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VULNERABILITY ASSESSMENT OF DIFFERENT TAHSILS OF SOUTHERN REGION OF WESTERN MAHARASHTRA, INDIA

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ABSTRACT

This study quantifies and classifies the vulnerability of 58 tahsils in Southern Western Maharashtra using a weighted multi-criteria framework that integrates climatic, demographic, and agricultural indicators. The analysis spans the period from 1982 to 2021, covering Pune, Kolhapur, Sangli, Satara and Solapur districts. A multi-criteria decision analysis framework with weighted normalization was employed to ensure a robust spatial classification of vulnerability. Data preprocessing, statistical computations and visualization were conducted using MS-Excel and R Studio, facilitating the development of targeted climate adaptation strategies.

The results reveal significant spatial disparities in vulnerability levels. Koregaon tahsil exhibits the highest contribution to the composite vulnerability index, heavily influenced by the agricultural sector (84.44%), whereas Pune city demonstrates minimal agricultural vulnerability, with the climatic sector contributing 61.06%. Vulnerability levels range from highly vulnerable tahsils such as Bhudargad, Baramati, and Mahabaleshwar to very highly vulnerable areas like Ajra, Kagal and Koregaon. Jat tahsil falls into the vulnerable category, while Pune City is classified as moderately vulnerable, indicating distinct regional variations in climate change impacts.

The study underscores the urgent need for climate-resilient strategies by quantifying tahsil-level vulnerability through a weighted multi-criteria framework. The findings emphasize the importance of targeted adaptation measures that integrate agricultural sustainability, livelihood security, and policy-driven resilience to mitigate climate-induced stressors. These insights provide a foundation for designing region-specific adaptation plans to enhance climate resilience and sustainability in the face of evolving environmental challenges.

Key words : Demographic, Climatic and Agriculture vulnerability assessment, Dimension index, Vulnerability indices.

Introduction

Climate change has emerged as a critical global challenge, significantly impacting agricultural systems, economic stability and social structures. The Intergovernmental Panel on Climate Change (IPCC) highlights that rising temperatures, erratic precipitation patterns, and increased frequency of extreme weather events have intensified the vulnerability of agrarian economies (IPCC, 2014). In the Indian context, climate variability poses substantial risks, particularly in regions where agriculture is the primary source of livelihood. Western Maharashtra, characterized by diverse agro-climatic zones is highly susceptible to climate-induced fluctuations, making vulnerability assessment an essential tool for informed decision-making.

The southern region of Western Maharashtra comprises 58 tahsils with distinct climatic, demographic, and agricultural profiles. However, the spatial heterogeneity of these regions results in varied levels of vulnerability to climate change. The lack of a comprehensive vulnerability assessment framework integrating multi-dimensional indicators leads to inefficiencies in policy formulation and resource allocation. Existing studies emphasize climate change impacts on agricultural productivity (Fulekar and Kale, 2010 and Rahase *et al*., 2023), yet systematic vulnerability quantification at the tahsil level remains limited. Without precise classification and quantification of vulnerability, adaptation strategies may be misdirected or inadequate.

This study aims to develop a weighted multi-criteria framework for quantifying and classifying the vulnerability of 58 tahsils in Southern Western Maharashtra. By integrating climatic, demographic, and agricultural indicators, this framework will provide a robust methodology for identifying high-risk areas and recommending targeted adaptation measures. Such an approach ensures a holistic understanding of vulnerability, enabling policymakers to prioritize interventions based on region-specific susceptibility levels.

Several methodologies have been employed globally to assess vulnerability, including indicator-based approaches, econometric models, and simulation techniques. Cutter *et al*. (2003) proposed a Social Vulnerability Index (SoVI), emphasizing socio-economic factors in vulnerability assessment. In the agricultural context, Hahn *et al.,* (2009) introduced the Livelihood Vulnerability Index (LVI), integrating climatic exposure with socio-economic resilience. In India, studies by Mall *et al.* (2006) and O'Brien *et al.* (2004) have underscored the differential vulnerability of states and districts to climate change. However, limited research has been conducted at the tahsil level, particularly using a multi-criterion weighted approach that accounts for both biophysical and socio-economic dimensions. This study fills this critical gap by adopting a comprehensive indicator-based methodology tailored to the regional context of Western Maharashtra.

