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COMPARATIVE ANALYSIS OF FUZZY REGRESSION MODELS AND MULTICRITERIA DECISION-MAKING FOR COMMODITY MARKET FORECASTING SCENARIOS

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ABSTRACT

This paper presents a comparative analysis of fuzzy regression models and constructs a scenario using fuzzy multi-criteria decision-making (MCDM) based on subjective market expectations for commodities and grains in the international market. The study evaluates the effectiveness of Fuzzy Linear Regression (FLR) and Multi-Objective Fuzzy Linear Regression (MOFLR) in predicting commodity prices and applies the fuzzy 2-*tuple* TOPSIS and VIKOR methods for decision-making under uncertainty. To ensure robustness, a Monte Carlo simulation is employed, generating numerous random samples to evaluate the stability of the rankings. The findings indicate that MOFLR is more robust in handling outliers and data variability compared to FLR. The combined use of fuzzy regression models and MCDM methods provides a comprehensive framework for forecasting and decision-making in volatile markets, supporting more informed and effective strategic planning.

KEYWORDS. Fuzzy Regression, Multi-Criteria Decision-Making, Commodity Forecasting

Paper topics: ADM, AG&MA, EST&MP

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1. Introduction

In recent years, the complexity and volatility of global commodity markets have presented significant challenges for accurate forecasting and decision-making. Commodity prices are influenced by a wide range of factors, including weather patterns, geopolitical tensions, currency fluctuations, and shifts in global supply and demand. In agricultural markets, these challenges are even more pronounced, as crop yields and quality are highly dependent on unpredictable weather conditions, such as droughts or floods, and other environmental variables. The growing interdependence of global economies further complicates these dynamics, as trade policies and international relations can rapidly alter market conditions.

Accurate forecasting in such a dynamic environment is crucial for stakeholders, including farmers, investors, and policymakers, who rely on these predictions to make informed decisions regarding production, trading, and risk management. Traditional regression models, while widely used, often fail to capture the inherent uncertainties and nonlinearities present in these markets. For instance, linear regression models are not well-suited to handle sudden market shocks or the gradual, uncertain impacts of climate change on crop production.

Fuzzy regression models, such as Fuzzy Linear Regression (FLR) and Multi-Objective Fuzzy Linear Regression (MOFLR), offer powerful alternatives by incorporating fuzziness to handle imprecise and uncertain data. Unlike traditional models, fuzzy regression allows for the inclusion of ambiguity in both the dependent and independent variables, which is particularly useful in agricultural commodity markets where data uncertainty is high. FLR, introduced by Tanaka et al. [1982], provides a flexible framework for modeling relationships in the presence of fuzzy data, enabling more accurate and nuanced forecasts. MOFLR, developed by Nasrabadi et al. [2005], builds upon this by incorporating multiple objectives, such as minimizing error spread and improving robustness against outliers, which are common in datasets affected by extreme weather events or other sudden market disruptions.

The primary innovation of this paper lies in the combination of fuzzy regression models with Multi-Criteria Decision-Making (MCDM) methods, specifically the use of fuzzy 2-tuple TOPSIS and VIKOR. This unique integration allows for more robust scenario forecasting in highly volatile markets, providing stakeholders with a tool that can accommodate both quantitative data and subjective market expectations. Additionally, we employ Monte Carlo simulations to assess the stability of the rankings produced by these methods, ensuring reliability even in the face of uncertainty.

By providing actionable insights for stakeholders, this paper contributes to the growing body of literature on the application of fuzzy and MCDM techniques in commodity market forecasting. For farmers, investors, and policymakers, this approach offers a means to enhance strategic planning, optimize risk management, and navigate market volatility with greater confidence.

In the following section, we review recent developments in the fields of fuzzy regression and MCDM, highlighting key contributions that provide the foundation for our methodology.

2. Literature Review

The use of fuzzy regression models and multi-criteria decision-making (MCDM) techniques has gained prominence in commodity price forecasting, particularly due to their ability to handle uncertainty and imprecise data in volatile markets such as agriculture. This section reviews key studies on fuzzy regression and MCDM, highlighting their contributions and applicability to agricultural commodity markets.

2.1. Fuzzy Regression Models

Fuzzy regression models are well-suited for handling the uncertainty typical in agricultural markets. These models extend traditional regression by incorporating fuzzy logic, providing more flexibility when modeling imprecise data.

