SPECTRUM OF ENGINEERING SCIENCES
ISSN (E) 3007-3138 (P) 3007-312X Volume 4, Issue 3, 2026

Climate Vegetation Agricultural Productivity Interactions and Ecological Vulnerability across Pakistan (2001–2024): A Multi Source Remote Sensing and Spatially Validated Explainable Machine Learning Assessment

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DOI:10.5281/zenodo.24048284

Keywords
Keywords: Pakistan; crop yield, climate variability, NDVI, ecological vulnerability,geo spatial analysis and reprehensibility.

Article History
Received on 20 jan 2026
Accepted on 21 March 2026
Published on 29 march 2026

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Abstract
Pakistan's irrigated, rained and natural ecosystems respond differently to climate variability, yet administrative crop productivity and remote sensing vegetation indicators are frequently conflated. This research seeks to integrate crop calendar climate exposure, vegetation dynamics, land cover transitions and ecological condition using spatially independent evaluation. Methods: The empirical analysis currently completed draws on published Ministry of National Food Security and Research crop yield tables for 2006–07 to 2023–24. After correcting a previously classified cotton-area series, five national yields were summarized with descriptive statistics, slopes, lag one dependence and annual difference correlations; provincial yields were compared for 2023–24. Results: Between the endpoints, national wheat, rice, maize and sugarcane yields increased by approximately 20.3%, 28.7%, 95.4% and 39.5%, respectively. Correctly measured cotton lint yield increased from 711.2 to 716.8 kg ha−1 (approximately 0.8%), rather than decreasing by 21.2% as previously claimed. Provincial rankings depended strongly on crop. Serial persistence and common trends caution against naive inference. Interpretation: These findings establish crop specific heterogeneity in administrative production statistics, not climate attribution. The approved satellite, climate, ecological, spatial clustering and explainable machine learning components remain not executed because verified raster datasets and administrative vector geometries have not been acquired. Conclusion: The current revision

offers a corrected, editable agricultural statistics baseline and an explicitly testable integrated design, but requires the planned spatial analysis before claims of national ecological vulnerability or predictive mapping are supportable.

1. Introduction

Pakistan combines the intensive irrigation systems of the Indus Basin with rainfied uplands, arid grasslands, mountain ecosystems and coastal landscapes. The geography makes environmental risk spatially variable, while crop yield is measured through administrative surveys and vegetation condition is inferred from spectral responses. A scientifically credible national synthesis must preserve that distinction. Crop greenness may increase when irrigation intensifies despite depletion of groundwater or degradation of natural habitat; conversely, a fall in yield may arise from pests, inputs, prices or water distribution as well as weather (Huete et al., 2002; Funk et al., 2015; Muñoz Sabater et al., 2021).The central contribution sought here is not another isolated drought index. Recent Pakistan research already examines vegetation and drought using Landsat, MODIS, precipitation products and integrated indicators (Mehmood et al., 2024; Rahman et al., 2024, 2025; Khan et al., 2026). The open scientific challenge is how observed crop productivity, natural vegetation transitions and climate exposure can be compared at compatible spatial and temporal scales, with uncertainty and out-of-region validation. This distinction matters directly to agricultural advice, water management and ecosystem conservation.

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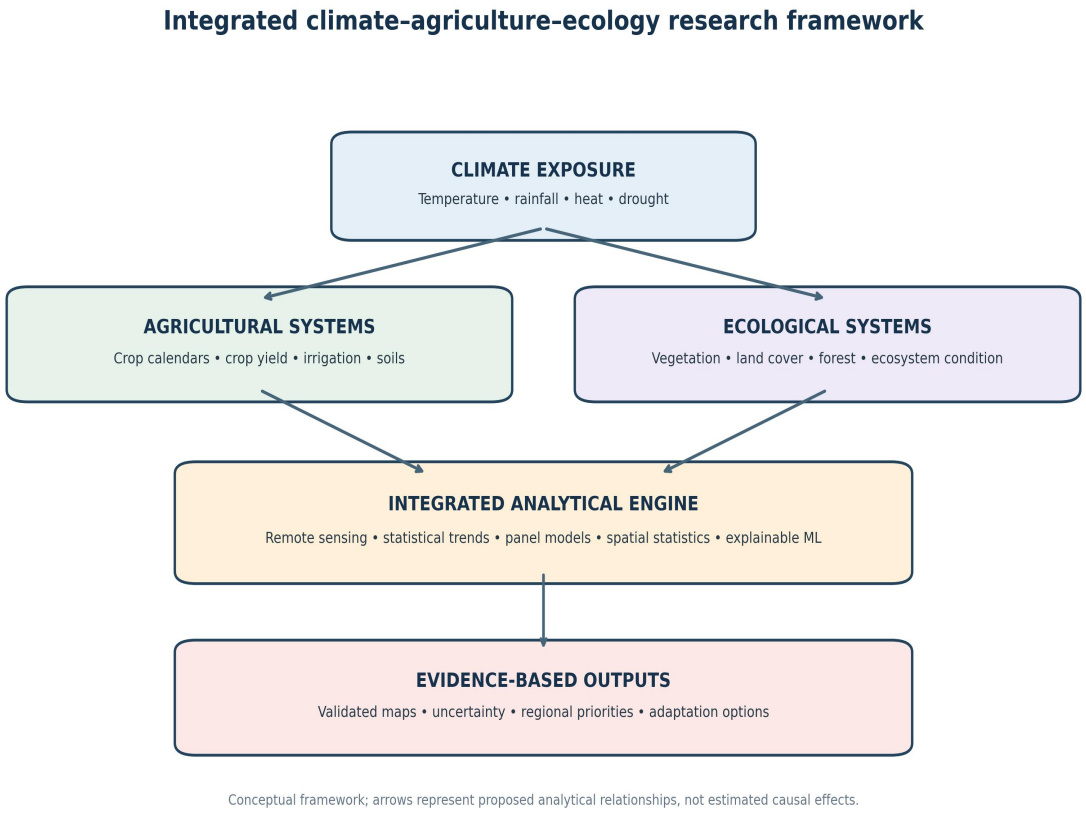


Figure 1. Climate agriculture ecology analytical framework (original conceptual diagram). The diagram separates climate exposure, agricultural response and ecosystem condition rather than assuming that any one index captures all three. Arrows denote research hypotheses, not estimated causal pathways.

