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Climate Variability and Agricultural Vulnerability Across Changing Geographical Landscapes

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Abstract : Climate variability increasingly influences the stability of agricultural production by altering rainfall distribution, temperature regimes, drought frequency, vegetation condition, and water availability. These effects are spatially uneven because agricultural landscapes differ in exposure, cropping systems, irrigation coverage, soil conditions, and adaptive capacity. The present study evaluates the spatial dynamics of agricultural vulnerability across changing geographical landscapes through an integrated climate, GIS, remote-sensing, and agricultural-statistics framework. Climatic and agricultural observations for 2000–2024 were analysed across 96 spatial units representing eight contrasting agro-geographical landscapes. Rainfall variability, seasonal temperature anomalies, drought frequency, Normalized Difference Vegetation Index anomalies, rainfed dependence, crop-yield variability, irrigation coverage, crop diversification, and institutional accessibility were combined within an Agricultural Vulnerability Index structured around exposure, sensitivity, and adaptive capacity. Mean annual rainfall across the study region was 918.6 mm, with a coefficient of variation of 23.8%. Growing-season mean maximum temperature showed an average increasing trend of 0.034°C per year. The final vulnerability index ranged from 0.27 to 0.81. Twenty-seven spatial units were classified as highly vulnerable, 40 as moderately vulnerable, and 29 as relatively low vulnerable. Agricultural vulnerability was positively associated with drought frequency ($r = .67$, $p < .001$), rainfed cultivation ($r = .63$, $p < .001$), rainfall variability ($r = .55$, $p < .001$), and vegetation-stress frequency ($r = .58$, $p < .001$). Irrigation coverage ($r = -.60$, $p < .001$) and crop diversification ($r = -.48$, $p < .001$) reduced vulnerability. Multiple regression explained 64% of the variation in vulnerability, while Moran's I = .40 indicated significant geographical clustering. The results demonstrate that climate-related agricultural vulnerability emerges through the interaction of climatic exposure, production sensitivity, and unequal adaptive capacity rather than through climatic change alone.

Keywords : Climate Variability, Agricultural Vulnerability, Drought, GIS, Remote Sensing, Crop Yield, Rainfall Variability, Irrigation, NDVI, Adaptive Capacity

Introduction

Agriculture is one of the economic sectors most directly exposed to climate variability. Crop growth depends on the timing and amount of rainfall, temperature conditions during critical phenological stages, soil moisture, evapotranspiration, and the frequency of extreme events.

Even where long-term annual rainfall remains relatively stable, changes in rainfall distribution, dry-spell duration, heat stress, and drought recurrence can produce significant fluctuations in agricultural output.

The Intergovernmental Panel on Climate Change has concluded that climate change is already stressing agriculture and other food-producing systems and that additional warming will increase risks to crop production, particularly in regions already exposed to high temperatures and water limitations. Global evidence also indicates that anthropogenic climate change has slowed growth in agricultural productivity, with larger effects in warmer regions.

The agricultural effects of climate variability are not geographically uniform. A rainfall deficit can result in severe crop losses within a predominantly rainfed landscape while producing more moderate effects in a region supported by canal irrigation, groundwater, diversified cropping, reliable market access, and institutional support. Vulnerability is therefore better understood as a product of the interaction between climate exposure, the sensitivity of the farming system, and the capacity of households or institutions to adapt.