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Mustafa et al. [2022] introduced the FGARCH model, which improves price prediction accuracy using fuzzy least squares techniques. Although developed for stock markets, this modelâs ability to handle volatility is highly relevant for commodities affected by external shocks. Similarly, Pushpa and Muruganandam [2014] proposed a fuzzy linear regression model for gold prices, improving forecast precision in non-linear markets, a common characteristic of agricultural commodities due to fluctuating weather conditions.

Efendi et al. [2018] introduced a fuzzy random auto-regression model, using triangular fuzzy numbers to improve accuracy in volatile markets. This modelâs adaptability to variability makes it suitable for agricultural commodities. However, its complexity in defining fuzzy parameters can be a limitation in practical applications.

Finally, Maciel et al. [2017] developed a possibilistic fuzzy model, demonstrating robustness in the presence of noise and outliers. Although promising for markets impacted by unpredictable events, its application to agricultural commodities remains limited.

While fuzzy regression models have proven effective in various financial contexts, their application in agriculture is still underexplored. Given the unique challenges of agricultural commodities, further empirical studies are needed to validate these models in this context.

2.2. Fuzzy Multi-Criteria Decision Making (MCDM) Methods

MCDM methods provide structured frameworks for evaluating multiple criteria, making them valuable for decision-making in agricultural markets. These methods account for factors such as price volatility, global demand, and environmental risks.

Ceballos et al. [2017] compared fuzzy MCDM methods (MULTIMOORA, TOPSIS, VIKOR, WASPAS), offering insights into their flexibility in uncertain environments. Their focus was primarily on financial markets, but similar techniques can enhance decision-making in agricultural markets, which also face high levels of uncertainty.

Majhi and Anish [2015] integrated fuzzy logic with optimization models (MOPSO, NSGA-II) to improve stock market predictions. These adaptive approaches are relevant for agricultural commodities, where conditions change rapidly, requiring models that can respond to evolving data.

In addition, Tang and Liao [2018] applied fuzzy linguistic models to sales forecasting, which is applicable in agriculture where qualitative expert opinions are often as valuable as quantitative data. This combined approach could improve accuracy by integrating both qualitative and quantitative factors.

The integration of fuzzy regression with MCDM techniques in agricultural forecasting remains limited. This paper aims to bridge this gap, leveraging fuzzy regression models (FLR, MOFLR) alongside fuzzy MCDM methods (TOPSIS, VIKOR) to provide a comprehensive framework for decision-making in agricultural commodities.

2.3. Contributions of This Study

Although existing research on fuzzy regression and MCDM methods is extensive, the combination of these techniques for agricultural commodity forecasting remains underexplored. This study integrates fuzzy regression models and MCDM methods with Monte Carlo simulations to analyze their robustness and reliability, providing practical insights for stakeholders in agricultural commodity markets. By addressing uncertainties unique to agriculture, this study offers a valuable framework for more informed decision-making.

3. Methodology

This section presents the methodologies employed in our study, focusing on the application of fuzzy linear regression (FLR) models, the multi-objective fuzzy linear regression (MOFLR) approach, and the multi-criteria decision making (MCDM) methods using fuzzy 2-*tuple* TOPSIS and VIKOR. These methods were chosen due to their superior ability to handle imprecise and

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fuzzy data, which is prevalent in agricultural commodity markets. Alternative fuzzy methods such as Fuzzy Time Series and Fuzzy Inference Systems were considered, but they are less suited to continuous data environments or require additional complexities for handling multi-objective trade-offs, which MOFLR and MCDM naturally address. The rationale behind selecting these models is grounded in their robustness to outliers and capacity to provide more accurate estimates in uncertain environments.

3.1. Fuzzy Linear Regression (FLR)

Fuzzy linear regression (FLR) was introduced by Tanaka et al. [1982] and further developed by Diamond [1988]. This approach models the relationship between dependent and independent variables in situations where the data is imprecise or fuzzy. The general form of an FLR model can be expressed as:

$$\tilde{Y}_i = \tilde{A}_0 + \tilde{A}_1\tilde{X}_{i1} + \ldots + \tilde{A}_n\tilde{X}_{in}, \quad i = 1, 2, \ldots, m, \tag{1}$$

where $\tilde{X_{ij}} = (x_{ij}, r_{ij})$ are fuzzy numbers representing the j-th independent variable in the i-th observation, and $\tilde{A_j} = (a_j, a_j)$ are fuzzy parameters with a symmetric membership function:

