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Advancing agricultural risk assessment through entropy-weighted TOPSIS and the IPCC framework: Insights from the Eastern Himalayas

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Abstract
Climate change is increasingly threatening agricultural systems, particularly in the Eastern Himalayan Region, where predominantly agrarian livelihoods are exposed to multiple climatic hazards. Integrated assessment of agricultural risk is therefore important for identifying spatial differences and informing targeted risk management. This study constructs a multidimensional agricultural risk index for 33 districts of Assam using the IPCC risk framework, which conceptualizes risk through hazard, exposure, and vulnerability. Thirty-nine biophysical and socioeconomic indicators were integrated using Entropy-Weighted-TOPSIS. The results show substantial spatial variation in agricultural risk across Assam. Dima Hasao recorded the highest hazard proneness, Dibrugarh the highest vulnerability, and Nagaon the highest exposure. Overall, Kamrup (Rural) and Udalguri were identified as the highest and lowest agriculturally risk-prone districts, respectively. Districts in the Lower Brahmaputra Valley and Hills Temperate Zones were comparatively more risk-prone, whereas those in the Upper Brahmaputra Valley Zone were comparatively less risk-prone. The sensitivity analysis showed moderate to high agreement across alternative weighting approaches, with Spearman's rho ranging from 0.70 to 0.98, supporting the robustness of the district rankings. The findings demonstrate that agricultural risk varies substantially across districts and agro-climatic zones, highlighting the need for spatially differentiated risk management and extension services. The proposed assessment can support policymakers in identifying priority districts and tailoring interventions to the specific sources of agricultural risk.

Keywords SDG 13 · Hazard · Adaptive capacity · Vulnerability · Sensitivity · Exposure

1 Introduction

Climate change is a serious threat, that has been affecting the existing agro-economic systems of the world. Agriculture is foundational for human survival — providing food, raw materials, and livelihoods that are essential for sustaining a healthy life. However, it is a vul-

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nerable sector primarily due to its principal dependence on the climate and natural resource settings. It is estimated that agricultural activities contribute about 10–12% of global GHG emissions annually (Chachei, 2024). Compared to the other sectors, agricultural sector contributes, relatively less, to the global anthropogenic emissions. IPCC (Intergovernmental Panel on Climate Change) estimates global net anthropogenic emissions to be about 12% more in 2019 compared to 2010 and 54% more compared to 1990. Since the 1961, climate change has affected the global TFP (Total Factor Productivity), bringing down the agricultural productivity by 21% (Ortiz-Bobea et al., 2021). Further, it is estimated that crop yields may decline by 3% to 25% by the end of 2100 if warming conditions continue to grow extreme and there is no improvement in the adaptation strategies (Wing et al., 2021). A study on 1800 farming households of Ethiopia and South Africa reports that, despite being aware of changing patterns of temperature and rainfall, households implementing climate smart practices are largely low (Bryan et al., 2009). Another study on drought vulnerability among the smallholder farmers of semi-arid region of Brazil, reveals existence of significant differences across the municipalities. These differences are attributed to the institutional and socio-economic factors rather than climatic factors only (Lindoso et al., 2014). Another case study of a drought prone village in Western Bangladesh, reveal that farmers are aware of climate change but they prefer to work on farms rather than engage in off-farm activities. Primarily because, farm work generates higher returns, than the non-farm works. And effects of climate change intensify when there is limited access to climate smart agricultural techniques, lack of credit facilities, high cost of production, and inadequate extension services (Kabir et al., 2017). Another study by Clay and King (2019) reports that smallholder farmers ability to adapt to climate change is more constrained than others, as social institutions may constrain equitable adaptation rather than encourage it. The study investigates how Rwanda's Crop Intensification Program facilitates adaptation among the rich households but disadvantages the poorer households; by limiting the number of options available for climate risk management. Another study by Kalogiannidis et al. (2023) on 304 Greek farmers reveal that farmers have ceased to be at direct risk of food shortage or clothing, but they are faced with new challenges, like declining yield, and low productivity due to the changing climate. It is interesting to note that farmers attitude towards climate change may not be always stable. A study by Wheeler et al. (2021) reveals the same. The study found that farmers perceiving climatic risks are more likely to adapt risk reducing strategies. But farmers who ignored climatic risks often ended up making riskier production decisions and this behaviour later makes them even more vulnerable to the climatic risks. Currently, agriculture remains a primary source of livelihood for about 26.42% of the global population, as reported by ILOSTAT (International Labour Organization Database on International Labour Statistics) (Our World in Data, 2025). In this context, there is a continued need for rigorous scientific studies to assess the risk and vulnerability arising for the agricultural sector. This is essential for informing effective policies and building resilience among the population engaged in agro-economic pursuits.

Substantial advancement in the understanding of climate change impacts on agriculture is forwarded by the existing literature. But these studies have largely evaluated individual dimensions of climate variability by examining adaptation behaviour (Bryan et al., 2009; Kabir et al., 2017), adaptive capacity (Clay & King, 2019), drought vulnerability (Lindoso et al., 2014), and risk perceptions (Kalogiannidis et al., 2023; Wheeler et al., 2021). In parallel, Muti-Attribute or Multi-Criteria Decision Making (MADM/MCDM) approaches are

increasingly being utilised to account for heterogenous dimensions and to assist in multi-dimensional based decision making in different agro-economic sectors. For example, the study by Zhao et al. (2018), constructs a multi-dimensional weighted index to assess the environmental vulnerability between different regions of China and records a greater level of environmental vulnerability in Western China compared to Eastern Chinese region. Then another study by Li et al. (2019) develops a systematic framework to assess agricultural water resources management using maximum entropy and entropy weighted TOPSIS. And reports considerable applicability of the framework to better manage water resources. Although, MADM approach is widely used in the area of engineering and management sciences, but its application is limited in the area of social sciences. Particularly in the area of climate change impact on agriculture and livelihood opportunities. The application is further limited in the regional context of India.

Therefore, the objective of this study is to implement a weighted MADM approach to construct a composite agricultural risk index for Assam, a predominantly agrarian state of India. The study draws from the latest climate risk framework of IPCC forwarded in its 5th assessment report (IPCC, 2014) and re-established in its 6th assessment report (IPCC, 2023). Entropy-Weighted-TOPSIS is used to derive the baseline metric for this study at the district-level. Using the metric the study tries to obtain highest to lowest agriculturally risk prone districts. And also tries to identify the Agro-Climatic Zones, which has the highest and lowest number of risk prone districts.

2 Literature review

2.1 Climate change and agricultural risk: Indian context

India being a crucial contributor of agricultural products to the world (Hinz et al., 2020), significantly influences the global value chain. Currently, agriculture contributes 16% to the national GDP and employs approximately 46.1% of the workforce according to a 2023–24 report (Ministry of Statistics and Programme Implementation [MoSPI], 2025). The Indian agricultural sector is ranked 2nd largest in the world as it accounts for 8% of the world farm GDP (approx.) and it is valued at 405 billion USD. The Indian Chamber of Food and Agriculture, reports that, the Indian economy is projected to double to $5 trillion by 2024–25. But a recent study Guntukula (2020) has found evidence on declining yield for the major crops in India. This decline is primarily attributed to increasing rainfall and temperature. Another study by Gupta et al. (2025) also finds that principal food crop like rice, is experiencing a steady decline in yield, as a result of rapid climate change and rising emissions. It is important to prevent yield decline and improve productivity to ensure agricultural sustainability and food security.

Following global studies and given the importance of agriculture in India, several attempts have been made to examine the sector's vulnerability and risk. A study by Rao et al. (2025) conducts district level climate risk assessment for the Indian agriculture sector, to facilitate adaptation planning. Das et al. (2025) uses PCA (Principal Component Analysis) and entropy weighting methods to analyse the vulnerability of agriculture due to climate change in the coastal districts of India. Similarly, many studies like – Balaganesh et al. (2025); Das and Goswami (2021); Dasgupta et al. (2024), and Shukla et al. (2018), have assessed risks

and vulnerabilities arising for the agricultural sectors, belonging to the different regions of India. However, there are several caveats in these studies. [1] Das and Goswami (2021), give a holistic review of the vulnerability and risk studies in Indian agriculture. They have highlighted that, while several studies have assessed climate risks to Indian agriculture; but these studies often do not comprehensively account for socioeconomic factors. [2] Further, India is sub-divided into 15 agro-climatic zones (NITI Aayog, 2025). Among them, the Eastern Himalayan Region (EHR) is particularly vulnerable to climate change (Shukla et al., 2018). And yet, there is a minuscule number of studies assessing the vulnerability and risk in this region (Das & Goswami, 2021). [3] Only few of the risk studies on agriculture, like Dasgupta et al. (2024) have adopted the latest IPCC's climate impact risk framework (IPCC, 2014).

2.2 Agricultural climate risk in the Eastern Himalayan Region

The present study, thus, pins focus to the state of Assam, located in the EHR of India, and seeks to quantify district-level agricultural risk to climate change and other hazards using the latest IPCC-AR5 (Intergovernmental Panel on Climate Change – Assessment Report 5) framework. Earlier studies by Alam et al. (2022) and Department of Science and Technology (DST, 2018) have identified Assam to be one of the most vulnerable Indian Himalayan state affected by climate change. While DST (2018) report includes a district-level vulnerability assessment, it does not specifically address agriculture, and omits important biophysical variables such as temperature and precipitation, along with several socio-economic factors. Dasgupta et al. (2024) constructed district level risk index for India, but the assessment is limited to drought and flood risks. In contrast, the present study has attempted to consider multi-hazards and a comprehensive set of factors that determine exposure and vulnerability of agriculture at the district level.

