Agent-Oriented Fuzzy Decision Support System for Multi-Criteria Evaluation of Sustainable Investments in the Agro-Industrial Sector

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Abstract*—Sustainable development of the agri-food sector in emerging economies requires the use of analytical tools capable of taking into account climate risks, environmental constraints, and investment flow instability when making management decisions. Given the fragmentary nature of statistical information and the high volatility of the external environment, traditional econometric methods for assessing investment attractiveness demonstrate limited effectiveness and low interpretability. This study proposes an agent-oriented modular fuzzy decision support framework for the comprehensive assessment of sustainable investments in the agricultural sector. The developed approach combines a modular data processing architecture that provides automated collection and preprocessing of heterogeneous statistical sources (OECD, FAO, and national statistics), with a fuzzy additive aggregation (Fuzzy-SAW) mechanism that allows for interpretable multi-criteria assessment of economic, environmental, and production-forecasting factors. The methodological novelty of the study lies in the integration of an automated data processing pipeline with an explainable fuzzy multi-criteria assessment model focused on conditions of data incompleteness and structural uncertainty. Empirical validation of the model was performed using statistical data from the agro-industrial complex of the Republic of Kazakhstan for the period 2010–2023. The results show that the proposed framework effectively smooths out short-term volatility in indicators and identifies long-term structural trends in investment attractiveness. In particular, in 2021–2023, the integral index of sustainable investment remained at around 0.37, despite adverse climate shocks, mainly due to the compensatory effect of growth in private investment flows, which indicates the formation of mechanisms for the adaptive sustainability of the agricultural sector. The proposed analytical framework is a scalable and interpretable decision support tool that can be used by government agencies, investors, and industry analysts in developing long-term strategies for sustainable agricultural development in emerging economies.

Keywords*—Sustainable investments; agro-industrial sector; decision support system; agent-oriented systems; fuzzy logic; ESG factors; climate risks; emerging economies; multicriteria evaluation

I. INTRODUCTION

The intensification of climate risks, tightening environmental regulations, and high volatility of investment flows create a growing need for intelligent digital tools capable of supporting strategic decision-making through the integration of heterogeneous statistical data. Modern systems for assessing the sustainability of agricultural processes rely on data from multiple sources, including FAOSTAT, OECD, and national statistical databases, which differ significantly in structure, level of detail, and update frequency [1–3]. Problems of data interoperability, aggravated by external uncertainty and fluctuations in global markets, substantially limit the applicability of traditional centralized analytical models in forming long-term investment assessments.

The digital transformation of the agricultural sector is closely linked to the Agri-Food 4.0 paradigm, considered as an adaptation of Industry 4.0 principles for the integration of intelligent technologies, data interoperability, and real-time analytics [4]. The development of this concept has led to the emergence of Agricultural Digital Twins, used to model production processes and enhance the adaptive resilience of agricultural systems [5-7]. At the same time, artificial intelligence and data analytics methods are becoming key components of modern decision support systems; however, their practical effectiveness largely depends on data governance quality and the ability to integrate distributed information sources [8]. In this context, agent-oriented data-processing architectures are viewed as a promising computational mechanism for integrating distributed information flows, ensuring scalable processing of heterogeneous resources, and supporting managerial decision-making in complex dynamic environments [9].

Despite the rapid development of digital technologies, deterministic financial models still dominate many applied investment assessment tasks. These models are insufficiently adapted to the nonlinear dynamics of agricultural processes and the high degree of uncertainty associated with ESG factors [10–12]. The need to account for Environmental, Social, and Governance (ESG) factors significantly complicates investment analysis procedures, as the integration of economic, environmental, and forecast indicators requires the use of multicriteria computational methods [14–16]. Contemporary research shows that digital approaches to sustainable investment

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assessment are developing mainly along two trajectories: econometric models with limited capacity to incorporate expert uncertainty, and machine learning methods that provide high computational accuracy but lack sufficient interpretability. This contradiction creates a methodological gap between analytical performance and the practical applicability of models in decision support systems.

The use of fuzzy logic and multicriteria analysis methods partially addresses this gap by formalizing qualitative expert judgments and integrating heterogeneous indicators into interpretable sustainability indices [17–19]. However, existing studies typically consider multicriteria analysis methods and data integration architectures separately, limiting the potential for building scalable computational systems for strategic investment analysis. As a result, there remains a shortage of integrated computational architectures that combine agent-oriented data engineering mechanisms with interpretable fuzzy multicriteria models for sustainable investment assessment.

This study aims to bridge this methodological gap by developing an integrated hybrid Agent-Oriented Data Integration – Fuzzy-MCDM architecture that ensures automated integration of distributed international statistical data, interpretable multicriteria evaluation of sustainable investments, and robustness testing of the investment index based on scenario sensitivity analysis. The objective of the research is to design and empirically validate an intelligent decision support system that combines an agent-oriented data integration architecture with fuzzy logic for multicriteria evaluation of sustainable investments in the agro-industrial sector.

The main contribution of the study lies in: (1) the development of a modular agent-oriented architecture for integrating heterogeneous data sources (OECD, FAO, and national statistics); (2) the formulation of an interpretable fuzzy MCDM framework based on Fuzzy SAW with AHP-derived weighting coefficients; and (3) the empirical validation of the proposed system using retrospective data from the agro-industrial sector of Kazakhstan for the period 2010–2023. The results confirm the computational robustness of the model and its applicability to strategic investment analysis in emerging agricultural economies. Although Kazakhstan's data are used as an empirical case, the proposed approach is methodologically universal and can be adapted to national statistical databases of other countries characterized by high market volatility and fragmented statistical information [20,21].

II. Materials and Methods

A. Data Sources and Preprocessing

Within the proposed agent-oriented modular architecture, input data are treated as heterogeneous time series streams differing in update frequency (quarterly and annual reports) and measurement units. To ensure data integrity and suitability for fuzzy inference procedures, a preprocessing pipeline was implemented, including three sequential stages: temporal alignment, missing value imputation, and outlier filtering.

