Scientific Research Publishing

Theoretical Economics Letters, 2025, 15(3), 674-688
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

Adaptive Learning in Short Time Series

Georgios Prokopos, Foteini Kyriazi

Department of Agribusiness & Supply Chain Management, Agricultural University of Athens, Athens, Greece
Email: fkyriazi@aua.gr

How to cite this paper: Prokopos, G., & Kyriazi, F. (2025). Adaptive Learning in Short Time Series. *Theoretical Economics Letters, 15,* 674-688.
https://doi.org/10.4236/tel.2025.153036

Received: January 8, 2025
Accepted: June 9, 2025
Published: June 12, 2025

Abstract

This paper applies the novel adaptive learning methodology to forecast agricultural and energy prices in Greece's volatile, data-scarce markets. We combine traditional ordinary least squares with quantile regression techniques within this framework, achieving up to 27% lower forecast errors compared to conventional benchmarks. Our analysis reveals distinct performance patterns: quantile regression demonstrates superior accuracy for volatile commodities (e.g., barley), while ordinary least squares performs better for stable markets (e.g., maize). The learning rate parameter γ proves crucial in adapting to market conditions. These findings provide policymakers with an enhanced tool for analyzing energy-agriculture price linkages and managing market volatility, particularly in small, open economies facing data limitations.

Keywords

Price Forecasting, Adaptive Learning, Quantile Regression, Energy-Agriculture Nexus, Volatility

1. Introduction

Agricultural and energy markets are among the most volatile sectors in the global economy, shaped by unpredictable factors such as extreme weather events, geopolitical tensions, and shifting consumer demand (Fowowe, 2016; Ben-Ari et al., 2016). For many European nations, where agriculture remains a cornerstone of rural economies and energy security is increasingly tied to renewable transitions, the ability to forecast price movements accurately is not just an academic exercise; it is a practical necessity. Traditional forecasting models, while foundational, often fall short in this context. Methods like ARIMA, though reliable for stable series (Naylor et al., 1972), struggle with the non-stationarity and sparse data common in agricultural datasets (Manogna & Mishra, 2021), where critical variables such as crop yields or regional energy use may only be recorded annually.

The interplay between energy costs and agricultural production adds another layer of complexity. Fluctuations in natural gas prices directly impact fertilizer costs, while the adoption of renewable energy influences irrigation efficiency (Gargano & Timmermann, 2014a; Shafiee & Topal, 2010). Machine learning techniques such as long Short-term memory networks have improved predictive accuracy in volatile markets (Herrera et al., 2019; Wang et al., 2020), but their reliance on extensive datasets limits utility in Europe's context, where many time series—such as durum wheat (DWW) prices or fossil energy consumption (FSE)—are short and fragmented. This gap underscores the need for adaptive frameworks that can leverage limited data while remaining responsive to structural shifts, such as abrupt policy changes or climate-induced disruptions (Kehagia & Kyriazi, 2021; Xiong et al., 2015).

In this paper, first we address these challenges by constructing composite indices based on a range of energy-related variables, including renewables, natural gas, and solid fossil fuels for forecasting agricultural commodity prices. These indices are created to capture the influence of different energy sources. Second, we estimate several benchmark models, including a first-order autoregressive model (AR), a first-order delay model (using only the lag of the index) and a combined autoregressive delay model, to enhance the robustness of our research findings. Third and most important we include the adaptive learning methodology, introduced by Kyriazi et al. (2019), which combines forecast averaging with learning from past forecast errors to improve prediction accuracy.[1] Our main forecasting framework combines Quantile Regression (QR) and Ordinary Least Squares (OLS) to capture not only volatility but also asymmetric risks, such as energy price spikes during droughts. Empirical results show that the adaptive learning approach consistently outperforms traditional benchmarks, reducing forecasting errors by up to 27%. Moreover, QR outperforms OLS, particularly in high-uncertainty environments. These findings provide valuable insights for policymakers addressing the intertwined challenges of energy transition and agricultural sustainability.

The paper proceeds as follows: Section 2 reviews advancements and limitations in energy-agriculture forecasting. Section 3 presents our methodology and the data used. Section 4 analyzes our results for all commodities, and Section 5 discusses implications for European economies and future research directions.

2. Literature Review

The systematic research of energy prices forecasting reveals a continuously evolving landscape due to the non-stationarity of markets (Manogna & Mishra, 2021; Kyriazi, 2024) and various factors such as load fluctuations and weather extremes (Gargano & Timmermann, 2014a). According to Sun et al. (2023), traditional methods like the autoregressive integrated moving average model still remain

---

[1] See other methodological contributions in Guerard et al., 2024; Kyriazi and Thomakos, 2020a, 2020b.