The vulnerability assessment conducted in this study will serve as a decision-support tool for climate-resilient planning in the southern tahsils of Western Maharashtra. By employing a weighted multi-criteria framework, the study ensures an objective evaluation of risk factors, thereby facilitating resource-efficient adaptation planning. The results will be instrumental for policymakers, researchers, and agricultural stakeholders in designing targeted interventions that enhance resilience against climate variability. Furthermore, this approach can be adapted and replicated in other agro-climatic zones, contributing to broader climate adaptation strategies in India and beyond.

By addressing the spatial variability in vulnerability and integrating multiple indicators, this research provides an evidence-based foundation for mitigating climate-induced risks in Maharashtra's agricultural landscape.

Materials and Methods

Study area

The present study evaluates the vulnerability index (VI) for 58 tahsils across Pune, Kolhapur, Sangli, Satara, and Solapur districts in the for the period 1982–2021.

Data collection

The historical data on different weather parameters was collected from, India Meteorological Department, Pune (https://dsp.imdpune.gov.in/

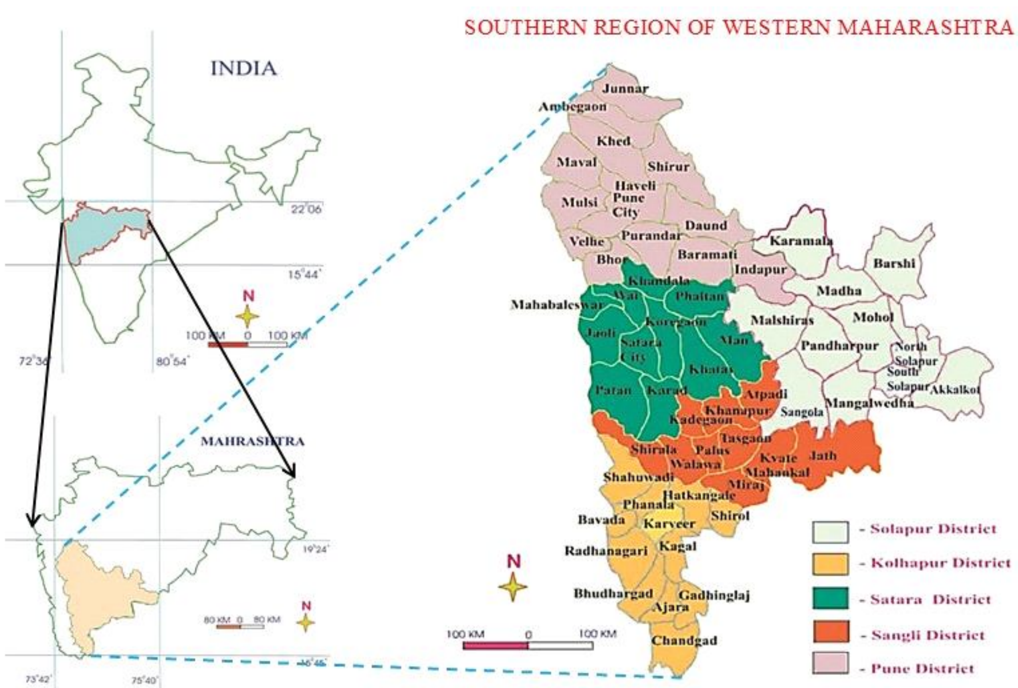

Fig. 1 : Study Area: Southern Region of Western Maharashtra.

data_supply_service.php; Veer *et al*., 2024), Department of Agricultural Meteorology, College of Agriculture, Pune. State Agriculture Department, Pune and Censes Department Government of Maharashtra.

Software/Programme

Data processing, statistical analysis, and visualization were performed using Microsoft Office sub-module MS-Excel and RStudio. Microsoft Excel was utilized for handling large datasets, executing multi-criteria assessments, and generating essential statistical summaries (Microsoft Corporation, 2023). Additionally, RStudio was employed for advanced data visualization, specifically for generating stacked bar charts using the ggplot2 package, ensuring clear representation of vulnerability classification across 58 tahsils in Southern Western Maharashtra (RStudio Team, 2023). The integration of these tools facilitated a robust analytical workflow, improving the accuracy and interpretability of the results.