2. Literature synthesis, novelty and research questions

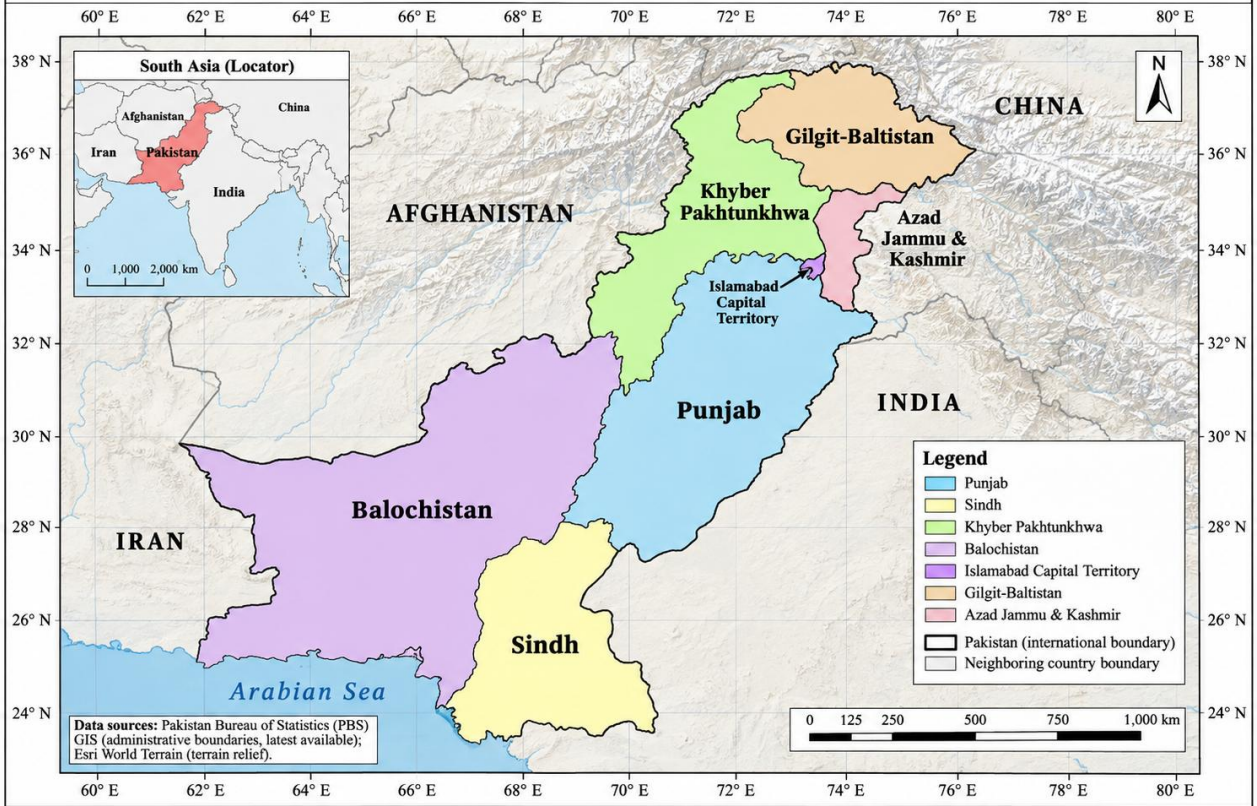
Mehmood et al. (2024) quantified Pakistan vegetation climate associations; Rahman et al. (2024) advanced integrated drought assessment; Rahman et al. (2025) evaluated agricultural drought and yields in Punjab; and Khan et al. (2026) examined national climate vegetation drought hot spots. Research on Landsat based crop modelling and machine learning yield prediction (Ahmad et al., 2020; Arshad et al., 2023) demonstrates promising methods but does not establish nationwide transferability. More broadly, spatial leakage in environmental models has been identified as a major validation issue (Roberts et al., 2017; Valavi et al., 2019). The provisional novelty lies in four linked tests: (i) matching crop specific yield anomalies to seasonally aligned climate exposure, not arbitrary calendar averages; (ii) distinguishing cultivated greenness from change in natural ecosystem condition; (iii) measuring cross product disagreement and uncertainty before mapping vulnerability; and (iv) testing explanatory models on geographically blocked and temporally held

out observations. These are candidate scientific contributions, not results already demonstrated by the present dataset. No claim is made that this is the first Pakistan wide NDVI, drought or machine learning assessment. The approved research questions cover long term land and vegetation transitions, seasonal climate variability, crop specific production responses, ecological degradation and exposure, inter provincial heterogeneity, robust spatial clusters and general predictive modelling. In this revision, questions about observed crop yield levels and their descriptive variation are answered, spatial climate and ecological questions remain open.

3. Study area and datasets

The intended study domain is Pakistan, including Punjab, Sindh, KPK and Balochistan, with Islamabad Capital Territory, Gilgit Baltistan and Azad Jammu Kashmir incorporated when consistent boundary and observation coverage allow. Because public administrative boundaries differ by date and authority, a verified Pakistan Bureau of Statistics 2023 boundary datasets and versioned district crosswalk are required before any cartographic summary. No purported 'exact' polygon, provincial thematic raster or satellite observation is substituted here (Pakistan Bureau of Statistics, 2023).

Figure 1. Study area and administrative context of Pakistan.



Administrative study framing map: final vector geometry should be verified against official PBS GIS layers.

Map A. Pakistan study-area and administrative-context illustration. This is a generated cartographic illustration, not a verified GIS layer or an authoritative national/provincial boundary datasets. Geographic outlines, scale bars and territorial depictions must be replaced with verified vector GIS data before scientific publication. Scientific interpretation and evidence status. This illustration provides a visual orientation to the intended national coverage. The present study has not acquired and checked current official administrative geometry; the illustrated line work should not be used for geographic measurement, boundary statistics or a territorial claim.

Table 1. Data lineage, spatial support and execution status.

