

## Article

# Climate Variability, Energy-Related CO<sub>2</sub> Emissions, and Cereal Yields in Romania and Serbia: An ARDL Analysis

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## Abstract

This study examines the associations of land temperature anomalies and energy-related CO<sub>2</sub> emissions per hectare with wheat and maize yields in Romania and Serbia during 1992–2023. Energy-related CO<sub>2</sub> emissions per hectare are used as a scale-adjusted proxy for energy-use intensity and emissions associated with agricultural energy consumption, rather than as an indicator of climate intensity. The study contributes to the literature by applying a comparative ARDL framework to Romania and Serbia, two Central and Southeast European agricultural systems with different institutional contexts, integrating climate variability, nitrogen fertilizer use and energy-use-related emissions into a unified crop-specific analysis. Using the Autoregressive Distributed Lag (ARDL) framework, we estimate long-run equilibrium relationships and short-run dynamics between cereal yields and the selected explanatory variables. The results partially support the proposed hypotheses by indicating heterogeneous country- and crop-specific relationships. In Romania, nitrogen fertilizer use is positively associated with wheat and maize yields, while rising land temperature anomalies are negatively associated with maize productivity. In Serbia, energy-related CO<sub>2</sub> emissions per hectare show a statistically significant negative long-run relationship with maize yields, whereas no statistically robust long-run relationships are identified for wheat. The findings highlight the importance of energy efficiency, input optimization and country-specific decarbonization strategies for sustainable cereal production.

**Keywords:** climate variability; CO<sub>2</sub> emissions; cereal yields; ARDL model; Romania; Serbia



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## 1. Introduction

Climate change has become one of the important structural factors linked to agricultural productivity, particularly in cereal-based agro-food systems that rely heavily on rainfall and short-term meteorological variability. Rising temperatures, more frequent extremes, and higher interannual variability are associated with changes in both long-run yield trajectories and year-to-year volatility, increasing exposure to production risk. Empirical evidence consistently shows that wheat and maize yields can respond strongly—and often asymmetrically—to climatic variability, especially in regions where heat stress and water deficits coincide during critical phenological stages [1,2].

A large and growing body of time-series research examines climate–yield relationships using dynamic econometric frameworks that distinguish long-run equilibrium relationships from short-run adjustment mechanisms. In this literature, autoregressive distributed lag (ARDL) approaches are widely used because they can accommodate mixed integration orders and provide estimates of short-run and long-run relationships in relatively small samples. ARDL-based evidence across diverse contexts suggests that climatic variables (temperature and precipitation proxies) are frequently cointegrated with cereal yields, while short-run responses are heterogeneous and sensitive to structural characteristics and adaptation capacity [3–9]. The ARDL framework is particularly suitable in this context because agricultural yield series and input indicators frequently exhibit mixed integration orders, rendering conventional cointegration techniques inappropriate or inefficient in small samples.

Alongside climate drivers, mineral fertilisers, particularly nitrogen, are an important factor associated with yield changes, yet the magnitude and timing of fertiliser-related associations appear context-dependent. While several studies report positive long-run associations between nitrogen use and cereal output, short-run yield responses are often weaker, unstable, or statistically insignificant, suggesting that annual weather conditions, management timing, and soil–climate interactions can dominate near-term outcomes [9,10]. Based on micro-level data obtained from field experiments, Liu et al. explain that in subtropical China, soil moisture and precipitation (as key climatic drivers) lead to nitrogen contributing more to harmful gas emissions ( $\text{N}_2\text{O}$  and  $\text{NO}$ ) than to wheat and maize yields [11]. Moreover, evidence suggests that intensification through fertiliser inputs may be linked to diminishing or even adverse short-run outcomes under climate stress, reinforcing the importance of analysing input–climate interactions rather than treating inputs as uniformly productive across years [5,10]. Wu et al. demonstrate that in East China, long-term assessments indicate that over-reliance on synthetic nitrogen has not only increased the carbon footprint and energy intensity of rice–wheat systems, but has also contributed to soil pollution, thereby necessitating a transition toward integrated nutrient management in order to maintain yield stability under increasing climatic uncertainty [12].

An additional, less standard dimension in yield modelling concerns greenhouse gas emissions and the energy system. The empirical literature reports mixed findings: direct  $\text{CO}_2$  fertilisation arguments coexist with evidence suggesting negative indirect associations linked to a higher frequency of extremes, altered water balance, and broader degradation of production conditions. Consequently, emissions variables are commonly analysed jointly with climate proxies to avoid interpreting energy and climate-related factors in isolation [2,6–8]. For transition-economy agriculture, energy-related  $\text{CO}_2$  emissions reflect emissions generated through the use of different energy sources in agriculture and can be interpreted as a scale-adjusted proxy associated with energy use in agricultural production systems. In this study, the variable of energy-related  $\text{CO}_2$  emissions is constructed based on FAOSTAT methodology and comprises four components: emissions from petroleum products, natural gas, electricity, and heat used in agriculture. Specifically, these emissions include  $\text{CO}_2$  generated from the combustion of petroleum products (e.g., diesel and gasoline used in agricultural machinery), emissions associated with natural gas use (e.g., heating and drying processes), as well as indirect emissions related to electricity consumption and emissions associated with heat use in agricultural activities, consistent with FAOSTAT methodology. In this research, energy-related  $\text{CO}_2$  emissions per hectare are not interpreted as reflecting direct physiological  $\text{CO}_2$  fertilisation, but rather as a scale-adjusted proxy for emissions associated with energy use in agriculture. Accordingly, Energy $\text{CO}_2$  is treated as an energy-use intensity proxy rather than as a measure of climate intensity. Therefore, the theoretical position adopted in this study aligns with the interpretation of

CO<sub>2</sub> as an indirect proxy associated with energy use and broader production conditions in agricultural systems rather than a source of biological yield enhancement. In this context, the relationship between CO<sub>2</sub> emissions and agricultural productivity is interpreted as context-dependent and non-causal, potentially reflecting heterogeneous associations across production systems.

Within Central and Eastern Europe, comparative econometric evidence remains limited despite the region's strategic role in cereal markets and its growing exposure to heat and drought episodes. In particular, dynamic time-series analyses that simultaneously incorporate climate variability, fertiliser intensity, and energy-related emissions in Romania and Serbia remain scarce. Available country-focused studies for Serbia and Romania highlight pronounced sensitivity of wheat and maize yields to drought risk, temperature extremes, and water deficits, but they often rely on descriptive, panel, or forecasting approaches rather than unified comparative dynamic time-series designs [13–18]. Findings for Serbia emphasise that drought periods can trigger substantial maize yield losses and that, in the absence of adequate irrigation, production stability remains constrained [13,14,19]. Complementary evidence suggests that yield variability may be more closely related to climatic conditions and production-year characteristics than to input intensity alone, while the economic and energy dimensions of fertiliser use remain relevant for the sustainability of cereal production decisions [16,19].