To integrate these indicators, the study employs entropy-weighted TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), that is a MADM (Multi-Attribute Decision Making) method that produces a composite index from multi-dimensional data to rank alternatives. Although TOPSIS was previously applied in climate change risk studies, examples include—Malakar et al. (2021) and Shah and Malakar (2024), but previous applications have not been in the context of agriculture and have typically used unweighted TOPSIS. Originally proposed by Hwang and Yoon (1981), TOPSIS has since been widely applied across disciplines for index construction (Barman et al., 2024; Zou et al., 2023).

3 Methodology

3.1 Indicators and data

An extensive review of the literature and available datasets enabled us to compile a wide range of indicators representing different components of risk. To retain only relevant indicators and exclude less pertinent ones, correlation was assessed for all the indicators under each component, using Spearman's Rank Correlation. After careful literature survey and correlation testing, 39 indicators were chosen for the study. 11 under the hazard component, 19 under vulnerability, and 9 under exposure. These indicators are presented in detail in

(Table 1), which presents the components, sub-components, indicators, contribution of the indicators to risk, and the data sources. Both biophysical and socio-economic indicators are considered under the sub-components for understanding the agricultural risks arising due to climate change. Detailed information about the rationale behind selection of the 39 indicators, in total, is provided in the Supplementary Information, as (Table S1 Risk indicators and the rationale behind its selection). For complete details on the citations used for the database, please check the reference list of (Table S1) of the Supplementary Material.

3.2 Study area

Assam, is a state in the north-east of India lying between 24° 07' to 28° 00' N latitudes and 89° 42' to 96° 02' E longitudes (Forest Survey of India [FSI], 2023). It is a land locked region sharing boundary with states of Arunachal Pradesh, West Bengal, Nagaland, Manipur, Mizoram, Tripura, and Meghalaya. The state also shares international boundary with, Bangladesh (in the south-west) and Bhutan (in the north-west). The Barak and Brahmaputra are the two prominent river systems present in the state. The mighty Brahmaputra has a drainage area of 70,634 sq. km. in Assam. Besides these two river system, there are many sub-tributaries traversing the plains and valleys of Assam. The state of Assam has a total geographical area of 78438 sq. km. under its administrative jurisdiction, and has a total of 35 districts (Directorate of Economics & Statistics, 2024a).

The districts are – Karimganj, Baksa, Biswanath, Bongaigaon, Cachar, Chirang, Darrang, Dhemaji, Morigaon, Dhubri, Dibrugarh, Dima Hasao, Goalpara, Golaghat, Hojai, Jorhat, Kamrup (Metro), Kamrup (Rural), Karbi Anglong, Charaideo, Kokrajhar, Lakhimpur, Majuli, Nagaon, Nalbari, Sivasagar, Sonitpur, South Salmara Mancachar, Tinsukia, Udalguri, Barpeta, West Karbi Anglong, Hailakandi, Bajali, and Tamulpur. The last two districts, Bajali, and Tamulpur, were created not long ago, and they were bifurcated from erstwhile Barpeta and Baksa district, respectively. Based on the data availability, only 33 districts were considered for this study out of the total 35 districts as shown in (Fig. 1.) Around 75% of the state population is dependent upon the state agricultural sector (directly as well as indirectly) (Assam Climate Change Management Society [ACCMS], 2021) and about 69% of the state's population is directly engaged in agricultural activities. The state of Assam has a unique amalgamation of topography ranging from hills in the north, to plains in between, to valleys in the south, so this study also takes note of this unique feature and looks into the diverse Sub-Agro-Climatic Zones (ACZ) as shown in (Fig. 2).

Assam is sub-divided into six ACZs, namely – Upper Brahmaputra Valley Zone (UPVZ); North Bank Plain Zone (NBPZ); Central Brahmaputra Valley Zone (CBVZ); Hills Temperate Zone (HTZ); Lower Brahmaputra Valley Zone (LBVZ); and Barak Valley Zone (BVZ). [1] Districts which are part of the UPVZ are – Tinsukia, Dibrugarh, Sivasagar, Charaideo, Jorhat, Majuli, Golaghat. [2] Districts which are part of the NBPZ are – Dhemaji, Lakhimpur, Biswanath, Sonitpur, Darrang, Udalguri. [3] Districts which are part of the CBVZ are – Nagaon, Morigaon, Hojai. [4] Districts which are part of the HTZ are – Dima Hasao, Karbi Anglong, West Karbi Anglong. [5] Districts which are part of the LBVZ are Kamrup (M), Kamrup (R), Barpeta, Baksa, Chirang, Kokrajhar, Goalpara, Bongaigaon, Dhubri, South Salmara Mancachar, Nalbari. [6] Districts which are part of the BVZ are – Cachar, Karimganj, Hailakandi (Ministry of Agriculture and Farmers Welfare [MoAFW], 2025; National Bank for Agriculture and Rural Development [NABARD], 2024).

Table 1 Details of components and indicators of risk

Risk components	Sub-components	Sl. No	Source of hazard/exposure/vulnerability	Indicators	Hypothesized influence over risk	Databases
Hazard	**Geogenic (natural-caused)**	**1**	Water Hazard	District-wise Land Degradation due to Water Erosion (2005–2006) & (2015–2016) (in %)	(+)	Statistical Handbook Assam, 2024 (DoES, 2024a, b)
		2		District-wise Land Degradation due to Water Logging (2005–2006) & (2015–2016) (in %)	(+)	
		3	Flood Hazard	District-wise Frequency of Flood Events from (1969–2019) (in no.)	(+)	Climate Hazard & Vulnerability Atlas of India (BMTPC, 2019; IMD, 2019)
		4		District-wise Average no. of Thunderstorm Days Annually (1981–2010) (in no.)	(+)	
		5		District-wise Rainfall DLPA (Deviation from Long period Average), for 2024 (1992–2024) (in %)	(+)	IMD (1992–2024) (IMD, n.d.-b)
		6	Extreme temperature hazard (may lead to drought, flood, or hailstorm)	District-wise T-Min DLPA (Deviation from Long period Average) for 2024 (1992–2024) (in %)	(+)	
		7		District-wise T-Max DLPA (Deviation from Long Period Average) for 2024 (1992–2024) (in %)	(+)	

Table 1 (continued)

Risk components	Sub-components	Sl. No	Source of hazard/exposure/vulnerability	Indicators	Hypothesized influence over risk	Databases
Hazard	**Geogenic (natural-caused)**	**8**	Wind Hazard	District-wise Extreme Wind Speed, Annually (in mps)	(+)	Climate Hazard & Vulnerability Atlas of India (BMTPC, 2019; IMD, 2019)
		9	Sand Hazard	District-wise Sand Affected Agricultural Land (2013–2014) (in %)	(+)	Human Development Report, Assam (2013–14) (P&DD, 2014)
	Anthropogenic	**10**	Natural & Man-made Hazard	District-wise Agricultural Land Affected by Industrial Pollutants (2013–2014) (in %)	(+)	
	Geogenic+Anthropogenic	**11**		District-wise Land Degradation due to Acidification (2015–2016)	(+)	Statistical Handbook Assam, 2024 (DoES, 2024a, b)
Exposure	**Physical Exposure**	**12**	Land Exposure	District-wise Net Area Sown (in hect.)	(+)	
		13		District-wise Permanent Pastures and Other Grazing Lands (in hect.)	(+)	
		14	Ecosystem (Environmental functions/resources/assets) Exposure	District-wise Derelict water Bodies/ Swamps (in hect.)	(+)	Statistical Handbook Assam, 2024 (DoES, 2024a, b)
		15	Livelihood Exposure+Asset Exposure (Economic/Social/Cultural)	District-wise "Open-Water Fisheries" (river/beel/forest/others) (in hect.)	(+)	
		16		District-wise Rain fed Agricultural Area (in %)	(+)	
		17		District-wise Flood Affected Agricultural Area (in %)	(+)	North Eastern Regional Node for Disaster Risk Reduction (NERDRR, n.d.)

Table 1 (continued)

Risk components	Sub-components	Sl. No	Source of hazard/exposure/vulnerability	Indicators	Hypothesized influence over risk	Databases
Exposure	**Socio-Economic Exposure**	**18**	Demographic Exposure	District-wise Decadal Population Growth Rate (2001–2011) (in %)	(+)	Census 2011 (ORGCI, 2011)
		19		District-wise Population Density (2001–2011) (in %)	(+)	
		20	Livelihood Exposure + Asset Exposure (Economic/Social/Cultural)	District-wise Cropping Intensity (in %)	(+)	Statistical Handbook Assam, 2023 (DoES, 2024a, b)
Vulnerability	**Sensitivity**	**21**	System Vulnerability (indirect impact)	District-wise Villages Affected due to Flood (1998–2015) (in %)	(+)	District-wise disaster management plans, 2024–2025 & Statistical Handbook Assam, 2023 (ASDMA, 2024; DoES, 2024a, b)
		22		District-wise Employment in Agriculture (2013–2014) (in %)	(+)	
		23		District-wise Household Income from Agriculture & Farming (2013–2014) (in %)	(+)	Human Development Report, Assam 2014 (P&DD, 2014)
		24		District-wise Agricultural Asset Poverty (2013–2014) (in %)	(+)	
		25		District-wise Financial Asset Poverty (2013–2014) (in %)	(+)	

Table 1 (continued)