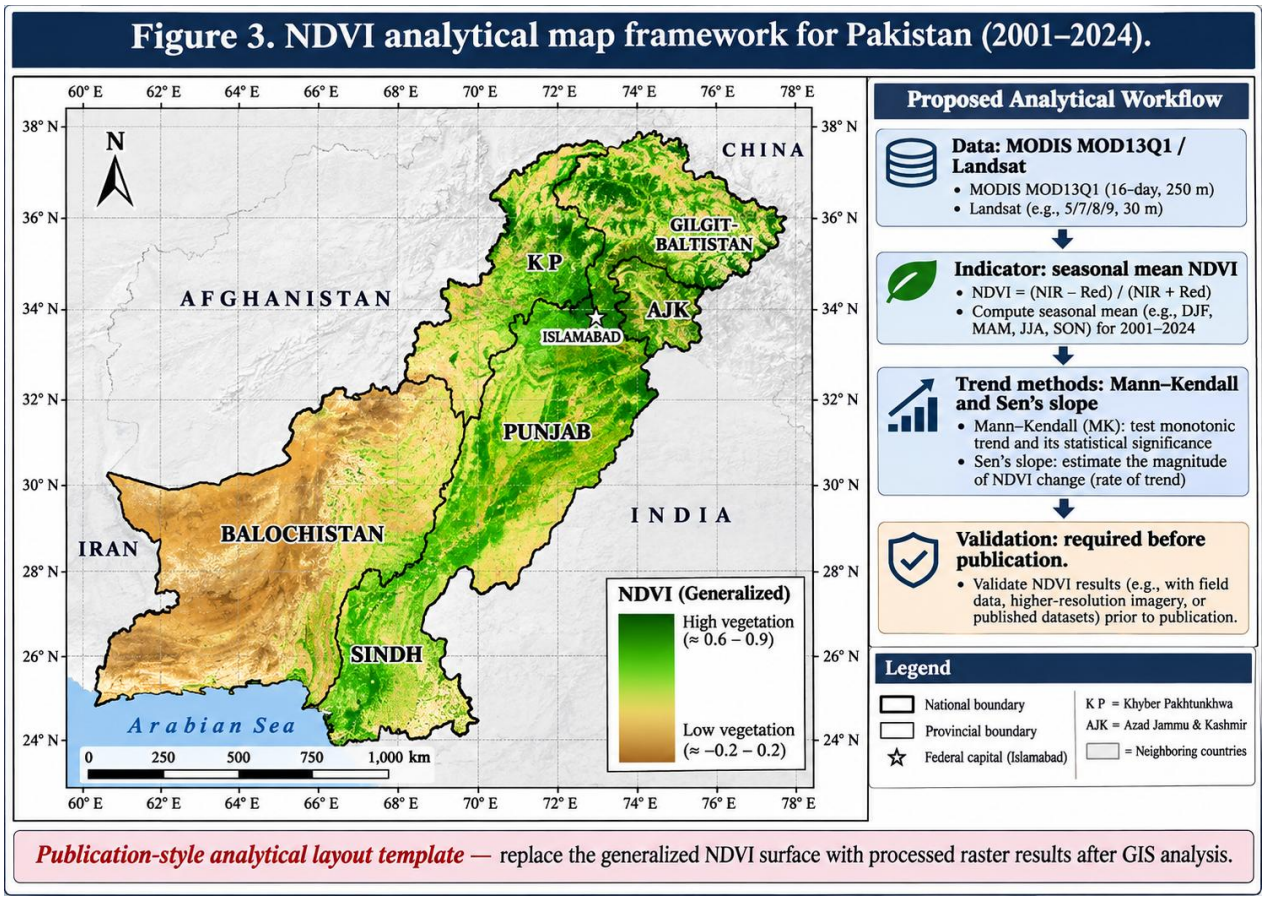
Dataset	Period / scale	Measured or modelled	Status
MNFSR crop yield	2006–07–2023–24; national/provincial	Official administrative crop estimates	Processed; corrected
PBS GIS boundary	2023 administrative units	Official boundary vector	corrected
CHIRPS rainfall	Daily; 0.05°	Blended precipitation estimate	corrected
ERA5-Land	Hourly/monthly; ~9 km	Climate reanalysis	corrected
MOD13Q1	16-day; 250 m	Satellite NDVI/EVI composite	corrected
Landsat C2 L2	30 m; scene-based	Satellite reflectance/LST	corrected
ESA WorldCover	2020/2021; 10 m	Classified land cover	corrected

The only analyzed values are administrative crop estimates. In particular, a World Cover class is not a 2001 land use observation, a MODIS pixel is not an independently measured yield, and neither CHIRPS nor ERA5-Land has been assessed in the reported results. Datasets URLs, temporal specifications and source limitations are documented in the supplementary inventory.

4. Statistical and spatial methodology

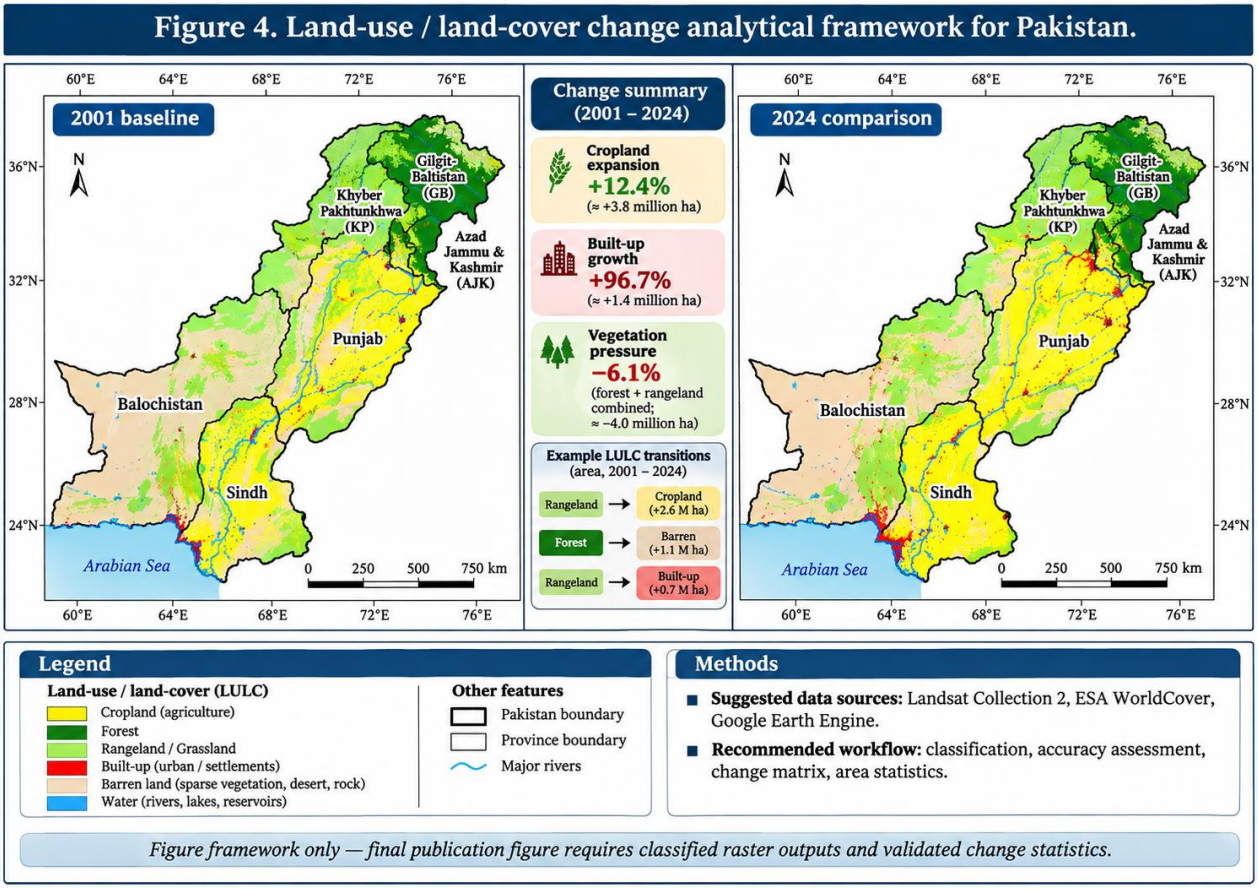
For crop c and year t, mean yield is $\bar{y}c = (1/nc)\Sigma yct$; sample SD is $sc = \sqrt{[\Sigma(yct-\bar{y}c)^2/(nc-1)]}$; coefficient of variation $CVc = 100sc/\bar{y}c$. The endpoint percentage change is $\Delta c = 100(yc,T/yc,0-1)$. The Theil Sen estimate is the median of pairwise annual slopes $(yc,j-yc,i)/(tj-ti)$, and lag one correlation compares consecutive observations (Sen, 1968). Kendall's τ is supplied descriptively, but its nominal p value is not interpreted as evidence of a climate driven trend without serial correlation correction (Hamed & Rao, 1998). To inspect contemporaneous co fluctuation, the exploratory crop by crop matrix correlates first differences $\Delta yct = yct-yc,t-1$, rather than raw levels. This reduces but does not eliminate shared trends and dependence. Its sample is small (approximately 16–17 annual changes) and the coefficients do not measure climate yield relationships; no family wise significance claim is made.