Arrangement of data

For each indicator of vulnerability, the collected data is arranged in the form of a rectangular matrix with rows representing tahsils and columns representing indicators. Let there be M tahsils and let us say we have collected K indicators. Let X_{ij} be the value of the indicator *j* corresponding to tahsils *i*. Then the table has *m* rows and *k* columns are as shown below:

Table 1 : Arrangement of data for each indicator of vulnerability.

Tahsils	Indicators					
	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}

Estimation of Vulnerability Index (VI)

Normalization of indicators using functional relationship

Here, we calculated the geometric mean of demographic, climatic and agricultural indicators through the dimension index. Two type of functional relationship is possible *i.e.* positive functional relationship and negative functional relationship. Dimension index scores should be lie between 0 and 1. The value 1 is corresponding to that tahsil/ district/ zone with maximum value and 0 is corresponding to the tahsil/district/zone with minimum value (Patnaik and Narayanan, 2005).

All climatic and population density sub-indicator has positive functional relationship with vulnerability, then the index is calculated as-

$$\text{Dimension index} = \frac{Actual\ X_I - Minimum\ X_I}{Maximum\ X_I - Minimum\ X_I} \quad (1)$$

Where,

Actual X_I=Actual value of respective indicators

Minimum X_I=Minimum value of respective indicators

Maximum X_I =Maximum value of respective indicators

Whenever, all agricultural and literacy rate sub-indicator has negative functional relationship with vulnerability then the index is calculated as-

$$\text{Dimension index} = \frac{Maximum\ X_I - Actual\ X_I}{Maximum\ X_I - Minimum\ X_I} \quad (2)$$

This method of dimension index 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 is misleading (Patnaik and Narayanan, 2005).

Iyenger and Sudarshan's method for construction of vulnerability index

The method of simple averages gives equal importance for all the indicators, which are not necessarily correct. Hence many authors prefer to give weights to the indicators. Iyengar and Sudarshan (1982) developed a method to work-out a composite index from multivariate data and it is used to rank the tahsils in terms of their economic performance. This methodology is well suited for the development of composite index of vulnerability to climate change.

In all, based on the availability of data, 17 sub-indicators are used in the construction of vulnerability indices for 1981-2021 time periods, out of the 17 sub-indicators, 2 sub-indicators are concerned with demographic indicators, 4 sub-indicators are related to climatic indicators and 11 sub-indicators deal with agricultural indicators vulnerability.

A brief discussion about the methodology is given below

It is assumed that there are M Tahsil/Districts/zone, K sub-indicators of indicators vulnerability and *xij*, *i*= 1, 2, ….M ; *j*=1, 2, ….k are the normalized scores. The level or stage of development of i^t zone, $\bar{y}_t$ is assumed to be a linear sum *xij* as

$$\bar{y}_t = \sum_{j=1}^{k} WjXij \tag{3}$$

Where, w's (0<w<1 and $\sum_{j=1}^{k} Wj = 1$) are the weights. In Iyenger and Sudarshan's method, the weights are assumed to vary inversely as the variance over the Tahsil/District/zone in the respective sub-indicators of indicators vulnerability. That is, the weight W_j is determined by

$$W_j = c \Big/ \sqrt{\operatorname{var} x_{ij}}$$

Where, c is a normalizing constant such that

$$C = \left\| \sum_{j=1}^{k} 1 \Big/ \sqrt{\operatorname{var} x_{ij}} \right\|^{-1}$$

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-tahsil/District 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 tahsils based on the indices *viz.*, $\bar{y}_t$ would be enough. However, 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). This distribution is the probability density given by:

$$f(z) = \frac{Z^{a-1}(1-z)^{b-1}\, dx}{B(a,b)}, \quad 0 < z < 1 \text{ and } a, b > 0$$

Where, B(a, b) is the beta function defined by

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

The two parameters *a* and *b* of the distribution can be estimated by using the method by Iyenger and Sudarshan (1982). The beta distribution is skewed. 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 are used to characterize the various stages of vulnerability as shown below:

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

Results and Discussion

To evaluate the vulnerability of 58 tahsils in the southern region of Western Maharashtra, a composite vulnerability index was developed for the period 1982–2021. This index integrates key climatic, demographic, and agricultural factors, offering a comprehensive measure of how different regions respond to environmental and socio-economic stressors. The calculated indices were then compared and categorized to highlight variations in vulnerability across tahsils. This classification helps in identifying priority areas for intervention and supports the development of targeted adaptation strategies to enhance regional resilience.