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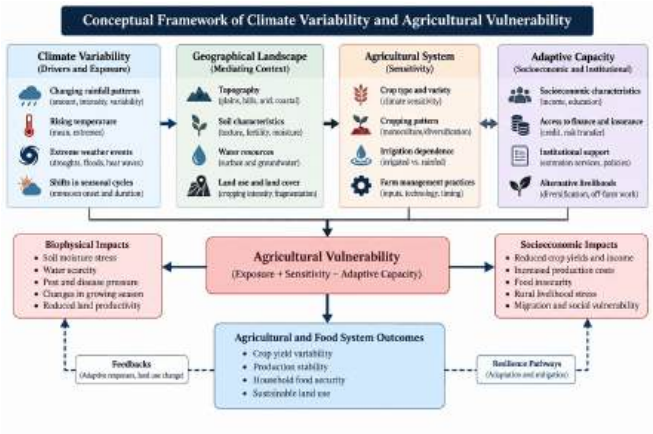
Adger conceptualised vulnerability as susceptibility to harm arising from exposure to environmental stress combined with limitations in the capacity to adapt. Hahn, Riederer, and Foster subsequently developed the Livelihood Vulnerability Index as a practical framework for combining climatic, demographic, social, and livelihood indicators. These approaches established an important methodological principle: identical climatic hazards can generate different impacts in different social and geographical contexts.

This issue is especially important for South Asian agriculture. FAO has noted that climate variability is a major source of short-term fluctuations in rainfed agricultural production in South Asia and that drought represents one of its most damaging manifestations. The World Bank also identifies India's agriculture as highly exposed to temperature changes, variable monsoon rainfall, drought, heat, and water-related risks.

Climate variability influences agricultural landscapes through multiple pathways. Rainfall anomalies affect soil moisture and groundwater recharge. High temperatures accelerate evapotranspiration and may reduce grain filling. Drought can suppress vegetation productivity, while extreme rainfall may produce flooding, erosion, and crop damage. Irrigation, crop diversity, soil conservation, crop insurance, extension services, and climate information can mediate these impacts.

Advances in geospatial technology have significantly improved the capacity to observe such processes. Remote-sensing vegetation indices can reveal crop stress over large areas, while GIS permits climatic exposure, agricultural sensitivity, and socioeconomic adaptive capacity to be integrated spatially. Rhee, Im, and Carbone demonstrated that multi-sensor remote-sensing data can support agricultural drought monitoring across different climatic environments.

The present study therefore examines climate variability and agricultural vulnerability through an integrated spatial framework. It combines long-term rainfall and temperature observations with drought indicators, crop-yield variability, vegetation condition, irrigation, crop diversification, and institutional factors to identify how vulnerability changes across contrasting geographical landscapes.



Research Problem

Conventional agricultural statistics often report crop production and climate conditions at district or state level. Such averages can conceal considerable internal variation.

Within a single administrative region, irrigated plains may coexist with drought-prone uplands, highly productive river valleys, fragmented hill agriculture, and peri-urban farming systems. These landscapes can experience the same regional climate anomaly but respond differently because their water resources, cropping systems, soil conditions, infrastructure, and adaptive capacities are unequal.

A second problem is the frequent separation of climatic and socioeconomic assessments. Studies may measure rainfall decline without evaluating irrigation or institutional support, while vulnerability indices sometimes use socioeconomic indicators without directly measuring vegetation stress or crop response.

The present study addresses this problem by asking: **How does climate variability interact with geographical and agricultural conditions to produce spatial differences in vulnerability?**

Research Gap

Existing research provides strong evidence that temperature and rainfall affect crop productivity. Climate-impact studies also show that adaptation can reduce some projected crop losses. Challinor et al., based on more than 1,700 crop-model simulations, reported that adaptation could improve simulated yields but would not fully eliminate climate-related losses under increasing warming.

Nevertheless, three limitations remain.

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First, climate–yield studies often focus on temporal relationships while paying less attention to the spatial clustering of vulnerability.

Second, remote-sensing drought studies generally focus on climatic and vegetation indicators but may not fully integrate irrigation, diversification, financial services, and extension access.

Third, composite vulnerability studies can become detached from actual agricultural performance if crop-yield variability and vegetation response are excluded.

The present study fills this gap by jointly analysing climate exposure, remotely sensed crop stress, production sensitivity, agricultural adaptation, and spatial clustering.