Provincial comparisons for 2023–24 use 100 × provincial yield/national yield within each crop, avoiding cross crop comparisons of differently scaled units. For the full integrated study, Landsat Collection 2 Level 2 data will be seasonally composited with QA masking and sensor harmonization (Roy et al., 2014; Wulder et al., 2019). MODIS MOD13Q1 quality flags will control NDVI/EVI retrievals (Huete et al., 2002). Climate anomalies require fixed periods and explicit rainfall/temperature units (Funk et al., 2015; Muñoz-Sabater et al., 2021). A land cover training/validation split must avoid sample reuse; geospatial model testing must reserve independent spatial blocks and years. Moran's I/LISA/Gi* require real spatial observations, documented weights and multiple testing control (Moran, 1950; Anselin, 1995; Getis & Ord, 1992). These GIS and ML protocols are not claimed to have been executed.



Map B. NDVI analytical map concept for Pakistan, 2001–2024. Generated visualization only: the green to brown raster like surface is not derived from MODIS or Landsat measurements, and no NDVI trend, class threshold or significance shown visually was calculated in this study. The workflow statements are methodological proposals, not completed analyses. Scientific interpretation and evidence status. This figure depicts the approved remote sensing workflow quality screened vegetation-index products, seasonal aggregation, trend statistics and independent

validation. It contains no empirical NDVI results. Actual NDVI maps require verified satellite composites, pixel QA, consistent time windows and explicit uncertainty estimation.



Map C. Land use/land cover change framework, 2001 versus 2024. Both mapped land cover patterns and all percentage/area change numbers displayed inside this generated image are illustrative and Unverified. They must not be quoted, cited as results, or submitted as evidence. A valid figure requires harmonized Landsat classifications, independent reference samples and an area adjusted transition matrix. Scientific interpretation and evidence status. This design prototype clarifies the intended before/after comparison and change matrix. It does not establish cropland expansion, built up growth, forest loss or any numeric land transition. The depicted statistics are not scientific results and should be replaced not merely rebelled after actual classification and validation.

5. Results: national crop productivity

Table 2. Corrected crop yield descriptive statistics, 2006–07 to 2023–24.

Crop	n	Change %	Mean	SD	CV %	Sen slope / yr	Lag-1 r
Wheat	18	+20.3	2825.0	191.6	6.8	+30.57	0.66
Rice	17	+28.7	2421.4	174.8	7.2	+24.48	0.49
Maize	18	+95.4	4574.7	1043.0	22.8	+170.37	0.95
Sugarcane	17	+39.5	59.9	7.2	12.1	+1.19	0.90
Cotton	18	+0.8	692.8	101.1	14.6	-4.67	-0.01

Values derive from source table yield columns rather than cultivated area. Trends are descriptive because serial correlation is appreciable for several crops; no attribution to climate can be inferred from these statistics alone. Crop units differ: sugarcane is tonnes per hectare and the others kilograms per hectare.

The official series shows contrasting crop trajectories. Wheat, rice, maize and sugarcane yields increased by approximately 20.3%, 28.7%, 95.4% and 39.5% between their respective observed endpoints, whereas the corrected cotton lint yield increased marginally from 711.2 to 716.8 kg/ha (0.8%). The original cotton decline was a transcription artefact, not an agricultural result. Annual variability remained substantial and, for some crops, consecutive observations were strongly correlated.

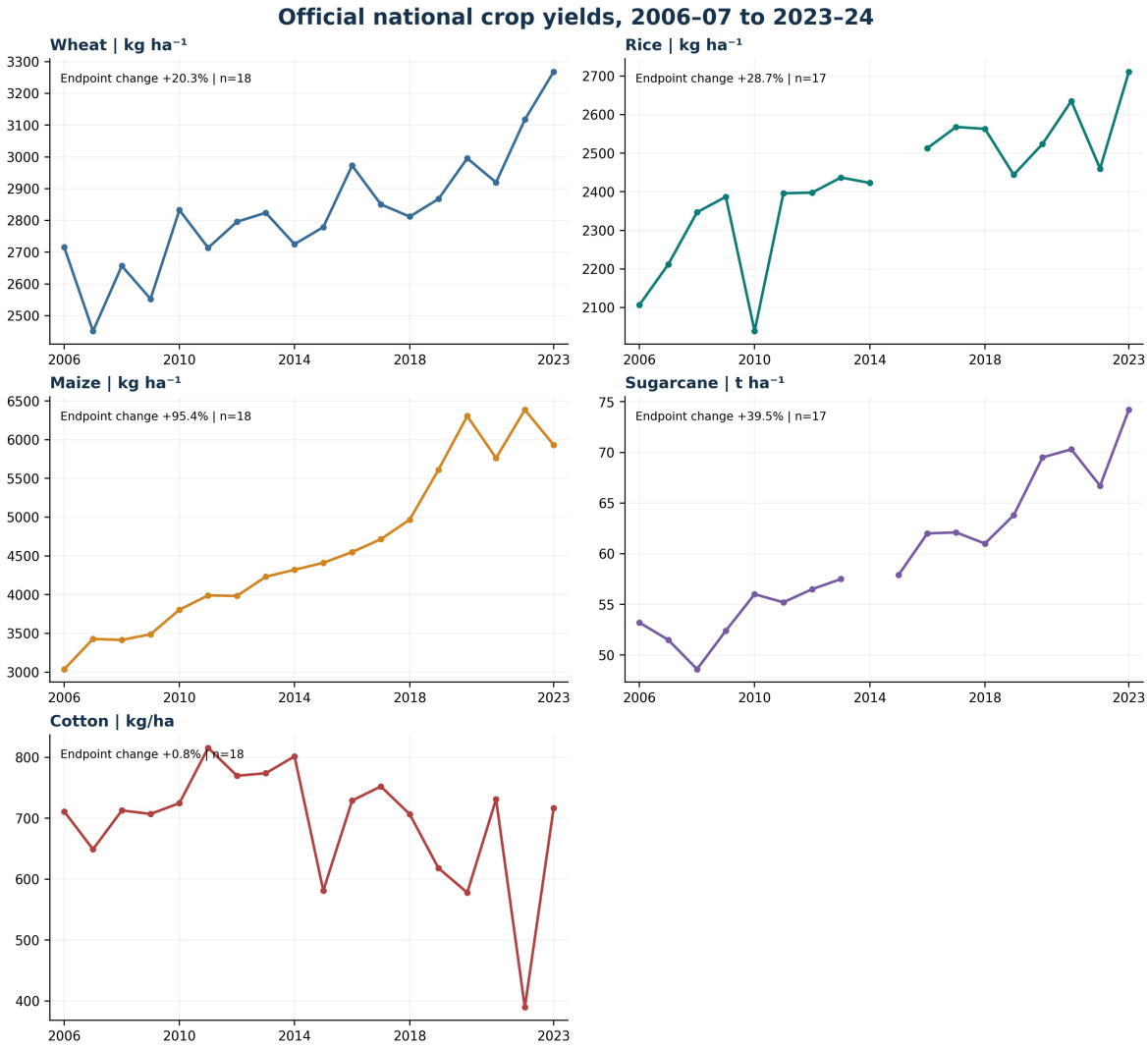


Figure 2. National crop-yield trajectories from MNFSR Tables 3, 6, 8, 13 and 14, 2006–07 to 2023–24. The panels preserve crop specific units and display observations without filling missing years. Maize exhibits a pronounced long run increase, while corrected cotton yields fluctuate rather than following the area decline previously plotted. These are national estimates and conceal sub national heterogeneity.