widely used for their holistic approach (Naylor et al., 1972), but advanced techniques now demonstrate higher level performances. Meanwhile, wavelet analysis achieves lower prediction errors than ARIMA in forecasting Henry Hub natural gas prices from 1997 to 2025 (Rostan & Rostan, 2021). Similarly, machine learning and deep learning models, particularly in long-short term memory networks and random forest model, demonstrate exceptional accuracy in volatile energy markets (Herrera et al., 2019; Wang et al., 2020). For short-term volatility forecasting, long-short term time series networks, (Ouyang et al., 2019) and random forest model are currently characterized as the state of the art, revealing high performance through consistent reductions in both Root Mean Square Error and Mean Absolute Percentage Error relative to traditional benchmarks (Ben Ameur et al., 2024; Divina et al., 2019). While simulation based approaches provide valuable theoretical insights, their practical application is constrained by computational limitations in real time settings (Bastian et al., 1999, Lehmann & Romano, 2020), highlighting the critical demand for flexible analytical frameworks when working with limited data. Although hybrid systems blending ensemble approaches with machine learning enhance residential energy demand forecasts (Chou & Tran, 2018), their nature increases vulnerability to adjust in insufficient datasets (Zhang et al., 2020). Moreover, while the cutting-edge explainable AI methods show effectiveness in uncovering significant factors including CO_2 emissions and renewable energy integration (Shafiee & Topal, 2010), their reliance on sufficient data, sets limitations for analyses with short time horizons (Tudor et al., 2025). For such cases, Thomakos et al. (2023) proposed a novel forecasting model optimized for short time series with limited data.

Agricultural forecasting has surprisingly marked an ongoing evolution framework, transitioning from traditional econometric models (Allen, 1994) to advanced machine learning techniques. Early methodologies, such as Moore's (1917) linear regression for cotton prices, laid the foundation, but also proved insufficient for nonlinear price dynamics (Wang et al., 2020). Modern approaches now leverage hybrid models and artificial neural networks, proving especially adept at characterizing multi-scale parameters (Ferrari et al., 2021). In precision agriculture applications, Support Vector Regression (SVR) has proven crucial for generating crop specific forecasts. For instance, Parviz (2018) identified air temperature as the dominant parameter for barley (BAP) yields using SVR, highlighting the method's sensitivity to regional conditions. Similarly, Shahhosseini et al. (2020) achieved 12% to 18% Root Mean Square Error improvements in corn yield predictions by integrating climate conditions and soil data into optimized ML ensembles. In this vein, the predictability of agricultural markets is further influenced by climate variability and annual economic cycles. Ben-Ari et al. (2016) revealed that climate indicators could also predict extreme yield losses in wheat and maize as effectively as multivariate crop models. In arid environments, for example, MODIS derived vegetation indices have proven valuable for early yield prediction and performance (Qader et al., 2018), despite existing barriers in data availability. Macroeconomic instability further elaborates forecasting efforts, with Gargano and Timmermann (2014b) referring to that price predictability is maximized at quarterly frequencies, but also differs by each commodity type, which means that recessions increase volatility (Fowowe, 2016). To address these challenges, Xiong et al. (2015), pioneered the VECM-SVR model, integrating error correction with machine learning to control commodity price irregularities, while Kyriazi et al. (2024), reduced forecasting errors by ensemble averaging.

Adaptive learning has revolutionized forecasting by improving predictions based on past errors, offering significant improvements over traditional methods (Schachinger et al., 2018). Kyriazi et al. (2019) highlighted that the adaptive learning method is not limited to enhancing forecasting performance in agricultural products but also extends to various other fields by dynamically incorporating past forecast errors and improving key metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The methodological foundation of adaptive learning traces back to Kofi's (1973) research on adaptive weighting in multivariate time series, which demonstrated the necessity of continuous parameter updates. Modern studies, such as the three-step framework by Zhang et al. (2020), integrate the minimum redundancy maximum relevance method for feature selection (Hong et al., 2020), aiming to achieve the highest possible precision in commodity price forecasting. Furthermore, recent investigations into leading indicators (Heij et al., 2011) note that even optimal static models offer limited forecasting improvements, with RMSE reductions substantially lower than those achieved by adaptive learning methods. Groen and Pesenti (2011) reveal how traditional econometric models fail to approach macroeconomic uncertainty in commodity markets, while adaptive methods dynamically adjust to new datasets. In energy and agricultural markets, adaptive learning addresses these challenges by dynamically adjusting to new data, ensuring robust forecasts in volatile environments (Ben Ameur et al., 2024; Nikolopoulos & Thomakos, 2019). Traditional methods often struggle with correlated variables (Pierce, 1977) and stochastic errors (Cleveland, 1971), but on the other hand, adaptive learning's updates successfully address these challenges.

3. Methodology and Data

3.1. Methodology

In this section, we present our methodology, following a three-step approach to evaluate the efficacy of energy-based indices in forecasting agricultural commodity prices.

In the first step, we create a composite index derived from a set of energy-related variables. These variables represent different energy products such as Barley (BAP), Sunflower (SUN), Durum Wheat (DWW), and also Maize (MPP) and Fossil Energy Consumption (FSE), or any other relevant indicator that are deemed to have an influence on agricultural commodity prices. Let x_t be the index by normalizing these variables and taking their average growth rate over time. Specifically, the index is calculated as the average of the normalized values of selected energy products. We denote the energy variables as $E_1, E_2, \cdots, E_n$, where n is the number of the products used to construct the index.

$$\text{index} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{E_{i,t}}{E_{i,t-1}}\right) \tag{1}$$

where $E_{i,t}$ denotes the value of the i-th energy variable at time *t*, and $E_{i,t-1}$ is the value of the i-th energy variable at the previous time period $t-1$. The index is computed as the average of the normalized values of the energy variables. In what follows, we calculate the growth rate of our index using log-difference transformation, to achieve stationarity on our data $x_t = \ln(index_t) - \ln(index_{t-1})$.

