International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(1), 858-869.

Energy Shocks and Coffee Market Resilience under a Machine Learning Framework with the SDI+ Index

Carlos Hernán Suárez-Rodríguez[1], Diego Fernando Manotas-Duque[2], Esteban Largo-Avila[3]*

[1]Doctoral Candidate in Industrial Engineering, School of Industrial Engineering, Universidad del Valle, 76001 Cali, Colombia, [2]School of Industrial Engineering, Universidad del Valle, 76001 Cali, Colombia, [3]Regionalization System, Caicedonia Campus, Universidad del Valle, 762540 Caicedonia, Colombia. *Email: esteban.largo@correounivalle.edu.co

Received: 06 July 2025 **Accepted:** 17 November 2025 **DOI:** https://doi.org/10.32479/ijeep.21925

ABSTRACT

This study analyzes the dynamic interdependence between Arabica coffee and Brent oil markets amid global energy shocks from 2010 to 2025. It employs a new Structural Decoupling Index (SDI+) combined with unsupervised machine learning algorithms, including K-Means, Gaussian Mixture Models, and Spectral Clustering. The analysis uncovers multiple dependence regimes and structural shifts. Findings indicate that 52% of the identified episodes involve strong decoupling, highlighting the fragile and episodic nature of the relationship between coffee and energy. The SDI+ predicts structural breaks up to 15 days in advance of traditional DCC-GARCH models, showcasing its potential as an early warning tool. Empirical results demonstrate that geopolitical and climatic shocks-particularly the Russia-Ukraine conflict and the 2023/24 ENSO event-heighten volatility and disrupt price transmission mechanisms. These insights advance the energy-agriculture literature by incorporating multiscale dependence metrics and machine learning for assessing commodity risk. The study provides practical recommendations for policymakers, cooperatives, and investors seeking to enhance the resilience of coffee-dependent economies against external energy shocks and global uncertainties.

Keywords: Arabica Coffee, Brent Oil, Machine Learning, Structural Decoupling, Energy Shocks
JEL Classifications: Q40, Q41, Q56, C63, F64

1. INTRODUCTION

In recent decades, the interaction between agricultural and energy commodity markets has attracted increasing scholarly attention, especially in contexts marked by high volatility and financial interdependence. Among agricultural products, Arabica coffee (*Coffea arabica*) plays a key role in food security, foreign exchange earnings, and rural livelihoods in producing countries. Understanding how coffee prices react to external shocks, especially those transmitted from energy markets, is essential for developing effective agricultural policies, supporting cooperatives, and safeguarding farmers' incomes (Gilbert, 2010; Headey and Fan, 2008).

Recent literature emphasizes that the energy–agriculture nexus has become increasingly complex, involving feedback loops between production costs, climate variability, and market speculation (Kabir & Ekici, 2024). This complexity aligns with empirical evidence showing that energy markets exhibit strong volatility spillovers and heightened sensitivity to global uncertainty, reinforcing their influence on downstream agricultural commodities (Usman & Okey, 2022). The transition toward low-carbon energy systems has further deepened the link between fossil and renewable energy prices and agricultural commodities. Around 30% of global energy consumption is associated with agri-food systems, highlighting how volatility in oil or clean-energy markets can cascade into agricultural supply chains (Mai et al., 2025). Empirical studies also reveal that agriculture contributes significantly to greenhouse-gas emissions while depending heavily on fossil-fuel inputs, making it both a driver and a victim of climate shocks (Raihan et al., 2023).

The Law of One Price (LOOP) principle states that, in efficient markets, similar commodities tend to converge toward global price parity through arbitrage. However, extensive empirical work shows that this idea often does not hold in real-world settings due to transactions costs, frictions, and persistent market segmentation (Taylor & Taylor, 2004). Many studies have recorded recurring episodes of market segmentation and distortions in how prices are transmitted, influenced not only by macroeconomic and financial shocks but also by climatic variability, speculative actions, and institutional limits (Conforti, 2004; Baquedano and Liefert, 2014; Gong and Xu, 2022). These results highlight the need for analytical methods that can identify both stable connections and sudden structural changes within agro-food systems.

While traditional econometric tools such as VAR and DCC-GARCH models have been widely used to measure interdependence (Gao, Li, & Zhu, 2022), recent research shows that these frameworks often fail to capture nonlinear or regime-switching behaviors in commodity markets. For instance, Ozkan et al. (2024) demonstrated that volatility connectedness between fossil and clean-energy assets is highly time-varying and sensitive to geopolitical shocks such as the Russia-Ukraine conflict. Similarly, Cocca et al. (2023) proposed an R^2-decomposed DCC-GARCH framework to better quantify network risk transmission across renewable-energy portfolios. These findings confirm that energy shocks propagate through heterogeneous and evolving channels, motivating the adoption of multiscale and machine-learning approaches to detect structural decoupling events, consistent with evidence that machine-learning models excel at capturing complex nonlinear dependencies and improving return and risk forecasting (Gu, Kelly, & Xiu, 2020), and aligned with empirical results showing that oil price shocks generate asymmetric and time-varying volatility spillovers across financial markets (He, Ng, & Xie, 2021).

To address this challenge, we propose a hybrid analytical framework that integrates dynamic correlations, unsupervised learning algorithms (K-Means, Gaussian Mixture Models, and Spectral Clustering), and a proprietary indicator: the Structural Decoupling Index (SDI^+). This index combines exponentially weighted multiscale correlations, enabling early detection of structural divergence episodes and providing a more accurate segmentation of coupling and decoupling regimes than traditional econometric metrics. Brent oil futures are included as an exogenous determinant, considering their significant influence on agricultural markets through production costs, input prices, and trade dynamics (Balcombe and Rapsomanikis, 2008; Baffes and Gardner, 2003).

The analysis uses daily data from January 2010 to July 2025, obtained from ICE Data Services, ensuring high-frequency resolution and minimizing biases associated with incomplete or low-frequency series (Intercontinental Exchange, 2025a, 2025b). The findings indicate that although convergence episodes still occur, decoupling has become more frequent and persistent, weakening traditional price-transmission mechanisms. This aligns with recent studies showing that climate-induced events such as ENSO 2023/24 droughts and energy-transition shocks amplify volatility spillovers across sectors (Ozkan et al., 2024; Cheng et al., 2023).

This study makes two main contributions. First, it enhances understanding of how coffee futures react to exogenous energy shocks by identifying multiple dependence regimes and their changes over time. Second, it offers a practical analytical framework for public-policy design and risk-management strategies aimed at boosting the resilience of coffee producers and cooperatives. Prior research highlights that agricultural risk management should promote adaptability through financial innovation, supply-chain diversification, and technological modernization (Saiti et al., 2018; Kanamura, 2018; Kabir and Ekici, 2024). By measuring the size and duration of dependence regimes and enabling early detection of structural disruptions, the SDI^+ provides an empirical foundation for predicting risk scenarios, improving hedging strategies, and reducing the vulnerability of coffee-dependent economies to global uncertainty.

2. MATERIALS AND METHODS

2.1. Research Design and Data Sources

The empirical design comprises three interconnected stages: (i) dynamic correlation analysis, (ii) application of unsupervised learning algorithms, and (iii) development and evaluation of a proprietary indicator, the Structural Decoupling Index (SDI^+). Following the data-driven methodology proposed by Kallimal Aishwarya et al. (2024) and consistent with Kabir and Ekici (2024), each methodological decision, from preprocessing and debugging of time series to model selection, was guided by empirical evidence and objective performance metrics. This approach minimizes subjective bias and enhances replicability across financial and agricultural contexts.

The dataset consists of daily futures prices for Arabica coffee and Brent oil from January 2010 to April 2025, obtained from ICE Data Services. This period covers multiple market cycles and major macroeconomic events, ensuring high-frequency information. Coffee prices, originally expressed in U.S. cents per pound, were standardized to U.S. dollars per pound. Data preprocessing included synchronization of both series, elimination of missing or anomalous records, logarithmic transformation to stabilize variance, and computation of daily log returns to capture temporal dependencies.

