

Agricultural land-use composition modulates hydroclimatic coupling of
cropland water use efficiency under prolonged aridification: sub-watershed
evidence from Chile's megadrought

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Abstract

Cropland water-use efficiency (WUE; net primary productivity divided by actual evapotranspiration) is widely expected to improve under technological intensification, yet its response to prolonged aridification at regional scales is poorly understood. We analyzed spatiotemporal patterns of WUE across 127 Chilean agricultural sub-watersheds from 2001 to 2020, a period spanning an unprecedented megadrought. WUE responses were spatially heterogeneous: arid and semi-arid sub-watersheds showed predominantly negative Δ WUE, while irrigated Mediterranean sub-watersheds showed positive Δ WUE; negative long-term trends and structural breaks concentrated in the 30–35°S band. Precipitation deficit indices dominated cross-sectional WUE sensitivity; at the 36-month accumulation scale, SPEI (Standardized Precipitation-Evapotranspiration Index) and SPI (Standardized Precipitation Index) showed practically equivalent explanatory power (two one-sided test $p < 0.001$, 90% CI $[-0.004, +0.003]$). Crop system composition is associated with WUE drought sensitivity through two contrasting patterns, each constrained by a different form of confounding. Annual-crop prevalence is robustly and negatively associated with drought sensitivity across all latitude-control specifications (spatial error model [SEM] β range: -0.341 to -0.591 , $p < 0.01$); whether this reflects structural buffering or drought-driven reduction of annual cultivation cannot be established from the observational data alone. Irrigation infrastructure prevalence shows a positive association with WUE-drought coupling that is not distinguishable from the latitudinal aridity gradient: it is significant in the full sample (SEM $\beta = +0.438$, $p < 0.001$) but attenuates to non-significance when latitude is explicitly controlled ($\beta = +0.117$, $p = 0.309$;

$\Delta\text{AIC} = 19.8$). Geographic cross-validation confirms that the quantitative crop-composition model does not transfer across latitude bands within Chile (per-block out-of-sample R^2 range: -1.25 to -0.29), every held-out block being predicted worse than its own mean, indicating that the coefficients capture a spatially contingent configuration rather than generalizable structural parameters. Both crop-composition associations are correlational; causal inference is precluded by the observational design and spatial confounding. These findings are consistent with crop-portfolio flexibility reducing structural drought exposure under prolonged aridification, and with WUE-based efficiency metrics being insufficient indicators of agricultural resilience where irrigation supply is hydrologically coupled to the same signals that suppress crop productivity. These results carry implications for water governance and agricultural planning in snowmelt-dependent dryland regions globally.

Keywords: water use efficiency, megadrought, aridification, SPEI, Chile, NPP/ET, crop composition

1. Introduction

Global agriculture consumes approximately 70% of freshwater withdrawals (Hoekstra and Mekonnen, 2012), yet whether irrigation infrastructure buffers or amplifies cropland ecosystem water use efficiency (WUE; NPP/ET) sensitivity under prolonged drought remains poorly understood. This ecosystem-scale WUE formulation is distinct from agronomic WUE (yield per unit of water supplied or consumed), which is conditioned on crop-specific harvest indices and management decisions at the field scale (Stanhill, 1986; Zwart and Bastiaanssen, 2004); ecosystem WUE is the appropriate metric for regional remote sensing monitoring and cross-system structural comparison at the sub-watershed scale, where agronomic WUE would require crop-specific calibration unavailable across the study domain. The widely held assumption that irrigation protects crop production from meteorological variability has been challenged on two fronts. The irrigation efficiency paradox shows that technical efficiency gains can paradoxically increase aggregate water consumption by enabling crop intensification (Grafton et al., 2018; Ward and Pulido-Velázquez, 2008). Demand-hardening dynamics predict that structural commitment to irrigation infrastructure creates inelastic water demand that amplifies drought vulnerability when supply fails, while annual crop flexibility provides only partial adjustment capacity (Grafton et al., 2018). Whether these mechanisms operate at the watershed scale under a multi-year megadrought remains poorly established. As aridification intensifies across dryland

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and Mediterranean-climate regions (Gebrechorkos et al., 2025; Zambrano et al., 2025), whether managed irrigation systems buffer or transmit hydroclimatic stress is a critical question for adaptive water governance (FAO y ONU Agua, 2025; Howden et al., 2007; Wallace, 2000). Chile’s central Mediterranean zone, where irrigated perennial agriculture draws on Andean snowmelt-fed rivers under a decade-long megadrought (Boisier et al., 2018; Garreaud et al., 2020), provides a natural experiment at the intersection of these questions.

Cropland ecosystem WUE drought sensitivity at the regional scale has received growing attention, yet critical empirical gaps limit predictive understanding. Most analyses of WUE variability under drought focus on global or continental means, obscuring the sub-watershed scale heterogeneity that governs local management relevance (Ito and Inatomi, 2012; Yu et al., 2025). Sub-watershed hydrological boundaries, rather than administrative communes or arbitrary grid cells, align with Chile’s water allocation governance framework (Malagueño and D’Odorico, 2024; Rivera et al., 2016), making this the operationally relevant spatial unit for connecting biophysical drought responses to water management decisions. Studies comparing irrigated and rainfed systems have concentrated on yield or harvested-area adjustments rather than on the integrated net primary productivity (NPP) per evapotranspiration (ET) signal that ecosystem WUE captures, leaving unclear how irrigation infrastructure and crop type jointly modulate WUE drought sensitivity (Chakraborti et al., 2023; Davis et al., 2017). The distinct contributions of precipitation deficits versus atmospheric evaporative demand to WUE variability have rarely been quantified simultaneously across contrasting crop systems, so which aridification process drives WUE coupling most strongly remains an open question (AghaKouchak et al., 2015; Hobbins et al., 2016; Zambrano et al., 2025). Most critically, the demand-hardening prediction that structural irrigation infrastructure amplifies rather than buffers drought vulnerability has not been tested against observed WUE data across a sustained multi-year megadrought, where supply constraints accumulate rather than recover between seasons (Grafton et al., 2018; Tahasin et al., 2024; Ward and Pulido-Velázquez, 2008). Whether annual-crop portfolio flexibility provides structural buffering at the sub-watershed scale, independent of the latitudinal aridity gradient that co-varies with both irrigation prevalence and drought intensity, remains untested (FAO y ONU Agua, 2025; Howden et al., 2007).

This paper examines how agricultural crop system composition modulates WUE drought sensitivity across 127 Chilean sub-watersheds (2001–2020). Crop composition likely mediates the response to supply constraints: perennial fruit crops maintaining year-round root systems may sustain productivity under partial deficits, whereas annual crops allow area-based adjustment when supply falls critically short (Chakraborti et al., 2023;

(Davis et al., 2017). We address three objectives. First, we test whether annual-crop prevalence is associated with lower WUE drought sensitivity independently of the latitudinal aridity gradient. Second, we test whether irrigation infrastructure prevalence is associated with amplified WUE-drought coupling, consistent with demand-hardening dynamics (Grafton et al., 2018), and whether this association survives explicit latitude control. Third, we determine which aridification signal (Standardized Precipitation Evapotranspiration Index [SPEI], Standardized Precipitation Index [SPI], or Evaporative Demand Drought Index [EDDI]) most strongly predicts WUE variability and whether WUE responses are spatially clustered. Aridification is treated as multi-process using three complementary drought indices: SPEI (Vicente-Serrano et al., 2010) (hydroclimatic balance), SPI (McKee et al., 1993) (precipitation deficit), and EDDI (AghaKouchak et al., 2015; Hobbins et al., 2016; McEvoy et al., 2016) (atmospheric evaporative demand). The primary analysis uses a spatial error model framework with 2021 post-drought census crop composition data. All findings are associative; causal inference is not possible given the cross-sectional observational design and spatial confounding.

2. Data and Methods

2.1. Study area

Continental Chile (approximately 17°S to 56°S) spans extreme latitudinal climate gradients, from the hyperarid Atacama in the north to the Mediterranean zone (32°S–38°S) concentrating the majority of irrigated agriculture, viticulture, and fruit export production, and a humid-temperate zone supporting rainfed cereals and forages south of 38°S (Figure 1). The megadrought most severely affected the 30°S–42°S band, where precipitation deficits of 25–45% relative to the twentieth-century mean have persisted since 2010 (Boisier et al., 2018; Garreaud et al., 2020). The study uses sub-watershed-level spatial units based on Chilean National Water Authority (DGA) hydrological boundaries, which align with the country’s water allocation governance framework (Rivera et al., 2016). Chile’s 1981 Water Code established a privatized, market-based water governance system in which water rights are tradeable property and drought allocation is governed primarily by seniority and market exchange rather than state emergency intervention (Malagueño and D’Odorico, 2024). Agricultural land use in central Chile is dominated by long-horizon perennial investments (orchards, vineyards) with decade-scale persistence; the 2007 and 2021 census snapshots therefore capture the structural crop composition at the beginning and end of the study period, with limited within-period turnover in perennial crop area.

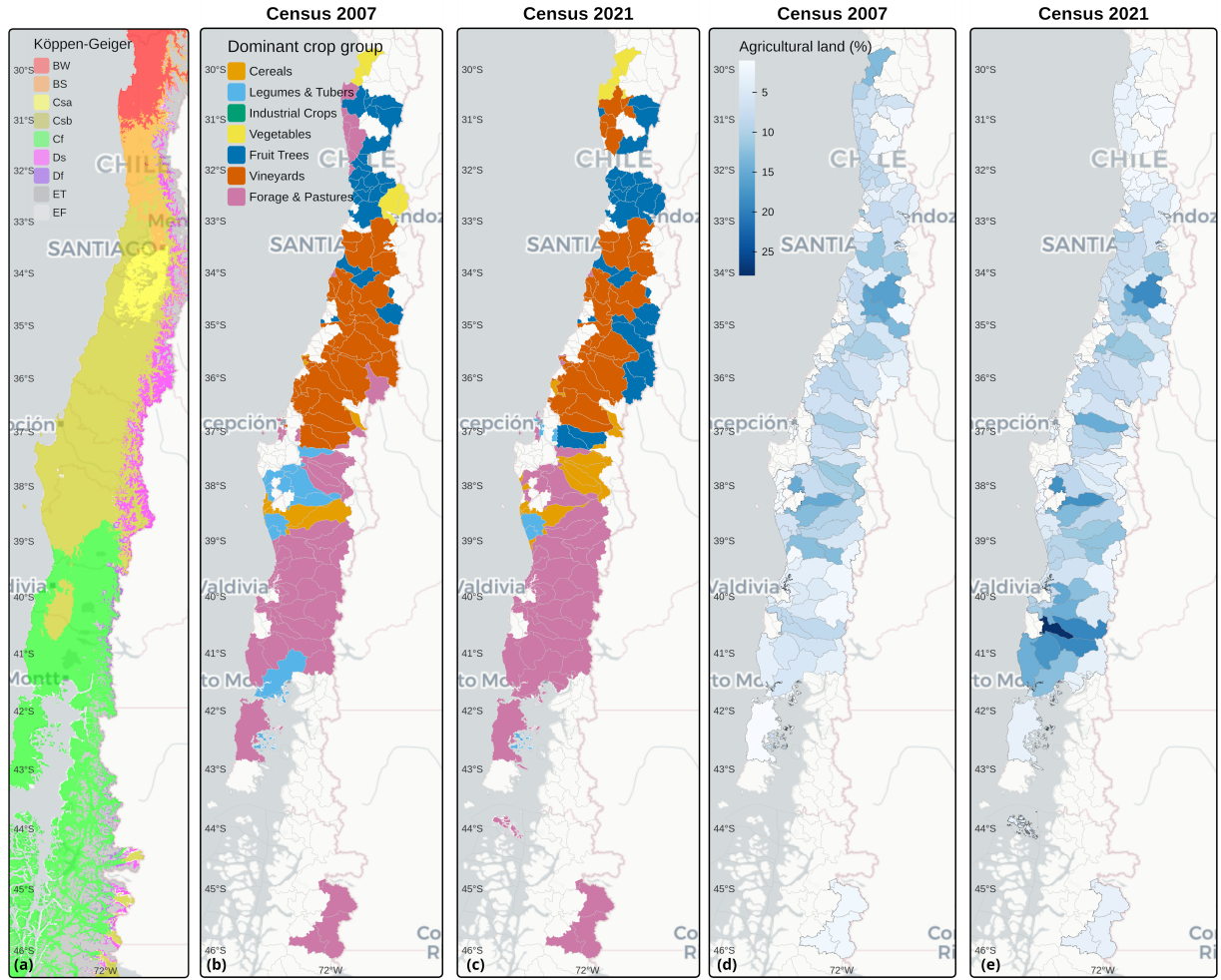


Figure 1: Study area and agricultural context across central Chile. (a) Köppen-Geiger climate classification across the study domain, spanning arid (BW) and semi-arid (BS) zones in the north, the warm- and hot-summer Mediterranean centre (Csa, Csb), and the humid-temperate south (Cf). (b-c) dominant agricultural crop group per sub-watershed, derived from the VII (2007) and VIII (2020-2021) Chilean Agricultural and Forestry Censuses. (d-e) agricultural land as a percentage of total sub-watershed area for the same two census years. Sub-watershed boundaries (DGA) are outlined in grey.

2.2. WUE data

Annual cropland WUE ($\text{g C kg}^{-1} \text{H}_2\text{O yr}^{-1}$), defined as $WUE = NPP/ET$, was obtained from the global cropland WUE dataset of [Jiang et al. \(2025\)](#), providing 1-km annual rasters for 2001–2020. This NPP/ET formulation represents the ecosystem WUE concept, which quantifies biophysical carbon-water coupling efficiency across the land surface, and is distinct from the agronomic WUE metric (crop yield per unit of water applied or consumed) used in irrigation management; both capture efficiency but over different process domains and at incompatible scales of observation. NPP was estimated using an Evaporative Fraction Light-Use Efficiency (EF-LUE) model driven by ERA5-Land reanalysis, GLASS fAPAR and LAI, and ESA CCI-LC land cover, calibrated against FLUXNET2015 flux towers across multiple climate zones. ET was obtained from the ETMonitor product ([Hu and Jia, 2015](#)), validated against flux towers ($r > 0.75$). Because NPP and ET are estimated on the same 1-km grid at annual resolution, the resulting WUE product is internally consistent in space and time. [Jiang et al. \(2025\)](#) report component-level validation (NPP calibrated against FLUXNET2015; ET validated at $r > 0.75$ against flux towers) but do not report ratio-level validation of the composite WUE product; component-level accuracy does not guarantee ratio-level accuracy, and no sub-watershed-scale ground-truth WUE measurements exist across Chile against which to independently validate the composite product. WUE rasters were cropped to Chile’s extent and annual mean WUE was extracted per sub-watershed by spatial averaging. The 20-year series (2001-2020) spans a pre-megadrought reference period (2001-2009) and the megadrought period (2010-2020). The WUE was standardized using z-scores for the years 2001-2020 and will be used in this context.

2.3. Drought drivers and WUE mechanistic components

2.3.1. Aridification drivers

Three complementary drought indices characterize distinct aridification dimensions ([AghaKouchak et al., 2015](#); [Zambrano et al., 2025](#)). SPEI (primary driver) captures the hydroclimatic balance incorporating both precipitation and atmospheric evaporative demand ([Vicente-Serrano et al., 2010](#)). It was computed from CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) monthly precipitation ([Funk et al., 2015](#)) and reference evapotranspiration estimated via the Hargreaves-Samani method ([Zambrano et al., 2025](#)) using CHIRTS-daily temperature data (Climate Hazards Center Infrared Temperature with Stations, [Funk et al., 2019](#)), then aggregated to a monthly basis. SPI isolates precipitation deficits from the same CHIRPS series ([Mckee et al., 1993](#)). EDDI characterizes anomalies in atmospheric evaporative demand independently of precipitation ([Hobbins et al., 2016](#); [McEvoy et al., 2016](#)), computed from CHIRTS-based

derived reference evapotranspiration. We used the EDDI sign convention to indicate that positive values represent below-normal evaporative demand, while negative values signify above-normal demand, thereby aligning EDDI with the polarity of SPEI and SPI. Each index was computed at 12, 24, and 36-month accumulation scales. The three indices were standardized via the empirical probability-weighted normal approximation. The December value for each year was retained as the annual index observation.

All three drought indices are derived from CHIRPS precipitation and CHIRTS temperature data, observation-based satellite-gauge merged products independent of the ERA5-Land reanalysis used by the EF-LUE model; the crop composition spatial error model uses relative cross-watershed sensitivity rankings unaffected by any spatially uniform forcing. Mean within-sub-watershed temporal R^2 at the per-family optimal scales was 0.277 for SPEI-12, 0.264 for SPI-12, and 0.168 for EDDI-24; SPEI-12 and SPI-12 show practically equivalent temporal explanatory power (TOST [Two One-Sided Tests] within ± 0.05 margin: $p < 0.001$, 90% confidence intervals [CI] [+0.007, +0.019]), indicating that the precipitation component dominates the temporal WUE signal and that redundancy among indices is assessed empirically through equivalence testing rather than assumed a priori. Drought indices are standardized temporal anomalies relative to each sub-watershed’s local historical mean and carry little information about the absolute spatial aridity gradient at any single time point; near-zero unique cross-sectional variance attributable to drought indices is a dimensional artefact of standardization, not evidence that drought matters less than crop composition for WUE. The SPEI-SPI cross-sectional equivalence result is reported in Section 3.4.

2.3.2. WUE mechanistic components

We used the NPP (MOD17A3HGF, MODIS Terra, 500 m, Collection 6.1), which was z-score standardized within 2001-2020 (zNPP), which will be called NPP hereafter; and SETI-12 (Paruelo et al., 2016) (Standardized Evapotranspiration Index, 12-month scale; derived from MOD16A2GF actual evapotranspiration Running et al. (2021)). These are used exclusively as descriptive spatial context variables for the trend comparison in Section 3.1. The primary CASEarth WUE dataset does not distribute its internal NPP (EF-LUE model) and ET (ETMonitor) component layers separately, making algebraic decomposition infeasible. Because MOD17 and MOD16 have different sensitivities and error structures from the EF-LUE and ETMonitor models, NPP and SETI-12 are not used for formal component attribution of WUE variance, and no cross-product comparison of their relative sensitivities is presented.

2.4. Agricultural census data

Crop composition data were obtained from the VII Census (2007, pre-drought baseline) (INE, 2007) and the VIII Census (2020–2021, endpoint) (INE, 2021), both reporting cultivated area by crop category and management type at commune level. Commune-level data were spatially aggregated to sub-watershed level using area-weighted means. Three functional aggregates were computed for use as regression predictors: *pct_perennials* (fruit trees + vineyards), *pct_annuals* (cereals + vegetables + legumes + industrial crops), and *pct_forage* (forage/pasture; reference category). The variable *pct_irrigated* measures the census-reported proportion of agricultural land classified as irrigated, reflecting irrigation infrastructure and historical water rights, not the volume of water actually delivered in any given year. Sub-watersheds with high *pct_irrigated* have more irrigation-dependent cropping systems and greater structural exposure to supply disruptions. Dominant crop type per sub-watershed was assigned using a 40% area threshold. The 2021 census is used as a structural endpoint descriptor rather than a time-varying predictor: agricultural land use in central Chile is dominated by long-horizon perennial investments (orchards, vineyards) with decade-scale persistence, making the endpoint census informative for the structural crop-system configuration resulting from two decades that include the megadrought. The 2007 census provides a pre-drought baseline for structural stability comparison (Supplementary Table S-9).

The 2021 census irrigated area variable is derived entirely from directly reported data and underpins the primary spatial error model results. The 2007 irrigated area variable required partial imputation for six of ten crop categories using a commune-level residual ratio; because this single ratio is applied uniformly across categories with very different true irrigation intensities, it fundamentally distorts the cross-sectional variance structure of the 2007 *pct_irrigated* variable, and measurement error in this predictor spills over to bias the coefficients of correlated predictors in the same multiple regression. The 2007 model is therefore reported only in Supplementary Table S-9. Crucially, the imputation affects only the riego/secano split, not the total cultivated area per category, which is directly and completely reported in the VII Census for all ten crop groups. The 2007 baseline model therefore deliberately excludes *pct_irrigated* and relies exclusively on total area proportions. A sensitivity comparison adding the imputed irrigation predictor (Supplementary Table S-9) shows that the fruit-tree coefficient attenuates substantially from $\beta = +0.732$ ($p < 0.001$) to $\beta = +0.264$ ($p = 0.028$), consistent with measurement-error spillover from the imputed irrigation variable (Frisch–Waugh–Lovell theorem).