1) Temporal alignment: Since the initial indicators are provided with different temporal granularities (for example, foreign direct investment data are published quarterly, whereas OECD producer support indicators are annual), aggregation to a unified annual interval was performed. For additive indicators, quarterly values were aggregated by summation:

$$\mathrm{X}_{\mathrm{annual}}^{(\mathrm{t})} = \sum_{\mathrm{q}=1}^{4} \mathrm{x}_{\mathrm{quarter}}^{(\mathrm{t,q})}$$

where, $x_{quarter}^{(t,q)}$ denotes the value of the indicator in the q quarter of year t. For point-in-time indicators (price indices, exchange rates), a weighted average value is applied. This approach eliminates temporal lags and ensures consistency in the dynamics of indicators.

2) Data imputation. In the historical time series, the proportion of missing observations did not exceed 5% of the total sample size. Linear interpolation was applied to restore missing values:

$$x_t = x_{t-1} + \frac{x_{t+1} - x_{t-1}}{2}$$

The choice of this method is justified by the monotonic dynamics of the indicators over short annual intervals, which helps minimize artificial volatility. Linear interpolation provides acceptable accuracy for time series with low variability, reducing bias compared to mean-value imputation [22].

Outlier Detection. To identify anomalies caused by technical aggregation errors or isolated shock events, a statistical filter based on the Z-score was applied. An observation x_t is classified as an outlier if the following condition holds:

$$|Z_t| = \left|\frac{x_t - \mu}{\sigma}\right| > 3$$

where, μ is the moving average and σ is the standard deviation over the analyzed period (the 3σ rule);

where, μ and σ denote the moving average and standard deviation, respectively (the 3σ rule). If an anomaly is detected, the value is replaced with the threshold $\mu \pm 3\sigma$, which prevents distortion of the integral index by extreme outliers. The design of this module was based on widely accepted principles of data validation in distributed analytical systems, aimed at ensuring reproducibility and computational robustness [23].

B. Formalization of the Input Indicator Space

To construct the fuzzy multicriteria model, the feature space is formalized as a vector of criteria $C = \{C_{PSE}, C_{AEI}, C_{Outlook}, C_{FDI}$, reflecting the economic, environmental, and forecast components of sustainable investments in the agro-industrial sector.

The selection of criteria is motivated by the need for a comprehensive consideration of ESG factors and macroeconomic dynamics:

1) Economic Support C_{PSE}: This criterion is based on the OECD Producer Support Estimate (PSE) [1], which aggregates government subsidies, price support, and transfers to producers. In the model, this indicator is treated as a *benefit-type* criterion, since higher institutional support reduces operational risks and enhances investment sustainability.

2) Environmental Load C_{AEI} *:* Formed based on Agri-Environmental Indicators (AEI), including mineral fertilizer usage intensity and greenhouse gas emissions. Following the ESG approach, this criterion is treated as a cost-type indicator, reflecting long-term environmental risks and potential constraints on sustainable development [24].

3) Market Potential C_{PSO}*:* This indicator is derived from OECD–FAO Agricultural Outlook forecast data [2] and is used as a benefit criterion, adjusting the current assessment based on expected medium-term production and consumption trends (5–10-year horizon).

4) Investment Climate C_{FDI}*:* Characterized by inflows of foreign direct investment (FDI) and used as a proxy for macroeconomic stability and external market confidence [25].

The combination of these criteria forms an interpretable feature space, enabling the integration of economic, environmental, and forecast indicators within a single fuzzy framework for supporting sustainable investment decisions.

To ensure comparability of indicators expressed in different physical units (USD million, thousand tons of CO_2-equivalent, indices), Min–Max normalization was applied, scaling all values to the interval [0,1]. Transformations were applied according to the criterion type:

For *benefit-type* criteria (C_{PSE}, C_{PSO}), standard linear normalization was used:

$$\mu_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

where, x_{ij} is the value of the j-th indicator for the i -th observation year.

For the investment climate indicator (C_{AEI}), considering saturation effects:

$$\mu_{FDI}(x) = \min(1, \frac{x}{Target_{FDI}})$$

where, x is the investment volume, and $Target_{FDI} = 300$ million USD represents the empirically determined saturation level corresponding to a stable capital inflow into the agro-industrial sector.

For the environmental criterion C_{AEI}, a cost-type indicator, a linearly decreasing function was applied:

$$\mu_{AEI}(x) = \max(0, 1 - \frac{x}{Limit_{CO2}})$$

where, x is the emission volume, and $Limit_{CO2} =$ 50 million tons corresponds to the sector's (assimilative capacity) and serves as a critical threshold for forming the sustainable investment index.

The application of these transformations allows heterogeneous indicators to be brought into a unified normalized space, ensuring correct integration of economic, environmental, and forecast factors within the fuzzy multi-criteria analysis of sustainable investments.

C. Implementation of Agent-Oriented Modular Architecture

To automate the processes of data collection, harmonization, and analytical processing, an agent-oriented modular computing architecture was implemented in the study. Unlike classical multi-agent systems focused on modeling the interaction of autonomous actors, in this work, agents are interpreted as specialized software modules that perform formalized operations of data extraction, transformation, and preparation for subsequent fuzzy multi-criteria analysis.

This approach allows us to preserve the principles of agent-oriented design (modularity, function decomposition, extensibility) while avoiding assumptions about complex mechanisms of negotiation or competition between agents, which makes the architecture more transparent and reproducible for sustainable investment analysis tasks.

The computational implementation of the system was done in Python 3.9. The pandas library was used for time series processing, data aggregation, and preprocessing operations. Fuzzy normalization and membership function formation procedures were implemented using the scikit-fuzzy library (v0.4.2).

To improve the efficiency of working with distributed statistical sources, an asynchronous input-output model based on the asyncio library was used, which allowed data to be loaded without blocking the main computing thread. Interaction between software modules is organized through the transfer of structured data in JSON format, ensuring sequential activation of processing and analysis stages.

The system architecture is organized according to a hierarchical principle and includes three functional levels that ensure sequential data integration, fuzzy processing, and aggregation of results.