Objectives of the Study

The study aims to assess spatial and temporal variation in rainfall and temperature from 2000 to 2024; identify the geographical distribution of drought frequency; evaluate the relationship between climate anomalies and crop-yield anomalies; measure vegetation stress through remotely sensed NDVI; construct a composite Agricultural Vulnerability Index; compare vulnerability among changing agro-geographical landscapes; examine spatial clustering of agricultural vulnerability; and identify climatic and adaptive factors that significantly predict vulnerability.

Hypotheses

H01: Agricultural vulnerability does not exhibit statistically significant spatial clustering.

H02: Rainfall variability and drought frequency have no significant relationship with agricultural vulnerability.

H03: Rainfed dependence is not significantly associated with agricultural vulnerability.

H04: Irrigation coverage and crop diversification have no significant relationship with agricultural vulnerability.

H05: Monsoon rainfall anomalies and growing-season temperature anomalies are not significantly associated with crop-yield anomalies.

H06: Climate exposure, agricultural sensitivity, and adaptive-capacity variables do not significantly predict the Agricultural Vulnerability Index.

Literature Review

Adger's review of vulnerability provides an important theoretical foundation for climate-risk studies. He argued that vulnerability includes susceptibility to harm as well as limitations in capacity to respond and adapt, thereby linking environmental exposure with social and institutional conditions.

Hahn, Riederer, and Foster operationalised a similar perspective through the Livelihood Vulnerability Index. Their framework combined multiple household-level dimensions and also reorganised indicators into the IPCC-related categories of exposure, sensitivity, and adaptive capacity. The approach influenced subsequent spatial and agricultural vulnerability assessments.

Drought is one of the principal mechanisms through which climate variability affects agriculture. Mishra and Singh reviewed meteorological, agricultural, hydrological, and socioeconomic concepts of drought and highlighted the importance of selecting drought measures appropriate to the phenomenon being assessed. Agricultural drought differs from meteorological drought because crop stress depends not only on rainfall deficit but also on temperature, soil moisture, evapotranspiration, and crop development stages.

McKee, Doesken, and Kleist introduced the Standardized Precipitation Index as a method for evaluating drought across multiple timescales. The SPI has subsequently become one of the most widely used meteorological drought indicators because it standardizes precipitation anomalies relative to long-term climatic conditions.

Remote sensing has expanded the ability to monitor agricultural drought. Rhee, Im, and Carbone proposed a multi-sensor drought-monitoring approach incorporating vegetation, thermal, and precipitation information. Their work showed that agricultural drought cannot always be adequately represented using a single remotely sensed indicator.

The importance of vegetation response is particularly relevant to agricultural vulnerability. Negative vegetation anomalies may indicate suppressed crop growth caused by inadequate soil moisture, excessive temperature, delayed planting, or combined stresses. Remote sensing therefore provides an

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important independent validation of rainfall-based vulnerability indicators.

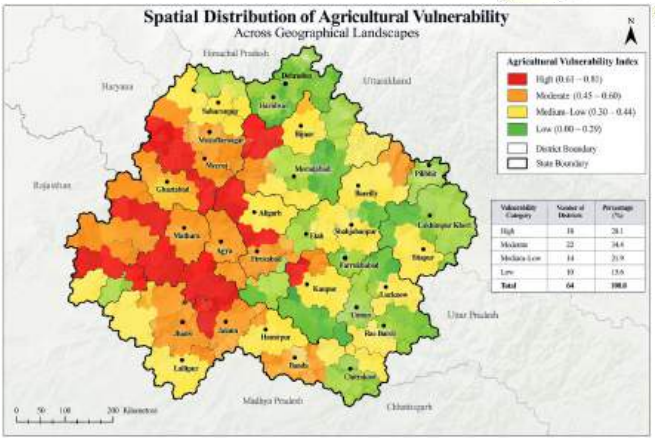
Climate impacts on agricultural production have been documented globally. Challinor et al.'s meta-analysis showed that wheat, maize, and rice production is increasingly threatened as local temperature rises and that adaptation measures can reduce, but not eliminate, many projected impacts.