All transformations were validated through descriptive statistics, trend visualization, and unit-root tests to ensure that they preserved the essential structure of the data and did not distort the underlying dynamics.

2.2. Dynamic Correlation Analysis

Rolling correlations between coffee and Brent returns were estimated using 30-, 60-, and 120-day windows to capture short-, medium-, and long-term dependencies (Inacio and David, 2022; Vijayakumar, 2022). These time-varying correlations identify phases of coupling and decoupling between markets. Thresholds were classified as strong ($|\rho| > 0.6$), moderate ($0.3 \leq |\rho| \leq 0.6$), weak ($|\rho| \leq 0.2$), and decoupled ($\rho \leq -0.3$). This approach allows for the detection of structural changes in co-movements, complementing traditional econometric measures with higher temporal sensitivity.

2.3. Temporal Clustering and Unsupervised Learning

To identify latent dependency regimes, three complementary unsupervised learning algorithms were applied: K-Means (KM), Gaussian Mixture Models (GMM), and Spectral Clustering (SC). These methods were chosen for their distinct strengths in capturing different data structures.K-Means serves as a conventional benchmark for linear segmentation and is computationally efficient for high-frequency data (Nie et al., 2023). GMM extends this analysis by enabling soft clustering and capturing heterogeneity through probabilistic assignments, assuming data follow Gaussian mixtures (Crespo-Roces et al., 2018). Spectral Clustering, on the other hand, leverages graph-based similarity matrices to detect nonlinear patterns and complex boundaries within the time series (Jeong et al., 2020).

The optimal number of clusters was determined using multiple validation indices, including Inertia, Silhouette, Calinski–Harabasz, and Davies–Bouldin, prioritizing compactness, separation, and temporal stability. This hybrid clustering design aligns with recent advances in volatility connectedness and energy–agriculture analytics (Ozkan et al., 2024; Raihan et al., 2023), allowing for robust segmentation of dependence regimes.

2.4. Structural Decoupling Index (SDI^+)

The Structural Decoupling Index (SDI^+) was developed to quantify the divergence between short- and medium-term dependencies. It integrates Pearson and Spearman correlations exponentially weighted over two horizons (30 and 120 days). The indicator is normalized by its historical standard deviation, allowing classification of decoupling intensity as moderate ($SDI^+ > 0.30$) or strong ($SDI^+ > 0.50$). Unlike conventional dependence metrics (Longin and Solnik, 2001; Forbes and Rigobon, 2002) or parametric models such as DCC-GARCH, the SDI^+ anticipates structural breaks by combining multiscale correlations and nonparametric adaptability, consistent with evidence that traditional MGARCH and DCC models often fail to capture abrupt shifts in volatility spillovers driven by oil-price uncertainty (Wang et al., 2023). The index is formulated as (1):

$$SDI^+(t) = \frac{\left|I_{w_2}(t) - I_{w_1}(t)\right|}{\sigma!\left(I_{w_2} - I_{w_1}\right)} \tag{1}$$

Where $I_w(t)$ represents the exponentially weighted average of Pearson and Spearman correlations over window w. Applied coverage case (February-June 2022).

2.5. Comparative Performance and Robustness

The performance of the SDI^+ was evaluated against the Dynamic Conditional Correlation GARCH (DCC-GARCH) model (Engle, 2002), a benchmark for dynamic dependence estimation. Three evaluation criteria were applied:

1. Contemporaneous correlation between SDI^+ and DCC signals
2. Cross-correlation analysis to measure temporal anticipation
3. Event identification for $SDI^+ \geq 0.5$, corresponding to structural decoupling episodes.

A coverage case was conducted for February to June 2022, coinciding with the Russia–Ukraine conflict (Chowdhury et al., 2025). Two hedging strategies were compared: one based on DCC-GARCH estimates and another triggered by SDI^+ alerts. The SDI^+ demonstrated superior early-warning capabilities and higher temporal responsiveness to volatility shocks.

2.6. Practical Relevance

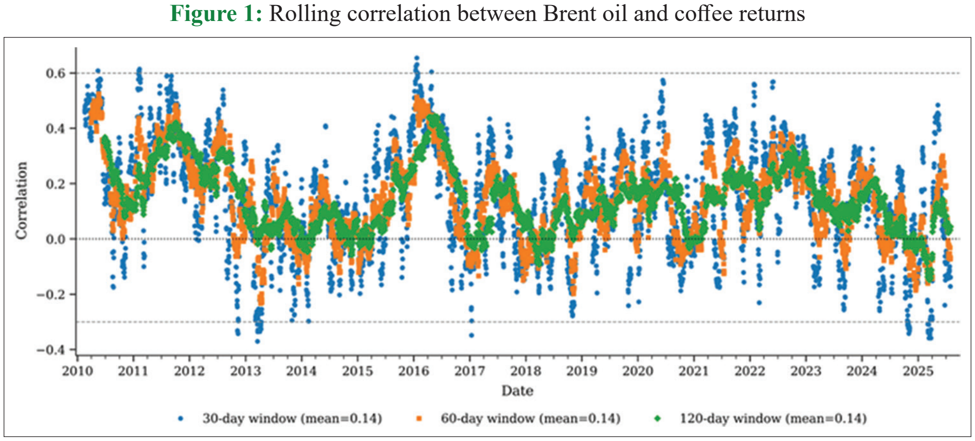
Beyond its technical rigor, the proposed framework enhances the capacity of stakeholders, including producers, cooperatives, and policymakers, to identify periods of systemic vulnerability in coffee markets. The SDI^+ supports adaptive decision-making for hedging, contract timing, and diversification, thereby contributing to resilience against global energy and climatic shocks (Kabir and Ekici, 2024; Mai et al., 2025).

3. RESULTS

3.1. Rolling Correlation Analysis at Multiple Horizons

The results of rolling correlations over 30, 60, and 120-day moving windows revealed dynamic regimes of dependence, showing variations in both the strength and direction of intermarket linkages. Figure 1 emphasizes episodes of positive coupling, phases of decoupling, and, at times, patterns of negative

Figure 1: Rolling correlation between Brent oil and coffee returns



correlation, reflecting the unstable and episodic nature of the interaction between the two markets.

The analyses show that, using a 30-day window, the dependence between coffee and Brent oil returns exhibits high volatility and sudden shifts, with maximum values of approximately 0.60 and minimum values of around −0.40, reflecting the impact of external shocks on very short-term interdependence. When extending the horizon to 60 days, the correlation range narrows to approximately between 0.50 and −0.20, which reduces high-frequency noise and allows us to identify patterns of partial convergence, with notable oscillations during 2013-2014 and 2016 periods. Finally, with a 120-day window, correlations fall within the 0.45 to −0.10 range, indicating prolonged phases of moderate positive correlation interspersed with episodes of low dependence, confirming that sustained convergence between the two markets is rare and limited in magnitude.

Overall, the findings from the three windows confirm that the interdependence between coffee and Brent oil is weak and unstable, consistent with the lack of structural integration noted in previous analyses. This fragility was also evident in recent events, such as the 50% increase in tariffs imposed by the United States on Brazilian products, including coffee, which temporarily boosted comovements and highlighted the high sensitivity of this relationship to context (Wall Street Journal, 2025). The instability, heightened by shocks of a geopolitical and trade nature, such as tariff imposition, aligns with what Gong and Xu (2022) documented, showing that geopolitical risk amplifies the transmission of shocks between agricultural and energy markets. Based on this, the next section demonstrates how to apply unsupervised learning algorithms to segment the observed dependence regimes.

