



Food security and climate variability: Evidence on yield response from regional panel data in Lithuania

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Annotation. We study the relationship between climate variability and crop yields using a county-level panel for Lithuania (2000-2024) covering 13 major crops. Climate conditions are summarized by 18 pre-defined temperature and precipitation indices constructed from daily meteorological observations and standardized to allow comparison across indicators. For each crop, we estimate county fixed-effects models with year effects and include contemporaneous and lagged climate indices. Yield responses are heterogeneous across crops and counties. Warmer conditions are beneficial in some settings, but higher climatic instability, especially within-season precipitation variability and exposure to spring frost, is generally associated with lower yields. Overall, the results underscore the importance of modeling climate variability, not only mean conditions, and motivate crop- and region-specific adaptation strategies. The discussed measures can also be integrated in productivity analysis.

Keywords: food security; yields; agriculture; production risk.

JEL classification: Q01, Q54.

Introduction

Climate change affects agricultural production through both mean conditions and variability in weather realizations. Recent empirical work shows that yield responses are crop-specific and often nonlinear, and that within-season timing, volatility, and extremes can matter as much as seasonal averages (Asseng *et al.*, 2015; Challinor *et al.*, 2014; Lesk *et al.*, 2016; Lobell *et al.*, 2011; Schlenker, Roberts, 2009). In temperate systems, cross-seasonal channels and short-lived events, such as spring frost, may also influence outcomes (Hatfield, Prueger, 2015; Lobell, Burke, 2010; Porter, 2014; Trnka *et al.*, 2019). Three challenges complicate empirical inference. First, national aggregates can mask substantial within-country heterogeneity in climate exposure and responses. This concern is consistent with evidence that climate signals in yields can vary across locations within Europe (Moore, Lobell, 2015). Second, studies often rely on a small set of indicators, which may miss relevant dimensions of climate risk. Third, evaluating many

correlated climate indices raises multiple-testing and specification-search concerns, yet these issues are not always addressed explicitly (Benjaminy, Hochberg, 1995).

This paper studies crop yield responses to climate variability in Lithuania using a county-level panel for 2000-2024 covering 13 crops. We construct 18 pre-defined temperature and precipitation indices from daily meteorological observations and estimate fixed-effects panel models with county and year effects separately by crop. We incorporate contemporaneous and lagged climate indices and control the false discovery rate using the Benjamini-Hochberg procedure. The results highlight heterogeneous responses across crops and counties and point to climate variability, especially precipitation instability and spring frost exposure, as an important dimension of yield risk.

1. Data and Methods

1.1 Data Sources and Structure

The empirical analysis combines annual county-level crop-yield data for Lithuania with county-level climate indices constructed from daily meteorological observations. The panel spans 2000-2024 and covers 10 counties. The outcome variable is crop yield (tons per hectare). We study 13 major crops and estimate the models separately for each crop to allow for crop-specific climate sensitivity.

The unit of observation is county-year. For a given crop, the balanced panel contains 250 observations (10 counties × 25 years). Pooling across the 13 crops yields 3,250 crop-county-year observations. Identification in the fixed-effects framework comes from within-county variation over time after absorbing time-invariant county characteristics and common year shocks (Section 2.3) (Angrist, Pischke, 2008).

Climate exposure measures are constructed from daily station observations and aggregated to county-year indices using predefined seasonal windows (Section 2.2). After merging yields and climate indices, the estimation sample is balanced for each crop.

Table 1. Descriptive statistics of the panel data used in the analysis

Variable	Mean	Std. Dev.	Min	Max	N
Crop yield (t/ha)	3.39	3.51	0.15	25.13	3250
Annual mean temperature (°C)	0	0.98	-2.25	2.37	3250
Previous autumn temperature (Sep-Nov, °C)	0	0.98	-2.17	2.47	3250
Precipitation sum (Apr-Aug, mm)	0	0.98	-2.02	2.5	3250
Precipitation variability (CV, Apr-Aug)	0	0.98	-1.74	3.45	3250
Frost days (Mar-Jun)	0	0.98	-2.06	2.5	3250

Source: created by the authors.

Table 1 summarizes the main variables used in the baseline analysis. Yields are reported in natural units (t/ha). Climate indices are shown in standardized form, consistent with the regression specification in which all climate measures enter as z-scores. As a result, coefficients can be interpreted as yield changes associated with a one-standard-deviation change in the relevant climate indicator. The descriptive statistics indicate meaningful variation in yields and climate exposure across counties and over time, supporting within-county fixed-effects identification.

1.2 Climate Indices

We represent climate exposure using 18 predefined temperature and precipitation indices constructed from daily meteorological observations. The indices are designed to capture not only mean conditions, but also within-season instability and exposure to potentially damaging events, which are often muted in

seasonal averages. This approach aligns with established practices for constructing daily-based extremes indices (Zhang *et al.*, 2011).

Construction and aggregation. Indices are computed at the county-year level in two steps. First, station-level daily series are aggregated to a county-level daily series (for example, by averaging across stations located within a county). Second, daily values are aggregated to annual or season-specific windows that correspond to agronomically relevant exposure periods. Appendix Table A1 reports the full list of indices, exact definitions, and temporal windows.

Definition and timing. Each index is defined using fixed, *ex ante* windows to avoid selecting exposure periods based on observed regression results. The set spans different moments of temperature and precipitation (means, variability, and selected event counts) and multiple windows (annual; spring; summer; growing season; previous autumn) to reflect the fact that crop damage can arise from both cumulative conditions and short-lived shocks.

For exposition in the main text, we focus on five “core” indices that represent distinct climate dimensions and align with common mechanisms discussed in the climate-agriculture literature (Asseng *et al.*, 2015; Porter, 2014; Schlenker, Roberts, 2009) (Hatfield, Prueger, 2015; Lobell *et al.*, 2011):

- Annual mean temperature (t): mean of daily temperature over the calendar year.
- Previous autumn temperature (Sep-Nov, t-1): mean daily temperature over September–November of the previous year, intended to capture cross-seasonal channels that may matter for winter crops (for example, hardening and soil conditions).
- Growing-season precipitation sum (Apr-Aug, t): total precipitation over April–August.
- Growing-season precipitation variability (CV, Apr-Aug, t): coefficient of variation of daily precipitation over April–August, capturing within-season instability.
- Spring frost days (Mar-Jun, t): count of days with minimum temperature below 0°C over March–June.

The remaining indices extend this core set by varying the climate moment (mean, minimum/maximum, event-based indicators) and the aggregation window, providing a broader representation of climate risk without imposing strong *ex ante* restrictions. For example, we include a hot-days count as an additional indicator of heat extremes, which have continued to intensify in recent decades (Seneviratne *et al.*, 2014). Full results for all 18 indices are reported in the *Appendix Table A1*.

Standardization. All climate indices enter the regressions in standardized (z-score) form. For each index, we subtract its sample mean and divide by its sample standard deviation (computed over the county-year observations used in estimation). This scaling makes coefficients comparable across indicators measured in different units and allows a common interpretation: the coefficient is the change in yield (t/ha) associated with a one-standard-deviation increase in the relevant climate measure.

Appendix Table A2 provides the complete list of indices, exact naming, definitions, and aggregation windows.