$$\tilde{A}(t) = L\left(\frac{t-a}{a}\right), \quad a \geq 0. \tag{2}$$

Using the extension principle and the approximation formula presented by Dubois and Prade [1980], the fuzzy parameters $\tilde{Y_i}$ can be approximated by symmetric fuzzy numbers (y_i, e_i), where:

$$y_i = a_0 + \sum_{j=1}^{n} a_j x_{ij}, \tag{3}$$

$$e_i = a_0 + \sum_{j=1}^{n} \left(a_j|x_{ij}| + r_{ij}|a_j|\right). \tag{4}$$

The FLR model seeks to minimize the total spread of the fuzzy parameters while ensuring the support of the estimated values covers the observed values' support at a certain h-level. Despite its strengths, the FLR model has been criticized for its sensitivity to outliers and the widening spread of estimated values as more data are included [Nasrabadi et al., 2005].

3.2. Multi-Objective Fuzzy Linear Regression (MOFLR)

To address the shortcomings of the traditional FLR model, Nasrabadi et al. [2005] developed the multi-objective fuzzy linear regression (MOFLR) model. This approach introduces multiple objectives to improve the robustness and accuracy of the regression analysis in the presence of outliers.

The MOFLR model is formulated as follows:

$$\begin{aligned}
\min \quad & D^2(h) = \sum_{i=1}^{m} (e_i - \hat{e_i})^2, \\
\min \quad & E^2(h) = \sum_{i=1}^{m} (e_{i,L}^2 + e_{i,R}^2), \\
\text{s.t.} \quad & y_i - \hat{y}_i \leq e_{i,L}, \quad i = 1, \ldots, m, \\
& \hat{y}_i - y_i \leq e_{i,R}, \quad i = 1, \ldots, m, \\
& e_i \geq 0, \quad e_{i,L}, e_{i,R} \geq 0, \quad i = 1, \ldots, m,
\end{aligned} \tag{5}$$

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where $D^2(h)$ represents the total error of fit, measuring the squared differences between observed errors e_i and predicted errors $\hat{e}_i$. On the other hand, $E^2(h)$ represents the deviation due to outliers, with $e_{i,L}$ and $e_{i,R}$ being the relaxation variables that account for the left and right deviations, respectively. This model ensures that all data points contribute to the parameter estimation, enhancing the model's robustness against outliers.

The choice of the fuzzy least squares (FLS) model, as proposed by Diamond [1988], and the MOFLR model by Nasrabadi et al. [2005] is driven by their respective advantages in handling fuzzy data. The FLS model is favored for its simplicity and computational efficiency, making it suitable for initial estimations. In contrast, the MOFLR model offers enhanced robustness and accuracy, especially in datasets with significant outliers, thus providing a comprehensive approach to fuzzy regression analysis.

3.3. Multi-Criteria Decision Making with Fuzzy *2-Tuple*

In this study, we employed the fuzzy 2-*tuple* methodology for multi-criteria decision making (MCDM) using the TOPSIS and VIKOR methods. This approach is particularly effective in handling linguistic and imprecise data, making it suitable for evaluating future price scenarios of agricultural commodities.

3.3.1. TOPSIS *2-Tuple*

The fuzzy TOPSIS method, as outlined by Roghanian et al. [2010] and extended by Wei et al. [2010], involves several steps. First, the decision matrix is constructed and normalized:

$$\mathbf{R} = [r_{ij}]_{m\times n}, \quad r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{6}$$

where x_{ij} represents the fuzzy evaluation value of the i-th alternative with respect to the j-th criterion. Then, the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS) are determined:

$$\text{PIS: } A^+ = \{\max(r_{ij}) \mid j \in J\}, \quad \text{NIS: } A^- = \{\min(r_{ij}) \mid j \in J\} \tag{7}$$

Next, the separation measures are calculated:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}(r_{ij} - r_j^+)^2}, \quad S_i^- = \sqrt{\sum_{j=1}^{n}(r_{ij} - r_j^-)^2} \tag{8}$$

where S_i^+ and S_i^- are the distances of each alternative from PIS and NIS, respectively. The relative closeness to the ideal solution is then computed:

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \tag{9}$$

Finally, the alternatives are ranked based on the values of C_i^*, with higher values indicating closer proximity to the ideal solution.