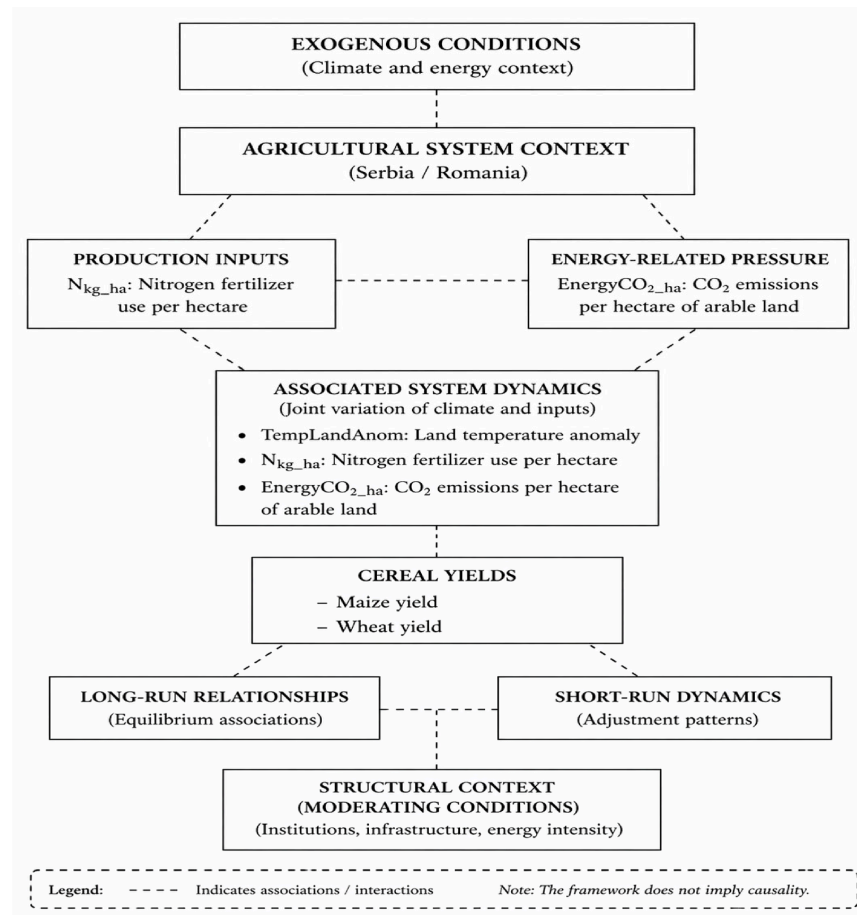
Against this background, this study investigates the long-run and short-run relationships between wheat and maize yields, nitrogen fertiliser use, climate variability (temperature anomaly), and energy-related CO<sub>2</sub> emissions normalised per hectare of arable land in Romania and Serbia over 1992–2023. Methodologically, the analysis relies on the ARDL bounds-testing framework to separate long-run cointegration relationships from short-run dynamic adjustments in a setting characterised by relatively short annual time series [20,21].

The present research contributes to the existing literature in three main dimensions: (i) extending ARDL-based climate–yield evidence to a comparative transition-economy setting, (ii) operationalising energy-related CO<sub>2</sub> emissions in a scale-adjusted way (per hectare) to strengthen cross-country comparability, and (iii) highlighting crop-and country-specific heterogeneity that is directly relevant for climate adaptation and sustainable intensification policies. From a theoretical perspective, this study contributes to several research streams. First, it extends the climate–agriculture nexus literature by integrating energy-related emissions into the analysis of agricultural productivity. Second, it contributes to the literature on sustainable intensification by highlighting the role of energy-related emissions as an indicator of production conditions in transition economies. Third, it enriches the comparative institutional economics perspective by demonstrating how similar agroecological conditions may produce different outcomes depending on institutional and policy frameworks.

The findings may be informative for other transition economies with similar structural characteristics, particularly in Central and Eastern Europe, where agricultural systems operate under varying degrees of institutional support and exposure to climate and energy-related CO<sub>2</sub> emissions. While the ARDL framework captures dynamic relationships through lag structures and error-correction mechanisms [20], it identifies statistical associations rather than underlying structural mechanisms; therefore, the estimated relationships should not be interpreted as causal relationships [22].

To provide a clearer understanding of the relationships examined in this study, a conceptual framework is introduced. The framework illustrates the interaction between climate variability, energy-related CO<sub>2</sub> emissions and agricultural productivity. Climate variables, particularly temperature anomalies, are associated with crop yields through

physiological stress mechanisms. At the same time, energy-related CO<sub>2</sub> emissions per hectare are interpreted as a scale-adjusted proxy associated with energy use in agriculture, reflecting differences in energy sources and production conditions across agricultural systems. These factors are jointly associated with agricultural outcomes, while the observed relationships may vary according to structural and institutional characteristics of the observed economies. To provide a clearer and structured representation of the relationships examined in this study, a conceptual framework is presented in Figure 1.



**Figure 1.** Conceptual framework illustrating the relationships between climate variability, energy-related CO<sub>2</sub> emissions, and cereal yields. Source: authors' calculations.

Rather than representing independent and unrelated propositions, the hypotheses are conceptually interconnected and collectively capture the multidimensional nature of the relationship between climate variability, energy-related CO<sub>2</sub> emissions, and agricultural productivity.

The study tests the following hypotheses:

**H1.** *Climate variability, measured by land temperature anomalies, is associated with heterogeneous long-run relationships with cereal yields in Romania and Serbia, with crop-specific sensitivity patterns.*

**H2.** *Energy-related CO<sub>2</sub> emissions per hectare are associated with statistically significant long-run relationships with cereal yields in selected country–crop combinations, indicating differentiated relationships across agricultural systems.*

**H3.** *The magnitude, direction, and statistical significance of long-run and short-run relationships differ between Romania and Serbia and across crops, reflecting structural and institutional differences in agricultural systems. Taken together, these hypotheses form a unified analytical framework for simultaneously examining climatic, energy-related, and structural factors associated with agricultural performance.*

By integrating emission-related indicators into agricultural productivity analysis, this research contributes to carbon footprint quantification at the macro-agricultural level and provides empirical evidence relevant for climate mitigation and sustainable cereal production policies.

## 2. Materials and Methods

### 2.1. Data and Variable Selection

The empirical analysis is based on annual time-series data for Romania and Serbia covering the period 1992–2023. The time span was selected according to the availability of consistent and comparable macro-agricultural, environmental, and climate-related indicators for both countries. In addition to data availability considerations, the selected horizon ensures a sufficient number of observations for the application of time-series econometric techniques.

The selected time span (1992–2023) ensures data consistency and provides a sufficient number of observations for ARDL estimation in a small-sample context [20,21]. It also aligns with standard practices in climate analysis based on multi-decadal observation windows [23,24].

The dependent and independent variables incorporated into the empirical models, including their measurement units and theoretically expected associations with cereal yields, are summarized in Table 1.

**Table 1.** Specification of variables used in the models.

| Variable Notation         | Variable Name                                                               | Unit of Measurement | Expected Relationship |
|---------------------------|-----------------------------------------------------------------------------|---------------------|-----------------------|
| MaizeYield                | Maize yield                                                                 | kg/ha               | Dependent variable    |
| WheatYield                | Wheat yield                                                                 | kg/ha               | Dependent variable    |
| EnergyCO <sub>2</sub> _ha | CO <sub>2</sub> emissions from the energy sector per hectare of arable land | t/ha                | ±                     |
| N_kg_ha                   | Nitrogen mineral fertilizer use per hectare                                 | kg/ha               | +                     |
| TempLandAnom              | Land temperature anomaly                                                    | °C                  | –                     |

Note: The “+” sign indicates an expected positive association, the “–” sign indicates an expected negative association, and the “±” sign indicates that both positive and negative associations are theoretically and empirically possible, depending on climatic and structural conditions.

The dependent variables are maize yield and wheat yield, expressed in kilograms per hectare. These indicators represent agricultural productivity and serve as proxies for cereal output performance under varying climatic and economic conditions.

The key explanatory variables include:

Nitrogen fertilizer use per hectare (N\_kg\_ha), capturing input intensity and technological intensification in crop production.