3.2. Application of Unsupervised Learning Algorithms

3.2.1. Selection of the optimal number of clusters and description of regimes

The procedure shifted from a purely chronological approach to a classification into four recurrent regimes, identified through an unsupervised machine learning (KM) method applied to the correlation series estimated in section 3.1. The regimes identified were: High coupling (characterized by positive correlations of large magnitude), Moderate coupling (positive correlations of lower intensity), Low coupling (values near zero), and Uncoupling (characterized by negative correlations).

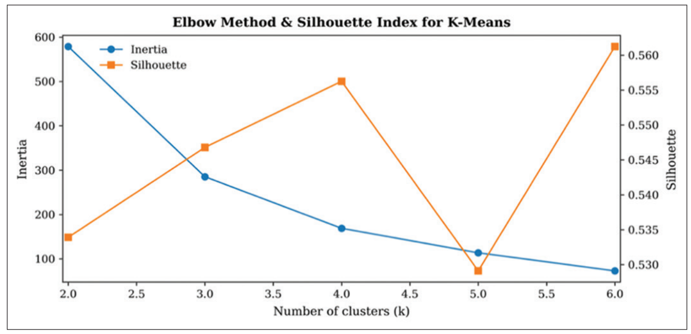
Estimation used a 60-day window for calculating the rolling correlation, selected for its balance between sensitivity and statistical stability. Shorter windows (30 days) tend to add noise, while longer ones (120 days) can oversmooth data and hide structural breaks. Studies like Cheng et al. (2023) and Jeon and McCurdy (2017) support using horizons between 30 and 60 days to detect quick changes in financial correlations.

The optimal number of clusters was identified by testing different values of k using internal validation metrics, including inertia, the Silhouette index, Calinski-Harabasz, and Davies-Bouldin. The results for k = 2 to k = 6 are presented in Table 1 below.

Table 1: Performance indicators of K-Means clustering applied to the rolling correlation series

k	Inertia	Silhouette	Calinski-Harabasz	Davies-Bouldin
2	578.921	0.533	2,371.011	0.640
3	285.142	0.546	3,174.781	0.563
4	168.924	0.556	3,912.635	0.517
5	115.094	0.523	4,478.822	0.516
6	072.999	0.559	5,817.042	0.471

Figure 2: Elbow method and Silhouette index for K-Means in selecting the optimal number of k clusters



Internal validation indices confirmed that k = 4 provides an optimal balance, showing a clear elbow in inertia, a local maximum in the Silhouette index (0.556), and a lower Davies-Bouldin score (0.517), supporting its selection as the primary configuration. Although k = 6 offers slight improvements in some metrics, the gains are minimal, and the interpretability is compromised by the over-fragmentation of the regimes. Figure 2 visually illustrates this choice, highlighting the inflection point at k = 4 and the stability of the Silhouette, in line with the quantitative criteria.

Under this setup, analyzing the clusters enabled the identification of correlation regimes with distinct statistical and economic profiles, whose distribution and color coding are shown in Figure 3.

Cluster 0 indicates moderate coupling, with correlations between 0.10 and 0.25, making it the most common state and representing a balance point in the partial transfer of information between markets. Cluster 1 shows low coupling, characterized by correlations near zero or slightly negative, implying weak and volatile interactions. Cluster 2 is associated with high coupling, characterized by correlations exceeding 0.30 and strong synchronization driven by global macroeconomic factors or energy shocks. Finally, Cluster 3 signifies clear decoupling, with consistently negative correlations, indicating no price transmission and the presence of inverse relationships.

The algorithm's ability to identify and link these regimes to specific historical contexts enhances its usefulness as a tool for real-time monitoring and early detection of structural shifts. At the practical level, this segmentation can be incorporated into warning systems and risk management models, aiding the adjustment of hedging strategies and trading decisions to the current market phase. Table 2 presents historical examples of segmentation produced by the algorithm, highlighting its practical significance.

Figure 3: Rolling correlation regimes between coffee and Brent oil

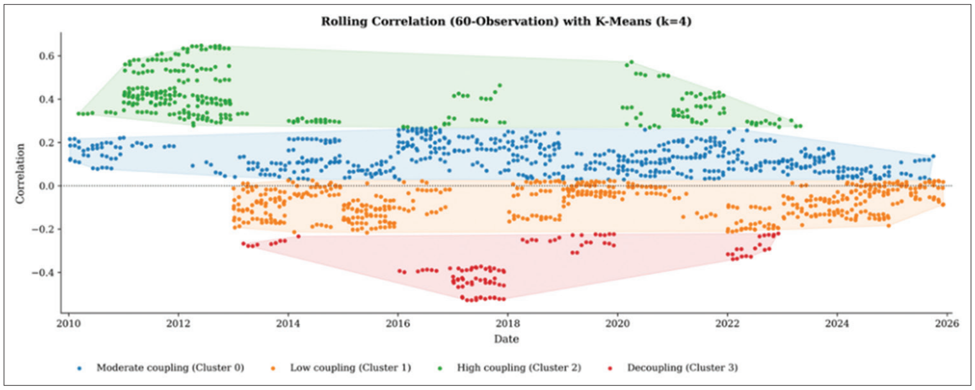


Table 2: Correspondence between coupling regimes and some relevant macroeconomic events

Cluster	Period	Relevant macroeconomic episode	Academic references
High coupling	2024-07-06 a 2025-03-29	Extreme drought in Brazil (El Niño 2023/24) associated with food price spikes (including coffee).	Kotz et al., 2025, Environmental Research Letters
High coupling	2022-01-08 a 2023-06-17	Russia-Ukraine war: energy and fertilizer shock with energy-food comovements.	Arndt et al., 2023, Global Food Security; Cheng et al. (2025), Humanities and Social Sciences Communications.
Moderate coupling	2020-01-04 a 2021-12-11	Post-COVID reopening and time- frequency connectivity between oil and agricultural.	Hung (2021), Resources Policy; Energy Economics; International Economics 2022-2024
Low coupling	2014-01-04 a 2016-12-31	Oil price collapse (-70%) due to oversupply; asynchronies with agricultural.	Orlowski and Sywak (2019). Quantitative Finance and Economics
Uncoupling	2014-01-04 a 2015-12-26	Southeastern Brazil drought with agricultural impacts as oil collapses.	Nobre et al., 2016, Journal of Water Resource and Protection; Finke et al., 2020, Climate Dynamics.

In this way, descriptive analysis is enhanced by precise quantification of the magnitude and duration of coupling or disconnection episodes, which strengthens the understanding of the factors that influence such relationships across different market contexts. The use of clustering techniques to segment regimes is supported by existing literature; Guhathakurta et al. (2020) show that dividing by specific pricing regimes improves portfolio decision-making, underscoring the importance of incorporating SDI$^+$ as a composite metric.

3.2.2. Comparison of multiple algorithms and pattern validation

The inter-algorithm comparison showed that the coupling patterns identified using KM are highly consistent when GMM and SC are compared. In all three cases, similar regimes in number and type were found, confirming the stability of the segmentation. Differences mainly appeared in the average duration of the clusters and in the assignment of certain boundary periods, but these did not alter the classification.

Overall, the results demonstrate a high degree of consistency between the KM and GMM algorithms, both in the frequency of regime occurrences and in the associated mean correlations. In both instances, the moderate coupling regime was identified as the most prevalent, with 221 periods in KM, a mean duration of 7.28 days, and an average correlation of 0.149. The high coupling regime, although less frequent (116 periods), exhibited higher correlations, reaching 0.310 in KM. This pattern was replicated by GMM, with minimal variations in the duration and magnitude of the values.

