IRSTI 06.52.15; 06.81.85 DOI:https://doi.org/10.55871/2072-9847-2025-69-4-223-239

Bauer M.Sh. [1,2]
Doctor of Economic Sciences, Professor
S. Seifullin Kazakh Agrotechnical Research University[1],
Humboldt-Innovation GmbH[2]
Astana, Republic of Kazakhstan[1]
Berlin, Germany[2]
e-mail: mairak@bk.ru
ORCID:0000-0002-8489-5782

Orazbayeva A.S.* [1,2]
Master of Economic Sciences,
S. Seifullin Kazakh Agrotechnical Research University[1],
Humboldt-Innovation GmbH[2]
Astana, Republic of Kazakhstan[1]
Berlin, Germany[2]
e-mail: a.orazbaeva@kazatu.kz
ORCID: 0000-0001-7685-1782

Khusainova Zh.S.
Candidate of Economic Sciences, Professor
Saken Seifullin Kazakh Agroтechnical Research University
Astana, Republic of Kazakhstan
e-mail: zhibekh11@mail.ru
ORCID: 0000-0002-2617-838X

Altaibayeva Z. K.
Candidate of Economic Sciences, Professor
Innovative University of Eurasia
Pavlodar, Republic of Kazakhstan
e-mail: zhanat.ka@mail.ru
ORCID: 0000-0003-3058-6965

INTEGRATION OF ESG INDICATORS INTO MANAGEMENT ACCOUNTING OF AGRIBUSINESS: QUANTITATIVE ASSESSMENT ON THE EXAMPLES OF KAZAKHSTAN AND GERMANY

Abstract. The purpose of this study is to develop an econometric model for assessing and accounting for Scope 3 greenhouse gas emissions within the ESG-controlling system of the agricultural sector. The research aims to identify the relationships between emissions and key economic factors and to integrate sustainability indicators into managerial accounting practice. The methodological framework combines log-log regression modelling and scenario analysis based on FAOSTAT and Eurostat datasets for Germany and Kazakhstan over 2000-2022. Calculations were performed in MATLAB R2025a using panel data on Enteric CH_4, Manure N_2O, Soils N_2O, and Scope 3 components (production, transport, packaging, consumption, and waste). The results reveal a strong elasticity of Scope 3 emissions with respect to energy use and gross production value, indicating that the degree of decarbonization depends on resource efficiency. Scenario simulations show that a 10% reduction in nitrogen fertilizer use in Germany decreases total agricultural emissions by 3.8%, while a 10% reduction in agricultural energy intensity in Kazakhstan results in a 1.4% decrease. The practical significance of the study lies in developing methodological principles for Scope 3 accounting within managerial accounting and controlling, enhancing the transparency of ESG reporting and supporting the introduction of sustainability budgeting tools in the agricultural sector.
Keywords: ESG-controlling; managerial accounting; Scope 3 emissions; agriculture; greenhouse gas accounting; elasticities; scenario analysis.