Risk components	Sub-components	Sl. No	Source of hazard/exposure/vulnerability	Indicators	Hypothesized influence over risk	Databases
Vulnerability	**Sensitivity**	**26**	System Vulnerability (indirect impact)	District-wise Percentage of Households without Homestead Land (2013–2014) (in %)	(+)	Human Development Report, Assam 2014 (P&DD, 2014)
		27		District-wise Percentage of Households without a Cultivable land (2013–2014) (in %)	(+)	
		28		District-wise Percentage of Households without any Irrigated land (2013–2014) (in %)	(+)	
		29		District-wise Marginal & Small Land Holdings (2024–25) (in %)	(+)	NABARD Report (2024–25) (NABARD, 2024)
		30	Autonomous Adaptation	District-wise literacy rate (in %)	(-)	Census 2011 (ORGCI, 2011)
		31	Anticipatory Adaptation	District-wise Area under High Yielding Variety (HYV) Paddy (in %)	(-)	Statistical handbook Assam, 2023 (DoES, 2024a, b)
		32	Institutional Adaptation	District-wise Road Density (in km^2)	(-)	Statistical handbook Assam, 2024 (DoES, 2024b)
		33	Ecosystem Adaptation	District-wise Area under Aquaculture (in km^2)	(-)	

Table 1 (continued)

Risk components	Sub-components	Sl. No	Source of hazard/exposure/vulnerability	Indicators	Hypothesized influence over risk	Databases
Vulnerability	**Adaptive Capacity**	**34**	Household Adaptation	District-wise No. of Households Engaged in Sericulture (2023–2024) (in %)	(-)	Directorate of Sericulture, Assam, 2023–24 (DoES, 2024a, b)
		35		District-wise Man-days under MGNREGA Scheme relative to the State Total (2023–2024) (in %)	(-)	Statistical handbook Assam, 2024 (DoES, 2024b)
		36	Institutional + System Adaptation	District-wise Proportion of Crop Area Insured under Pradhan Mantri Fasal Bima Yojana (PMFBY) (2023–2024) (in km^2)	(-)	NABARD Report 2024–2025 (NABARD, 2024)
		37		District-wise No. of Registered FPOs (2024–2025) (in no.)	(-)	
		38	Ecosystem Adaptation	District-wise Forest Area (2023) (in km^2)	(-)	Statistical handbook Assam, 2024 (DoES, 2024a, b) and Agricultural Contingency Plans (MoAFW, 2025)
		39		District-wise Area Under Horticultural Crops (in 1000 hect.)	(-)	

DoES = Directorate of economics and statistics; *BMTPC* = Building materials & technology promotion council; *IMD* = India meteorological department

P&DD = Planning and development department

NERDRR = North Eastern Regional Node for Disaster Risk Reduction

ORGCI = Office of the Registrar General & Census Commissioner, India; ASDMA = Assam State Disaster Management Authority

Aquaculture includes – Ponds & Tanks; and Advance technology Bio-floc & Recirculating Aquaculture System (RAS); NABARD = National Bank for Agriculture and Rural Development

Sericulture = type of sericulture is Eri, Muga, mulberry; MoAFW = Ministry of Agriculture and Farmers Welfare

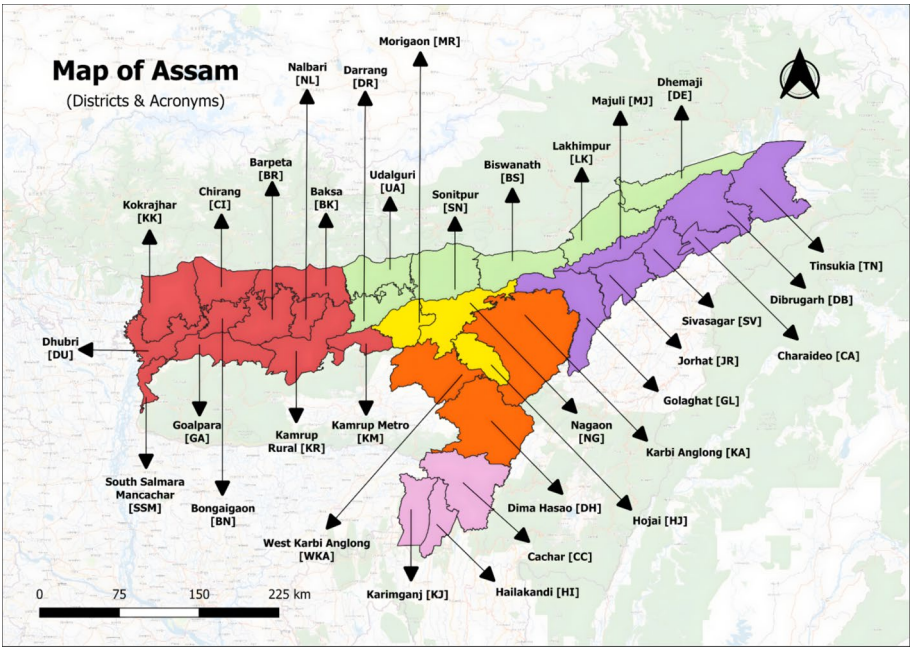


Fig. 1 Location of the districts and the geographical extent of the state of Assam, India. Source: Author's preparation based on Soil and Land Use Survey of India (SLUSI, n.d.)

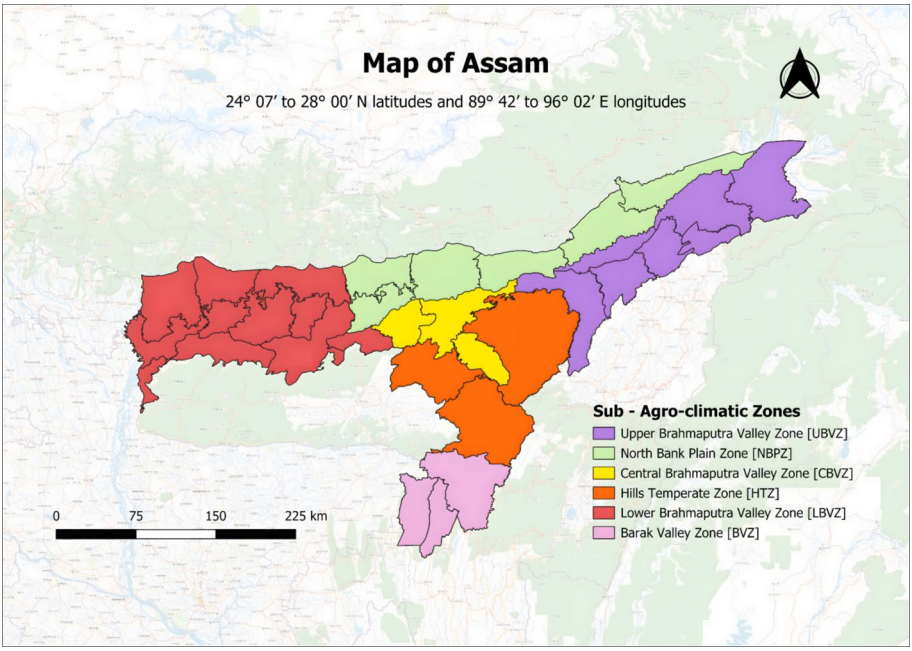


Fig. 2 Sub-agro-climatic zones in the state of Assam, India. Source: Author's preparation based on Soil and Land Use Survey of India (SLUSI, n.d.)

Historically, Assam has been witnessing natural disasters like – annual floods, soil erosion, landslides, seismic activities, thunder-storms, hail-storms and so on. Recent reports reveal that the frequency and intensity of all these hazards, have surged, manifold, and in addition to this, there has been reports about episodes of droughts, dam failures, industrial disasters, and forest fires from many parts of Assam (ACCMS, 2021). A substantial part of the state economy is agrarian and therefore the population dependent on it is highly exposed to the climate change risks. The principal crops cultivated in the state include – paddy (summer, autumn, winter), wheat, maize, potato, sugarcane, jute, oil seeds, and other cereals and small millets. Approximately 19.182% (Advance Estimates) of GSDP (Gross State Domestic Product, 2024–25) of Assam comes from the agriculture and allied activities (livestock, forestry & logging, fishing & aquaculture) (DoES, 2024b). Of the 19.182% GSDP, 12.05% (approx.) is contributed by the crops produced; 2.28% (approx.) is contributed by livestock rearing; 1.82% (approx.) is contributed by forestry & logging activities and 3.02% (approx.) is contributed by the aquaculture & fishing activities. In our study we look into the percentage of area devoted to HYV (High Yielding Variety) paddy cultivation, and the hectares of agricultural land dedicated to the cultivation of horticulture crops; among many other indicators, to understand the agricultural risk scenario for the farmers of Assam.

3.3 IPCC risk framework – AR5

Risk framework forwarded in IPCC reports – AR5 (IPCC, 2014) is utilised for constructing a composite agricultural risk index for the districts of Assam. Risk can be understood as the occurrence of any unforeseen events triggered by natural change (climate change, change in biogeochemical cycles, surge in natural disasters, and so on) or human interference (extensive industrialisation, anthropogenic pollution, population growth, and so on), that is uncertain and poses threat to life and impacts existing environmental systems (IPCC, 2014).

IPCC defines risk as a function of Hazard (H); Vulnerability (V); and Exposure (E); as shown in Eq. (1) –

$$\text{Risk}(R) = f[\text{Hazard}(H) \times \text{Vulnerability}(V) \times \text{Exposure}(E)] \quad (1)$$

These sub-components of risk are elaborated in the following sub-sections, and the entire methodology adopted for the study is presented in (Fig. 3).