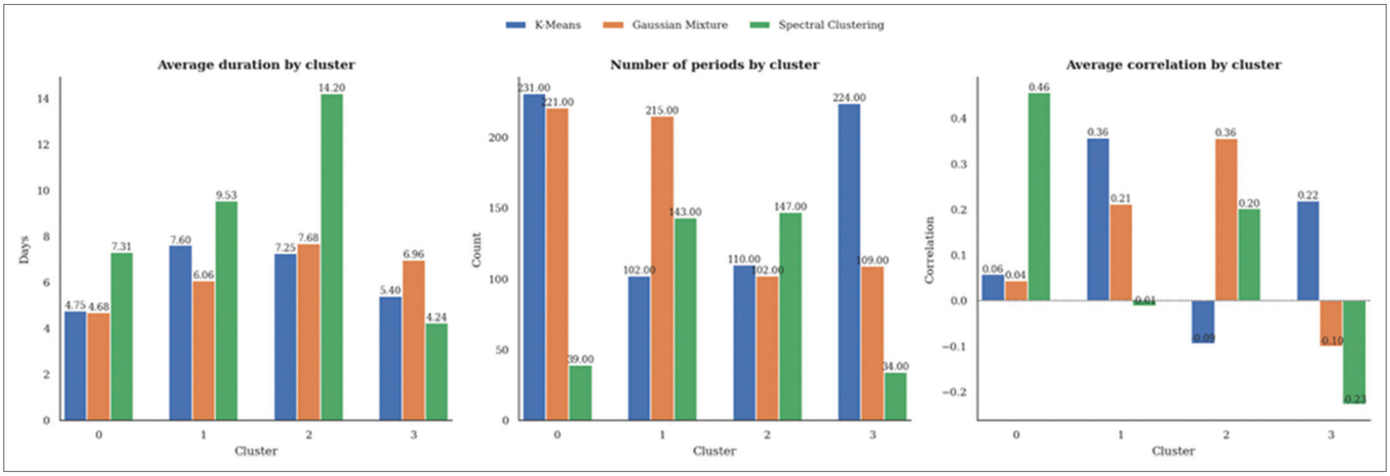
In contrast, SC showed more distinct differences in the persistence and strength of the regimes. This method assigned moderate coupling a higher average duration of 11.53 days and captured the extreme values of correlation, recording the highest in the high coupling regime (0.367) and the most negative in decoupling (−0.095). Figure 4 summarizes the key metrics for each cluster, making it easier to see how the choice of algorithm affects the characterization of interdependence patterns.

Across all methods, the average durations range from 4 to 14 days, thereby confirming the predominantly transient nature of these relationships. The consistency observed between KM and GMM, coupled with SC's capacity to detect variations in highly nonlinear contexts, reinforces the validity of the identified regimes and reduces the likelihood that the results are solely dependent on the chosen methodology. This multi-algorithm validation enhances the robustness of the identified patterns and provides a solid foundation for calculating the SDI$^+$, which is intended to quantify, in an integrated manner, the magnitude and duration of episodes of market disconnection.

3.3. Structural Decoupling Index (SDI$^+$)

The SDI$^+$ is a proprietary tool designed to measure, accurately and in real time, episodes of structural divergence between commodity markets. Its development combines correlations calculated over different timeframes and using various statistical methods, blending parametric and non-parametric data through weightings that emphasize the most recent observations. This approach enables the simultaneous detection of short- and medium-term changes, overcoming the limitations of traditional metrics and

Figure 4: Comparison of cluster metrics by algorithm



providing a reliable measure of the size and duration of decoupling. The mathematical formalization of the index is outlined below.

Let P_t^C be the daily price of Arabica coffee (USD/lb) and P_t^B be the daily price of Brent oil (USD/barrel). From these series, the logarithmic returns are calculated as shown in (2):

$$r_t^C = \Delta \ln P_t^C, \quad r_t^B = \Delta \ln P_t^B \tag{2}$$

For each date *t*, correlations are evaluated within two time windows: short term (w_s = 30 days) and medium term (w_m = 120 days). Two measures of dependence are considered in each window:

a. Exponentially weighted Pearson correlation $\left(\rho_w^P(t)\right)$ to capture recent linear relationships.
b. Spearman correlation $\left(\rho_w^S(t)\right)$ to reflect monotonic relationships and reduce sensitivity to outliers.

Correlations are combined for each window as a simple average, expressed as (3):

$$\rho_w^*(t) = \frac{\rho_w^P(t) + \rho_w^S(t)}{2}, \quad w \in \{w_s, w_m\} \tag{3}$$

The unnormalized SDI+ is defined as the absolute difference between the short- and medium-term correlations as shown in (4):

$$IDE_{raw}(t) = \left|\rho_{w_s}^*(t) - \rho_{w_m}^*(t)\right| \tag{4}$$

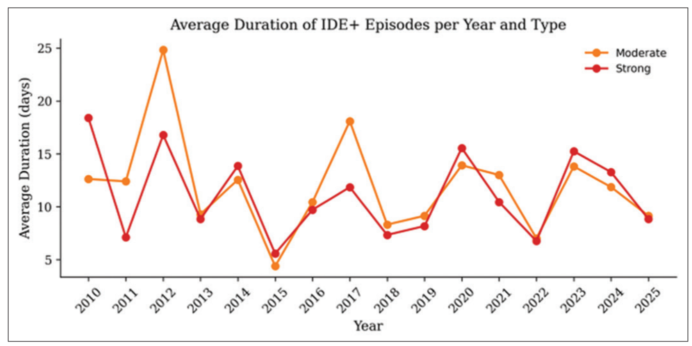
Finally, to ensure intertemporal comparability, the index is standardized by dividing by the historical standard deviation of SDI_{raw}, which can be written as (5).

$$IDE^+(t) = \frac{IDE_{raw}(t)}{\sigma_{IDE_{raw}}} \tag{5}$$

Thus, the SDI+ summarizes the magnitude of the multiscale divergence between coffee and oil returns, weighting both linear and monotonic coherence, and expressing it in normalized units.

The resulting value of the SDI+ indicates the level of decoupling relative to its typical variability, allowing episodes to be classified as moderate (SDI+ > 0.30) or strong (SDI+ > 0.50) based on their intensity and persistence. Applying this criterion to the analyzed historical series, the index identified a total of 216 episodes of structural decoupling between the returns of both commodities. Of these, 113 were strong events (52.31%) and 103 were moderate events (47.69%). On average, moderate episodes lasted 46.45 days, while strong ones averaged 38.53 days, showing that lower-intensity events tend to last longer. The maximum SDI+ value during the period was 4.53, recorded on November 04, 2021, amid high global volatility in energy and food markets, driven by the post-COVID logistics crisis, commodity supply tensions, and climate shocks (Figure 5).

Figure 5: Average duration of SDI+ episodes



In terms of total annual duration, 2017 recorded the highest moderate coupling with 383 days, while 2023 experienced the longest duration of strong episodes at 349 days, amidst an environment characterized by geopolitical tensions, logistical disruptions, and high volatility in commodities (Figure 6a and b).

Analysis of the frequency and duration of SDI+ episodes from 2010 to 2025 indicates a strong link with major macroeconomic and financial shocks. Significant events in 2014, 2017, 2020, and 2023 coincided with increased global uncertainty, including commodity price collapses, oil shocks, the COVID-19 pandemic, and volatility caused by the war in Ukraine. During these periods, structural decoupling between coffee and oil was more frequent and lasted longer, increasing their effect on hedging strategies, price formation, and production planning. As of July 2025, the incidence

Figure 6: Duration and annual frequency of SDI+ episodes by intensity. (a) Total annual duration of moderate and severe episodes. (b) Annual number of moderate and severe episodes.