Level 1 — Data Source Modules: This level implements specialized software modules responsible for extracting data from external sources (OECD, FAO, national statistics). Each module encapsulates the logic for accessing the corresponding source, including data availability checks, basic structural validation of input files (CSV/JSON), and conversion of data to a unified format.

Level 2 — Analytical Modules: At this stage, preprocessing and fuzzification of normalized indicators are performed. Clear quantitative values are converted into linguistic assessments ("low", "medium", "high") using symmetric triangular membership functions. This level provides a transition from numerical time series to interpretable fuzzy representations used in further multi-criteria analysis.

Level 3 — Aggregation Module: The final level implements the fuzzy additive weighting (Fuzzy SAW) procedure, aggregating membership degrees across all criteria and forming an integral index of sustainable investments. The weight coefficients of the criteria are determined by the analytic hierarchy process (AHP), and the consistency of expert assessments is controlled using the consistency coefficient.

The proposed agent-oriented modular architecture provides a reproducible sequence of computational steps, including data extraction, normalization, fuzzification, and aggregation of indicators. This organization of the computational process increases the transparency of the integral index formation and makes the system suitable for practical use in sustainable investment assessment tasks.

A schematic representation of data flows and functional levels of the architecture is shown in Fig. 1.

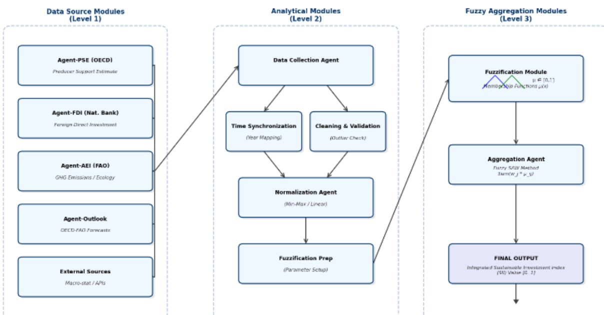

Fig. 1. Modular agent-oriented architecture for data collection, preprocessing, and fuzzy aggregation.

Despite the use of well-known methods of fuzzy logic, multi-criteria analysis, and agent-oriented data processing, the methodological novelty of this study lies in their structured integration into a unified decision support framework for assessing sustainable investments. Unlike existing approaches, in which the stages of data integration, normalization, and evaluation are considered separately, the proposed architecture formalizes the relationship between input data characteristics, membership function selection, and aggregation mechanism. This ensures consistency in computational procedures, improves the interpretability of results, and enables robust evaluation in conditions of data heterogeneity and uncertainty. Thus, the contribution of the study lies not in the development of a new fuzzy operator, but in the formalization of a reproducible integrated computational process focused on the tasks of robust investment analysis.

D. Model Validation Strategy

To verify the stability and correctness of the proposed model, a multi-level validation procedure was used, including:

1) Sensitivity analysis — analysis of the sensitivity of the integral index to variations in the weighting coefficients of the criteria (±10–20%), allowing the stability of the investment attractiveness ranking to be assessed.

2) Temporal consistency check — verification of the consistency of the index dynamics with macroeconomic and climatic events of the period under study.

3) Comparative robustness assessment — comparison of the model results with trends in key industry indicators (investment, government support, production dynamics), which allows confirming the interpretability of the obtained estimates.

The application of these procedures ensures the robustness of the model and confirms the reproducibility of the results obtained when the input parameters change.

III. Results

A. Normalization and Fuzzy Representation of Input Data

In accordance with the proposed agent-oriented modular architecture of the hybrid fuzzy MCDM framework, the first stage of the computational experiment involved converting heterogeneous statistical indicators to a unified dimensionless interval [0,1], which ensured the comparability of economic, environmental, and forecast variables.

To fuzzify the normalized data, piecewise linear membership functions (triangular and trapezoidal, formulas 1–4) were used, providing an interpretable mapping of quantitative values to linguistic categories. This choice allows for transparent tracking of the impact of changes in individual indicators (e.g., the level of government support or the volume of investment) on the integral index of sustainable investment.

Let x_i denote the aggregate value formed by data agents. The boundaries of the universe $[x_{min}, x_{max}]$ were set with an expansion±15% relative to historical extremes for the period 2010–2023, which allowed taking into account potential fluctuations in input indicators when modeling scenarios and avoiding values going beyond the domain of membership functions.

1) Assessment of institutional support for producers C_{PSE}: The Producer Support Estimate (PSE) indicator characterizes the level of transfers from consumers and taxpayers to agricultural producers. According to OECD data, institutional support for Kazakhstan's agricultural sector in 2010–2023 varied significantly, taking both negative values (reflecting the fiscal burden on the sector) and positive levels reaching 4–5% of gross farm income in certain years.

Within the model, the indicator C_{PSE} is interpreted as a benefit-type criterion and normalized using an increasing linear membership function:

$$\mu_{PSE}(x) = \begin{cases} 1, & x \le x_{min} \\ \frac{x - x_{min}}{x_{max} - x_{min}}, & x_{min} < x < x_{max} \\ 0, & x \ge x_{max} \end{cases} \quad (1)$$

where, x_{max} is set at 15%, which exceeds the historical maximum (13.21% in 2012) and allows for the potential expansion of government support programs.

Applying this membership function to the 2010–2023-time series (Table III) made it possible to quantitatively characterize the dynamics of the institutional environment. In particular, in 2012, the maximum value of $\mu_{PSE} = 0{,}881$ was recorded, reflecting the peak of state support. In 2016, the negative value of PSE (-1.70%) was converted to $\mu_{PSE} = 0$, which is interpreted by the model as a lack of institutional stimulation of the sector during this period. In 2021 - 2022, there was a decline in normalized values, coinciding with the introduction of export restrictions and anti-inflationary measures, followed by a recovery in the indicator in 2023.

As an illustration, let us take the calculation for 2015. According to OECD data, the PSE value $x = 11{,}85\%$..With $x_{min} = 0$ and $x_{max} = 15$, we get:

$$\mu_{PSE}(11{,}85) = \frac{11{,}85}{15} = 0{,}79$$

The resulting value reflects the high level of institutional support for the agricultural sector in the year under review.