Energy-related CO<sub>2</sub> emissions per hectare (EnergyCO<sub>2</sub>\_ha) are constructed as a scale-adjusted indicator based on FAOSTAT data and represent emissions associated with energy use in agriculture. The variable comprises four components: emissions from petroleum products, natural gas, electricity, and heat used in agricultural activities. Specifically,



petroleum-related emissions include CO<sub>2</sub> generated from the combustion of fuels such as diesel, gasoline, and fuel oil used in agricultural machinery and on-farm transport. Emissions related to natural gas refer to energy used for heating and drying processes in agricultural production. Electricity-related emissions represent indirect CO<sub>2</sub> emissions associated with the consumption of electric energy for irrigation, storage, and operation of equipment. Heat-related emissions capture CO<sub>2</sub> associated with the use of thermal energy, including heating in greenhouses and drying facilities. These components represent emissions resulting from both direct and indirect energy use in agriculture and are disaggregated by energy source. Importantly, these emissions are a result of energy use and do not represent direct production inputs. The emissions variable is normalised per hectare of agricultural land to ensure comparability across countries and over time. In this context, the variable is used as a scale-adjusted proxy for emissions associated with energy use in agricultural systems. Therefore, this variable is interpreted as an energy-use intensity proxy rather than as a climatic intensity indicator. Recent ARDL-based studies have similarly incorporated emission-related variables alongside climatic and input factors, highlighting the relevance of environmental conditions in explaining agricultural performance [25]. Land temperature anomaly (TempLandAnom), representing deviations from long-term climatic averages, is used as an indicator of climate variability and thermal conditions. This selection of variables enables a simultaneous assessment of input intensity, energy-related emissions, and climate variability in relation to cereal yields. The choice is guided by three criteria: the availability of consistent long-term data (1992–2023), cross-country comparability, and suitability for ARDL modeling in a small-sample context. Priority is given to variables capturing production, climatic, and energy-related emission dynamics while avoiding policy-driven indicators in order to ensure a stable and comparable empirical framework.

Given data constraints and the relatively short time span (31 years), the model adopts a parsimonious specification with a limited number of variables and lag structures. Nevertheless, the selected variables capture the core dimensions of agricultural production-input intensity, climate variability, and energy-related emissions, allowing for a focused and methodologically consistent analysis. All variables, except the temperature anomaly, are expressed in natural logarithms to allow coefficient interpretation as elasticities and to improve variance stability. The temperature anomaly remains at certain levels due to its deviation-based nature and potential negative values.

It should be acknowledged that the climatic dimension of the model is represented by single-variable temperature anomalies. While temperature is a key climatic factor associated with crop yields, other climatic indicators, such as precipitation, drought indices, evapotranspiration, and wind conditions, are also relevant for agricultural production. As previously stated, the exclusion of these variables is primarily due to limitations in the availability of consistent long-term data for both countries.

The selection of Romania and Serbia is based on structural comparability and data availability rather than geographical proximity. While both countries share similar agroecological conditions, differences in institutional frameworks are considered as contextual factors for interpreting the results [14,18].

## 2.2. Testing for Stationarity of Time Series

Prior to estimating the ARDL models and conducting the cointegration analysis, the stochastic properties of all time series were examined using the Augmented Dickey–Fuller (ADF) test [26] and the Phillips–Perron (PP) test [27]. Both tests were applied under two alternative deterministic specifications: (i) with intercept only and (ii) with intercept and

linear trend. This dual specification allows for distinguishing between level-stationary, trend-stationary, and difference-stationary processes.

For the ADF test, the optimal lag length was selected using the Bayesian Information Criterion (BIC), ensuring parsimony given the relatively small annual sample. The absence of residual serial correlation in the auxiliary regressions was additionally verified using the Breusch–Godfrey LM test [28,29]. For the PP test, heteroskedasticity- and autocorrelation-consistent standard errors were employed following the Newey–West procedure [30].

The results of the unit root testing indicate heterogeneous integration orders across variables but no evidence of integration of order two.

Maize yield ( $\ln\_maizeyield$ ) in both Romania and Serbia is found to be stationary in levels according to both ADF and PP tests, under specifications with and without a deterministic trend. Therefore, maize yield is classified as  $I(0)$ .

Wheat yield ( $\ln\_wheatyield$ ) displays mixed behavior. Under specifications without trend, the null hypothesis of a unit root cannot always be rejected, while under trend specifications, both ADF and PP statistics indicate stationarity. Accordingly, wheat yield is classified as trend-stationary.

Nitrogen fertilizer use per hectare ( $\ln\_n$ ) exhibits non-stationarity in levels under most specifications but becomes stationary after first differencing, implying integration of order one,  $I(1)$ .

$CO_2$  emissions from the energy sector per hectare of arable land ( $\ln\_energyco2$ ) are non-stationary in levels according to both ADF and PP tests and become stationary in first differences, indicating  $I(1)$  behavior.

The land temperature anomaly ( $templandanomc$ ) shows non-stationarity in levels without trend but stationarity when a deterministic trend is included, implying trend-stationary characteristics.

Importantly, none of the analyzed variables exhibits integration of order two, thereby satisfying the necessary preconditions for applying the ARDL bounds-testing framework [20]. A summary of the stationarity classification based on the ADF and PP tests is presented in Table 2.

**Table 2.** Stationarity summary of variables (ADF and PP results).

| Variable                       | Romania          | Serbia           | Order of Integration                          |
|--------------------------------|------------------|------------------|-----------------------------------------------|
| Maize yield ( $\ln$ )          | $I(0)$           | $I(0)$           | Level-stationary ( $I(0)$ )                   |
| Wheat yield ( $\ln$ )          | Trend-stationary | Trend-stationary | $I(0)$ with trend                             |
| Nitrogen use ( $\ln$ )         | Trend-stationary | $I(1)$           | $I(0)$ with trend/First difference stationary |
| Energy $CO_2$ per ha ( $\ln$ ) | $I(1)$           | $I(1)$           | First difference stationary                   |
| Land temperature anomaly       | Trend-stationary | Trend-stationary | $I(0)$ with trend                             |

Note: Classification is based on ADF and PP unit root tests conducted with and without a deterministic trend. Variables are considered  $I(0)$ ,  $I(1)$ , or trend-stationary according to statistical significance at conventional levels.

### 2.3. Methodological Framework and Model Specification

To examine long-run equilibrium relationships and short-run dynamic adjustments between cereal yields and the selected explanatory variables, the Autoregressive Distributed Lag (ARDL) methodology is employed. The ARDL framework is particularly appropriate in empirical settings characterized by mixed integration orders, where regressors may be integrated of order zero or one, and by relatively small sample sizes, as is the case in this study (1992–2023). The methodological validity of the ARDL bounds-testing approach under such conditions has been formally established by Pesaran et al. [20] and further supported by Narayan [21], especially in small-sample contexts.

The general form of the ARDL model can be expressed as follows:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^p \alpha_i \Delta y_{t-i} + \sum_{j=0}^q \beta_j \Delta x_{t-j} + \gamma y_{t-1} + \delta x_{t-1} + \varepsilon_t \quad (1)$$

where:

$\Delta$  denotes the first-difference operator;

$y_t$  represents the natural logarithm of cereal yield (maize or wheat);

$x_t$  is a vector of explanatory variables, including nitrogen fertilizer use per hectare, carbon dioxide (CO<sub>2</sub>) emissions from the energy sector per hectare of arable land, and the land temperature anomaly;

$\alpha_0$  is the constant term;

$\alpha_i$  and  $\beta_j$  represent coefficients of short-run dynamic adjustments;

$\gamma$  and  $\delta$  are coefficients describing the long-run relationship between cereal yields and the explanatory variables;

$\varepsilon_t$  is a white-noise error term.