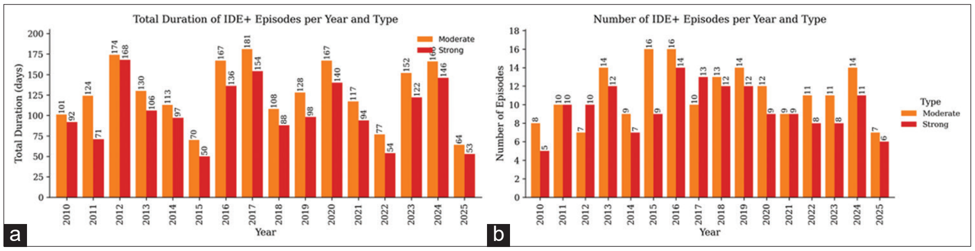
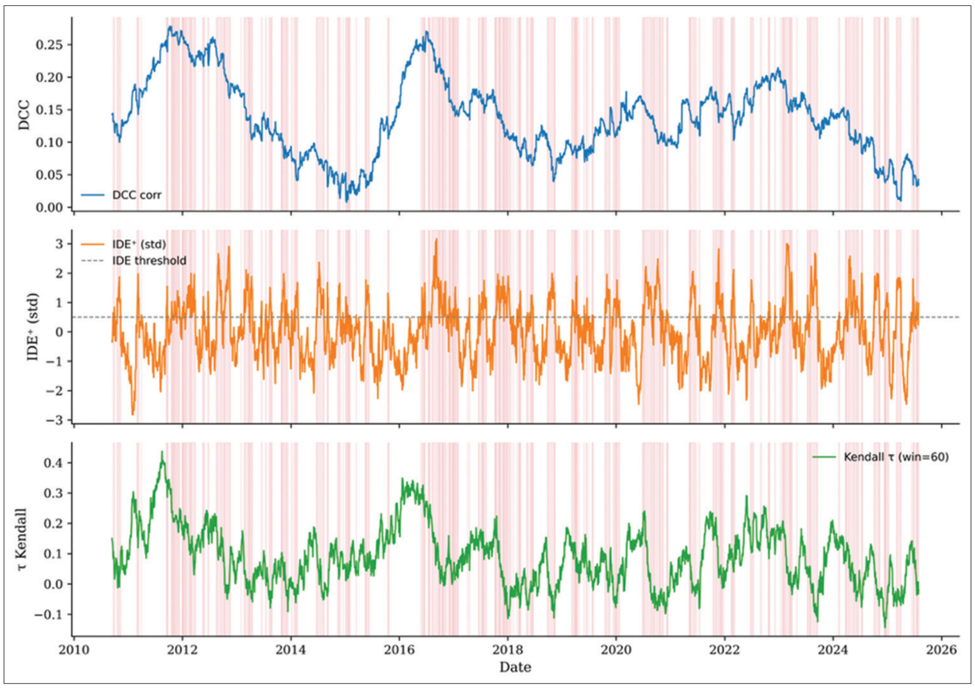


Figure 7: Comparison between SDI+, DCC-GARCH(1,1), and Kendall's τ (2010-2025)



remains high but with shorter overall durations, suggesting that the market has a better capacity to adjust to recent shocks.

3.3.1. Performance analysis of the SDI+ in relation to the DCC-GARCH model

The analysis was based on 3,933 daily observations of logarithmic returns for Arabica coffee and Brent crude oil from 2010 to 2025. First, the dynamic conditional correlation was estimated using a DCC-GARCH(1,1) model fitted to the standardized returns of each series. Simultaneously, the SDI+ was calculated from the same return series, combining exponentially weighted Pearson and Spearman correlations over two windows: short term (w_1 = 30 days) and medium term (w_2 = 120 days). Figure 7 shows the comparison between the SDI+, the dynamic conditional correlation estimated with DCC-GARCH(1,1), and Kendall's τ coefficient calculated in 60-day moving windows as a nonparametric dependence measure. Episodes where SDI+ exceeded the 0.50 threshold are shaded in red, helping to visualize the frequency and magnitude of structural decoupling episodes.

Figure 7 shows the comparison between the SDI+, the dynamic conditional correlation estimated with DCC-GARCH(1,1), and Kendall's τ coefficient calculated in 60-day moving windows as a nonparametric dependence measure. Episodes where SDI+ exceeded the 0.50 threshold are shaded in red, helping to visualize the frequency and magnitude of structural decoupling episodes.

The results expose a significant methodological and empirical distinction. Whereas the DCC correlation indicates the average progression of conditional dependence over short-term horizons, with values that infrequently surpass 0.3 and tend to remain around 0.15, the SDI+ demonstrates recurrent episodes of high dispersion and interruptions in multiscale coherence. This finding is consistent with prior research, which has recognized the effectiveness of DCC models in representing mean correlation dynamics (Engle, 2002; Aielli, 2013), while also noting their shortcomings in identifying sudden regime changes or sustained deviations across different time horizons (Forbes and Rigobon, 2002; Reboredo, 2012).

During periods of heightened market stress, such as 2011-2012 and 2015-2016, the SDI+ series displays pronounced spikes that signal episodes of structural decoupling, even as the conditional correlation estimated via DCC remains moderate. This trend is observed again in the most recent timeframe (2022-2025), where SDI+ indicators point to elevated structural instability and increased variability in dependency structures, despite persistently low DCC correlations. The integration of Kendall's τ offers further corroboration: in earlier events, such as October 2010, τ values remained exceptionally low (around 0.03) even when SDI$^+$ exceeded 1.8. In contrast, during subsequent events like September 2011, τ exhibited moderate values (near 0.32), though the magnitude and temporal alignment differed from those of the initial SDI$^+$ escalation. Collectively, these results demonstrate that SDI$^+$ identifies structural breaks more rapidly and sensitively than traditional dependence metrics.

These findings show that the SDI$^+$ offers additional information to the DCC-GARCH, not only by identifying structural breaks that the traditional metric misses but also by differentiating between average dependence and multiscale stability. In this way, the SDI$^+$ can be seen as a second-generation tool for interdependence analysis, capable of detecting periods of systemic vulnerability and regime shifts in commodity markets. These features have direct implications for risk management and hedging strategies. To validate these results, three statistical tests were conducted.

1. Contemporaneous correlation between SDI$^+$ and DCC, expressed as Equation (6):
$$\rho^{(0)} = corr\left(\mathrm{SDI}^+(\mathrm{t}), \mathrm{DCC}(\mathrm{t})\right) \tag{6}$$
−0.04, whose result was −0.04, evidencing the absence of real-time co-movement.
2. Cross-correlation between SDI$^+$ and DCC to detect possible lags, defined as (7):
$$\rho^{(k)} = corr\left(\mathrm{SDI}^+(\mathrm{t}-\mathrm{k}), \mathrm{DCC}(\mathrm{t})\right), \quad \mathrm{k} \in \mathrm{Z} \tag{7}$$
0.15, which reached a maximum of 0.15 with SDI advanced 15 days, indicating an anticipatory capacity of between 2 and 3 weeks.
3. Conditional evaluation of episodes, defined as dates on which SDI$^+$(t) ≥ 0.5; was written as (8):
$$\mathcal{E} = \left\{\mathrm{t} : \mathrm{IDE}^+(\mathrm{t}) \geq 0.5\right\} \tag{8}$$

During such episodes, it was observed that mean DCC values stayed at low to moderate levels (0.10-0.26), while Kendall's τ coefficient also remained lower in the early stages. Table 3 summarizes the main findings.

Overall, the results confirm that the SDI$^+$ is not redundant compared to the DCC-GARCH. First, the absence of contemporaneous correlation shows that the two indices capture different aspects of dependence. Second, the approximately 15-day anticipatory ability highlights the predictive power of the SDI$^+$ in identifying structural divergence before it appears in the conditional correlation. Finally, episode analysis indicates that the SDI$^+$ activates specifically during times of instability, even when traditional models suggest stable correlations. Therefore, the SDI$^+$ serves as a second-generation methodological complement, capable of predicting decoupling episodes and systemic risks in commodity markets.

