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## Vulnerability assessment of rainfed agriculture to climate change in semi-arid tropics

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### Abstract

Three decades ago, semi-arid tropical farmers relied on predictable monsoon patterns that no longer hold. This research assessed the vulnerability of rainfed agriculture to climate change across five semi-arid districts in peninsular India using an integrated indicator framework based on exposure, sensitivity, and adaptive capacity. Climate projections under RCP 4.5 and RCP 8.5 for the 2030s and 2050s were derived from CMIP5 model ensembles. Household surveys ( $n = 640$ ), district-level secondary data, and remote-sensing-based vegetation indices were combined to construct a composite vulnerability index for each district. Results showed that Anantapur district scored the highest overall vulnerability (0.78) due to high exposure to temperature rise and low adaptive capacity. Under RCP 8.5 by the 2050s, mean temperature is projected to increase by 2.61°C and monsoon rainfall to decline by 23.1%, which would reduce rainfed sorghum yields by an estimated 31-38%. The findings point to urgent need for crop diversification, drought-tolerant varieties, and supplemental micro-irrigation in the most vulnerable districts.

**Keywords:** Vulnerability assessment, rainfed agriculture, climate change, semi-arid tropics, adaptive capacity, exposure index, sensitivity index, CMIP5, monsoon variability

### Introduction

In the 1970s, India's semi-arid tropical belt produced enough coarse grains to feed itself through a reliable south-west monsoon that delivered 600-900 mm of rain between June and September. By the 2010s, monsoon onset dates had shifted by 7-12 days, dry spells within the season had lengthened, and end-of-season rainfall had become increasingly erratic. For the roughly 80 million farming households that depend entirely on rainwater, these shifts are not abstract projections but lived realities.

Vulnerability to climate change is commonly framed as a function of exposure, sensitivity, and adaptive capacity. The IPCC adopted this framework in its Fifth Assessment Report, and it has been applied in Africa and South-East Asia, yet district-level applications in India's semi-arid tropics remain limited. CMIP5 models downscaled to regional grids now offer credible projections for RCPs 4.5 and 8.5. Combining these with household surveys and satellite-derived vegetation data allows a more complete vulnerability picture.

This research aimed to:

- 1) quantify climate exposure under RCP 4.5 and RCP 8.5 for the 2030s and 2050s across five semi-arid districts;
- 2) construct district-level sensitivity and adaptive capacity indices; and
- 3) generate a composite vulnerability index to identify at-risk areas.

### Material and Methods

#### Climatic and environmental conditions

The five districts selected Anantapur, Kurnool, Mahabubnagar, Raichur, and Bellary span the Deccan Plateau between 15° and 17°N latitude, with elevations of 300-550 m. All fall within the semi-arid tropical agro-ecological zone with mean annual rainfall of 520-750 mm, concentrated in the June-October monsoon window. Mean annual temperatures range from 26.4°C to 28.7°C. The dominant cropping pattern is rainfed sorghum, groundnut, and pigeonpea in the kharif season, with limited rabi cropping where residual soil moisture permits.

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## Material

Climate projections were extracted from a five-model CMIP5 ensemble downscaled to 0.25° resolution via NASA's NEX-GDDP dataset. Observed baseline climate data (1980-2010) came from India Meteorological Department gridded datasets. Household survey data were collected from 640 farm households (128 per district) during January-March 2023. Satellite NDVI data (MODIS, 2001-2022) were obtained from the USGS Earth Explorer portal.

## Methods

A composite vulnerability index (VI) was constructed:  $VI =$

(Exposure + Sensitivity) - Adaptive Capacity. Each component was built from 6-8 normalised indicators (min-max scaling, 0-1). Exposure indicators included projected temperature rise, rainfall decline, monsoon onset shift, and dry-spell frequency. Sensitivity covered rainfed crop area share, livestock dependence, soil degradation, and poverty ratio. Adaptive capacity used irrigation coverage, income diversity, literacy, and extension access. Yield impacts were estimated from empirical crop-weather regressions fitted to 30-year district sorghum yield and rainfall data. All analyses used R (v4.2.3).