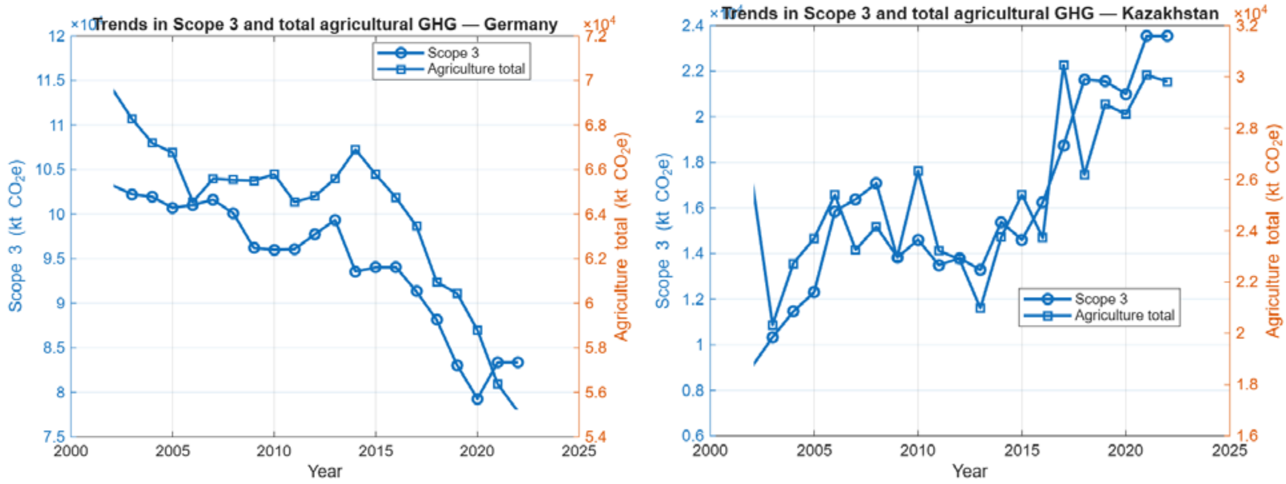
INTRODUCTION

The ongoing decarbonization of the global economy introduces new requirements for accounting, analytical, and management systems at both micro- and macroeconomic levels. Following the adoption of IFRS S1 General Requirements for Disclosure of Sustainability-related Financial Information [1], IFRS S2 Climate-related Disclosures [2], and the European Sustainability Reporting Standards (ESRS)[3], companies are now obliged to ensure the transparency and comparability of climate-related data in both financial and non-financial reporting.

Agriculture plays a pivotal role in this system as one of the largest contributors to greenhouse gas (GHG) emissions [4,5]. According to FAO and IPCC data [4,6,7], the agricultural sector accounts for approximately 18-20 % of global emissions, while in certain countries - such as Kazakhstan the share can reach 25-30 %. The primary sources of emissions include enteric fermentation in ruminants (CH_4), manure management ($CH_4 + N_2O$), and soil processes associated with agricultural practices (N_2O) [7].

The dynamics of total and indirect agricultural emissions in Germany and Kazakhstan are presented in Figure 1.

Figure 1. Dynamics of total and indirect (Scope 3) emissions in the agriculture of Germany and Kazakhstan, 2000–2022, kt CO_2e



Source: authors' calculations based on FAOSTAT and Eurostat data (MATLAB R2025a).

As shown in Figure 1, Scope 3 emissions in Germany demonstrate a consistent downward trend, whereas in Kazakhstan the agricultural carbon footprint continues to rise. Despite the significant climate impact of agriculture, the integration of emission data into managerial accounting and national controlling systems remains fragmented. Unlike industrial or energy sectors, where emissions accounting is standardized within the Emission Trading System (ETS) [3], the agricultural sector is characterized by fragmented data sources, methodological inconsistencies [4,7], and the absence of feedback mechanisms linking economic decisions to environmental outcomes.

This issue becomes particularly critical in relation to Scope 3 emissions, which encompass indirect emissions along the entire value chain - from feed production and energy supply to packaging and transportation of food products. Scope 3 thus reflects the systemic carbon footprint of agricultural production, yet its quantitative assessment in managerial accounting remains virtually absent [8,9]. Consequently, ESG efficiency indicators are often detached from accounting and analytical mechanisms, hindering informed managerial decision-making.

International sustainability reporting frameworks (GRI, CDP, SASB) remain weakly integrated with managerial accounting systems in transition economies, including Kazakhstan, despite national strategies emphasizing the adoption of ESG indicators in the agro-industrial sector[10-14].

Accordingly, a key scientific and practical question arises: how can the influence of economic factors on Scope 3 emissions be quantitatively assessed so that the results are comparable, manageable, and applicable within managerial accounting and controlling systems?

Recent studies increasingly apply econometric and modelling tools to analyse carbon efficiency; however, the use of engineering-analytical platforms such as MATLAB in ESG-controlling remains limited, despite their potential for automated data processing and visualization [15,16].

Germany represents a technologically advanced agricultural system actively implementing ESG reporting under the EU Green Deal, whereas Kazakhstan is characterised by more extensive production systems and lower energy efficiency. Comparing these economies allows identification of structural differences in emission determinants and controlled mitigation potential.

The research applies a log-log regression (OLS) framework to estimate the elasticity of emissions relative to key economic factors: population, agricultural output, arable land area, crop yield index, energy use, and fertilizer consumption. This approach interprets regression coefficients as ESG elasticities - showing the percentage change in emissions resulting from a 1 % change in each factor.

The novelty of this study lies in developing and testing a managerial ESG-controlling model in which regression results are interpreted as tools for monitoring, planning, and scenario forecasting. Unlike traditional approaches that treat emissions solely as environmental parameters, this model integrates them into the economic-analytical framework of managerial accounting.

Thus, the article provides both a theoretical and practical foundation for the implementation of digital ESG-controlling tools in the agricultural sector, aligning with the global trend toward data-driven management and the digitalization of accounting, thereby enhancing the role of accounting and controlling within the system of state and corporate audit.