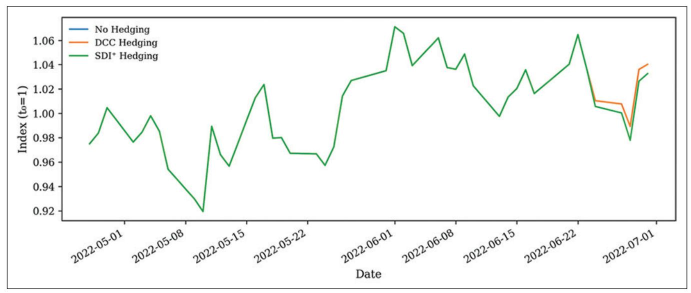
Table 3: Correlations between the SDI$^+$index and DCC in different episodes

Metric	Value	
Contemporaneous SDI$^+$-DCC correlation	−0.04	
Best lag SDItDCC (days)	15	
Correlation at best lag	0.15	
Episode (SDI$^+$max)	**Mean DCC**	**τ Kendall mean**
2010-10-19/2010-11-10 (1.87)	0.11	0.03
2011-09-15/2011-09-22 (1.55)	0.24	0.32

Table 4: Hedging strategies used from February to June 2022

Strategy	Cumulative return (%)	Days with signal
Without hedging	4.03	-
Coverage with DCC-GARCH	4.03	0
Coverage with SDI$^+$	3.27	5

Figure 8: Hedging signals during the period February-June 2022



3.3.2. Applied hedging case (February-June 2022)

The DCC-GARCH model, which captures the conditional correlation dynamics between coffee and Brent oil prices, did not generate warning signals throughout the analyzed interval, maintaining a strategy that is equivalent to not implementing hedging. In contrast, the SDI$^+$ identified five days with significant volatility, triggering hedging signals that helped reduce risk exposure, although with a slight decrease in the overall return.

Table 4 summarizes the results of each strategy. It shows that the DCC model generated no alerts, indicating its performance was equivalent to that of the unhedged portfolio. In contrast, the SDI$^+$ triggered five signals, resulting in a lower cumulative return (3.27%) compared to 4.03% without hedging, but it reduced exposure to extreme risks.

Figure 8 illustrates how the SDI$^+$ acted as an early warning system on specific days, unlike the DCC model, which did not respond to structural shifts in the relationship between coffee and Brent oil. This emphasizes the practical usefulness of the SDI$^+$ as a decision-making tool for hedging.

The study's findings provide useful practical insights for different economic actors involved in commodity markets. First, for investors and portfolio managers, identifying dynamic correlation regimes is essential for hedging and diversification strategies. During periods of low or negative correlation between Arabica coffee and Brent crude oil, diversification opportunities grow, making risk optimization easier. Conversely, when correlations are high, diversification benefits decrease, and more direct hedges become necessary. The SDI+ functions as an operational tool that enables quick detection of these regime changes and allows for proactive adjustment of investment strategies.

Secondly, for coffee producers and exporters, especially those in regions heavily reliant on this industry, the ability to anticipate episodes of structural decoupling is a vital component of resilience. Continuous monitoring of SDI+ offers advanced indications that support informed decision-making regarding pricing strategies, contract renegotiation, and income risk mitigation. This proactive approach enables industry participants to minimize vulnerability to abrupt price fluctuations and sustain more stable revenue streams.

Third, the SDI+ functions as an early warning tool for regulators and policymakers, signaling systemic vulnerabilities. The timely identification of sustained divergences among key commodities facilitates the anticipation of macroeconomic shock transmission, enabling the formulation of adaptive policy responses. Potential interventions encompass credit support initiatives, government-backed hedging arrangements, and inventory management strategies designed to mitigate adverse effects on producers and exporters.

Finally, the SDI+ can be integrated into real-time financial risk dashboards, creating a system for continuous monitoring of market interdependence. Its incorporation into visualization platforms, alongside traditional metrics such as volatility or value at risk (VaR), would enable the generation of automatic alerts when structural breaks are detected. This integration not only enhances decision-making under uncertainty but also provides a scalable and adaptable framework, suitable for both multi-commodity portfolios and emerging markets, establishing the SDI+ as a versatile tool for risk management in dynamic environments.

3.4. Implications for Small-Holder Producers and Agricultural Policies

The findings of this study have direct implications for small coffee producers, coffee cooperatives, and policymakers in producing countries. First, cooperatives can use SDI+ as a decision-making tool to develop hedging strategies, negotiate better contract terms, and modify storage or export schedules in response to structural decoupling episodes. Additionally, governments and regulatory agencies can integrate SDI+ monitoring into agricultural risk management systems to anticipate income shocks in coffee-dependent areas. This allows for the timely deployment of support measures such as emergency credit lines, stabilization funds, or government-backed hedging plans. Moreover, using SDI+ supports broader goals of sustainability and food security. By reducing income volatility, producers become less exposed to sudden market shocks, which helps sustain rural livelihoods and strengthen supply chain resilience. Given the close connection between coffee markets and global trade, SDI+ offers valuable insights for international negotiations and policy coordination, enabling better management of external shocks in energy markets and limiting their adverse effects on agricultural economies.

4. DISCUSSION

The results substantiate the episodic and volatile characteristics of the linkage between Arabica coffee and Brent crude oil futures. Notably, the increasing prevalence and magnitude of decoupling events in 2023 point to the asymmetric influence of geopolitical disruptions, such as the Russia–Ukraine conflict and energy supply interruptions, on agricultural and energy commodity markets, consistent with evidence that black-swan events significantly reshape the dynamic connectedness of global energy markets (Hu et al., 2023). Oil prices exhibit near-immediate responses to global supply shocks, whereas coffee prices are predominantly shaped by idiosyncratic climatic and agricultural factors. This divergence validates the notion of structural segmentation across asset classes, illustrating that shocks of comparable scale can generate heterogeneous market dynamics.

For coffee supply chains, such divergence underscores the vulnerability of rural livelihoods to asymmetric global shocks, where farmers and cooperatives face income instability even when energy markets adjust more rapidly. These conclusions align with the findings of Chowdhury et al. (2025), who document distinct transmission patterns of geopolitical risk across agricultural and energy commodities, highlighting their uneven short-term sensitivities, and are consistent with evidence that agricultural livelihoods are highly exposed to price volatility, climate shocks, and adverse economic variables, which makes integrated financial risk-management strategies essential to protect producers' income and resilience (Costa, 2024).

From both economic and quantitative perspectives, these insights cast doubt on the presumption of persistent integration embedded in conventional risk management frameworks. Hedging strategies based on static correlation structures may overlook market risks arising from simultaneous but divergent shocks, a pattern that mirrors the contagion-driven loss of diversification benefits documented in financial markets under stress (Hadad, 2025). The identification of multiple dependency regimes, ranging from strong coupling to pronounced decoupling, provides a nuanced understanding of inter-asset relationships and a robust empirical foundation for adaptive hedging approaches that accommodate evolving market conditions, consistent with evidence showing that economic systems exhibit alternating phases of convergence and decoupling over time (Kose et al., 2012).

In the agricultural context, these adaptive strategies are particularly relevant for coffee cooperatives, which can leverage early-warning signals from the SDI+ to renegotiate contracts, adjust storage and commercialization policies, and design collective hedging mechanisms. By doing so, cooperatives strengthen their role in protecting smallholder farmers from abrupt income disruptions and contribute to the overall resilience of coffee-producing regions.

In this context, Chowdhury et al. (2025) emphasize the distinctiveness of political risk transmission channels across commodities, advocating for the integration of this heterogeneity into risk analysis and management frameworks. For policymakers in coffee-producing countries, recognizing these heterogeneous transmission channels is essential to anticipate and mitigate crises in regions heavily dependent on coffee revenues. Incorporating tools such as the SDI+ into agricultural policy design can facilitate the early detection of systemic vulnerabilities, enabling the implementation of timely stabilization measures. Such measures may include government-backed hedging facilities, countercyclical credit lines, or buffer stock programs to protect producers from income shocks. Embedding early-warning systems into policy frameworks strengthens the resilience of rural economies and safeguards food security objectives against external volatility.