2.5. Statistical analyses

Two sub-watershed sample sizes appear throughout the analyses $n = 131$ sub-watersheds have a complete 20-year WUE time series and are used for analyses requiring only the WUE series. The Pettitt change-point test and the two-way fixed-effects panel regression $n = 127$ sub-watersheds additionally satisfy two requirements: a valid prewhitened Mann-Kendall trend slope, and complete census-derived crop composition and irrigation data. This set is used for Mann-Kendall trend analysis, per-sub-watershed WUE-drought sensitivity slopes, and all crop composition regression models. The 127-sub-watershed set is a strict subset of the 131-sub-watershed set; the four sub-watersheds present in the larger set lack complete census or irrigation coverage and are excluded from composition analyses only. A full analytical inventory is provided in Supplementary Table S-1.

2.5.1. Trend and change-point analyses

Mann-Kendall trend tests and Sen's slope estimates (with prewhitening) were computed per sub-watershed for WUE, NPP, SETI-12, and EDDI-12 (2001-2020). The Pettitt test (Pettitt, 1979) was applied to each WUE series to detect the most probable year of mean-level shift. Benjamini-Hochberg (BH) false-discovery-rate (FDR) correction was applied across 131 simultaneous tests. Sub-watersheds were classified by significance ($p < 0.05$) and proximity to megadrought onset (break years within ± 2 years of 2010). A permutation null model ($B = 1000$ iterations per sub-watershed, seed = 2026) tested whether the observed break-year concentration near 2010 is distinguishable from a SPEI-step-change tracking null. Within-sub-watershed residuals from a SPEI-12 OLS (ordinary least squares) regression were resampled with replacement and the Pettitt test was re-run on each reconstructed null series. Observed and null break-year distributions were compared using a two-sample Kolmogorov-Smirnov (KS) test. Mean WUE was compared between the pre-megadrought (2001-2009) and megadrought (2010-2020) periods using Wilcoxon signed-rank tests, stratified by Köppen climate class.

2.5.2. WUE-aridification relationships

Spearman correlations and OLS sensitivity slopes ($\Delta WUE / \Delta Index$) were computed per sub-watershed across the 20-year series. Per-sub-watershed maps are treated as descriptive summaries given strong spatial autocorrelation (Moran's $I = 0.503-0.683$); confirmatory inference rests on the spatial error models and FDR-corrected Pettitt analysis. Moran's I and Getis-Ord G_i^* local statistics identified spatial clustering and hotspots of WUE trend slope using queen contiguity weights. A two-way fixed-effects (TWFE) panel regression estimated:

$$WUE_{it} = \beta \cdot Index_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (1)$$

where μ_i and τ_t are sub-watershed and year fixed effects. Standard errors are Driscoll-Kraay (DK; Driscoll and Kraay (1998); bandwidth = 2), consistent for both serial correlation and cross-sectional spatial dependence. DK SEs (standard errors) inflate 3-4 $\times$ relative to conventional HC1 (Heteroskedasticity-Consistent) clustered SEs, reflecting the strong spatial common component (full comparison in Supplementary Table S-11).

2.5.3. Crop composition and WUE sensitivity

The per-sub-watershed OLS slope of WUE regressed on SPEI-12 was used as the outcome in a multiple regression:

$$Sensitivity_i = \beta_0 + \beta_1 \cdot pct_perennials_i + \beta_2 \cdot pct_annuals_i + \beta_3 \cdot pct_irrigated_i + \varepsilon_i \quad (2)$$

with forage/pasture as the reference category. Variance inflation factors confirmed the absence of harmful multicollinearity (all VIF < 5). Where OLS residuals were spatially autocorrelated (Moran's I, $p < 0.05$), a spatial error model (SEM) was fitted as the primary inferential model.

The TWFE panel introduced in Section 2.5.2 is estimated over the same 127 sub-watersheds; its non-significant Driscoll-Kraay results (Section 3.5) may appear to undermine the two-stage SEM, but the two approaches ask fundamentally different questions and address distinct statistical quantities. The panel estimates the *pooled mean* $\bar{\beta} = E[\beta_i]$, Driscoll-Kraay SEs make this uncertain because contemporaneous cross-sectional dependence reduces the effective independent information available to pin down the common temporal slope. The SEM, by contrast, uses the *cross-sectional dispersion* of per-sub-watershed slopes β_i , testing whether irrigation-dense sub-watersheds show systematically larger β_i than rainfed sub-watersheds. These are separable quantities, $E[\beta_i]$ can be uncertain while $Var(\beta_i)$ is real and structured. A concern that per-sub-watershed OLS slopes are “spurious” because they capture a common year-effect conflates these two estimands. When a common drought signal simultaneously depresses SPEI across all sub-watersheds, β_i measures how strongly each sub-watershed's WUE co-moves with that signal, a valid and interpretable measure of local coupling strength. An irrigation-dense sub-watershed with $\beta_i = 0.8$ genuinely shows stronger drought coupling than a rainfed sub-watershed with $\beta_i = 0.1$, regardless of whether the pooled mean is identifiable. Moran's I = 0.811 ($p < 0.001$) on the observed β_i values shows this cross-sectional variation is

spatially organized rather than noise. Because β_i is subsequently modelled as a function of spatially clustered predictors, this statistic alone cannot separate genuine differential coupling from spatially patterned noise in an underpowered per-unit slope; a falsification check addressing this is reported in Section 3.7.

A supplementary pre-drought comparison using the 2007 census is reported in Supplementary Table S-9; as detailed in Section 2.4, imputation issues render it uninformative for all three predictors. Robustness was verified through: (i) restriction to within-Csb warm-summer Mediterranean sub-watersheds ($n = 70$); (ii) a synchronized-time bootstrap ($B = 1000$) propagating stage-1 estimation uncertainty while preserving cross-sectional spatial covariance (Supplementary Table S-10); (iii) a barren-exclusion dynamic land-cover filter excluding MODIS-confirmed non-vegetated pixels (Supplementary Table S-7); (iv) a parallel SEM using the Standardized Snow Water Equivalent Index (SWEI) from ERA5-Land as the drought predictor (Supplementary Table S-6); and (v) addition of sub-watershed centroid latitude as a direct covariate to test whether the irrigation association persists after explicit control for the latitudinal aridity gradient (Table 1).

2.6. Software

All statistical analyses and spatial processing were conducted in R (v4.5.2; R Core Team (2025)). Raster operations and spatial aggregation used `terra` (v1.8.54; Hijmans (2025)). Vector geometries and spatial joins used `sf` (v1.0.23; Pebesma (2018), Pebesma and Bivand (2023)). Spatiotemporal array operations used `stars` (v0.6.8; Pebesma and Bivand (2023)). Mann-Kendall trend tests and Sen’s slope estimation with prewhitening used `modifiedmk` (v1.6; Patakamuri and O’Brien (2021)) and `trend` (v1.1.6; Pohlert (2023)). Spatial autocorrelation (Moran’s I, Getis-Ord G_i^*) and spatial weight matrices used `spdep` (v1.4.1; Bivand and Wong (2018)). Spatial Error Model was made using `{spatialreg}` (Bivand et al., 2021). Panel regression with fixed effects used `plm` (Croissant and Millo, 2008); Driscoll-Kraay standard errors via `plm::vcovSCC` (Driscoll and Kraay, 1998); HC1 clustered SEs via `plm::vcovHC` with `lmtest::coeftest`. Variance inflation factors used `car` (v3.1.3; Fox and Weisberg (2019)). General-purpose data manipulation and reshaping used `tidyverse` (v2.0.0; Wickham et al. (2019)), including `dplyr`, `tidyr`, `readr`, `stringr`, `purrr`, and `lubridate`. Thematic maps used `tmap` (v4.2; Tennekes (2018)). Statistical graphics used `ggplot2` (v3.5.2; Wickham (2016)). Multi-panel figure layout used `patchwork` (v1.3.1; Pedersen (2025)).

3. Results

3.1. Long-term WUE trends

Trend analysis across 127 Chilean agricultural sub-watersheds revealed predominantly negative WUE trends across the Mediterranean-climate zone (approximately 30°S–35°S), consistent with megadrought onset and intensification (Figure 2).

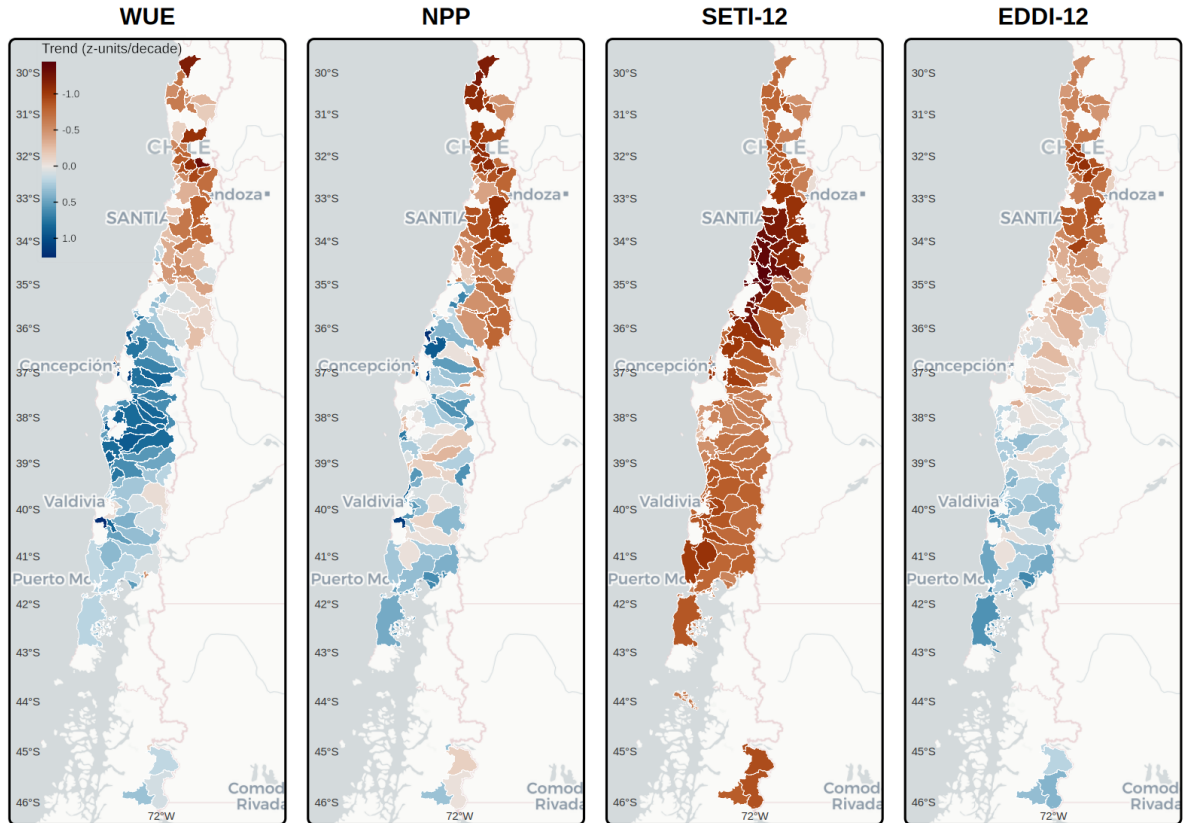


Figure 2: Spatial distribution of long-term trends in zWUE (WUE anomaly), zNPP (NPP anomaly), SETI-12 (12-month ET anomaly), and EDDI-12 (12-month atmospheric evaporative demand) across Chilean sub-watersheds (2001-2020). Trend magnitudes are expressed as z-score standardized Sen’s slope estimates.

NPP (MOD17A3HGF) and SETI-12 (MOD16A2GF) are independent proxy products that do not decompose the CASEarth WUE directly; the following patterns are descriptive spatial co-variation, not formal component attribution. NPP trends exhibit strong spatial covariance with WUE, with negative anomalies concentrated in the same central Mediterranean sub-watersheds where WUE declines are most pronounced. SETI-12 trends are more spatially complex: sub-watersheds where ET declined less steeply than NPP tend to show WUE decline, while those where ET reduction exceeded NPP reduction tend toward stable or improving WUE.

Declining WUE is spatially co-located with negative NPP anomalies, while ET responses are heterogeneous and modulated by irrigation access and crop type. Whether NPP suppression is a more proximate correlate of WUE decline than ET cannot be formally established from these proxy data, as the independent products may differ in sensitivity and error structure from the EF-LUE and ETMonitor components underlying the CASEarth WUE (Fifth limitation, Section 4.6).

3.2. WUE change-point analysis

The Pettitt test detected FDR-significant mean-level change points in 22 of 131 sub-watersheds (adjusted p range: 0.019–0.047), all dated 2009–2012. The permutation null model showed that 72.1% of null Pettitt tests also had break years within ± 2 years of 2010 (observed: 84.1%); the Kolmogorov-Smirnov test detected no significant difference ($D = 0.153$, $p = 0.255$), a failure to reject the null. The observed break-year concentration near 2010 is therefore not distinguishable from what would be expected under SPEI-step-change tracking alone. Break years were not significantly spatially clustered (Moran's $I = 0.018$, $p = 0.345$), consistent with common large-scale forcing rather than spatial propagation. The geographic distribution of FDR-significant breaks, concentrated in the central Mediterranean zone while the arid north and wet south show no aligned breaks (Boisier et al., 2018; Garreaud et al., 2020), is provided for descriptive reference (Figure 3 a).

3.3. WUE before and after the megadrought

Mapping $\Delta WUE = WUE_{post} - WUE_{pre}$ per sub-watershed revealed pronounced spatial heterogeneity (Figure 3 b). Arid and semi-arid sub-watersheds showed predominantly negative ΔWUE , while irrigated Mediterranean and humid-temperate sub-watersheds showed positive ΔWUE . The aggregate Wilcoxon signed-rank test was positive and significant ($p = 0.007$), but this reflects the numeric dominance of irrigated Mediterranean sub-watersheds, not widespread drought resilience; composition effects render the aggregate statistic uninformative, and the stratified analysis that follows is the appropriate summary. Köppen-stratified analyses resolve the heterogeneity (Supplementary Table S-2). BW (hot desert; $n = 8$) showed significant declines (Hodges-Lehmann [HL] estimate = -0.535 , 95% Confidence Intervals [CI]: -0.862 to -0.335 ; $p = 0.008$), as did BS (semi-arid steppe; $n = 14$; HL = -0.643 , $p < 0.001$). Csb (warm-summer Mediterranean; $n = 71$) and Cf (humid subtropical; $n = 26$) exhibited significant WUE increases (HL = $+0.374$, $p < 0.001$ and HL = $+0.367$, $p < 0.001$, respectively). Violin-boxplot distributions stratified by Köppen class (Figure 3 c) confirm this divergence.

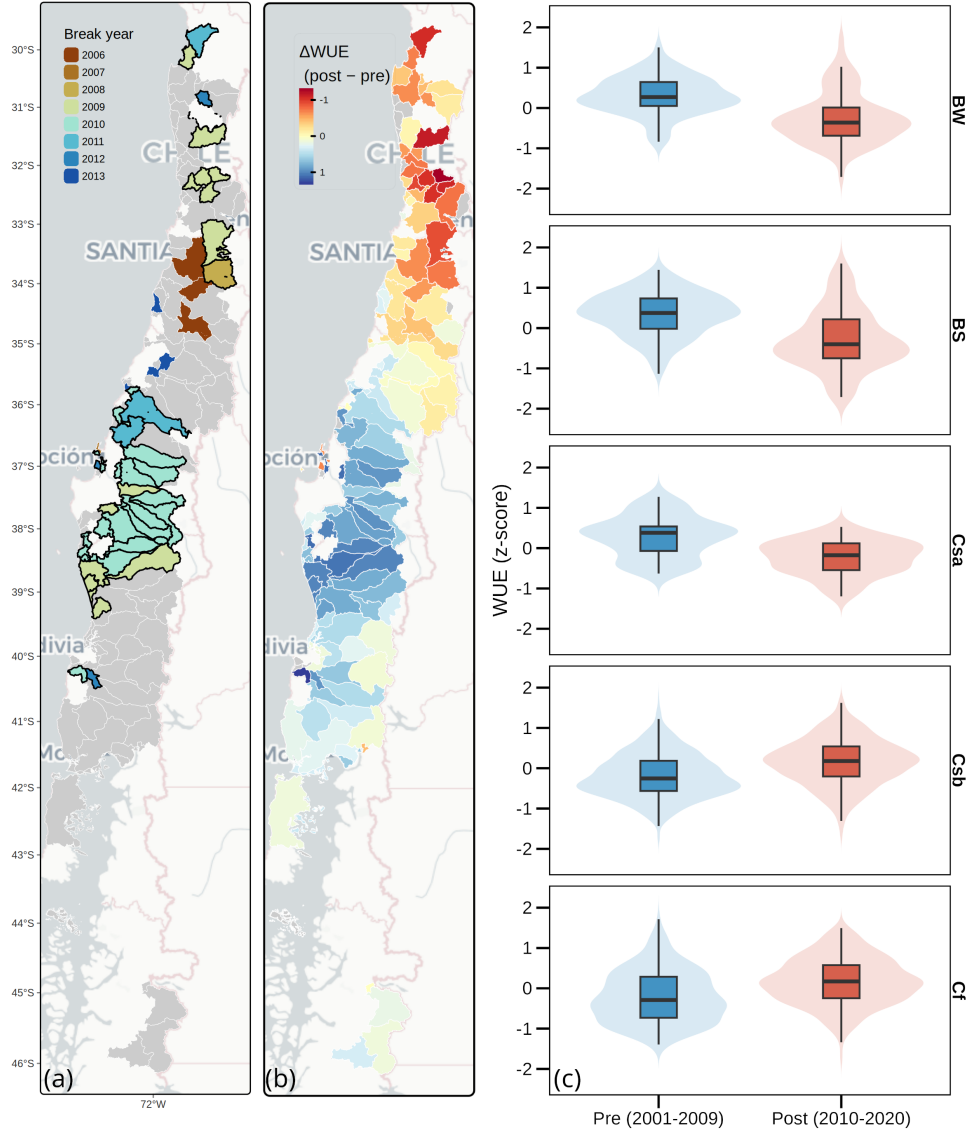


Figure 3: (a) Spatial distribution of Pettitt change-point years in annual WUE per sub-watershed (FDR-significant at adjusted $p < 0.05$). Sub-watersheds with change-point years within ± 2 years of 2010 are highlighted with bold borders. FDR-significant breaks concentrate in the central Mediterranean zone; the permutation null model does not distinguish this concentration from SPEI-step-change tracking (KS $p = 0.255$; Section 3.2). Provided for descriptive geographic reference. Non-significant change points are shown in grey. (b) Spatial map of WUE change between the megadrought period (2010–2020) and the pre-megadrought period (2001–2009) ($\Delta WUE = WUE_{post} - WUE_{pre}$) per sub-watershed. Positive values (blue) indicate net WUE increase; negative values (red) indicate WUE decline. Köppen climate zone boundaries (dashed lines) are overlaid. (c) Violin-boxplot distributions of annual WUE for the pre-megadrought (blue, 2001–2009) and megadrought (red, 2010–2020) periods, stratified by Köppen climate class. Each panel corresponds to one climate class; y-axes are free-scaled.

3.4. WUE responses to aridification signals

Spearman correlation analysis at the per-family optimal scales (SPEI-12, SPI-12, EDDI-24) revealed positive associations between annual WUE and drought indices across most Chilean sub-watersheds (Figure 4), with wetter years generally associated with higher WUE.

At the 36-month scale, SPEI and SPI showed practically equivalent associations with WUE (mean $R^2 = 0.240$ and 0.229 ; TOST within ± 0.05 margin: $p < 0.001$, 90% CI $[-0.004, +0.003]$), both significantly outperforming EDDI-36 (mean $R^2 = 0.140$; $p < 0.001$; Supplementary Figure S-2). The precipitation component dominates the spatial gradient in WUE variability at multi-year accumulation scales.

3.5. Panel regression: temporal WUE-drought relationships

Under Driscoll-Kraay standard errors, no panel coefficient reaches conventional significance at any index or accumulation scale. SPEI-12 ($\beta = -0.112$, DK $p = 0.273$), SPI-12 ($\beta = -0.170$, DK $p = 0.053$), and Mediterranean-restricted SPEI-24 ($\beta = +0.193$, DK $p = 0.458$) and SPI-24 ($\beta = +0.141$, DK $p = 0.579$) are all non-significant (Supplementary Table S-11). The negative signs at the 12-month scale arise from humid-temperate Cf sub-watersheds ($n = 26$), where rainfed annual systems transiently raise WUE under mild moisture stress (Yu et al., 2020). The substantive interpretation is that WUE-drought co-variation in the temporal panel is largely a spatially common signal. The same calendar years are simultaneously wet or dry across all Mediterranean sub-watersheds, leaving insufficient independent within-unit variation to support inference once cross-sectional dependence is properly accounted for. The drought index's physical role in determining WUE sensitivity is established through the cross-sectional sensitivity slopes (Section 3.6, Section 3.7) and the DGA streamflow validation (Section 4.3), not through the panel temporal analysis. Full HC1 vs. DK comparison is in Supplementary Table S-11. A linear HC1 post-2010 interaction model at SPEI-36 yields a positive intensification term ($\beta = +0.281$, $p = 0.012$; Supplementary Figure S-6), but Supplementary Table S-8 shows this pattern is attributable to the concentration of strongly negative SPEI-36 values after 2010 operating on a concave WUE-SPEI relationship, not a discrete temporal structural break.