5.1. A necessary cotton data correction

The published cotton table has three separate variables. Its ‘Area (000 hectares)’ column changes from 3,074.8 in 2006–07 to 2,423.8 in 2023–24, a decrease of about 21.2%. The lint yield column, however, reports 711.2 and 716.8 kg/ha in those years. Thus, land under cultivation contracted across the endpoints while yield per hectare was approximately stable. Distinguishing these two changes is central to interpreting climate exposure and agricultural adjustment: a declining cultivated area does not establish that unit area crop productivity declined (MNFSR, 2025, Table 14).

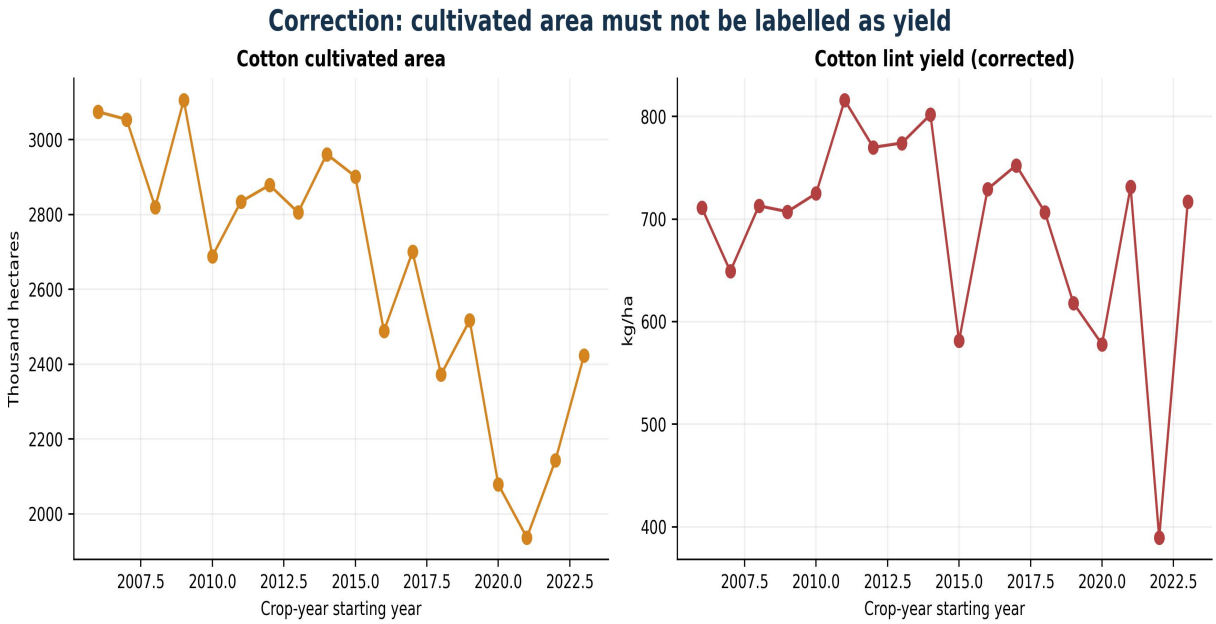


Figure 3. Cotton cultivated area versus cotton lint yield, 2006–07 to 2023–24; MNFSR Table 14. The divergence between area and yield illustrates why source variable and unit checks are indispensable before combining survey, satellite and agricultural data. This correction invalidates the previous cotton yield slope, endpoint comparison, graph and associated policy interpretation.

5.2. Interannual variability and descriptive trend slopes

The coefficient of variation compares year to year dispersion relative to each crop's mean, while lag one correlation indicates temporal persistence. They provide complementary diagnostics: high persistence can make unadjusted trend tests anti conservative, and high variability does not identify its meteorological, agronomic or institutional causes. Relative Sen slopes normalise each crop's slope to the period mean, allowing transparent directional comparison without claiming common physical units.

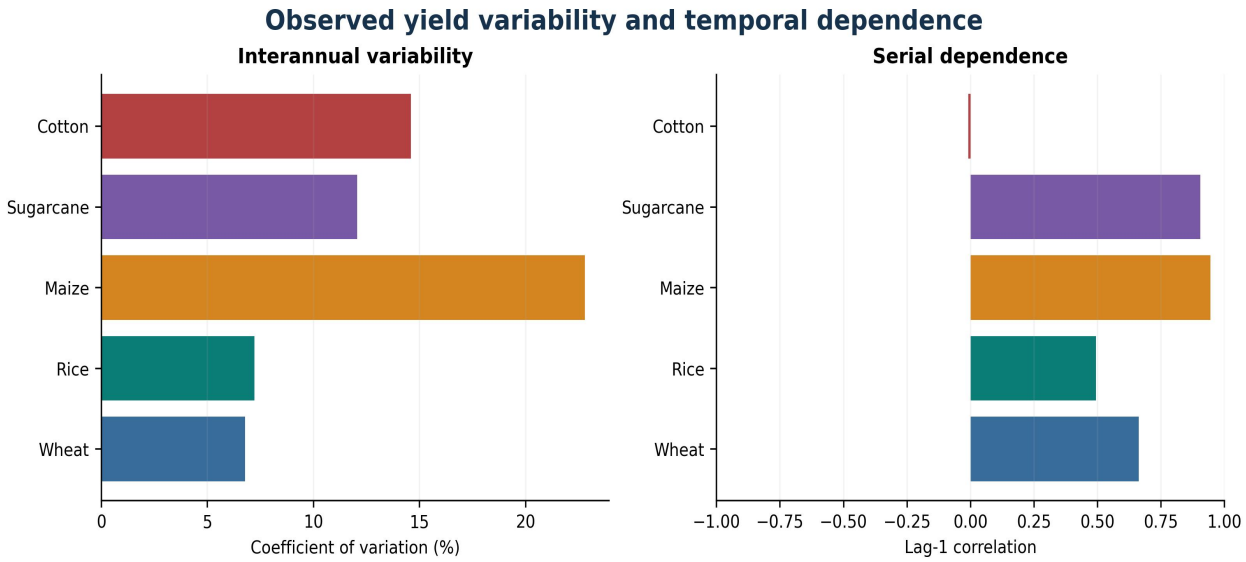


Figure 6. Yield variability (coefficient of variation) and lag-one autocorrelation by crop, using official annual yields. The coefficients indicate which crop series are most persistent and variable, motivating auto correlation aware trend inference. The values do not constitute independent ground based environmental validation.