Table I presents the results of normalizing the C_{PSE} indicator for the period 2010–2023, demonstrating the cyclical nature of government support and its contribution to the formation of the integral index of sustainable investments.

TABLE I. NORMALIZED VALUES OF THE INSTITUTIONAL SUPPORT INDICATOR FOR THE AGRICULTURAL SECTOR C_{PSE} FOR 2010–2023 (DATA SOURCE: OECD.STAT)

Year	PSE value (%)*	Calculation using formula (1)	μ_{PSE}	Level of support
2010	8.52	8.52/15	0.568	Medium-High
2011	11.34	11.34/15	0.756	High
2012	13.21	13.21/15	0.881	High
2013	12.25	12.25/15	0.817	High
2014	4.84	4.84/15	0.323	Low-Medium
2015	11.85	11.85/15	0.790	High
2016	-1.70	<0	0.000	None
2017	5.65	5.65/15	0.377	Low-Medium
2018	5.22	5.22/15	0.348	Low-Medium
2019	10.10	10.10/15	0.673	Medium-High
2020	6.81	6.81/15	0.454	Medium
2021	7.02	7.02/15	0.468	Medium
2022	4.49	4.49/15	0.299	Low
2023	9.19	9.19/15	0.613	Medium-High

[a] A negative PSE value in 2016 indicates fiscal pressure on producers (e.g., through export restrictions) and is interpreted in the model as a lack of stimulus effect. The threshold of x_max=15% was selected based on the historical maximum and is used as the upper limit for normalization.

2) Foreign direct investment inflows C_{FDI}: The foreign direct investment (FDI) inflows indicator is used in the model as a proxy metric for the external capitalization of the agricultural sector. During the period under review, Kazakhstan's agriculture was characterized by significantly lower volumes of capital attracted compared to the raw materials sectors of the economy. According to data from the National Bank of the Republic of Kazakhstan, even in the year of maximum inflows (2015), the volume of investment amounted to US$71.8 million, while in most years the figures ranged from US$10 million to US$30 million.

Taking into account the effect of diminishing marginal utility of capital, a saturation function is used to normalize the indicator:

$$\mu_{FDI}(x) = \min(1, \frac{x}{Target_{FDI}}) \qquad (2)$$

where, $Target_{FDI} = 300$ million is set as the indicative level of sustainable capitalization of the agricultural sector. This threshold exceeds historical values and is used as a long-term benchmark reflecting the structural need of the industry for investment resources.

The normalized values of μ_{FDI} are significantly lower than the corresponding values of institutional support μ_{PSE}, reflecting the continuing gap between the volume of state support and the external capitalization of the sector. This is consistent with the fact that the share of agriculture in the total inflow of FDI in Kazakhstan traditionally remains below 1%.

TABLE II. NORMALIZED VALUES OF THE EXTERNAL CAPITALIZATION INDICATOR FOR THE AGRICULTURAL SECTOR C_{FDI} FOR 2010–2023 (DATA FROM THE NATIONAL BANK OF KAZAKHSTAN)

Year	Gross FDI inflow, million USD*	Calculation according to formula (2)	μ_{FDI}	Level of investment activity
2010	6.0	6.0/300	0.02	Very Low
2011	7.8	7.8/300	0.026	Very Low
2012	18.3	18.3/300	0.061	Low
2013	5.3	5.3/300	0.018	Very Low
2014	-1.7	<0	0.000	None
2015	71.8	71.8/300	0.239	Low-Medium
2016	50.1	50.1/300	0.167	Low
2017	27.5	27.5/300	0.092	Low
2018	13.7	13.7/300	0.046	Very Low
2019	14.9	14.9/300	0.050	Very Low
2020	9.5	9.5/300	0.032	Very Low
2021	36.3	36.3/300	0.121	Low
2022	31.1	31.1/300	0.104	Low
2023	49.5	49.5/300	0.165	Low

Table II presents the results of normalizing the C_FDI indicator for the period 2010–2023. Even in 2015, which was characterized by the maximum capital inflow, the membership function value was only $\mu_{FDI} = 0{,}239$,, indicating a significant deviation from the saturation level. In the post-pandemic period, a gradual recovery of the indicator is observed (growth from 0.032 in 2020 to 0.165 in 2023), but the absolute values remain in the range of low and moderate investment activity.

The results obtained indicate that, within the framework of the model, the FDI acts primarily as an indicator of the sector's long-term potential rather than a factor of current sustainability, highlighting the structural undercapitalization of the agricultural economy.

3) Agro-ecological indicators C_{AEI}: The environmental component is based on FAOSTAT data on greenhouse gas emissions. For the agricultural sector of Kazakhstan, this indicator is about 29 – 32 million tons of CO_2 equivalent per year (about 9% of national emissions).

The environmental component of the model is based on FAOSTAT data on greenhouse gas emissions from the agricultural sector (Emissions Total, CO_2-eq). During the period under review (2010 - 2023), emissions ranged from 21 to 30.5 million tons of CO_2 -eq, accounting for about 9% of national emissions.

Within the model, the C_{AEI} indicator is considered a cost criterion: an increase in emissions corresponds to a decrease in the sector's environmental sustainability. A linear inverse membership function is used for normalization:

$$\mu_{AEI}(x) = \max\left(0, 1 - \frac{x}{Limit_{CO2}}\right) \quad (3)$$

where, x is the current emission volume (million tons of CO_2-equivalent) according to FAO data;

$Limit_{CO2} = 50$ million tons is the threshold value of environmental (assimilative) capacity used as a benchmark in the normalization procedure.