3.6. Spatial distribution and clustering of WUE sensitivity

The WUE-SPEI-12 sensitivity map (Figure 5 a) shows the OLS slope per sub-watershed. Sensitivity broadly follows the latitudinal aridity gradient, with central Mediterranean sub-watersheds exhibiting higher values than humid southern sub-watersheds and locally elevated sensitivity in perennial-dominated irrigated zones (Figure 5 b and c).

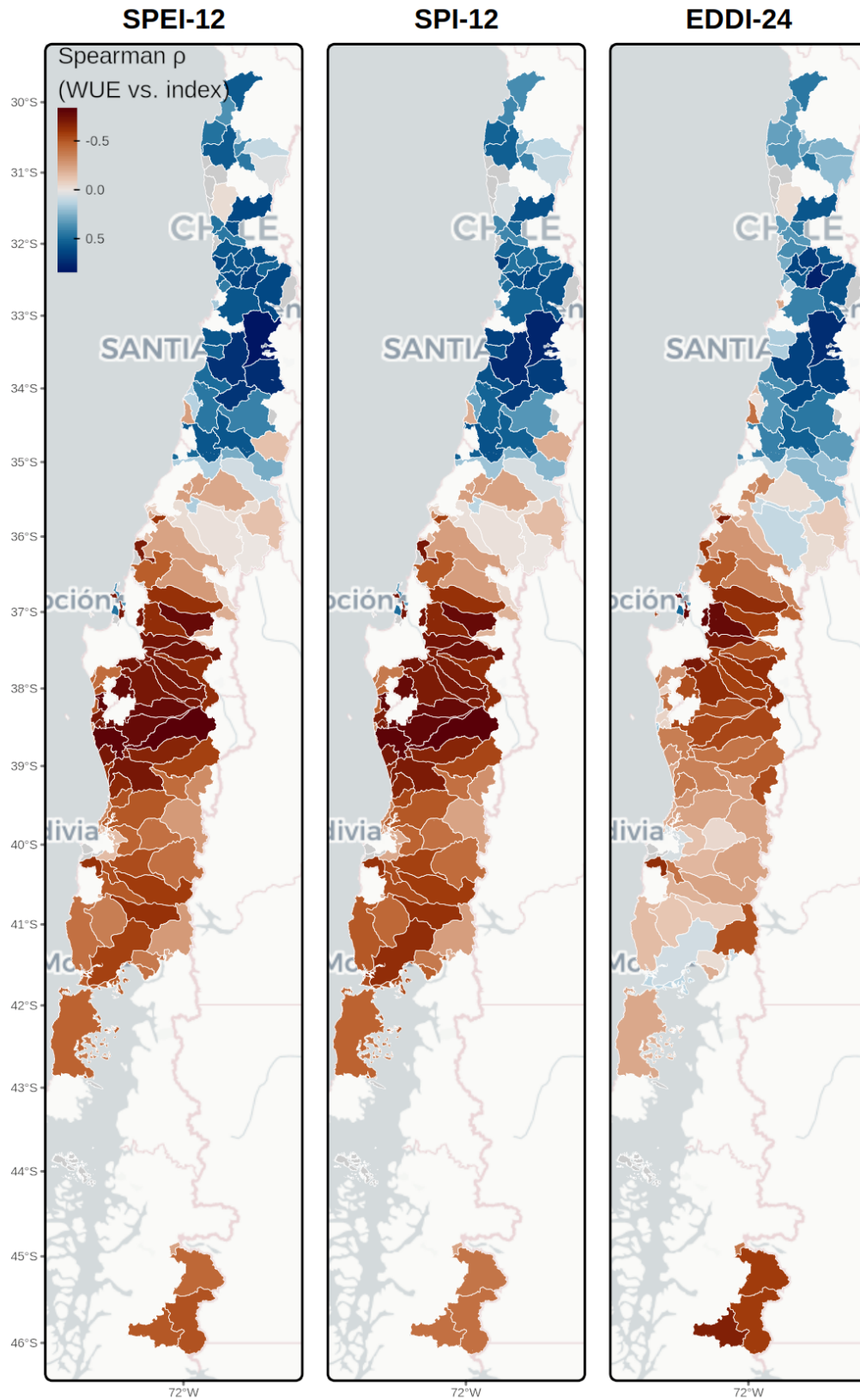


Figure 4: Spatial maps of Spearman ρ (WUE vs. drought index) for sub-watershed, faceted by drought index at the accumulation scales used for the per-sub-watershed spatial analyses (SPEI-12, SPI-12, EDDI-24). Diverging colour scale (blue = positive correlation, red = negative correlation).

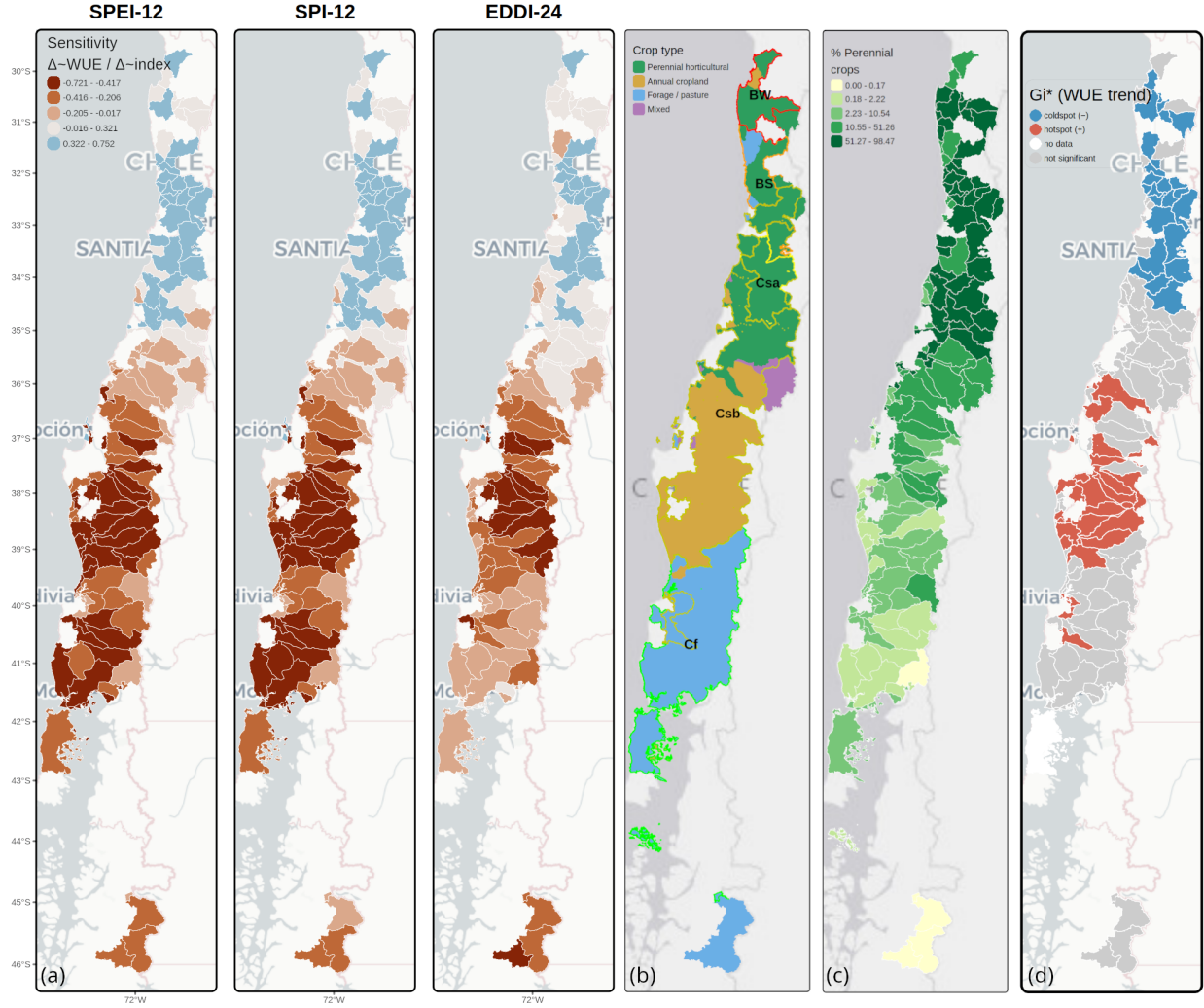


Figure 5: (a) Spatial distribution of WUE-drought sensitivity ($\Delta WUE / \Delta Index$, the OLS slope of the annual WUE ~ index regression per sub-watershed, 2001-2020) for SPEI-12, SPI-12, and EDDI-24. High positive values indicate strong positive WUE response; near-zero or negative values indicate weak or inverted coupling. (b) Choropleth map of dominant crop type per sub-watershed, classified by the agricultural functional group exceeding 40% of total agricultural area (Perennial horticultural, Annual cropland, Forage/pasture, Mixed). (c) Choropleth map of perennial crop share (% of total agricultural area under fruit trees and vineyards) per sub-watershed. (d) Getis-Ord Gi* hotspot analysis of WUE trend slope across Chilean sub-watersheds. Red sub-watersheds are statistically significant hotspots (positive WUE trend clusters; $Gi^* > 1.96$); blue are coldspots (negative WUE trend clusters; $Gi^* < -1.96$); grey are not significant at the 95% level.

Moran's I for WUE trend slope was $I = 0.683$ ($p < 0.001$) and for WUE-SPEI-12 R^2 was $I = 0.503$ ($p < 0.001$), confirming strong geographic clustering. Getis-Ord G_i^* hotspot analysis identified coherent coldspots in the central Mediterranean zone and localized hotspots in transitional zones (Figure 5 d). Pettitt change-point years were not significantly spatially clustered ($I = 0.018$, $p = 0.345$), indicating that the temporal concentration near 2010 reflects common large-scale forcing rather than spatial propagation. Hydroclimate governs when and how strongly WUE shifts over time; crop composition modulates the spatial magnitude of each sub-watershed's drought sensitivity. These two axes are complementary rather than competing.

3.7. Agricultural crop composition and WUE sensitivity

Integration of census-derived crop composition with WUE-SPEI-12 sensitivity estimates ($n = 127$ sub-watersheds) revealed contrasting patterns by crop system. Annual cropland sub-watersheds showed lower sensitivity than forage/pasture watersheds, while perennial horticultural sub-watersheds showed the highest median sensitivity (Figure 6 a); because perennial crop distribution, aridity, and WUE sensitivity all co-vary with latitude (Figure 7 c), the perennial pattern likely reflects the underlying climate gradient rather than an isolated crop-system effect (Section 4.6). Irrigated area share was positively associated with sensitivity in the full-sample pooled analysis (Figure 7 a).

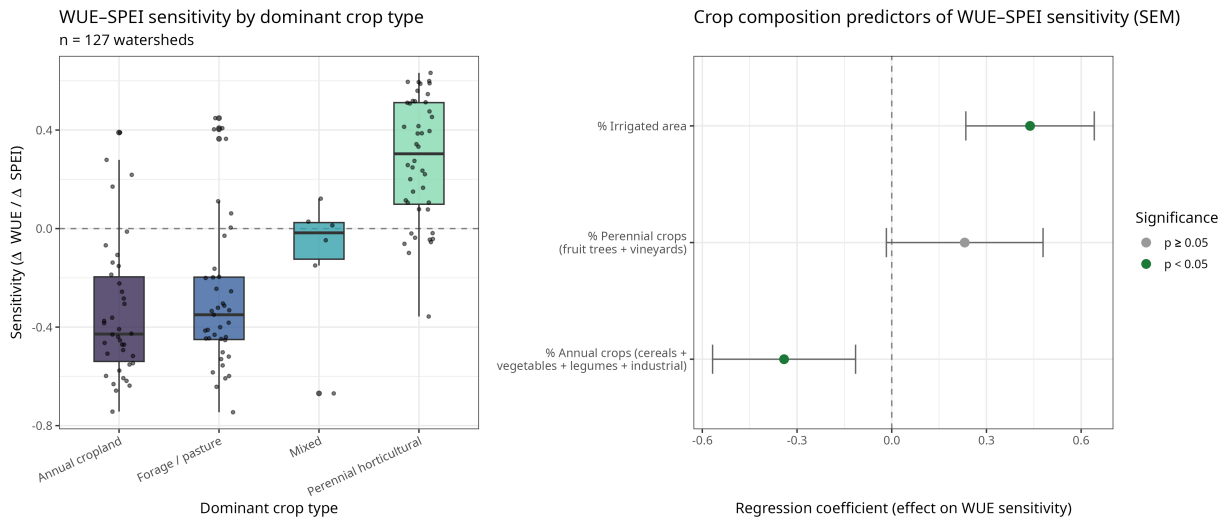


Figure 6: WUE-SPEI-12 sensitivity by dominant crop type ($n = 127$ sub-watersheds). (a) Boxplot distributions of per-sub-watershed OLS sensitivity slopes stratified by dominant agricultural system: perennial horticultural (fruit trees + vineyards), annual cropland (cereals + vegetables + legumes + industrial crops), mixed systems (no single group exceeds 40% of agricultural area), and forage/pasture. Perennial-dominated sub-watersheds show the highest median sensitivity; forage/pasture sub-watersheds show the lowest. (b) Full-sample SEM coefficient plot for the three functional-aggregate predictors (perennial crops, annual crops, irrigated area; reference: forage/pasture) with 95% confidence intervals; filled symbols indicate $p < 0.05$. Numeric values and within-Csb comparisons are in Table 1.

Three strategies address confounding between crop composition, aridity, and latitude: (i) a within-Csb

restriction controlling the latitudinal gradient through climate-zone stratification, (ii) a direct latitude covariate test, and (iii) geographic cross-validation assessing out-of-sample portability. None of these strategies establishes causality; all findings remain associative.

The multivariate OLS regression ($n = 127$ sub-watersheds) returned annual crop share as a significant negative predictor ($\beta = -0.293$, $p = 0.001$), consistent with buffering relative to the forage/pasture reference; perennial crop share as a positive but subsequently attenuated predictor ($\beta = 0.398$, $p = 0.001$); and irrigated area share as the strongest positive predictor ($\beta = 0.461$, $p < 0.001$), reflecting the association between irrigation infrastructure prevalence and drought coupling rather than actual water volumes delivered in drought years.

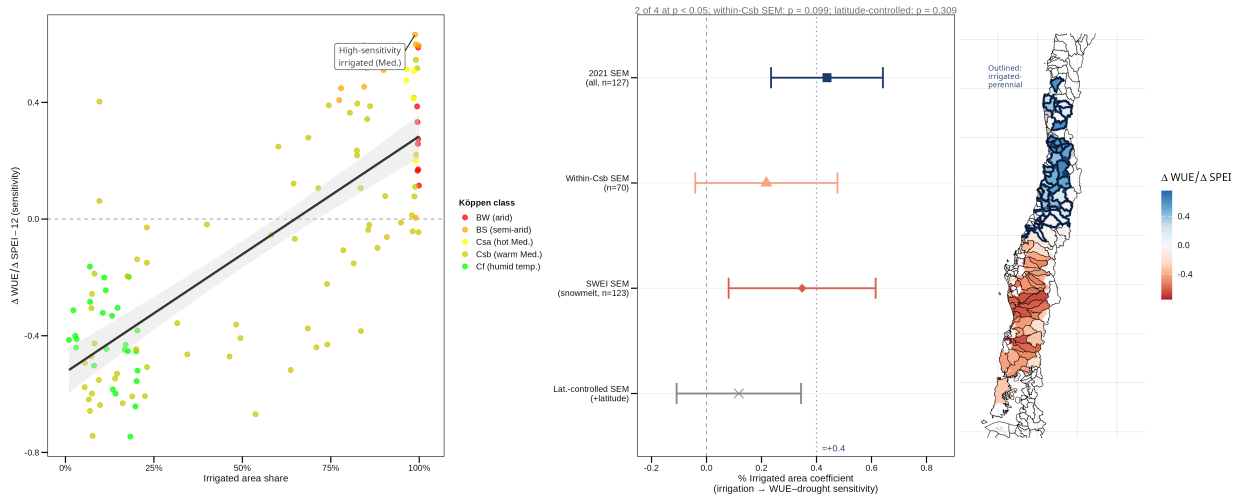


Figure 7: (a) Scatter plot of WUE-SPEI-12 sensitivity versus irrigated area share per sub-watershed ($n = 127$), coloured by Köppen climate class, with a pooled OLS regression line ($\pm 95\%$ CI). Points in the upper-right cluster (high irrigation, high sensitivity) correspond to Mediterranean irrigated-perennial systems; points in the lower-left correspond to rainfed or annual-crop dominated systems. (b) Forest plot of the irrigated area share regression coefficient ($\pm 95\%$ CI) across four model specifications: 2021 full-sample SEM, within-Csb warm-summer Mediterranean SEM, SWEI-based SEM using snowmelt index as the drought predictor, and a latitude-controlled SEM with sub-watershed centroid latitude added as a covariate. The 2007 pre-drought SEM is omitted from this figure because imputation issues render it uninformative (Supplementary Table S-9). Two specifications are significant at $p < 0.05$ (full-sample SEM and SWEI SEM); the within-Csb SEM is not significant ($\beta = +0.218$, $p = 0.099$); the latitude-controlled SEM attenuates to $\beta = +0.117$ ($p = 0.309$), consistent with partial confounding by the latitudinal aridity gradient. The vertical dotted line marks +0.4 for reference. (c) Choropleth of WUE-SPEI-12 sensitivity (OLS slope per sub-watershed, 2001–2020); solid blue borders outline perennial-horticultural-dominant sub-watersheds, which concentrate in the central Mediterranean zone and correspond to the high-sensitivity cluster in panel (a). Table 1 reports the same coefficients with full numeric values and confidence intervals.

Table 1 reports the same coefficients presented visually in Figure 7 with full numeric values and confidence intervals. Moran's I on OLS residuals was $I = 0.216$ ($p < 0.001$), so a spatial error model (SEM; queen-contiguity weights) was fitted as the primary inferential model ($\lambda = 0.435$, $p < 0.001$). The SEM attenuated but largely preserved the OLS conclusions: annual crop share ($\beta = -0.341$, 95% CI $[-0.568, -0.115]$, p

= 0.003), perennial crop share ($\beta = 0.231$, 95% CI $[-0.017, +0.479]$, nominal $p = 0.068$; Figure 6 b), and
 irrigated area share ($\beta = 0.438$, 95% CI $[+0.235, +0.642]$, $p < 0.001$). A synchronized-time bootstrap
 (Supplementary Table S-10) confirmed significance for all three predictors ($p = 0.002$ - 0.036) with bootstrap
 SEs 0.74 - $0.94\times$ nominal for the three slope coefficients. Bootstrap SEs below the nominal SEM SEs warrant
 explanation, since propagating stage-1 uncertainty would naively be expected to widen them. The explanation
 is that the synchronized design resamples the same calendar years for all 127 sub-watersheds in each iteration,
 so a resampled year set that is unusually wet or dry shifts every β_i in the same direction. That common
 shift is absorbed almost entirely by the intercept, whose bootstrap SE is correspondingly *inflated* to $1.49\times$
 nominal, while the cross-sectional contrasts among sub-watersheds that identify the slope coefficients are
 left comparatively stable. The nominal SEM SEs, by contrast, treat each sub-watershed's stage-1 error as
 independent and so attribute part of this common component to the slopes. Consistent with this account, a
 pairs bootstrap that resamples years independently per sub-watershed destroys the common shift and yields
 still narrower slope SEs (0.54 - $0.75\times$ nominal) with no intercept inflation ($0.71\times$ nominal). WLS estimates
 (Supplementary Table S-5) confirm no sign changes under stage-1 uncertainty weighting.

To test whether associations are crop-system properties robust to the latitudinal aridity gradient, the model
 was restricted to Csb warm-summer Mediterranean sub-watersheds ($n = 70$). The three predictors behave
 differently across specifications (Table 1):

Table 1. Comparison of WUE-SPEI-12 sensitivity regressions across model specifications, reported as
 β with 95% confidence intervals. Full-sample SEM: $n = 127$ (all climate classes); within-Csb OLS and
 SEM: $n = 70$ (warm-summer Mediterranean, $\lambda = 0.254$, $p = 0.054$); latitude-controlled SEM: $n = 127$
 with sub-watershed centroid latitude added as a covariate. Reference category: forage/pasture. *** $p <$
 0.001 ; ** $p < 0.01$; * $p < 0.05$. Intervals rather than significance labels are the basis for interpretation
 throughout, particularly in the within-Csb subsample where $n = 70$ yields wide intervals. Full model outputs
 in Supplementary Tables S-4 (within-Csb) and S-14 (latitude-controlled).