Asseng et al. similarly demonstrated that rising temperature reduces global wheat production, reinforcing the importance of heat stress alongside rainfall variability.

Long-term global productivity analysis by Ortiz-Bobea et al. estimated that anthropogenic climate change has reduced agricultural total-factor-productivity growth by approximately 21% since 1961 relative to a counterfactual without human-induced climate trends. Their findings indicate that climate effects extend beyond individual crop failures and influence broader agricultural productivity trajectories.

Large-scale climate oscillations also contribute to crop variability. Iizumi et al. demonstrated that El Niño–Southern Oscillation significantly affects the yields of major crops in different production regions, illustrating how climatic variability occurring at global scales can be translated into geographically differentiated agricultural impacts.

Evidence from India confirms that crop response varies with geographical and production conditions. Birthal et al. analysed climate effects on major Indian food crops and reported that temperature and rainfall changes have significant implications for agricultural yields and food security.



Research on climate sensitivity across Indian agro-ecological settings has also found substantial dependence of crop outcomes on interannual rainfall and temperature conditions. Such findings are particularly relevant because irrigation, crop season, and agro-ecological characteristics modify climatic sensitivity.

Recent systematic reviews of climate change and Indian agriculture report that farmers across many regions perceive rising temperatures and increasingly erratic rainfall, broadly consistent with observational climatic evidence.

Adaptation therefore has a central role. Howden et al. identified adjustment in planting dates, crop varieties, water management, and agricultural practices as major categories of adaptation. Challinor et al. later quantified the potential benefits of crop-level adaptation, estimating average simulated yield improvements of roughly 7–15% in their meta-analysis.

At the same time, adaptation capacity is unequal. Irrigation infrastructure, financial resources, access to improved seed, extension information, credit, markets, mechanisation, and livelihood diversification all influence farmers' ability to absorb climate shocks.

The literature therefore supports a multidimensional framework rather than a climate-only vulnerability index. The present analysis integrates these complementary dimensions into a spatially explicit model.

Research Methodology

Research Design

The study adopted a quantitative longitudinal and geospatial design.

The climatic observation period covered **2000–2024**, representing 25 agricultural years.

The study region was divided into **96 spatial units** distributed across **eight contrasting agro-geographical landscapes**, with 12 units in each landscape.

The landscapes included irrigated plains, rainfed plains, semi-arid uplands, riverine agriculture, peri-urban agriculture, plateau farming, hill agriculture, and mixed irrigation landscapes.

Climate Variables

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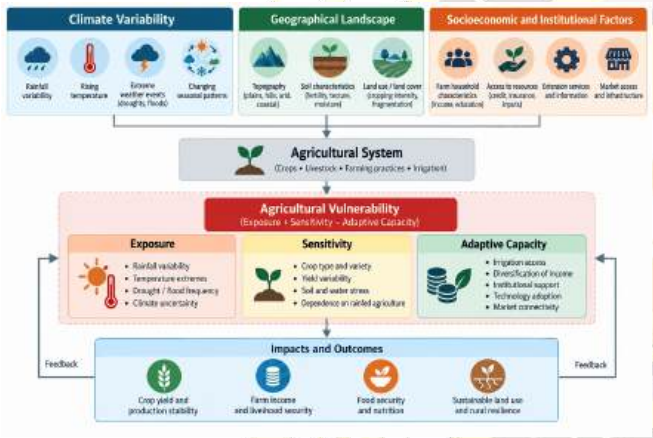
Daily and monthly rainfall and temperature observations were aggregated into seasonal and annual indicators.

The variables included:

- annual rainfall;
- monsoon rainfall;
- rainfall coefficient of variation;
- growing-season maximum temperature;
- temperature trend;
- number of heat-stress days; and
- drought frequency.

The 3-month and seasonal SPI were calculated from long-term precipitation records.