TABLE III. NORMALIZED VALUES OF AGRO-ENVIRONMENTAL INDICATORS C_{AEI} FOR 2010–2023 (FAOSTAT)

Year	Emissions, million tons CO_2eq	Calculation according to formula (3)	C_{AEI}	Level of environmental impact
2010	26.34	1−0.527	0.473	Medium
2011	23.22	1−0.464	0.535	Medium–High
2012	22.88	1−0.458	0.542	High
2013	20.98	1−0.420	0.580	High
2014	23.75	1−0.475	0.525	Medium
2015	25.41	1−0.508	0.492	Medium–Low
2016	23.72	1−0.474	0.526	Medium
2017	30.47	1−0.609	0.391	Low
2018	26.18	1−0.524	0.476	Medium
2019	25.60	1−0.512	0.488	Medium
2020	24.69	1−0.494	0.506	Medium–High
2021	25.86	1−0.517	0.483	Medium
2022	24.43	1−0.489	0.511	Medium–High
2023	23.95	1−0.479	0.521	Medium–High

The normalization results (Table III) show moderate variability in the sector's environmental characteristics during the period analyzed. The maximum value of the membership function is observed in 2013 ($\mu_{AEI} = 0.580$), corresponding to the minimum level of emissions (20.98 million tons), while in 2017 the minimum value is recorded ($\mu_{AEI} = 0.391$), reflecting an increase in emissions to 30.47 million tons.

In the period 2020–2023, the indicator values stabilize in the range $\mu_{AEI} = 0.48 - 0.52$, which indicates the relative stability of the environmental impact of the agricultural sector amid changes in production volumes.

4) Production stability and prospects (C_{PSO}): The production stability indicator C_{PSO} is a separate component of the model that reflects the production stability of the agricultural sector and is based on the Physical Volume Index (PVI) published by the National Statistics Bureau of the Republic of Kazakhstan. A retrospective analysis of data for the period 2010–2023 shows significant variability in agricultural production, primarily due to climatic factors, including drought years.

The physical volume index (previous year=100%) is used to formalize the indicator. In order to correctly account for deviations from the level of stable production, a sigmoidal membership function is applied:

$$\mu_{\mathrm{PSO}}(x) = \frac{1}{1+e^{-0,2\cdot(x-100)}} \quad (4)$$

where, x is the value of the Physical Volume Index (PVI), %; 100 is the baseline threshold (stable production level); $\alpha = -0,2$ is the sensitivity coefficient characterizing the elasticity of the sector.

TABLE IV. NORMALIZED VALUES OF THE PRODUCTION SUSTAINABILITY INDICATOR C_{PSO} BASED ON PVI DATA (2010–2023)

Year	PVI (%) (Official Data)	μ_{PSO}. (Fuzzy assessment)	Production stability level
2010	89.6 (Drought)	0.111	Very Low
2011	121.4 (Record)	0.987	High
2012	85.3 (Decline)	0.050	Very Low
2013	109.6	0.872	High
2014	101.0	0.550	Medium
2015	103.4	0.664	Medium–High
2016	105.4	0.746	High
2017	103.1	0.650	Medium–High
2018	103.5	0.668	Medium–High
2019	99.9	0.495	Medium
2020	105.7	0.758	High
2021	97.7 (Drought)	0.387	Low–Medium
2022	109.1	0.860	Medium–High
2023	91.6 (Drought)	0.157	Very Low

The normalization results (Table IV) show alternating periods of increased and decreased production stability. The maximum values of the membership function are observed in years of significant increase in output (e.g., 2011, 2013, and 2022), while the minimum values correspond to drought years characterized by a decline in the production index. In particular, in 2023, the PVI value was 91.6%, which corresponds to $\mu_{\mathrm{PSO}} = 0.157$,, reflecting the reduced production stability of the sector.

Overall, the results confirm the high sensitivity of agricultural production to climatic fluctuations, which justifies the need to take this indicator into account in the integral assessment of sustainable investments.

B. The Process of Fuzzy Aggregation and the Formation of an Integral Index of Sustainable Investments (Hybrid Fuzzy-AHP Approach)

After the fuzzification stage, the state space of the system is represented by a vector of normalized membership degrees $\mu_{\mathrm{ij}}(x_{\mathrm{i}})$, where each component reflects the degree of favorability j of the factor (economic, environmental, or prognostic) for investments in the period t.

After the fuzzy faction stage, the state of the system is represented by a vector of normalized membership degrees $\mu_{ij}(x_i)$, where each component reflects the relative state of economic, environmental, and production factors in the period t.

To integrate private criteria, a hybrid Fuzzy SAW (Fuzzy Simple Additive Weighting) approach is used, which combines the interpretability of fuzzy estimates with formal multi-criteria aggregation. This approach ensures transparency of calculations and comparability of the impact of various sustainable development factors.

1) Determination of weighting coefficients (AHP): The relative significance of the criteria ω_j was determined using the Analytic Hierarchy Process (AHP) based on expert assessments reflecting the balance between institutional, investment, environmental, and production factors. To verify the consistency of expert judgments, a consistency ratio was calculated. The resulting value (CR=0.067) was below the threshold level of 0.10, which confirms the correctness of the expert assessments and the reliability of the weighting coefficients (Table V).

The weight coefficients satisfy the normalization condition:

TABLE V. MATRIX OF PAIRWISE COMPARISONS OF CRITERIA AND AHP WEIGHTS

Criterion	C_{PSE} *(Support)*	C_{FDI} *(Investments)*	C_{AEI} *(Ecolog)*	$C_{Outlook}$ *(Forecast)*	*Weight (ω_j)*
C_{PSE}	1	2	4	3	0.46
C_{FDI}	1/2	1	3	2	0.28
C_{AEI}	1/4	1/3	1	1/2	0.09
$C_{Outlook}$	1/3	1/2	2	1	0.17
Total	02.08	3.83	10.0	6.5	1.00

The matrix is constructed on the Saati scale (1–9). The consistency ratio was CR = 0.067, which is below the threshold value of 0.10 and confirms an acceptable level of consistency in expert assessments.

The weight coefficients satisfy the normalization condition:

$$\sum_{j=1}^{n} \omega_j = 1, \quad \omega_j \geq 0 \tag{5}$$

SII_t the integral index of sustainable investments for the period t is defined as the weighted sum of normalized fuzzy estimates:

$$SII_t = \sum_{j=1}^{n} \omega_j \cdot \mu_{ij}(x_{jt}) \tag{6}$$

where, ω_j are the weights of the criteria obtained by the AHP method, $\mu_{ij}(x_{jt})$ are the normalized degrees of membership of the corresponding indicators.