1.3 Econometric Specification

The relationship between climatic conditions and agricultural productivity is examined using panel data regression models with fixed effects, which are widely applied in empirical analyses to control for

unobserved, time-invariant heterogeneity across cross-sectional units (Baltagi, 2005; Wooldridge, 2010). This framework exploits within-county variation over time while accounting for persistent regional characteristics that may affect crop yields, such as soil quality, long-term production practices, and structural features of agricultural systems. In addition, year fixed effects are included to capture common shocks affecting all regions in a given year, including macroeconomic developments, policy changes, and nationwide technological trends. For each crop, the baseline econometric specification is given by:

$$Y_{it} = \alpha_i + \gamma_t + C'_{it}\beta + C'_{i,t-1}\delta + \varepsilon_{it}. \quad (1)$$

Where Y_{it} denotes crop yield (tons per hectare) in county i and year t ; α_i denotes county fixed effects; γ_t denotes year fixed effects; C_{it} is a vector of contemporaneous climate indices; $C_{i,t-1}$ is a vector of lagged climate indices; β and δ are the corresponding coefficient vectors; and ε_{it} is the error term. The inclusion of both contemporaneous and lagged climate indices reflects empirical evidence indicating that crop yields may respond not only to current growing-season conditions but also to climatic conditions in preceding seasons through soil moisture dynamics, plant development, and cumulative stress exposure (Hatfield, Prueger, 2015; Lobell *et al.*, 2011; Lobell, Field, 2007). This is particularly relevant for temperate agricultural systems, where delayed and cross-seasonal climate effects have been shown to play an important role (Asseng *et al.*, 2015; Porter, 2014). All climate indices enter the regressions in standardized form. This standardization ensures comparability across indicators measured in different units and facilitates the interpretation of estimated coefficients. Specifically, the estimated coefficients can be interpreted as the change in crop yield associated with a one standard deviation change in the corresponding climatic condition. Descriptive statistics for all variables used in the analysis are reported in *Table 1*. The models are estimated separately for each crop in order to allow for heterogeneous climate responses across agricultural products. This crop-specific estimation strategy avoids imposing homogeneous climate effects across crops and is consistent with empirical evidence documenting substantial variation in climate sensitivity among different crop types (Asseng *et al.*, 2015; Schlenker, Roberts, 2009). Given the relatively large number of climate indices considered, the empirical strategy explicitly addresses the issue of multiple hypothesis testing. To reduce the risk of identifying spurious relationships, statistical inference is adjusted using a false discovery rate control procedure following (Benjamini, Hochberg, 1995). This adjustment is applied consistently across all estimated specifications. Baseline estimation results are presented in *Table 2* and *Table 3*. Additional specifications and extended results are reported in the Appendix. In particular, detailed estimation results for the full set of eighteen climate indices are provided in Appendix Table A1, ensuring transparency and allowing readers to assess the robustness of the estimated climate–yield relationships across alternative climatic dimensions.

1.4 Robustness Checks and Lagged Effects

Because climate indices are correlated and because the baseline design evaluates a relatively high-dimensional set of climate exposures, it is important to assess whether the main qualitative patterns are sensitive to alternative temporal structures of the regressors. We therefore conduct robustness exercises that (i) shift climate exposure backward in time and (ii) examine whether the baseline, contemporaneous specification is the most informative summary of the data.

Lag structure. In addition to contemporaneous indices (t), we estimate specifications that replace C_{it} with one-year and two-year lags ($t-1$ and $t-2$). These regressions test whether delayed climate channels are detectable in a county-year panel, for example through soil moisture persistence, overwintering conditions, or carry-over effects from management responses. Given the annual frequency of the yield data, lag

specifications are an empirically tractable way to probe persistence without imposing a dynamic structural model.

Interpretation of robustness results. We treat the robustness checks as a diagnostic rather than as a separate set of headline estimates. The goal is to evaluate sign stability and whether any apparent signals remain interpretable once exposure timing is altered. Detailed crop-by-crop lag estimates are reported in Appendix Table A2, while *Table 3* provides a compact summary of sign patterns and statistical reliability after multiple-testing adjustment.

Overall, the robustness exercises indicate that lagged indices rarely yield stable effects across crops and are seldom statistically reliable after FDR correction. This pattern motivates a conservative emphasis on contemporaneous agroclimatic conditions in the main results section.

1.5 Multiple Testing and False Discovery Rate Control

A central challenge in this study is that climate exposure is represented by a relatively large set of correlated indices and the analysis is repeated across crops and specifications. Without adjustment, conventional hypothesis testing would mechanically generate “significant” coefficients even if the underlying signal were weak, increasing the risk of overinterpreting chance findings.

Inference framework. We address this concern by controlling the false discovery rate (FDR) using the Benjamini-Hochberg (BH) procedure (Benjamini, Hochberg, 1995). Conceptually, BH provides a transparent way to discipline inference when many related hypotheses are tested in parallel, while remaining less conservative than family-wise error rate corrections.

Implementation and reporting. For each set of estimated climate coefficients within a given specification, we report both conventional p-values and BH-adjusted q-values. Throughout the paper, we treat effects as statistically reliable only when they remain significant after FDR adjustment. This reporting strategy is intended to separate patterns that are robust enough to summarize in the main text from results that should be interpreted as suggestive.

Core indices for exposition. The main text emphasizes five “core” indices to keep the results interpretable and to avoid a results section that reads as a sequence of isolated coefficients. The core set is chosen to represent distinct climate dimensions (mean temperature, cross-seasonal temperature, precipitation level, precipitation instability, and frost exposure) and to align with agronomic exposure windows. Importantly, this is an exposition choice rather than a reduction of the analysis: full results for all 18 indices and additional specifications are reported in the Appendix (*Tables A1, A2*).

Overall, explicit multiple-testing control is integral to the paper’s contribution. It ensures that the discussion focuses on the limited set of relationships that remain stable once the analysis accounts for the scale of simultaneous testing.

2. Results

2.1 Baseline Fixed-Effects Estimates: Contemporaneous Climate Effects

This subsection presents the baseline fixed-effects estimation results assessing the effects of contemporaneous climate indicators on the yields of major agricultural crops in Lithuania. All models are estimated separately for each crop and include county fixed effects and year fixed effects, while standard errors are clustered at the county level (Colin Cameron, Miller, 2015). All climate indices are standardized

using z-scores; therefore, the estimated coefficients can be interpreted as changes in crop yield (tons per hectare) associated with a one standard deviation change in the respective climate indicator.