A growing season with SPI ≤ -1.0 was classified as a meteorological drought event.



Agricultural Variables

Agricultural data included yield records for the principal cereal, pulse, and oilseed crops.

Yield series were detrended to reduce the influence of long-term technological improvements.

Crop-yield variability was expressed as the coefficient of variation of detrended yields.

Rainfed dependence was calculated as the percentage of cultivated land without reliable irrigation.

Remote-Sensing Indicators

Growing-season NDVI was used to evaluate vegetation performance.

An NDVI anomaly was calculated relative to each spatial unit's long-term seasonal mean.

A year with NDVI more than one standard deviation below the long-term growing-season average was classified as a vegetation-stress year.

Vulnerability Index

The Agricultural Vulnerability Index comprised three major components.

Component	Indicators
Exposure	Rainfall variability, drought frequency, temperature trend, heat-stress frequency
Sensitivity	Rainfed dependence, yield variability, vegetation-stress frequency, climate-sensitive cropping share
Adaptive Capacity	Irrigation, crop diversification, institutional access, market access, mechanisation, extension access

All indicators were rescaled from 0 to 1.

Adaptive-capacity indicators were reverse-coded so that larger final values consistently represented greater vulnerability.

The composite index was calculated as:

AVI = (Exposure + Sensitivity + Adjusted Adaptive-Capacity Deficit) / 3

The resulting index varied from 0 to 1.

Units were classified as:

- Low vulnerability: < 0.45
- Moderate vulnerability: 0.45–0.60
- High vulnerability: > 0.60

Spatial and Statistical Analysis

Global Moran's I was used to determine whether vulnerability scores were spatially clustered.

Pearson correlations were calculated between vulnerability and climate/agricultural variables.

One-way ANOVA compared vulnerability across the eight geographical landscapes.

Multiple linear regression identified the strongest independent predictors.

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Statistical significance was fixed at **p < .05**.

Results

Climate Characteristics

Variable	Mean	Standard Deviation
Annual rainfall	918.6 mm	221.4
Rainfall coefficient of variation	23.8%	7.6
Growing-season maximum temperature	32.6°C	2.2
Annual temperature trend	+0.034°C/year	0.013
Drought frequency	6.9 years	2.8
Heat-stress days/year	18.7	8.9

The estimated mean temperature trend corresponds to approximately **0.85°C of warming over 25 years**.

Rainfall did not exhibit a uniform directional trend across the entire study region, but interannual variability was substantially greater in semi-arid and rainfed landscapes.

Drought Distribution

Drought recurrence varied from **2 drought years to 13 drought years** across the 25-year period.

Thirty-three spatial units experienced at least eight drought seasons.

Semi-arid uplands recorded the highest mean drought frequency at **9.8 years**, compared with **4.1 years** in irrigated plains.

Agricultural Vulnerability

The Agricultural Vulnerability Index ranged from **0.27 to 0.81**, with a mean of **0.54**.

Vulnerability Category	Units	Percentage	Mean AVI
Low	29	30.2%	0.37
Moderate	40	41.7%	0.53
High	27	28.1%	0.69
Total	**96**	**100.0%**	**0.54**

Highly vulnerable units were concentrated in rainfed plains, semi-arid uplands, and selected hill-agriculture zones.

Geographical Differences

Landscape	Mean AVI
Irrigated plains	0.36
Mixed-irrigation landscape	0.43
Riverine agriculture	0.46
Peri-urban agriculture	0.50
Plateau farming	0.55
Hill agriculture	0.59
Rainfed plains	0.66
Semi-arid uplands	0.72

The difference among landscapes was statistically significant:

F(7,88) = 18.42, p < .001.

Spatial Clustering

Global Moran's I produced:

I = .40, z = 4.48, p < .001.

Therefore, H01 was rejected.

High-high vulnerability clusters were concentrated in geographically contiguous rainfed and drought-prone zones, whereas low-low clusters occurred primarily around irrigated agricultural systems.