Additionally, these findings contribute to the ongoing debate on the financialization of commodity markets. Although studies by Da et al. (2024) and Aït-Youcef and Joëts (2024) argue that increased participation by financial investors amplifies price comovements during global uncertainty, the current evidence indicates that financialization alone cannot fully explain coffee–oil interactions. While speculation might strengthen short-term correlations, structural and idiosyncratic disruptions primarily drive decoupling episodes. This interpretation aligns with agricultural economics research on asymmetric price transmission, which shows that shocks in the global coffee market are only partially passed through to producer or farm-gate prices (Gilbert, 2010; Baquedano and Liefert, 2014). This incomplete and uneven transmission amplifies producer vulnerability, reinforcing the need for commodity-specific approaches that account for both financial and real-sector dynamics.

From a methodological perspective, the SDI+ developed through computational algorithms consolidates as an innovative tool capable of detecting abrupt transitions between coupling and decoupling phases with high temporal resolution. Unlike conventional econometric methods, this index provides early signals of structural breaks and improves the segmentation of market dynamics, enhancing its practical utility in hedging strategies and risk management. Its adaptable design also allows extension to multi-commodity portfolios and emerging markets, facilitating cross-asset comparisons.

This anticipatory capacity aligns with Yang et al. (2021), who emphasize the importance of multiscale dependence metrics in understanding market resilience. By linking dependency regimes with macroeconomic and climatic drivers (Ledwaba et al., 2025; Aysan et al., 2025; Melawanki et al., 2025), the SDI+ approach reinforces the interpretive depth of energy–agriculture linkages and establishes a robust foundation for composite indicators. Beyond financial applications, the SDI+ contributes to agricultural sustainability by guiding diversification strategies and enabling cooperatives and policymakers to anticipate systemic shocks and strengthen rural resilience.

In summary, integrating advanced data science and machine learning into the SDI+ framework broadens the energy-agriculture nexus literature by providing a scalable and predictive early-warning system. This system not only improves market modeling accuracy but also supports sustainable policies aimed at protecting livelihoods in coffee-dependent economies affected by energy and climate volatility.

5. CONCLUSIONS

The analysis reveals that Arabica coffee and Brent crude oil markets are episodically and non-stationarily interconnected, with recurrent phases of coupling, weak coupling, and decoupling. The identification of 216 structural decoupling episodes between 2010 and 2025 (52% strong) confirms the persistent segmentation between agricultural and energy commodities, challenging the assumption of stable long-term integration.

The SDI+ anticipates structural breaks up to 15 days earlier than DCC-GARCH models, demonstrating enhanced early-warning capacity for systemic risk monitoring. By integrating linear and nonparametric correlations across multiple horizons, the SDI+ enables the early detection of regime shifts and provides a methodological contribution that strengthens commodity market research while remaining highly applicable to agricultural risk analysis.

Robustness tests show strong consistency between K-Means and Gaussian Mixture Models in identifying dependency regimes, while Spectral Clustering captures more extreme and persistent patterns, highlighting the added value of nonlinear validation. This convergence supports the reliability of the dependency structure and reinforces the relevance of advanced machine learning in the analysis of agricultural markets exposed to complex external shocks.

The SDI+ effectively detected major divergence episodes linked to the post-COVID logistics crisis (2021), the Russia–Ukraine war (2022-2023), and the ENSO 2023/24 drought. Connecting quantitative evidence with real-world events enhances the external validity of the results and demonstrates the tool's potential for applied risk monitoring in coffee markets.

The applied hedging case study (February-June 2022) shows that SDI+ signals can help reduce exposure to extreme shocks, even when cumulative returns are slightly lower, confirming that adaptive, regime-sensitive strategies are more resilient than static approaches. For exporters, cooperatives, and regulators, this represents a practical decision-support tool for managing uncertainty in highly volatile environments.

Finally, the identification of distinct dependency regimes offers tangible insights for agricultural and policy design. High-coupling phases demand rapid and coordinated responses, while low-coupling or decoupling periods open opportunities for diversification and gradual stabilization. For coffee-dependent economies, the use of adaptive indicators such as the SDI+ strengthens systemic resilience, supports income stabilization for farmers, and contributes to sustainable rural development and food security.

Overall, this study extends the energy–agriculture nexus literature by introducing a scalable and predictive early-warning framework that bridges financial modeling, sustainability, and agricultural policy.

This study has three main limitations that suggest directions for further research. First, the analysis focuses exclusively on Arabica coffee and Brent oil, which may limit the generalizability of the findings. Expanding to other agricultural products, metals, or energy derivatives would provide a broader assessment. Second, the models concentrate on price interactions without incorporating other financial and macroeconomic factors such as exchange rates, interest rates, or implied volatility, which could improve understanding of convergence and decoupling phases. Third, regime detection through clustering methods may be affected by parameter selection (for example, window length or number of clusters). Future work could explore adaptive or Bayesian approaches to minimize this bias and enhance robustness.

ACKNOWLEDGMENTS

The authors express their sincere appreciation to the GIIDCE Research Group and the RoastLab Laboratory at Universidad del Valle for their invaluable support in the development of this study.

REFERENCES

Aielli, G.P. (2013), Dynamic conditional correlation: On properties and estimation. Journal of Business and Economic Statistics, 31(3), 282-299.

Aït-Youcef, C., Joëts, M. (2024), The role of index traders in the financialization of commodity markets: A behavioral finance approach. Energy Economics, 136, 107641.

Arndt, C., Diao, X., Dorosh, P., Pauw, K., Thurlow, J. (2023), The Ukraine war and rising commodity prices: Implications for developing countries. Global Food Security, 36, 100680.

Baffes, J., Gardner, B. (2003), The transmission of world commodity prices to domestic markets under policy reforms in developing countries. Journal of Policy Reform, 6(3), 159-180.

Balcombe, K., Rapsomanikis, G. (2008), Bayesian estimation and selection of nonlinear vector error correction models: The case of the sugar-ethanol-oil nexus in Brazil. American Journal of Agricultural Economics, 90(3), 658-668.

Baquedano, F.G., Liefert, W.M. (2014), Market integration and price transmission in consumer markets of developing countries. Food Policy, 44, 103-114.

Cheng, D., Liao, Y., Pan, Z. (2023), The geopolitical risk premium in the commodity futures market. Journal of Futures Markets, 43(8), 1069-1090.

Cheng, P., Zhang, Y., Liu, K., Kong, X., Wu, S., Yan, H., Jiang, P. (2025), Continuing the continuous harvests of food production: From the perspective of the interrelationships among cultivated land quantity, quality, and grain yield. Humanities and Social Sciences Communications, 12, Article 46.

Chowdhury, M.A.F., Hassan, M.K., Abdullah, M., Hossain, M.M. (2025), Geopolitical risk transmission dynamics to commodity, stock, and energy markets. Quantitative Finance and Economics, 9(1), 76-99.

Conforti, P. (2004), Price transmission in selected agricultural markets (FAO Commodity and Trade Policy Research Working Paper No. 7). Food and Agriculture Organization of the United Nations.

Cocca, T., Gabauer, D., Pomberger, S. (2024), Clean energy market connectedness and investment strategies: New evidence from DCC-GARCH R2 decomposed connectedness measures. Energy Economics, 136, 107680.

Costa, A. S. S. F. da. (2024), Financial risk management in agriculture: mitigation strategies and protection against economic variables. International Journal of Scientific Management and Tourism, 10(4), e1045.

Crespo-Roces, D., Méndez-Jiménez, I., Salcedo-Sanz, S., Cárdenas-Montes, M. (2018), Generalized probability distribution mixture model for clustering. In: de Cos Juez, F., Villar, J.R., de la Cal, E.A., Herrero, A., Quintián, H., Sáez, J.A., Corchado, E. Hybrid Artificial Intelligent Systems. HAIS 2018. Lecture Notes in Computer Science. Vol. 10870. Cham: Springer.

