Multi-Dimensional Relative Vulnerability Assessment of Santhal Pargana, Jharkhand

Abstract

~~The concept of vulnerability is multifaceted, encompassing a range of socio-economic, environmental, and climatic elements that necessitate comprehensive analysis to fully grasp its implications for affected populations. Our research employs a Fuzzy-AHP methodology to conduct a multi-dimensional relative vulnerability assessment in Santhal Pargana, located in Jharkhand. The study examines six districts: Godda, Deoghar, Dumka, Jamtara, Sahibganj, and Pakur. We evaluated 19 distinct parameters across three main categories: Meteorological, Agricultural, and Socio-economic Vulnerability. Notably, rainfall data from 1900 to 2020 revealed a downward trend. Based on our analysis, we classified the districts into five vulnerability levels, spanning from very low to very high. Our findings indicate that Sahibganj exhibits the lowest vulnerability, while Godda faces the highest risk. To validate the model's accuracy, we calculated the Area Under Curve (AUC), which yielded a value of 84.3, demonstrating the robustness of our assessment approach.~~

Rainfall was declining at Santhal Pargana, Jharkhand from 1900 to 2020. The study on vulnerability assessment indicated that Sahibganj exhibits the lowest vulnerability while the highest at Godd. The calculated value of Area Under Curve (AUC) was 84.3, indicating accuracy of the model for relative vulnerability assessment.

Keywords: Rainfall trend; FUZZY-AHP; Relative Vulnerability; Santhal Pargana

~~**1. Introduction**~~

~~On a global scale, the impacts of climate change have become increasingly apparent, manifesting through shifts in temperature patterns, precipitation regimes, and the frequency and intensity of extreme weather events. The Intergovernmental Panel on Climate Change (IPCC) reports that global surface temperature has increased by approximately 1.1°C since the pre-industrial era, with the rate of warming accelerating in recent decades (Canadell et al. 2023). This warming trend has far-reaching consequences for agricultural systems, water resources, and human livelihoods across the planet (du Plessis & du Plessis 2019).Agriculture, which forms the backbone of many developing economies, is particularly vulnerable to these climatic shifts. Changes in temperature and precipitation patterns can~~

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~~affect crop yields, alter growing seasons, and increase the prevalence of pests and diseases. The Food and Agriculture Organization (FAO) estimates that climate change could reduce global agricultural productivity by up to 17% by 2050, with some regions experiencing even more severe impacts (Kogo et al. 2021).The socio-economic ramifications of these environmental changes are profound. Climate-induced agricultural challenges can exacerbate poverty, food insecurity, and social inequality, particularly in regions heavily dependent on rain-fed agriculture. The World Bank projects that climate change could push an additional 100 million people into extreme poverty by 2030, with the majority of these affected populations residing in South Asia and Sub-Saharan Africa (Jafino et al. 2020).~~

~~India, with its diverse agro-climatic zones and large agrarian population, faces significant challenges in the context of climate change and agricultural vulnerability. The country has experienced a notable increase in average temperature, with the India Meteorological Department (IMD) reporting a rise of about 0.7°C over the past century (Krishnan et al. 2020). This warming trend is accompanied by changes in monsoon patterns, increased frequency of droughts and floods, and greater variability in seasonal rainfall.These climatic shifts have substantial implications for Indian agriculture, which employs nearly half of the country's workforce and contributes approximately 17% to its GDP (Balaji & Babu 2020). Studies indicate that climate change could reduce yields of major crops like rice, wheat, and maize by up to 25% in some regions of India by the end of the century (Shekhar & Singh 2021). The impact is particularly severe in rain-fed agricultural areas, which account for about 60% of India's cultivated land (Sathyan et al. 2018).~~

~~The socio-economic landscape of India is closely tied to its agricultural sector, making it highly sensitive to climate-induced vulnerabilities. According to the National Sample Survey Office (NSSO), about 22.5% of farmers in India live below the poverty line (Chandra et al. 2019). Climate change threatens to exacerbate this situation by increasing the volatility of agricultural production and income, potentially pushing more rural households into poverty and food insecurity.~~

Santhal Pargana, a division in the northeastern part of Jharkhand state, presents a microcosm of the broader challenges facing India's rural and tribal regions. This area, predominantly inhabited by the Santhal tribe and other indigenous communities, is characterized by its unique cultural heritage, rich biodiversity, and challenging socio-economic conditions. The meteorological scenario in Santhal Pargana reflects the broader trends observed across India, with some region-specific variations. Local climate data indicate a gradual increase in

Formatted: Indent: First line: 0", Space Before: 0 pt, After: 8 pt, Line spacing: Multiple 1.08 li average temperatures and greater unpredictability in rainfall patterns over the past few decades. The region, which primarily relies on the southwest monsoon for agricultural activities, has experienced more frequent instances of delayed monsoon onset, prolonged dry spells, and intense rainfall events. Agriculture in Santhal Pargana is predominantly rain-fed and subsistence-oriented, making it highly vulnerable to climatic variations. The main crops cultivated include rice, maize, and various pulses. Traditional agricultural practices, while well-adapted to historical climate patterns, are increasingly challenged by the changing environmental conditions. Crop yields in the region have shown greater fluctuations in recent years, with some studies suggesting a decline in productivity for certain staple crops. The socio-economic landscape of Santhal Pargana is characterized by high poverty rates, low literacy levels, and limited access to modern agricultural technologies and market linkages. According to state government reports, a significant proportion of the population in this region lives below the poverty line, with tribal communities being particularly vulnerable. The heavy reliance on agriculture and forest resources for livelihoods makes the local economy highly sensitive to environmental changes.