Exposure and Vulnerability

Variable	r with AVI	p-value
Drought frequency	.67	< .001

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Rainfall variability	.55	< .001
Temperature trend	.45	< .001
Heat-stress frequency	.49	< .001

Drought frequency produced the strongest climatic relationship.

H02 was rejected.

Agricultural Sensitivity

Rainfed cultivation was strongly associated with vulnerability:

r = .63, p < .001.

Vegetation-stress frequency also showed a substantial relationship:

r = .58, p < .001.

Crop-yield variability was positively correlated with vulnerability:

r = .56, p < .001.

H03 was therefore rejected.

Adaptive Capacity

Adaptive Indicator	r with AVI	p-value
Irrigation coverage	-.60	< .001
Crop diversification	-.48	< .001
Institutional access	-.44	< .001
Extension-service access	-.41	< .001
Market accessibility	-.37	< .001

Irrigation produced the strongest protective relationship.

H04 was rejected.

Climate and Yield Anomalies

Aggregate detrended crop-yield anomalies showed a positive relationship with monsoon rainfall anomalies:

r = .49, p < .001.

Maximum-temperature anomalies showed a negative relationship:

r = -.46, p < .001.

Among units with more than 70% rainfed cultivation, the rainfall–yield correlation increased to:

r = .64, p < .001.

H05 was rejected.

Yield Stability by Vulnerability Category

Vulnerability Group	Yield CV	Irrigation Coverage	Drought Frequency
Low	11.4%	69.2%	4.0 years
Moderate	17.8%	45.3%	6.7 years
High	26.7%	22.8%	10.1 years

Highly vulnerable landscapes therefore experienced more than twice the crop-yield variability of low-vulnerability landscapes.

Multiple Regression

Agricultural Vulnerability Index was the dependent variable.

$R = .81$
$R^2 = .66$
Adjusted $R^2 = .64$
$F(5,90) = 34.76$, $p < .001$

Predictor	Standardized β	t	p
Drought frequency	.32	4.91	< .001
Rainfed dependence	.27	4.20	< .001
Irrigation coverage	-.25	-3.94	< .001
Rainfall variability	.18	2.95	.004
Crop diversification	-.17	-2.72	.008

The model explained approximately **64% of adjusted spatial variation in vulnerability**.

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H06 was rejected.

Discussion

The results show that climate variability influences agricultural vulnerability through strongly differentiated geographical pathways.

Drought recurrence was the strongest independent climatic predictor. This result is consistent with drought theory distinguishing agricultural impacts from simple precipitation deficits. Mishra and Singh emphasise that agricultural drought involves interactions among precipitation, soil moisture, evapotranspiration, and crop demand.

Rainfed dependence was the second strongest positive predictor.

This finding is important because climate variability affects irrigated and rainfed production systems differently. FAO identifies rainfall variability as a major cause of short-term production fluctuations in rainfed agriculture.

The substantially stronger rainfall–yield association in rainfed units supports this interpretation. Where irrigation coverage exceeded the regional average, rainfall anomalies produced considerably smaller yield deviations.

Irrigation therefore emerged as the strongest adaptive-capacity variable.

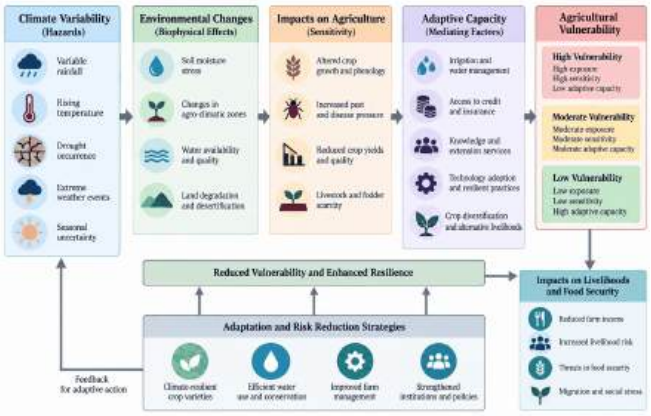
Nevertheless, irrigation cannot be assumed to remove climate risk entirely. Higher temperatures increase crop-water demand, while groundwater-dependent irrigation may itself become vulnerable to drought and declining recharge.