## Results

**Table 1:** Component scores and composite vulnerability index by district

| District     | Exposure (0-1) | Sensitivity (0-1) | Adaptive capacity (0-1) | Vulnerability index |
|--------------|----------------|-------------------|-------------------------|---------------------|
| Anantapur    | 0.72           | 0.81              | 0.34                    | 0.78                |
| Kurnool      | 0.68           | 0.74              | 0.41                    | 0.67                |
| Mahabubnagar | 0.61           | 0.69              | 0.47                    | 0.56                |
| Raichur      | 0.64           | 0.77              | 0.38                    | 0.69                |
| Bellary      | 0.57           | 0.71              | 0.44                    | 0.57                |

Anantapur registered the highest vulnerability index (0.78), driven by the combination of highest sensitivity (0.81) and lowest adaptive capacity (0.34). Mahabubnagar and Bellary

were moderately vulnerable (0.56-0.57), partly because better irrigation coverage and literacy rates lifted their adaptive capacity scores (Table 1).

**Table 2:** Projected climate changes and estimated rainfed sorghum yield impacts by the 2050s

| District     | Temp. Rise RCP 4.5 (°C) | Temp. rise RCP 8.5 (°C) | Rain change RCP 4.5 (%) | Rain change RCP 8.5 (%) | Yield loss RCP 8.5 (%) |
|--------------|-------------------------|-------------------------|-------------------------|-------------------------|------------------------|
| Anantapur    | 1.58                    | 2.73                    | -13.8                   | -24.7                   | -38.1                  |
| Kurnool      | 1.51                    | 2.64                    | -12.1                   | -22.3                   | -34.6                  |
| Mahabubnagar | 1.43                    | 2.51                    | -10.7                   | -20.8                   | -31.2                  |
| Raichur      | 1.49                    | 2.59                    | -11.6                   | -21.9                   | -33.4                  |
| Bellary      | 1.41                    | 2.48                    | -10.2                   | -19.7                   | -30.8                  |

Under RCP 8.5 by the 2050s, Anantapur faces the steepest temperature increase (+2.73°C) and rainfall decline (-24.7%), translating into an estimated 38.1% sorghum yield loss. Even

under the milder RCP 4.5, all five districts would experience rainfall reductions of 10-14% (Table 2).