3.4 Risk components

(1) Hazard

IPCC defines hazard as "the potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources." In this study the indicators that represent trends of natural hazards, specific to the agricultural sector of Assam, were chosen. Total 11 indicators were chosen under the hazard component. Indicators like – District-wise land degradation due to water erosion and water logging (2005–06 and 2015–16); were chosen, as Assam is a land of abundant

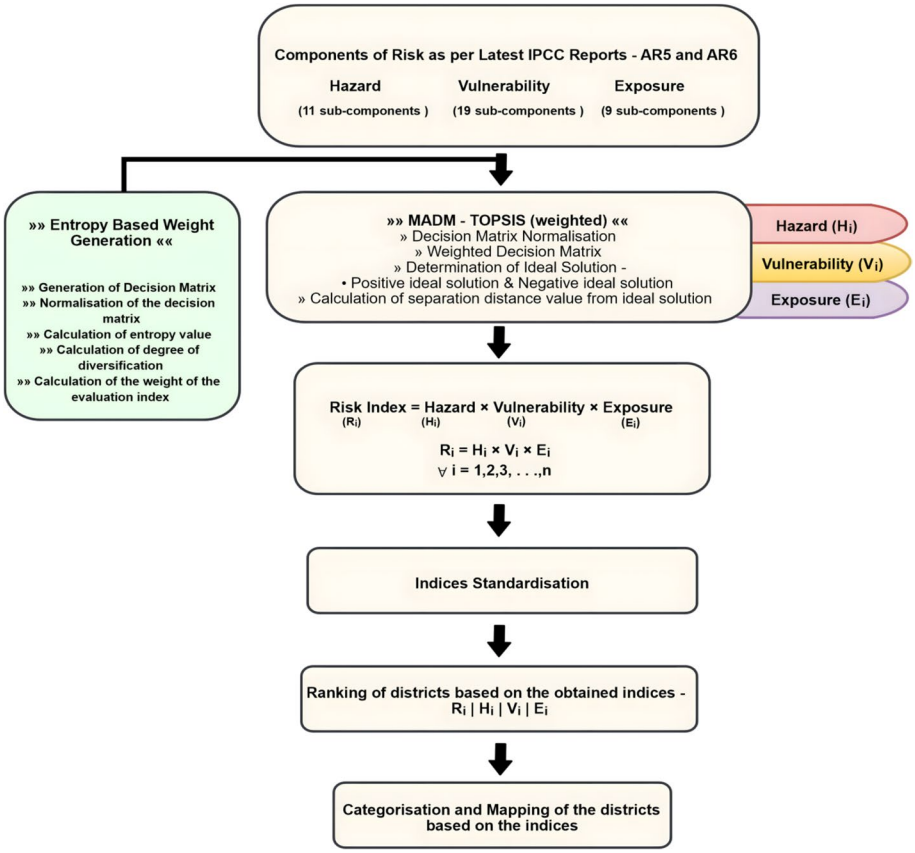


Fig. 3 A step-by-step representation of the methodology adopted for calculating indices of risk and its components (H | V | E). Source: Author's preparation based on previous literature (Hwang & Yoon, 1981; IPCC, 2014; Shannon, 1948; Shah & Malakar, 2024)

rainfall. Alluvium soil is the prevalent soil type throughout the state, which holds water for a long period; often degrading and eroding the agricultural land and the crops standing on it (Dekaraja & Mahanta, 2021). Also, the Brahmaputra and Barak are perennial rivers; along with their tributaries, these two river system constantly cause erosion and degradation to the land along their course, and the agricultural land being positioned (usually) along the river-banks face frequent degradation (Saikia & Mahanta, 2024). Then indicators like – district-wise deviation of rainfall and temperature (min & max) from their long period (1992–2024) average were chosen, as multiple studies (NABARD, 2024; Swami & Parthasarathy, 2021) have frequently highlighted the importance of studying meteorological factors associated with rainfall and temperature for understanding and mitigating the variability and risks arising to agriculture due to its influence on the changing climate. The data for temperature (at a coarser grid resolution of $1.0° \times 1.0°$) and rainfall (at a finer grid resolution of $0.25° \times 0.25°$) were sourced from IMD Pune's online data repository following the studies by Pai et al. (2014) and Srivastava et al. (2009). Q-GIS version 3.38 was utilised to extract the data from

the files; and a brief 7 step process of extracting climate data is explained in Section S9 of the Supplementary Material.

Deviation from Long Period Average (DLPA) for rainfall was computed, following the study by Swami et al. (2018), and using the Eqs. (2 to 4) –

$$\overline{\mathrm{X}}_{\mathrm{y}} = \sum_{\mathrm{d}=1}^{\mathrm{D}} X_{dy} \Big/ \mathrm{D} \tag{2}$$

$$\overline{\mathrm{X}} = \sum_{\mathrm{y}=1}^{\mathrm{Y}} \overline{\mathrm{X}}_{y} \Big/ \mathrm{Y} \tag{3}$$

$$X_{DLPA}^{rainfall} = \overline{\mathrm{X}}_{y} - \overline{\mathrm{X}} \tag{4}$$

where,

d = days

D = total no. of days

y = year

Y = total no. of years

X_{dy} = daily rainfall for each district (annually)

$\overline{\mathrm{X}}_{y}$ = average daily rainfall for each year

$\overline{\mathrm{X}}$= average rainfall for 33 years (Long Period Average)

$X_{DLPA}^{rainfall}$ = deviation of rainfall of each year from LPA (Long Period Average)

DLPA for temperature maximum and minimum (T-min and T-max) was computed following the approach of Swami et al. (2021); in the referred study, the deviation is computed by subtracting minimum and maximum temperature required by crops from the average daily temperature (T-Min & T-Max) for each year ($\overline{\mathrm{X}}_{y}$); but in the present study average temperature (of T-Min & T-Max) for 33 years is chosen in place of crop temperature (X_{T-Max}^{C} and X_{T-Min}^{C}). The Eqs. (5 to 8) show the steps involved in the calculation.

$$\overline{\mathrm{X}}_{\mathrm{y}} = \sum_{\mathrm{d}=1}^{\mathrm{D}} X_{dy} \Big/ \mathrm{D} \tag{5}$$

$$\overline{\mathrm{X}} = \sum_{\mathrm{y}=1}^{\mathrm{Y}} \overline{\mathrm{X}}_{y} \Big/ \mathrm{Y} \tag{6}$$

(here, $\overline{\mathrm{X}} = \overline{\mathrm{X}}_{\mathrm{T-Min}}$ or $\overline{\mathrm{X}}_{\mathrm{T-Max}}$)

$$X_{DLPA}^{T-Min} = \overline{\mathrm{X}}_{y} - \overline{\mathrm{X}}_{\mathrm{T-Min}} \tag{7}$$

and

$$X_{DLPA}^{T-Max} = \overline{X}_y - \overline{X}_{\mathrm{T-Max}} \tag{8}$$

where,

d = days

D = total no. of days

y = year

Y = total no. of years

X_{dy} = daily temperature (T-Min or T-Max) for each district (annually)

$\overline{X}_y$= average daily temperature (T-Min or T-Max) for each year

$\overline{X}_{\mathrm{T-Min}}$ = average temperature T-Min for 33 years (LPA)

$\overline{X}_{\mathrm{T-Max}}$= average temperature T-Max for 33 years (LPA)

X_{DLPA}^{T-Min} = deviation of T-Min of each year from LPA (i.e. year 2024 for this study)

X_{DLPA}^{T-Max} = deviation of T-Max of each year from LPA (i.e. year 2024 for this study)

After obtaining, values of $X_{DLPA}^{rainfall}$, X_{DLPA}^{T-Min}, X_{DLPA}^{T-Max} for the year 2024 for each district, the values were used as indicators of hazard, as listed in (Table 1). Factors like – district-wise frequency of flood events (1969–2019); district-wise extreme wind speed and sand affected agricultural land (2013–2014); and district-wise number of thunderstorm days annually (1981–2010); were considered as these are some of the prevalent hazards affecting the agricultural sector of Assam. Studies like Alam et al. (2022) has also found evidences on similar lines. Former studies on the agricultural sector of Assam have not utilised indicators pertaining to the hazards arising due to human interference, like – district-wise agricultural land affected by industrial pollutants and district-wise land degradation due to acidification. Therefore, inclusion of such indicators in the present study will greatly improve the study of risks associated with multi-hazards affecting the agricultural sector of Assam.

(2) Vulnerability

IPCC defines vulnerability as "the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt." It is expressed as the function of sensitivity (S) and lack of adaptive capacity (AC), as shown in Eq. (9) –

$$\text{Vulnerability (V)} = \text{f}\left[\text{Sensitivity (S)} \times \text{Lack of Adaptive Capacity (AC)}\right] \tag{9}$$

A total of 19 indicators were considered under vulnerability representing sensitivity and adaptive capacity.

(3) Exposure

IPCC defines exposure as "the presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected." In total 19 indicators were considered under this component that resonated with the objective of the present study. This study considers indicators for both physical and socio-economic exposure.

3.5 Index calculation

Entropy-Weighted-TOPSIS approach was chosen for formulating the three sub-components of the risk index. TOPSIS was chosen for this study as it is widely preferred across disciplines, for reasons like – (1) Data requirement is minimum; (2) It can handle large (as well as negative value) data sets; (3) Subjective inputs requirement is minimum for decision making (Yadav et al., 2019).

Before conducting TOPSIS, weights for the indicators are generated based on the Shannon's Entropy approach, proposed in Shannon (1948). The steps undertaken to create an index based on Entropy-Weighted TOPSIS (Barman et al., 2024) are described in the following sub-sections.