Tahsil-wise share to the vulnerability to climate change

Vulnerability assessment is a vital tool for developing effective policy responses to climate variability. It plays a crucial role in identifying vulnerable regions and assessing the potential impact of environmental changes on factors such as livelihoods, agriculture, and other regional aspects. This study examines three key sources of vulnerability demographic, climatic and agricultural and their contributions to the composite vulnerability index (CVI) of specific regions. Climatic vulnerability emerges as a major determinant, indirectly influencing demographic and agricultural vulnerability indices. This analysis captures tahsil-wise vulnerability to climate change during the period 1982–2021, with findings presented in Tables 2, 3 and 4.

According to Table 2, Pune City tahsil ranked highest in terms of demographic vulnerability with an index of 0.076, followed by Akkalkot (0.042) and Jat (0.040), indicating higher vulnerability. On the other hand, Satara tahsil exhibited the lowest demographic vulnerability (0.005), followed by Khandala (0.009) and Wai (0.011), marking them as less vulnerable in this category.

The findings reveal that Bawada and Radhanagari tahsils were the most vulnerable to climate change, with indices of 0.216, followed by Khed (0.206) and Khandala (0.191). Conversely, South Solapur exhibited the least climatic vulnerability, with an index of 0.062, followed by

Table 2 : Indicator-wise and composite vulnerability index for period 1982-2021.

S. no.	Tahsil Name	DVI	Rank	CVI	Rank	AVI	Rank	CoVI	Rank
1	Ajra	0.029	12	0.134	8	0.335	33	0.498	21
2	Bawada	0.039	4	**0.216**	**1**	0.344	30	**0.599**	**2**
3	Bhudargad	0.022	19	0.118	15	0.309	42	0.449	37
4	Chandgad	0.032	10	0.130	9	**0.258**	**49**	0.420	43
5	Gadhingalaj	0.026	15	0.134	8	0.383	17	0.543	9
6	Hatkanagale	0.019	22	0.116	17	0.338	32	0.473	28
7	Kagal	0.023	18	0.128	10	0.350	28	0.500	19
8	Karveer	0.014	27	0.115	18	0.406	11	0.536	11
9	Panhala	0.021	20	0.100	21	0.338	32	0.459	33
10	Radhanagari	0.023	18	**0.216**	**1**	0.306	43	0.546	7
11	Shahuwadi	0.033	9	0.181	4	0.402	12	**0.616**	**1**
12	Ambegaon	0.013	28	0.126	12	0.432	5	0.571	5
13	Baramati	0.016	25	0.076	29	0.297	45	**0.389**	**47**
14	Bhor	0.017	24	0.125	13	**0.442**	**1**	**0.584**	**3**
15	Daund	0.024	17	0.078	28	0.364	23	0.465	32
16	Haveli	0.020	21	0.119	14	**0.438**	**3**	0.577	4
17	Indapur	0.018	23	0.072	33	0.380	19	0.470	30
18	Junnar	0.012	29	0.126	12	0.327	37	0.465	32
19	Khed	0.021	20	**0.206**	**2**	0.289	47	0.516	15
20	Mawal	0.018	23	0.119	14	0.399	13	0.536	11
21	Mulshi	0.026	15	0.119	14	0.346	29	0.491	23
22	Pune city	**0.076**	**1**	0.119	14	**0.000**	**51**	**0.195**	**49**
23	Purandhar	0.014	27	0.113	19	0.306	43	0.433	40
24	Shirur	0.018	23	**0.066**	**36**	0.318	39	0.402	46
25	Velhe	0.027	14	0.116	17	0.303	44	0.445	38
26	Atpadi	0.034	8	0.072	33	0.375	21	0.481	26
27	Jat	**0.040**	**3**	0.073	32	**0.198**	**50**	**0.312**	**48**
28	Kadegaon	0.017	24	0.100	21	0.389	15	0.506	17
29	Kavathemahankal	0.023	18	0.125	13	0.419	7	0.567	6
30	Khanapur	0.015	26	**0.069**	**35**	0.382	18	0.466	31
31	Miraj	0.015	26	0.115	18	0.386	16	0.516	15
32	Palus	0.009	31	0.093	23	0.408	10	0.510	16
33	Shirala	0.021	20	0.086	25	0.429	6	0.536	11
34	Shirol	0.016	25	0.118	15	0.364	23	0.499	20
35	Tasgaon	0.013	28	0.099	22	0.414	9	0.525	13
36	Walwa	0.011	30	0.117	16	0.317	40	0.445	38
37	Dahiwadi	0.034	8	0.080	27	0.314	41	0.428	41
38	Jawali	0.015	26	0.086	25	0.416	8	0.516	15
39	Karad	0.013	28	0.080	27	0.331	36	0.424	42
40	Khandala	**0.009**	**31**	**0.191**	**3**	0.344	30	0.545	8
41	Khatav	0.017	24	0.080	27	0.372	22	0.470	30
42	Koregaon	0.009	31	0.072	33	0.437	4	0.517	14
43	Mahabaleshwar	0.019	22	0.138	7	0.288	48	0.445	38
44	Patan	0.024	17	0.146	6	0.332	35	0.503	18
45	Phaltan	0.020	21	0.072	33	0.326	38	0.417	44