Numerous studies have explored vulnerability by considering multiple dimensions and employing various methodologies. For instance, Goto et al. (2022) developed the Social Vulnerability Index (SoVI) using socioeconomic and demographic factors. Muleia et al. (2023) assessed climate change vulnerability in Mozambique, incorporating socio-economic, demographic, and health indicators. Williams et al. (2018) examined agricultural vulnerability in South Africa, combining biophysical and socio-economic factors. Pandey (2021) used a composite index approach to assess social and ecological vulnerability in Nepal. Derbile et al. (2022) employed a comprehensive evaluation method to analyze agricultural vulnerability in Ghana. Furlan et al. (2021) developed a multi-dimensional vulnerability assessment framework in the Italian coast, integrating meteorological, agricultural, and socio-economic factors. Sahoo & Bhaskaran (2018) used spatial multi-criteria analysis to assess coastal vulnerability in Odisha. Yang, & Pan (2021) have tried to measure the rural vulnerability of China. Williams et al. (2020) used a livelihood vulnerability index to examine climate variability impacts on smallholder farming communities in Ghana. Lastly, Sathyan et al. (2018) have tried to measure a Climate vulnerability in rainfed farming. Keeping the above in view, an attempt has been made to examine the relative vulnerability of Santhal Pargana, Jharkhand by considering meteorological, agricultural, and socio-economic factors.

~~This research article aims to examine the relative vulnerability of Santhal Pargana, Jharkhand by considering meteorological, agricultural, and socio-economic factors.~~

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~~2.~~ 2. Study area

Santhal Pargana, a division in the northeastern part of Jharkhand, India. It consists of 6 districts. They are Sahibganj, Godda, Pakur, Dumka, Deoghar, Jamtara (Fig. 1). It experiences a subtropical climate characterized by hot summers and mild winters. The region typically sees temperatures ranging from about 10°C in winter to over 40°C in summer, with monsoon rains occurring between June and September. This climate pattern significantly

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influences agricultural practices in the area. The soil composition in Santhal Pargana varies, but it predominantly consists of red and laterite soils, which are generally less fertile and require careful management for productive agriculture. Some areas also feature alluvial soils near river basins, offering better cultivation prospects. Demographically, Santhal Pargana is known for its diverse population, with a significant presence of tribal communities, particularly the Santhals, after whom the region is named. The area has a predominantly rural population, with agriculture and forest-based activities being the primary sources of livelihood. The region faces challenges related to literacy, healthcare access, and economic development, which are common to many rural areas in Jharkhand. Despite these challenges, Santhal Pargana's unique cultural heritage and natural resources present opportunities for sustainable development and cultural preservation.

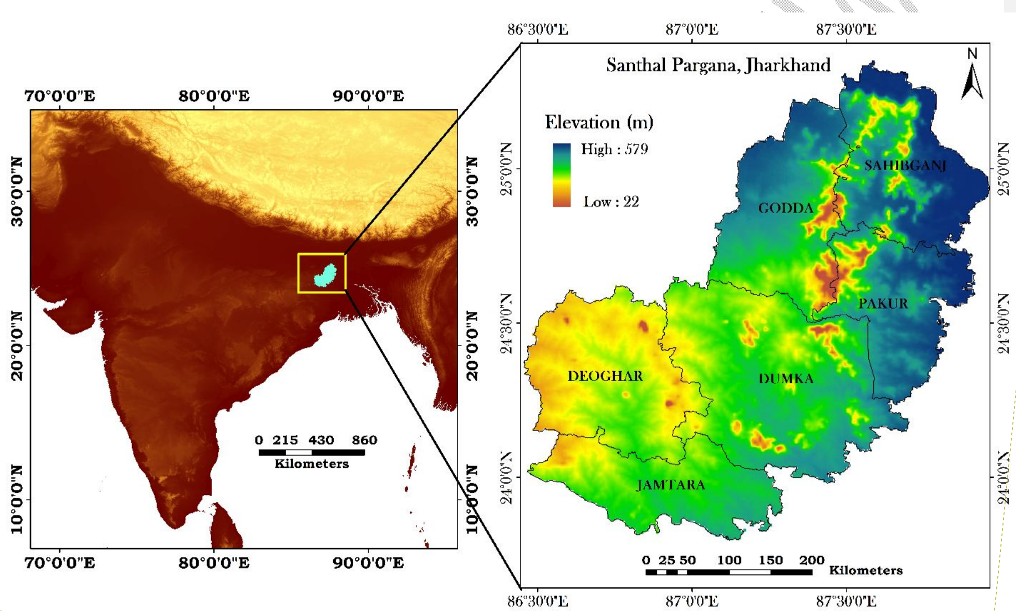

Fig.1. Study area map (retain Fig 1.)