3.5.1 Weights generated using Shannon's Entropy

(1) Generation of a decision matrix

The decision matrix of the form $n \times m$ is formed which represents the intersection of the i^{th} district with the j^{th} indicator,

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{x}_{11} & \cdots & \boldsymbol{x}_{1\boldsymbol{m}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x}_{\boldsymbol{n}1} & \cdots & \boldsymbol{x}_{\boldsymbol{nm}} \end{bmatrix} \tag{10}$$

where i = 1,..., n is the number of districts, and j = 1,..., m is the number of indicators and x_{ij} is the performance value of the i^{th} district with the j^{th} indicator.

(2) Normalization of the decision matrix

To obtain the normalised decision matrix Eq. (11) is applied,

$$\boldsymbol{t_{ij}} = \boldsymbol{y_{ij}} \Big/ \sum_{\boldsymbol{i}=1}^{\boldsymbol{n}} \boldsymbol{y_{ij}} \quad (\mathrm{i} = 1,2,...,\mathrm{n};\ \text{and}\ \mathrm{j} = 1,2,...,\mathrm{m}) \tag{11}$$

where t_{ij} represents the normalised decision matrix of i^{th} district with the j^{th} indicator.

(3) Calculation of the entropy value ($\boldsymbol{e_j}$)

$$e_j = -h \sum_{i=1}^{n} t_{ij} \ln(t_{ij}) \ \ (\mathrm{i} = 1,2,...,\mathrm{n};\ \text{and}\ \mathrm{j} = 1,2,...,\mathrm{m}) \tag{12}$$

where, $h = 1 \Big/ ln(n)$, is the constant or the multiplicative factor and n is the number of districts.

(4) Calculation of ($\boldsymbol{d_j}$) (or divergence or information utility or redundancy)

$$\boldsymbol{d_j} = 1 - \boldsymbol{e_j} \tag{13}$$

d_j is calculated to measure variability or deviation of entropy values.

(5) Entropy based weight ($\boldsymbol{w_j}$) calculation to determine the criteria's relative importance

$$\boldsymbol{w_j} = \boldsymbol{d_j} \Big/ \sum_{j=1}^{\boldsymbol{m}} \boldsymbol{d_j} \tag{14}$$

where, w_j is the entropy-based weight obtained for the j^{th} index. After obtaining the final weight it is incorporated with TOPSIS for further analysis as previously followed in the studies like Vagiona (2025). We have opted to use entropy weights in our study, as it provides advantages like – minimal subjective bias as weights is derived mathematically from the decision matrix; this approach ensures that the criteria which has more information gain more weights. It uses the information content of the criteria to award weights. Criteria with more variability is awarded more weight than the criteria with lower variability. In addition, the weighting procedure is transparent and easily replicable because it is based on a well-defined mathematical formulation. Please refer to the sub-section S2.3 of the Section S2 of the Supplementary Material for details on indicators with highest and lowest weights.

3.5.2 Entropy-weighted-TOPSIS approach

(1) Decision matrix normalisation

After establishing the decision matrix as presented in Eq. (10), normalisation of the decision matrix is done using vector normalisation as presented in Eq. (15) –

$$V_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{n} x_{ij}^2} \quad (i = 1,2,...,n;\ \text{and}\ j = 1,2,...,m) \tag{15}$$

where, V_{ij} is the normalised decision matrix, and x_{ij} is the value of i^{th} district with j^{th} indicator.

(2) Construction of a weighted matrix

$$W_{ij} = (\boldsymbol{w_j} \times V_{ij}) \quad (i = 1,2,...,n;\ \text{and}\ j = 1,2,...,m) \tag{16}$$

where, W_{ij} is the weighted decision matrix, obtained by multiplying the entropy-based weight (w_j) with the vector normalised decision matrix (V_{ij}).

(3) Determining the ideal best (V_j^+) and ideal worst (V_j^-) solutions

$$V_j^+ = \begin{cases} max W_{ij};\ if\ j\ is\ a\ benefit\ criteria \\ min W_{ij};\ if\ j\ is\ a\ cost\ criteria \end{cases}$$
$$V_j^- = \begin{cases} min W_{ij};\ if\ j\ is\ a\ benefit\ criteria \\ max W_{ij};\ if\ j\ is\ a\ cost\ criteria \end{cases} \quad (17)$$

The present study aims to represent the districts that are more prone to hazard, vulnerability, and exposure with the increasing values. Therefore, for (V_j^+): indicators that are perceived to have a positive contribution or increases (+) the risks occurring due to climate change (Table 1), have positive ideal solution as maximum of W_{ij} and have negative ideal solution as minimum of W_{ij}. And for (V_j^-): indicators that are perceived to have a negative contribution or decreases (–) the risks occurring due to the climate change (Table 1), have positive ideal solution as minimum of W_{ij} and have negative ideal solution as maximum of W_{ij}. This is because maximum influence of positive indicators is desired, and minimum influence of negative indicators is desired.

(4) Euclidean distance calculation

The positive ideal and negative ideal solution from the weighted decision matrix is calculated.

$$S_i^+ = \sqrt{\sum_{j=1}^{m} \left(V_{ij} - V_j^+\right)^2} \quad (i = 1,2,...,n;\ \text{and}\ j = 1,2,...,m) \quad (18)$$

$$S_i^- = \sqrt{\sum_{j=1}^{m} \left(V_{ij} - V_j^-\right)^2} \quad (i = 1,2,...,n;\ \text{and}\ j = 1,2,...,m) \quad (19)$$

Equation (18) assists in obtaining positive Euclidean distances (S_i^+) and Eq. (19) assists in obtaining the negative Euclidean distances (S_i^-). Where, V_{ij} indicates the real value of each district, V_j^+ indicates the ideal best solution and, V_j^- indicates the ideal worst solutions.

(5) Calculation of the queuing score or the relative closeness score

$$P_i = S_i^- \Big/ S_i^+ + S_i^- \quad (20)$$

where, P_i indicates the performance score (or queuing) obtained, which shows the relative closeness to the ideal solution values. A score close to 1 indicates higher proneness to hazard, vulnerability, and exposure. All the steps from Eq. (10) to (20) are repeated for all the risk components.

Lastly, the composite risk index is obtained as the product of the three components. Symbolically, this can be represented as – (IPCC, 2014, 2023).

$$\text{Risk} = [\text{Hazard} \times \text{Vulnerability} \times \text{Exposure}] \quad (21)$$

To ease illustration of the indices obtained for Risk (R_i), Hazard (H_i), Vulnerability (V_i), and Exposure (E_i) the obtained closeness scores are standardised following Eq. (22) –

$$Z_i = \left. Y_i - Y_{min} \right/ Y_{max} - Y_{min} \tag{22}$$

where, Z_i is the standardised index and Y_i is the individual values from the index, and Y_{min} and Y_{max} are the minimum and maximum value of the index, respectively. The obtained indices are then arranged in a descending order, from highest to lowest. Based on the indices the districts are categorised into five categories (Lowest, Low, Medium, High, Highest), using Jenk's Natural Break Algorithm. After the categorisation, mapping of the districts is done using Q-GIS (Shah & Malakar, 2024).

Once the risk indices were obtained, we additionally computed CRITIC (Criteria Importance Through Intercriteria Correlation)-weighted TOPSIS to examine the robustness of district rankings under alternative weighting approaches. Although CRITIC-weighted TOPSIS does not constitute the core methodology of this study, it was employed as part of the sensitivity analysis to assess the consistency of rankings across different weighting schemes. Comparisons were undertaken between Entropy-weighted and Unweighted TOPSIS, CRITIC-weighted and Unweighted TOPSIS, and CRITIC-weighted and Entropy-weighted TOPSIS.

CRITIC was originally proposed by Diakoulaki et al. (1995) and has since been applied across a wide range of disciplines. CRITIC is an objective method and it is widely used in MADM studies, as it offers multiple advantages compared to other weighting techniques. The advantages are – (1) Both correlation and variation of a criterion is considered before assigning weights. (2) It is a good weighting strategy in absence of reliable expert judgement, and avoids inconsistencies arising from subjectivity, and judgements. (3) CRITIC is a data-driven straight-forward technique which is easy to compute with any dataset. (4) It is a reliable method for robustness testing, against other objective weighting techniques like entropy. In the present study, the CRITIC approach was incorporated following previous applications in the literature (e.g., Barman et al., 2024). A detailed description of the methodology and results is provided in Section S5 of the Supplementary Material.

4 Results

4.1 Relative position of districts according to the risk components

(1) Multi-hazard analysis

In the hazard analysis, Dima Hasao is identified as the, top hazard prone district as shown in (Fig. 4). This district is under the Hills Temperate Zone. It has attained the top spot in hazard proneness, as the indicators which showcase the impact of hazards on its agricultural sector is highest. This district has the highest percentage of land degraded due to water erosion; its rainfall DLPA for 2024 is around 25% that is considered as excessive rainfall (India Meteorological Department [IMD], n.d.-a); average number of thunderstorm days are high; and the percentage of land degraded due to acidification, is also highest for this district. In high-hazard prone category, four districts were identified namely – Kamrup (R), Karbi Anglong, West Karbi Anglong, and Barpeta. Among these four districts – Kamrup (R) (0.28) has one of the highest percentage of land degraded due to water logging, industrial pollutants, and acidification.