3.3.2. VIKOR *2-Tuple*

The VIKOR method, as introduced by Opricovic and Tzeng [2004] and extended to fuzzy environments by Sanayei et al. [2010], follows a similar multi-step process. First, the best and worst values for each criterion are determined:

$$f_j^* = \max_i f_{ij}, \quad f_j^- = \min_i f_{ij} \tag{10}$$

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where f_{ij} represents the fuzzy evaluation value of the i-th alternative with respect to the j-th criterion. The utility measure S_i and the regret measure R_i for each alternative are computed:

$$S_i = \sum_{j=1}^{n} w_j \frac{f_j^* - f_{ij}}{f_j^* - f_j^-}, \quad R_i = \max_j \left[w_j \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right] \tag{11}$$

where w_j is the weight of the j-th criterion. The VIKOR index Q_i is then calculated:

$$Q_i = v \left(\frac{S_i - S^*}{S^- - S^*} \right) + (1 - v) \left(\frac{R_i - R^*}{R^- - R^*} \right) \tag{12}$$

where $S^* = \min_i S_i$, $S^- = \max_i S_i$, $R^* = \min_i R_i$, $R^- = \max_i R_i$, and v is the weight of the strategy of the majority rule. The alternatives are ranked based on the values of Q_i, with lower values indicating better performance.

The use of fuzzy 2-*tuple* representation in these methods allows for the effective handling of linguistic terms and imprecise data, providing a robust framework for multi-criteria decision making. This approach has been successfully applied in various fields, demonstrating its versatility and effectiveness [Wei et al., 2010; Sanayei et al., 2010; Roghanian et al., 2010].

3.4. Monte Carlo Simulation for Fuzzy *2-Tuple* MCDM

To enhance the robustness of our evaluation and address uncertainty, we employed Monte Carlo Simulation. This involves generating numerous random samples to simulate variations in evaluation criteria and weights. The main steps are:

Algorithm 1 Monte Carlo Simulation for Fuzzy *2-Tuple* MCDM

Require: Evaluation criteria and weights ranges
Ensure: Mean and standard deviation of scores and rankings
Generate random variations of the evaluation criteria and weights within predefined ranges
Normalize the randomly generated evaluation matrices
for each simulation iteration **do**
Apply the fuzzy 2-*tuple* TOPSIS and VIKOR methods to rank the alternatives
end for
Calculate the mean and standard deviation of scores and rankings across all simulations to assess stability and reliability

This simulation provides insights into the variability of rankings, helping to identify the most robust alternatives under different scenarios. By integrating FLS and MOFLR models with fuzzy *2-Tuple* TOPSIS and VIKOR methods, our study offers a comprehensive and robust framework for evaluating future price scenarios of agricultural commodities.

We chose these linguistic variables because they provide a qualitative assessment framework that aligns with the inherent uncertainties in our data. This approach enhances the robustness and interpretability of the analysis, accommodating expert opinions and subjective market expectations effectively. Table 1 provides a summary of the linguistic variables and their 2-*tuple* equivalents.

We designed five future price scenarios (S_1, S_2, S_3, S_4, S_5) based on subjective market expectations. The evaluation criteria include Price Stability (C1), Growth Potential (C2), Market Risk (C3), Climate Impact (C4), and Global Demand (C5). All criteria are considered benefit criteria, except for Market Risk, which is treated as a minimization criterion. Table 2 summarizes the evaluation of these criteria with their respective linguistic variables and 2-*tuple* equivalents.

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Table 1: Linguistic Variables and 2-*tuple* Equivalents

Linguistic Variable	**2-*tuple* Equivalent**
Very Poor (VP) / Very Low (VL)	$(S_0, 0)$
Poor (P) / Low (L)	$(S_1, 0)$
Medium Poor (MP) / Medium Low (ML)	$(S_2, 0)$
Fair (F) / Medium (M)	$(S_3, 0)$
Medium Good (MG) / Medium High (MH)	$(S_4, 0)$
Good (G) / High (H)	$(S_5, 0)$
Very Good (VG) / Very High (VH)	$(S_6, 0)$

Table 2: Evaluation of Criteria with Linguistic Variables and 2-*tuple* Equivalents