~~3.~~ 3. Materials and Methods

~~**3.1 Identification of rainfall trend by Mann-Kendall test**~~

~~The Mann-Kendall test, a non-parametric statistical method, evaluates temporal trends in rainfall data without assuming normal distribution. The procedure compares each data point with subsequent values chronologically, tallying the instances of increases (+1), decreases (-1), and no changes (0).~~

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~~The Sen's slope estimator, a robust non parametric method, effectively quantifies rainfall trends by calculating the median of slopes between all possible pairs of observations in a time series. This technique proves particularly valuable for meteorological data analysis as it remains unaffected by outliers and missing values, making it ideal for potentially non-normal and incomplete rainfall datasets. The method first computes slope between all data pairs, then determines the median slope as the trend indicator. A positive Sen's slope suggests an increasing rainfall trend, while a negative value indicates a decreasing pattern, providing researchers with a reliable measure of precipitation changes over time.~~

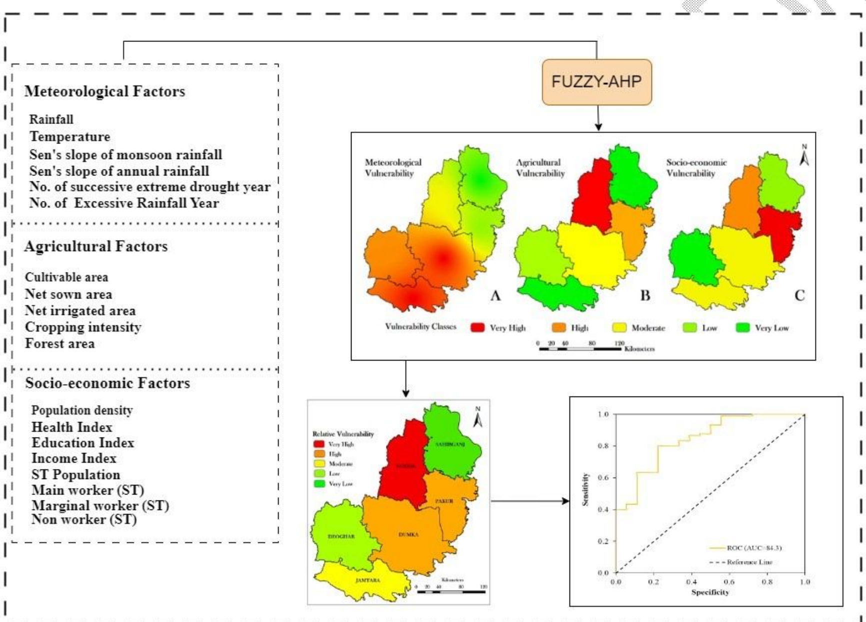
~~3.2 Vulnerability parameters~~

~~This table outlines a comprehensive set of vulnerability parameters used in a research study, categorized into three main domains: Meteorological, Agricultural, and Socio-economic. It totally consists of 19 factors. The meteorological parameters include rainfall and temperature data from the Indian Meteorological Department, as well as calculated Sen's slopes for monsoon and annual rainfall. It also incorporates data on extreme drought years and excessive rainfall years from the Climate of Jharkhand, IMD. Agricultural parameters encompass various land use factors such as cultivable area, net sown area, net irrigated area, cropping intensity, and forest area, sourced from Agriculture contingency plans. The socio-economic domain covers a wide range of demographic and development indicators, including population density from the 2011 Census of India, health, education, and income indices from Deogharia 2021, and specific data on Scheduled Tribe (ST) populations, including their workforce participation. This comprehensive set of parameters suggests a multifaceted approach to assessing vulnerability, likely aimed at understanding the complex interplay between climate, agriculture, and socio-economic factors in the region.~~

~~**Table. 1.** Selected Parameters with their sources~~

~~**Vulnerability**~~	~~**Parameters**~~	~~**Source**~~
~~Meteorological~~	~~Rainfall~~	~~Indian Meteorological Department~~
	~~Temperature~~	~~Indian Meteorological Department~~
	~~Sen's slope of monsoon rainfall~~	~~Calculated~~
	~~Sen's slope of annual rainfall~~	~~Calculated~~
	~~No. of successive extreme drought year~~	~~Climate of Jharkhand, IMD~~
	~~No. of Excessive Rainfall Year~~	~~Climate of Jharkhand, IMD~~
~~Agricultural~~	~~Cultivable area~~	~~Agriculture contingency plan~~
	~~Net sown area~~	~~Agriculture contingency plan~~

	~~Net irrigated area~~	~~Agriculture contingency plan~~
	~~Cropping intensity~~	~~Agriculture contingency plan~~
	~~Forest area~~	~~Agriculture contingency plan~~
~~Socio-economic~~	~~Population density~~	~~Census of India 2011~~
	~~Health Index~~	~~Deogharia 2021~~
	~~Education Index~~	~~Deogharia 2021~~
	~~Income Index~~	~~Deogharia 2021~~
	~~ST Population~~	~~Census of India 2011~~
	~~Main worker (ST)~~	~~Census of India 2011~~
	~~Marginal worker (ST)~~	~~Census of India 2011~~
	~~Non worker (ST)~~	~~Census of India 2011~~