Table 2 continued...

Table 2 continued...

46	Satara	**0.005**	**32**	0.149	5	0.342	31	0.497	22
47	Wai	**0.011**	**30**	0.127	11	0.392	14	0.530	12
48	Akkalkot	**0.042**	**2**	0.083	26	0.290	46	0.415	45
49	Barshi	0.022	19	0.074	31	0.361	25	0.457	35
50	Karmala	0.029	12	0.072	33	0.352	27	0.453	36
51	Madha	0.027	14	0.070	34	0.379	20	0.475	27
52	Malshiras	0.029	12	0.080	27	0.363	24	0.472	29
53	Mangalwedha	0.037	5	0.101	20	0.379	20	0.517	14
54	Mohol	0.030	11	0.092	24	0.364	23	0.486	25
55	North Solapur	0.025	16	0.086	25	0.379	20	0.490	24
56	Pandharpur	0.028	13	0.075	30	0.356	26	0.458	34
57	Sangola	0.036	6	0.073	32	0.334	34	0.443	39
58	South Solapur	0.035	7	**0.062**	**37**	**0.440**	**2**	0.537	10

*DVI - Demographic Vulnerability Index, CVI – Climatic Vulnerability Index, AVI - Agriculture Vulnerability Index, CoVI - Composite Vulnerability Index.