Criteria	**D1**	**D2**	**D3**	**2-*tuple* Avg.**
C1: Price Stability	$(S_4, 0.2)$	$(S_5, -0.1)$	$(S_3, 0.5)$	$(S_4, 0.2)$
C2: Growth Potential	$(S_5, 0)$	$(S_4, 0.3)$	$(S_6, -0.2)$	$(S_5, 0.03)$
C3: Market Risk	$(S_3, -0.4)$	$(S_2, 0.1)$	$(S_4, 0)$	$(S_3, -0.1)$
C4: Climate Impact	$(S_5, 0.1)$	$(S_4, -0.3)$	$(S_5, 0.2)$	$(S_5, 0)$
C5: Global Demand	$(S_6, -0.2)$	$(S_5, 0.4)$	$(S_6, 0)$	$(S_6, 0.07)$

Table 3 presents the aggregated evaluation of the five scenarios ($S1, S2, S3, S4, S5$) against the criteria of Price Stability, Growth Potential, Market Risk, Climate Impact, and Global Demand, using the 2-*tuple* format.

Table 3: Aggregated Evaluation of Alternatives in 2-*tuple* Format

Alt.	**C1**	**C2**	**C3**	**C4**	**C5**
S1	$(S_3, 0.1)$	$(S_6, -0.3)$	$(S_2, 0.4)$	$(S_5, -0.2)$	$(S_4, 0.3)$
S2	$(S_4, -0.2)$	$(S_5, 0.1)$	$(S_3, -0.3)$	$(S_6, 0.1)$	$(S_3, -0.4)$
S3	$(S_5, 0)$	$(S_4, 0.2)$	$(S_2, 0.1)$	$(S_4, 0.3)$	$(S_6, 0.2)$
S4	$(S_4, 0.3)$	$(S_5, -0.1)$	$(S_3, 0.2)$	$(S_3, -0.1)$	$(S_5, -0.3)$
S5	$(S_3, -0.1)$	$(S_6, 0)$	$(S_4, -0.2)$	$(S_5, 0.2)$	$(S_4, 0.1)$

By integrating these comprehensive evaluation frameworks and utilizing the fuzzy 2-*tuple* methodology, we ensure that our analysis accounts for both quantitative and qualitative aspects of the decision-making process. This robust approach provides a deeper understanding of the potential future price scenarios for agricultural commodities, enabling informed and effective decision-making. Furthermore, the Monte Carlo simulation enhances the reliability of our results by addressing uncertainties and variability in the data, ultimately supporting more resilient strategic planning.

4. Discussion of Results

The data was collected using the Yahoo!Finance API via the R package *quantmod* [Ryan and Ulrich, 2023], including the following tickers: ZC=F (Corn Futures), ZO=F (Wheat Futures), KE=F (KC HRW Wheat Futures), ZR=F (Rough Rice Futures), GF=F (Feeder Cattle Futures), ZS=F (SoyMeal Futures), ZM=F (Soybean Meal Futures), and ZL=F (Soybeans Futures). The dataset spans from 2010-01-01 to 2024-05-24, comprising daily prices and their respective log returns calculated to ensure stationarity and financial purpose adherence.

The time series data was processed to handle missing values using linear interpolation and subsequently converted to daily returns, as shown in Figure 1, illustrating the volatility and trends of the selected commodities.

We ran and compared FLS (Fuzzy Least Squares) and MOFLR (Multi-Objective Fuzzy Linear Regression) models for each series of price returns to evaluate their capacity to generalize the behavior of each commodity. The comparison results are shown in Table 4.