~~**Fig.2.** Methodological Framework~~

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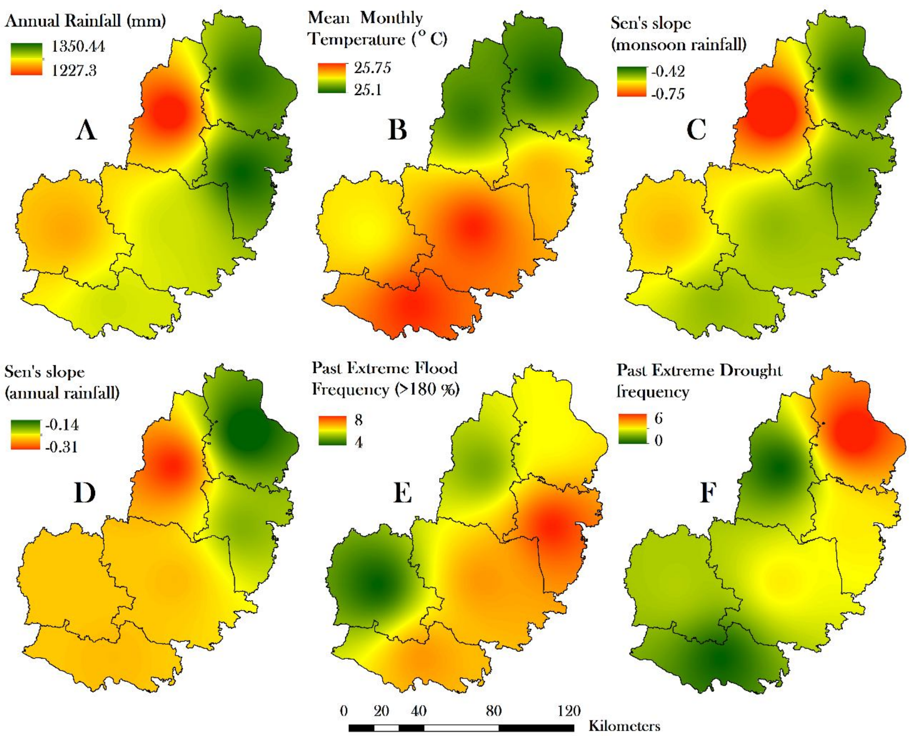
~~3.3 Preparation of data layers~~

~~3.3.1 Meteorological Factors~~



~~**Fig.3.** Meteorological Vulnerability Factors~~

~~The maps (Fig. 3) represent the vulnerability parameters related to meteorological factors. It showcases the range of rainfall, with the high value at 1350.44 and the low at 1227.3, alongside temperature variations from 25.75 to 25.1. Sen's slope, a measure of trend, is provided for both monsoon and annual rainfall, indicating decreasing trends with values ranging from -0.42 to -0.75 for monsoon rainfall and -0.14 to -0.31 for annual rainfall. The frame also highlights extreme weather events, noting that the high value area experienced 8 successive extreme drought years and 6 excessive rainfall years, while the low value area faced 4 extreme drought years and no excessive rainfall years. These parameters collectively offer insights into the meteorological vulnerabilities of the studied regions, emphasizing the contrasts between areas with high and low susceptibility to climate-related risks.~~

~~**3.3.2 Agricultural Factors**~~

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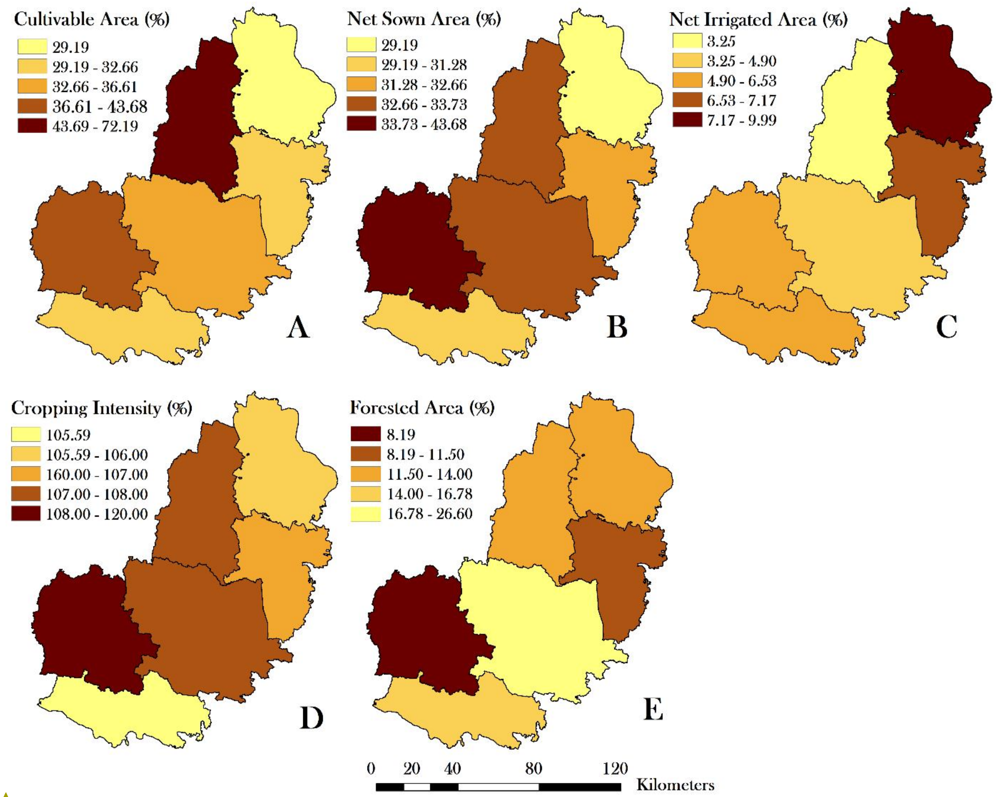