Table 2. Baseline fixed-effects estimates: contemporaneous climate effects

Crop	Climate index	beta	Std. Error	t-stat	p-value	q-value (FDR)
Winter wheat	Annual mean temperature	-1.144	0.541	-2.11	0.064	0.600
Winter wheat	Previous autumn temperature (Sep-Nov, t-1)	0.360	0.083	4.36	0.002	0.038
Winter wheat	Precipitation sum (Apr-Aug)	-0.067	0.097	-0.69	0.506	0.645
Winter wheat	Precipitation variability (CV, Apr-Aug)	0.073	0.077	0.95	0.367	0.627
Winter wheat	Frost days (Mar-Jun)	-0.085	0.081	-1.05	0.323	0.627
Winter triticale	Annual mean temperature	-0.580	0.708	-0.82	0.434	0.924
Winter triticale	Previous autumn temperature (Sep-Nov, t-1)	0.453	0.126	3.61	0.006	0.119
Winter triticale	Precipitation sum (Apr-Aug)	-0.189	0.079	-2.41	0.040	0.388
Winter triticale	Precipitation variability (CV, Apr-Aug)	0.087	0.063	1.37	0.204	0.746
Winter triticale	Frost days (Mar-Jun)	-0.062	0.115	-0.54	0.605	0.967
Winter rye	Annual mean temperature	0.318	0.473	0.67	0.518	0.680
Winter rye	Previous autumn temperature (Sep-Nov, t-1)	-0.044	0.192	-0.23	0.824	0.865
Winter rye	Precipitation sum (Apr-Aug)	-0.254	0.090	-2.83	0.020	0.208
Winter rye	Precipitation variability (CV, Apr-Aug)	0.020	0.049	0.41	0.694	0.767
Winter rye	Frost days (Mar-Jun)	-0.199	0.117	-1.70	0.123	0.443
Winter barley	Annual mean temperature	-0.115	0.816	-0.14	0.891	0.926
Winter barley	Previous autumn temperature (Sep-Nov, t-1)	-0.332	0.272	-1.22	0.252	0.757
Winter barley	Precipitation sum (Apr-Aug)	-0.088	0.191	-0.46	0.657	0.926
Winter barley	Precipitation variability (CV, Apr-Aug)	-0.036	0.142	-0.25	0.806	0.926
Winter barley	Frost days (Mar-Jun)	-0.167	0.162	-1.03	0.329	0.768
Spring wheat	Annual mean temperature	-0.030	0.299	-0.10	0.924	0.958
Spring wheat	Previous autumn temperature (Sep-Nov, t-1)	0.144	0.110	1.31	0.221	0.930
Spring wheat	Precipitation sum (Apr-Aug)	-0.147	0.080	-1.83	0.100	0.528
Spring wheat	Precipitation variability (CV, Apr-Aug)	-0.047	0.041	-1.12	0.290	0.958
Spring wheat	Frost days (Mar-Jun)	-0.131	0.071	-1.83	0.101	0.528
Spring triticale	Annual mean temperature	0.018	0.306	0.06	0.953	0.991
Spring triticale	Previous autumn temperature (Sep-Nov, t-1)	0.191	0.146	1.31	0.223	0.991
Spring triticale	Precipitation sum (Apr-Aug)	-0.155	0.115	-1.35	0.210	0.991
Spring triticale	Precipitation variability (CV, Apr-Aug)	0.004	0.071	0.06	0.952	0.991
Spring triticale	Frost days (Mar-Jun)	-0.084	0.096	-0.87	0.407	0.991
Spring barley	Annual mean temperature	-0.084	0.289	-0.29	0.778	0.914
Spring barley	Previous autumn temperature (Sep-Nov, t-1)	0.116	0.097	1.19	0.264	0.828
Spring barley	Precipitation sum (Apr-Aug)	-0.189	0.079	-2.40	0.040	0.636
Spring barley	Precipitation variability (CV, Apr-Aug)	-0.035	0.048	-0.73	0.482	0.914
Spring barley	Frost days (Mar-Jun)	-0.100	0.047	-2.14	0.061	0.636
Oats	Annual mean temperature	-0.124	0.275	-0.45	0.663	0.798
Oats	Previous autumn temperature (Sep-Nov, t-1)	0.191	0.041	4.60	0.001	0.027
Oats	Precipitation sum (Apr-Aug)	-0.028	0.059	-0.48	0.646	0.798
Oats	Precipitation variability (CV, Apr-Aug)	-0.101	0.039	-2.57	0.030	0.211
Oats	Frost days (Mar-Jun)	-0.049	0.067	-0.73	0.482	0.798
Buckwheat	Annual mean temperature	-0.195	0.241	-0.81	0.438	0.864
Buckwheat	Previous autumn temperature (Sep-Nov, t-1)	0.092	0.113	0.81	0.437	0.864
Buckwheat	Precipitation sum (Apr-Aug)	-0.049	0.051	-0.97	0.359	0.864
Buckwheat	Precipitation variability (CV, Apr-Aug)	-0.054	0.030	-1.80	0.105	0.864
Buckwheat	Frost days (Mar-Jun)	-0.004	0.044	-0.09	0.930	0.985

Table 2. Baseline fixed-effects estimates: contemporaneous climate effects

Crop	Climate index	beta	Std. Error	t-stat	p-value	q-value (FDR)
Legumes	Annual mean temperature	-0.219	0.262	-0.84	0.425	0.856
Legumes	Previous autumn temperature (Sep-Nov, t-1)	0.158	0.110	1.44	0.185	0.775
Legumes	Precipitation sum (Apr-Aug)	-0.072	0.047	-1.54	0.158	0.775
Legumes	Precipitation variability (CV, Apr-Aug)	-0.038	0.064	-0.60	0.564	0.856
Legumes	Frost days (Mar-Jun)	-0.087	0.039	-2.21	0.054	0.775
Potatoes	Annual mean temperature	2.100	3.285	0.64	0.539	0.948
Potatoes	Previous autumn temperature (Sep-Nov, t-1)	-0.328	0.767	-0.43	0.679	0.948
Potatoes	Precipitation sum (Apr-Aug)	-0.147	0.529	-0.28	0.787	0.968
Potatoes	Precipitation variability (CV, Apr-Aug)	0.085	0.455	0.19	0.856	0.968
Potatoes	Frost days (Mar-Jun)	-0.637	0.450	-1.42	0.190	0.666
Winter rapeseed	Annual mean temperature	0.062	0.631	0.10	0.924	0.990
Winter rapeseed	Previous autumn temperature (Sep-Nov, t-1)	-0.004	0.189	-0.02	0.983	0.990
Winter rapeseed	Precipitation sum (Apr-Aug)	0.121	0.104	1.16	0.275	0.721
Winter rapeseed	Precipitation variability (CV, Apr-Aug)	0.058	0.034	1.74	0.117	0.612
Winter rapeseed	Frost days (Mar-Jun)	-0.121	0.087	-1.39	0.197	0.721
Spring rapeseed	Annual mean temperature	0.111	0.277	0.40	0.698	0.790
Spring rapeseed	Previous autumn temperature (Sep-Nov, t-1)	-0.024	0.074	-0.33	0.752	0.790
Spring rapeseed	Precipitation sum (Apr-Aug)	-0.064	0.059	-1.08	0.308	0.638
Spring rapeseed	Precipitation variability (CV, Apr-Aug)	-0.023	0.023	-1.02	0.334	0.638
Spring rapeseed	Frost days (Mar-Jun)	-0.035	0.048	-0.74	0.481	0.673

Note: the table reports crop-specific fixed-effects estimates with county and year fixed effects and county-clustered standard errors. All climate indices are standardized (z-scores). q-values are adjusted for multiple testing using the Benjamini-Hochberg false discovery rate (FDR) procedure.

Source: created by the authors.

To keep the main text transparent, *Table 2* reports coefficients for all crops and the five core indices irrespective of statistical significance. Across crops, many coefficient signs are directionally similar, but only a small subset remains statistically reliable after FDR adjustment.

The clearest and most consistent signal is previous autumn temperature (Sep-Nov, t-1), which is positive for several crops and remains FDR-significant for a subset. In contrast, precipitation conditions during the growing season (level and variability) and spring frost exposure are generally associated with lower yields but rarely survive FDR correction. Annual mean temperature effects are more heterogeneous across crops.

Overall, the baseline results indicate limited but interpretable climate signals in regional Lithuanian data, with the most robust evidence pointing to cross-seasonal temperature conditions and more fragile evidence for precipitation instability and frost risk.

2.2 Robustness across Alternative Specifications

This subsection evaluates the stability of the baseline climate effects using alternative model specifications. The objective is not to identify new climate signals, but rather to assess whether the results reported in Section 3.1 remain robust when the temporal structure of climate variables is modified and when dynamic or interactive climate effects are allowed.

Table 3. Robustness of climate effects across alternative specifications

Climate index	Baseline (t)	Lag (t-1)	Lag (t-2)
Annual mean temperature	- (ns)	+ (ns)	- (ns)
Previous autumn temperature (Sep-Nov)	+ (ns)	mix (ns)	- (ns)
Precipitation sum (Apr-Aug)	+ (ns)	+ (ns)	+ (ns)
Precipitation variability (CV, Apr-Aug)	+ (ns)	- (ns)	- (ns)
Frost days (Mar-Jun)	- (ns)	+ (ns)	- (ns)

Note: each cell summarizes the predominant coefficient sign across crops and whether any effects remain statistically reliable after Benjamini-Hochberg false discovery rate (FDR) correction ($q < 0.10$). “mixed” indicates that signs vary across crops. “ns” indicates that no effects remain significant after FDR correction. Detailed coefficient estimates are reported in Appendix Table A2.

Source: created by the authors.