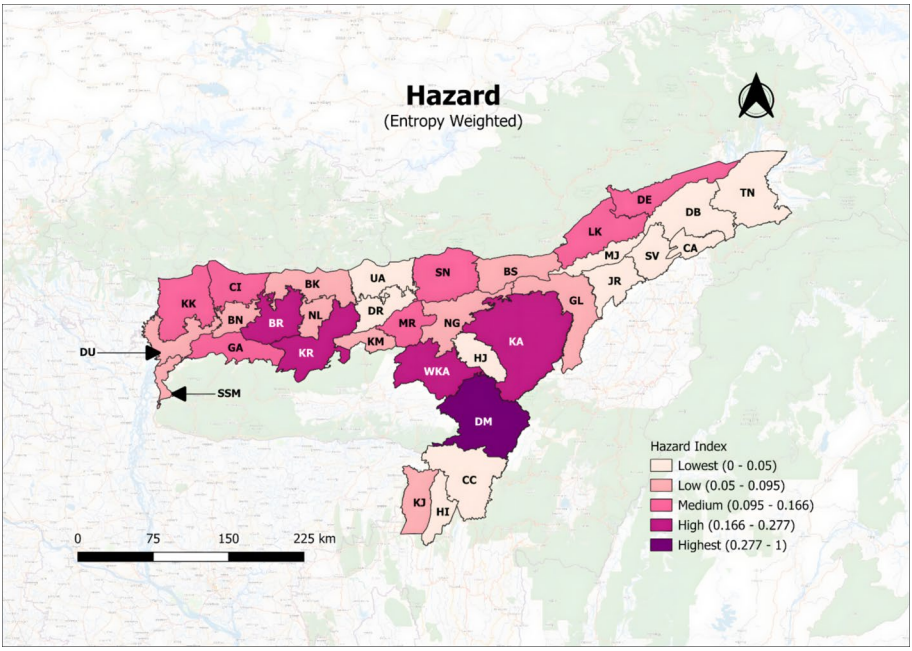


Fig. 4 Entropy-Weighted Hazard Index Map for Assam's Districts. Source: Author's preparation based on Soil and Land Use Survey of India (SLUSI, n.d.)

Karbi Anglong (0.23) has one of the highest percentage of degraded land due to water erosion; agricultural land affected by sand infiltration; and the average number of thunderstorm days is also high for this district. Similarly, for the districts of West Karbi Anglong (0.202) and Barpeta (0.201), the percentage of land degraded is high, as well as the frequency of flood events to deviation in rainfall and temperature is also high resulting in their high rankings. In the medium to low-hazard prone category, seven to ten districts were identified respectively. Many studies like Mohanty and Wadhawan (2021) flags Assam as the flood capital of India. And finds multiple districts of Assam, to be affected by extreme flood events. But the present study, further adds to the discussion by incorporating multiple other hazards, specifically affecting the agriculture. Multiple government reports, including district handbooks, NABARD reports, and agricultural contingency files, confirms the frequency and intensity of these hazards.

(2) Vulnerability analysis

The district of Dibrugarh has the highest vulnerability rank among all the districts of Assam as shown in (Fig. 5). This district has received the highest vulnerability rank, as the indicators contributing to the vulnerability, of its agricultural sector, are highest for this district. Sensitivity indicators like – irrigated land area, and percentage of households without homestead land, is highest for this district. Other sensitivity indicators like – agricultural assets poverty, and villages affected due to floods, is also high for this district. And indicators pertaining to the adaptive capacity like – literacy rate, area under HYV paddy, road density,

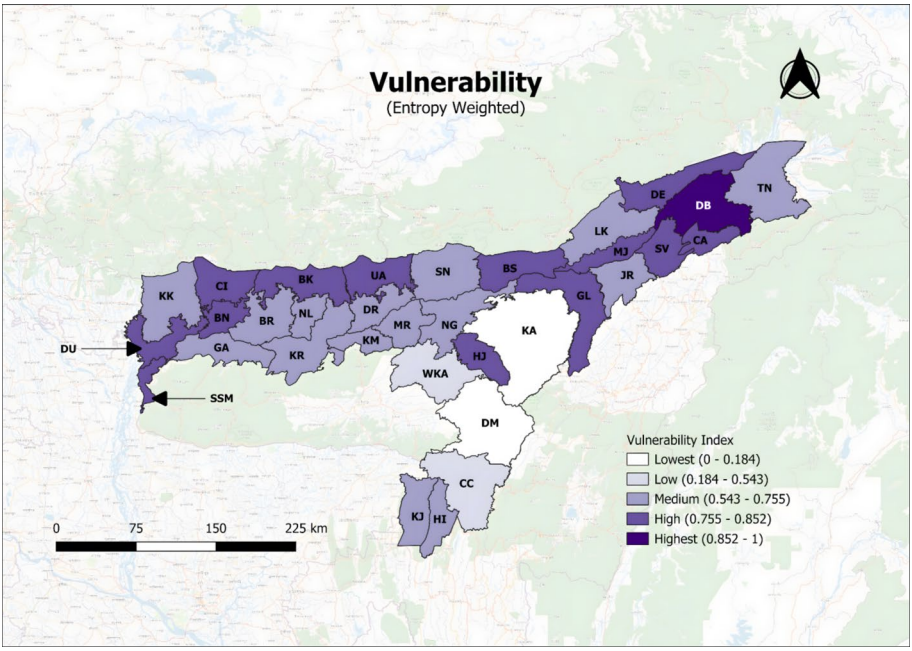


Fig. 5 Entropy-weighted vulnerability index map for Assam's Districts. Source: Author's preparation based on Soil and Land Use Survey of India (SLUSI, n.d.)

engagement in alternative livelihood activities (sericulture, aquaculture, MGNREGA, horticulture), and agricultural area insured under PMFBY etc. are recorded low, for this district.

In the high vulnerability category thirteen districts were recorded, namely – Udalguri (0.85), Hojai (0.849), South Salmara Mancachar (0.848), Biswanath (0.848), Dhubri (0.822), Charaideo (0.821), Sivasagar (0.796), Dhemaji (0.786), Majuli (0.786), Golaghat (0.780), Bongaigaon (0.770), Chirang (0.766), and Baksa (0.764). All these districts have recorded high on the sensitivity indicators but low on adaptive capacity. Only two districts were recorded in the lowest vulnerability category – Dima Hasao (0.184) and Karbi Anglong (0). And the remaining 17 districts were categorised under medium to low vulnerability categories. The vulnerability analysis identified that the district with highest vulnerability proneness (Dibrugarh) belongs to the Upper Brahmaputra Valley Zone. The results obtained are consistent with those reported by a similar study by Alam et al. (2022). Although the degree of vulnerability reported in their study differs from that observed in the present study, this difference may be attributed to multiple factors. These include differences in the techniques used for index construction and the number of districts considered. While their study considered only 27 districts, the present study considers 33 districts, thereby providing a more comprehensive assessment. In another study, Barua et al. (2019) found that Assam ranked as the most vulnerable state among the 12 Indian Himalayan states. A comparison of the vulnerability map presented in their study with that of the present study reveals a high degree of similarity.

(3) Exposure analysis

The district of Nagaon ranks highest in the exposure index (Fig. 6). This is because indicators like – net-sown area, presence of derelict water bodies/swamps is the highest for Nagaon. Additionally, indicators like – presence of permanent pastures and other grazing lands, open water fisheries, flood affected agricultural area, presence of rainfed agricultural area etc. are comparatively high for this district. Four districts were identified under high exposure category, they are – Karbi Anglong, West Karbi Anglong, Hailakandi, and Sivasagar. Karbi Anglong (0.608) records high on permanent pasture and other grazing land, and also recorded high in other indicators like – net-sown area, cropping intensity etc. The district of West Karbi Anglong (0.604) recorded high for indicators like – permanent pasture and other grazing lands, along with indicators like cropping intensity etc. Likewise, Hailakandi (0.56), also recorded high on indicators like – population density, and growth rate, contributing to its high exposure. And Sivasagar (0.549) has recorded high on indicators like – net-sown area, permanent pasture and other grazing lands, existence of swamps and open-fisheries etc. which has contributed to its high exposure rank. The findings of exposure analysis are in line with government backed reports on Economic Survey of Assam, Statistical Handbook of Assam, and district contingency plans.

Insights obtained from the exposure analysis is relatively fresh, and no other study exists which has incorporated exposure indicators, to study climatic risk from the agricultural perspective. Therefore, these findings will be interesting for subsequent studies.

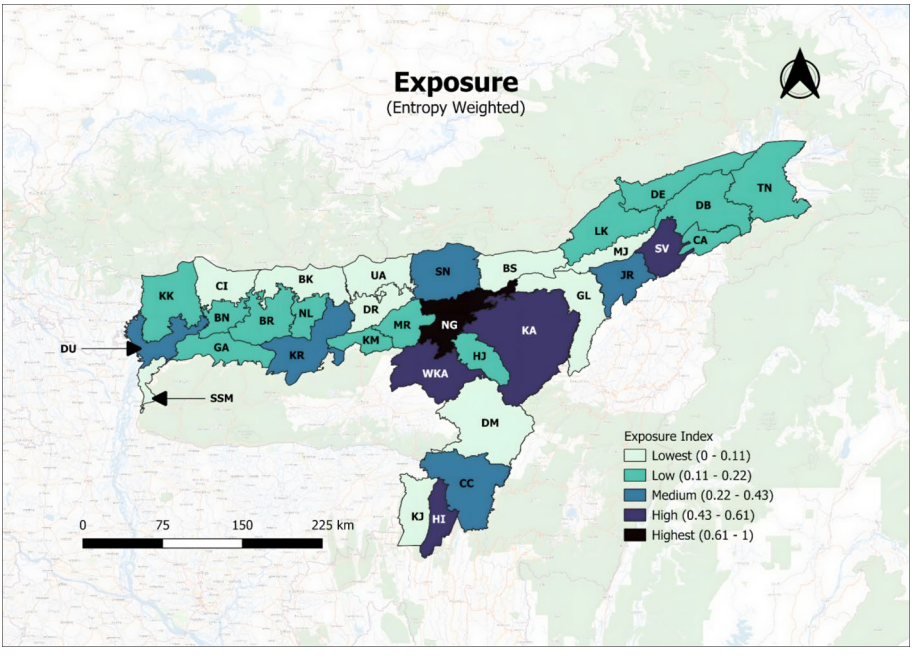


Fig. 6 Entropy-weighted exposure index map for Assam's Districts. Source: Author's preparation based on Soil and Land Use Survey of India (SLUSI, n.d.)