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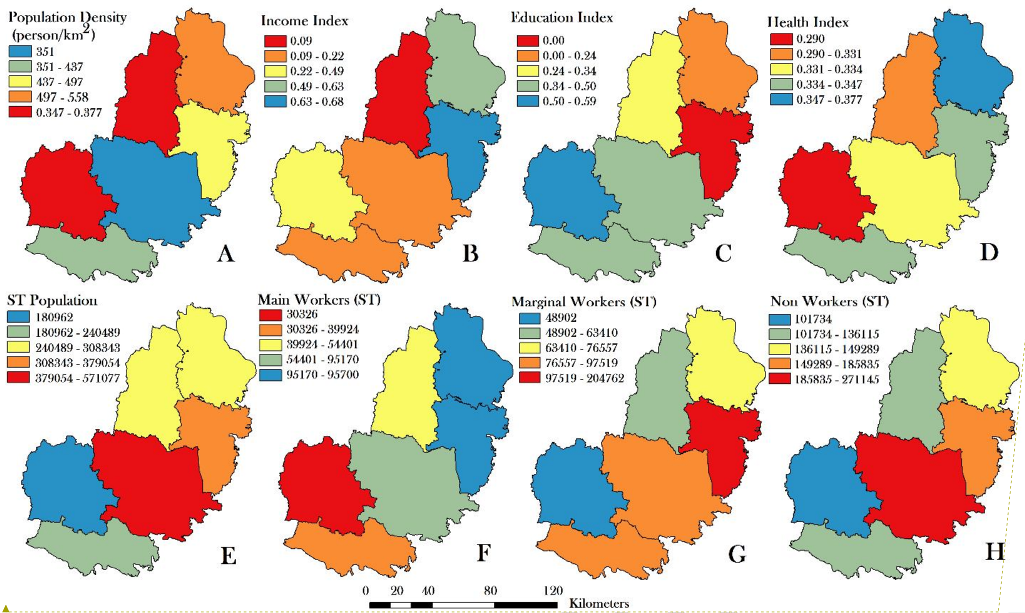
~~**Fig. 4.** Agricultural Vulnerability Factors~~

~~This frame (Fig. 4) presents a set of agricultural vulnerability parameters and their corresponding high and low values. The parameters include cultivable area, net sown area, net irrigated area, cropping intensity, and forest area. Cultivable area ranges from a high of 72.19 to a low of 29.19, while net sown area spans from 43.68 to 29.19. Net irrigated area shows a smaller range, from 9.99 at the high end to 3.25 at the low end. Cropping intensity varies between 120 and 105.59, indicating different levels of land use efficiency. Forest area exhibits a range from 26.6 to 8.19. These metrics provide insight into the agricultural landscape and potential vulnerabilities within the studied region, highlighting variations in land use, irrigation practices, and natural vegetation cover. The wide ranges in some parameters suggest significant disparities in agricultural conditions across the area, which could have implications for relative agricultural vulnerability.~~

~~3.3.3 Socio-economic Factors~~



~~Fig.5.~~ ~~Socio-economic Vulnerability Factors~~

~~The frame ((Fig. 5) presents socio-economic vulnerability parameters across different regions, highlighting disparities in various indicators. Population density shows a stark contrast, ranging from 1 to 351, indicating significant variations in settlement patterns. Health and education indices reveal moderate differences, with health index values between 0.29 and 0.377, and education index scores spanning from 0 to 0.59. The income index demonstrates a wider gap, from 0.09 to 0.68, suggesting considerable economic inequality. Scheduled Tribe (ST) population figures vary substantially, from 180,962 to 571,077, reflecting diverse tribal demographics. Employment patterns among ST populations also show notable differences, with main workers ranging from 30,326 to 95,700, marginal workers from 48,902 to 204,762, and non-workers from 101,734 to 271,145. These disparities across socio-economic parameters underscore the complex vulnerability landscape in the studied area, pointing to potential challenges in healthcare, education, economic opportunities, and tribal welfare.~~