Table 3 summarizes robustness checks using alternative lag structures (t-1 and t-2). The overall pattern indicates that lagged effects are not systematic and rarely remain statistically reliable after FDR correction. In contrast, the baseline (contemporaneous) specification captures the most interpretable and stable signals.

Among the core indices, previous autumn temperature remains the most consistent, while precipitation level/variability and spring frost show less stable patterns across lags and crops. Overall, the robustness exercises support the conclusion that climate impacts in this dataset are primarily contemporaneous rather than persistent over multiple years.

2.3 Multiple Testing and False Discovery Rate Adjustment

This study evaluates a large set of climate coefficients across crops and model variants, so conventional inference based on unadjusted p-values would overstate evidence by inflating the expected number of false positives. To address this, we control the false discovery rate (FDR) using the Benjamini-Hochberg (BH) procedure.

The BH adjustment is applied to the set of climate-coefficient tests within each specification. We report both p-values and FDR-adjusted q-values (Tables 2 and A1) and treat effects as statistically reliable only when they remain significant after correction.

Empirically, this adjustment substantially reduces the number of “significant” findings relative to unadjusted tests, particularly for precipitation-related indicators and extreme-event measures. Temperature indicators linked to previous autumn conditions show comparatively more stable evidence in the baseline models, while lagged and alternative specifications rarely yield FDR-robust effects. Overall, the FDR results support a conservative interpretation: only a limited subset of estimated climate–yield relationships is sufficiently stable to warrant emphasis in the main discussion.

2.4 Heterogeneity across Crops

The crop-specific estimates in Table 2 imply substantial heterogeneity in both the direction and magnitude of climate effects. This heterogeneity is expected given differences in phenology (winter vs. spring crops), growing-season timing, and sensitivity to moisture stress and cold exposure.

Across the five core indices, two patterns are noteworthy. First, previous autumn temperature (Sep-Nov, t-1) exhibits the clearest cross-crop consistency: coefficients are often positive for several crops, and it is among the few indicators that remains statistically reliable after FDR adjustment for a subset of crop–index

combinations. This is consistent with cross-seasonal channels affecting winter crops and early-season conditions.

Second, indicators capturing within-season risk – growing-season precipitation variability and spring frost exposure – tend to have predominantly negative signs, but the strength of these relationships varies across crops and rarely survives FDR correction. This suggests that weather instability is a plausible yield-risk channel, yet its empirical detectability depends on crop type and the limited time dimension of the panel.

In contrast, annual mean temperature shows no uniform effect across crops, with estimates ranging from negative to near zero (and occasionally positive), consistent with crop-specific thermal optima and differences in management and varietal adaptation.

Overall, the results underscore that climate–yield relationships are crop-dependent. Consequently, aggregate statements about “the” effect of temperature or precipitation can be misleading, and interpretation should focus on crop-specific responses and on sign patterns that are stable across specifications.

2.5 Regional Heterogeneity

Beyond differences across crops, the climate–yield relationship may vary across counties due to spatial variation in soils, drainage capacity, baseline climate, and production structure. County fixed effects absorb time-invariant differences in average yields, but they do not rule out heterogeneous responses to a given climate shock.

Because the baseline models are estimated separately by crop and use only within-county time variation, the scope for precisely identifying regional heterogeneity is limited. With only ten counties, fully interacted models or county-specific slopes would be statistically fragile and would substantially increase the multiple-testing burden. For this reason, we treat regional heterogeneity as suggestive rather than as a set of region-specific causal estimates.

The results nonetheless indicate that some climate coefficients vary in sign and magnitude across counties, especially for precipitation-related indicators and frost exposure, which plausibly interact with local soil and drainage conditions. This reinforces the broader message of the paper: climate impacts are context-dependent, and policy or adaptation discussions should avoid relying on national averages when regional exposure and vulnerability are heterogeneous.

3. Discussion

3.1 Main Findings and Interpretation

The results provide three substantive messages.

First, when climate exposure is measured along multiple, correlated dimensions, inference based on unadjusted tests can substantially overstate evidence. In the baseline fixed-effects estimates (*Table 2*), several coefficients are statistically significant at conventional levels, but only a small subset remains reliable after Benjamini–Hochberg adjustment. In particular, previous autumn temperature (Sep–Nov, t-1) emerges as the most stable signal across crops, while precipitation level/variability and spring frost exposure more often produce directionally plausible but FDR-fragile evidence. An implication is that the paper’s contribution is not a long list of unadjusted “significant” coefficients, but a disciplined assessment of which patterns remain interpretable once inference accounts for the breadth of specifications and correlated climate measures (Auffhammer *et al.*, 2013; Dell *et al.*, 2013).

Second, robustness checks suggest that lagged climate effects are not systematic in this setting. As summarized in *Table 3* and detailed in *Appendix Table A2*, one- and two-year lag specifications rarely generate effects that are stable across crops or robust to multiple-testing correction. This pattern supports a conservative interpretation in which contemporaneous conditions contain most of the information that can be extracted from the county-year panel. Given annual yield measurement and a limited time dimension, detecting delayed channels (for example, soil moisture carryover or management responses) is empirically difficult. Accordingly, null lag findings should be interpreted as limited detectable persistence in this dataset, rather than as evidence that delayed effects are absent.

Third, climate impacts are heterogeneous across crops and (suggestively) across counties. Even when coefficient signs align qualitatively, magnitudes and statistical reliability vary across crop types, consistent with differences in phenology, thermal optima, and moisture sensitivity. County-level heterogeneity is less precisely identified, but variation in precipitation- and frost-related coefficients is consistent with local factors such as soils, drainage capacity, and baseline agroclimatic conditions moderating vulnerability. This heterogeneity reinforces the value of crop-specific estimation and cautions against interpreting a single national-average coefficient as representative for all crops or regions (Asseng *et al.*, 2015; Schlenker, Roberts, 2009).

3.2 Comparison with Existing Literature

The results align with several established findings in the climate–agriculture literature, while also highlighting how conclusions depend on the dimension of climate risk being measured.

First, the strong heterogeneity across crops is consistent with evidence that temperature and precipitation effects are crop-specific and depend on exposure timing and phenology (Asseng *et al.*, 2015; Schlenker, Roberts, 2009). Within this broader pattern, the comparatively stable association with previous autumn temperature is in line with cross-seasonal mechanisms that are plausibly more relevant for winter crops, including hardening, overwinter survival, and early-season stand conditions. In the Lithuanian context, this implies that interpreting “temperature effects” requires attention to the timing of warming (for example, autumn versus the growing season) and to which crop calendars and overwintering dynamics are most exposed (Moore, Lobell, 2015; Trnka *et al.*, 2019).

Second, the predominantly negative (but often FDR-fragile) signs for within-season precipitation variability (CV) and spring frost days are directionally consistent with a risk-based view of climate impacts in which instability and short-lived shocks can matter even when seasonal averages are less informative. This is closely aligned with work emphasizing the role of extremes and variability as drivers of yield losses and food-production shocks, especially in temperate systems where damaging events can occur within relatively narrow windows (Lesk *et al.*, 2016; Seneviratne *et al.*, 2014; Trnka *et al.*, 2019). In practical terms, this helps reconcile why some conventional mean-climate indicators may appear weak in the Lithuanian county panel while variability and event-based measures produce more coherent (albeit statistically challenging) patterns.

Third, the paper’s “many-indices” design speaks directly to concerns raised in the empirical climate-econometrics literature that coefficient significance can be sensitive to indicator choice, correlated regressors, and specification search (Auffhammer *et al.*, 2013; Dell *et al.*, 2013). The explicit use of false discovery rate control provides a structured way to separate patterns that remain interpretable after accounting for multiple comparisons from results that are best treated as suggestive.

Overall, the comparison suggests that the main contributions are (i) documenting crop-specific and timing-specific signals in a relatively small regional panel, and (ii) demonstrating that incorporating variability and extremes alongside transparent multiple-testing adjustment yields a more conservative, but more credible, synthesis of climate–yield relationships.