Let y be our dependent variable, where in our case is chosen among Barley (BAP), Sunflower (SUN), Durum Wheat (DWW), Maize (MPP) and also Fossil Energy Consumption (FSE). Respectively, we calculate the growth rate of the dependent variable as: $ldiff(y_t) = \ln(y_t) - \ln(y_{t-1})$.

In the second step we compute the benchmark models for our dependent variable (which is also expressed as a growth rate) and these models are: a first order autoregressive model, a first order delay model (using only the lag of the index) and a first order autoregressive delay model (using the first lag of the dependent variable and of the index together);

$$\hat{y}_{t+1|t}^{ar} = \hat{\rho}_0 + \hat{\rho}_1 y_t \tag{2}$$

for the autoregressive model

$$\hat{y}_{t+1|t}^{delay} = \hat{\beta}_0 + \hat{\beta}_1 x_t \tag{3}$$

for the delay model

$$\hat{y}_{t+1|t}^{ar-delay} = \hat{\rho}_0 + \hat{\rho}_1 y_t + \hat{\beta}_1 x_t \tag{4}$$

for the autoregressive-delay model

$$\hat{y}_{t+1|t}^{adl} = \hat{y}_{t+1|t}^{j} + \gamma \cdot \hat{\epsilon}_{t|t-1}^{adl} \tag{5}$$

for the adaptive learning method

In the third step we estimate these models by recursive least squares and quantile regression (at the median) and forecast one-year ahead (we start with 4 or 6 years for least squares and quantile regression respectively and increase our sample), then we record the results and find the best performing model forecast which we pass on to the adaptive learning method.

3.2. Data and Forecast Evaluation

Our data stem from the official Eurostat database, specifically from the Agriculture, Forestry, Fisheries, Energy & Environment sections, covering the period from 1990 to 2023. The dataset pertains exclusively to Greece, ensuring a geographically focused analysis. Our study also employs annual time series data, with all agricultural commodity values reported in euros, consistent with Eurostat's default currency framework. A crucial characteristic of our data is the dynamic interplay between energy and agricultural commodity markets. This relationship brings significant implications for market participants and stakeholders (Cabrera & Schulz, 2016), demonstrating that understanding volatility linkages between these sectors is essential for decision-makers to develop effective strategies in volatile market conditions without sustainable and economic consistency (Han et al., 2015). In particular, several important time series of agricultural commodities are available only at low frequency, such as annual data, which presents both analytical challenges and opportunities for further analysis. This incident reduces the available information for building accurate forecasting. To address this challenge while also maintaining analytical consistency, we employ the idea of adaptive learning to such short time series in the context of annual growth rates for Greek agricultural commodities.

The analysis of the existing study relies on a wide range of variables, starting with the dependent variables, including the following: BAP, SUN, DWW and MPP prices, all measured in euros per 100 kg (Pp100 kg) and also FSE, measured in thousand tonnes of oil equivalent (TTOE). BAP is the fifth most widely cultivated cereal crop globally, known for its resilience under diverse environmental conditions and its economic viability due to lower input requirements and simpler agronomic management (Verstegen et al., 2014; Farooq, 2015). However, its cultivation area is going to get reduced in the upcoming years, making accurate forecasting essential, particularly given its strategic agricultural role (Parviz, 2018; Sharafi & Nahvinia, 2024). MPP is the most widely produced crop globally and serves as a vital energy source, particularly in developing countries, where it plays a key role in food and agriculture ecosystems (Zelingher & Makowski, 2022). Despite its global importance, maize prices are highly sensitive to production shocks in some regions, underscoring the need for reliable forecasting, especially as some countries depend heavily on this agricultural commodity and its prices (Zelingher et al., 2020). On the other hand, SUN is a key variable in this analysis due to its role as a substitute commodity influenced by biofuel markets (Paris, 2018). Also, DWW is considered as a crop of strategic importance in Greece, contributing to 1.3 million metric tons of production annually, reflecting its central role in the country's agricultural output and Mediterranean agricultural markets and systems (Toscano et al., 2014). Last but not least, FSE is critical for rational energy consumption strategic planning in the electricity sector, as power generation remains heavily reliant on fossil fuels and future consumption is expected to increase steadily (Sun, He, & Chang, 2015).

To improve forecasting accuracy, we create energy related indices, including fuel oil (FOL), hydro power (HYR), natural gas (NGS), renewables and biofuels (RNW), wind power (WND), lignite (LGN), other oleaginous products (OLE), oil and petroleum products (OPP), pumped hydro power (PHY), refinery gas (RFG), solid fossil fuels (SFF), and total energy consumption (TTL), which all serve as leading indicators for agricultural price fluctuations (Groen & Pesenti, 2011). These indices are analyzed through two estimation methods the QR and OLS methods, using the specific γ values[2] of 0.35, 0.40, and 0.50. Furthermore, in order to determine and select the most accurate forecasting model, we examine the performance of all indices across our dataset. To select the most accurate forecasting model, we created a ratio index which is calculated by dividing the adaptive learning value with each of the performance metric values. Our forecasting framework employs standard performance measures (MAE, MAPE, RMSE) in line with contemporary advances in adaptive learning applications for volatile markets, allowing for systemic evaluation of model performance across various specifications. We define the metrics as follows:

$$\begin{aligned} \mathrm{MSE}\left(m,n_1\right) &\overset{\mathrm{def}}{=} n_1^{-1}\sum_{t=n_0+1}^{n}\hat{\epsilon}_t^{m,2} \\ \mathrm{MAE}\left(m,n_1\right) &\overset{\mathrm{def}}{=} n_1^{-1}\sum_{t=n_0+1}^{n}\left|\hat{\epsilon}_t^{m}\right| \\ \mathrm{MAPE}\left(m,n_1\right) &\overset{\mathrm{def}}{=} n_1^{-1}\sum_{t=n_0+1}^{n}\left|\frac{\hat{\epsilon}_t^{m}}{y_t}\right|\times 100 \end{aligned} \tag{6}$$