In this specification, the differenced terms capture short-run adjustments, while the lagged level variables test for the existence of a stable long-run equilibrium relationship. The joint statistical significance of the level terms forms the basis of the bounds-testing procedure for cointegration [20].

The optimal lag structure for each estimated model was selected according to the Bayesian Information Criterion (BIC), ensuring parsimony given the relatively limited number of annual observations and preserving sufficient degrees of freedom. Separate ARDL models were estimated for maize and wheat in Romania and Serbia, while maintaining an identical set of explanatory variables to ensure full cross-country and cross-crop comparability.

Within this framework, the ARDL specification enables the examination of:

- (i) long-run elasticities between yields and the selected explanatory variables;
- (ii) short-run dynamic responses to changes in climate, fertilizer intensity, and energy-related emissions; and
- (iii) the speed of adjustment toward equilibrium following short-term shocks.

This dual dynamic structure makes the ARDL approach particularly suitable for analyzing agricultural productivity in environments exposed to climatic variability and structural economic conditions.

#### 2.4. Cointegration Testing and Error Correction Model

The existence of a long-run (levels) relationship between cereal yields and the selected explanatory variables was examined using the ARDL bounds-testing approach to cointegration. The bounds test evaluates the null hypothesis of no level relationships by comparing the joint significance of the lagged level terms against the lower and upper critical bounds reported by Pesaran, Shin, and Smith [20]. Although the Bounds test provides evidence of long-run equilibrium relationships in all estimated specifications, the statistical significance and magnitude of individual long-run coefficients differ across crops and countries, indicating heterogeneous associations involving climate variability and energy-use-related emissions in Romania and Serbia. In addition to the asymptotic bounds, finite-sample critical values and approximate *p*-values (as reported by estat ectest) were consulted to account for the relatively small annual sample.

Overall, the reported bounds-test results indicate the presence of a long-run equilibrium relationship between yields and the explanatory variables (temperature anomaly, nitrogen use, and energy-related CO<sub>2</sub> emissions per hectare), as the calculated F-statistics



(and corresponding t-statistics) are sufficiently large in absolute value relative to the relevant upper bounds at conventional significance levels.

Given evidence of cointegration, the ARDL models were reparameterized into an error correction model (ECM), which enables the estimation of short-run dynamics and adjustment toward long-run equilibrium. The error-correction term (ECT) is negative and statistically significant, indicating a stable adjustment process.

### 2.5. Diagnostic Tests and Model Stability

To assess the statistical adequacy of the estimated ARDL models, a comprehensive set of diagnostic tests was performed.

Serial correlation of the residuals was examined using the Breusch–Godfrey LM test. In all estimated ARDL specifications for both maize and wheat, the null hypothesis of no serial correlation could not be rejected at conventional significance levels, indicating the absence of autocorrelation in the residuals.

Heteroskedasticity was tested using both the Breusch–Pagan/Cook–Weisberg test and White’s general test for heteroskedasticity. The results consistently failed to reject the null hypothesis of homoskedasticity, confirming constant error variance across observations.

The normality of residuals was evaluated using the Shapiro–Wilk test. The obtained *p*-values indicate that the null hypothesis of normally distributed residuals cannot be rejected, suggesting that the assumption of residual normality is satisfied.

Potential multicollinearity among explanatory variables was assessed using Variance Inflation Factors (VIF). The mean VIF values remain below commonly accepted critical thresholds, indicating that multicollinearity does not pose a significant concern in the estimated models.

In the analysis of wheat and maize yields in Serbia and Romania, nitrogen fertilizer use ( $\ln\_n$ ) is considered a potential source of endogeneity due to possible simultaneity, as farmers may adjust input intensity based on expected yields within a given season. Although CO<sub>2</sub> emissions ( $\ln\_energyco2$ ) are treated as a scale-adjusted proxy for emissions associated with energy use in agriculture, their potential endogeneity is explicitly tested to ensure the robustness of the results.

Endogeneity is formally tested using the Durbin–Wu–Hausman (DWH) procedure, implemented within a two-stage least squares (2SLS) framework, whereby standard estimates are compared with those obtained using instrumental variables [31–33]. Instrument strength is assessed using the first-stage F-statistic, with values below 10 indicating potentially weak instruments. Instrument validity is further evaluated using Sargan’s  $\chi^2$  test of overidentifying restrictions [34]. However, given that these tests rely on asymptotic properties, their application in small-sample settings with internal instruments may be limited, and the results are therefore interpreted with appropriate caution. The null hypothesis of the DWH test assumes exogeneity of the regressors and is not rejected when the *p*-value exceeds 0.05.

Due to the difficulty of identifying strong external instruments in small-sample time-series analyses, lagged values of the variables are employed as internal instruments, in line with common practice in the empirical literature [35,36]. These lagged variables are treated as predetermined, implying a lower likelihood of correlation with contemporaneous shocks in the error term. It should be emphasized that the use of lagged variables as instruments does not fully eliminate potential endogeneity, but rather represents a pragmatic approach under conditions of limited data availability and small sample size.

In a broader methodological context, the application of instrumental variables in such empirical settings is further constrained by the lack of clear consensus regarding the selection of appropriate instruments, particularly in agricultural and development

economics analyses based on limited time-series data [35]. Under these conditions, the use of weak instruments may lead to biased and unstable estimates, thereby limiting the reliability of standard IV approaches. Therefore, the results should be interpreted with caution, as the estimated relationships may reflect underlying simultaneity rather than variation attributable solely to exogenous factors.

Finally, parameter stability was evaluated using the CUSUM test [37]. The recursive residuals remain within the 5% critical bounds throughout the sample period, providing support for the absence of structural instability and supporting the robustness of the estimated long-run relationships. It should be noted that the ARDL framework identifies statistical relationships rather than causal mechanisms; therefore, the results should be interpreted as associations and not as evidence of causality.

### 3. Results

#### 3.1. Results of Stationarity Tests

Prior to cointegration analysis, the stationarity properties of all variables were examined using the Augmented Dickey–Fuller (ADF) [26] and Phillips–Perron (PP) [27] tests under specifications with and without a deterministic trend. Lag length selection in the ADF test was based on the Bayesian Information Criterion, with additional checks for residual serial correlation. In cases of conflicting results, the PP test, adjusted using the Newey–West correction [30], was used as a robustness check.

The results reported in Tables 3 and 4 indicate that maize yields are stationary in levels ( $I(0)$ ) in both countries, while wheat yields and temperature anomalies exhibit trend-stationary behavior. Nitrogen use in Romania also shows trend-stationarity. These variables are therefore treated as  $I(0)$  processes with deterministic components.

