



International Journal of Research in Agronomy

E-ISSN: 2618-0618

P-ISSN: 2618-060X

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www.agronomyjournals.com

2024; 7(6): 117-119

Received: 01-04-2024

Accepted: 05-05-2024

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Spatiotemporal analysis of aridity index and its relationship with crop productivity trends

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DOI: <https://doi.org/10.33545/2618060X.2024.v7.i6b.5040>

Abstract

While global crop production has risen 40% since 1990, aridity-driven losses have offset an estimated one-fifth of those gains in dryland regions. This research analysed the UNEP aridity index (P/PET) across the North China Plain (1990-2020) and its relationship with wheat, maize, and rice yield anomalies using CRU TS 4.06 climate data at 0.5° resolution. Arid plus hyper-arid area expanded from 23.6% to 28.9%. Yield anomaly correlated quadratically with AI ($R^2 = 0.78-0.84$), peaking at AI = 0.65-0.70. Counties with AI decline > 0.05 per decade showed 12-18% lower yield trends. These results quantify the productivity cost of aridification in a major global breadbasket.

Keywords: Aridity index, crop productivity, north china plain, spatiotemporal analysis, dryland agriculture, climate change, penman-monteith, yield anomaly

Introduction

The North China Plain produces roughly 60% of China's wheat and 35% of its maize, yet the region has experienced sustained decline in its precipitation-to-evapotranspiration ratio^[1, 2]. This contrast between the plain's critical food security role and worsening moisture deficit raises questions about how much productivity has been lost to aridification.

The aridity index (AI = P/PET) provides a standardised measure of moisture availability^[3]. UNEP classifies AI < 0.20 as arid, 0.20-0.50 as semi-arid, 0.50-0.65 as sub-humid, and > 0.65 as humid^[4]. Although AI trends have been mapped globally, few studies link county-level AI trajectories to crop yield series at the resolution needed for local adaptation^[5, 6, 7]. This research mapped 30 years of AI change and quantified the AI-yield relationship for three major crops, testing whether counties with steeper aridity trends show lower productivity gains.

Materials and Methods

Study area

The study area covers 34°-41°N, 113°-121°E, encompassing 412 counties across Hebei, Henan, Shandong, and parts of Jiangsu and Anhui provinces. Elevation ranges from sea level in the east to 200 m on the western piedmont. The climate is temperate monsoon with 450-900 mm annual precipitation declining from southeast to northwest.

Model configuration and data sources

The aridity index was computed as $AI = P / PET$ using CRU TS 4.06 monthly precipitation and FAO-56 Penman-Monteith reference evapotranspiration at 0.5° spatial resolution^[8]. PET was calculated from CRU temperature, vapour pressure, cloud cover, and wind speed fields using the FAO-56 method implemented in the PyET Python library^[9]. County-level crop yield data (1990-2020) were obtained from the National Bureau of Statistics of China. Yield anomalies were computed as percentage deviations from the 5-year running mean to remove technology trends^[10].

Performance evaluation and validation

CRU-derived PET was validated against pan evaporation at 42 stations across the NCP ($R^2 = 0.91$, RMSE = 68 mm yr⁻¹).

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AI values were cross-checked against MODIS NDVI moisture classifications; agreement exceeded 84% across UNEP classes. County yield anomalies correlated with provincial totals ($r = 0.94$).

Methods

Decadal aridity class maps were generated for three periods. Transition matrices quantified shifts between UNEP classes.

County AI trends were estimated by Sen’s slope with Mann-Kendall significance ($p \leq 0.05$). Yield anomaly-AI relationships were fitted with quadratic regression per crop. Counties were grouped by AI trend magnitude (< -0.05 , ± 0.05 , $> +0.05$ per decade) to compare trajectories. Spatial analysis in QGIS 3.28; statistics in R 4.2.

Results

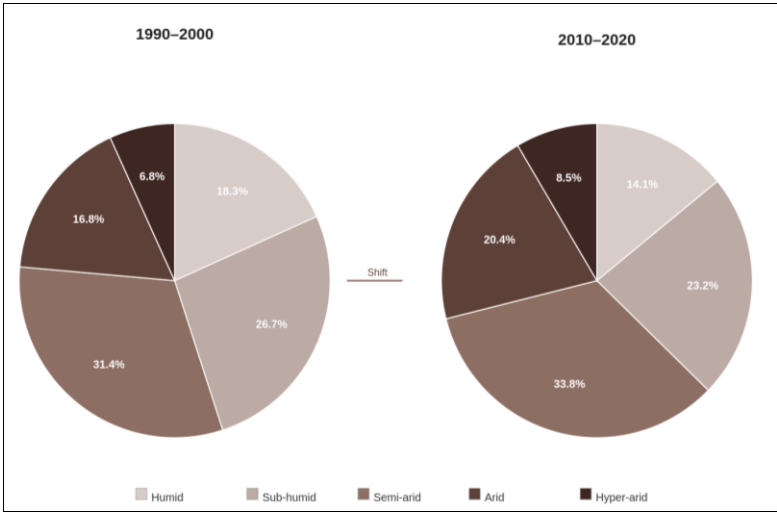


Fig 1: Proportion of North China Plain area under five UNEP aridity classes, 1990-2000 vs 2010-2020