4. Discussion of Results

In this section we present the results of our analysis focusing on how volatile energy markets affect the prices of agricultural commodities and which forecasting approach provides the most accurate results. The fossil driven NGS-SFF-TTL index combines NGS, SFF, which includes lignite and coal, and TTL to quantify traditional energy inputs critical for BAP and DWW production, where fuel intensive farming and processing dominate cost structures. The renewable integrated NGS-WND-HYR index connects NGS with WND and HYR, designed specifically for SUN markets to reflect how renewable adoption balances against fossil fuel volatility. Each index is constructed in three analytical stages through normalized growth rate aggregation and average computing of its constituent components-measured in TTOE for energy and Pp100 kg (€/100kg) for agricultural commodities and serving as the main core of our forecasting framework.

First of all, we set the benchmark models including a first-order autoregressive model, an autoregressive model, a delay model and an autoregressive-delay model. Second, we employ both recursive least squares and median quantile regression to estimate the models, forecasting one year ahead and identifying the best-performing model forecast, which is passed on to the adaptive learning method. The estimation of the models and their results are presented using rolling windows of 28 and 30 months. Moreover, we use this approach serves as a test of the adaptive learning method allowing us to achieve errors reduction. As shown in Table 1 (variable explanations and units of measurement), Table 2 and Table 3 (performance results), this structured approach allows for precise identification of which energy indicators exert dominant influence on specific agricultural commodities under different market circumstances.

---

[2] The parameter γ refers to the learning rate used in the adaptive learning forecasting model introduced by Kyriazi et al. (2019). This parameter controls how much weight is placed on recent forecast errors in updating future predictions.

Table 1. Abbreviations of energy and agricultural variables.

Abbreviation	Explanation	Unit of Measurement
FOL	Fuel oil	TTOE
HYR	Hydro	TTOE
LGN	Lignite	TTOE
NGS	Natural gas	TTOE
OLE	Other oleaginous products	TTOE
OPP	Oil and petroleum products	TTOE
PHY	Pumped hydro power	TTOE
RFG	Refinery gas	TTOE
RNW	Renewables and biofuels	TTOE
WND	Wind	TTOE
SFF	Solid fossil fuels	TTOE
TTL	Total	TTOE
BAP	Barley	Pp100 kg
DWW	Durum wheat	Pp100 kg
MPP	Maize	Pp100 kg
FSE	Fossil energy	TTOE
SUN	Sunflowers	Pp100 kg

1) Pp100 kg is set as Prices per 100 kg (€/100 kg); 2) TTOE is set as Thousand tonnes of oil equivalent; 3) OPP: Oil and petroleum products exclude biofuel content.

We start off our discussion with Table 2, including the analysis of BAP, SUN and DWW. For BAP, the QR method paired with the NGS-SFF-TTL index, yields the most accurate predictions, achieving a MAPE ratio of 0.269 at a γ value of 0.50. This finding aligns with the broader economic literature emphasizing the outsized role of fossil fuel costs in agricultural production, transportation, and processing (Koenker & Bassett, 1978). The superiority of QR over the OLS estimation method in this context likely stems from its ability to model extreme price fluctuations caused by energy shortages, which are common in volatile markets. On the other side, the OLS shows a weaker performance, with a MAPE ratio of 0.471 at a γ value of 0.35 for the SFF-TTL-LGN index, indicating only a 52.9% reduction, while at the same time the WND-RNW-FOL index performs best for OLS in terms of RMSE, revealing a ratio value of 0.927. SUN prices benefit most from indices combine NGS-WND-HYR, with QR achieving an RMSE ratio of 0.856. This suggests that renewable energy sources play a stabilizing role in mitigating fossil fuel price shocks-a phenomenon noted in studies of sunflower oil production (Serra & Gil, 2013). The NGS-WND-HYR index also performs well in terms of MAPE at a ratio of 0.513. Interestingly, OLS performs comparably well for SUN MAE (ratio: 0.872), indicating that linear models may suffice during periods of relative market calm, while struggling with a MAPE ratio of 0.784. In contrast, DWW forecasts remain challenging, with MAE ratios hovering near 1.0. This weakness likely reflects unmodeled factors such as geopolitical disruptions (e.g., export restrictions in Mediterranean regions) or climate variability, underscoring the need for expanded variable selection in future work. Using the QR, the RFG-OLE-FOL index achieves the best RMSE ratio of 0.926 with a γ value of 0.40, while the FOL-TTL-RNW index shows almost zero improvement in terms of MAE (ratio: 0.999). According to the OLS, both MAE (ratio: 0.997) and RMSE (ratio: 0.949) remain close to 1.00. In addition, the HYR-LGN-WND index presents the greatest MAPE ratio value of 0.569—among the estimation methods—associated with a γ value of 0.35, clearly outperforming QR estimation in this performance measure.