**Table 3.** Results of the ADF and PP unit root tests for Romania.

| Variable      | Model         | ADF Z(t)<br>at Level<br>(p-Value) | PP Z(t)<br>at Level<br>(p-Value) | ADF Z(t) at<br>First<br>Difference<br>(p-Value) | PP Z(t)<br>at First<br>Difference<br>(p-Value) | Conclusion<br>(Levels) |
|---------------|---------------|-----------------------------------|----------------------------------|-------------------------------------------------|------------------------------------------------|------------------------|
| ln_maizeyield | Without trend | −4.020 ***<br>(0.0013)            | −4.037 ***<br>(0.0012)           | −5.306 ***<br>(0.0000)                          | −10.384 ***<br>(0.0000)                        | I(0)                   |
|               | With trend    | −5.027 ***<br>(0.0002)            | −5.008 ***<br>(0.0002)           | −5.220 ***<br>(0.0001)                          | −10.231 ***<br>(0.0000)                        |                        |
| ln_wheatyield | Without trend | −1.854 (0.3538)                   | −3.584 ***<br>(0.0061)           | −6.828 ***<br>(0.0000)                          | −15.855 ***<br>(0.0000)                        | I(0) with trend        |
|               | With trend    | −3.593 **<br>(0.0304)             | −5.954 ***<br>(0.0000)           | −6.711 ***<br>(0.0000)                          | −15.553 ***<br>(0.0000)                        |                        |
| ln_energyco2  | Without trend | −2.687 *<br>(0.0763)              | −2.272 (0.1812)                  | −4.610 ***<br>(0.0001)                          | −4.720 ***<br>(0.0001)                         | I(1)                   |
|               | With trend    | −2.644 (0.2600)                   | −1.871 (0.6695)                  | −5.237 ***<br>(0.0001)                          | −5.311 ***<br>(0.0001)                         |                        |
| ln_n          | Without trend | 0.260 (0.9754)                    | −1.032 (0.7415)                  | −6.297 ***<br>(0.0000)                          | −8.272 ***<br>(0.0000)                         | I(0) with trend        |
|               | With trend    | −3.709 **<br>(0.0218)             | −3.908 **<br>(0.0118)            | −6.500 ***<br>(0.0000)                          | −9.434 ***<br>(0.0000)                         |                        |
| templandanomc | Without trend | −2.282 (0.1780)                   | −2.774 *<br>(0.0620)             | −8.051 ***<br>(0.0000)                          | −9.472 ***<br>(0.0000)                         | I(0) with trend        |
|               | With trend    | −4.528 ***<br>(0.0014)            | −5.345 ***<br>(0.0000)           | −7.905 ***<br>(0.0000)                          | −9.270 ***<br>(0.0000)                         |                        |

Note: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.10$ . All variables are estimated in natural logarithms, except for the temperature anomaly.

**Table 4.** Results of the ADF and PP unit root tests for Serbia.

| Variable      | Model         | ADF Z(t)<br>at Level<br>(p-Value) | PP Z(t)<br>at Level<br>(p-Value) | ADF Z(t)<br>at First<br>Difference<br>(p-Value) | PP Z(t)<br>at First<br>Difference<br>(p-Value) | Conclusion<br>(Levels) |
|---------------|---------------|-----------------------------------|----------------------------------|-------------------------------------------------|------------------------------------------------|------------------------|
| ln_maizeyield | Without trend | −3.926 ***<br>(0.0019)            | −3.889 ***<br>(0.0021)           | −9.180 ***<br>(0.0000)                          | −13.514 ***<br>(0.0000)                        | I(0)                   |
|               | With trend    | −6.467 ***<br>(0.0000)            | −7.291 ***<br>(0.0000)           | −9.047 ***<br>(0.0000)                          | −13.555 ***<br>(0.0000)                        |                        |
| ln_wheatyield | Without trend | −1.679<br>(0.4420)                | −2.980 **<br>(0.0368)            | −8.488 ***<br>(0.0000)                          | −15.065 ***<br>(0.0000)                        | I(0) with trend        |
|               | With trend    | −4.778 ***<br>(0.0005)            | −6.047 ***<br>(0.0000)           | −8.567 ***<br>(0.0000)                          | −15.627 ***<br>(0.0000)                        |                        |
| ln_energyco2  | Without trend | −1.396<br>(0.5843)                | −1.359<br>(0.6018)               | −5.480 ***<br>(0.0000)                          | −11.411 ***<br>(0.0000)                        | I(1)                   |
|               | With trend    | −1.171<br>(0.9164)                | −3.088<br>(0.1091)               | −5.572 ***<br>(0.0000)                          | −11.850 ***<br>(0.0000)                        |                        |
| ln_n          | Without trend | −3.184 **<br>(0.0209)             | −2.363<br>(0.1525)               | −5.532 ***<br>(0.0000)                          | −8.757 ***<br>(0.0000)                         | I(1)                   |
|               | With trend    | −2.206<br>(0.4863)                | −2.574<br>(0.2922)               | −6.226 ***<br>(0.0000)                          | −9.636 ***<br>(0.0000)                         |                        |
| templandanomc | Without trend | −1.916<br>(0.3245)                | −2.415<br>(0.1374)               | −7.899 ***<br>(0.0000)                          | −9.067 ***<br>(0.0000)                         | I(0) with trend        |
|               | With trend    | −4.014 ***<br>(0.0084)            | −4.839 ***<br>(0.0004)           | −7.761 ***<br>(0.0000)                          | −8.899 ***<br>(0.0000)                         |                        |

Note: \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ . All variables are estimated in natural logarithms, except for the temperature anomaly.

Trend-stationarity implies that non-stationarity in levels reflects deterministic trends rather than stochastic unit root processes.

For the explanatory variables, in the case of Serbia, both nitrogen use and energy-related CO<sub>2</sub> emissions per hectare display non-stationarity at levels in at least one of the standard test specifications and are treated as integrated of order one, I(1), given that their first differences are clearly stationary. In the case of Romania, energy-related CO<sub>2</sub> emissions per hectare are the only variable found to be integrated of order one. Importantly, none of the series is integrated of order two, I(2).

This integration structure satisfies the fundamental requirement of the ARDL bounds-testing framework, namely that the variables are either I(0) or I(1), but not I(2), thereby validating the subsequent cointegration analysis.

### 3.2. Results of the ARDL Model for Romania

#### 3.2.1. Wheat Yields in Romania

For clarity and direct comparison across crops, the key results of the ARDL models, including long-run coefficients, the error-correction adjustment term, and diagnostic statistics, are summarized in Table 5.

The ARDL specification for wheat yields in Romania is ARDL(1,0,1,0). The bounds test (reported via `estat ectest`) rejects the null of no level relationship ( $F = 7.163$ ;  $t = -5.122$ ), indicating a long-run (cointegrating) relationship among wheat yields, nitrogen fertilizer use, energy-related CO<sub>2</sub> emissions, and land temperature anomalies.

**Table 5.** Long-run and short-run ARDL results for wheat and maize in Romania.

| Variable                                             | Wheat (ARDL 1,0,1,0)           | Maize (ARDL 1,2,0,0)           |
|------------------------------------------------------|--------------------------------|--------------------------------|
|                                                      | Coefficient ( <i>p</i> -value) | Coefficient ( <i>p</i> -value) |
| Nitrogen use (ln_N)                                  | 0.498 ** (0.011)               | 0.933 *** (0.001)              |
| CO <sub>2</sub> emissions (ln_CO <sub>2</sub> )      | −0.077 (0.436)                 | −0.093 (0.472)                 |
| Land temp. anomaly (TempLandAnom)                    | 0.052 (0.424)                  | −0.204 ** (0.021)              |
| Adjustment Mechanism ECT(−1)                         | −1.096 *** (0.000)             | −1.024 *** (0.000)             |
| Short-Run Coefficients (SR)                          |                                |                                |
| Δ Nitrogen (D1.ln_N)                                 | -                              | −0.252 (0.524)                 |
| Δ Nitrogen lag (LD.ln_N)                             | -                              | 0.650 * (0.075)                |
| Δ CO <sub>2</sub> emissions (D1.ln_CO <sub>2</sub> ) | −0.248 (0.365)                 | -                              |
| Constant (_cons)                                     | 6.756 *** (0.000)              | 5.262 *** (0.000)              |
| Model Fit & Diagnostics                              |                                |                                |
| R-squared                                            | 0.541                          | 0.706                          |
| Adjusted R-squared                                   | 0.449                          | 0.630                          |
| Autocorrelation (BG test)                            | 0.188                          | 0.179                          |
| Heteroscedasticity (White test)                      | 0.149                          | 0.413                          |
| Normality (Shapiro–Wilk test)                        | 0.106                          | 0.196                          |
| Multicollinearity (average VIF)                      | 4.82                           | 2.99                           |
| CUSUM Stability                                      | Stable                         | Stable                         |

Note: “-” indicates that the variable or lagged term was not included in the final ARDL specification selected by the Bayesian Information Criterion. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.10$ .