Table 1: Decadal distribution of UNEP aridity classes across the North China Plain (% of total area)

Aridity class	1990-2000 (% area)	2000-2010 (% area)	2010-2020 (% area)	Change (pp)
Humid (>0.65)	18.3	16.4	14.1	-4.2
Sub-humid (0.50-0.65)	26.7	25.1	23.2	-3.5
Semi-arid (0.20-0.50)	31.4	32.6	33.8	+2.4
Arid (0.05-0.20)	16.8	18.7	20.4	+3.6
Hyper-arid (<0.05)	6.8	7.2	8.5	+1.7

Arid plus hyper-arid area expanded from 23.6% to 28.9% over three decades, while humid area contracted from 18.3% to 14.1% (Figure 1, Table 1). Transition analysis showed 68% of

counties that shifted class moved drier. Northwestern Hebei showed the steepest AI decline ($-0.08/\text{decade}$).

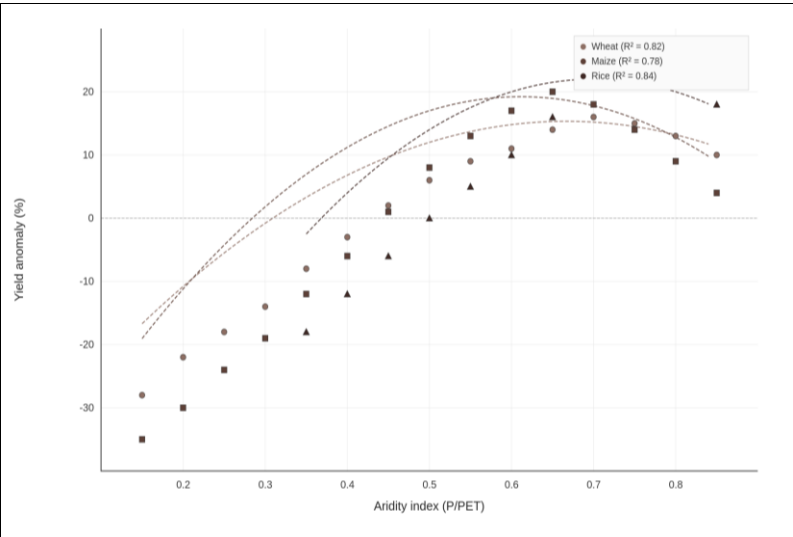


Fig 2: Quadratic relationship between aridity index and yield anomaly for wheat, maize, and rice across NCP counties. Dashed lines = fitted curves

Yield anomaly showed a quadratic relationship with AI for all crops (Figure 2). Peak anomaly occurred at AI 0.65-0.70 for wheat and maize, 0.70-0.75 for rice. Below AI 0.40, negative anomalies exceeded 10%. Maize was most sensitive: -35% at AI

0.15 vs -28% for wheat. Counties with AI decline $> 0.05/\text{decade}$ had 12-18% lower yield trends than stable counties (Table 2), with the gap largest for maize (18.2%) and smallest for wheat (12.4%).

Table 2: Yield trend gap (%) relative to stable counties, grouped by AI trajectory over 1990-2020 (mean $\pm$ SE)

AI trend group	Wheat yield gap (%)	Maize yield gap (%)	Rice yield gap (%)
Drying ($< -0.05/\text{dec}$)	-12.4 ± 2.1	-18.2 ± 2.8	-15.6 ± 3.1
Stable ($\pm 0.05/\text{dec}$)	Reference	Reference	Reference
Wetting ($> +0.05/\text{dec}$)	$+4.8 \pm 1.6$	$+6.3 \pm 1.9$	$+5.1 \pm 2.2$

Discussion

The 5.3 percentage-point expansion of arid plus hyper-arid area over three decades confirms that the NCP is on a drying trajectory consistent with regional climate projections under RCP 4.5 and 8.5 ^[11, 12]. The quadratic yield-AI relationship implies that counties currently near the optimum (AI 0.65-0.70) face asymmetric risk: a small decline in moisture availability produces a disproportionately larger yield penalty than an equivalent increase would produce a gain ^[13, 14]. This nonlinearity has policy implications because it means marginal counties are more vulnerable than linear models would suggest ^[15]. The 12-18% yield gap between drying and stable counties quantifies a “hidden cost” of aridification that is not captured in aggregate national production statistics, which are dominated by irrigated, high-AI counties in the southeast ^[16].

Limitations

The 0.5° CRU resolution may smooth localised drought events that affect individual counties. Irrigation, which covers approximately 65% of NCP cropland, was not explicitly modelled; AI captures atmospheric demand rather than actual crop water supply. Yield anomaly detrending assumes technology trends are smooth, which may not hold during periods of rapid varietal change.

Conclusion

The North China Plain experienced measurable aridification from 1990 to 2020, with arid and hyper-arid area expanding by 5.3 percentage points. Crop yield anomaly followed a quadratic relationship with aridity index, peaking at AI 0.65-0.70. Counties with steeper AI decline showed 12-18% lower yield trends. These findings highlight the need for county-specific adaptation strategies that account for nonlinear moisture-productivity relationships rather than relying on regional averages.

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