Predictor	Full-sample SEM β [95% CI]	Within-Csb OLS β [95% CI]	Within-Csb SEM β [95% CI]	Lat.-controlled SEM β [95% CI]
% Irrigated area	+0.438 *** [+0.235, +0.642]	+0.264 * [+0.016, +0.511]	+0.218 [-0.041, +0.476]	+0.117 [-0.109, +0.344]
% Annual crops	-0.341 ** [-0.568, -0.115]	-0.488 ** [-0.772, -0.203]	-0.591 *** [-0.895, -0.287]	-0.511 *** [-0.725, -0.298]

	Full-sample SEM β	Within-Csb OLS β	Within-Csb SEM β	Lat.-controlled
Predictor	[95% CI]	[95% CI]	[95% CI]	SEM β [95% CI]
% Perennial crops	+0.231 [−0.017, +0.479]	+0.305 [−0.041, +0.652]	+0.175 [−0.175, +0.525]	+0.022 [−0.221, +0.266]

The annual-crops association strengthens within Csb (SEM $\beta = -0.591$, 95% CI [−0.895, −0.287]), the only predictor whose interval excludes zero in this subsample, supporting it as a crop-system property that persists once the latitudinal gradient is restricted. The irrigated area association is weaker and its interval includes zero under the SEM ($\beta = +0.218$, 95% CI [−0.041, +0.476]), though it excludes zero under the within-Csb OLS ($\beta = +0.264$, 95% CI [+0.016, +0.511]; Figure 7 b). Perennial crop share is likewise indistinguishable from zero ($\beta = +0.175$, 95% CI [−0.175, +0.525]). At $n = 70$ the irrigation and perennial intervals overlap substantially and are consistent with effects of similar magnitude; we therefore describe both as unresolved at this sample size rather than assigning them different qualitative labels on the basis of their p-values.

Geographic cross-validation reinforces this assessment of spatial contingency. When the crop-composition model is trained on four out of five equal-latitude-quantile holdout bands and tested on the held-out band, all five per-block out-of-sample R^2 values are negative (range −1.25 to −0.29; Figure 8), indicating that the quantitative model does not transfer across latitude bands within Chile and does worse than predicting the block mean. The coefficients capture a spatially contingent configuration specific to the training latitudinal range rather than generalizable structural parameters.

A direct latitude-control test, adding sub-watershed centroid latitude as a covariate to the full-sample SEM, is presented in Table 1 (rightmost columns). The irrigation coefficient attenuates from $\beta = +0.438$ to $\beta = +0.117$ ($p = 0.309$; $\Delta\text{AIC} = 19.8$), confirming partial confounding with the latitudinal aridity gradient. The annual-crops coefficient strengthens ($\beta = -0.511$, $p < 0.001$), establishing annual-crop buffering as the more latitude-robust result. The perennial coefficient collapses to near zero ($\beta = +0.022$, $p = 0.858$).

A falsification check tested whether the spatial structure in per-sub-watershed WUE-SPEI sensitivity slopes (β_i) survives after residualizing out irrigation share and centroid latitude. The original Moran’s I on β_i is 0.811 ($p < 0.001$). After regressing β_i on irrigation share and latitude and computing Moran’s I on the residuals, the spatial autocorrelation is substantially attenuated ($I = 0.397$, $p < 0.001$), with 51% of the original spatial structure removed. The residual spatial autocorrelation remains significant, indicating that

β_i retains spatial structure beyond what irrigation and latitude jointly capture, and is therefore not reducible to the spatial pattern of the predictors used to model it.

A second diagnostic addresses whether the latitude covariate and the SEM spatial error term compete for the same north-south variance, which would produce an attenuation of the irrigation coefficient that mimics confounding without being it. Three results argue against this reading. First, the fitted spatial error component and centroid latitude are only moderately correlated ($r = 0.400$) with a variance inflation factor of 1.21, far below conventional thresholds. Second, adding latitude barely changes the spatial error parameter itself ($\lambda = 0.435$ without latitude, $\lambda = 0.396$ with it), so latitude is not displacing the variance the error term absorbs. Third, and most directly, the same attenuation occurs in an OLS specification containing no spatial error term at all, where competition with λ is impossible by construction: the irrigation coefficient falls from $\beta = +0.461$ ($p < 0.001$) to $\beta = +0.219$ ($p = 0.032$) when latitude is added (Supplementary Table S-14). The attenuation is therefore attributable to latitude itself rather than to overlap between two spatial terms. We note that the irrigation coefficient retains an interval excluding zero in the latitude-controlled OLS but not in the latitude-controlled SEM, so the strength of the residual association depends on whether spatial dependence is modelled; we treat the SEM, the primary model throughout, as the conservative reading.

The pre-drought census comparison is reported in Supplementary Table S-9; imputation issues render it uninformative for distinguishing structural from adaptive effects (Section 2.4). The causal direction of the 2021 negative association is discussed in Section 4.3.

Natural vegetation contamination within the agricultural mask was non-significant as a control covariate ($\beta = 0.098$, $p = 0.509$; Supplementary Figure S-3).

4. Discussion

4.1. The megadrought as a driver of persistent WUE change

WUE undergoes a mean-level shift concurrent with the megadrought onset is a physically expected consequence of WUE being hydroclimate-driven, not a novel finding. The permutation null model provides no evidence to distinguish the observed break-year concentration from simple SPEI step-change tracking (KS $p = 0.255$), confirming this expectation. The geographic distribution of FDR-significant breaks, concentrated in the central Mediterranean zone, is descriptively consistent with megadrought forcing but does not establish coupling beyond what SPEI-step-change tracking alone would produce. The aggregate WUE increase (Wilcoxon $p = 0.007$) masks pronounced spatial heterogeneity. Arid northern sub-watersheds declined

while the irrigated Mediterranean zone rose, coinciding with the elevated drought coupling documented in Section 4.3.

4.2. Multidimensional aridification: why index choice matters

The practically equivalent performance of SPEI-36 and SPI-36 in cross-sectional analyses (TOST: $p < 0.001$) indicates that the precipitation component dominates the spatial gradient in WUE sensitivity under megadrought conditions. The TWFE panel provides no statistically significant evidence for within-unit temporal WUE-drought coupling at any index or scale once cross-sectional dependence is accounted for through Driscoll-Kraay SEs (Supplementary Table S-11). The substantive interpretation is that WUE-drought co-variation in the temporal panel is largely a spatially common phenomenon. The same calendar years are wet or dry across all Mediterranean sub-watersheds simultaneously, leaving insufficient independent within-unit variation to support inference. Drought’s physical role in determining WUE sensitivity is established through the cross-sectional sensitivity slopes and the DGA streamflow validation, not through the panel temporal analysis.

4.3. Irrigation infrastructure and WUE drought sensitivity

In the full-sample SEM, irrigated area share is positively associated with WUE-drought sensitivity ($\beta = +0.438$, $p < 0.001$), with snowmelt co-variation supported by $\rho(\text{SPEI-12, DGA streamflow}) = 0.72\text{-}0.83$ and $\rho(\text{streamflow, WUE}) = 0.38\text{-}0.68$ in the three northern basins (Supplementary Table S-13). Adding centroid latitude attenuates this to non-significance ($\beta = +0.117$, $p = 0.309$; Table 1), while the within-Csb restriction yields a non-significant association under the SEM ($\beta = +0.218$, $p = 0.099$). The evidence does not contradict demand-hardening dynamics (Grafton et al., 2018; Ward and Pulido-Velázquez, 2008) but cannot establish the irrigation association as latitude-independent.

The annual-crops association is robust to latitude control, strengthening from $\beta = -0.341$ to $\beta = -0.511$ when latitude is added (Table 1); the causal direction is ambiguous and is addressed in limitation (vii, Section 4.6).

The perennial crop coefficient is non-significant in all specifications (full-sample $p = 0.068$; within-Csb SEM $p = 0.327$; latitude-controlled $p = 0.858$; Table 1), most plausibly reflecting statistical inseparability from the irrigation coefficient in Chile’s Mediterranean zone, where irrigation enables perennial cultivation that creates inelastic water demand (Grafton et al., 2018). Both associations are hypotheses consistent with the data,

each constrained by a distinct confound, and should not be interpreted as established causal mechanisms (Boser et al., 2024; FAO y ONU Agua, 2025; Hellegers and Van Halsema, 2021; Wang et al., 2024).

4.4. Spatial structure, global implications, and limits of adaptation

WUE coldspots are concentrated in the Aconcagua, Maipo, Rapel, Mataquito, and Maule basins (32-36°S), precisely the zone concentrating Chile’s export fruit and wine production. Because the central agricultural corridor stresses simultaneously, water-market transfers under Chile’s privatized Water Code have limited scope to buffer basin-scale shortfalls (Budds, 2020; Malagueño and D’Odorico, 2024; Rivera et al., 2016). Drought-driven WUE decline means more water is consumed per unit of biomass produced; sustaining production in high-sensitivity basins requires proportionally greater withdrawals precisely when supply is lowest.

The supply-failure mechanism applies conceptually to snowmelt-dependent irrigated agriculture globally (Barnett et al., 2008; Immerzeel et al., 2020; Lutz et al., 2014), but the quantitative crop composition model is a within-Chile spatial descriptor and does not transfer geographically (Figure 8); the coefficients are not portable and should not be applied to other regions. We are deliberate about what does carry over. What generalizes is the conceptual expectation that irrigation supply coupled to the same hydroclimatic signals that suppress productivity offers less drought protection than supply that is decoupled from them, a proposition that rests on the hydrological argument and the streamflow validation (Section 4.3) rather than on the transferability of our fitted coefficients. The cross-validation result additionally leaves open whether those coefficients reflect a crop-system mechanism at all, as opposed to the specific latitude-aridity-irrigation configuration of this dataset (limitation viii, Section 4.6). The paragraphs that follow should be read as an interpretation of the Chilean case under that constraint, not as quantitative predictions for other regions. Institutional buffering capacity also differs substantially. Chile’s privatized water market, where simultaneous basin-scale droughts exhaust reallocation capacity, represents one end of a governance spectrum, while state-managed systems with groundwater banking may partially decouple farm-gate delivery from meteorological signals.

Where irrigation supply is hydrologically coupled to the same climate signals that drive drought, expanding irrigation infrastructure without securing supply independence may increase aggregate drought exposure. This does not argue against irrigation per se, but distinguishes between systems with independent supply and those coupled to snowmelt and precipitation, a distinction with direct relevance for investment prioritization and drought-contingency planning (FAO y ONU Agua, 2025).

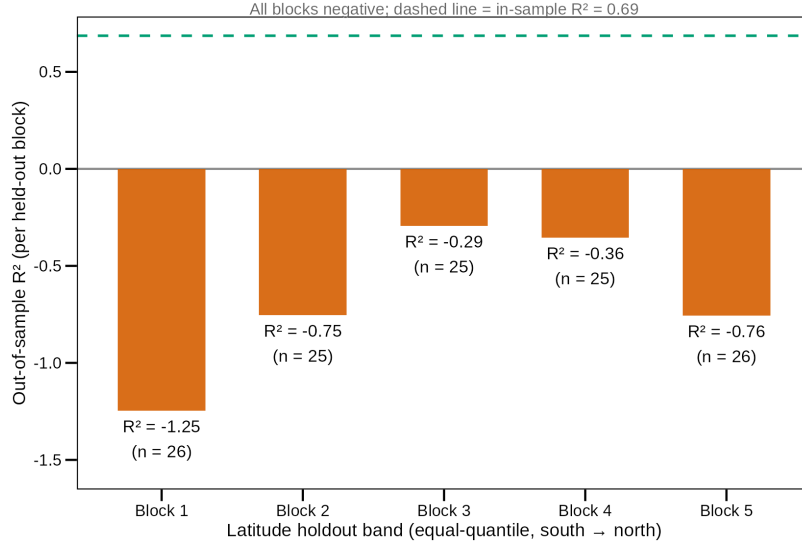


Figure 8: Geographic cross-validation of the crop composition-WUE-SPEI-12 sensitivity model. Continental Chile was partitioned into five equal-latitude-quantile holdout bands (ordered south to north); each band was predicted from a model trained on the remaining four. All five per-block out-of-sample R^2 values are negative (range -1.25 to -0.29), well below the in-sample R^2 of 0.69 (dashed line), meaning the model predicts a held-out latitude band worse than that band’s own mean. The quantitative coefficients are not geographically portable; only the supply-failure mechanism transfers conceptually to other snowmelt-dependent irrigation systems.

The coldspot concentration in the five key basins is quantifiable in terms directly relevant to water allocation and planting decisions. Sub-watersheds in the Aconcagua and Maipo basins show the highest mean WUE-SPEI-12 sensitivities in the dataset (mean $\beta = 0.45$ and 0.54 respectively; individual sub-watershed peaks of 0.50 and 0.63), combined with near-complete irrigation infrastructure prevalence (mean $\text{pct_irrigated} > 0.97$) and confirmed hydrological coupling ($\rho(\text{SPEI-12}, \text{streamflow}) = 0.75$ and 0.82 ; $\rho(\text{streamflow}, \text{WUE}) = 0.61$ and 0.68). These basins concentrate Chile’s export fruit and wine production under a regime where rights granted by the 1981 Water Code are permanent and freely tradeable, but where basin-scale reallocation cannot buffer a deficit that reduces supply for all rights holders simultaneously (Budds, 2020; Rivera et al., 2016). By contrast, Mataquito and Maule sub-watersheds show markedly lower mean sensitivities (0.12 and -0.03) despite similarly high irrigation prevalence (mean pct_irrigated 0.96 and 0.92), consistent with greater rainfall supplementation of snowmelt at higher latitudes. This north-to-south gradient implies that the lock-in risk of new perennial investment is not uniform across the Mediterranean zone. The same commitment to perennial horticulture or viticulture that carries moderate coupling risk in Maule carries substantially higher coupling risk in Aconcagua and Maipo, where meteorological drought and surface-water supply failure are most tightly linked. Under a sustained aridification trend, water-rights allocation frameworks that do not account for basin-level hydrological coupling may systematically underestimate the structural demand gap

that long-horizon perennial commitments create.

These findings carry different implications depending on whether the management horizon is framed around transient drought or prolonged aridification. Contingency responses (groundwater banking, interbasin reallocation, reservoir buffering) cannot resolve structural exposure under directional aridification, because supplementary reserves are progressively depleted when below-normal conditions become the persistent baseline. Expanding snowmelt-dependent irrigation infrastructure or establishing new perennial orchards and vineyards during an ongoing aridification trend deepens crop-system lock-in, committing a watershed to inflexible water demand at precisely the timescale at which aridification operates. Conversely, annual-crop portfolio flexibility is associated with lower sensitivity and preserves capacity to adjust planted area during sustained supply deficits. WUE-based efficiency metrics are insufficient indicators of resilience under aridification. Efficiency gains do not reduce supply coupling, and supply independence and crop-portfolio flexibility are the structural properties that differentiate lower-sensitivity from higher-sensitivity systems.

4.5. Ecosystem WUE and agronomic WUE: interpreting biophysical signals in an agricultural context

The metric analyzed throughout this study, $WUE_{eco} = NPP/ET$ (g C kg⁻¹ H₂O yr⁻¹), quantifies ecosystem-scale carbon assimilation efficiency per unit of total water loss, integrating soil evaporation, canopy transpiration, and the full phenological cycle across the sub-watershed footprint (Beer et al., 2010; Ito and Inatomi, 2012). This is conceptually distinct from agronomic WUE (WUE_{agro}), defined as harvestable yield per unit of water supplied or consumed (Stanhill, 1986; Zwart and Bastiaanssen, 2004). WUE_{eco} is a biophysical ecosystem property appropriate for regional remote sensing monitoring and cross-site structural comparison; WUE_{agro} is a production ratio conditioned on crop-specific biomass partitioning, harvest timing, and management decisions operating below the spatial resolution at which WUE_{eco} is observed. The two metrics should not be treated as interchangeable, and changes in one do not imply proportional changes in the other.

The theoretical linkage between WUE_{eco} and WUE_{agro} runs through the harvest index (HI, the fraction of above-ground NPP allocated to harvestable organs) and the transpiration fraction of total ET: $WUE_{agro} \approx WUE_{eco} \times (HI/f_{T/ET})$. Under water stress, both parameters are unstable in crop-type-specific ways. In annual cereals and legumes, mild deficit can increase HI by accelerating reproductive development, partially decoupling WUE_{agro} from WUE_{eco} trajectories, whereas severe drought suppresses HI through grain abortion while soil evaporation sustains ET above levels proportional to biomass production (Feres and Soriano, 2006; Sinclair, 1998). In perennial tree crops and vineyards, multi-year carbon allocation to structural woody

biomass means annual NPP does not map onto harvestable productivity within the same growing season. This may partly explain the non-significant perennial coefficient across all model specifications (full-sample SEM $p = 0.068$; within-Csb $p = 0.327$; Table 1), reflecting the indirect and temporally lagged linkage between perennial-system WUE_{eco} and single-year harvestable output, compounded by collinearity with the irrigation variable.

The positive aggregate ΔWUE in irrigated Mediterranean sub-watersheds (Wilcoxon $p = 0.007$) is consistent with three non-exclusive mechanisms: maintained irrigation supply sustaining NPP while rainfed vegetation declines; drought-induced stomatal up-regulation increasing intrinsic WUE under rising vapor pressure deficit (Keenan et al., 2013; Medlyn et al., 2011); and rising atmospheric CO_2 over the study window independently increasing intrinsic WUE through partial stomatal closure (Keenan et al., 2013). Because the CASEarth dataset does not distribute internal component layers (limitation v, Section 4.6), formal attribution among these contributions is not feasible. The critical implication is that positive WUE_{eco} does not indicate agronomic resilience: a system maintaining high NPP/ET under increasing irrigation inputs may simultaneously reduce WUE_{agro} if water application rises faster than yield, reproducing the efficiency paradox at the landscape scale (Grafton et al., 2018). The buffered WUE sensitivity of annual-dominated sub-watersheds (SEM $\beta = -0.341$, $p = 0.003$) carries a parallel ambiguity: annual systems can contract planted area proportionally under supply deficit, stabilizing NPP/ET even as production volume declines. Whether this reflects structural portfolio flexibility or drought-driven abandonment cannot be established from the cross-sectional design alone (limitation vii), and the two interpretations carry opposite agronomic implications.

WUE_{eco} is a robust and spatially scalable indicator for detecting shifts in ecosystem carbon-water coupling that would be undetectable from yield statistics alone, and is the appropriate metric for the structural comparisons undertaken here. It should not, however, be deployed as a proxy for WUE_{agro} in policy discourse without explicit crop-type stratification, harvest index estimation, and calibration against yield census data. The Chilean patterns expose where ecosystem functioning has been most strongly disrupted by prolonged aridification and which land-use structural properties modulate that disruption. Whether these trajectories translate into proportional agronomic losses requires integration of interannual yield census data at the sub-watershed scale, representing the necessary next step for translating WUE_{eco} signals into actionable inference for water allocation and agricultural planning.

4.6. Methodological limitations and future directions

All findings are associative, derived from cross-sectional observational data. The paired-census quasi-experimental design provides evidence against drought-driven adaptive confounding but cannot establish that irrigation infrastructure is associated with heightened WUE sensitivity through a causal pathway. Findings should be interpreted as structurally stable associations consistent with the proposed mechanisms.

Key limitations are: (i) the static agricultural mask may integrate natural vegetation patches, though matorral contamination was non-significant as a covariate and a barren-exclusion filter confirmed results (Supplementary Table S-7); (ii) the latitudinal gradient is the primary limitation for the irrigation result: adding centroid latitude attenuates the irrigation coefficient to non-significance (Table 1; Figure 8), while the annual-crops association strengthens, establishing it as the more latitude-robust result; (iii) *pct_irrigated* does not distinguish surface from groundwater irrigation, though DGA streamflow validation and aquifer co-decline evidence (Donoso, 2018) make groundwater confounding unlikely; (iv) spatial collinearity between irrigation and perennial crop share prevents isolation of a perennial-specific effect; non-significance of *pct_perennials* likely reflects collinearity rather than an absent pathway; (v) the CASEarth WUE dataset does not distribute component layers, so no formal NPP/ET attribution is presented; (vi) the 2007 census comparison is limited by imputation quality and is reported in Supplementary Table S-9 only; (vii) the cross-sectional design cannot establish the causal direction of the annual-crops association. The negative sign in 2021 (drought-sensitive sub-watersheds have fewer annuals) is consistent with both structural buffering and drought-driven abandonment of annual cultivation; longitudinal data would allow discrimination between these mechanisms (Chakraborti et al., 2023; Xie et al., 2023).