~~3.3.4 Fuzzy Analytic Hierarchy Process (Fuzzy AHP)~~

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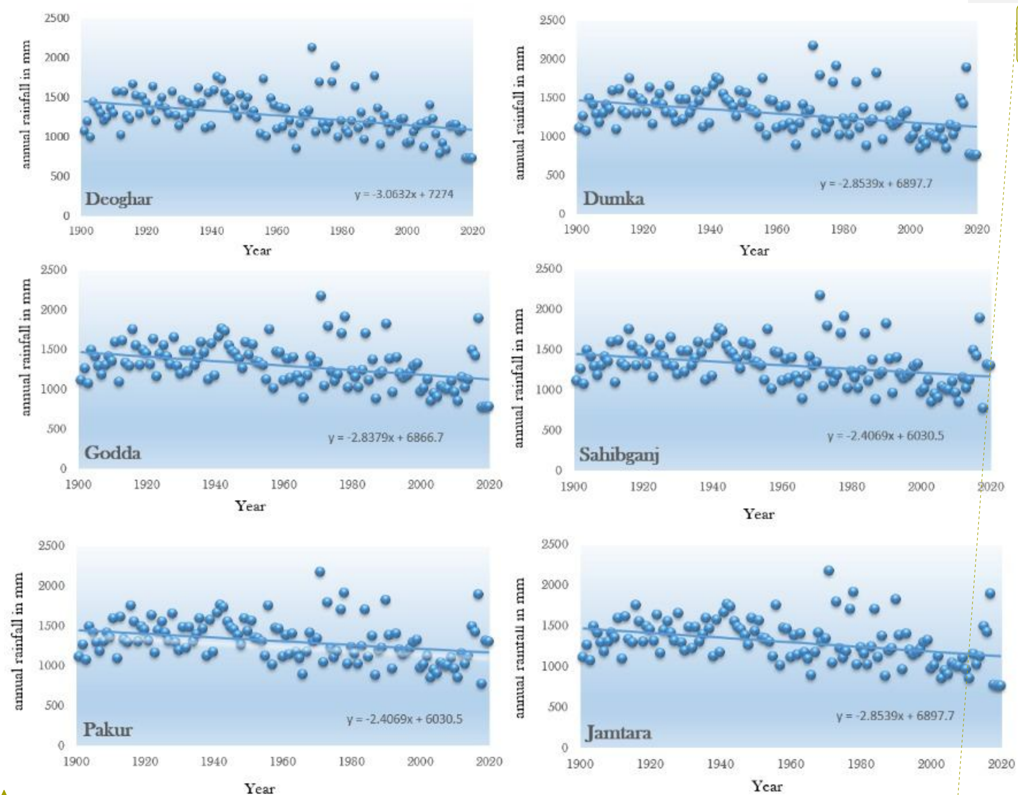
~~The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) extends the traditional AHP by incorporating fuzzy set theory to handle uncertainty and vagueness in decision-making (Tyagi et al. 2018). This methodology begins by structuring the decision problem as a hierarchy, with the goal at the top, criteria in the middle, and alternatives at the bottom. Pairwise comparisons are then conducted using linguistic variables, which are converted into triangular fuzzy numbers. These fuzzy numbers represent the degree of preference between elements. The fuzzy comparison matrices are synthesized using the extent analysis method, which involves calculating fuzzy synthetic extent values and the degree of possibility of dominance. The weights of criteria and alternatives are then derived by defuzzifying and normalizing these values. Finally, the global priorities are computed by aggregating the weights across the hierarchy, enabling decision makers to rank alternatives and make informed choices while accounting for imprecision in human judgments.~~

~~3.3.5 Area Under Curve (AUC)~~

~~The Area Under the Curve (AUC) methodology involves plotting the Receiver Operating Characteristic (ROC) curve and calculating the area beneath it (Richardson et al. 2024). This curve is created by graphing the true positive rate against the false positive rate at various classification thresholds. To compute the AUC, we integrate the ROC curve from 0 to 1 using numerical methods such as the trapezoidal rule. The resulting value, ranging from 0 to 1, quantifies the model's ability to distinguish between classes. A higher AUC indicates better classification performance, with 1.0 representing perfect discrimination and 0.5 equivalent to random guessing. This metric is particularly useful for evaluating binary classifiers and comparing different models' performance.~~

~~4. Result and Discussion~~

~~4.1 Trend of annual rainfallassessed by Mann-Kendall test~~



~~**Fig.6.** Trend of rainfall in different districts of Santhal pargana~~

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~~**Table. 2.** Value of Sen's slope~~

~~Rainfall data from 1900 to 2020~~			
~~**Districts**~~	~~**Sen's slope**~~	~~**Districts**~~	~~**Sen's slope**~~
~~Sahibganj~~	~~-0.148~~	~~Deoghar~~	~~-0.26~~
~~Godda~~	~~-0.316~~	~~Dumka~~	~~-0.264~~
~~Pakur~~	~~-0.203~~	~~Jamtara~~	~~-2.85~~

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4. Result and Discussion

The analysis of long-term rainfall trends from 1900 to 2020 across six districts in Table. 2 revealed a consistent pattern of declining precipitation, as indicated by negative Sen's slope values throughout the region. Jamtara district exhibited the most dramatic decrease with a Sen's slope of -2.85, signifying a substantial reduction in rainfall over the 120-year period. This was followed by Godda and Dumka districts, which showed moderate declines with slopes of -0.316 and -0.264, respectively. Deoghar displayed a similar trend with a slope of -0.26, while Pakur and Sahibganj demonstrated relatively milder, yet still noteworthy, decreases with slopes of -0.203 and -0.148, respectively. These findings collectively suggest a significant shift in the precipitation patterns across the region, with potential implications for water resources, agriculture, and local ecosystems.