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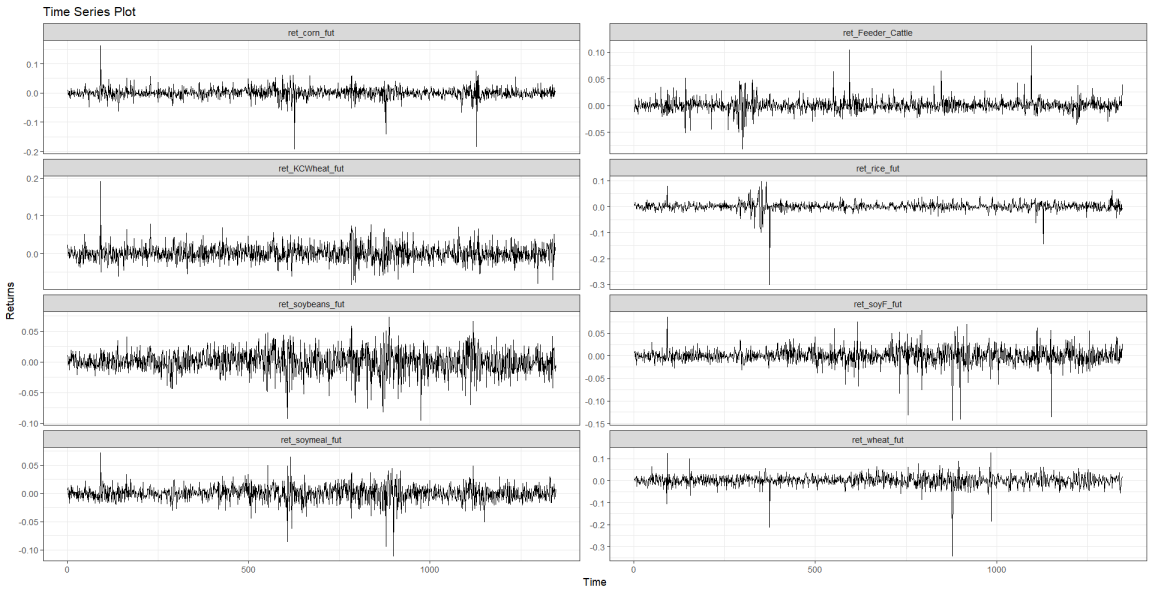


Figure 1: Time series plot of daily returns for selected commodities.

Table 4: Comparison of FLS and MOFLR models for selected commodities.

Commodity Returns	TEF (FLS)	GOF (FLS)	TEF (MOFLR)	GOF (MOFLR)
ret_corn_fut	1734.999	0.001042122	4438.785	0.002842122
ret_wheat_fut	1910.501	0.001691584	4652.082	0.003491584
ret_KCWheat_fut	1956.114	0.001411337	4652.891	0.003211337
ret_rice_fut	1501.889	0.0008639284	4324.661	0.002663928
ret_Feeder_Cattle	1328.712	0.0004457271	4241.282	0.002245727
ret_soymeal_fut	1576.067	0.0005532561	4314.819	0.002353256
ret_soyF_fut	1714.919	0.0009160664	4420.871	0.002716066
ret_soybeans_fut	1922.630	0.001045771	4557.949	0.002845771

The analysis of the results reveals that the Total Error Fit (TEF) values for the FLS model are consistently lower across all commodities compared to the MOFLR model, indicating a tighter fit around the central tendency of the data.

The confidence intervals for the MOFLR model are significantly wider than those for the FLS model, reflecting the MOFLR model's ability to handle greater variability and incorporate fuzziness in the data. This pattern holds true across all commodities in the portfolio.

The FLS model assumes a more deterministic approach, minimizing the sum of squared errors and resulting in narrower confidence intervals, while the MOFLR model accommodates multiple objectives, including the fitting of central tendency and fuzziness, leading to wider confidence intervals.

The estimated equations for the central tendency and boundaries of the support interval for both models for corn futures returns are presented in Table 5.

The broader confidence intervals of the MOFLR model indicate its robustness in handling greater variability and uncertainty, making it suitable for complex and noisy datasets.

The equations reveal that both models predict a constant return of 0.001 for the corn futures, with no dependence on the variable x. This suggests that, on average, the expected return remains stable over time, as represented by the zero slope in the equations. The support interval for the FLS model ranges from -0.009 to 0.011. This relatively narrow band indicates that the FLS

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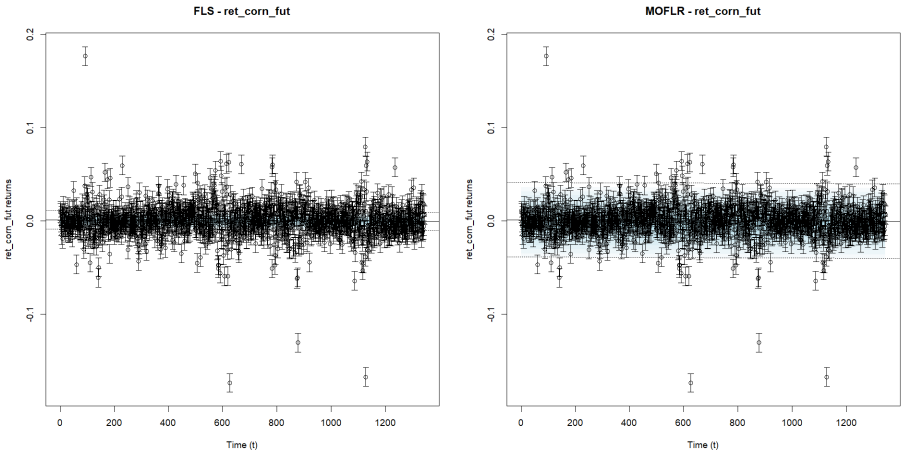


Figure 2: Comparison of FLS and MOFLR models for corn futures returns.