An eighth limitation warrants separate statement because it qualifies the crop-composition results as a whole rather than any single coefficient. (viii) The model has no demonstrated out-of-sample predictive skill, even within Chile. Under latitude-block cross-validation every held-out block returns a negative R^2 (-1.25 to -0.29 ; Figure 8), meaning the fitted model predicts a withheld latitude band worse than that band's own mean would. This is a stronger statement than non-portability of coefficient magnitudes. It leaves open the possibility that the SEM coefficients reflect the particular latitude-aridity-irrigation configuration of this dataset rather than a crop-system mechanism that would recur elsewhere. We regard the annual-crop association as the most defensible finding on this criterion, since it is the only one that survives every latitude control we applied, but we do not claim that any of the estimated coefficients constitute generalizable structural parameters. Discriminating a genuine crop-system mechanism from a dataset-specific spatial

configuration would require either replication in an independent region with a different latitude-aridity arrangement, or longitudinal within-unit identification.

5. Conclusions

Across 127 Chilean agricultural sub-watersheds (2001-2020), four principal conclusions emerge:

1. WUE decline is spatially concentrated in the central Mediterranean zone, co-located with NPP suppression (descriptive co-variation only). Negative trends and structural breaks both concentrate in the 30°S-35°S band.
2. SPEI and SPI carry practically equivalent cross-sectional information about WUE drought sensitivity (TOST equivalence $p < 0.001$). Precipitation dominates the spatial gradient in WUE sensitivity at multi-year scales.
3. Annual crop share is robustly negatively associated with drought sensitivity across all latitude specifications (SEM $\beta = -0.341$ to -0.591 , $p < 0.01$). The negative sign is consistent with both structural buffering and drought-driven abandonment; causal direction cannot be established.
4. Irrigation infrastructure prevalence is positively associated with WUE-drought sensitivity in the full sample ($\beta = +0.438$, $p < 0.001$), but this association attenuates substantially when latitude is controlled ($\beta = +0.117$, $p = 0.309$) and cannot be statistically isolated from the latitudinal aridity gradient. The evidence is consistent with demand-hardening theory but does not establish it.

Both crop-composition patterns are hypotheses warranting longitudinal validation. Neither can be treated as an established causal mechanism; effective governance under aridification requires explicit accounting for whether irrigation supply is genuinely decoupled from the same hydroclimatic signals that suppress crop productivity.

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8. Code and Data Availability

All analysis code is publicly available at https://github.com/frzambra/WUE_article (R scripts for all preprocessing, statistical analysis, and figure generation steps, with package versions managed via **renv** for reproducibility), enabling immediate reviewer access during manuscript evaluation. A permanent citable archive with a DOI will be deposited at Zenodo upon acceptance.

Annual cropland WUE rasters (NPP/ET, 1 km, 2001-2020) were obtained from Jiang et al. (2025), available at the CASEarth Data Platform (<https://data.casearth.cn/dataset/640f0132819aec3f2b52a4bb>). NPP data (zNPP) were obtained from MOD17A3HGF (MODIS Terra, 500 m, Collection 6.1) for descriptive trend comparison only. ET anomaly data (SETI-12 December) were derived from MOD16A2GF (MODIS Terra, 500 m 8-day, Collection 6.1) for descriptive trend analysis only; no formal component attribution is presented as independent MODIS proxies do not algebraically reproduce the CASEarth WUE. For cross-product validation purposes, annual ET (zET) was additionally obtained from MOD16A3GF (MODIS Terra, 500 m annual, Collection 6.1; Supplementary Figure S-7). All MODIS products are available from NASA Earthdata (<https://earthdata.nasa.gov>). Drought index raster time series (SPEI, SPI, EDDI) were computed from CHIRPS v2.0 monthly precipitation (Funk et al., 2015) and CHIRTS-daily temperature (Funk et al., 2019), with SPEI and EDDI using Hargreaves-Samani reference evapotranspiration derived from CHIRTS-daily temperature data (Zambrano et al., 2025). Snow Water Equivalent Index (SWEI) was derived from ERA5-Land monthly snow water equivalent reanalysis data. Agricultural census microdata for the 2007 and 2020-2021 censuses are publicly available from the Chilean Instituto Nacional de Estadísticas (INE; <https://www.ine.gob.cl>). Full software version details are listed in Section 2.6.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Claude (Anthropic) to assist with the statistical analysis and to improve the English grammar. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the published article.

References

- AghaKouchak, A., Farahmand, A., Melton, F.S., Teixeira, J., Anderson, M.C., Wardlow, B.D., Hain, C.R., 2015. Remote sensing of drought: Progress, challenges and opportunities. *Reviews of Geophysics* 53, 452–480. doi:[10.1002/2014RG000456](https://doi.org/10.1002/2014RG000456).
- Barnett, T.P., Pierce, D.W., Hidalgo, H.G., Bonfils, C., Santer, B.D., Das, T., Bala, G., Wood, A.W., Nozawa, T., Mirin, A.A., et al., 2008. Human-induced changes in the hydrology of the western United States. *Science* 319, 1080–1083. doi:[10.1126/science.1152538](https://doi.org/10.1126/science.1152538).
- Beer, C., Reichstein, M., Tomelleri, E., Ciais, P., Jung, M., Carvalhais, N., Rödenbeck, C., Arain, M.A., Baldocchi, D., Bonan, G.B., Bondeau, A., Cescatti, A., Lasslop, G., Lindroth, A., Lomas, M., Luyssaert, S., Margolis, H., Oleson, K.W., Rouspard, O., Veenendaal, E., Viovy, N., Williams, C., Woodward, F.I., Papale, D., 2010. Terrestrial Gross Carbon Dioxide Uptake: Global Distribution and Covariation with Climate. *Science* 329, 834–838. URL: <https://www.science.org/doi/10.1126/science.1184984>, doi:[10.1126/science.1184984](https://doi.org/10.1126/science.1184984).
- Bivand, R., Millo, G., Piras, G., 2021. A Review of Software for Spatial Econometrics in R. *Mathematics* 9, 1276. URL: <https://www.mdpi.com/2227-7390/9/11/1276>, doi:[10.3390/math9111276](https://doi.org/10.3390/math9111276).
- Bivand, R., Wong, D.W.S., 2018. Comparing implementations of global and local indicators of spatial association. *TEST* 27, 716–748. doi:[10.1007/s11749-018-0599-x](https://doi.org/10.1007/s11749-018-0599-x).
- Boisier, J., Alvarez-Garretón, C., Cordero, R., Damiani, A., Gallardo, L., Garreaud, R., Lambert, F., Ramallo, C., Rojas, M., Rondanelli, R., 2018. Anthropogenic drying in central-southern Chile evidenced by long-term observations and climate model simulations. *Elementa* 6, 74. doi:[10.1525/elementa.328](https://doi.org/10.1525/elementa.328).
- Boser, A., Caylor, K., Larsen, A., Pascolini-Campbell, M., Reager, J., Carleton, T., 2024. Field-scale crop water consumption estimates reveal potential water savings in California agriculture. *Nature Communications* 15, 2366. doi:[10.1038/s41467-024-46031-2](https://doi.org/10.1038/s41467-024-46031-2).

694 Budds, J., 2020. Securing the market: Water security and the internal contradictions of chile's water code.
695 Geoforum 113, 165–175. doi:[10.1016/j.geoforum.2018.09.027](https://doi.org/10.1016/j.geoforum.2018.09.027).

696 Chakraborti, R., Davis, K.F., DeFries, R., Rao, N.D., Joseph, J., Ghosh, S., 2023. Crop switching for water
697 sustainability in india's food bowl yields co-benefits for food security and farmers' profits. Nature Water 1,
698 864–878. doi:[10.1038/s44221-023-00135-z](https://doi.org/10.1038/s44221-023-00135-z).

699 Croissant, Y., Millo, G., 2008. Panel data econometrics in R: The plm package. Journal of Statistical
700 Software 27, 1–43. doi:[10.18637/jss.v027.i02](https://doi.org/10.18637/jss.v027.i02).

701 Davis, K., Rulli, M., Seveso, A., D'Odorico, P., 2017. Increased food production and reduced water use
702 through optimized crop distribution. Nature Geoscience 10, 919–924. doi:[10.1038/s41561-017-0004-5](https://doi.org/10.1038/s41561-017-0004-5).

703 Donoso, G. (Ed.), 2018. Water Policy in Chile. Springer International Publishing, Cham. doi:[10.1007/978-](https://doi.org/10.1007/978-3-319-76702-4)
704 [3-319-76702-4](https://doi.org/10.1007/978-3-319-76702-4). global Issues in Water Policy, Vol. 21.

705 Driscoll, J.C., Kraay, A.C., 1998. Consistent covariance matrix estimation with spatially dependent panel
706 data. Review of Economics and Statistics 80, 549–560. doi:[10.1162/003465398557825](https://doi.org/10.1162/003465398557825).

707 FAO y ONU Agua, 2025. Progreso del cambio en la eficiencia del uso del agua. doi:[10.4060/cd2023es](https://doi.org/10.4060/cd2023es).

708 Fereres, E., Soriano, M.A., 2006. Deficit irrigation for reducing agricultural water use. Journal of Experimental
709 Botany 58, 147–159. URL: <https://academic.oup.com/jxb/article-lookup/doi/10.1093/jxb/erl165>, doi:[10.](https://doi.org/10.1093/jxb/erl165)
710 [1093/jxb/erl165](https://doi.org/10.1093/jxb/erl165).

711 Fox, J., Weisberg, S., 2019. An R Companion to Applied Regression. 3 ed., Sage, Thousand Oaks, CA.

712 Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison,
713 L., Hoell, A., et al., 2015. The climate hazards infrared precipitation with stations—a new environmental
714 record for monitoring extremes. Scientific Data 2, 1–21. doi:[10.1038/sdata.2015.66](https://doi.org/10.1038/sdata.2015.66).

715 Funk, C., Peterson, P., Peterson, S., Shukla, S., Davenport, F., Michaelsen, J., Knapp, K.R., Landsfeld,
716 M., Husak, G., Harrison, L., et al., 2019. A high-resolution 1983–2016 t_{max} climate data record based
717 on infrared temperatures and stations by the climate hazard center. Journal of Climate 32, 5639–5658.
718 doi:[10.1175/JCLI-D-18-0698.1](https://doi.org/10.1175/JCLI-D-18-0698.1).

719 Garreaud, R., Boisier, J., Rondanelli, R., Montecinos, A., Sepúlveda, H., Veloso-Aguila, D., 2020. The central
720 chile mega drought (2010–2018): A climate dynamics perspective. International Journal of Climatology 40,
721 421–439. doi:[10.1002/joc.6219](https://doi.org/10.1002/joc.6219).

Gebrechorkos, S.H., Sheffield, J., Vicente-Serrano, S.M., Funk, C., Miralles, D.G., Peng, J., Dyer, E., Talib, J., Beck, H.E., Singer, M.B., Dadson, S.J., 2025. Warming accelerates global drought severity. *Nature* doi:[10.1038/s41586-025-09047-2](https://doi.org/10.1038/s41586-025-09047-2).

Grafton, R.Q., Williams, J., Perry, C.J., Molle, F., Ringler, C., Steduto, P., Udall, B., Wheeler, S.A., Wang, Y., Garrick, D., et al., 2018. The paradox of irrigation efficiency. *Science* 361, 748–750. doi:[10.1126/science.aat9314](https://doi.org/10.1126/science.aat9314).

Hellegers, P., Van Halsema, G., 2021. Sdg indicator 6.4.1 “change in water use efficiency over time”: Methodological flaws and suggestions for improvement. *Science of The Total Environment* 801, 149431. doi:[10.1016/j.scitotenv.2021.149431](https://doi.org/10.1016/j.scitotenv.2021.149431).

Hijmans, R.J., 2025. terra: Spatial Data Analysis. URL: <https://CRAN.R-project.org/package=terra>, doi:[10.32614/CRAN.package.terra](https://doi.org/10.32614/CRAN.package.terra). r package version 1.8-54.

Hobbins, M.T., Wood, A., McEvoy, D.J., Huntington, J.L., Morton, C., Anderson, M., Hain, C., 2016. The evaporative demand drought index. part i: Linking drought evolution to variations in evaporative demand. *Journal of Hydrometeorology* 17, 1745–1761. doi:[10.1175/JHM-D-15-0121.1](https://doi.org/10.1175/JHM-D-15-0121.1).

Hoekstra, A., Mekonnen, M., 2012. The water footprint of humanity. *Proceedings of the National Academy of Sciences* 109, 3232–3237. doi:[10.1073/pnas.1109936109](https://doi.org/10.1073/pnas.1109936109).

Howden, S., Soussana, J.F., Tubiello, F., Chhetri, N., Dunlop, M., Meinke, H., 2007. Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences* 104, 19691–19696. doi:[10.1073/pnas.0701890104](https://doi.org/10.1073/pnas.0701890104).

Hu, G., Jia, L., 2015. Monitoring of Evapotranspiration in a Semi-Arid Inland River Basin by Combining Microwave and Optical Remote Sensing Observations. *Remote Sensing* 7, 3056–3087. URL: <https://www.mdpi.com/2072-4292/7/3/3056>, doi:[10.3390/rs70303056](https://doi.org/10.3390/rs70303056).

Immerzeel, W.W., Lutz, A.F., Andrade, M., Bahl, A., Biemans, H., Bolch, T., Hyde, S., Brumby, S., Davies, B.J., Elmore, A.C., et al., 2020. Importance and vulnerability of the world’s water towers. *Nature* 577, 364–369. doi:[10.1038/s41586-019-1822-y](https://doi.org/10.1038/s41586-019-1822-y).

INE, 2007. VII Censo nacional agropecuario y forestal. Instituto Nacional de Estadística. Informe Agropecuarias 2007. Technical Report.

749 INE, 2021. VIII Censo Nacional Agropecuario y Forestal. Instituto Nacional de Estadísticas. Santiago, Chile.
 750 URL: <https://www.ine.gob.cl/estadisticas-por-tema/agricultura-y-medio-ambiente/censo-agropecuario>.
 751 resultados finales publicados en octubre de 2022.

752 Ito, A., Inatomi, M., 2012. Water-use efficiency of the terrestrial biosphere: A model analysis focusing
 753 on interactions between the global carbon and water cycles. *Journal of Hydrometeorology* 13, 681–694.
 754 doi:[10.1175/JHM-D-10-05034.1](https://doi.org/10.1175/JHM-D-10-05034.1).

755 Jiang, M., Zheng, C., Jia, L., Chen, J., 2025. A 20-year dataset (2001–2020) of global cropland water-use
 756 efficiency at 1-km grid resolution. *Scientific Data* 12, 574. doi:[10.1038/s41597-025-04904-1](https://doi.org/10.1038/s41597-025-04904-1).

757 Keenan, T.F., Hollinger, D.Y., Bohrer, G., Dragoni, D., Munger, J.W., Schmid, H.P., Richardson, A.D.,
 758 2013. Increase in forest water-use efficiency as atmospheric carbon dioxide concentrations rise. *Nature* 499,
 759 324–327. URL: <https://www.nature.com/articles/nature12291>, doi:[10.1038/nature12291](https://doi.org/10.1038/nature12291).

760 Lutz, A.F., Immerzeel, W.W., Shrestha, A.B., Bierkens, M.F., 2014. Consistent increase in High Asia’s
 761 runoff due to increasing glacier melt and precipitation. *Nature Climate Change* 4, 587–592. doi:[10.1038/](https://doi.org/10.1038/nclimate2237)
 762 [nclimate2237](https://doi.org/10.1038/nclimate2237).

763 Malagueño, B.R., D’Odorico, P., 2024. ¿libre de la maleza estatista? Assessing neoliberal promises and water
 764 markets in Chile. *Earth’s Future* doi:[10.1029/2024EF004963](https://doi.org/10.1029/2024EF004963).

765 McEvoy, D.J., Huntington, J.L., Hobbins, M.T., Wood, A., Morton, C., Anderson, M., Hain, C., 2016. The
 766 evaporative demand drought index. part ii: Conus-wide assessment against common drought indicators.
 767 *Journal of Hydrometeorology* 17, 1763–1779. doi:[10.1175/JHM-D-15-0122.1](https://doi.org/10.1175/JHM-D-15-0122.1).

768 McKee, T.B., Doesken, N.J., Kleist, J., 1993. The relationship of drought frequency and duration to time
 769 scales, in: *Proceedings of the Ninth Conference on Applied Climatology*, American Meteorological Society,
 770 Boston. pp. 179–184.

771 Medlyn, B.E., Duursma, R.A., Eamus, D., Ellsworth, D.S., Prentice, I.C., Barton, C.V.M., Crous, K.Y.,
 772 De Angelis, P., Freeman, M., Wingate, L., 2011. Reconciling the optimal and empirical approaches to
 773 modelling stomatal conductance: RECONCILING OPTIMAL AND EMPIRICAL STOMATAL MODELS.
 774 *Global Change Biology* 17, 2134–2144. URL: [https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2486](https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2486.2010.02375.x).
 775 [2010.02375.x](https://onlinelibrary.wiley.com/doi/10.1111/j.1365-2486.2010.02375.x), doi:[10.1111/j.1365-2486.2010.02375.x](https://doi.org/10.1111/j.1365-2486.2010.02375.x).

776 Paruelo, J.M., Texeira, M., Staiano, L., Mastrángelo, M., Amdan, L., Gallego, F., 2016. An integrative
777 index of ecosystem services provision based on remotely sensed data. *Ecological Indicators* 71, 145–154.
778 doi:[10.1016/j.ecolind.2016.06.054](https://doi.org/10.1016/j.ecolind.2016.06.054).

779 Patakamuri, S.K., O'Brien, N., 2021. *modifiedmk*: Modified Versions of Mann Kendall and Spearman's Rho
780 Trend Tests. URL: <https://CRAN.R-project.org/package=modifiedmk>, doi:[10.32614/CRAN.package.modifiedmk](https://doi.org/10.32614/CRAN.package.modifiedmk). r package version 1.6.

782 Pebesma, E., 2018. Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal* 10,
783 439–446. URL: <https://doi.org/10.32614/RJ-2018-009>, doi:[10.32614/RJ-2018-009](https://doi.org/10.32614/RJ-2018-009).

784 Pebesma, E., Bivand, R., 2023. *Spatial Data Science: With applications in R*. Chapman and Hall/CRC.
785 URL: <https://r-spatial.org/book/>, doi:[10.1201/9780429459016](https://doi.org/10.1201/9780429459016).

786 Pedersen, T.L., 2025. *patchwork*: The Composer of Plots. URL: [https://CRAN.R-project.org/package=](https://CRAN.R-project.org/package=patchwork)
787 [patchwork](https://CRAN.R-project.org/package=patchwork), doi:[10.32614/CRAN.package.patchwork](https://doi.org/10.32614/CRAN.package.patchwork). r package version 1.3.1.

788 Pettitt, A.N., 1979. A non-parametric approach to the change-point problem. *Journal of the Royal Statistical*
789 *Society: Series C (Applied Statistics)* 28, 126–135. doi:[10.2307/2346729](https://doi.org/10.2307/2346729).

790 Pohlert, T., 2023. *trend*: Non-Parametric Trend Tests and Change-Point Detection. URL: [https://CRAN.R-](https://CRAN.R-project.org/package=trend)
791 [project.org/package=trend](https://CRAN.R-project.org/package=trend), doi:[10.32614/CRAN.package.trend](https://doi.org/10.32614/CRAN.package.trend). r package version 1.1.6.

792 R Core Team, 2025. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical
793 Computing. Vienna, Austria. URL: <https://www.R-project.org/>.

794 Rivera, D., Godoy-Faúndez, A., Lillo, M., Alvez, A., Delgado, V., Gonzalo-Martín, C., Menasalvas, E.,
795 Costumero, R., García-Pedrero, Á., 2016. Legal disputes as a proxy for regional conflicts over water rights
796 in chile. *Journal of Hydrology* 535, 36–45. doi:[10.1016/j.jhydro.2016.01.057](https://doi.org/10.1016/j.jhydro.2016.01.057).

797 Running, S., Mu, Q., Zhao, M., Moreno, A., 2021. MODIS/Terra net evapotranspiration Gap-Filled 8-day
798 L4 global 500m SIN grid V061.

799 Sinclair, T.R., 1998. Historical Changes in Harvest Index and Crop Nitrogen Accumulation. *Crop Science* 38,
800 638–643. URL: <https://acsess.onlinelibrary.wiley.com/doi/10.2135/cropsci1998.0011183X003800030002x>,
801 doi:[10.2135/cropsci1998.0011183X003800030002x](https://doi.org/10.2135/cropsci1998.0011183X003800030002x).

802 Stanhill, G., 1986. Water Use Efficiency, in: *Advances in Agronomy*. Elsevier. volume 39, pp. 53–85. URL:
803 <https://linkinghub.elsevier.com/retrieve/pii/S0065211308604654>, doi:[10.1016/S0065-2113\(08\)60465-4](https://doi.org/10.1016/S0065-2113(08)60465-4).