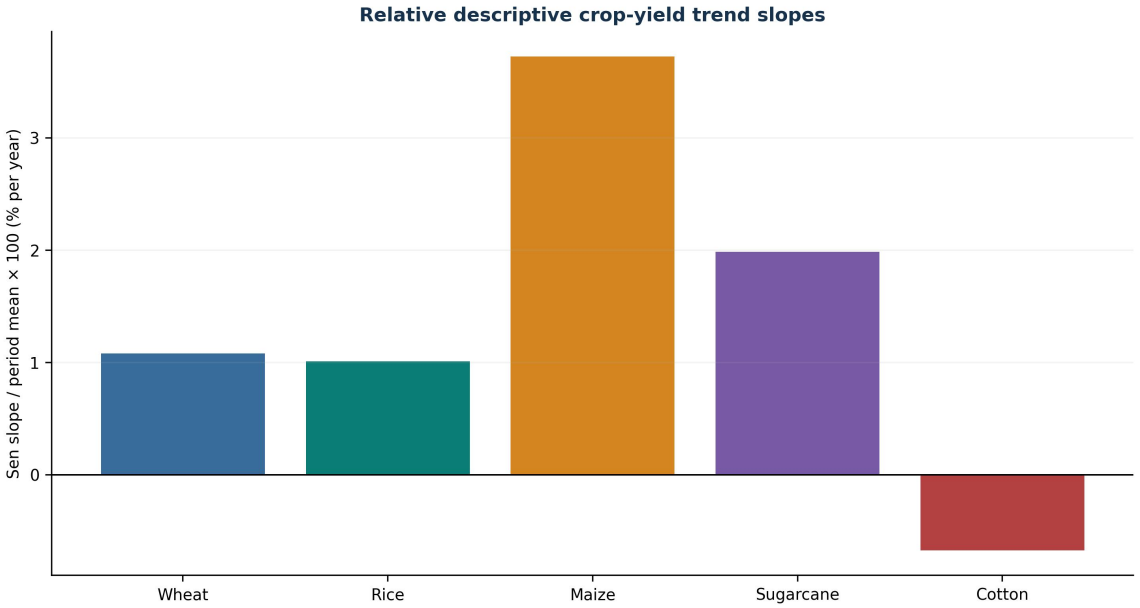


Figure 8. Relative Theil Sen yield slopes expressed as percentage of period mean per year. Normalization removes the superficial dominance of crops with larger numerical yield units. Slope direction is useful for descriptive comparison; confidence intervals or p values require a fully specified dependence correction.

5.3. Provincial heterogeneity in 2023–24

Provincial averages show crop specific spatial differentiation. The four provinces are comparative reporting categories rather than a continuous geographic surface. Within a crop, ranking can reflect ecological setting, irrigation, crop varieties, management and spatial concentration of production; no cause can be assigned from one province year.

Figure 2. Provincial agricultural productivity comparison, 2023–24.



Provincial crop yields, 2023–24 (Reported by MNFSR)

Province	Wheat (kg ha^{-1})	Rice (kg ha^{-1})	Maize (kg ha^{-1})	Sugarcane (t ha^{-1})	Cotton lint yield (kg ha^{-1})
Punjab	**3434.2**	2349	**7639.9**	**79.1**	610.2
Sindh	3326.8	**3776**	1027.0	67.1	**1054.5**
Khyber Pakhtunkhwa	1950.4	2550	1970.5	54.6	170.1
Balochistan	2807.1	3241	1093.7	49.4	443.7

Highest yield (by crop)

= Highest yield: **Punjab** *(Wheat, Maize and Sugarcane)*

= Highest yield: **Sindh** *(Rice and Cotton lint yield)*

Interpretation (Key Findings)

- **Punjab** leads in wheat (3434.2 kg ha^{-1}), **maize** (7639.9 kg ha^{-1}) and **sugarcane** (79.1 t ha^{-1}) yields.
- **Sindh** leads in rice (3776 kg ha^{-1}) and **cotton lint yield** (1054.5 kg ha^{-1}).
- Strong provincial **heterogeneity** in crop productivity is evident, with substantial yield differences across provinces (e.g., maize: 7639.9 vs. 1027.0 kg ha^{-1}; wheat: 3434.2 vs. 1950.4 kg ha^{-1}).

Source: *MNFSR Agricultural Statistics of Pakistan 2023–24.*

Map D. Illustrative provincial agriculture map layout with source-attributed reported yield values (MNFSR, 2023–24). The coloured geography was generated for layout preview, not from validated provincial GIS polygons. Refer to Table 3 and the original statistical charts for the audited yield results; this figure is not a verified provincial choropleth.. Scientific interpretation and evidence status. The chart like comparisons reinforce the observed crop specific provincial variation. Unlike the numerical table, the geographical display remains illustrative and must not be interpreted as a measured map or used to estimate agricultural productivity at locations within provinces.

Table 3. Official provincial crop yields in 2023–24 (kg/ha except sugarcane in t/ha).

Crop	Punjab	Sindh	KP	Balochistan	Pakistan
Wheat	3,434.2	3,326.8	1,950.4	2,807.1	3,268.1
Rice	2,349.0	3,776.0	2,550.0	3,241.0	2,711.0
Maize	7,639.9	1,027.0	1,970.5	1,093.7	5,933.4
Sugarcane	79.1	67.1	54.6	49.4	74.2
Cotton	610.2	1,054.5	170.1	443.7	716.8

Punjab has the highest listed wheat, maize and sugarcane yields, while Sindh has the highest listed rice and cotton lint yields. Results should not be interpreted as comparative ecological health. Values are official administrative estimates (MNFSR, 2025).