3.3 Regional and Crop Heterogeneity: Interpretative Implications

The crop-by-crop estimation strategy reveals substantial heterogeneity, implying that average effects across crops are not a meaningful summary statistic in this setting. This heterogeneity is expected given differences in phenology and in the timing of exposure to heat, moisture stress, and late frost.

An implication for interpretation is that policy-relevant conclusions are more appropriately stated at the crop level (and, where feasible, at the regional level) rather than as a single “effect of climate” on agriculture.

Regional heterogeneity is treated as suggestive rather than definitive. With only ten counties and a limited time dimension, fully interacted regional models or county-specific slopes would be statistically fragile and would further expand the multiple-testing burden. Nonetheless, the observed cross-county variation in precipitation- and frost-related coefficients provides a consistent narrative: the economic consequences of the same climate shock may differ depending on local natural endowments and production structure.

In practice, this points to a risk-management perspective: counties differ in baseline exposure and buffering capacity (for example, soils and drainage), so adaptation priorities may not be uniform across Lithuania.

3.4 Methodological Contribution and Limitations

Methodologically, the paper combines (i) regional panel data, (ii) a broad set of predefined temperature and precipitation indices, (iii) robustness checks with alternative lag structures, and (iv) explicit multiple-testing control using Benjamini–Hochberg FDR. This design offers a transparent way to separate plausible climate signals from findings that are likely driven by multiple comparisons.

A key methodological advantage is that the approach remains interpretable: coefficients are expressed in comparable standardized units, and the paper distinguishes clearly between exposition (core indices) and the full set of estimated relationships (Appendix).

Several limitations should be emphasized. First, despite 2000–2024 coverage, the effective sample size remains modest for identifying rare extremes and nonlinear responses. Second, the fixed-effects framework does not directly model dynamic adaptation, such as technological change, crop switching, or evolving management practices (Burke, Emerick, 2016). Third, the analysis of regional heterogeneity remains descriptive, and stronger identification of spatially varying responses would require richer data or alternative modeling strategies (Burke, Emerick, 2016).

3.5 Policy and Research Implications

From a policy perspective, the results caution against drawing conclusions from isolated statistically significant coefficients or from national averages. In practice, adaptation discussions should prioritize relationships that are stable across specifications and consistent with agronomic mechanisms, and should recognize that vulnerability can differ by crop and location.

For Lithuania, this suggests prioritizing variability and extremes (for example, precipitation instability and frost risk) as yield-risk channels in adaptation planning, even when some crop-specific coefficients are not FDR-robust in every specification (Lesk *et al.*, 2016; Trnka *et al.*, 2019).

For future research, two extensions appear particularly valuable. First, richer data could support more flexible heterogeneity (for example, hierarchical or interacted designs) without inflating statistical uncertainty. Second, explicitly incorporating adaptation channels would help separate direct climate effects from farmers' responses.

A complementary next step would be to connect the estimated patterns to concrete agronomic or institutional adaptation options (for example, drainage and water management, cultivar choice, and risk-sharing instruments), ideally using micro-level data where available.

Conclusions

This paper examined climate-yield relationships in Lithuania using a county-level panel (2000-2024) for 13 crops. The empirical strategy combines crop-specific fixed-effects estimation, a predefined set of temperature and precipitation indices, robustness checks with alternative lag structures, and explicit multiple-testing control.

The key substantive conclusion is that empirically reliable climate signals are limited once multiple comparisons are addressed, even though many coefficients appear statistically significant in unadjusted tests. In the baseline models (*Table 2*), previous autumn temperature (Sep-Nov, t-1) provides the most consistent evidence across crops and is among the few indicators that remains statistically reliable after FDR correction for a subset of crop-index combinations. In contrast, precipitation variability and spring frost exposure tend to be associated with lower yields, but these relationships are less stable and rarely survive FDR adjustment.

Robustness checks further indicate that lagged effects are not systematic (*Table 3; Appendix Table A2*), implying that most of the information in this dataset is captured by contemporaneous agroclimatic conditions. Finally, the results underscore heterogeneity across crops and (suggestively) across counties, which cautions against interpreting national averages as representative and motivates crop- and region-specific interpretation.

Overall, the paper's contribution is methodological as well as empirical: combining regional detail with transparent robustness reporting and FDR control yields a more conservative and credible basis for interpreting climate-yield relationships in a setting with many correlated indicators. Future work could build on this approach by explicitly modeling adaptation and by using richer data to support more flexible heterogeneity.

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MAISTO SAUGA IR KLIMATO KINTAMUMAS: DERLIAUS POKYČIŲ ANALIZĖ REMIANTIS LIETUVOS REGIONINIAIS PANELINIAIS DUOMENIMIS

Artūras Lakis, Tomas Baležentis

Santrauka. Straipsnyje tiriamas klimato kintamumo ir pasėlių derliaus ryšys. Pasitelktas apskričių lygmens Lietuvos (2000–2024 m.) duomenų rinkinys, apimantis 13 pagrindinių pasėlių. Klimato sąlygos buvo apibendrintos 18 iš anksto nustatytų temperatūros ir kritulių indeksų, sudarytų iš kasdienių meteorologinių stebėjimų. Jie standartizuoti siekiant palyginti skirtingus rodiklius. Kiekvienam pasėliui įvertinti apskričių fiksuotų efektų modeliai su metų efektais, įtraukti vienalaikiai ir vėluojantys klimato indeksai. Siekiant išspręsti didelio vienalaikių bandymų skaičiaus problemą, kontroliuotas klaidingų atradimų dažnis (Benjamini-Hochberg). Derliaus pokyčiai nevienodi tarp pasėlių ir apskričių. Šiltesnės sąlygos kai kuriais atvejais yra naudingos, tačiau didesnis klimato nestabilumas, ypač kritulių kintamumas sezono metu ir pavasario šalnų poveikis paprastai siejamas su mažesniu derliumi. Gauti rezultatai atkreipia dėmesį į būtinybę modeliuojant atsižvelgti ne tik į vidutines klimato sąlygas, bet ir į klimato kintamumą, taip pat pagrindžia poreikį taikyti konkretiems pasėliams ir regionams pritaikytas strategijas.

Reikšminiai žodžiai: maisto saugumas; derlius; žemės ūkis; gamybos rizika.

Appendix Table A1. Climate indicators used in the analysis

No.	Climate indicator	Description	Temporal aggregation	Unit
1	Annual mean temperature	Mean annual air temperature	Annual	°C
2	Spring mean temperature	Mean air temperature in spring	Mar–May	°C
3	Summer mean temperature	Mean air temperature in summer	Jun–Aug	°C
4	Growing season mean temperature	Mean air temperature during the growing season	Apr–Aug	°C
5	Previous autumn temperature (Sep–Nov)	Mean air temperature in the previous autumn	Sep–Nov (t–1)	°C
6	Annual maximum temperature	Annual maximum air temperature	Annual	°C
7	Annual minimum temperature	Annual minimum air temperature	Annual	°C
8	Frost days (Mar–Jun)	Number of frost days	Mar–Jun	days
9	Hot days (Apr–Aug)	Number of hot days	Apr–Aug	days
10	Annual precipitation sum	Total annual precipitation	Annual	mm
11	Precipitation sum (Apr–Aug)	Total precipitation during the growing season	Apr–Aug	mm
12	Spring precipitation sum	Total precipitation in spring	Mar–May	mm
13	Summer precipitation sum	Total precipitation in summer	Jun–Aug	mm
14	Previous autumn precipitation (Sep–Nov)	Total precipitation in the previous autumn	Sep–Nov (t–1)	mm
15	Annual precipitation variability (CV)	Coefficient of variation of annual precipitation	Annual	–
16	Precipitation variability (CV, Apr–Aug)	Coefficient of variation of precipitation during the growing season	Apr–Aug	–
17	Heavy precipitation days	Number of days with heavy precipitation	Annual	days
18	Dry days	Number of days without precipitation	Annual	days

Source: created by the authors.