Table 5: Estimated Equations for FLS and MOFLR Models

	FLS Model	**MOFLR Model**
Central tendency	$\hat{y} = 0.001 + 0 \cdot x$	$\hat{y} = 0.001 + 0 \cdot x$
Lower boundary	$\hat{y}_{\text{lower}} = -0.009 + 0 \cdot x$	$\hat{y}_{\text{lower}} = -0.039 + 0 \cdot x$
Upper boundary	$\hat{y}_{\text{upper}} = 0.011 + 0 \cdot x$	$\hat{y}_{\text{upper}} = 0.041 + 0 \cdot x$

model assumes a tighter fit to the central tendency, suggesting less variability and uncertainty in the returns. The FLS model's narrower confidence intervals imply that it is more confident about the central prediction, but this could also mean that it is less robust to outliers and data noise.

The support interval for the MOFLR model ranges from -0.039 to 0.041. This significantly wider band reflects the model's approach to handling greater variability and incorporating fuzziness in the data. The broader confidence intervals indicate that the MOFLR model is designed to account for a higher degree of uncertainty and potential outliers in the returns. By accommodating more variability, the MOFLR model provides a more robust and flexible representation of the data's inherent uncertainty.

The FLS and MOFLR models differ in their handling of data variability. The FLS model, aiming for precise fit, results in narrower confidence intervals, making it suitable for datasets with minimal error. On the other hand, the MOFLR model, accounting for broader variability and uncertainty, produces wider confidence intervals, making it more robust for noisy and outlier-prone datasets. This aligns with the multi-objective programming framework to enhance predictability while reducing computational complexity. The consistent performance of both models across different series of commodity returns highlights the FLS model's deterministic fit and the MOFLR model's flexibility and robustness in capturing data variability and extremes.

To further explore the implications of the differences in model performance, we applied multicriteria decision-making methods, specifically the VIKOR and TOPSIS 2-*tuple* fuzzy approaches, to simulate different scenarios based on subjective market expectations for our grains commodities portfolio. The scenarios were defined based on five criteria: Price Stability, Growth Potential, Market Risk, Climate Impact, and Global Demand.

The rationale for this approach is grounded in the superior ability of the MOFLR model to capture the uncertainties and variability in historical data compared to the FLS model. By using

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the MOFLR model, we can more accurately reflect the potential impact of outliers and data noise in our forecasts. This capability is crucial for constructing robust future scenarios that account for subjective expectations of economic agents.

We did not validate the historical data with the FLS and MOFLR models (as train x test) to measure their effectiveness in capturing uncertainties. Instead, we aimed to determine which model would better capture the inherent uncertainties in the historical data. The ideal model for forecasting and scenario planning is the one that considers these uncertainties effectively, which we identified as the MOFLR model. This model can then be used to design future scenarios based on the criteria and alternatives outlined below.

To further explore the implications of the differences in model performance, we applied multi-criteria decision-making methods (VIKOR and TOPSIS 2-*tuple* fuzzy approaches) to simulate different scenarios based on subjective market expectations for our grains commodities portfolio. The scenarios were defined based on five criteria: Price Stability, Growth Potential, Market Risk, Climate Impact, and Global Demand.

4.1. Monte Carlo Simulation Results

We conducted a robustness analysis using Monte Carlo simulation to assess the stability and reliability of the rankings obtained through the TOPSIS and VIKOR 2-tuple methods. The simulation parameters were set to 1000 iterations, with evaluations and weights randomized within a variation range of 0.5.

The results of the Monte Carlo simulation are summarized in terms of means and standard deviations of the TOPSIS scores and VIKOR Q values for the alternative scenarios S1 to S5, as shown in Table 6.