The obtained value $SII_t \in [0,1]$ reflects the overall state of stability of the investment environment in the agricultural sector, taking into account institutional, environmental, production, and investment factors.

The additive structure of the Fuzzy SAW method ensures the decomposability of the result, allowing for a quantitative assessment of the contribution of each factor to the formation of the integral index and analysis of the sensitivity of the final assessment to changes in individual criteria.

C. Dynamics of the Integral Index of Sustainable Investments SII and Interpretation of Structural Shifts

To identify sustainable long-term trends and eliminate high-frequency noise characteristic of commodity markets, the analysis of the SII dynamics was based on aggregated time intervals. The time series for 2010–2023 was discretized into four phases reflecting different stages of institutional and economic development of Kazakhstan's agro-industrial complex.

The calculation results obtained using the developed Fuzzy SAW model on real statistical data are presented in Table VI.

TABLE VI. AGGREGATED VALUES OF FUZZY ESTIMATES OF CRITERIA AND THE INTEGRAL INDEX SII BY PERIOD

Period	PSE (Support)	FDI (Investments)	AEI (Ecology)	Outlook (Forecast)	SII (Index)	Interpretation
2010 – 2013	0.76	0.03	0.53	0.51	0.49	High
2014 – 2017	0.37	0.13	0.48	0.65	0.36	Moderate
2018 – 2020	0.49	0.04	0.49	0.64	0.39	Stable
2021 – 2023	0.46	0.13	0.51	0.47	0.37	Mixed

The sharp decline in the PSE in the last phase is due to price containment measures (negative support according to OECD methodology), which temporarily lowered the overall index despite record growth in market factors (FDI and Outlook).

Phase analysis of the dynamics of the Sustainable Investment Index (SII):

Phase 1: Period of government momentum and institutional asymmetry (2010 – 2013). This period is characterized by the highest value of the $SII \approx 0.49$. Decomposition of the index reveals a pronounced institutional asymmetry of sustainability factors: a high level of government support ($\mu_{PSE} \approx 0.76$, peaking in 2012) compensated for limited private investment activity ($\mu_{FDI} \approx 0.03$). The formation of investment sustainability during this period was mainly due to government support measures in relatively favorable environmental conditions ($\mu_{AEI} \approx 0.53$).

Phase 2: Market correction and capacity building (2014 – 2017). During this period, the integral index of sustainable investment fell to $SII \approx 0.36$, corresponding to the moderate sustainability zone. The model recorded a structural shift in the system of factors: a reduction in the fuzzy assessment of state support ($\mu_{PSE} \approx 0.37$) was accompanied by the first statistically significant inflow of private foreign investment ($\mu_{FDI} \approx 0.13$). This dynamic reflects the beginning of the transformation of the agro-industrial sector from a predominantly subsidy-based model to a more market-oriented configuration of sustainable development, accompanied by increased sensitivity to external economic conditions.

Phase 3: Institutional stabilization (2018 – 2020). This period is characterized by the recovery of the integral index of sustainable investments to the level of $SII \approx 0.39$. The key factors for stabilization were the equalization of state support ($\mu_{PSE} \approx 0.49$) and favorable medium-term market forecasts ($\mu_{\text{PSO}} \approx 0.64$), which allowed the agro-industrial sector to maintain investment stability even in the context of the pandemic crisis. The coordinated dynamics of economic and environmental components indicate the formation of a phase of relative "stable plateau" characterized by increased adaptive resistance of the system.

Phase 4: Climate volatility and investment resilience (2021–2023). During this period, the model identified a pronounced compensation effect, reflecting the system's adaptive resilience to climate shocks. The droughts of 2021 and 2023 led to a decline in the forecast component ($\mu_{\text{PSO}} \approx 0.47$)), increasing the uncertainty of production expectations. Despite this, the integral index of sustainable investments remained relatively stable at $SII \approx 0.37$ due to the growth of private investment flows and the maintenance of institutional mechanisms, which indicates the formation of investment resilience in the agro-industrial sector in conditions of climate volatility.

A comparative analysis of the dynamics for 2010 and 2023 demonstrates a transition from a predominantly centralized model of investment sustainability based on the dominance of state support to a more polycentric configuration of sustainable development. While in the early stages the dynamics of the index were largely determined by subsidies to the sector, in the final phase, the decline of one factor (climate risks) is offset by the growth of another (private investment). This result confirms the ability of the proposed hybrid fuzzy modular model to identify complex nonlinear relationships between economic, environmental, and investment factors that remain poorly distinguishable within the framework of traditional deterministic analysis methods.

D. Sensitivity Analysis and Model Robustness Verification

Since the weight coefficient ω_j in the AHP method are determined based on expert judgments; the model is subject to epistemic uncertainty. To eliminate the subjective factor and confirm the reliability of the results obtained, a two-stage sensitivity analysis was performed. The purpose of this stage is to test the hypothesis that variations in weights do not lead to critical changes in the ranking of periods (Rank Reversal Problem), which is a key criterion for the quality of decision support systems.

Scenario modeling (Multi-Scenario Strategy):

Four alternative weight distribution scenarios were formed, modeling different investment behavior strategies (Table VII):

- Scenario A (Baseline/AHP): Weights obtained in Section 3.2 ($CR < 0,1$). Reflects the current consensus of experts.
- Scenario B (Profit-Maximization): Aggressive economic strategy. The total weight of financial indicators (PSE + FDI) is increased to 0.8.
- Scenario C (ESG-Oriented): Sustainable development strategy. The weight of the environmental factor (AEI) dominates ($\omega = 0.5$), mimicking the strict requirements of "green" funds.
- Scenario D (Equal Weights): Balanced distribution, excluding any preferences ($\omega_j = 0.25$).