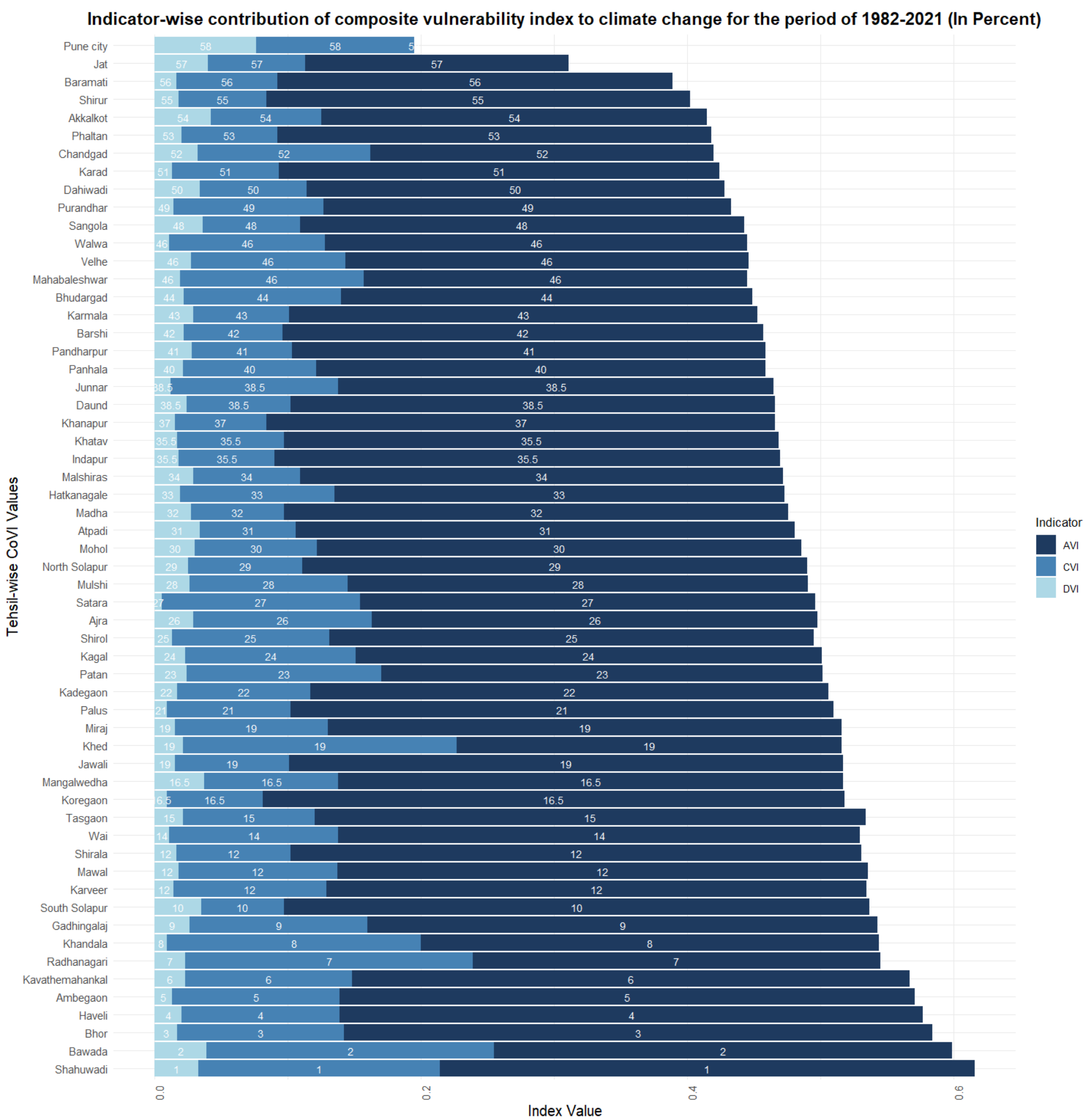

Fig. 2 : Indicator wise contribution of Composite Variability Index to Climate Change for the period of 1982-2021 (In Per cent).

Shirur (0.066) and Khanapur (0.069).

In terms of agricultural vulnerability, Bhor ranked highest with an index of 0.442, followed closely by South Solapur (0.440) and Haveli (0.438), indicating significant susceptibility in this sector. However, Pune City (0.000) showed no agricultural vulnerability, while Jat (0.198) and Chandgad (0.258) ranked among the least vulnerable tahsils during the study period.

The composite vulnerability index (CVI) highlighted Shahuwadi (0.616), Bawada (0.599) and Bhor (0.584) as the most vulnerable tahsils overall. In contrast, Pune City (0.195) was the least vulnerable, followed by Jat (0.332) and Baramati (0.389). These findings emphasize the variability in vulnerability across tahsils and the need for tailored mitigation strategies. Similar results found with the Adhav *et al.* (2021), TERI (2014), Palanisami *et al.* (2009), Bharti *et al.* (2017) and Rao *et al.* (2016).

The indicator-wise contributions to the composite vulnerability index (CVI) due to climate change for the period 1982–2021 are presented in Table 3. The data indicate that out of 58 tahsils, Koregaon ranked first, with the highest contribution from the agricultural sector at 84.44%, followed by the climatic sector (13.90%) and the demographic sector (1.67%). Khanapur ranked second, with contributions of 82.05%, 14.82%, and 3.12% from the agricultural, climatic and demographic sectors, respectively. South Solapur ranked third, with agricultural, climatic, and demographic sector contributions of 81.94%, 11.48%, and 6.58%, respectively.