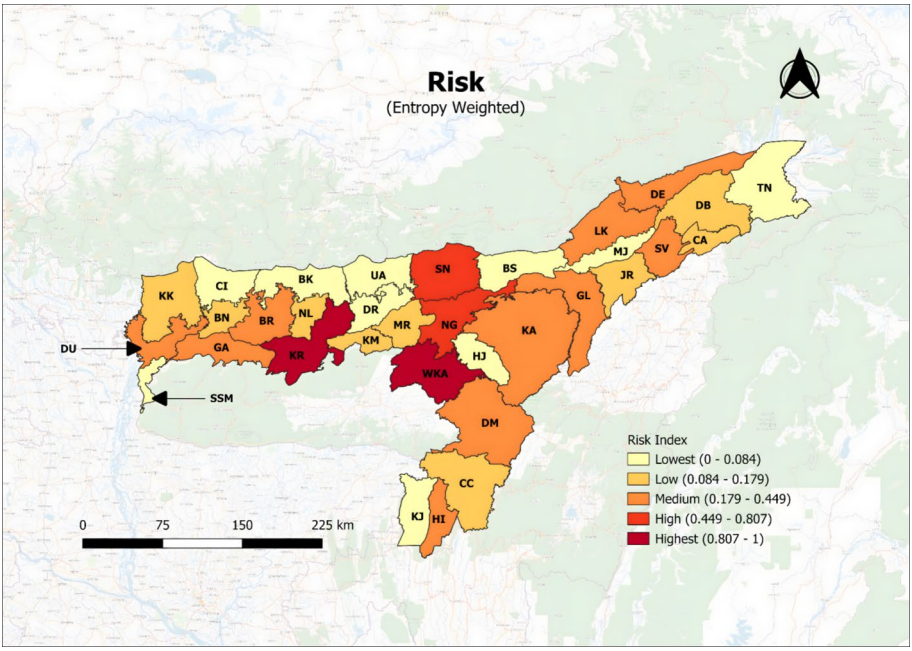


Fig. 7 Entropy-weighted risk index map for Assam's Districts. Source: Author's preparation based on Soil and Land Use Survey of India (SLUSI, n.d.)

4.2 Risk analysis

As represented in (Fig. 7) Kamrup (R) (1) of the Lower Brahmaputra Valley Zone, and West Karbi Anglong (0.947) of the Hills Temperate Zone, are two of the highest agriculturally risk prone districts of Assam. Then, two districts fall into the high-risk category — Sonitpur (0.644) from the North Bank Plain Zone and Nagaon (0.806) from the Central Brahmaputra Valley Zone. Medium risk prone category includes ten districts, of which – three districts are from the Lower Brahmaputra Valley Zone: Dhubri (0.338), Goalpara (0.268), and Barpeta (0.306); two districts are from the North Bank Plain Zone: Lakhimpur (0.348) and Dhemaji (0.346)); two districts are from the Upper Brahmaputra Valley Zone: Sivasagar (0.386) and Golaghat (0.255); and two districts are from Hills Temperate Zone: Karbi Anglong (0.448) and Dima Hasao (0.349); and one district is from the Barak Valley Zone: Hailakandi (0.424).

In the low risk category, nine districts are present – Lower Brahmaputra Valley Zone includes four districts: Kokrajhar (0.154), Bongaigaon (0.144), Nalbari (0.166), and Kamrup (M) (0.133)); Central Brahmaputra Valley Zone includes one district: Morigaon (0.179). Upper Brahmaputra Valley Zone includes three districts: Jorhat (0.172), Charaideo (0.113), and Dibrugarh (0.129). And Barak Valley Zone includes one district: Cachar (0.139). Then in the lowest risk category, remaining ten districts are present, of which – three districts belong to the Lower Brahmaputra Valley Zone: South Salmara Mancachar (0.0255), Chirang (0.0023), and Baksa (0.0348); three districts belong to the North Bank Plain Zone: Udalguri (0), Darrang (0.022), Biswanath (0.0717); two districts belong to the Upper Brahmaputra Valley Zone: Majuli (0.0372) and Tinsukia (0.0576). And one district each belong

to the Central Brahmaputra Valley Zone: Hojai (0.0836); and Barak Valley Zone: Karimganj (0.0412). Therefore, the obtained results indicate that, the districts belonging to the Lower Brahmaputra Valley Zone and Hills Temperate Zone are comparatively higher in agricultural risk proneness compared to the districts of other ACZs. And the districts belonging to the North Bank Plain Zone and Central Brahmaputra Valley Zone are relatively more risk prone compared to the districts of the Upper Brahmaputra Valley Zone and Barak Valley Zone.

It is interesting to note that, districts within the same agro-climatic zone do not exhibit uniform patterns of risk. This is noteworthy because agro-climatic zones are generally characterised by similar climatic conditions, soil profile, topography, and crop-growing conditions that support specific type of agricultural practices and crop species. These variation suggests that additional factors — such as differences, in the prevailing socio-economic and environmental conditions — play a critical role in shaping the risk scenarios.

In this study, Agro-Climatic Zones (ACZs) are primarily used to provide ecological and climatic context for interpreting the results. However, the unit of analysis is the district, rather than the agro-climatic zone itself. Consequently, the study focuses on district-level patterns of agricultural risk rather than microclimatic or farm-level variability.

4.3 Sensitivity analysis and robustness checks

In addition to the Entropy-Weighted-TOPSIS analysis, we conducted a sensitivity analysis comparing the Unweighted, Entropy-Weighted, and CRITIC-Weighted-TOPSIS; using Spearman's Rank Correlation and Kendall's Tau tests. The results confirm that the district rankings are fairly consistent across different weighting techniques. For the Risk Index, the results indicate moderate to high agreement among rankings, with Spearman's rho values ranging from 0.70 to 0.98. To identify the source of sensitivity, we also conducted separate analyses for the hazard, vulnerability, and exposure components. The results suggest that the hazard component contributes moderately to the variability in ranking, whereas the vulnerability and exposure components remain comparatively stable across the weighting approaches. Since the hazard component comprises several climatic indicators, that exhibit greater spatial variability across districts, differences in weighting schemes may have a minor influence on the resulting ranks. Nevertheless, the final risk Index rankings remains highly consistent across all the alternative weighting approaches; indicating robustness of the assessment framework. A detailed presentation and interpretation of the sensitivity analysis results are provided in Section S5 of the Supplementary Material.

As part of the robustness assessment, we have also conducted external validation of the risk indices with data on average insurance claimed per farmer (2018–2025) and average insurance claimed per hectare of insured area (2018–2025) for the districts of Assam, collected from the Pradhan Mantri Fasal Bima Yojana (PMFBY) (Ministry of Agriculture & Farmers Welfare, Government of India [MoAFW, GoI], n.d.) The results revealed weak and statistically insignificant associations. A detailed presentation of the results is provided in Section S8 of the Supplementary Material. These findings suggest that insurance claim is influenced by several factors beyond climatic risk, including farmer awareness, access to institutional credit, administrative outreach, and local institutional arrangements, ability to afford insurance premium, efficiency of policy implementation, insurance claim filing

behaviour, duration of claim settlement etc. Therefore, insurance claim under PMFBY-may not represent a direct proxy for agricultural risk. Although outcome-based indicators such as crop yield variability, agricultural losses, disaster damage records, etc. would have provided a stronger basis for validation, such datasets were not consistently available at the district level for the study area.

To ascertain if the utilised entropy weights are reliable we have also conducted a Weight Stability Interval analysis following the study of Mareschal (1988). It is a foundational study in the area of MADM studies. And based on the obtained intervals, we obtain strong evidence on the stability of the TOPSIS results obtained using entropy weights. The analysis is discussed in detail in the S6 section of the supplementary material. Another complementary analysis; visual comparison of the choropleth maps obtained using different weight techniques, also indicated, towards stability in the entropy weighted results. This can be viewed in the S7 section of the supplementary material.

5 Policy implications

Assam is situated at the heart of Barak – Brahmaputra river system. The mighty Brahmaputra and the Barak rivers are perennial, and replenishes the region with abundant water supply throughout the year, which supports many riparian communities, and exotic ecosystems. The state is a part of the Eastern Indian Himalayan Region, as such it comprises of many biodiversity hotspots and sensitive zones. The state's unique topography comprises of plains, valleys as well as hills, which supports diverse agro-economic activities and ethnic communities. Because of its unique geo-climatic, geography, and physiography, it is confronted with hazards arising from annual floods, seismic activities, droughts, storms, landslides, forest fires, pest attacks etc. (Assam State Disaster Management Authority [ASDMA], 2024). The study found that all the districts of Assam are prone to the agricultural risks as a result of climate change (as discussed in Sections 4.1. to 4.2.), but few of the districts like Kamrup (R), West Karbi Anglong, Sonitpur, and Nagaon are relatively more risk-prone compared to the other districts. Furthermore, the districts that lie in the medium to low risk category, have ranked high either in vulnerability or exposure index. Government intervention in the form of structural as well as non-structural measures is necessary to manage these multi-dimensional risks, arising for the agricultural sector of the districts. Structural measures include – (1) Strategic construction of flood walls or embankments to prevent damage of the standing crop and reduce erosion; (2) Construction of rainwater drainage and harvesting systems to maintain optimum water level for the agricultural land; and (3) Investment in climate smart agricultural strategies (like – agroforestry, raised agricultural seed beds, construction of greenhouses, and construction of modern storage silos) among others. Non-structural measures include – (1) Climate risk zoning; (2) Promoting adoption of insurance schemes among the agricultural communities; (3) Building community resilience through awareness programs; (4) Availability of agricultural extension services, and encouraging adoption of climate smart agricultural practices (like – use of drought resistant or flood resistant seeds, crop rotation, crop diversification, livelihood diversification etc.) among the farmers of Assam.