Da, Z., Tang, K., Tao, Y., Yang, L. (2024), Financialization and commodity markets serial dependence. Management Science, 70(4), 2122-2143.

Engle, R. (2002), Dynamic conditional correlation: A simple class of multivariate GARCH models. Journal of Business and Economic Statistics, 20(3), 339-350.

Forbes, K.J., Rigobon, R. (2002), No contagion, only interdependence: Measuring stock market comovements. The Journal of Finance, 57(5), 2223-2261.

Gao, S., Li, D., Zhu, J. (2022), Dynamic spillover effects and portfolio strategies between crude oil, gold and Chinese stock markets related to new energy vehicle. Energy Economics, 113, 106245.

Gilbert, C.L. (2010), How to understand high food prices. Journal of Agricultural Economics, 61(2), 398-425.

Gong, X., Xu, J. (2022), Geopolitical risk and dynamic connectedness between commodity markets. Energy Economics, 110, 106028.

Gu, S., Kelly, B., Xiu, D. (2020), Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223-2273.

Guhathakurta, K., Dash, S.R., Maitra, D. (2020), Period-specific volatility spillover-based connectedness. Energy Economics, 85, 104566.

Hadad, E. (2025), Does trading mechanism shape cross-market integration? Evidence from stocks and corporate bonds on the Tel Aviv Stock Exchange. Journal of Economics, Finance and Administrative Science, 30(59), 169-188.

He, X., Ng, L., Xie, S. (2021), Oil price shocks and stock market volatility: Evidence of asymmetric and time-varying spillovers. Journal of Financial Economics, 142(1), 411-436.

Headey, D., Fan, S. (2008), Anatomy of a crisis: The causes and consequences of surging food prices. Agricultural Economics, 39(s1), s375-s391.

Hu, Y., Lang, C., Corbet, S., Hou, Y.G., Oxley, L. (2023), Exploring the dynamic behaviour of commodity market tail risk connectedness. Energy Economics, 125, 106829.

Hung, N.T. (2021), Oil prices and agricultural commodity markets: Evidence from pre and during COVID-19 outbreak. Resources Policy, 73, 102236.

Inacio, C.M.C. Jr., David, S.A. (2022), Price dynamics and measuring the contagion between brent crude and heating oil (US-diesel) pre and post COVID-19 outbreak. Engineering Proceedings, 18(1), 8.

Intercontinental Exchange. (2025a), Coffee Historical Prices [Dataset]. ICE Data Services. Available from: https://www.ice.com/publicdocs/futures_us_reports/coffee/coffee_historical_prices.xls [Last accessed on 2025 Jul 31].

Intercontinental Exchange. (2025b), Brent Crude Oil Futures Historical Prices [Dataset]. ICE Data Services. Available from: https://www.ice.com/products/219/brent-crude-futures [Last accessed on 2025 Jul 31].

Jeon, Y., McCurdy, T. (2017), Time-varying window length for correlation forecasts. Econometrics, 5(4), 54.

Jeong, S., Bae, S., Kim, C. (2020), Spectral clustering: Summary and recent research issues. The Korean Journal of Applied Statistics, 33(2), 115-122.

Kabir, M., Ekici, S. (2024), Energy-agriculture nexus: Exploring the future of AI applications. Energy Nexus, 13, 100263.

Kallimal Aishwarya, C., Siri Lahari, C., Himam Saheb, S. (2024), Data analytics tools and applications for business and finance systems. En: Khang, A., Gujrati, R., Uygun, H., Tailor, R.K., Gaur, S.S., editors.

Data-Driven Modelling and Predictive Analytics in Business and Finance: Concepts, Designs, Technologies, and Applications. United States: Auerbach Publications, CRC Press. p18-34.

Kanamura, T. (2018), Diversification effect of commodity futures on financial markets. Quantitative Finance and Economics, 2(4), 821-836.

Kose, M.A., Otrok, C., Prasad, E. (2012), Global business cycles: Convergence or decoupling? International Economic Review, 53(2), 511-538.

Kotz, M., Donat, M.G., Lancaster, T., Parker, M., Smith, P., Taylor, A., Vetter, S.H. (2025), Climate extremes, food price spikes. Environmental Research Letters, 20(8), 081001.

Ledwaba, L.J., Nkoro, E., Sikhosana, L.S. (2024), Climate variability, food security and agricultural productivity in Sub-Saharan Africa: A panel data analysis. Food Security, 16(5), 1123-1141.

Longin, F., Solnik, B. (2001), Extreme correlation of international equity markets. The Journal of Finance, 56(2), 649-676.

Mai, E.N.Z., Inoue, N., Uenishi, Y. (2025), The food-water-energy nexus in agriculture. Sustainability, 17(10), 4428.

Melawanki, M., Pradeepa Babu, B.N., Vedamurthy, K.B. (2025), Empirical study on interdependence of coffee futures prices and farm gate prices in major coffee producing countries. Asian Journal of Agricultural Extension, Economics and Sociology, 43(1), 11-19.

Nie, F., Li, Z., Wang, R., Li, X. (2023), An effective and efficient algorithm for k-means clustering. IEEE Transactions on Knowledge and Data Engineering, 35(4), 3433-3443.

Nobre, C.A., Marengo, J.A., Seluchi, M.E., Cuartas, L.A., Alves, L.M. (2016), Some characteristics and impacts of the drought and water crisis in Southeastern Brazil during 2014 and 2015. Journal of Water Resource and Protection, 8(2), 252-262.

Orlowski, L.T., Sywak, M. (2019), Wavering interactions between commodity futures prices and U.S. dollar exchange rates. Quantitative Finance and Economics, 3(2), 221-243.

Ozkan, O., Yousaf, I., Yarovaya, L., Uddin, G. S. (2024). Spillover effects between fossil fuel and clean energy markets during the Russia–Ukraine conflict. Energy Reports, 11, 101-116.

Raihan, A., Voumik, L.C., Mohajan, B., Rahman, M.S., Zaman, M.R. (2023), Economy-energy-environment nexus. Carbon Research, 2(1), 43.

Reboredo, J. C. (2012), Do food and oil prices co-move? Energy Policy, 49, 456-467.

Saiti, B., Dahiru, A., Yumusak, I.G. (2018), Diversification benefits in energy, metal and agricultural commodities for Islamic investors. Quantitative Finance and Economics, 2(3), 733-756.

Taylor, A.M., Taylor, M.P. (2004), The purchasing power parity debate. Journal of Economic Perspectives, 18(4), 135-158.

Usman, M., Loves, L., Russel, E., Ansori, M., Warsono, W., Widiarti, W., Wamiliana, W. (2022), Analysis of some energy and economics variables by using VECMX model in Indonesia. International Journal of Energy Economics and Policy, 12(2), 91-102.

Vijayakumar, A.N. (2022), Impact of the US Dollar index and crude oil on prices of Arabica and Robusta varieties of Indian Coffee. Business Perspectives and Research. https://doi.org/10.1177/22785337221077399

Wall Street Journal. (2025), Tariffs for Brazil now Max Out at 50%, Including on Coffee. Wall Street Journal. Available from: https://www.wsj.com/livecoverage/stock-market-today-dow-sp-500-nasdaq-08-06-2025/card/tariffs-for-brazil-now-max-out-at-50-including-on-coffee-S1YJ7RGgPo8ANv90Tag8

Wan, Z. (2024), An Evaluation of U.S. economic decoupling from China. Finance and Economics, 1(6), 531.

Wang, Y., Yan, K. (2023), Machine learning-based quantitative trading strategies. Quantitative Finance and Economics, 7(4), 569-594.

Yang, J., Li, Z., Miao, H. (2021), Volatility spillovers in commodity futures markets: A network approach. Journal of Futures Markets, 41(12), 1959-1987.