In contrast, Pune City tahsil ranked last, showing no contribution from the agricultural sector (0.00%). Its CVI was primarily influenced by the climatic sector (61.06%) and the demographic sector (38.94%). These findings suggest that Koregaon, Khanapur and South Solapur were significantly more vulnerable to agriculture-related climate impacts, whereas Pune City was minimally affected in the agricultural sector during the study period.

Categorization of Tahsils based on Vulnerability levels

To classify tahsils into various vulnerability categories, the vulnerability indices were subjected to statistical analysis using a beta probability distribution. Percentile

Table 3 : Indicator- wise contribution of composite vulnerability index to climate change for the period of 1982-2021 (in Per cent).

S. no.	Tahsil Name	Demographic Vulnerability Index	Climatic Vulnerability Index	Agriculture Vulnerability Index	Total
1	Ajra	5.76	26.99	67.24	100
2	Bawada	6.51	36.12	57.38	100
3	Bhudargad	4.89	26.35	68.76	100
4	Chandgad	7.53	31.09	61.38	100
5	Gadhingalaj	4.78	24.72	70.50	100
6	Hatkanagale	4.05	24.44	71.51	100
7	Kagal	4.56	25.56	69.88	100
8	Karveer	2.70	21.41	75.90	100
9	Panhala	4.62	21.71	73.68	100
10	Radhanagari	**4.22**	**39.68**	**56.11**	100
11	Shahuwadi	5.43	29.32	65.24	100
12	Ambegaon	2.25	22.05	75.71	100
13	Baramati	4.11	19.60	76.30	100
14	Bhor	2.89	21.47	75.64	100
15	Daund	5.10	16.73	78.17	100
16	Haveli	3.50	20.59	75.91	100
17	Indapur	3.92	15.20	80.88	100
18	Junnar	2.65	27.06	70.29	100
19	Khed	**4.10**	**39.88**	**56.01**	100
20	Mawal	3.37	22.17	74.46	100
21	Mulshi	5.35	24.22	70.42	100
22	Pune city	**38.94**	**61.06**	**0.00**	100
23	Purandhar	3.23	26.03	70.74	100

Table 3 continued...

Table 3 continued...

24	Shirur	4.39	16.54	79.07	100
25	Velhe	6.02	26.02	67.96	100
26	Atpadi	7.01	14.95	78.04	100
27	Jat	12.84	23.54	63.62	100
28	Kadegaon	3.37	19.70	76.94	100
29	Kavathemahankal	3.98	22.13	73.88	100
30	Khanapur	**3.12**	**14.82**	**82.05**	100
31	Miraj	2.93	22.29	74.78	100
32	Palus	1.69	18.23	80.07	100
33	Shirala	3.89	16.06	80.05	100
34	Shirol	3.18	23.74	73.08	100
35	Tasgaon	2.40	18.80	78.79	100
36	Walwa	2.38	26.31	71.31	100
37	Dahiwadi	7.99	18.68	73.33	100
38	Jawali	2.84	16.61	80.54	100
39	Karad	3.16	18.83	78.01	100
40	Khandala	1.74	35.11	63.16	100
41	Khatav	3.70	17.07	79.23	100
42	Koregaon	**1.67**	**13.90**	**84.44**	100
43	Mahabaleshwar	4.28	30.97	64.75	100
44	Patan	4.83	29.06	66.11	100
45	Phaltan	4.77	17.14	78.09	100
46	Satara	1.07	29.99	68.94	100
47	Wai	2.02	24.03	73.95	100
48	Akkalkot	10.17	19.91	69.92	100
49	Barshi	4.92	16.11	78.98	100
50	Karmala	6.47	15.78	77.75	100
51	Madha	5.63	14.68	79.69	100
52	Malshiras	6.20	16.94	76.86	100
53	Mangalwedha	7.18	19.52	73.31	100
54	Mohol	6.22	18.94	74.83	100
55	North Solapur	5.15	17.62	77.23	100
56	Pandharpur	6.03	16.31	77.66	100
57	Sangola	8.18	16.45	75.37	100
58	South Solapur	**6.58**	**11.48**	**81.94**	100

values at 20, 40, 60, 80 and 100 were used as cut-off points to define five categories: less vulnerable, moderately vulnerable, vulnerable, highly vulnerable, and very highly vulnerable. The threshold (*Zi*) values were determined as 0.12, 0.25, 0.37, 0.49 and 0.62, respectively.