- Tahasin, A., Haydar, M., Hossen, M.S., Sadia, H., 2024. Drought vulnerability assessment and its impact on crop production and livelihood of people: An empirical analysis of Barind Tract. *Heliyon* 10, e39067. URL: <https://linkinghub.elsevier.com/retrieve/pii/S2405844024150980>, doi:10.1016/j.heliyon.2024.e39067.
- Tennekes, M., 2018. tmap: Thematic maps in R. *Journal of Statistical Software* 84, 1–39. doi:10.18637/jss.v084.i06.
- Vicente-Serrano, S.M., Beguería, S., López-Moreno, J.I., 2010. A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate* 23, 1696–1718. doi:10.1175/2009JCLI2909.1.
- Wallace, J., 2000. Increasing agricultural water use efficiency to meet future food production. *Agriculture, Ecosystems & Environment* 82, 105–119. URL: [http://dx.doi.org/10.1016/S0167-8809\(00\)00220-6](http://dx.doi.org/10.1016/S0167-8809(00)00220-6), doi:10.1016/s0167-8809(00)00220-6.
- Wang, T., Sun, S., Yin, Y., Zhao, J., Tang, Y., Wang, Y., Gao, F., Luan, X., 2024. Status of crop water use efficiency evaluation methods: A review. *Agricultural and Forest Meteorology* 349, 109961. doi:10.1016/j.agrformet.2024.109961.
- Ward, F.A., Pulido-Velázquez, M., 2008. Water conservation in irrigation can increase water use. *Proceedings of the National Academy of Sciences* 105, 18215–18220. doi:10.1073/pnas.0805554105.
- Wickham, H., 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. URL: <https://ggplot2.tidyverse.org>.
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L.D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T.L., Miller, E., Bache, S.M., Müller, K., Ooms, J., Robinson, D., Seidel, D.P., Spinu, V., Takahashi, K., Vaughan, D., Wilke, C., Woo, K., Yutani, H., 2019. Welcome to the tidyverse. *Journal of Open Source Software* 4, 1686. doi:10.21105/joss.01686.
- Xie, W., Zhu, A., Ali, T., Zhang, Z., Chen, X., Wu, F., Huang, J., Davis, K., 2023. Crop switching can enhance environmental sustainability and farmer incomes in china. *Nature* 616, 300–305. doi:10.1038/s41586-023-05799-x.
- Yu, L., Gao, X., Zhao, X., 2020. Global synthesis of the impact of droughts on crops' water-use efficiency (WUE): Towards both high WUE and productivity. *Agricultural Systems* 177, 102723. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0308521X19301568>, doi:10.1016/j.agry.2019.102723.

- 832 Yu, X., Yin, Q., Zhao, T., Chen, K., Qian, L., Wang, W., Hu, X., Zhang, B., 2025. Detecting ecosystem
833 water use efficiency responses to drought from long-term remote sensing data. *Ecological Indicators* 177,
834 113734. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1470160X25006648>, doi:10.1016/j.ecolind.
835 2025.113734.
- 836 Zambrano, F., Vrieling, A., Meza, F., Duran-Llacer, I., Fernández, F., Venegas-González, A., Raab, N.,
837 Craven, D., 2025. From Drought to Aridification: Land-Cover Fingerprints of a Drying Chile. *Earth's*
838 *Future* 13, e2025EF006744. URL: <https://agupubs.onlinelibrary.wiley.com/doi/10.1029/2025EF006744>,
839 doi:10.1029/2025EF006744.
- 840 Zwart, S.J., Bastiaanssen, W.G., 2004. Review of measured crop water productivity values for irrigated
841 wheat, rice, cotton and maize. *Agricultural Water Management* 69, 115–133. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0378377404001416>, doi:10.1016/j.agwat.2004.04.007.
842

843 **Supplementary Material**

844 *Supplementary Table S-1 - Sample sizes by analytical step*

Analysis	n	Spatial unit	Notes
WUE trend (Mann-Kendall)	127	Sub-watershed	Agricultural sub-watersheds with complete 2001-2020 WUE data
WUE-SPEI-12 sensitivity (OLS slope)	127	Sub-watershed	Same set; one per-sub-watershed regression per index
Pettitt change-point test	131	Sub-watershed	All sub-watersheds with a complete annual WUE series for the Pettitt test (4 more than the trend set, which additionally requires a valid prewhitened Mann-Kendall slope); 33.6% raw-significant change points reference this set
Panel regression (two-way FE)	131	Sub-watershed	Balanced panel; $131 \times$ $20 = 2,620$ sub-watershed-year obs.
Panel regression — Mediterranean subset	76	Sub-watershed	Mediterranean-climate sub-watersheds (Csa+Csb); panel N = $76 \times 20 = 1,520$ sub-watershed-year obs.

Analysis	n	Spatial unit	Notes
Crop composition OLS (2021 census)	127	Sub-watershed	Sub-watersheds with complete WUE, irrigation, and census data; three-predictor functional-aggregate specification
Crop composition spatial error model (2021)	127	Sub-watershed	Same set; <code>spatialreg::errorsarlm</code> , queen contiguity; $\beta = 0.435$, $p < 0.001$
Crop composition OLS (2007 harmonized baseline)	127	Sub-watershed	2007 VII Census proportions; three-predictor functional-aggregate specification
Crop composition SEM (2007 baseline)	127	Sub-watershed	<code>spatialreg::errorsarlm</code> , queen contiguity; $\beta = 0.640$, $p < 0.001$
Within-Csb crop composition (OLS + SEM)	70	Sub-watershed	Csb (warm-summer Mediterranean) subset; three-predictor functional-aggregate specification; OLS $R^2 = 0.595$, $F(3,66) = 32.3$, $p < 0.001$; SEM $\beta = 0.254$, $p = 0.054$ (Supplementary Table S-4)

Analysis	n	Spatial unit	Notes
NPP and ET component sensitivity (zNPP-SPEI-12, SETI-12 Dec-SPEI-12)	143	Sub-watershed	Larger than 127: zNPP (MOD17A3HGF) and SETI-12 December (MOD16A2GF) are available for more sub-watersheds than the cropland-restricted Jiang WUE mask; n = sub-watersheds with complete MODIS sensitivity, irrigation, and census data

Supplementary Table S-2 - Köppen-stratified Wilcoxon signed-rank tests

Wilcoxon signed-rank tests comparing mean WUE in the pre-megadrought (2001-2009) versus megadrought (2010-2020) periods, stratified by Köppen climate class. Hodges-Lehmann median difference and 95% confidence interval are reported alongside p-values. Full numerical results are available in `outputs/tables/wilcox_by_climate_koppen.csv`.

Supplementary Table S-3 - Köppen-stratified panel regression (36-month indices)

Two-way fixed-effects panel regression coefficients for SPEI-36, SPI-36, and EDDI-36, estimated separately within each Köppen climate class with 5 sub-watersheds. Classes with $n < 5$ (Csa and extreme classes) were excluded. Full results for all nine indices (12/24/36-month) are in `outputs/tables/panel_regression_by_climate.csv`.

Köppen class	n sub-watersheds	Index		SE	p
BS (semi-arid)	14	SPEI-36	-0.307	0.213	0.150
BS	14	SPI-36	-0.079	0.190	0.679
BS	14	EDDI-36	-0.194	0.122	0.113

Köppen class	n sub-watersheds	Index		SE	p
BW (arid)	8	SPEI-36	0.015	0.147	0.917
BW	8	SPI-36	−0.168	0.123	0.176
BW	8	EDDI-36	0.190	0.123	0.123
Cf (humid-temperate)	26	SPEI-36	−0.287	0.088	0.001
Cf	26	SPI-36	−0.187	0.081	0.022
Cf	26	EDDI-36	−0.068	0.050	0.172
Csa (hot-summer Med.)	5	SPEI-36	0.085	0.280	0.763
Csa	5	SPI-36	0.263	0.216	0.228
Csa	5	EDDI-36	0.375	0.144	0.011
Csb (warm-summer Med.)	71	SPEI-24	0.180	0.062	0.004
Csb	71	SPEI-36	0.068	0.068	0.320
Csb	71	SPI-24	0.131	0.059	0.026
Csb	71	SPI-36	0.067	0.061	0.278
Csb	71	EDDI-36	−0.011	0.029	0.709

Bold p-values indicate significance at $p < 0.05$. The 24-month accumulation scale rows are included for Csb because SPEI-24 and SPI-24 show the strongest within-unit coupling in this class. Reference: `outputs/tables/panel_regression_by_climate.csv` and `outputs/tables/panel_cluster_robust_koppen.csv`.

Supplementary Table S-4 - Within-Csb crop-composition regression

Full version of Table 1 in Section 3.7. Crop-composition regression of WUE-SPEI-12 sensitivity restricted to warm-summer Mediterranean (Csb) sub-watersheds ($n = 70$), where the latitudinal aridity gradient is minimised, using the three-predictor functional-aggregate specification (reference category: forage/pasture). OLS $R^2 = 0.595$ ($F(3,66) = 32.3$, $p < 0.001$); SEM = 0.254 ($p = 0.054$).

Predictor	OLS	OLS 95% CI	OLS p	SEM	SEM 95% CI	SEM p
% Perennial crops	+0.305	[−0.041, +0.652]	0.083	+0.175	[−0.175, +0.525]	0.327

Predictor	OLS	OLS 95% CI	OLS p	SEM	SEM 95% CI	SEM p
% Annual crops	−0.488	[−0.772, −0.203]	0.001	−0.591	[−0.895, −0.287]	<0.001
% Irrigated area	+0.264	[+0.016, +0.511]	0.037	+0.218	[−0.041, +0.476]	0.099

Only the annual-crops interval excludes zero under both estimators within this single climate zone, supporting it as a crop-system property that persists once the latitudinal gradient is restricted. The irrigation interval excludes zero under OLS but includes zero under the SEM, which is the primary estimator; the perennial interval includes zero under both. At $n = 70$ the irrigation and perennial intervals overlap over most of their range and are consistent with effects of similar magnitude, so we do not treat the difference in their p-values as evidence of a qualitative distinction between them. Bold p-values indicate significance at $p < 0.05$. Reference: `outputs/tables/sensitivity_crop_within_csb.csv`.

Supplementary Table S-5 - WLS robustness check for the generated-regressor problem

Weighted least squares (WLS) regression of WUE-SPEI-12 sensitivity on 2021 functional crop group proportions ($n = 127$ sub-watersheds; reference category: forage/pasture), where each sub-watershed is weighted by the inverse squared standard error of its stage-1 sensitivity estimate ($1/SE^2$), down-weighting sub-watersheds whose WUE-SPEI-12 slopes are poorly constrained. Model fit: $R^2 = 0.712$, adj. $R^2 = 0.705$. Full results: `outputs/tables/sensitivity_crop_wls_regression.csv`.

Predictor	WLS	SE	95% CI	p
(Intercept)	−0.361	0.048	[−0.456, −0.266]	< 0.001
% Perennial crops	+0.501	0.115	[+0.274, +0.729]	< 0.001
% Annual crops	−0.265	0.080	[−0.423, −0.108]	0.001
% Irrigated area	+0.362	0.086	[+0.192, +0.533]	< 0.001

No sign changes relative to the primary OLS or SEM estimates: all three predictors retain direction and significance under stage-1 uncertainty weighting, confirming robustness to the generated-regressor design. Perennial crops (WLS = +0.501) is stronger under WLS weighting, consistent with high-irrigation/perennial sub-watersheds having more precisely estimated stage-1 slopes.

Supplementary Table S-6 - SWEI-based SEM (snowmelt robustness check)

Spatial error model (SEM) of WUE-SWEI sensitivity on 2021 functional crop group proportions (n = 123 sub-watersheds, four fewer than the SPEI-12 model because the complete-case requirement on the ERA5-Land SWEI series excludes four sub-watersheds; reference category: forage/pasture; $\beta = 0.470$, $p < 0.001$). Annual SWEI is defined as the August sub-watershed-mean ERA5-Land SWE standardized using the EDDI procedure (Section 2.3.1). This model substitutes August peak SWEI for SPEI-12 as the drought index; the SPEI-12 SEM column reflects the updated CHIRPS/CHIRTS primary results ($\beta = 0.435$). All three predictors preserve their sign relative to the SPEI-12 SEM. Full results are available in `outputs/tables/swei_sem_results.csv`.

Predictor	SPEI-12 SEM	SWEI SEM	95% CI (SWEI)	p (SWEI)	Sign consistent?
% Perennial crops	+0.231	+0.376*	[+0.055, +0.697]	0.022	Yes
% Annual crops	−0.341**	−0.139	[−0.447, +0.170]	0.378	Yes
% Irrigated area	+0.438***	+0.348*	[+0.080, +0.615]	0.011	Yes
(spatial error)	0.435***	0.470***	[+0.291, +0.648]	<0.001	—

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Reference category: forage/pasture (*pct_forage*). Predictors are functional aggregates as defined in Section 2.4: perennial crops = fruits + vineyards; annual crops = cereals + vegetables + legumes + industrial crops. Median Spearman ρ (SPEI-12, SWEI) across sub-watersheds = 0.296; in the top quartile of irrigated area share, median $\rho = 0.549$.

Supplementary Table S-7 - Barren-exclusion dynamic mask robustness check

Crop-composition spatial error model (SEM) re-estimated after applying a barren-exclusion dynamic filter to address the static-mask / land-abandonment concern. For each year 2001–2020, pixels within the CASEarth “Cropland” static mask were additionally excluded where MODIS MCD12Q1.061 IGBP annual land-cover classified them as Barren (class 16), Urban (class 13), or Water bodies (class 17). Per-watershed mean zWUE was re-extracted from the year-specific masked rasters, WUE-SPEI-12 sensitivity slopes

were recomputed, and the three-predictor functional-aggregate SEM (reference category: forage/pasture) was refitted. The sample size was unchanged at $n = 127$ sub-watersheds. Full results are available in `outputs/tables/dynamic_mask_sem_comparison.csv`.

Predictor	Static-mask SEM	Barren-excl. SEM	95% CI (barren-excl.)	p (barren-excl.)	Sign consistent?
% Perennial crops	+0.231	+0.205	[−0.033, +0.443]	0.091	Yes
% Annual crops	−0.341**	−0.326**	[−0.550, −0.102]	0.004	Yes
% Irrigated area	+0.438***	+0.425***	[+0.228, +0.622]	<0.001	Yes
(spatial error)	0.435***	0.482***	[+0.302, +0.662]	<0.001	—

** $p < 0.01$; *** $p < 0.001$. All three substantive predictors are sign-consistent and statistically equivalent across both mask specifications, confirming that drought-driven land abandonment detectable as confirmed non-vegetation transitions in MODIS land cover does not materially alter the primary crop-composition findings.

Supplementary Table S-8 - Nonlinearity robustness check for post-2010 interaction

Two-way fixed-effects (within-unit) panel models for SPEI-36 testing whether the $\text{SPEI-36} \times \text{post-2010}$ interaction term captures non-linear physiological responses to severe drought rather than a genuine temporal structural break. M0 = linear baseline; M1 = adds quadratic SPEI^2 term; M2 = piecewise specification with extra slope for $\text{SPEI} < 0$; M3 = quadratic + post-2010 interaction. Full results are available in `outputs/tables/nonlinearity_panel_comparison.csv`.

Model	Term		SE_{std}	P_{std}
M0: linear	SPEI-36	−0.025	0.047	0.595
M1: +quadratic	SPEI-36	+0.109	0.057	0.054
M1: +quadratic	SPEI-36^2	−0.131	0.032	<0.001

Model	Term		SE _{std}	p _{std}
M2: +piecewise	SPEI-36	−0.187	0.060	0.002
M2: +piecewise	SPEI-36 × I(SPEI < 0)	+0.509	0.117	<0.001
M3: quadratic+post- 2010	SPEI-36	+0.329	0.152	0.030
M3: quadratic+post- 2010	SPEI-36 ²	−0.218	0.064	<0.001
M3: quadratic+post- 2010	SPEI-36 × post-2010	−0.312	0.200	0.119

All models: n = 131 sub-watersheds, 2,620 observations, two-way FE (unit + year). The M0 linear baseline is no longer significant ($\beta = -0.025$, $p = 0.595$), consistent with the absence of a pooled within-unit SPEI-36 signal documented in Section 3.5. Nevertheless, M1 reveals a significant concave non-linear WUE-SPEI-36 relationship ($\text{SPEI-36}^2 = -0.131$, $p < 0.001$): the slope is steeper at negative SPEI values (drought conditions), as confirmed by the piecewise model M2 ($\text{SPEI-36} \times I(\text{SPEI} < 0) = +0.509$, $p < 0.001$). In M3, after controlling for this non-linearity, the post-2010 interaction is not significant ($\beta = -0.312$, $p = 0.119$), indicating that the post-2010 intensification observed in the linear HC1 interaction model (Supplementary Figure S-6, $\beta = +0.281$, $p = 0.012$) is largely attributable to the concentration of strongly negative SPEI-36 values in the 2010–2020 period operating on this concave response, rather than a discrete temporal structural break in the WUE-drought relationship.

Supplementary Table S-9 - Pre-drought (2007) crop composition regression and symmetric 2007 vs 2021 comparison

Panel A - Individual crop-category OLS regression

Individual crop-category OLS regression of WUE-SPEI-12 sensitivity on crop-area shares, reported at the disaggregated category level rather than the functional aggregates (% Perennial crops, % Annual crops, %

927 Irrigated area) used elsewhere in the manuscript. Column S1 (primary specification) uses 2007 census total
928 area shares and excludes the irrigated-area predictor, since the 2007 irrigation split required imputation for six
929 of ten categories (Section 2.4). Column S2 adds the imputed 2007 irrigated-area share as a sensitivity check.
930 Column S3 reports the analogous regression using 2021 census data, included for directional comparison with
931 the 2007 results only.

	(S1) 2007 Baseline	(S2) 2007 + Irrig.	(S3) 2021	
Predictor ^b	(primary)	(sensitivity)	comparison ^d	Direction ^e
<i>Perennial crops</i>				
Fruit trees (%)	0.732*** [0.529, 0.936]	0.264* [0.029, 0.498]	0.191*** [0.098, 0.284]	same sign
Vineyards (%)	0.695*** [0.353, 1.037]	0.273 [−0.056, 0.603]	0.063 [−0.124, 0.249]	same sign
<i>Annual crops</i>				
Cereals (%)	−0.296† [−0.632, 0.039]	−0.280† [−0.575, 0.014]	−0.093† [−0.197, 0.011]	same sign
Vegetables (%)	1.975*** [1.291, 2.660]	1.619*** [1.008, 2.230]	−0.111 [−0.252, 0.030]	opposite sign
Legumes/Tubers (%) ^c	−0.757** [−1.221, −0.293]	−0.226 [−0.668, 0.215]	—	—
Industrial crops (%) ^c	−0.762 [−2.160, 0.637]	−1.512* [−2.762, −0.263]	—	—
<i>Irrigation control</i>				
Irrigated area (%) ^a	—	0.468*** [0.316, 0.621]	0.113** [0.047, 0.180]	—
<i>Model statistics</i>				
R ²	0.666	0.745	0.555	
Adjusted R ²	0.649	0.730	0.533	
F-statistic	39.79***	49.71***	24.70***	
df	6, 120	7, 119	5, 100	
n (sub-watersheds)	127	127	106	
Reference category	Forage/Pasture	Forage/Pasture	Forage/Pasture	

	(S1) 2007 Baseline	(S2) 2007 + Irrig.	(S3) 2021	
Predictor ^b	(primary)	(sensitivity)	comparison ^d	Direction ^e

Notes to Panel A. Coefficients represent change in WUE-SPEI-12 sensitivity ($\Delta\text{WUE}/\Delta\text{SPEI}$) per unit increase in crop share (proportion 0-1). Values in brackets are 95% confidence intervals. $\dagger p < 0.10$; $* p < 0.05$; $** p < 0.01$; $*** p < 0.001$.

^a 2007 irrigation data (column S2): the irrigated area split was directly reported for only 4 of 10 crop categories (cereals, legumes/tubers, industrial crops, vineyards). The remaining 6 required imputation via a commune-level residual ratio applied uniformly across categories with heterogeneous true irrigation intensities. This uniform ratio distorts the cross-sectional variance of the 2007 irrigated area variable; measurement error propagates to attenuate coefficients of correlated crop-type predictors (Frisch-Waugh-Lovell theorem). Column S1 is therefore the primary 2007 specification.

^b 2007 total crop areas (all predictor rows except irrigated area) are derived from the directly reported cultivated area per category in the VII Agricultural Census main publication, without imputation.

^c Categorical scope: the 2021 census combines legumes/tubers and industrial crops into a broader “annuals” aggregate; the 2007 model retains these categories disaggregated. Forage/pasture is the omitted reference category in all models.