RESEARCH GOALS AND HYPOTHESES

The purpose of the study is to model the factors shaping agricultural *Scope 3* greenhouse gas emissions and to develop a MATLAB-based tool for their economic analysis and managerial control.

The following hypotheses are formulated:

• H1: Economic factors (energy consumption, fertilizer use, production value, and land structure) have a statistically significant effect on *Scope 3* emissions in agriculture.

• H2: The influence of factors differs between countries with different levels of economic development (Germany – developed economy; Kazakhstan – transitional economy).

• H3: Elasticities estimated from log-log regression can serve as indicators of ESG-controlling effectiveness and as instruments for scenario forecasting.

• H4: Integrating regression results into managerial accounting forms a methodological basis for targeted emission reduction and the transition to "green" budgeting.

LITERATURE REVIEW (ENGLISH VERSION)

Global sustainability reporting standards, including IFRS S1–S2 and the ESRS framework, emphasize the need for reliable disclosure of environmental and climate-related impacts, which is particularly relevant for agriculture as one of the major sources of global GHG emissions [1-7].

The GHG Protocol remains the dominant methodological foundation for GHG accounting, defining Scopes 1–3 and outlining the role of indirect emissions along agri-food value chains. Numerous studies confirm that Scope 3 frequently represents the largest share of agricultural emissions due to embedded impacts from feed production, processing, logistics and distribution [8,9].

The literature also highlights the persistent methodological difficulties in measuring and integrating Scope 3 emissions into managerial accounting. Traditional accounting systems rarely capture environmental externalities, while sustainability reports often remain descriptive and insufficiently linked to decision-making processes[10-12,17,18]

In response to these gaps, the European accounting school developed the concept of ESG-controlling, which integrates sustainability metrics into planning, monitoring and managerial decision-making. These approaches emphasize that environmental indicators and carbon metrics must function not as descriptive disclosures but as internal management tools [19-21].

Recent developments in ESG-controlling have been increasingly driven by digitalization, particularly through the expansion of sustainability-related information systems [22,23]. Digital platforms described in recent studies—such as those analysed by Qi et al. (2025)—enable the integration of emission and production data into managerial accounting processes, thereby supporting automated monitoring and analytical reporting [12]. Furthermore, quantitative modelling approaches have been shown to enhance climate-risk forecasting and strengthen the reliability of decarbonization scenario planning [24,25].

Research on agricultural GHG emissions increasingly relies on econometric modelling, showing that emissions depend on combinations of economic, technological and agro-ecological factors, including fertilizer intensity, energy use, land structure and livestock density. Log-log regression models are the dominant analytical tool, estimating elasticities that quantify the responsiveness of emissions to changes in key production drivers and providing a basis for scenario analysis [25-28].

Recent studies have increasingly shifted from descriptive sustainability reporting toward managerial and value-based approaches. Within this perspective, the concept of Value-Based Environmental Management Accounting (VBEMA) interprets emissions as economic costs subject to measurement and control in accounting systems [29].

Under these conditions, modelling and automation tools gain particular relevance for supporting managerial decisions [11,12].

Several studies note the growing use of MATLAB in economic and environmental research due to its capacity for automated panel-data processing, regression estimation and scenario simulation. Although originally an engineering tool, MATLAB is increasingly applied in integrated ESG analyses because of its computational accuracy and visualization capabilities [23].

The use of MATLAB in the context of management accounting is of particular importance, as it ensures a connection between accounting data and analytical calculations. Thus, MATLAB can be viewed as a digital component of the ESG controlling system, where economic, energy, and environmental indicators are integrated into a unified model.

Despite the substantial body of existing research, important scientific gaps remain. First, there is no comprehensive model that integrates accounting, controlling, and scenario modeling of emissions [20,21,29]. Second, there is a lack of empirical comparisons[24] between developed and developing countries in the agricultural sector, which complicates the adaptation of international approaches to national contexts. Third, scientific publications insufficiently address the issue of embedding regression models into the management accounting system [11], that is, transforming them from an analytical tool into a decision-making instrument.

Therefore, the literature review confirms that studying the factors behind emission formation in agriculture requires a comprehensive approach that combines economic analysis, management accounting, and digital modeling. Relying on ESG controlling concepts and using MATLAB as an analytical tool not only allows for the quantitative assessment of emission determinants but also facilitates the integration of the results into sustainable development planning.