5.1 Policy recommendations according to the category of risk

(1) Recommendations for districts, with highest to high risk proneness

Districts which are in the highest to high risk category, have scored relatively high on all dimensions of risk. There is an urgent need, for these districts, to adopt climate smart agricultural practices. And concerned authority need to invest plentily on the existing risk management infrastructure concerning—rainwater drainage and harvesting systems, promoting crop insurance among the farmers, agricultural risk zoning etc. The state disaster management authority, should closely monitor these districts to abate yield losses and to prevent, future loss of livelihood.

(2) Recommendations for districts, which are in medium to low risk category

These districts have scored high, on few of the, risk increasing factors, and have relatively scored high, on few of the risk reducing factors. As such, concerned authorities should, promote community awareness programmes on risk reducing factors (like education, extension services, dissemination of weather information, promotion of soil testing, correct irrigation practices etc.) to prevent transition of these districts from low to medium risk; and from medium to high risk. Climate risk zoning and encouraging climate smart practices are indispensable.

(3) Recommendations for districts, which are seemingly low on risk proneness

Districts under this category were found to be relatively resilient, in terms of, agricultural riskiness. Therefore, it is important to promote their 'good practices' (or risk reducing factors) to the other districts of the state. It is also important to monitor these districts, to prevent transition from a low risk to a high risk category. This may be ensured by promoting adoption of crop insurance, climate smart practices, easy access to credit facilities and so on.

5.2 Recommendations suggesting extension of the existing policies

Additionally, conserving natural vegetation is another great way of safeguarding agriculture from the changing climate. At present government schemes like – 'Aapda Mitra' has been implemented in the districts of Jorhat and Kamrup, to equip individuals with skills to respond to their community's need in the aftermath of disasters like – cyclones, floods, flash floods etc. (ASDMA, 2022). This can be extended to other districts, of the state. Schemes like – MGNREGA (Mahatma Gandhi National Rural Employment Guarantee Act), mission organic value chain development (a sub-mission under National Mission for Sustainable Agriculture) for North-East India, Pradhan Mantri Matsya Sampada Yojana (PMMSY), Assam Agri-business and Rural Transformation Project (APART), Mission for Integrated Development of Horticulture (under National Horticulture Mission) are some of the non-structural measures operational under the government of Assam. These schemes should be used for promoting livelihood diversification among the farmers of Assam. The total num-

ber of Krishi Vigyan Kendras operational in Assam is less, compared to the total number of districts, at present (Indian Council of Agricultural Research [ICAR], 2025). There is a need to establish additional extension service centres to cater to the needs of farmers, even in the remotest parts of Assam. Although, district wise Agricultural Contingency Plans (ACPs) exist for channelling district wise activities, but no plans are yet operational to tackle, agriculture specific risks and disasters. Therefore, it is important that, the state government initiate plans that have unified reporting format for information on agricultural risks (encompassing hazard, vulnerability, and exposure). The present contingency plans lack uniform format for reporting agriculture related data; mandating districts to follow uniformity in reporting, will better enable the government to look into key details under concern and carefully plan future initiatives. Further, inclusion of the proposed methodology (Entropy-Weighted-TOPSIS based on IPCC's AR5 Risk Framework) for agricultural risk assessment at the district level will better inform the policy makers and stakeholders about the specific sources, that are causing the agricultural risks, and assist in formulating targeted policies to address the same.

6 Conclusion

Among all the other, North-East Indian states, Assam was chosen for the study of agricultural risk scenario, as it lies at the heart of the mighty river, Brahmaputra. Owing to its unique topography, which includes – flood plains, valleys, and hills; the state is confronted with multiple hazardous events, annually. The hazards include – annual floods, soil and water erosion, land acidification, and storms etc. The economy of the state, is largely agrarian. A significant majority of the population, is directly, as well as indirectly, affected by the present socio-economic set-up, and environmental system. In this study, Entropy-Weighted-TOPSIS is used to construct an agricultural risk index, based on IPCC's latest risk framework, which defines risk as a product of interaction, between hazard, vulnerability, and exposure. Indices are developed for hazard, vulnerability, and exposure, considering 33 out of 35 districts of Assam. These indices were then combined, to derive a composite agricultural risk index. It was found that, the district of Dima Hasao is the highest hazard prone district and Udalguri is the least hazard prone district. Dibrugarh is the most vulnerable district, and Karbi Anglong is the least vulnerable district. Nagaon was found to be, highest agriculturally exposed and Chirang, was found to be lowest agriculturally exposed. Overall, the study found, Kamrup (R) and Udalguri to be the highest and lowest risk prone districts. District comparisons across the sub-agro-climatic zones reveals that, districts across all zones are agriculturally risk prone, although to a varying degree. Robustness for the obtained results were validated through, a weight sensitivity analysis and an external validation. The sensitivity analysis was conducted to check baseline rank stability across other weighting techniques. The results suggest, strong agreement among the final rankings. However, the external validation exercise revealed weak associations between the baseline metric and the external indicators. In addition, to this, the study generates visual outputs in the form of maps depicting risk, hazard, vulnerability, and exposure across the ACZs of Assam. These maps will be particularly useful for the disaster management authorities and concerned ministries to understand and build better strategies for the agricultural sector of Assam. This methodology is particularly resourceful as it assists in understanding the

risk scenario associated with the agricultural sector; and will assist in better management of risks and devise stronger adaptation strategies. The methodology can also be replicated for other states (or agro-climatic zones) of India and the world. This study also contributes to the enrichment of the existing risk literature. Also, new valuable insights were obtained regarding the intra-state agri-risk scenario, which will be of interest to the policy makers, academicians, and stakeholders.

While interpreting the results of this study, one is expected to take note of its several limitations, primarily arising due to lack of availability of systematically organised data. **First,** the datasets used for the study were obtained from government platforms, reports, and freely accessible documents; however, they are drawn from different time periods, and many of them are over a decade old. Wherever latest data were not available, we have used previous year's data points. **Second,** there has been increasing reports of droughts, landslides, seismic events, and forest fires across Assam, but dedicated databases for such hazards are not yet available, and therefore could not be incorporated into the analysis. **Third,** Assam currently comprises of 35 districts, but reliable data were only available for the erstwhile 33 districts. **Fourth,** outlier management was not undertaken in this study; as the objective was to retain the original variability present in the dataset. While outlier treatment may improve model stability, the choice of an appropriate outlier management technique is itself subjective and there is no universally accepted approach. **Fifth,** entropy determines weights for the indicators based on the degree of variation across the alternative. Therefore, indicators exhibiting higher variability receive greater weights, while indicators with relatively uniform distributions receive lower weights. Consequently, the method may overemphasize high-variance indicators and underemphasize conceptually important indicators with lower variation. **Sixth,** data on hazard indicators such as T-max and T-min were not readily available for all districts of Assam, as the India Meteorological Department (IMD) provides these data at a relatively coarse spatial resolution. Therefore, deviations from the long-period average (DLPA) for temperature variables were considered at the agro-climatic zone level, based on the data available for districts within each zone, rather than for individual district boundaries. Since, temperature observations were available only for few districts within each agro-climatic zone, values for neighbouring districts were adjusted using climatological similarity. Although every effort was made to ensure the accuracy of the extracted and processed data, the use of higher-resolution datasets or alternative extraction approaches may yield different results. In addition to this, the spatial resolution of the underlying climate datasets may not fully capture local topographic and microclimatic variations, particularly in districts where the geography is hilly and heterogeneous. Therefore, the results should be interpreted as district-level comparative assessments rather than representations of farm-level microclimatic conditions. Future studies may benefit from the use of higher-resolution climate datasets, where available. **Seventh,** the MADM (Multiple Attribute Decision Making) approach used for the study, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) although an ex-ante approach, requires data from past events to facilitate decision making and cannot be relied on to actually predict the future outcomes, in real time. Since, the agricultural sector of Assam is rapidly evolving along with the ever changing climate, the results obtained from this study cannot be claimed to be final and binding. **Eight,** uncertainty quantification would greatly strengthen MADM studies such as ours, but this is beyond the scope of this study. The indices in our study were constructed, with the motive of comparative analysis so, predictive power of the indices is limited.

Future works may incorporate uncertainty quantification of risk indices in their study using reliable district-level yield loss data, which was unavailable in our context. Future studies may also incorporate advance statistical tests like bootstrapping, Monte Carlo Simulations to ascertain the precision of the ranks and to report on whether there is any indistinguishable noise in the form of inter district (or region) differences. Future studies, may benefit by implementing this decision making strategy, for research at macro levels like – states, countries; or at micro levels like – villages, or rural development units. The approach of this study can also be reprogrammed or used for decision making or for study of the sectors which are relatively under explored like – organic farming, horticulture, and sericulture etc.

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Declarations

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