^d Column S3 reports the analogous individual-category OLS regression using 2021 census data (parallel specification to S1/S2), included for directional comparison with the 2007 results only; it is distinct from the functional-aggregate spatial error model reported in Table 1. The 2021 irrigated area variable is derived entirely from directly reported data, with no imputation.

^e Direction: “same sign” = same sign in 2007 and 2021; “opposite sign” = sign reversal. Directional consistency is assessed only for predictors present in both models. Vegetable share is highly significant and positive in 2007 (S1: $\beta = +1.975$, $p < 0.001$) but non-significant and negative in 2021; the sign reversal likely reflects the concentration of intensive irrigated horticulture in high-sensitivity Mediterranean sub-watersheds in 2007, a pattern that diminished by the 2021 endpoint.

Panel B - Functional-aggregate SEM comparison (2007 vs 2021)

The exact same three-predictor functional-aggregate specification (pct_perennials + pct_annuals + pct_irrigated, forage/pasture as reference category, spatial error model) applied to both the 2007 (pre-drought) and 2021 (post-drought) census data at $n = 127$ sub-watersheds. Only the census year differs, enabling a symmetric quasi-experimental test of whether the crop composition-WUE sensitivity relationship is structural or an artefact of drought-driven adaptation. Full results are available in `outputs/tables/symmetric_census_comparison.csv`.

Predictor	2007				2021			
	OLS	SEM	95% CI (2007 SEM)	p (2007 SEM)	SEM	95% CI (2021 SEM)	p (2021 SEM)	Sign consistent?
% Perennial crops	+0.386**	+0.017	[-0.206, +0.241]	0.880	+0.231	[-0.017, +0.479]	0.068	Yes
% Annual crops	-0.385**	-0.152	[-0.444, +0.139]	0.306	-0.341**	[-0.568, -0.115]	0.003	Yes
% Irrigated area	+0.476***	+0.470***	[+0.272, +0.669]	<0.001	+0.438***	[+0.235, +0.642]	<0.001	Yes
(spatial error)	—	0.640***	[+0.501, +0.779]	<0.001	0.435***	[+0.252, +0.618]	<0.001	—
n	127	127	—	—	127	—	—	—

** $p < 0.01$; *** $p < 0.001$. All three predictors are sign-consistent between census years. The irrigated area coefficient is sign-consistent and positive across both years (2007: $= +0.470$ vs 2021: $= +0.438$), a pattern consistent with structural stability; note that the 2007 value is partially imputed (Section 2.4) and direct quantitative comparison with the fully reported 2021 value is limited by imputation quality. Annual crops is sign-consistent but attenuated and non-significant in the 2007 SEM, partly reflecting stronger spatial autocorrelation ($= 0.640$ vs 0.435). Perennial crops is positive and sign-consistent in both SEM specifications but non-significant, consistent with the latitudinal confound (Section 4.6). Reference: `outputs/tables/symmetric_census_comparison.csv`.

Supplementary Table S-10 - Synchronized-time bootstrap two-stage uncertainty propagation

Bootstrap inference for the stage-2 spatial error model (SEM) of WUE-SPEI-12 sensitivity on 2021 crop composition (n = 127 sub-watersheds). Two bootstrap variants were implemented (code: `scripts/analysis/15_bootstrap_two_stage.R`; B = 1000 iterations each; seed = 2026):

Variant A — Pairs bootstrap (independent within-sub-watershed): Each sub-watershed draws its own random year indices. Captures within-sub-watershed temporal sampling uncertainty but does not preserve the cross-sectional spatial covariance of stage-1 estimation errors.

Variant B — Synchronized-time bootstrap (primary): All 127 sub-watersheds receive the SAME randomly drawn year indices in each iteration. Because the same calendar years are selected for all sub-watersheds simultaneously, the spatial covariance of (SPEI-12, WUE) at each time point is preserved, and the resulting stage-1 slope estimates retain the cross-sectional spatial dependence present in the observed slopes (Moran's I = 0.811). Variant B is the primary inference reported here; Variant A is reported in `outputs/tables/bootstrap_comparison_variants.csv`.

Bootstrap 95% CIs are percentile intervals. Bootstrap p-values are two-sided: $2 \times \min(\text{proportion} = 0, \text{proportion} < 0)$. SE ratio = bootstrap SE / nominal SEM SE. Full results: `outputs/tables/bootstrap_two_stage_sem.csv`.

Predictor	Nominal		Synced-		Synced-		SE ratio
	Nominal	SE	Nominal p	time SE	time 95% CI	time p	
(Intercept)	−0.284	0.064	< 0.001	0.095	[−0.426, −0.053]	0.018	1.491
% Perennial crops	+0.231	0.127	0.068	0.095	[+0.016, +0.374]	0.036	0.748
% Annual crops	−0.341	0.116	0.003	0.109	[−0.596, −0.150]	0.002	0.943
% Irrigated area	+0.438	0.104	< 0.001	0.077	[+0.229, +0.536]	0.002	0.742

985 The synchronized-time bootstrap produces SE ratios of 0.74–0.94× the nominal SEM SEs for the three
986 substantive predictors, notably more conservative than the pairs bootstrap (0.54–0.75×). All three predictors
987 remain significant under the spatially-correct bootstrap ($p = 0.002$ – 0.036). The intercept behaves in the
988 opposite direction, with a synchronized-time SE ratio of 1.49× against 0.71× under the pairs bootstrap.
989 This contrast is diagnostic: synchronizing the resampled years imposes a year-set-specific common shift on
990 all 127 stage-1 slopes, which is absorbed by the intercept rather than by the slope coefficients, and which
991 the pairs bootstrap destroys by resampling years independently per sub-watershed. The slope SEs falling
992 below nominal therefore reflects that the nominal SEM treats each sub-watershed’s stage-1 estimation error
993 as independent, attributing to the slopes part of a component that is in fact common across units. Compare
994 Supplementary Table S-5 (WLS robustness check) for the complementary inverse-variance weighting approach;
995 full variant comparison in `outputs/tables/bootstrap_comparison_variants.csv`.

996 *Supplementary Table S-11 - Complete within-unit panel regression: HC1 vs Driscoll-Kraay standard errors*

997 Two-way fixed-effects panel regression coefficients for all nine index × accumulation-scale combinations,
998 estimated in the full study domain ($n = 131$ sub-watersheds, 2,620 obs.) and restricted to Mediterranean-
999 climate sub-watersheds (Csa+Csb, $n = 76$, 1,520 obs.). **Two SE variants are reported:** HC1 (clustered
1000 by sub-watershed, accounts for within-unit serial correlation only; assumes cross-sectional independence)
1001 and Driscoll-Kraay (DK; [Driscoll and Kraay \(1998\)](#), bandwidth = $\lfloor T^{1/4} \rfloor = 2$, accounts for both serial
1002 correlation AND cross-sectional spatial dependence). The DK estimator is the methodologically appropriate
1003 choice given Moran’s $I = 0.503$ – 0.811 for the WUE-SPEI sensitivity surface. Bold p-values indicate p
1004 < 0.05 under DK SEs. Full results: `outputs/tables/panel_driscoll_kraay.csv` (DK primary) and
1005 `outputs/tables/panel_cluster_robust.csv` (HC1 for reference).

Index	Scale		HC1 SE	HC1 p	DK SE	DK p	DK ratio
SPEI	12	−0.112	0.034	0.001	0.102	0.273	3.0×
SPEI	24	+0.046	0.046	0.316	0.156	0.769	3.4×
SPEI	36	−0.025	0.042	0.553	0.146	0.879	3.5×
SPI	12	−0.170	0.027	<0.001	0.087	0.053	3.2×
SPI	24	+0.001	0.037	0.968	0.139	0.994	3.8×
SPI	36	−0.026	0.040	0.513	0.156	0.870	3.9×
EDDI	12	−0.009	0.019	0.633	0.056	0.873	3.0×

Index	Scale		HC1 SE	HC1 p	DK SE	DK p	DK ratio
EDDI	24	−0.021	0.024	0.377	0.074	0.778	3.1×
EDDI	36	−0.036	0.026	0.178	0.086	0.682	3.3×

1006 *All sub-watershed panel ($n = 131$). None of the nine indices reach DK significance at any accumulation*
1007 *scale. HC1 p-values for SPEI-12 (0.001) and SPI-12 (<0.001) reflect within-unit serial correlation corrections*
1008 *that do not account for the strong cross-sectional spatial dependence.*

Index	Scale	(Med.)	HC1 SE	HC1 p	DK SE	DK p
SPEI	24	+0.193	0.046	<0.001	0.259	0.458
SPI	24	+0.141	0.041	0.001	0.254	0.579
SPEI	12	+0.080	0.051	0.102	0.132	0.555
SPI	12	−0.025	0.045	0.576	0.119	0.963
SPEI	36	+0.082	0.047	0.079	0.170	0.630

1009 *Mediterranean subset ($n = 76$). All coefficients are non-significant under DK SEs. Because the DK*
1010 *correction renders these estimates statistically indistinguishable from zero, their signs cannot be reliably*
1011 *interpreted as physical signals; the panel provides no statistically reliable evidence for within-unit temporal*
1012 *coupling in this subset.*

1013 Several patterns are noteworthy. First, SPEI-12 and SPI-12 are significantly negative in the full panel ($p =$
1014 0.001 and $p < 0.001$, respectively). This is a heterogeneity average: humid-temperate Cf sub-watersheds (n
1015 $= 26$) exhibit strong negative within-unit coupling (SPEI-36 $= -0.287$; Supplementary Table S-3), where
1016 rainfed annual systems raise WUE under mild drought by suppressing ET more than NPP (Yu et al., 2020).
1017 Removing Cf watersheds and restricting to Mediterranean (Csa+Csb) reverses the 12-month sign and reveals
1018 positive within-unit coupling at 24 months. Second, within Mediterranean sub-watersheds, EDDI-12 ($=$
1019 -0.064 , $p = 0.009$) and EDDI-24 ($= -0.079$, $p = 0.010$) are negative in the cluster-robust panel analysis. All
1020 EDDI values reported in this table use the manuscript’s sign convention (positive = below-normal demand;
1021 negative = drought, inverted from Hobbins et al. (2016); Section 2.3.1). Under this convention, a negative
1022 within-unit EDDI coefficient means years with below-normal evaporative demand are associated with lower
1023 WUE within Mediterranean watersheds, a result consistent with irrigated perennial systems sustaining higher

actual ET in mild-demand years without a proportional NPP gain, reducing the NPP/ET ratio. The EDDI within-unit finding is not central to any primary manuscript conclusion; SPEI-12 and SPI-12 are the main cross-product validated indices, and EDDI results are reported for completeness. Third, neither SPEI nor SPI shows significant within-unit coupling at the 36-month scale in any subset, and only the 24-month Mediterranean results are clearly positive and consistent across both precipitation-based indices.

Supplementary Table S-12 - Cross-sectional variance partition: contextual analysis with dimensional caveat

Important methodological caveat (see Section 2.3.1): Drought indices (SPEI-12, SPI-12) are standardized temporal anomalies relative to each sub-watershed’s local historical mean; they contain very little information about the absolute spatial aridity gradient at a single time point. WUE in 2020 and crop composition both co-vary with the spatial climatology (latitudinal aridity gradient). The near-zero unique cross-sectional variance attributable to drought indices is therefore a dimensional artifact: SPEI/SPI have been standardized to remove the same spatial gradient that drives both WUE and crop composition. **This table should not be interpreted as showing that drought is less important than crop composition for explaining WUE.** The table is retained for transparency and to document why adding drought indices to the cross-sectional model produces negligible R^2 gain. Full results: `outputs/tables/r2_variance_partition.csv`.

Variance partition of the 2020 cross-sectional regression of zWUE on drought index and crop composition ($n = 131$ sub-watersheds). Crop proportions: `pct_frutales`, `pct_vides`, `pct_cereales`, `pct_hortalizas`, `pct_forrajas_y_praderas`.

	R^2 (index only)	R^2 (crops only)	R^2 (full)	Unique to index	Shared	Unique to crops
SPEI-12	0.100	0.436	0.451	0.015	0.085	0.351
SPI-12	0.005	0.436	0.438	0.002	0.003	0.432
EDDI-24	0.213	0.436	0.454	0.018	0.196	0.240

The near-zero unique drought-index variance ($\text{SPEI-12} = 0.015$; $\text{SPI-12} = 0.002$) is a consequence of standardization: SPEI removes the spatial mean, leaving only the 2020 temporal anomaly, which explains little of the spatial variance that both WUE and crop composition carry through the absolute aridity gradient. The larger unique contribution of EDDI-24 (0.018) and its higher shared variance with crops (0.196) reflects evaporative demand’s stronger spatial structure; even here, the dimensional limitation applies.

Supplementary Table S-13 - DGA streamflow validation: delivery co-variation in key irrigation basins

Panel A — Cuenca-level delivery validation (primary analysis). Cross-product correlations between CHIRPS/CHIRTS SPEI-12 (December, cuenca mean across study sub-watersheds) and DGA annual streamflow anomaly (all gauges within each cuenca; calendar-year mean, standardised) for five key irrigation basins over 2001–2019 (n = 19 years each; data: CR2 cr2_qflxDaily_2020; code: scripts/analysis/18b_dga_delivery_validation_mediterranean.R; full results: outputs/tables/delivery_validation_

Cuenca	n gauges	(SPEI-12, Q _{annual})	(Q _{annual} , WUE)	(SPEI-12, WUE)
Aconcagua (054)	14	0.746	0.614	0.560
Maipo (057)	25	0.816	0.684	0.763
Rapel (060)	19	0.723	0.384	0.461
Mataquito (071)	7	0.828	0.289	0.033
Maule (073)	46	0.809	−0.198	−0.160
Median	—	0.809	0.384	0.461

All five basins show (SPEI-12, Q_{annual}) = 0.72 (all positive and strong): drought years (lower SPEI-12) consistently delivered lower annual streamflow. WUE was positively correlated with streamflow in the three northern irrigation basins (Aconcagua, Maipo, Rapel), confirming the SPEI to streamflow to WUE co-variation chain. Mataquito and Maule show weaker WUE-streamflow coupling consistent with their transitional hydroclimatic position toward the humid-temperate zone. All correlations are fully cross-product (CHIRPS/CHIRTS SPEI vs. independently observed DGA streamflow) with no shared forcing.

Panel B — Sub-watershed-level analysis (supporting). Sub-watershed analysis using only gauges that fall inside the DGA sub-watershed polygons (n = 16 sub-watersheds, Cf-dominated): median (SPEI-12, Q) = 0.57 (range 0.13–0.78). Sub-watershed coverage is geographically biased toward the humid-temperate Cf zone; the cuenca-level analysis (Panel A) is the primary validation. Full results: outputs/tables/streamflow_spei_wue_correlations.csv.

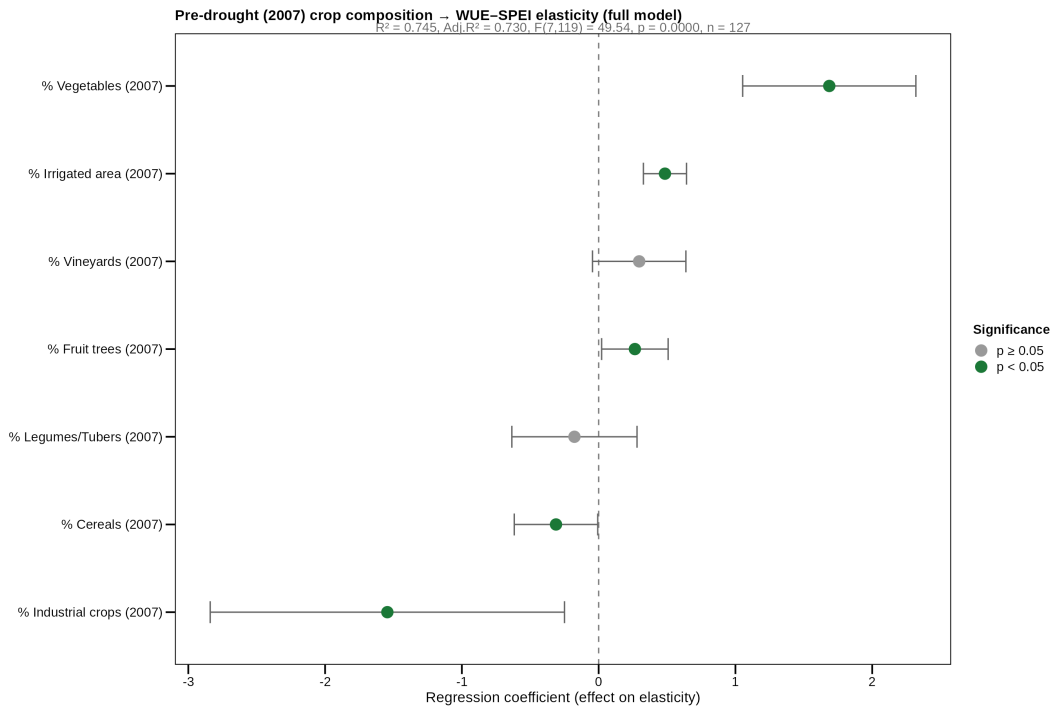


Figure 9: Pre-drought (2007) crop composition as a predictor of WUE-SPEI-12 sensitivity. OLS and spatial error model (SEM) regression coefficient plots using VII Agricultural and Forestry Census (2007) individual-category proportions aggregated to sub-watershed level as predictors (reference category: forage/pasture; $n = 127$ sub-watersheds). The harmonized OLS uses a five-predictor individual-category specification; the SEM uses the full seven-predictor specification (including legumes/tubers and industrial crops). Only the irrigated area coefficient is significant in the 2007 SEM ($= +0.470$, $p < 0.001$), consistent with irrigation amplification being a pre-drought structural property, though the 2007 imputation (Section 2.4) limits the reliability of this comparison with the 2021 result. The cereal (annual-crops proxy) coefficient is directionally consistent with the 2021 result in OLS but not significant in the 2007 SEM; the 2007 and 2021 CIs overlap substantially and no formal test of coefficient difference has been conducted. Reference: `outputs/tables/elasticity_crop_2007_regression.csv`.

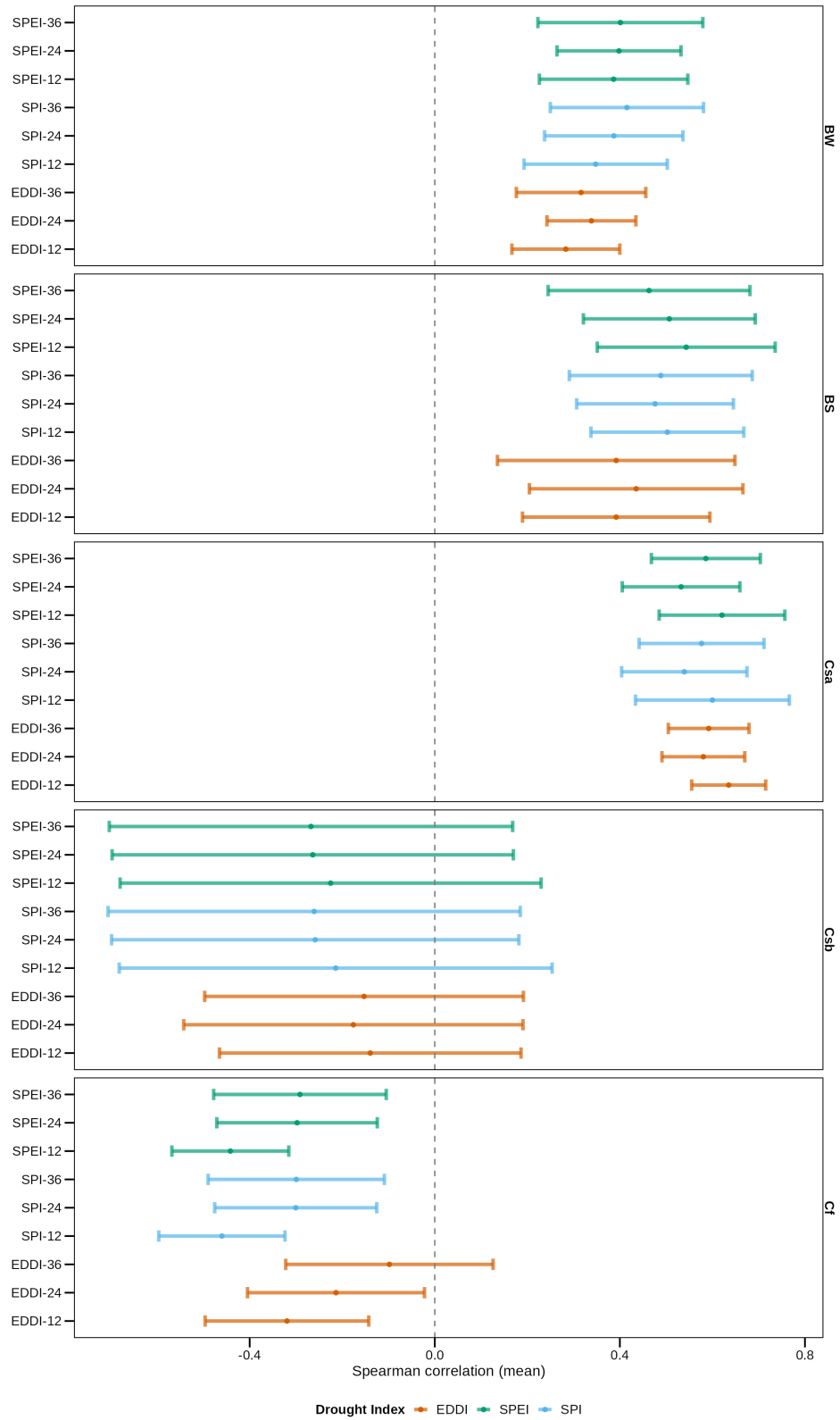


Figure 10: Mean per-sub-watershed Spearman correlation between annual WUE and each drought index (SPEI, SPI, EDDI) at the 12-, 24-, and 36-month accumulation scales, stratified by Köppen climate class. Points show the across-sub-watershed mean correlation; horizontal bars show the spread. This figure is the evidence base for foregrounding the 36-month accumulation scale and for the conclusion that SPEI and SPI carry comparable information while EDDI is weaker; it also exposes the Cf (humid-temperate) sign reversal that the panel regression formalizes.