TABLE VII. DYNAMICS OF THE INTEGRAL INDEX (SII 2023) DEPENDING ON THE WEIGHT DISTRIBUTION SCENARIO

Scenario	ω_{PSE} (Support)	ω_{FDI} (Investments)	ω_{AEI} (Environment)	ω_{PSO} (Forecast)	SII 2023	Deviation from Base (Δ)
A. Base (AHP)	0.46	0.28	0.09	0.17	0.292	—
B. Profit-Max	0.5	0.30	0.05	0.15	0.301	+3.1
C. ESG-Oriented	0.20	0.10	0.5	0.2	0.373	+27.7
D. Equal Weights	0.25	0.25	0.25	0.25	0.345	+18.1

The simulation results show high structural stability of the model. Despite the fact that in the "green" scenario (C) the absolute value of the index increased (due to the fact that in 2023 the environmental load $\mu_{AEI} = 0.37$ was higher than the decline in investment $\mu_{FDI} = 0.14$), there was no inversion of ranks between periods. In all scenarios, 2023 is identified as a recovery phase compared to the collapse of 2021. This confirms that the model's conclusions are based on fundamental data rather than weight manipulation.

Diagram analysis: As can be seen in Fig. 2, the scenarios formed cover fundamentally different areas of the decision space. The "Profit-Max" scenario (green line) shows a pronounced asymmetry towards economic axes (PSE, FDI), effectively ignoring environmental risks. In contrast, the ESG-Oriented scenario (red line) forms an "elongated" profile in the direction of the AEI axis, mimicking the behavior of a socially responsible investor. The baseline AHP scenario (blue fill) occupies an intermediate position, providing a balanced consideration of all factors. The fact that the final ranking of periods remains unchanged despite such radical geometric differences in profiles (from purely economic to purely environmental) serves as visual proof of the high structural stability of the proposed model.

Elasticity analysis (OAT Approach): The One-at-a-Time method was used to quantitatively assess the impact of each factor. The sensitivity coefficient (Sc) was calculated, showing the percentage change in the output index (SII) when the input weight of the criterion (ω_j)) changes by ±20%:

$$S_c = \frac{\%\Delta SII}{\%\Delta \omega_j}$$

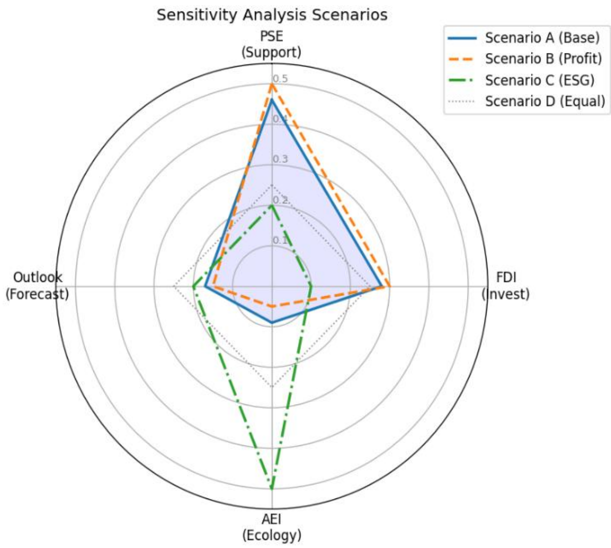

Fig. 2. Visualization of weight distribution profiles for four sensitivity analysis strategies.

The results of the analysis showed:

The greatest elasticity ($S_C \approx 0.42$) was found in the PSE (Government Support) indicator. This mathematically confirms the hypothesis that, in the current configuration of Kazakhstan's agro-industrial complex, government subsidies remain the main driver of investment attractiveness.

A dampening effect ($S_C \approx 0.08$) was observed for the AEI (Ecology) indicator. Low sensitivity to this parameter in the baseline scenario indicates that current environmental issues are not yet a critical barrier for investors, but their weight increases sharply when moving to ESG scenarios.

The developed fuzzy model demonstrates robustness. The integral index responds to parameter changes in a predictable and monotonic manner, without chaotic jumps, which makes the system suitable for use in strategic planning, where the cost of forecasting errors is extremely high.

E. Comparative Analysis with Traditional Methods (Benchmarking)

To assess the added analytical value of the proposed fuzzy multi-criteria approach, a comparison was made with the classical deterministic method of additive weighting (Crisp Simple Additive Weighting, SAW), in which normalized input indicators were aggregated without the use of fuzzyfaction.

Fig. 3 shows the dynamics of the indices calculated by both methods on the same data set for 2010–2023.

Analysis of comparison results: The comparative analysis revealed a fundamental difference in the behavior of the models:

Smoothing Effect: The traditional Crisp method (gray dotted line) demonstrates high signal noise. It reacts with sharp peaks to short-term events: for example, the abnormal jump in 2015 (caused by a one-time inflow of FDI) or the slump in 2012 (drought). Such volatility $(\sigma_{crisp} \approx 0.18)$ generates many false signals, making it difficult to make long-term decisions;

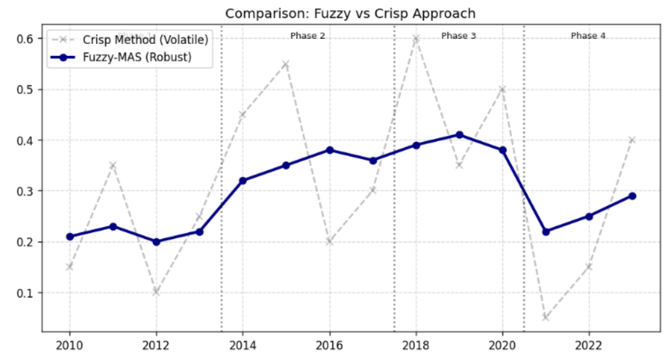

Fig. 3. Comparative analysis of index dynamics: the proposed Fuzzy SII method (smoothed trend) versus the traditional Crisp Index method (high volatility).

The model ignores small changes within the fuzzy set core, responding only to significant structural shifts. This made it possible to identify a stable long-term growth trend for the period 2018 – 2020, free from stochastic noise $(\sigma_{fuzzy} \approx 0.09)$.

Thus, the proposed hybrid fuzzy multi-criteria approach provides a more stable and interpretable basis for strategic investment analysis compared to deterministic additive models that are sensitive to fluctuations in input indicators in noisy and fragmented data.