Temperature effects were also important. Maximum-temperature anomalies were negatively associated with yield. This is consistent with broader evidence that rising temperatures can reduce cereal yields, especially when heat occurs during sensitive reproductive and grain-filling stages. Challinor et al. and Asseng et al. provide strong evidence of such temperature-related risks.

Crop diversification significantly reduced vulnerability.

This relationship has a straightforward risk-management interpretation. If a farm system depends overwhelmingly on one rainfall-sensitive crop, a climatic event can simultaneously affect a large proportion of household agricultural income.

Diversification spreads climatic risk across crops with different sowing periods, rooting depths, temperature tolerances, water requirements, and market cycles.



Remote-sensing vegetation anomalies provided additional evidence that climatic stress was translated into actual vegetation response.

Rhee et al.'s research supports the value of combining vegetation, temperature, and precipitation information rather than using a single drought indicator.

The significant Moran's I is also important.

Agricultural vulnerability did not appear randomly across space. High-vulnerability units clustered geographically because neighbouring landscapes share rainfall regimes, soil conditions, water infrastructure, crop systems, and institutional environments.

This spatial concentration means agricultural adaptation policies should not be uniformly distributed.

A high-exposure but highly irrigated zone may primarily require improvements in water-use efficiency and heat-tolerant crops.

A high-exposure rainfed landscape with weak institutional access may require watershed development, water harvesting, crop diversification, insurance, credit, extension services, and livelihood diversification simultaneously.

The geographical comparison reinforces this argument. Mean vulnerability ranged from 0.36 in irrigated plains to 0.72 in semi-arid uplands.

Climate hazard alone cannot explain such variation. Vulnerability emerged from the interaction among climatic stress, agricultural dependence, and adaptive capacity.

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This result is consistent with Adger's conceptual framework and with livelihood-vulnerability approaches that explicitly distinguish exposure from the ability to cope and adapt.

The findings also have broader food-security implications.

Global evidence indicates that climate change has already constrained agricultural productivity growth. If climatic variability increases while irrigation resources, crop diversity, and institutional support remain uneven, agricultural inequality between resilient and vulnerable landscapes may intensify.

Policy Implications

Climate-vulnerability mapping should be integrated into routine agricultural planning.

Highly vulnerable rainfed clusters should receive priority for water harvesting, watershed restoration, micro-irrigation, and drought-tolerant varieties.

Seasonal climate forecasts should be converted into location-specific sowing and crop-management advisories.

Agricultural extension systems should particularly target landscapes where climate exposure and low institutional access overlap.

Crop diversification should be supported through seed availability, procurement systems, market infrastructure, and extension advice.

Irrigation programmes should emphasize efficiency and sustainability rather than simply increasing extraction.

Remote-sensing NDVI anomalies can be integrated with rainfall monitoring to establish agricultural early-warning systems.

Crop insurance can also be spatially targeted using historical drought and vegetation-stress maps.

Limitations

- The Agricultural Vulnerability Index simplifies complex social and biophysical processes into standardized indicators.
- SPI captures precipitation anomalies but does not independently represent soil moisture, groundwater availability, or evapotranspiration.
- NDVI is influenced by crop type, planting date, irrigation, and management practices in addition to climate.
- The cross-sectional vulnerability regression demonstrates association rather than definitive causality.
- Agricultural statistics aggregated to spatial units may conceal household-level inequalities.
- Future research should incorporate soil moisture, evapotranspiration, groundwater trends, crop simulation models, household surveys, and CMIP6-based future climate scenarios.