The degree of vulnerability for the period 1982–2021, presented in Table 4, highlights the following:

i. Moderately Vulnerable: Only Pune City tahsil was categorized as moderately vulnerable.

ii. Vulnerable: Jat tahsil was classified as vulnerable.

iii. Highly Vulnerable: Tahsils such as Bhudargad, Chandgad, Hatkanagale, Panhala, Baramati, Daund, Indapur, Junnar, Purandhar, Shirur, Velhe, Atpadi, Khanapur, Walwa, Dahiwadi, Karad, Khatav, Mahabaleshwar, Phaltan, Akkalkot, Barshi, Karmala, Madha, Malshiras, Pandharpur and Sangola were classified as highly vulnerable.

iv. Very Highly Vulnerable: Tahsils such as Ajra, Bawada, Gadhingalaj, Kagal, Karveer, Radhanagari, Shahuwadi, Ambegaon, Bhor, Haveli, Khed, Mawal, Mulshi, Kadegaon, Kavathemahankal, Miraj, Palus, Shirala, Shirol,

Table 4 : Classification of 58 tahsils under different degree of vulnerability for the period of 1982-2021.

S. no.	Less Vulnerable (Category 1)	Moderately Vulnerable (Category 2)	Vulnerable (Category 3)	Highly vulnerable (Category 4)	Very Highly Vulnerable (Category 5)
1	-	Pune City	Jat	Bhudargad	Ajra
2	-	-	-	Chandgad	Bawada
3	-	-	-	Hatkanagale	Gadhingalaj
4	-	-	-	Panhala	Kagal
5	-	-	-	Baramati	Karveer
6	-	-	-	Daund	Radhanagari
7	-	-	-	Indapur	Shahuwadi
8	-	-	-	Junnar	Ambegaon
9	-	-	-	Purandhar	Bhor
10	-	-	-	Shirur	Haveli
11	-	-	-	Velhe	Khed
12	-	-	-	Atpadi	Mawal
13	-	-	-	Khanapur	Mulshi
14	-	-	-	Walwa	Kadegaon
15	-	-	-	Dahiwadi	Kavathemahankal
16	-	-	-	Karad	Miraj
17	-	-	-	Khatav	Palus
18	-	-	-	Mahabaleshwar	Shirala
19	-	-	-	Phaltan	Shirol
20	-	-	-	Akkalkot	Tasgaon
21	-	-	-	Barshi	Jawali
22	-	-	-	Karmala	Khandala
23	-	-	-	Madha	Koregaon
24	-	-	-	Malshiras	Patan
25	-	-	-	Pandharpur	Satara
26	-	-	-	Sangola	Wai
27	-	-	-	-	Mangalwedha
28	-	-	-	-	Mohol
29	-	-	-	-	North Solapur
30	-	-	-	-	South Solapur

Tasgaon, Jawali, Khandala, Koregaon, Patan, Satara, Wai, Mangalwedha, Moho, North Solapur and South Solapur were identified as very highly vulnerable. Similar outcome found with the Adhav *et al.* (2021), Bharti *et al.* (2017), Rao *et al.* (2016), TERI (2014) and Palanisami *et al.* (2009).

Conclusion

This study provides a comprehensive assessment of tahsil-wise vulnerability to climate change in the southern region of Western Maharashtra for the period 1982–2021. The findings highlight significant variations in vulnerability levels across tahsils, with climatic, demographic and agricultural factors playing a crucial role. The classification of vulnerability indices underscores the need for targeted adaptation strategies to enhance regional resilience. High-risk areas require immediate policy interventions, while less vulnerable regions must adopt preventive measures to mitigate future risks. The study's outcomes align with previous research, reinforcing the necessity for localized and evidence-based climate adaptation planning.

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Authors' contributions

Dhanaji M. Sawant conceptualized and designed the study, conducted the statistical analysis and drafted the initial version of the manuscript. Aasman M. Khobragade reviewed the cited literature and provided valuable insights for the study. Omkar D. Rajmane contributed to data analysis, including R Studio-based visualization and graph plotting, and provided significant input in drafting and refining the manuscript. All authors read and approved the final manuscript.

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