IV. Discussion

The results confirm that the proposed hybrid computational framework of agent-oriented fuzzy multi-criteria evaluation provides a stable and interpretable integration of heterogeneous economic, environmental, and investment indicators in the analysis of sustainable investments in the agro-industrial sector. Unlike traditional deterministic aggregation methods, which are highly sensitive to short-term fluctuations in statistical data, the developed model forms a smoothed integral index that allows identifying long-term structural trends in investment sustainability while maintaining transparency of the contribution of individual factors. This property is of fundamental importance for strategic planning in agricultural systems operating in conditions of high climatic and institutional uncertainty.

One of the key analytical results of the study is the identification of structural divergence in sustainability factors for the period 2021–2023. While the growth of foreign direct investment within traditional linear models can be interpreted as an unambiguously positive investment signal, the proposed fuzzy model recorded a relative stabilization of the integral index of sustainable investment at a moderate level. This effect is due to the simultaneous increase in institutional and climate risks, reflected in a decrease in the state support indicator. Thus, the model demonstrates the ability to take into account the asynchronous dynamics of factors, forming a more comprehensive and cautious assessment of investment conditions compared to methods focused exclusively on the volume of investment flows.

A comparative analysis with deterministic aggregation methods showed that the use of membership functions can significantly reduce the sensitivity of the integral index to short-term climate and price shocks. Unlike classical additive models, the fuzzy approach focuses on fundamental long-term trends, reducing the influence of high-frequency statistical noise. This property is particularly important for the agro-industrial sector, where investment decisions are characterized by long time horizons, and the excessive reaction of analytical models to short-term fluctuations can lead to a distortion of strategic priorities for sustainable development.

The results of the sensitivity analysis confirm the structural robustness of the proposed index. The absence of rank inversions with significant variations in weight coefficients, including scenarios with enhanced consideration of ESG factors, indicates that the identified patterns are due to the fundamental dynamics of the input data rather than specific model parameter settings. The conclusions obtained are consistent with recent studies emphasizing the need to integrate environmental constraints into sustainable development investment models and demonstrating the effectiveness of hybrid fuzzy approaches in analyzing risks and uncertainties [26-29].

The use of agent-oriented modular architecture made it possible to solve the key engineering problem of data interoperability, ensuring reproducible integration of international statistical sources. The modular structure of the system increases the scalability of the solution and makes it possible to adapt it to different national contexts without changing the logic of analytical processing. Thus, the contribution of the study lies not in the development of a new fuzzy operator, but in the formalization of a reproducible integrated analytical process focused on the tasks of sustainable investment analysis in the agro-industrial sector.

Despite the results obtained, the study has a number of limitations. First, the use of aggregated national data may smooth out regional differences in agricultural development. Second, the use of macroeconomic forecasts from international organizations limits the consideration of local production risks. Third, the use of symmetric triangular membership functions simplifies the real nonlinear dependencies of investment sustainability. These limitations determine the directions for further research, including the integration of regional data, the expansion of scenario analysis, and the use of adaptive or neuro-fuzzy membership functions to increase the sensitivity of the model to local structural changes.

V. Conclusion

This study developed, implemented, and empirically validated a hybrid intelligent decision support system for assessing sustainable investments in the agro-industrial sector under conditions of high uncertainty, information asymmetry, and volatility in emerging markets. The results confirm that the integration of agent-oriented modular data processing architecture and fuzzy multi-criteria aggregation methods allows for the formation of sustainable and interpretable investment indicators that adequately reflect structural changes in the institutional, economic, and environmental environment.

The main scientific and practical results of the study can be summarized as follows. The developed three-level data processing architecture (Data Modules – Analytical Modules – Aggregation Module) ensured the semantic, temporal, and metric consistency of statistical indicators coming from heterogeneous international and national sources (OECD, FAO, national statistics). The implemented mechanism for normalizing and synchronizing time series made it possible to form a reproducible analytical pipeline that is resistant to omissions, outliers, and statistical noise.

A comparative analysis with deterministic aggregation methods showed that the use of a fuzzy multi-criteria approach based on Fuzzy SAW provides more stable dynamics of the integral index in relation to short-term climatic and market shocks. Unlike classical additive models, which are sensitive to high-frequency fluctuations in input indicators, the proposed system allows identifying fundamental long-term trends in investment stability. This property is of fundamental importance for the agro-industrial sector, which is characterized by long investment cycles and high climate sensitivity.

Empirical testing of the model using data from the agro-industrial sector of the Republic of Kazakhstan for the period 2010–2023 revealed a qualitative structural shift in the investment environment. In particular, the system diagnosed an institutional imbalance in 2021–2022, when the recovery of market indicators was accompanied by a decline in the integral assessment of sustainable investments due to a reduction in state support. This result confirms the ability of the proposed model to identify hidden regulatory and institutional risks that remain difficult to distinguish using traditional linear methods of investment analysis.

The results of the sensitivity scenario analysis demonstrated the high structural robustness of the model. Variations in the weighting coefficients of the criteria across a wide range, including scenarios with priority consideration of ESG factors, did not lead to an inversion of the ranks of the analyzed periods. This indicates that the estimates obtained are determined by the fundamental dynamics of the input data, rather than subjective parameter settings, which is a critical requirement for strategic investment decision support systems.

The developed system can be considered a practical tool for strategic scenario analysis and support for sustainable investment policy. It can be used by government agencies to assess the impact of changes in the subsidy and regulatory system, as well as by private investors and analysts to make informed investment decisions that are less susceptible to short-term market noise.

The results obtained go beyond the national context. The modular and data-source-agnostic architecture allows the proposed approach to be adapted to the statistical systems of other countries with emerging economies while maintaining a unified logic for integrating economic, environmental, and institutional factors. This opens up opportunities to use the developed framework for cross-country comparative analysis and the formation of supranational systems for monitoring sustainable investments in the agro-industrial sector.

Further research could focus on increasing the spatial detail of the analysis, moving from the country to the regional level, and integrating adaptive neuro-fuzzy methods for calibrating membership functions. Another promising direction is the expansion of the analytical architecture by including machine learning forecasting modules to assess local climate and production risks in the context of sustainable development.

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