Table 6: Means and Standard Deviations of TOPSIS Scores and VIKOR Q Values with Monte Carlo Simulation

TOPSIS Alt.	μ **TOPSIS Score**	**TOPSIS** σ	**VIKOR Alt.**	μ **VIKOR** Q **Value**	**VIKOR** σ
S1	0.4512	0.0530	S3	0.3639	0.3038
S2	0.7441	0.0299	S4	0.3557	0.3588
S3	0.1054	0.0267	S1	0.5047	0.3838
S4	0.6753	0.0193	S5	0.5335	0.4016
S5	0.5527	0.0303	S2	0.5974	0.3834

Figure 3 provides a clear and comparative visualization of the results, combining the mean scores and values with their respective standard deviations.

The Monte Carlo simulation revealed that the TOPSIS scores exhibited lower variability compared to the VIKOR Q values, indicating greater stability in the rankings provided by TOPSIS. However, VIKOR remains valuable for identifying compromise solutions by considering trade-offs between different criteria.

In conclusion, the synergy between fuzzy regression models and multi-criteria decision-making methods (TOPSIS and VIKOR) through Monte Carlo simulations fosters a robust analysis framework. This framework ensures that decisions are based on comprehensive and reliable data analyses, significantly enhancing the decision-making process in the context of agricultural commodities.

5. Final considerations

This paper presents an approach for forecasting commodity prices and making informed decisions under uncertainty by combining fuzzy regression models and multi-criteria decision-making (MCDM) methods. Our study demonstrates the effectiveness of Fuzzy Linear Regression

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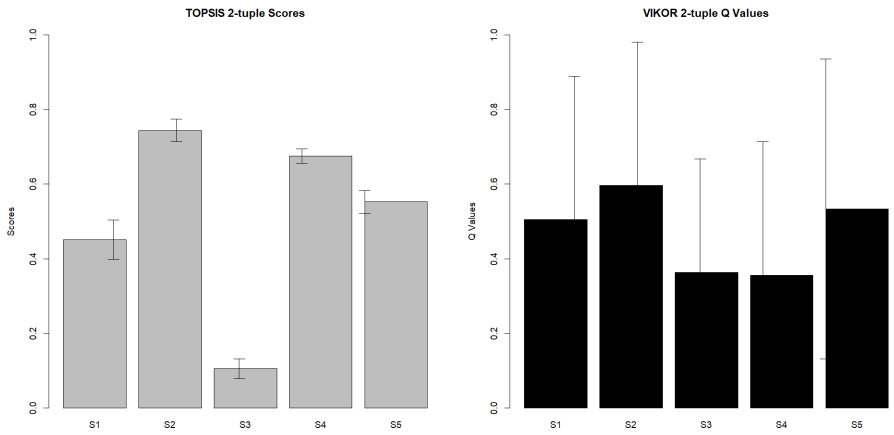


Figure 3: Comparison of TOPSIS Scores and VIKOR Q Values with Monte Carlo Simulation.

(FLR) and Multi-Objective Fuzzy Linear Regression (MOFLR) in handling variability and uncertainty in agricultural commodity markets. MOFLR, in particular, proves robust in managing outliers and data variability, making it suitable for market predictions.

The integration of fuzzy 2-*tuple* TOPSIS and VIKOR methods for MCDM offers a nuanced evaluation of future price scenarios, incorporating both quantitative data and expert judgments. The Monte Carlo simulation further enhances robustness, providing deeper insights into the stability of the rankings obtained. These methods were chosen for their capacity to handle multi-objective decision-making and uncertainties, particularly relevant in commodity markets.

Our findings highlight the robustness of scenario S4 across TOPSIS and VIKOR evaluations, supporting more informed strategic planning. Growth Potential emerged as the most significant criterion, reflecting the importance of market expansion. This framework is valuable for stakeholders in volatile markets, helping them navigate uncertainties and make strategic decisions.

Academically, our study contributes by applying FLR and MOFLR in conjunction with MCDM to commodity markets, a relatively unexplored area. The choice of FLR and MOFLR stems from their ability to manage imprecise data and outliers, common in agricultural datasets.

Future research could explore applying other fuzzy methods or incorporating real-time data and adaptive learning algorithms to improve the accuracy of predictions. As global markets evolve, developing flexible analytical frameworks remains essential for effective decision-making.

In conclusion, our study contributes to the literature on fuzzy regression and MCDM by providing insights and practical tools for managing uncertainty and complexity in agricultural commodity markets.

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