Turning to MPP and FSE, as shown in **Table 3**, hybrid indices like WND-RNW-FOL dominate performance. For MPP variable, OLS achieves a MAPE ratio of 0.738, outperforming QR. This divergence may reflect MPP dual role as both a food staple and biofuel feedstock, where symmetric price relationships (e.g., policy-driven biofuel demand) align better with linear methods (Reboredo, 2015). Moreover, the results for MPP demonstrate an interesting framework of discussion between the QR and the OLS. The WND-RNW-SFF index particularly achieves the lowest RMSE ratio of 0.926 for the OLS and on the opposite side the OPP-WND-PHY index also shows such a good performance in terms of MAE (ratio: 0.942). FSE proves inherently harder to forecast, with even the best performing HYR-PHY-WND yielding a MAE ratio of 0.943. The persistent gaps here likely stem from geopolitical shocks (e.g., OPEC supply decisions) not captured by current indices. The analysis of FSE in **Table 3** reveals distinct forecasting challenges compared to agricultural commodities. Under the QR estimation method, the SFF-TTL-RNW index achieves a MAPE ratio of 0.913, indicating a slight improvement, while the FOL-RFG-RNW index performs better in terms of RMSE (ratio: 0.946). In particular, the γ value of 0.50 continues to dominate in the majority of the cases discussed above, while lower γ values (e.g., 0.35) consistently underperform, suggesting that timid adaptation fails to counter rapid price fluctuations. Furthermore, given that the energy consumption framework closely follows economic activity, both in terms of industrial production and household usage (Baimpos & Kyriazi, 2025), it is clearly captured through indices that combine fossil and renewable energy consumption sources, mirroring real world trends toward energy diversification and having a critical role in enhancing human development (Lekana & Ikiemi, 2021). While QR excels in high-volatility scenarios (e.g., BAP and SUN), OLS remains viable for commodities with smoother price dynamics, such as MPP[3].

---

[3] To evaluate predictive validity, we first conducted Mincer-Zarnowitz test, which failed to reject the null hypothesis of unbiased and efficient forecasts for all top-performing models, confirming their statistical validity. Furthermore, Clark-West test for predictive ability showed mixed but generally favorable results, with our models frequently outperforming these conventional benchmarks.

Table 2. Forecasting performance of quantile regression and ordinary least squares for barley, sunflowers & durum wheat.

Metrics	Ratio	γ	Est. Method	Indices
Barley (BAP)				
MAE	0.922	0.50	QR	NGS RFG PHY
MAPE	0.269	0.50	QR	NGS SFF TTL
RMSE	0.944	0.50	QR	SFF LGN HYR
Barley (BAP)				
MAE	0.978	0.50	OLS	SFF TTL OPP
MAPE	0.471	0.35	OLS	SFF TTL LGN
RMSE	0.927	0.50	OLS	WND RNW FOL
Sunflowers (SUN)				
MAE	0.897	0.50	QR	OPP OLE FOL
MAPE	0.513	0.50	QR	NGS WND HYR
RMSE	0.856	0.50	QR	NGS WND HYR
Sunflowers (SUN)				
MAE	0.872	0.50	OLS	NGS WND HYR
MAPE	0.784	0.50	OLS	HYR LGN WND
RMSE	0.903	0.50	OLS	HYR LGN WND
Durum Wheat (DWW)				
MAE	0.999	0.40	QR	FOL TTL RNW
MAPE	0.752	0.40	QR	RFG OLE FOL
RMSE	0.926	0.40	QR	RFG OLE FOL
Durum Wheat (DWW)				
MAE	0.997	0.35	OLS	FOL TTL RNW
MAPE	0.569	0.35	OLS	HYR LGN WND
RMSE	0.949	0.40	OLS	NGS OLE WND

1) Performance metrics: MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Squared Error); 2) Ratio = Adaptive Learning/Performance Measure Value; 3) γ represents the optimal learning rate parameter, as discussed in the second footnote; 4) Estimation methods: QR (Quantile Regression), OLS (Ordinary Least Squares); 5) Indices represent combinations of energy-related variables.

Table 3. Forecasting performance of quantile regression and ordinary least squares for maize & fossil energy consumption.

Metrics	Ratio	γ	Est. Method	Indices
		Maize (MPP)		
MAE	0.942	0.50	QR	OPP WND PHY
MAPE	0.753	0.35	QR	OPP WND PHY
RMSE	0.926	0.35	QR	WND RNW SFF
		Maize (MPP)		
MAE	0.974	0.50	OLS	WND RNW FOL
MAPE	0.738	0.50	OLS	WND RNW FOL
RMSE	0.952	0.40	OLS	OPP WND PHY
		Fossil Energy (FSE)		
MAE	0.943	0.50	QR	HYR PHY WND
MAPE	0.913	0.50	QR	SFF TTL RNW
RMSE	0.946	0.40	QR	FOL RFG RNW
		Fossil Energy (FSE)		
MAE	0.954	0.50	OLS	WND RNW FOL
MAPE	0.974	0.50	OLS	LGN SFF OPP
RMSE	0.949	0.40	OLS	FOL RFG RNW

1) Performance metrics: MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), RMSE (Root Mean Squared Error); 2) Ratio = Adaptive Learning/Performance Measure Value; 3) γ represents the optimal learning rate parameter, as discussed in the second footnote; 4) Estimation methods: QR (Quantile Regression), OLS (Ordinary Least Squares); 5) Indices represent combinations of energy-related variables.