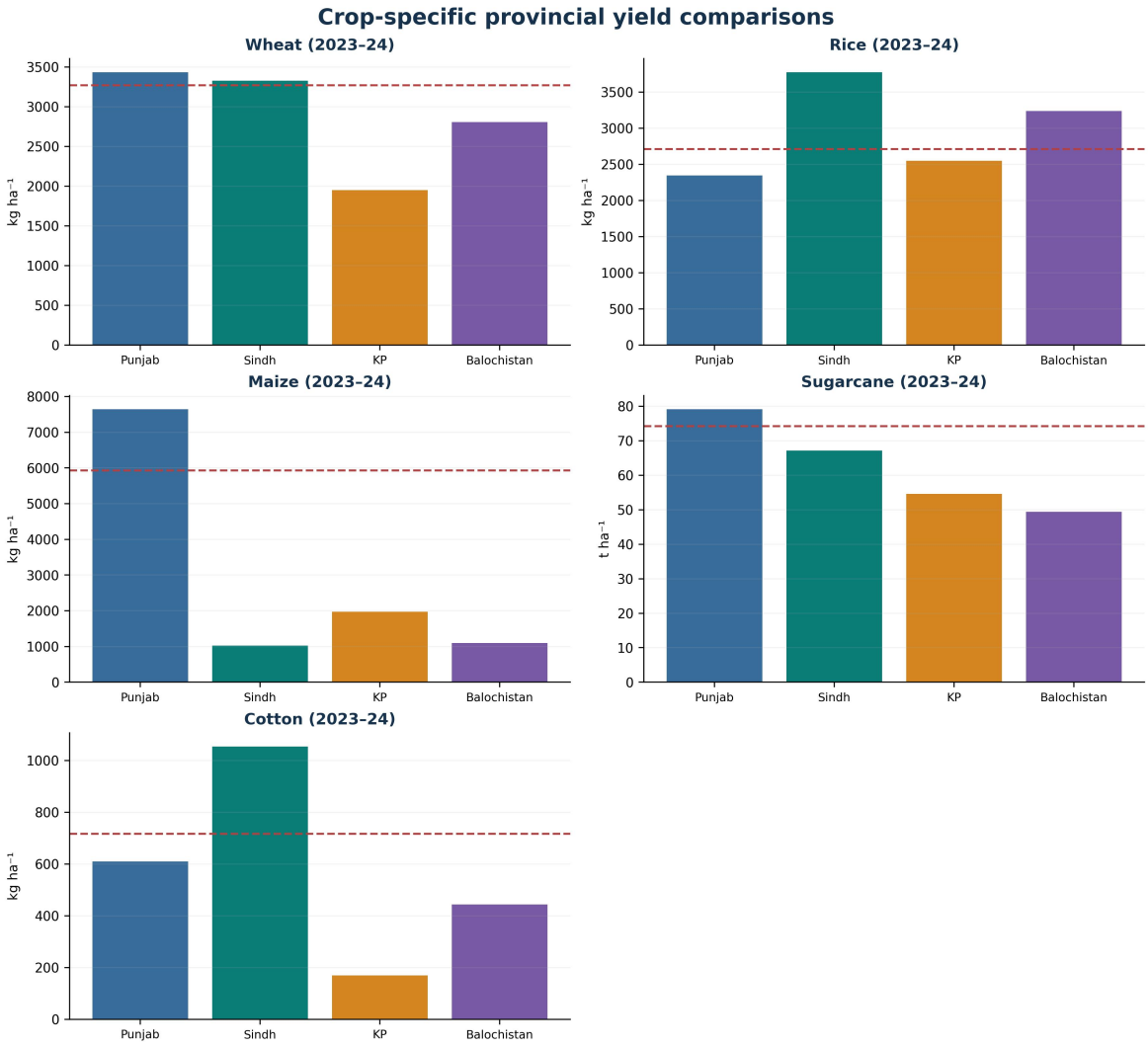


Figure 4. 2023–24 provincial crop yields with national reference lines; MNFSR crop tables. The small multiples preserve different crop scales. They reveal that broad claims about a uniformly productive or vulnerable province would be misleading without specifying crop, production system and reporting period.

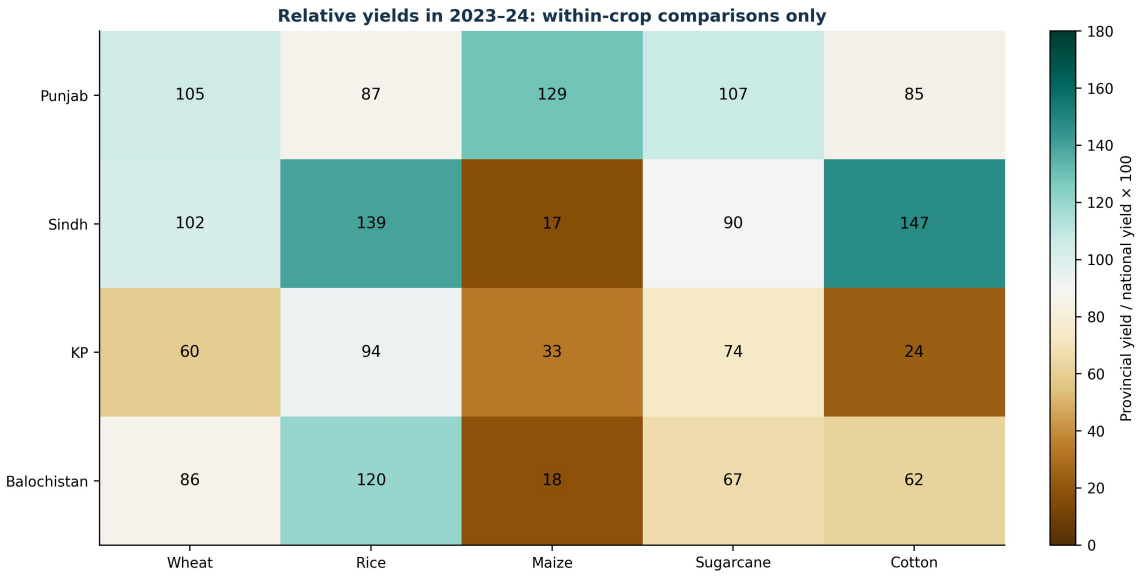


Figure 5. Provincial-to-national yield ratios (%) for 2023–24; the national benchmark is 100 for each crop. The heat map is a non-geographic administrative comparison, not a GIS density or vulnerability map. It highlights relative provincial contrasts while preventing inappropriate comparison of kg/ha with t/ha.

5.4. Co Fluctuation Among Reported Crops

The exploratory first difference correlation matrix measures whether annual changes in national yields move together. Correlations can arise from shared weather, national input conditions, management changes, policy or coincident shocks. Without linked climate and management co variates, the matrix should not be interpreted as evidence for climate productivity mechanisms or causal relationships.