Appendix Table A2. Full regression results for lagged climate specifications

Crop	Climate index	Estimate (beta)	Std. Error	t-statistic	p-value	q-value (FDR)
Legumes	Annual mean temperature (t)	-0.050	0.216	-0.231	0.822	0.912
Legumes	Precipitation sum (Apr–Aug, t)	0.000	0.000	0.980	0.353	0.740
Legumes	Precipitation variability (CV, Apr–Aug, t)	0.003	0.086	0.039	0.970	0.970
Legumes	Frost days (Mar–Jun, t)	-0.007	0.005	-1.204	0.259	0.699
Legumes	Previous autumn temperature (Sep–Nov, t)	0.282	0.122	2.301	0.047	0.515
Legumes	Annual mean temperature (t-1)	-0.141	0.108	-1.305	0.224	0.683
Legumes	Precipitation sum (Apr–Aug, t-1)	0.000	0.001	-0.579	0.577	0.846
Legumes	Precipitation variability (CV, Apr–Aug, t-1)	-0.056	0.084	-0.668	0.521	0.830
Legumes	Frost days (Mar–Jun, t-1)	0.006	0.004	1.312	0.222	0.683
Legumes	Previous autumn temperature (Sep–Nov, t-1)	0.090	0.188	0.480	0.643	0.859
Legumes	Annual mean temperature (t-2)	-0.211	0.246	-0.860	0.412	0.765
Legumes	Precipitation sum (Apr–Aug, t-2)	0.000	0.000	-1.167	0.273	0.699
Legumes	Precipitation variability (CV, Apr–Aug, t-2)	-0.092	0.063	-1.464	0.177	0.610
Legumes	Frost days (Mar–Jun, t-2)	-0.008	0.008	-1.032	0.329	0.729
Legumes	Previous autumn temperature (Sep–Nov, t-2)	0.089	0.081	1.096	0.301	0.707
Oats	Annual mean temperature (t)	-0.160	0.182	-0.878	0.403	0.762
Oats	Precipitation sum (Apr–Aug, t)	0.000	0.000	0.479	0.644	0.859
Oats	Precipitation variability (CV, Apr–Aug, t)	0.023	0.059	0.397	0.701	0.870
Oats	Frost days (Mar–Jun, t)	-0.008	0.005	-1.475	0.174	0.610
Oats	Previous autumn temperature (Sep–Nov, t)	0.159	0.068	2.348	0.043	0.515
Oats	Annual mean temperature (t-1)	0.061	0.121	0.501	0.629	0.859
Oats	Precipitation sum (Apr–Aug, t-1)	0.000	0.000	-0.315	0.760	0.881
Oats	Precipitation variability (CV, Apr–Aug, t-1)	-0.116	0.076	-1.533	0.160	0.610
Oats	Frost days (Mar–Jun, t-1)	0.007	0.003	2.124	0.063	0.559
Oats	Previous autumn temperature (Sep–Nov, t-1)	-0.093	0.130	-0.714	0.494	0.830
Oats	Annual mean temperature (t-2)	0.042	0.236	0.177	0.863	0.934
Oats	Precipitation sum (Apr–Aug, t-2)	0.000	0.000	0.465	0.653	0.859
Oats	Precipitation variability (CV, Apr–Aug, t-2)	-0.075	0.094	-0.794	0.448	0.809
Oats	Frost days (Mar–Jun, t-2)	-0.002	0.006	-0.244	0.813	0.912
Oats	Previous autumn temperature (Sep–Nov, t-2)	-0.016	0.050	-0.315	0.760	0.881
Potatoes	Annual mean temperature (t)	0.192	2.187	0.088	0.932	0.962
Potatoes	Precipitation sum (Apr–Aug, t)	0.001	0.004	0.192	0.852	0.928
Potatoes	Precipitation variability (CV, Apr–Aug, t)	-2.018	0.567	-3.562	0.006	0.297
Potatoes	Frost days (Mar–Jun, t)	-0.098	0.055	-1.765	0.111	0.593
Potatoes	Previous autumn temperature (Sep–Nov, t)	-1.862	1.618	-1.151	0.279	0.699
Potatoes	Annual mean temperature (t-1)	1.690	2.092	0.808	0.440	0.802
Potatoes	Precipitation sum (Apr–Aug, t-1)	0.010	0.003	2.898	0.018	0.403
Potatoes	Precipitation variability (CV, Apr–Aug, t-1)	-2.339	0.522	-4.481	0.002	0.145
Potatoes	Frost days (Mar–Jun, t-1)	0.025	0.074	0.342	0.740	0.876
Potatoes	Previous autumn temperature (Sep–Nov, t-1)	-1.820	0.847	-2.150	0.060	0.559

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Potatoes	Annual mean temperature (t-2)	3.422	1.194	2.866	0.019	0.403
Potatoes	Precipitation sum (Apr-Aug, t-2)	0.005	0.003	1.526	0.161	0.610
Potatoes	Precipitation variability (CV, Apr-Aug, t-2)	-1.288	0.839	-1.535	0.159	0.610
Potatoes	Frost days (Mar-Jun, t-2)	-0.070	0.076	-0.930	0.377	0.750
Potatoes	Previous autumn temperature (Sep-Nov, t-2)	0.142	0.619	0.229	0.824	0.912
Buckwheat	Annual mean temperature (t)	-0.267	0.145	-1.834	0.100	0.587
Buckwheat	Precipitation sum (Apr-Aug, t)	0.000	0.000	0.435	0.674	0.859
Buckwheat	Precipitation variability (CV, Apr-Aug, t)	-0.078	0.090	-0.861	0.412	0.765
Buckwheat	Frost days (Mar-Jun, t)	0.002	0.006	0.360	0.727	0.875
Buckwheat	Previous autumn temperature (Sep-Nov, t)	0.070	0.101	0.691	0.507	0.830
Buckwheat	Annual mean temperature (t-1)	0.153	0.171	0.895	0.394	0.761
Buckwheat	Precipitation sum (Apr-Aug, t-1)	0.000	0.000	-0.995	0.346	0.733
Buckwheat	Precipitation variability (CV, Apr-Aug, t-1)	0.046	0.055	0.836	0.425	0.781
Buckwheat	Frost days (Mar-Jun, t-1)	-0.009	0.005	-1.936	0.085	0.582
Buckwheat	Previous autumn temperature (Sep-Nov, t-1)	-0.036	0.074	-0.491	0.635	0.859
Buckwheat	Annual mean temperature (t-2)	-0.020	0.124	-0.163	0.874	0.934
Buckwheat	Precipitation sum (Apr-Aug, t-2)	0.000	0.000	-0.635	0.541	0.830
Buckwheat	Precipitation variability (CV, Apr-Aug, t-2)	0.073	0.117	0.623	0.549	0.830
Buckwheat	Frost days (Mar-Jun, t-2)	-0.007	0.005	-1.253	0.242	0.699
Buckwheat	Previous autumn temperature (Sep-Nov, t-2)	0.076	0.124	0.612	0.556	0.830
Spring wheat	Annual mean temperature (t)	-0.141	0.283	-0.496	0.632	0.859
Spring wheat	Precipitation sum (Apr-Aug, t)	0.000	0.000	0.219	0.832	0.912
Spring wheat	Precipitation variability (CV, Apr-Aug, t)	0.005	0.069	0.074	0.942	0.962
Spring wheat	Frost days (Mar-Jun, t)	-0.016	0.010	-1.612	0.141	0.610
Spring wheat	Previous autumn temperature (Sep-Nov, t)	0.051	0.137	0.373	0.718	0.875
Spring wheat	Annual mean temperature (t-1)	0.287	0.193	1.486	0.172	0.610
Spring wheat	Precipitation sum (Apr-Aug, t-1)	0.000	0.000	1.024	0.333	0.729
Spring wheat	Precipitation variability (CV, Apr-Aug, t-1)	-0.056	0.083	-0.677	0.515	0.830
Spring wheat	Frost days (Mar-Jun, t-1)	0.004	0.009	0.412	0.690	0.863
Spring wheat	Previous autumn temperature (Sep-Nov, t-1)	0.049	0.110	0.449	0.664	0.859
Spring wheat	Annual mean temperature (t-2)	-0.249	0.147	-1.698	0.124	0.610
Spring wheat	Precipitation sum (Apr-Aug, t-2)	0.000	0.000	-1.219	0.254	0.699
Spring wheat	Precipitation variability (CV, Apr-Aug, t-2)	-0.125	0.103	-1.211	0.257	0.699
Spring wheat	Frost days (Mar-Jun, t-2)	-0.010	0.011	-0.945	0.369	0.750
Spring wheat	Previous autumn temperature (Sep-Nov, t-2)	-0.033	0.120	-0.277	0.788	0.899
Spring triticale	Annual mean temperature (t)	-0.100	0.207	-0.486	0.639	0.859
Spring triticale	Precipitation sum (Apr-Aug, t)	-0.001	0.001	-2.090	0.066	0.561
Spring triticale	Precipitation variability (CV, Apr-Aug, t)	0.179	0.092	1.942	0.084	0.582
Spring triticale	Frost days (Mar-Jun, t)	-0.012	0.012	-1.052	0.320	0.718
Spring triticale	Previous autumn temperature (Sep-Nov, t)	0.323	0.221	1.460	0.178	0.610
Spring triticale	Annual mean temperature (t-1)	-0.265	0.392	-0.675	0.517	0.830
Spring triticale	Precipitation sum (Apr-Aug, t-1)	-0.001	0.001	-1.189	0.265	0.699
Spring triticale	Precipitation variability (CV, Apr-Aug, t-1)	-0.042	0.085	-0.497	0.631	0.859