5. Conclusion and Policy Implication

Our paper demonstrates the effectiveness of adaptive learning methodology in forecasting agricultural and energy commodity prices, particularly in volatile and data-limited contexts. By combining composite energy indices with quantile regression and ordinary least squares, the adaptive learning model achieves a significant reduction in forecasting errors—up to 27% compared to traditional benchmarks. Our results highlight the adaptability of QR in high-volatility markets, such as BAP and SUN, while confirming that OLS remains effective for commodities with more stable price trends, like MPP. The success of our adaptive learning approach, particularly with an optimal γ value of 0.50, underscores its ability to capture asymmetric risks and structural shifts, providing valuable insights for stakeholders in interconnected energy and agricultural markets.

Our findings suggest that policymakers should adopt adaptive learning models to improve decision-making in agricultural and energy sectors, especially in regions like Greece, where data scarcity and market volatility pose significant challenges. By utilizing composite indices that integrate both fossil and renewable energy variables, governments can better anticipate price fluctuations and mitigate risks linked to energy transitions or climate-related disruptions. Furthermore, our results emphasize the need for enhanced data infrastructure and cross-disciplinary research to address gaps in high-frequency data availability, ensuring more accurate and timely forecasts. Such measures would bolster sustainable agricultural practices, energy security, and economic resilience amid global uncertainties.

For industry stakeholders, our research underscores the benefits of diversifying energy sources and employing flexible forecasting tools to manage price volatility. Policymakers could integrate our models into early warning systems to proactively address food security and energy affordability challenges, fostering more stable and sustainable markets.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Allen, P. G. (1994). A Note on Forecasting with Econometric Models. *Northeastern Journal of Agricultural and Resource Economics, 13,* 264-267. https://doi.org/10.1017/s0899367x00000593

Baimpos, G., & Kyriazi, F. (2025). Nonlinear GDP Forecasting: A Threshold-ARDLX Approach with Leading Macroeconomic Indicators. *Theoretical Economics Letters, 15,* 446-460. https://doi.org/10.4236/tel.2025.152024

Bastian, J., Zhu, J. X., Banunarayanan, V., & Mukerji, R. (1999). Forecasting Energy Prices in a Competitive Market. *IEEE Computer Applications in Power, 12,* 40-45. https://doi.org/10.1109/67.773811

Ben Ameur, H., Boubaker, S., Ftiti, Z., Louhichi, W., & Tissaoui, K. (2024). Forecasting Commodity Prices: Empirical Evidence Using Deep Learning Tools. *Annals of Operations Research, 339,* 349-367. https://doi.org/10.1007/s10479-022-05076-6

Ben-Ari, T., Adrian, J., Klein, T., Calanca, P., Van der Velde, M., & Makowski, D. (2016). Identifying Indicators for Extreme Wheat and Maize Yield Losses. *Agricultural and Forest Meteorology, 220,* 130-140. https://doi.org/10.1016/j.agrformet.2016.01.009

Chou, J., & Tran, D. (2018). Forecasting Energy Consumption Time Series Using Machine Learning Techniques Based on Usage Patterns of Residential Householders. *Energy, 165,* 709-726. https://doi.org/10.1016/j.energy.2018.09.144

Cleveland, W. S. (1971). Stochastic Modeling of Economic Time Series. *Journal of the American Statistical Association, 66,* 552-564.

Divina, F., García Torres, M., Goméz Vela, F. A., & Vázquez Noguera, J. L. (2019). A Comparative Study of Time Series Forecasting Methods for Short Term Electric Energy Consumption Prediction in Smart Buildings. *Energies, 12,* Article No. 1934. https://doi.org/10.3390/en12101934

Farooq, S. (2015). Forecasting Area and Production of Barley in Punjab. *Pakistan Journal of Agricultural Research, 28,* 304-309.

Ferrari, D., Ravazzolo, F., & Vespignani, J. (2021). Forecasting Energy Commodity Prices: A Large Global Dataset Sparse Approach. *Energy Economics, 98,* Article ID: 105268. https://doi.org/10.1016/j.eneco.2021.105268

Fowowe, B. (2016). Do Oil Prices Drive Agricultural Commodity Prices? Evidence from South Africa. *Energy, 104,* 149-157. https://doi.org/10.1016/j.energy.2016.03.101

Gargano, A., & Timmermann, A. (2014a). Forecasting Commodity Prices. *Journal of Forecasting, 33,* 405-419.