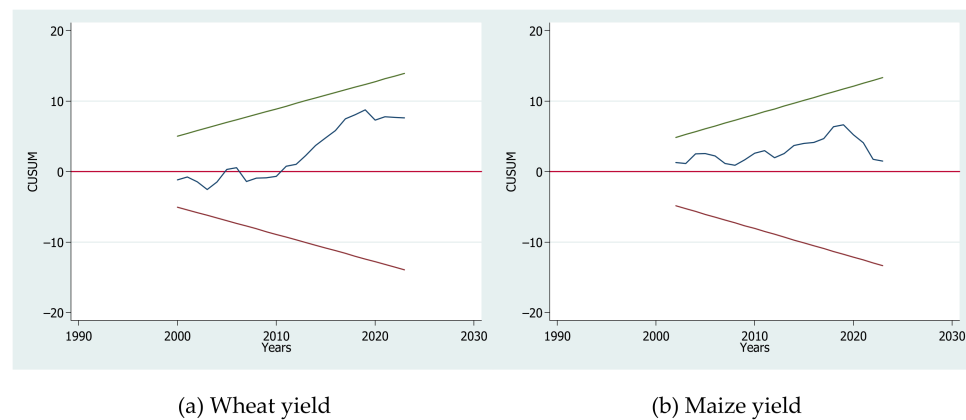
In the long run, nitrogen fertilizer use is positively associated with wheat yields ( $\ln\_N = 0.498$ ,  $p = 0.011$ ). In contrast, energy-related CO<sub>2</sub> emissions ( $\ln\_CO_2 = -0.077$ ,  $p = 0.436$ ) and temperature anomalies ( $\text{TempLandAnom} = 0.052$ ,  $p = 0.424$ ) do not show statistically significant associations, suggesting no robust long-run relationship within this specification. The error-correction term is negative and statistically significant ( $\text{ECT}(-1) = -1.096$ ,  $p < 0.001$ ), suggesting adjustment toward long-run equilibrium. The magnitude of the coefficient slightly exceeds unity in absolute value, suggesting a rapid adjustment process with possible short-run overshooting around the long-run equilibrium. However, the negative sign and high statistical significance of the ECT are consistent with a stable adjustment mechanism, which is also supported by the diagnostic and CUSUM stability results.

No statistically significant short-run relationships are identified in this specification. In particular, the contemporaneous change in energy-related CO<sub>2</sub> emissions is not statistically significant ( $\Delta \ln\_CO_2 = -0.248$ ,  $p = 0.365$ ).

Diagnostic tests do not indicate major econometric issues. Residuals are approximately normally distributed (Shapiro–Wilk test  $p = 0.106$ ), heteroskedasticity is not detected (White test  $p = 0.149$ ), and multicollinearity remains within acceptable bounds (mean VIF = 4.82). Serial correlation tests do not indicate significant autocorrelation (BG(2)  $p = 0.188$ ; BG(1)  $p = 0.084$ ), and the CUSUM test supports parameter stability over the sample period (Figure 2a).

The Durbin–Wu–Hausman tests for Romania do not reject the null hypothesis of exogeneity of the regressors in the wheat yield equation. Robust first-stage F-statistics (ranging from 27 to 102 for nitrogen use and energy-related CO<sub>2</sub> emissions, respectively) indicate satisfactory instrument relevance, while Sargan’s  $\chi^2$  tests of overidentifying restrictions do not provide statistical grounds for rejecting instrument validity, in line with the model specification. The results are broadly consistent with studies emphasizing the role of structural and agro-climatic conditions for agricultural productivity in Romania [38]; however,

in the present wheat specification, the temperature anomaly variable is not statistically significant, suggesting that no robust statistical relationship with wheat yields is identified once nitrogen use and emissions are controlled for.



**Figure 2.** CUSUM stability tests for cereal yields in Romania: (a) wheat yield model; (b) maize yield model. The blue line represents the CUSUM statistic, the green and brown/red lines indicate the upper and lower 5% critical bounds, respectively, and the horizontal red line represents the zero reference line. Source: authors' calculations.

### 3.2.2. Maize Yields in Romania

The model for maize yields is specified as ARDL(1,2,0,0) (Table 5). In the long run, nitrogen fertilizer use is again positive and statistically significant ( $\ln\_N = 0.933$ ,  $p = 0.001$ ), while energy-related CO<sub>2</sub> emissions remain statistically insignificant ( $\ln\_CO_2 = -0.093$ ,  $p = 0.472$ ). Unlike wheat, maize yields are negatively associated with temperature anomalies ( $TempLandAnom = -0.204$ ,  $p = 0.021$ ), indicating sensitivity to temperature variability.

The error-correction term is negative and highly significant ( $ECT(-1) = -1.024$ ,  $p < 0.001$ ), supporting the presence of a stable long-run relationship and fast adjustment to equilibrium following shocks. In the short run, the contemporaneous change in nitrogen use is not significant ( $\Delta \ln\_N = -0.252$ ,  $p = 0.524$ ), but the lagged change in nitrogen is weakly significant at the 10% level ( $LD.\Delta \ln\_N = 0.650$ ,  $p = 0.075$ ), suggesting that nitrogen adjustments may be associated with maize yields with a short delay rather than instantaneously.

Durbin–Wu–Hausman tests do not indicate statistically significant evidence of endogeneity in either specification ( $p > 0.30$  for nitrogen use and  $p > 0.50$  for energy-related CO<sub>2</sub> emissions). The instruments exhibit satisfactory relevance, and the Sargan test of overidentifying restrictions does not reject the null hypothesis of instrument validity ( $p > 0.05$ ). The CUSUM test provides support for parameter stability for the maize specification as well (Figure 2b) [37].

## 3.3. Results of the ARDL Model for Serbia

### 3.3.1. Wheat Yields in Serbia

This subsection presents the estimated ARDL results for wheat and maize yields in Serbia. For clarity and direct comparability with the Romanian case, the results are structured identically, covering the bounds test for cointegration, long-run coefficients, error-correction adjustment dynamics, short-run associations, and diagnostic tests. The key estimation results are summarized in Table 6.

