; Wardha, Gadchiroli, Amaravati, Yavatmal, Hingoli, Parbhani, Latur and Nanded are classified under least vulnerable wherealse the districts viz; Palghar, Nashik, Thane, Raigad, Sindhudurg, Ratnagiri and Ahmednagar values are near to 1.Hence, it is considered as most vulnerable districts.

1	Least vulnerable	Wardha
		Gadchiroli
		Amaravati
		Yavatmal
		Hingoli
		Parbhani
		Latur
		Nanded
2	Moderately vulnerable	Jalna
		Chandrapur
		Nagpur
		Gondia
		Bhandara
		Washim
3	Vulnerable	Jalgaon
		Kolhapur
		Sangli
		Buldhana
		Osmanabad
		Solapur
4	Highly vulnerable	Pune
		Aurangabad
		Satara
		Nandurbar
		Beed

		Dhule
		Akola
5	Most vulnerable	**Palghar**
		Nashik
		Thane
		Raigad
		Sindhudurg
		Ratnagiri
		Ahmednagar

Mapping of Districts

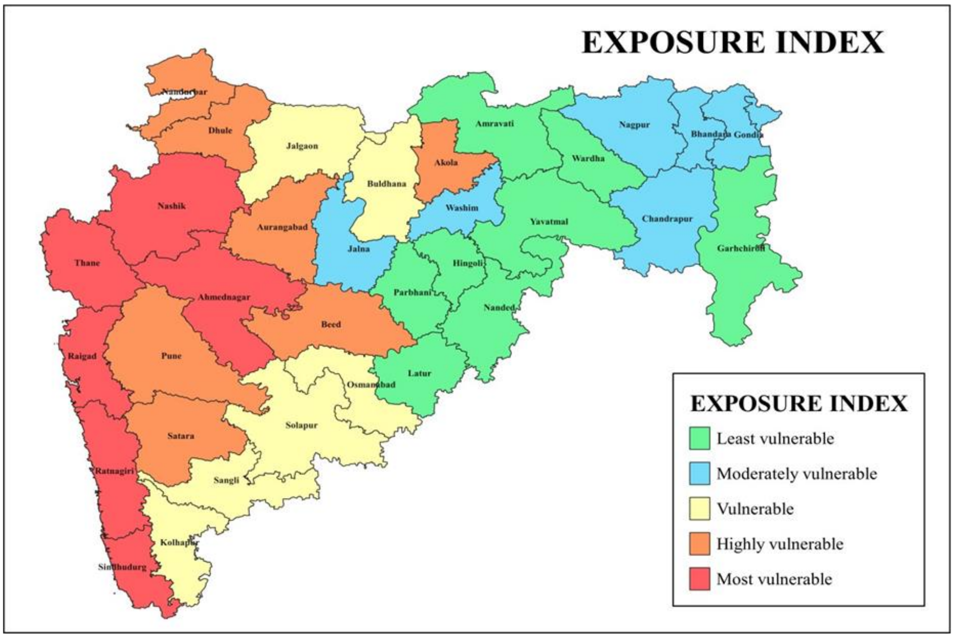

Figure : District wise map of exposure index in Maharashtra

With the help of Q-GIS, spatial data for each of the variables was processed to create a set of single-factor maps. Based on the map, The vulnerability of each area is assessed and locate several high risk areas to low risk areas (1 to 0). The figure 4.1 shows the least vulnerable to most vulnerable districts.

IV. Suggestions And Recommendations

- ❖District-level variations in sensitivity, exposure, and vulnerability exist in Maharashtra's Vidarbha, Marathwada, and Konkan regions, emphasizing the need for targeted district-level policies. To address climate change impacts, strategies include water conservation, proper credit distribution, early warnings, climate-proof shelters for animals, immunization, health checks, and diversified farming. Evaluating and disseminating local coping mechanisms is crucial for effective climate change.
- ❖Climate change significantly impacts agriculture, food security, and rural development in Maharashtra, hindering the district's ability to adapt. Mitigation is possible through adopting new technology, expanding irrigation on dry-land farms, increasing mechanization, and educating farmers on mitigation and adaptation measures.
- ❖Policy interventions should focus on enhancing climate risk management at household and public levels through risk mitigation and coping methods. Mitigation plans should include crop diversification and "climate-smart" agricultural practices. Public involvement should emphasize building water harvesting structures, utilizing irrigation potential in rainfed regions, implementing early warning systems, and providing timely disaster information and weather-based crop insurance.
- ❖Enhancing short-term variability and long-term climate change adaptation involves risk management through insurance plans and improved weather forecasting. Upgrading irrigation systems, adopting new technologies, and investing in agricultural R&D are crucial for improving farmer resource utilization and reducing risks. Diversifying crop rotations, integrating agricultural and livestock systems, and diversifying food systems contribute to building climate change resilience and improving farming efficiency.

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