Gargano, A., & Timmermann, A. (2014b). Forecasting Commodity Price Indexes Using Macroeconomic and Financial Predictors. *International Journal of Forecasting, 30,* 825-843. https://doi.org/10.1016/j.ijforecast.2013.09.003

Groen, J. J. J., & Pesenti, P. A. (2011). Commodity Prices, Commodity Currencies, and Global Economic Developments. In T. Ito, & A. K. Rose (Eds.), *Commodity Prices and Markets* (pp. 15-42). University of Chicago Press. https://doi.org/10.7208/chicago/9780226386904.003.0002

Guerard, J. B., Thomakos, D., Kyriazi, F., & Beheshti, B. (2024). The Development and Evolution of Mean-Variance Efficient Portfolios in the US and Japan: 30 Years after the Markowitz and Ziemba Applications. *Annals of Operations Research*. https://doi.org/10.1007/s10479-024-06138-7

Han, L., Zhou, Y., & Yin, L. (2015). Exogenous Impacts on the Links between Energy and Agricultural Commodity Markets. *Energy Economics, 49,* 350-358. https://doi.org/10.1016/j.eneco.2015.02.021

Heij, C., van Dijk, D., & Groenen, P. J. F. (2011). Real-Time Macroeconomic Forecasting with Leading Indicators: An Empirical Comparison. *International Journal of Forecasting, 27,* 466-481. https://doi.org/10.1016/j.ijforecast.2010.04.008

Herrera, G. P., Constantino, M., Tabak, B. M., Pistori, H., Su, J., & Naranpanawa, A. (2019). Long-Term Forecast of Energy Commodities Price Using Machine Learning. *Energy, 179,* 214-221. https://doi.org/10.1016/j.energy.2019.04.077

Hong, T., Pinson, P., Wang, Y., Weron, R., Yang, D., & Zareipour, H. (2020). Energy Forecasting: A Review and Outlook. *IEEE Open Access Journal of Power and Energy, 7,* 376-388. https://doi.org/10.1109/oajpe.2020.3029979

Kehagia, A., & Kyriazi, F. (2021). Structural Funds and Regional Economic Growth: The Greek Experience. *Review of Economic Analysis, 13,* 501-532. https://doi.org/10.15353/rea.v13i3.3481

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica, 46,* 33-50. https://doi.org/10.2307/1913643

Kofi, T. A. (1973). A Framework for Comparing the Efficiency of Futures Markets. *American Journal of Agricultural Economics, 55,* 584-594. https://doi.org/10.2307/1238343

Kyriazi, F. (2024). The Prescriptive Nature of Market Timing and Predictive Portfolios. *IMA Journal of Management Mathematics, 36,* 323-338. https://doi.org/10.1093/imaman/dpae027

Kyriazi, F., & Thomakos, D. D. (2020a). Foreign Exchange Rate Predictability: *Seek and Ye Shall Find It*. In J. B. Guerard, & W. T. Ziemba (Eds.), *Handbook of Applied Investment Research* (pp. 511-556). World Scientific. https://doi.org/10.1142/9789811222634_0020

Kyriazi, F., & Thomakos, D. D. (2020b). Distance-Based Nearest Neighbour Forecasting with Application to Exchange Rate Predictability. *IMA Journal of Management Mathematics, 31,* 469-490. https://doi.org/10.1093/imaman/dpz016

Kyriazi, F., Thomakos, D. D., & Guerard, J. B. (2019). Adaptive Learning Forecasting, with Applications in Forecasting Agricultural Prices. *International Journal of Forecasting, 35,* 1356-1369. https://doi.org/10.1016/j.ijforecast.2019.03.031

Kyriazi, F., Xylangouras, E., & Papadogonas, T. (2024). On the Forecastability of Agricultural Output. *Review of Economic Analysis, 16,* 443-467. https://doi.org/10.15353/rea.v16i4.5620

Lehmann, E. L., & Romano, J. P. (2020). *Testing Statistical Hypotheses* (4th ed.). Spring-er.

Lekana, H. C., & Ikiemi, C. B. S. (2021). Effect of Energy Consumption on Human Development in the Countries of the Economic and Monetary Community of Central Africa (EMCCA). *Theoretical Economics Letters, 11,* 404-421. https://doi.org/10.4236/tel.2021.113027

López Cabrera, B., & Schulz, F. (2016). Volatility Linkages between Energy and Agricultural Commodity Prices. *Energy Economics, 54,* 190-203. https://doi.org/10.1016/j.eneco.2015.11.018

Manogna, R. L., & Mishra, A. K. (2021). Forecasting Spot Prices of Agricultural Commodities in India: Application of Deep-Learning Models. *Intelligent Systems in Accounting, Finance and Management, 28,* 72-83. https://doi.org/10.1002/isaf.1487

Moore, H. L. (1917). Forecasting the Yield and Price of Cotton. *Journal of Political Economy, 25,* 1-24.

Naylor, T. H., Seaks, T. G., & Wichern, D. W. (1972). Box-Jenkins Methods: An Alternative to Econometric Models. *International Statistical Review, 40,* 123-137. https://doi.org/10.2307/1402755

Nikolopoulos, K. I., & Thomakos, D. D. (2019). Forecasting Analytics. In B. Pochiraju, & S. Seshadri (Eds.), *Essentials of Business Analytics* (pp. 381-420). Springer International Publishing. https://doi.org/10.1007/978-3-319-68837-4_12

Ouyang, H., Wei, X., & Wu, Q. (2019). Agricultural Commodity Futures Prices Prediction via Long- and Short-Term Time Series Network. *Journal of Applied Economics, 22,* 468-483. https://doi.org/10.1080/15140326.2019.1668664

Paris, A. (2018). On the Link between Oil and Agricultural Commodity Prices: Do Biofuels Matter? *International Economics, 155,* 48-60. https://doi.org/10.1016/j.inteco.2017.12.003

Parviz, L. (2018). Assessing Accuracy of Barley Yield Forecasting with Integration of Climate Variables and Support Vector Regression. *Annales Universitatis Mariae Curie-Sklodowska, Sectio C—Biologia, 73,* 19. https://doi.org/10.17951/c.2018.73.1.19-30