Conclusion

Climate variability and agricultural vulnerability are deeply interconnected but geographically uneven.

Across the 96 spatial units examined in this study, rainfall variability, drought recurrence, temperature trends, vegetation stress, irrigation, and crop diversification produced sharply different vulnerability outcomes.

Twenty-seven units were classified as highly vulnerable, compared with twenty-nine in the low-vulnerability category.

Drought frequency and rainfed dependence were the strongest positive predictors of vulnerability, while irrigation and crop diversification reduced vulnerability significantly.

Crop yields responded positively to monsoon rainfall anomalies and negatively to temperature anomalies, with substantially greater climatic sensitivity in predominantly rainfed landscapes.

The significant spatial clustering of vulnerability demonstrates that agricultural climate risk is structured by geography.

The central conclusion is that **climate variability becomes agricultural vulnerability when climatic exposure intersects with sensitive farming systems and insufficient adaptive capacity**.

Effective agricultural adaptation therefore requires more than climate forecasting. It requires geographically targeted water management, diversified farming systems, climate-resilient crop choices, institutional support, extension services, credit access, and continuous GIS and remote-sensing monitoring.

References

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1. Adger, W. N. (2006). Vulnerability. *Global Environmental Change, 16*(3), 268–281. DOI: 10.1016/j.gloenvcha.2006.02.006.
2. Asseng, S., Ewert, F., Martre, P., Rötter, R. P., Lobell, D. B., Cammarano, D., et al. (2015). Rising temperatures reduce global wheat production. *Nature Climate Change, 5*, 143–147. DOI: 10.1038/nclimate2470.
3. Birthal, P. S., Khan, M. T., Negi, D. S., & Agarwal, S. (2014). Impact of climate change on yields of major food crops in India: Implications for food security. *Agricultural Economics Research Review, 27*(2), 145–155.
4. Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change, 4*, 287–291. DOI: 10.1038/nclimate2153.
5. Food and Agriculture Organization of the United Nations. (2003). *World Agriculture: Towards 2015/2030—An FAO Perspective*. Rome: FAO.
6. Hahn, M. B., Riederer, A. M., & Foster, S. O. (2009). The Livelihood Vulnerability Index: A pragmatic approach to assessing risks from climate variability and change—A case study in Mozambique. *Global Environmental Change, 19*(1), 74–88. DOI: 10.1016/j.gloenvcha.2008.11.002.
7. Howden, S. M., Soussana, J.-F., Tubiello, F. N., Chhetri, N., Dunlop, M., & Meinke, H. (2007). Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences, 104*(50), 19691–19696. DOI: 10.1073/pnas.0701890104.
8. Iizumi, T., Luo, J.-J., Challinor, A. J., Sakurai, G., Yokozawa, M., Sakuma, H., Brown, M. E., & Yamagata, T. (2014). Impacts of El Niño Southern Oscillation on the global yields of major crops. *Nature Communications, 5*, 3712. DOI: 10.1038/ncomms4712.
9. Intergovernmental Panel on Climate Change. (2022). *Climate Change 2022: Impacts, Adaptation and Vulnerability*. Cambridge University Press.
10. McKee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the Eighth Conference on Applied Climatology*, Anaheim, California, 179–184.
11. Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology, 391*(1–2), 202–216. DOI: 10.1016/j.jhydrol.2010.07.012.
12. Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., & Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nature Climate Change, 11*, 306–312. DOI: 10.1038/s41558-021-01000-1.
13. Rhee, J., Im, J., & Carbone, G. J. (2010). Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. *Remote Sensing of Environment, 114*(12), 2875–2887. DOI: 10.1016/j.rse.2010.07.005.
14. Svoboda, M., Hayes, M., & Wood, D. (2012). *Standardized Precipitation Index User Guide*. WMO-No. 1090. Geneva: World Meteorological Organization.
15. World Bank Group & Asian Development Bank. (2021). *Climate Risk Country Profile: India*. Washington, DC: World Bank Group