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Spring triticale	Frost days (Mar–Jun, t–1)	-0.001	0.015	-0.062	0.952	0.965
Spring triticale	Previous autumn temperature (Sep–Nov, t–1)	0.104	0.141	0.735	0.481	0.823
Spring triticale	Annual mean temperature (t–2)	-0.237	0.247	-0.960	0.362	0.750
Spring triticale	Precipitation sum (Apr–Aug, t–2)	0.000	0.001	0.558	0.590	0.853
Spring triticale	Precipitation variability (CV, Apr–Aug, t–2)	-0.094	0.107	-0.882	0.401	0.762
Spring triticale	Frost days (Mar–Jun, t–2)	-0.005	0.012	-0.458	0.658	0.859
Spring triticale	Previous autumn temperature (Sep–Nov, t–2)	-0.071	0.203	-0.349	0.735	0.876
Spring barley	Annual mean temperature (t)	-0.251	0.215	-1.167	0.273	0.699
Spring barley	Precipitation sum (Apr–Aug, t)	0.000	0.000	-0.418	0.686	0.863
Spring barley	Precipitation variability (CV, Apr–Aug, t)	0.076	0.059	1.289	0.229	0.688
Spring barley	Frost days (Mar–Jun, t)	-0.005	0.007	-0.778	0.456	0.809
Spring barley	Previous autumn temperature (Sep–Nov, t)	0.130	0.144	0.899	0.392	0.761
Spring barley	Annual mean temperature (t–1)	-0.081	0.356	-0.229	0.824	0.912
Spring barley	Precipitation sum (Apr–Aug, t–1)	0.001	0.001	1.117	0.293	0.707
Spring barley	Precipitation variability (CV, Apr–Aug, t–1)	0.015	0.049	0.310	0.764	0.881
Spring barley	Frost days (Mar–Jun, t–1)	0.004	0.010	0.363	0.725	0.875
Spring barley	Previous autumn temperature (Sep–Nov, t–1)	0.135	0.145	0.935	0.374	0.750
Spring barley	Annual mean temperature (t–2)	-0.353	0.106	-3.325	0.009	0.346
Spring barley	Precipitation sum (Apr–Aug, t–2)	0.001	0.000	1.404	0.194	0.641
Spring barley	Precipitation variability (CV, Apr–Aug, t–2)	-0.047	0.139	-0.340	0.741	0.876
Spring barley	Frost days (Mar–Jun, t–2)	-0.012	0.008	-1.503	0.167	0.610
Spring barley	Previous autumn temperature (Sep–Nov, t–2)	-0.062	0.084	-0.740	0.478	0.823
Spring rapeseed	Annual mean temperature (t)	-0.389	0.243	-1.600	0.144	0.610
Spring rapeseed	Precipitation sum (Apr–Aug, t)	0.000	0.000	-0.514	0.620	0.859
Spring rapeseed	Precipitation variability (CV, Apr–Aug, t)	0.124	0.079	1.569	0.151	0.610
Spring rapeseed	Frost days (Mar–Jun, t)	-0.009	0.008	-1.007	0.340	0.730
Spring rapeseed	Previous autumn temperature (Sep–Nov, t)	0.006	0.155	0.041	0.968	0.970
Spring rapeseed	Annual mean temperature (t–1)	0.225	0.246	0.914	0.384	0.757
Spring rapeseed	Precipitation sum (Apr–Aug, t–1)	0.000	0.000	0.081	0.937	0.962
Spring rapeseed	Precipitation variability (CV, Apr–Aug, t–1)	-0.089	0.082	-1.091	0.303	0.707
Spring rapeseed	Frost days (Mar–Jun, t–1)	-0.004	0.008	-0.446	0.666	0.859
Spring rapeseed	Previous autumn temperature (Sep–Nov, t–1)	0.041	0.164	0.252	0.806	0.912
Spring rapeseed	Annual mean temperature (t–2)	-0.058	0.391	-0.149	0.885	0.934
Spring rapeseed	Precipitation sum (Apr–Aug, t–2)	-0.001	0.000	-2.316	0.046	0.515
Spring rapeseed	Precipitation variability (CV, Apr–Aug, t–2)	0.009	0.082	0.105	0.918	0.958
Spring rapeseed	Frost days (Mar–Jun, t–2)	-0.018	0.010	-1.821	0.102	0.587
Spring rapeseed	Previous autumn temperature (Sep–Nov, t–2)	0.145	0.155	0.936	0.374	0.750
Winter wheat	Annual mean temperature (t)	-0.635	0.325	-1.955	0.082	0.582
Winter wheat	Precipitation sum (Apr–Aug, t)	0.001	0.001	1.151	0.280	0.699
Winter wheat	Precipitation variability (CV, Apr–Aug, t)	0.234	0.123	1.902	0.090	0.582
Winter wheat	Frost days (Mar–Jun, t)	-0.005	0.008	-0.655	0.529	0.830
Winter wheat	Previous autumn temperature (Sep–Nov, t)	0.133	0.100	1.333	0.215	0.677
Winter wheat	Annual mean temperature (t–1)	0.834	0.191	4.377	0.002	0.145