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4.2 Meteorological, Agricultural and Socio-economic Vulnerability

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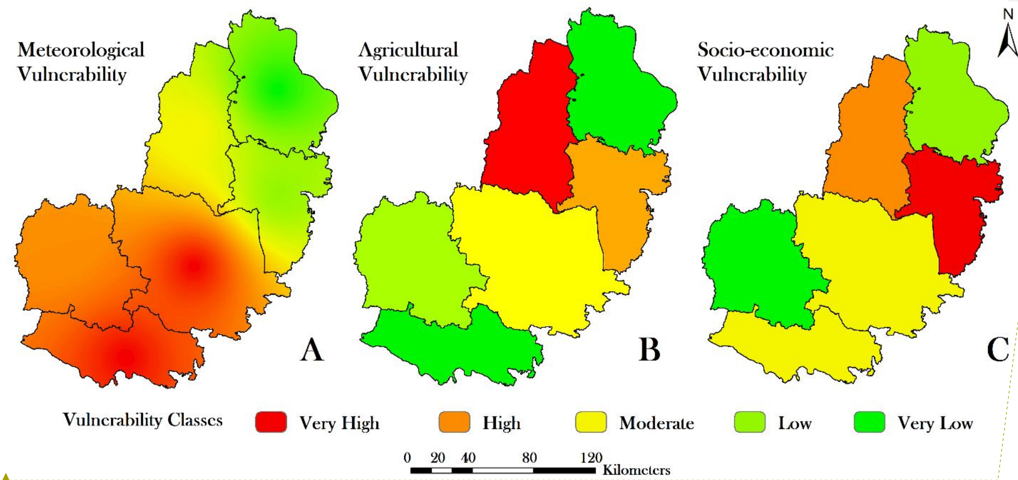
~~**Table. 3.** Considered parameters with their associated rank weight and directionality~~

~~**Vulnerability**~~	~~**Parameters**~~	~~**Rank**~~	~~**Weight**~~	~~**Directionality**~~
~~Meteorological~~	~~Rainfall~~	~~1~~	~~0.379~~	~~Negative~~
	~~Temperature~~	~~2~~	~~0.249~~	~~Positive~~
	~~Sen's slope of monsoon rainfall~~	~~3~~	~~0.16~~	~~Negative~~
	~~Sen's slope of annual rainfall~~	~~4~~	~~0.102~~	~~Negative~~
	~~No. of successive extreme drought year~~	~~5~~	~~0.065~~	~~Positive~~
	~~No. of Excessive Rainfall Year~~	~~6~~	~~0.043~~	~~Positive~~
~~Agricultural~~	~~Net sown area~~	~~1~~	~~0.416~~	~~Negative~~
	~~Cultivable area~~	~~2~~	~~0.262~~	~~Negative~~
	~~Net irrigated area~~	~~3~~	~~0.161~~	~~Negative~~
	~~Cropping intensity~~	~~4~~	~~0.099~~	~~Negative~~
	~~Forest area~~	~~5~~	~~0.062~~	~~Negative~~
~~Socio-economic~~	~~ST Population~~	~~1~~	~~0.327~~	~~Positive~~
	~~Education Index~~	~~2~~	~~0.227~~	~~Negative~~
	~~Income Index~~	~~3~~	~~0.157~~	~~Negative~~
	~~Health Index~~	~~4~~	~~0.108~~	~~Negative~~
	~~Marginal worker (ST)~~	~~5~~	~~0.073~~	~~Positive~~
	~~Non worker (ST)~~	~~6~~	~~0.05~~	~~Positive~~
	~~Main worker (ST)~~	~~7~~	~~0.034~~	~~Negative~~
	~~Population density~~	~~8~~	~~0.024~~	~~Positive~~



~~**Fig.7.** Meteorological, Agricultural and Socio-economic Vulnerability maps~~

~~The first map(Fig.7. A) presents a classification system ranging from "Very low" to "Very high" vulnerability, with specific districts assigned to each category.~~ Delete Tables. Retain Figs.

Sahibganj is classified as having very low vulnerability, while Pakur falls into the low vulnerability category. Godda is identified as having moderate vulnerability. Deoghar is categorized as highly vulnerable. Finally, Dumka and Jamtara are grouped together in the very high vulnerability class~~. This classification likely reflects an assessment of each district's susceptibility to climate-related vulnerabilities.~~ **(Fig. 7A – Change the Fig. Nos in revised version)**

~~The second map (Fig.7. B) presents a classification of agricultural vulnerability across several districts in what appears to be a specific region or state. The districts are categorized into five vulnerability classes ranging from "Very low" to "Very high".~~ Sahibganj and Jamtara are identified as having very low agricultural vulnerability, suggesting they may have more resilient agricultural systems or favorable conditions. Deoghar is classified as having low vulnerability, while Dumka falls into the moderate category. Pakur is designated as highly vulnerable, indicating it may face significant challenges in its agricultural sector. Finally, Godda is classified as having very high agricultural vulnerability, implying it could be the most susceptible to agricultural risks or stresses among the listed districts~~.~~ (Fig. 7B)