**Table 6.** Long-run and short-run ARDL results for wheat and maize in Serbia.

| Variable                                                 | Wheat (ARDL 1,0,1,0)           | Maize (ARDL 1,0,2,0)           |
|----------------------------------------------------------|--------------------------------|--------------------------------|
|                                                          | Coefficient ( <i>p</i> -value) | Coefficient ( <i>p</i> -value) |
| Long-Run Coefficients (LR)                               | Coef. ( <i>p</i> -value)       | Coef. ( <i>p</i> -value)       |
| Nitrogen use (ln_N)                                      | −0.021 (0.819)                 | −0.100 (0.446)                 |
| CO <sub>2</sub> emissions (ln_CO <sub>2</sub> )          | −0.075 (0.207)                 | −0.203 ** (0.011)              |
| Land temp. anomaly (TempLandAnom)                        | 0.095 (0.153)                  | −0.045 (0.592)                 |
| Adjustment Mechanism                                     |                                |                                |
| ECT(−1)                                                  | −0.919 *** (0.000)             | −1.221 *** (0.000)             |
| Short-Run Coefficients (SR)                              |                                |                                |
| Δ CO <sub>2</sub> emissions (D1.ln_CO <sub>2</sub> )     | 0.097 * (0.092)                | 0.289 *** (0.008)              |
| Δ CO <sub>2</sub> emissions lag (LD.ln_CO <sub>2</sub> ) | -                              | 0.165 (0.106)                  |
| Constant (_cons)                                         | 7.571 *** (0.000)              | 10.995 *** (0.000)             |
| Model Fit & Diagnostics                                  |                                |                                |
| R-squared                                                | 0.470                          | 0.641                          |
| Adjusted R-squared                                       | 0.364                          | 0.548                          |
| Autocorrelation (BG test)                                | 0.354                          | 0.939                          |
| Heteroscedasticity (White test)                          | 0.581                          | 0.399                          |
| Normality (Shapiro–Wilk test)                            | 0.182                          | 0.295                          |
| Multicollinearity (average VIF)                          | 4.19                           | 4.70                           |
| CUSUM Stability                                          | Stable                         | Stable                         |

Note: “-” indicates that the variable or lagged term was not included in the final ARDL specification selected by the Bayesian Information Criterion. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.10$ .

The ARDL specification selected for wheat yields in Serbia is ARDL(1,0,1,0).

The bounds test rejects the null hypothesis of no level relationships ( $F = 5.533$ ;  $t = -4.675$ ), indicating the existence of a long-run (cointegrating) relationship among wheat yields, nitrogen fertilizer use, energy-related CO<sub>2</sub> emissions, and land temperature anomalies.

In the long run, none of the explanatory variables shows a statistically significant relationship with wheat yields. Nitrogen fertilizer use ( $\ln\_N = -0.021$ ,  $p = 0.819$ ), energy-related CO<sub>2</sub> emissions ( $\ln\_CO_2 = -0.075$ ,  $p = 0.207$ ), and land temperature anomalies ( $\text{TempLandAnom} = 0.095$ ,  $p = 0.153$ ) are all statistically insignificant.

The estimated error-correction term is negative and highly statistically significant ( $\text{ECT}(-1) = -0.919$ ,  $p < 0.001$ ), suggesting the existence of a stable long-run equilibrium. The magnitude implies that approximately 92% of any short-run deviation from equilibrium is corrected within one year, indicating relatively rapid convergence toward the steady state.

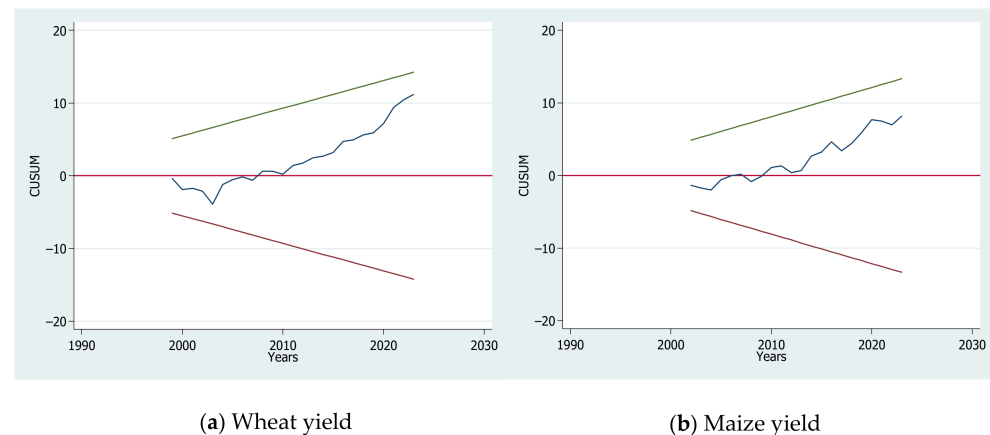
In the short run, the contemporaneous change in energy-related CO<sub>2</sub> emissions is positive and weakly statistically significant ( $\Delta \ln\_CO_2 = 0.097$ ,  $p = 0.092$ ). This indicates that short-run fluctuations in energy-related CO<sub>2</sub> emissions are associated with short-run variations in wheat yields, while no statistically significant long-run relationships are identified. Overall, the results suggest that yield adjustments in Serbian wheat production are more closely related to long-run structural processes, whereas short-run associations appear relatively weak and transitory.

Diagnostic tests support the statistical adequacy of the model. The Breusch–Godfrey test indicates no serial correlation ( $p = 0.354$ ), heteroskedasticity is not detected (White test  $p = 0.581$ ), residuals are approximately normally distributed (Shapiro–Wilk  $p = 0.182$ ), and multicollinearity remains within acceptable bounds (mean VIF = 4.19).

In the case of Serbia, the first-stage F-statistics ( $F < 10$ ) indicate potentially limited instrument strength, the Durbin–Wu–Hausman tests do not reject the null hypothesis of exogeneity of the key variables ( $p > 0.05$ ) [31–33], while the Sargan tests do not suggest statistical invalidity of the instruments. Nevertheless, given the weaker instrument relevance, the results should be interpreted with caution in terms of their stability.



Parameter stability over time is supported by the CUSUM test, as the recursive residuals remain within the 5% critical bounds throughout the sample period (Figure 3a).



**Figure 3.** CUSUM stability tests for cereal yields in Serbia: (a) wheat yield model; (b) maize yield model. The blue line represents the CUSUM statistic, the green and brown/red lines indicate the upper and lower 5% critical bounds, respectively, and the horizontal red line represents the zero reference line. Source: authors' calculations.

### 3.3.2. Maize Yields in Serbia

For maize yields in Serbia, the selected specification is ARDL(1,0,2,0).

The bounds test rejects the null hypothesis of no levels relationship ( $F = 9.692$ ;  $t = -6.214$ ), indicating the presence of a long-run equilibrium relationship among maize yields and the explanatory variables.

In the long run, energy-related CO<sub>2</sub> emissions are negatively associated with maize yields ( $\ln\_CO_2 = -0.203$ ,  $p = 0.011$ ). Nitrogen fertilizer use ( $\ln\_N = -0.100$ ,  $p = 0.446$ ) and land temperature anomalies ( $TempLandAnom = -0.045$ ,  $p = 0.592$ ) do not show statistically significant relationships.

The error-correction coefficient is negative and highly significant ( $ECT(-1) = -1.221$ ,  $p < 0.001$ ), being consistent with a stable adjustment mechanism. The magnitude exceeding unity in absolute value indicates very rapid correction and potential short-run overshooting around the long-run equilibrium, although stability is preserved due to the negative sign and strong statistical significance.

In the short run, the contemporaneous change in energy-related CO<sub>2</sub> emissions is positively and statistically significantly associated with maize yields ( $\Delta \ln\_CO_2 = 0.289$ ,  $p = 0.008$ ), while the lagged change is not statistically significant at conventional levels ( $LD.\Delta \ln\_CO_2 = 0.165$ ,  $p = 0.106$ ). Short-run changes in energy-related CO<sub>2</sub> emissions are positively associated with maize yields, while the corresponding long-run relationships are negative.

Model diagnostics again support the robustness: no serial correlation is detected (BG  $p = 0.939$ ), heteroskedasticity is rejected (White  $p = 0.399$ ), residuals are approximately normally distributed (Shapiro–Wilk test  $p = 0.295$ ), and multicollinearity remains within acceptable limits (mean VIF = 4.70).