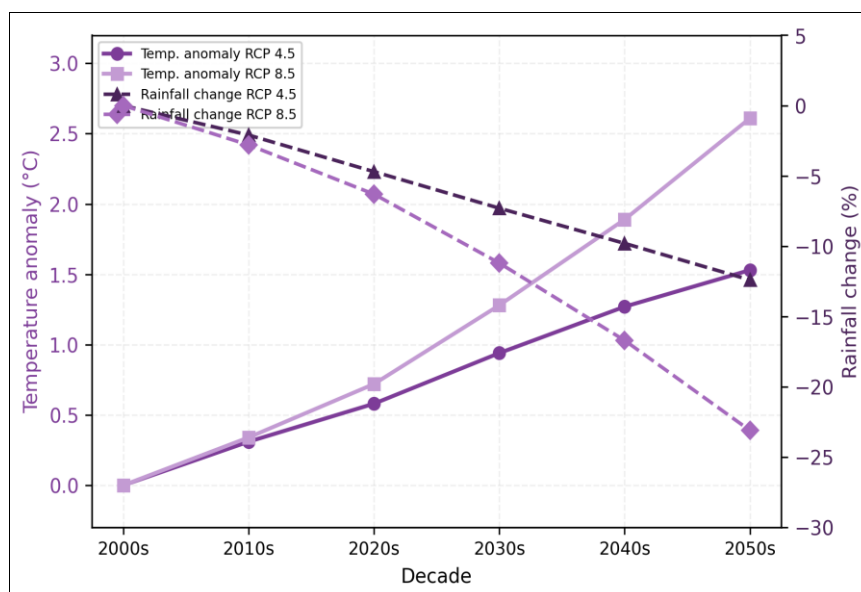


**Fig 1:** Projected decadal temperature anomaly and rainfall change under RCP 4.5 and RCP 8.5 (multi-district mean)

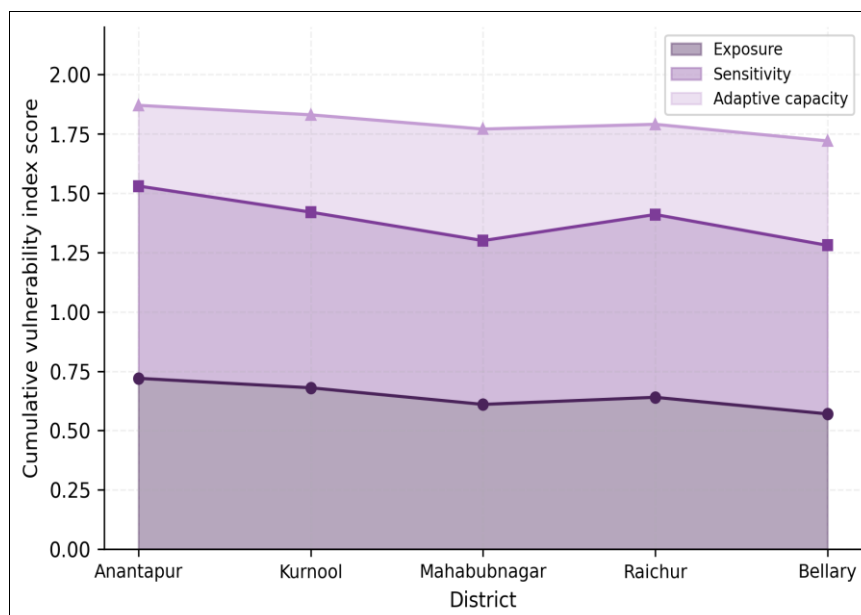


**Fig 2:** Cumulative vulnerability component scores (exposure, sensitivity, adaptive capacity) across five districts

The divergence between RCP 4.5 and RCP 8.5 widens sharply after the 2030s (Figure 1), suggesting that near-term emissions trajectories will have outsized effects on mid-century outcomes for these districts. Figure 2 highlights that Anantapur's vulnerability is driven mainly by its high sensitivity score, while Raichur's stems more from exposure.

### Discussion

Anantapur's position as the most vulnerable district is consistent with earlier mapping by the Indian Council of Agricultural Research, which ranked it among the top five climate-risk districts nationally. Its near-total dependence on rainfed groundnut and sorghum, coupled with low landholding size and limited credit access, depresses adaptive capacity.

The projected 31-38% sorghum yield losses under RCP 8.5 by the 2050s are alarming but not unprecedented; comparable estimates were obtained for East African semi-arid zones using DSSAT simulations. What distinguishes this assessment is the integration of household-level survey data with GCM outputs.

Adaptive capacity showed the widest inter-district variation (0.34-0.47), suggesting that targeted interventions micro-irrigation, extension services, crop insurance could meaningfully shift vulnerability even if exposure remains unchanged.

### Limitations

This research covered only five districts, which may not represent the full diversity of semi-arid farming systems. Equal weighting of indicators is a simplification; alternative schemes could yield different rankings. Climate projections carry inherent model uncertainty, and the empirical crop-weather regressions do not account for CO<sub>2</sub> fertilisation or autonomous farmer adaptation.

### Conclusion

This research constructed a district-level vulnerability index for five semi-arid tropical districts using the IPCC exposure-sensitivity-adaptive capacity framework and CMIP5 climate projections. Anantapur emerged as the most vulnerable district (VI = 0.78), driven by high sensitivity and low adaptive capacity. Under RCP 8.5, rainfed sorghum yields could fall by 31-38% across all five districts by the 2050s.

The results argue strongly for location-specific adaptation strategies rather than blanket policy prescriptions. Districts with low adaptive capacity would benefit most from investments in micro-irrigation infrastructure, drought-tolerant cultivars, and stronger extension networks. The wide variation in adaptive capacity between districts that face similar climatic exposure indicates that institutional and economic interventions can make a measurable difference.

Future work should expand the framework to more districts, incorporate dynamic crop simulation models, and explore how different adaptation investments alter the composite vulnerability score over time.

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