Pierce, D. A. (1977). Relationships—and the Lack Thereof—between Economic Time Series, with Special Reference to Money and Interest Rates. *Journal of the American Statistical Association, 72,* 11-22. https://doi.org/10.1080/01621459.1977.10479899

Qader, S. H., Dash, J., & Atkinson, P. M. (2018). Forecasting Wheat and Barley Crop Production in Arid and Semi-Arid Regions Using Remotely Sensed Primary Productivity and Crop Phenology: A Case Study in Iraq. *Science of the Total Environment, 613,* 250-262. https://doi.org/10.1016/j.scitotenv.2017.09.057

Reboredo, J. C. (2015). Is There Dependence and Systemic Risk between Oil and Renewable Energy Stock Prices? *Energy Economics, 48,* 32-45. https://doi.org/10.1016/j.eneco.2014.12.009

Rostan, P., & Rostan, A. (2021). Where Are Fossil Fuels Prices Heading? *International Journal of Energy Sector Management, 15,* 309-327. https://doi.org/10.1108/ijesm-07-2019-0009

Schachinger, D., Pannosch, J., & Kastner, W. (2018). Adaptive Learning-Based Time Series Prediction Framework for Building Energy Management. In *2018 IEEE International Conference on Industrial Electronics for Sustainable Energy Systems (IESES)* (pp. 453-

458). IEEE. https://doi.org/10.1109/ieses.2018.8349919

Serra, T., & Gil, J. M. (2013). Price Volatility in Food Markets: Can Stock Building Mitigate Price Fluctuations? *European Review of Agricultural Economics, 40,* 507-528. https://doi.org/10.1093/erae/jbs041

Shafiee, S., & Topal, E. (2010). A Long-Term View of Worldwide Fossil Fuel Prices. *Applied Energy, 87,* 988-1000. https://doi.org/10.1016/j.apenergy.2009.09.012

Shahhosseini, M., Hu, G., & Archontoulis, S. V. (2020). Forecasting Corn Yield with Machine Learning Ensembles. *Frontiers in Plant Science, 11,* Article No. 1120. https://doi.org/10.3389/fpls.2020.01120

Sharafi, S., & Nahvinia, M. J. (2024). Sustainability Insights: Enhancing Rainfed Wheat and Barley Yield Prediction in Arid Regions. *Agricultural Water Management, 299,* Article ID: 108857. https://doi.org/10.1016/j.agwat.2024.108857

Sun, W., He, Y., & Chang, H. (2015). Forecasting Fossil Fuel Energy Consumption for Power Generation Using QHSA-Based LSSVM Model. *Energies, 8,* 939-959. https://doi.org/10.3390/en8020939

Sun, Y., Zhang, X., Wang, H., & Li, J. (2023). Hybrid Forecasting Models for Agricultural Commodity Prices: A Review. *Journal of Agricultural Economics, 74,* 456-472.

Thomakos, D., Wood, G., Ioakimidis, M., & Papagiannakis, G. (2023). ShoTS Forecasting: Short Time Series Forecasting for Management Research. *British Journal of Management, 34,* 539-554. https://doi.org/10.1111/1467-8551.12624

Toscano, P., Gioli, B., Genesio, L., Vaccari, F. P., Miglietta, F., Zaldei, A. et al. (2014). Durum Wheat Quality Prediction in Mediterranean Environments: From Local to Regional Scale. *European Journal of Agronomy, 61,* 1-9. https://doi.org/10.1016/j.eja.2014.08.003

Tudor, C., Sova, R., Stamatiou, P., Vlachos, V., & Polychronidou, P. (2025). Future-Proofing EU-27 Energy Policies with AI: Analyzing and Forecasting Fossil Fuel Trends. *Electronics, 14,* Article No. 631. https://doi.org/10.3390/electronics14030631

Verstegen, H., Köneke, O., Korzun, V., & von Broock, R. (2014). The World Importance of Barley and Challenges to Further Improvements. In J. Kumlehn, & N. Stein (Eds.), *Bio-Technological Approaches to Barley Improvement. Biotechnology in Agriculture and Forestry* (pp. 3-19). Springer. https://doi.org/10.1007/978-3-662-44406-1_1

Wang, Y., Feng, L., Sui, X., Chu, J., & Mu, L. (2020). Nonlinear Regression Models for Agricultural Price Forecasting: A Comparative Study. *Agricultural Systems, 180,* 102-115.

Xiong, T., Li, C., Bao, Y., & Hu, Z. (2015). Forecasting Commodity Futures Prices: A Hybrid VECM-MSVR Approach. *Energy Economics, 50,* 1-12.

Zelingher, R., & Makowski, D. (2022). Forecasting Global Maize Prices from Regional Productions. *Frontiers in Sustainable Food Systems, 6,* Article ID: 836437. https://doi.org/10.3389/fsufs.2022.836437

Zelingher, R., Makowski, D., & Brunelle, T. (2020). *Forecasting Impacts of Agricultural Production on Global Maize Price*. CIRED Working Papers, HAL.

Zhang, D., Chen, S., Liwen, L., & Xia, Q. (2020). Forecasting Agricultural Commodity Prices Using Model Selection Framework with Time Series Features and Forecast Horizons. *IEEE Access, 8,* 28197-28209. https://doi.org/10.1109/access.2020.2971591