The CUSUM stability test provides support for parameter stability over the observed period (Figure 3b), indicating no evidence of structural instability in the maize specification.

In the case of Serbia, in the maize yield model, the econometric diagnostics indicate a mixed pattern of results. The Durbin–Wu–Hausman tests do not reject the null hypothesis of exogeneity ( $p > 0.05$ ), while the Sargan tests do not provide evidence against the validity of the instruments. However, first-stage F-statistics below 10 suggest relatively weak instrument strength, which may reduce the precision of the IV estimates. Accordingly,

the results for the maize yield specification should be considered with some reservation. The cumulative sums of recursive residuals remain within the 5% critical bounds for both models, supporting the temporal stability of the estimated ARDL parameters.

#### 4. Discussion

The results indicate substantial heterogeneity in the relationships between climatic variability, energy-related emissions, and cereal yields across countries and crops. This heterogeneity suggests that environmental factors and energy-related CO<sub>2</sub> emissions are associated with agricultural productivity in a context-dependent manner, reflecting structural and institutional differences.

The use of temperature anomalies as the sole climatic indicator represents a simplification of the climatic dimension. While temperature captures an important component of climate variability, the exclusion of additional indicators such as precipitation and drought conditions may limit the explanatory power of the model. This reflects a trade-off between theoretical completeness and data availability over the full time period.

Consistent with literature emphasizing context-dependent climate–productivity linkages [4,38], the results indicate that maize yields in Serbia are negatively associated with energy-related CO<sub>2</sub> emissions per hectare in the long run, while this relationship is not statistically identified in Romania. This pattern suggests differentiated structural conditions associated with energy use in agriculture, potentially reflecting differences in irrigation infrastructure, input efficiency, and adaptive capacity.

The role of energy-related CO<sub>2</sub> emissions in the estimated models should be interpreted as reflecting emissions associated with energy use in agriculture, rather than direct production inputs, which may explain the observed heterogeneity across countries and crops.

Regarding climatic variability, measured by land temperature anomalies, the results indicate crop-specific sensitivity patterns rather than uniform country-level relationships. While long-run temperature associations are statistically significant for maize in Romania, they are not statistically significant for Serbia. This suggests that the observed climate–yield relationships may be shaped by agronomic and phenological characteristics that vary by crop type and production structure.

The error-correction dynamics indicate relatively rapid adjustment toward long-run equilibrium across all specifications, suggesting stable adjustment processes in cereal production systems under changing environmental conditions.

Short-run relationships are more limited and crop-specific. In Serbia, short-run fluctuations in energy-related emissions are positively associated with yields, while long-run relationships are negative (for maize). This divergence suggests that short-term responses may reflect cyclical input use, whereas long-run relationships reflect more persistent associations within agricultural systems.

The findings partially support H1, indicating that climate variability is associated with heterogeneous and crop-specific long-run relationships. H2 is also partially supported, as energy-related CO<sub>2</sub> emissions show statistically significant long-run relationships only in specific country–crop combinations. H3 is supported, as the magnitude and statistical significance of both long-run and short-run relationships differ across Romania and Serbia and across crops, reflecting structural and institutional differences.

From a policy perspective, the results suggest that climate and energy-related strategies in agriculture should account for country-specific structural conditions. Measures aimed at improving energy efficiency and input management may support both environmental and productivity objectives, while adaptation strategies should reflect crop-specific sensitivities. Unlike studies that assume a direct and stable relationship between inputs and agricultural

output, the findings of this research indicate that such relationships may be conditional and context-dependent. This highlights the importance of considering structural and institutional heterogeneity when interpreting empirical results. The ARDL framework captures dynamic associations but does not fully account for all structural factors, which may also contribute to differences between the present findings and those reported in previous studies.

Overall, the results support the view that environmental factors and energy-related CO<sub>2</sub> emissions are associated with agricultural productivity in a context-dependent manner. The findings do not provide support for the CO<sub>2</sub> fertilization hypothesis and are more consistent with the interpretation that CO<sub>2</sub> emissions reflect emissions associated with energy use and broader production conditions in agricultural systems.

This finding is consistent with the broader literature emphasizing the role of agricultural inputs in productivity growth, where fertilizer use is identified as a key driver of yield improvements, particularly in developing and transition economies.

The results of the Durbin–Wu–Hausman tests do not reject the null hypothesis of exogeneity across all model specifications. First-stage diagnostics indicate satisfactory instrument relevance for Romania, whereas lower values for Serbia ( $F < 10$ ) suggest limited instrument strength. Sargan  $\chi^2$  tests do not provide grounds for rejecting instrument validity. Nevertheless, given the small sample size and the use of internal instruments, the results should be interpreted with caution, consistent with the empirical literature [35].

The ARDL framework provides a suitable approach for capturing dynamic relationships in small-sample time-series data, with diagnostic tests supporting the adequacy of the model specification [20].

## 5. Conclusions

This study examined the long-run and short-run relationships between cereal yields (wheat and maize), nitrogen fertilizer use, energy-related CO<sub>2</sub> emissions per hectare, and land temperature anomalies in Romania and Serbia using the ARDL bounds-testing approach. The applied framework accommodates heterogeneous integration orders and allows for the analysis of dynamic adjustment patterns across country–crop combinations.

The results indicate the presence of long-run equilibrium relationships across all estimated specifications, as confirmed by statistically significant bounds tests and negative error-correction terms. However, the direction and statistical significance of coefficients differ across countries and crops, highlighting substantial structural heterogeneity in climate–agriculture relationships.

With respect to climate variability (H1), the findings indicate crop- and country-specific sensitivity patterns. Land temperature anomalies are negatively associated with maize yields in Romania in the long run, while no statistically robust long-run relationship is identified for Serbia or for wheat production. This suggests that climate-related conditions are not uniform across agricultural systems but vary with agroecological and structural conditions.

Regarding energy-related CO<sub>2</sub> emissions (H2), the results indicate differentiated long-run relationships. A statistically significant negative association is identified for maize yields in Serbia, while no robust long-run relationship is observed for Romania or for wheat. At the same time, short-run changes in energy-related emissions are positively associated with yields in Serbia, suggesting that short-run relationships may be linked to cyclical input use, while long-run relationships reflect more persistent associations within agricultural systems.

Consistent with H3, the magnitude and statistical significance of both long-run and short-run relationships differ across Romania and Serbia and across crops, reflecting struc-

tural characteristics of agricultural systems, including technological intensity, input use patterns, and institutional conditions.

Overall, the findings contribute to the literature on climate–agriculture interactions by indicating that climatic factors and energy-related CO<sub>2</sub> emissions are associated with agricultural productivity in a heterogeneous and context-dependent manner.

From a practical perspective, the results suggest that improving input efficiency and adapting production practices to climate variability and energy-related conditions may support yield stability. Policy measures aimed at enhancing energy efficiency, supporting climate adaptation, and promoting sustainable agricultural practices should account for country-specific structural conditions.

Future research could extend the analysis by incorporating additional climatic indicators, nonlinear specifications, and broader comparative frameworks to further explore structural relationships.

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**Data Availability Statement:** The datasets analysed in this study are publicly available from FAOSTAT (<https://www.fao.org/faostat/en/#data>, accessed on 23 March 2026); World Bank Open Data (<https://data.worldbank.org>, accessed on 23 March 2026); and the World Meteorological Organization Climate Data Catalogue (<https://climatedata-catalogue-wmo.org>, accessed on 23 March 2026). The econometric code used in Stata 17 is available from the corresponding author upon reasonable request.

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**Conflicts of Interest:** The authors declare no conflicts of interest.

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