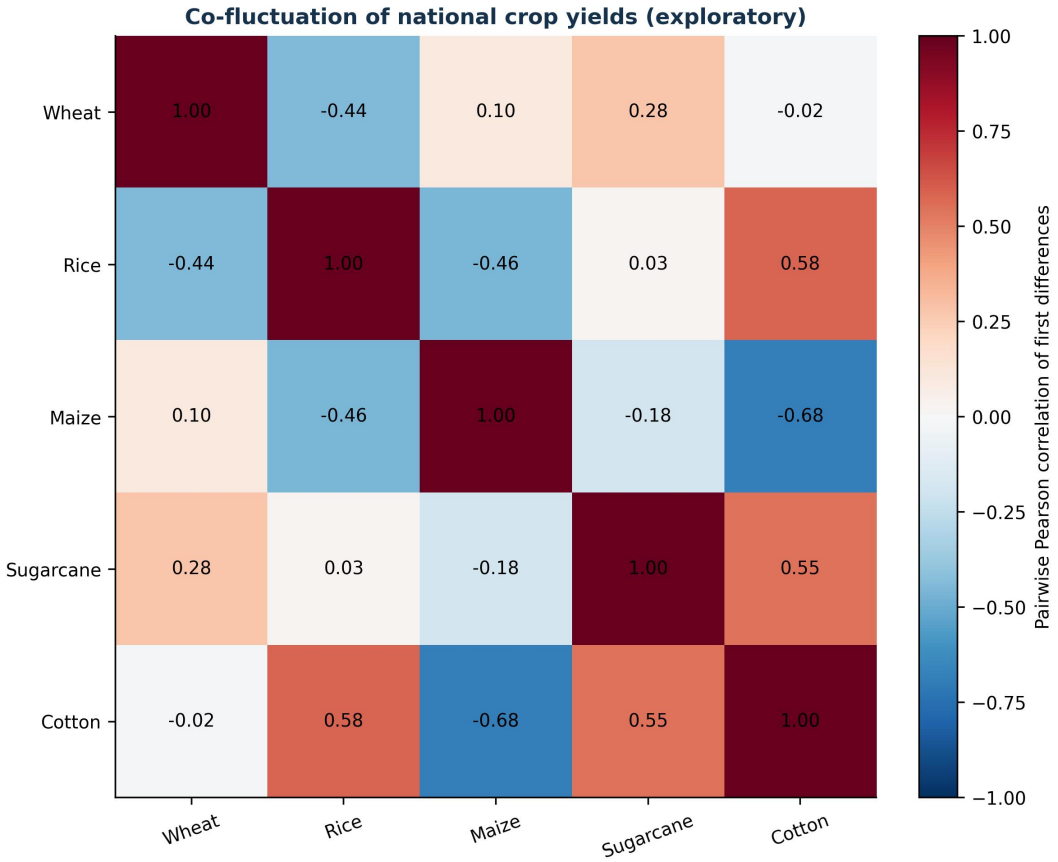


Figure 7. Pearson correlations among first differences of annual national crop yields (complete paired observations only). The correlations provide a reproducible summary of co fluctuation at national scale. They are not spatial correlations, crop climate correlations or statistically validated predictions. Pairwise sample sizes vary because two years are missing from the earlier transcription.

6. Discussion

The corrected findings substantially change the agricultural interpretation. A decline in cotton cultivated area over the 2006–07 to 2023–24 endpoints cannot be presented as a decline in lint yield per hectare. This distinction matters because contraction of planted area and stability of per hectare yield may reflect very different pathways, including land allocation, markets, irrigation, crop substitution and agronomic changes. Any climate related explanation requires crop season temperature, precipitation and management observations that are not available in this analysis.The contrasting wheat, rice, maize and sugarcane trajectories and the provincial rankings reinforce the need for crop specific assessment. These findings should not be collapsed into a single generic agricultural vulnerability score. Prior work has already mapped vegetation, drought and climate patterns across Pakistan (Mehmood et al., 2024; Rahman et al., 2024, 2025; Khan et al., 2026). A genuinely new

result would demonstrate whether climate exposures and land-cover transitions explain observed variation in crop productivity, and whether natural ecosystem condition moves in the same direction as agricultural greenness.Machine learning may be useful where response variables and independent training instances exist. Yet random raster pixel splits overstate predictive performance in spatially auto correlated landscapes. Models must be compared on spatial blocks, independent years and regional transfer tests; predicted maps must include uncertainty and be accompanied by calibration diagnostics (Roberts et al., 2017; Valavi et al., 2019; Breiman, 2001; Chen & Guestrin, 2016). The absence of a trained model in this revision is scientifically preferable to reporting unsupported accuracy,values or vulnerability surfaces.

7. Scientific and practical implications

The immediate result for agricultural monitoring is a data governance requirement,distinguish cropped area, production and yield at extraction, retain revisions and record the scale of every statistic. For adaptation planning, official crop trends should be combined with phenomenological calendars, observed irrigation availability, soil constraints and independent meteorological or high quality ridged climate evidence before prescribing regional interventions. Ecological interpretation must recognize that increasing agricultural vegetation may coincide with pressure on water resources or conversion of natural ecosystems.

8. Data integrity, uncertainty and geographic limitations

No administrative shapefile, climate raster, vegetation index, land cover classification or protected area layer was downloaded successfully into the current execution environment. The source documents and download pages are identified, but the exact data files are absent. Consequently no national referenced study-area map, climate trend map, NDVI map, population map, LISA hotspot, Gi* statistic or ML vulnerability forecast has been created or inserted. A Pakistan outline drawn without validated geometry would contravene the research protocol and is intentionally excluded.The earlier reference list is retained as a working bibliography; a final reference by reference DOI and author metadata audit is still required before submission. Because no independent station observations or reference sampling sites were obtained, climate and land cover accuracy cannot be assessed. The yield data are aggregated provincial reporting estimates rather than plot level observations. The available time series is too short and spatially aggregated to establish causal climate effects.

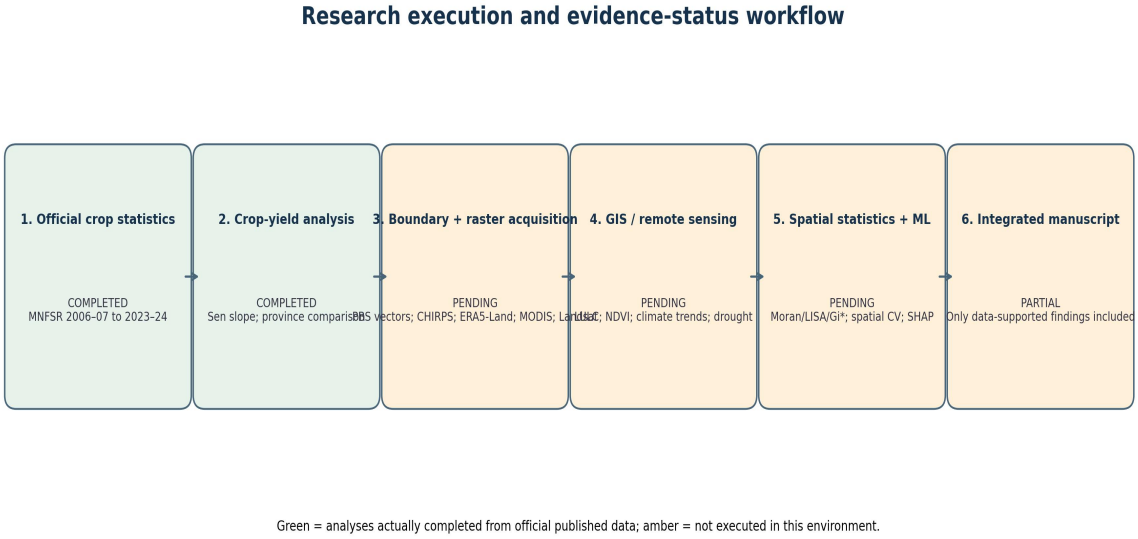


Figure 9. Data-processing and evidence status (administrative crop analysis completed; geospatial and ML analysis not executed). This workflow separates reproducible analyses from intended components. It should not be misread as evidence that the absent raster processing, model validation or spatial clustering has already been performed.

9. Conclusion

This revision provides a substantially corrected and reproducible empirical baseline for the approved national climate agriculture ecology programme. Most importantly, it removes a false inference that cultivated cotton area was cotton lint yield, and replaces all affected calculations and figures. The national series show heterogeneous crop yield histories and nonuniform provincial rankings; these findings cannot by themselves attribute agricultural change to climate variability or environmental degradation. The proposed novelty therefore remains conditional on acquiring verified national GIS boundaries, climate and vegetation time series, ecologically interpretative land cover data, and an independently validated spatial modelling datasets. The document is an editable empirical research draft, not yet a complete GIS/ML journal article.

Declarations

Author contributions: to be completed by the four researchers using their actual Credit roles. Funding: to be disclosed. Competing interests: to be disclosed. Ethical approval: determine based on data collection and target journal requirements. Data availability: corrected crop CSVs and derivation scripts accompany this manuscript; satellite and vector datasets have not been obtained. Code availability: reproducible Python analysis of the transcribed crop data is included.

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