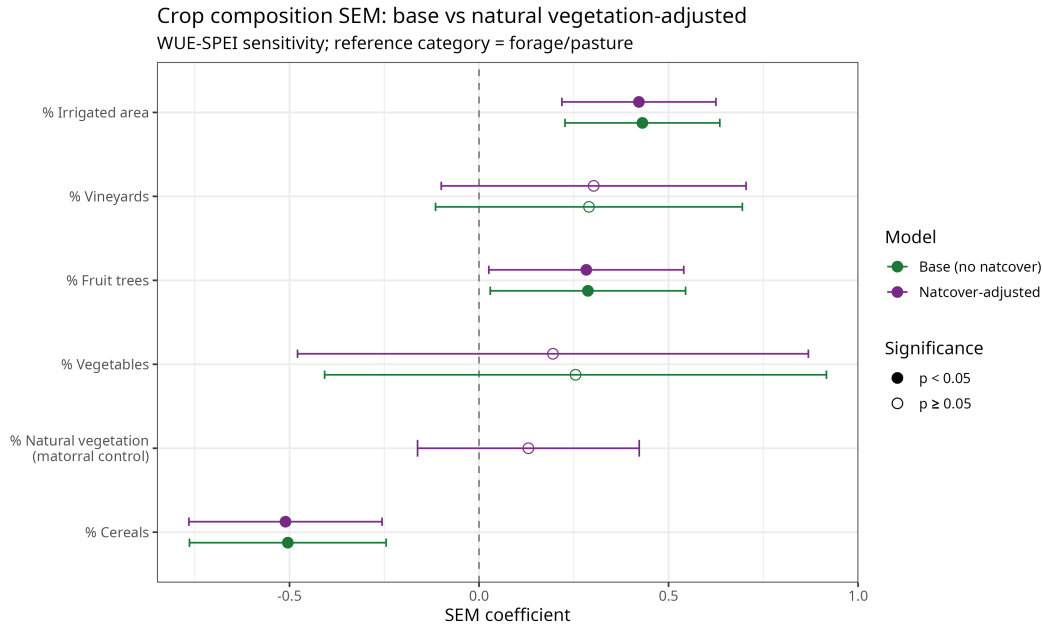


Figure 11: Robustness of the crop composition-WUE-SPEI-12 sensitivity associations to natural-vegetation (matorral) contamination within the agricultural mask. Spatial error model coefficients are compared between the base specification (green) and a specification that adds the natural-vegetation fraction (ESA CCI-LC 2016) as a control covariate (purple; reference category: forage/pasture). Solid symbols denote $p < 0.05$. The natural-vegetation coefficient is non-significant ($\beta = 0.098$, $p = 0.509$) and the cereal (negative) and irrigated-area (positive) effects are essentially unchanged, indicating that matorral fragmentation does not confound the crop composition-sensitivity relationship.

Supplementary Figure S-1 - Pre-drought (2007) crop composition and WUE sensitivity

Supplementary Figure S-2 - Mean WUE-drought correlation by index, accumulation scale, and Köppen class

Supplementary Figure S-3 - Natural-vegetation covariate robustness

Supplementary Figure S-4 - Geographic (latitude-block) cross-validation

This figure has been moved to the main text as Figure 8 (in Section 4.4). All five latitude-block holdout R^2 values are negative (range -1.25 to -0.29); full cross-validation results are in `outputs/tables/spatial_cv_by_block.csv`.

Supplementary Figure S-5 - Köppen-stratified panel regression coefficients

Supplementary Figure S-6 - Panel regression: pooled, Mediterranean, and post-2010 intensification

Supplementary Figure S-7 - Cross-product uncertainty analysis

Supplementary Table S-14 - Latitude-control robustness check for the irrigation effect

Spatial error model (SEM) of WUE-SPEI-12 sensitivity on 2021 functional crop group proportions ($n = 127$ sub-watersheds; reference category: forage/pasture), estimated under three specifications: M0 = primary

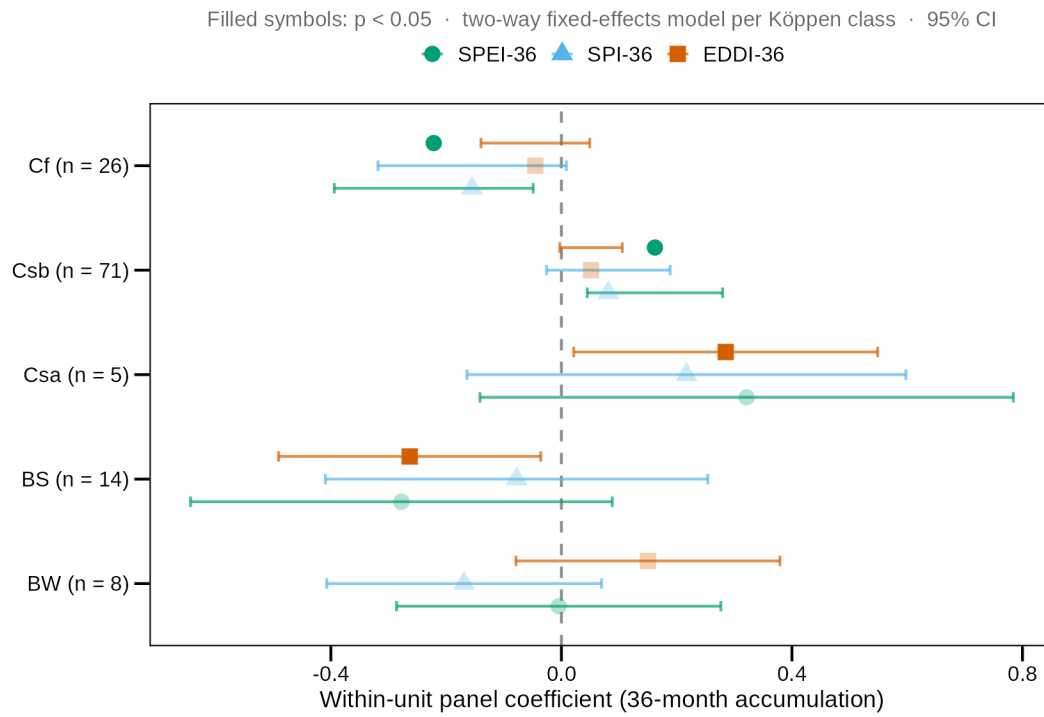


Figure 12: Two-way fixed-effects panel regression coefficients at the 36-month accumulation scale (SPEI-36, SPI-36, EDDI-36), estimated separately within each Köppen climate class (visualizing Supplementary Table S-3). Points show the within-unit coefficient with 95% confidence intervals; filled symbols denote $p < 0.05$. The figure makes explicit the divergence between Csb (warm-summer Mediterranean) sub-watersheds, which show significant positive WUE-drought coupling, and Cf (humid-temperate) sub-watersheds, which show a significant negative sign reversal at the 36-month scale; arid and semi-arid classes (BW, BS) show no significant within-unit coupling.

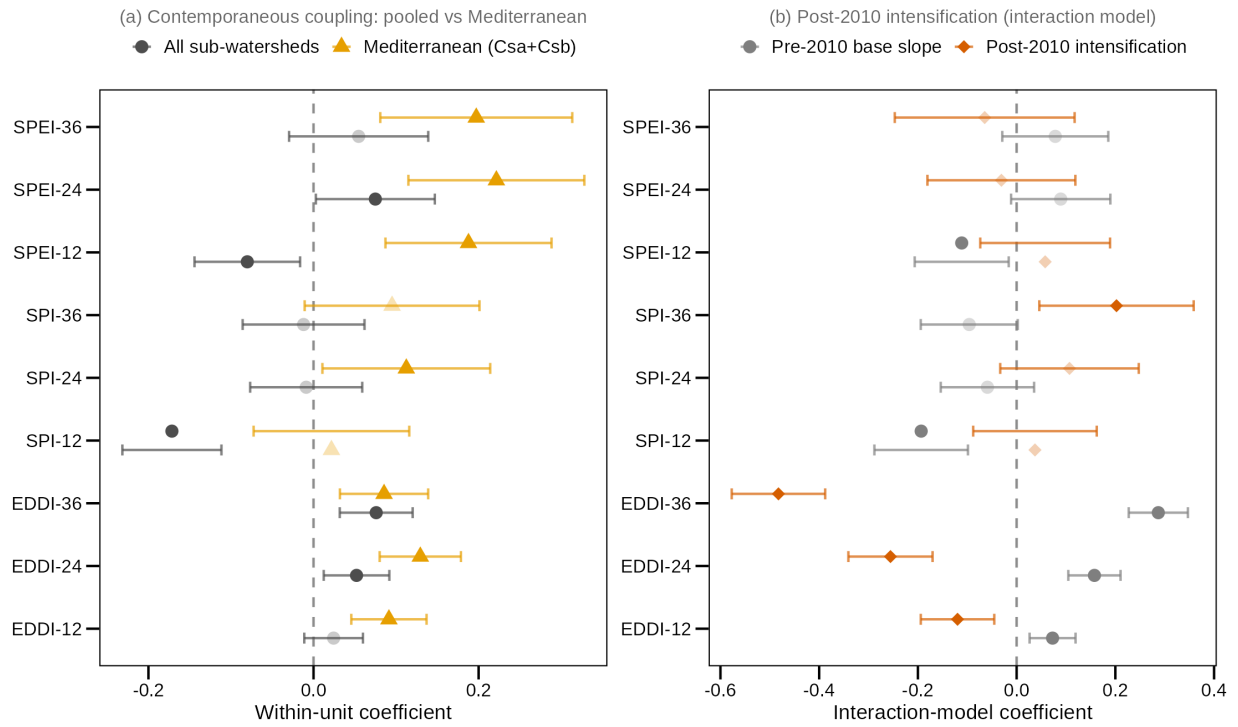


Figure 13: Two-way fixed-effects panel regression coefficients with 95% confidence intervals; filled symbols denote $p < 0.05$. (a) Contemporaneous within-unit WUE-drought coupling for SPEI, SPI, and EDDI at the 12-, 24-, and 36-month accumulation scales, comparing all sub-watersheds (grey) with the Mediterranean subset (Csa+Csb, orange). SPEI-24 and SPI-24 couple significantly within Mediterranean sub-watersheds; 36-month indices are non-significant in the all-watershed panel. (b) Interaction model contrasting the pre-2010 base slope (grey) with the post-2010 intensification term (vermillion). The post-2010 term is significant and positive for all three indices at the 36-month scale under HC1 standard errors (SPEI-36 post-2010 = +0.281, $p = 0.012$); this result does not survive Driscoll-Kraay correction and is explained by concave nonlinearity rather than a structural break (Supplementary Table S-8).

Cross-product uncertainty analysis (Response to Reviewer 3, Comment 3)

Panel A: per-watershed correlations between MODIS products and CAsEarth WUE quantify cross-product agreement. Panel B: crop composition SEM using the annual M

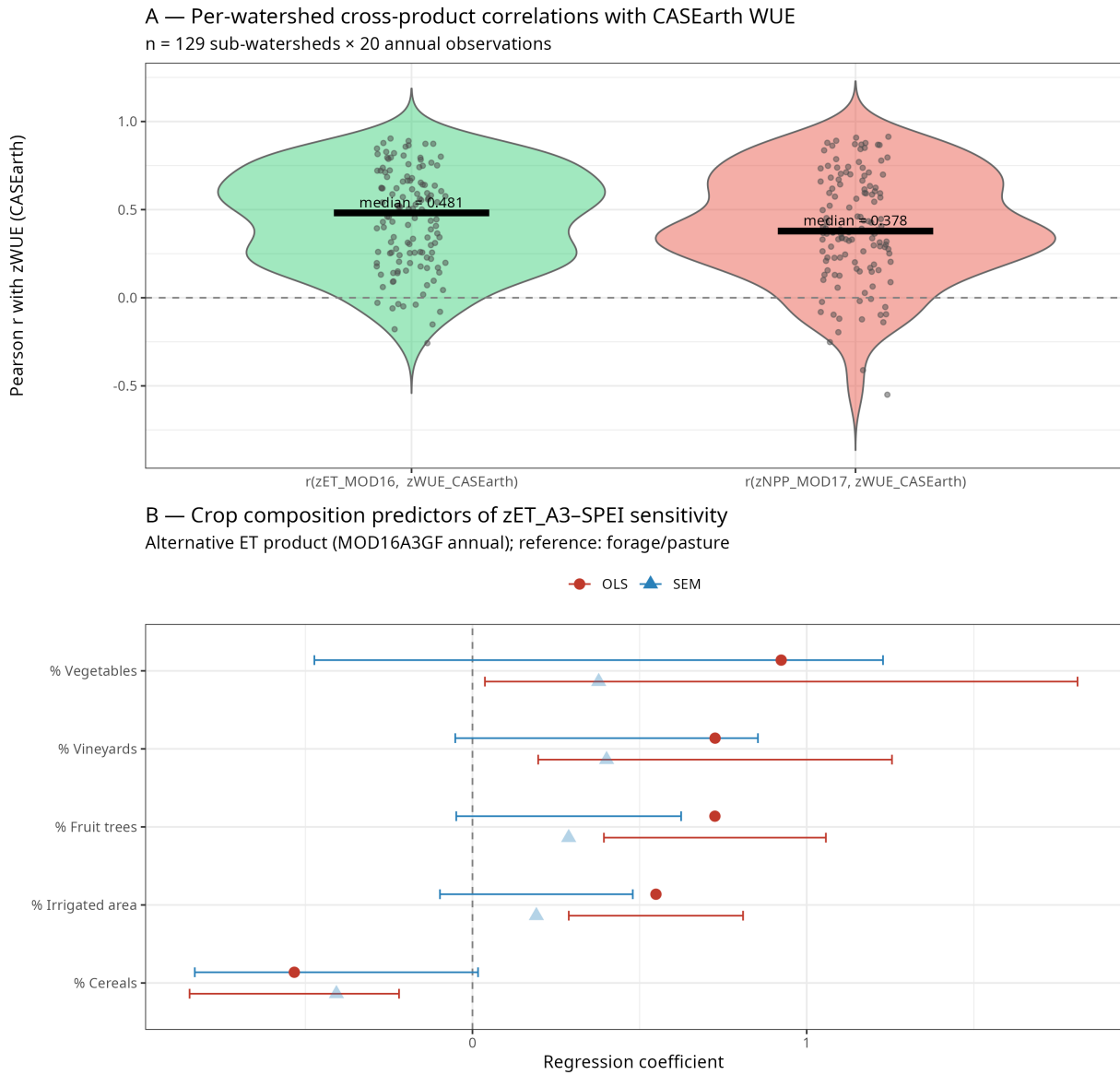


Figure 14: Cross-product uncertainty analysis for the WUE component sensitivity comparison (response to cross-product inconsistency concern, Section 2.3.2). Panel A: distributions of per-sub-watershed Pearson correlations between each MODIS product and CAsEarth zWUE ($n = 129$ sub-watersheds $\times$ 20 years). Median $r(zNPP_MOD17, zWUE_CAsEarth) = 0.378$ and $r(zET_MOD16, zWUE_CAsEarth) = 0.481$ are not significantly different (Wilcoxon paired test $p = 0.272$), confirming both products capture real WUE-relevant signals comparably. Panel B: crop-composition regression coefficients for the alternative annual ET product (MOD16A3GF; zET-SPEI-12 sensitivity), showing OLS (red circles) and SEM (blue triangles) estimates with 95% CI. Vineyard proportion is a significant positive predictor in SEM ($\beta = 0.519$, $p = 0.043$), confirming that the NPP-channel vineyard association is not a MODIS cross-product artefact.

model without latitude (replicates Table 1 full-sample SEM); M1 = adds sub-watershed centroid latitude (°S, negative values); M2 = adds centroid latitude and latitude². The Standardized Snow Water Equivalent Index (SWEI) procedure is defined in Section 2.3.1. Results address the reviewer concern that the irrigation association may be confounded with the latitudinal aridity gradient. Spatial weights: queen contiguity. Full results: `outputs/tables/latitude_control_sem_comparison.csv`.

Panel A - Latitude specifications within the SEM

Predictor	M0 (no lat)	M0 p	M1 (+ lat)	M1 p	M2 (+ lat ²)	M2 p
% Perennial crops	+0.231	0.068	+0.022	0.858	+0.016	0.894
% Annual crops	−0.341	0.003	−0.511	<0.001	−0.455	<0.001
% Irrigated area	+0.438	<0.001	+0.117	0.309	+0.127	0.261
Latitude (centroid)	—	—	+0.064	<0.001	+0.252	0.057
Latitude ² (spatial error)	—	—	—	—	+0.003	0.152
	0.435	<0.001	0.396	<0.001	0.371	<0.001
AIC	−26.5		−46.3		−46.3	

When latitude is explicitly controlled (M1), the irrigation coefficient attenuates from $\beta = +0.438$ to $\beta = +0.117$ and loses significance ($p = 0.309$), while latitude is highly significant ($\beta = +0.064$, $p < 0.001$). Model fit improves markedly ($\Delta AIC = 19.8$), confirming that latitude captures substantial variance in WUE sensitivity. The annual-crops buffering effect strengthens under latitude control (M0: $\beta = -0.341 \rightarrow$ M1: $\beta = -0.511$) and remains significant, establishing it as the more robustly latitude-independent result. The quadratic latitude term (M2) is non-significant ($p = 0.152$), indicating the latitudinal gradient is approximately linear over the study domain. Residual Moran's I is non-significant in all three models ($p > 0.70$), confirming adequate spatial error correction.

Panel B - Separating the latitude covariate from the spatial error term

Because the SEM already contains a spatial error term that absorbs geographic clustering, adding centroid latitude could in principle introduce a second variable tracking the same north-south pattern, so that the drop in the irrigation coefficient reflects two overlapping spatial terms competing for the same variance rather than the removal of confounding. Panel B crosses the two factors: presence or absence of the latitude covariate, and presence or absence of the spatial error term. Code: `scripts/analysis/20_reviewer_falsification_checks.R`; full results: `outputs/tables/latitude_spatial_error_model_variants.csv`.

Specification	Spatial error term	Latitude covariate	% Irrigated area	p	% Annual crops	p
OLS	No	No	+0.461	<0.001	-0.293	0.001
OLS + latitude	No	Yes	+0.219	0.032	-0.471	<0.001
SEM (primary)	Yes	No	+0.438	<0.001	-0.341	0.003
SEM + latitude	Yes	Yes	+0.117	0.309	-0.511	<0.001

The irrigation coefficient attenuates by a comparable proportion whether or not a spatial error term is present (OLS: $+0.461 \rightarrow +0.219$, a 53% reduction; SEM: $+0.438 \rightarrow +0.117$, a 73% reduction). Because the OLS specifications contain no spatial error term, the attenuation observed there cannot arise from competition with `latitude`, which isolates latitude itself as the source. Consistently, `irrigation` is nearly unchanged when latitude is added ($0.435 \rightarrow 0.396$), indicating that latitude does not displace the variance the spatial error term absorbs; the correlation between the fitted spatial error component and centroid latitude is $r = 0.400$ with a VIF of 1.21. The annual-crops coefficient strengthens under latitude control in both specifications, reinforcing its status as the latitude-robust result. We note that the latitude-controlled irrigation coefficient remains significant under OLS ($p = 0.032$) but not under the SEM ($p = 0.309$); since spatial dependence in the residuals is established (Moran's $I = 0.216$, $p < 0.001$), the SEM is the appropriate inferential model and we adopt its more conservative conclusion throughout.