~~The last one (Fig.7. C) appears to categorize districts based on their socio-economic vulnerability levels. It presents a classification system ranging from "Very low" to "Very high" vulnerability, with specific districts assigned to each category.~~ Deoghar is classified as having very low vulnerability, while Sahibganj is categorized as low. Dumka and Jamtara fall into the moderate vulnerability class. Godda is classified as having high vulnerability, and Pakur is identified as the most vulnerable district with a very high classification~~.~~ (Fig. 7C). It provides a snapshot of the relative socio-economic conditions across these districts, potentially highlighting areas that may require more focused attention or resources to address underlying vulnerabilities.

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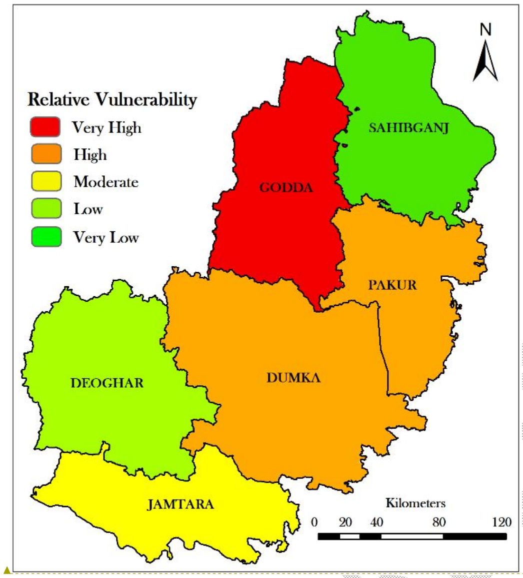
~~4.3~~ 4.3 Relative Vulnerability



~~**Fig.8.**Relative Vulnerability Map~~

~~This map(Fig. 8) presents a classification of districts based on their relative vulnerability levels. The districts are categorized into five vulnerability classes ranging from very low to very high.~~ Sahibganj is identified as having very low vulnerability, while Deoghar falls into the low vulnerability category. Jamtara is classified as moderately vulnerable. Two districts, Pakur and Dumka, are designated as highly vulnerable. Finally, Godda stands out as the only district in the very high vulnerability class~~. This classification system provides a quick overview of the relative vulnerability levels across these districts, which could be valuable for prioritizing resource allocation, policy interventions, or further research.~~ (Fig. 8).

~~4.4~~ 4.4 Validation

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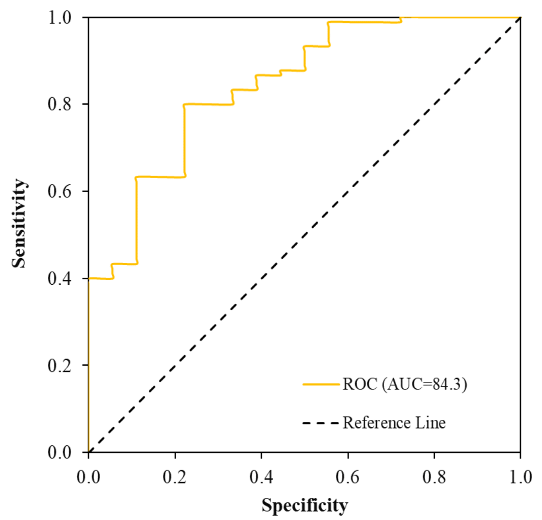

~~**Fig.9.** Area Under Curve~~

~~The Area Under Curve (AUC) value of 84.3 for a relative vulnerability model indicates a strong predictive performance (Fig. 9). In this context, the AUC represents the model's ability to distinguish between vulnerable and non-vulnerable entities.~~ A value of 84.3% suggests that the model correctly ranks a randomly chosen vulnerable entity higher than a randomly chosen non-vulnerable entity 84.3% of the time. This high AUC value demonstrates the model's robust discriminatory power in assessing relative vulnerability. It implies that the model effectively captures the factors contributing to vulnerability and can reliably identify at-risk entities. This performance metric supports the model's validity and potential utility in vulnerability assessment and risk management applications.

Section 4 – in one para only - including discussion

~~5~~ Conclusion

This study presents a thorough evaluation of vulnerabilities in Santhal Pargana, offering crucial information to guide targeted interventions and inform policy decisions. Our analysis uncovered notable disparities in vulnerability among the region's six districts. Notably, Godda emerged as an area of urgent concern, exhibiting extremely high vulnerability levels followed by Pakur. In contrast, Sahibganj demonstrated considerably lower vulnerability, suggesting greater resilience followed by Deoghar. A concerning trend of decreasing rainfall over the last hundred years highlights the necessity for region-wide adaptation strategies. The reliability of our findings is supported by a high Area Under Curve (AUC) value of 84.3%, validating the effectiveness of our chosen Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) methodology for assessing vulnerability. To build upon this work, we recommend that future studies explore temporal changes and incorporate a wider range of socio-economic and environmental factors to deepen our comprehension of vulnerability patterns in Santhal Pargana.

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