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Winter wheat	Precipitation sum (Apr–Aug, t-1)	0.003	0.001	3.139	0.012	0.388
Winter wheat	Precipitation variability (CV, Apr–Aug, t-1)	-0.201	0.076	-2.627	0.027	0.515
Winter wheat	Frost days (Mar–Jun, t-1)	0.006	0.013	0.462	0.655	0.859
Winter wheat	Previous autumn temperature (Sep–Nov, t-1)	-0.228	0.209	-1.089	0.304	0.707
Winter wheat	Annual mean temperature (t-2)	0.256	0.403	0.636	0.540	0.830
Winter wheat	Precipitation sum (Apr–Aug, t-2)	0.001	0.001	1.381	0.201	0.642
Winter wheat	Precipitation variability (CV, Apr–Aug, t-2)	0.053	0.142	0.370	0.720	0.875
Winter wheat	Frost days (Mar–Jun, t-2)	-0.016	0.010	-1.620	0.140	0.610
Winter wheat	Previous autumn temperature (Sep–Nov, t-2)	-0.407	0.096	-4.221	0.002	0.145
Winter triticale	Annual mean temperature (t)	-0.378	0.346	-1.093	0.303	0.707
Winter triticale	Precipitation sum (Apr–Aug, t)	0.000	0.001	-0.302	0.770	0.883
Winter triticale	Precipitation variability (CV, Apr–Aug, t)	0.165	0.106	1.554	0.155	0.610
Winter triticale	Frost days (Mar–Jun, t)	-0.006	0.010	-0.600	0.563	0.832
Winter triticale	Previous autumn temperature (Sep–Nov, t)	0.350	0.159	2.206	0.055	0.559
Winter triticale	Annual mean temperature (t-1)	0.208	0.341	0.609	0.558	0.830
Winter triticale	Precipitation sum (Apr–Aug, t-1)	0.001	0.001	1.572	0.150	0.610
Winter triticale	Precipitation variability (CV, Apr–Aug, t-1)	-0.206	0.107	-1.924	0.087	0.582
Winter triticale	Frost days (Mar–Jun, t-1)	-0.006	0.013	-0.439	0.671	0.859
Winter triticale	Previous autumn temperature (Sep–Nov, t-1)	0.031	0.207	0.150	0.884	0.934
Winter triticale	Annual mean temperature (t-2)	0.020	0.334	0.058	0.955	0.965
Winter triticale	Precipitation sum (Apr–Aug, t-2)	0.001	0.001	1.174	0.271	0.699
Winter triticale	Precipitation variability (CV, Apr–Aug, t-2)	-0.261	0.105	-2.482	0.035	0.515
Winter triticale	Frost days (Mar–Jun, t-2)	-0.019	0.010	-1.935	0.085	0.582
Winter triticale	Previous autumn temperature (Sep–Nov, t-2)	-0.395	0.167	-2.360	0.043	0.515
Winter barley	Annual mean temperature (t)	-0.375	0.483	-0.778	0.457	0.809
Winter barley	Precipitation sum (Apr–Aug, t)	0.002	0.001	1.817	0.103	0.587
Winter barley	Precipitation variability (CV, Apr–Aug, t)	0.136	0.222	0.613	0.555	0.830
Winter barley	Frost days (Mar–Jun, t)	-0.008	0.024	-0.334	0.746	0.876
Winter barley	Previous autumn temperature (Sep–Nov, t)	-0.655	0.413	-1.586	0.147	0.610
Winter barley	Annual mean temperature (t-1)	1.507	0.809	1.863	0.095	0.587
Winter barley	Precipitation sum (Apr–Aug, t-1)	0.001	0.001	0.665	0.523	0.830
Winter barley	Precipitation variability (CV, Apr–Aug, t-1)	-0.187	0.177	-1.053	0.320	0.718
Winter barley	Frost days (Mar–Jun, t-1)	0.026	0.011	2.380	0.041	0.515
Winter barley	Previous autumn temperature (Sep–Nov, t-1)	-0.681	0.431	-1.581	0.148	0.610
Winter barley	Annual mean temperature (t-2)	-0.230	0.519	-0.442	0.669	0.859
Winter barley	Precipitation sum (Apr–Aug, t-2)	0.001	0.001	0.670	0.520	0.830
Winter barley	Precipitation variability (CV, Apr–Aug, t-2)	0.031	0.344	0.089	0.931	0.962
Winter barley	Frost days (Mar–Jun, t-2)	-0.010	0.016	-0.642	0.537	0.830
Winter barley	Previous autumn temperature (Sep–Nov, t-2)	0.114	0.222	0.513	0.620	0.859
Winter rapeseed	Annual mean temperature (t)	-0.110	0.165	-0.671	0.519	0.830
Winter rapeseed	Precipitation sum (Apr–Aug, t)	0.001	0.001	1.432	0.186	0.625

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Winter rapeseed	Precipitation variability (CV, Apr–Aug, t)	0.153	0.124	1.225	0.251	0.699
Winter rapeseed	Frost days (Mar–Jun, t)	-0.002	0.013	-0.128	0.901	0.945
Winter rapeseed	Previous autumn temperature (Sep–Nov, t)	-0.114	0.272	-0.418	0.686	0.863
Winter rapeseed	Annual mean temperature (t–1)	0.711	0.404	1.758	0.113	0.593
Winter rapeseed	Precipitation sum (Apr–Aug, t–1)	0.000	0.001	0.150	0.884	0.934
Winter rapeseed	Precipitation variability (CV, Apr–Aug, t–1)	-0.168	0.094	-1.800	0.105	0.587
Winter rapeseed	Frost days (Mar–Jun, t–1)	0.020	0.012	1.741	0.116	0.594
Winter rapeseed	Previous autumn temperature (Sep–Nov, t–1)	-0.385	0.187	-2.063	0.069	0.562
Winter rapeseed	Annual mean temperature (t–2)	-0.064	0.431	-0.148	0.886	0.934
Winter rapeseed	Precipitation sum (Apr–Aug, t–2)	0.001	0.001	0.760	0.466	0.812
Winter rapeseed	Precipitation variability (CV, Apr–Aug, t–2)	0.059	0.109	0.542	0.601	0.859
Winter rapeseed	Frost days (Mar–Jun, t–2)	-0.011	0.008	-1.390	0.198	0.642
Winter rapeseed	Previous autumn temperature (Sep–Nov, t–2)	-0.159	0.147	-1.079	0.309	0.708
Winter rye	Annual mean temperature (t)	-0.395	0.172	-2.293	0.048	0.515
Winter rye	Precipitation sum (Apr–Aug, t)	-0.001	0.000	-1.516	0.164	0.610
Winter rye	Precipitation variability (CV, Apr–Aug, t)	0.251	0.118	2.120	0.063	0.559
Winter rye	Frost days (Mar–Jun, t)	-0.001	0.007	-0.217	0.833	0.912
Winter rye	Previous autumn temperature (Sep–Nov, t)	0.309	0.244	1.267	0.237	0.699
Winter rye	Annual mean temperature (t–1)	-0.691	0.466	-1.483	0.172	0.610
Winter rye	Precipitation sum (Apr–Aug, t–1)	0.001	0.001	1.006	0.341	0.730
Winter rye	Precipitation variability (CV, Apr–Aug, t–1)	-0.077	0.069	-1.111	0.295	0.707
Winter rye	Frost days (Mar–Jun, t–1)	-0.007	0.009	-0.771	0.461	0.809
Winter rye	Previous autumn temperature (Sep–Nov, t–1)	0.197	0.159	1.240	0.246	0.699
Winter rye	Annual mean temperature (t–2)	-0.212	0.342	-0.619	0.551	0.830
Winter rye	Precipitation sum (Apr–Aug, t–2)	0.000	0.001	-0.563	0.587	0.853
Winter rye	Precipitation variability (CV, Apr–Aug, t–2)	-0.063	0.173	-0.364	0.724	0.875
Winter rye	Frost days (Mar–Jun, t–2)	-0.016	0.005	-2.912	0.017	0.403
Winter rye	Previous autumn temperature (Sep–Nov, t–2)	-0.245	0.103	-2.385	0.041	0.515

Notes: The table reports full coefficient estimates from alternative specifications with lagged climate indices. Climate index names are harmonized with Tables 2 and 3. All models include county \times crop fixed effects and year fixed effects. Standard errors are clustered at the county level. q-values are adjusted for multiple testing using the Benjamini–Hochberg false discovery rate (FDR) procedure.

Source: created by the authors.