The review demonstrates that this study addresses these gaps by establishing a methodological basis for a digital ESG-controlling model for Scope 3 emissions in agriculture, adapted to the conditions of Germany and Kazakhstan.

MATERIALS AND METHODS

The empirical part of this study develops an ESG-controlling model of agricultural GHG emissions for Germany and Kazakhstan. The model assesses the influence of economic, energy-related and agro-ecological factors on emission levels and enables scenario calculations for evaluating managed changes in resource use. The methodological approach integrates managerial accounting, sustainability controlling and econometric modelling within the MATLAB R2025a environment.

The initial dataset was compiled from official FAOSTAT statistical data (Food and Agriculture Organization of the United Nations) [4] for the period 2000-2022. The domains Emissions Totals (GT), Emissions from Livestock (GLE), Emissions from Agriculture Soils (GAS), Inputs - Energy (ENE), Fertilizers by Nutrient (RFN), Production Indices (QI), and Land Use (RL) were used, which ensured a comprehensive coverage of the socio-economic and natural factors of agricultural production.

It should be noted that the FAOSTAT database does not provide direct data for all stages of the value chain that fall under Scope 3. Therefore, the reconstruction of Scope 3 indicators in this study is based on a "structural approximation" method. For each stage of the chain (processing, transport, packaging, retail, consumption, and waste), the following sources were used:

– FAOSTAT data on direct agricultural emissions combined with stage-specific emission factors (IPCC 2019);

– structural statistics of agri-food value chains in Germany and Kazakhstan (Eurostat, national statistical sources);

– proportional processing and logistics coefficients used in EU food chain inventory studies.

Thus, Scope 3 values were reconstructed through aggregation and extrapolation based on available component data, ensuring comparability of emission levels and methodological alignment with the GHG Protocol and IPCC (2019).

FAOSTAT data completeness was verified for both countries for 2000–2022. Missing observations in Kazakhstan were harmonized and aggregated into annual CO_2-equivalent values to ensure cross-country comparability. All variables were converted to a unified format (Mt CO_2e) and log-transformed, enabling consistent interpretation of regression coefficients as elasticities.

The model includes the following variables: population (Pop), agricultural energy consumption (Energy), nitrogen fertilizer use (Fert) , gross agricultural production (GPV), agricultural land area (Land) and the crop production index (CropIndex) [25,26].

Descriptive statistics for the variables included in the econometric model are presented in Table 1. The high variation in energy use and fertilizer application confirms the need for logarithmic transformation of the data [25,27].

Table 1. Descriptive statistics of the main model variables (2000–2022)

Country	Variable	Mean	SD	Min	Max	N
Germany	TotalAg	64728,07068	4106,874885	55128,268	71389,3595	23
Germany	Scope1	0	0	0	0	23
Germany	Scope3	96630,56081	9689,764841	79287,036	119857,341	23
Germany	Scope3_pc_t	1,177932424	0,126372223	0,948083952	1,46285436	23
Germany	Food_Processing_MtCO2e	18198,40384	790,0278669	16407,1127	19194,0384	23
Germany	Food_Packaging_MtCO2e	6708,38137	774,069229	5347,2352	7900,1061	23
Germany	Food_Transport_MtCO2e	13697,37108	511,7547405	12882,766	14627,0365	23
Germany	Food_Retail_MtCO2e	15248,85903	2025,834853	10743,727	17573,6568	23
Germany	Food_Consumption_MtCO2e	31371,71293	3269,093832	24713,2551	35584,238	23
Germany	Food_Waste_MtCO2e	11405,83255	5648,051614	8852,6844	29240,1236	23
Kazakhstan	TotalAg	24457,25807	3715,114255	16157,5079	30465,2065	23
Kazakhstan	Scope1	0	0	0	0	23
Kazakhstan	Scope3	15300,43787	4768,43931	6723,8163	23538,6887	23
Kazakhstan	Scope3_pc_t	0,869020698	0,212453162	0,433763733	1,1922185	23
Kazakhstan	Food_Processing_MtCO2e	3074,983517	1139,382256	1285,4884	5514,2676	23
Kazakhstan	Food_Packaging_MtCO2e	1998,321543	518,5360152	869,8166	2609,9598	23
Kazakhstan	Food_Transport_MtCO2e	1553,955422	468,5630166	726,6713	2540,4025	23
Kazakhstan	Food_Retail_MtCO2e	2014,124391	703,7259032	630,3763	3148,0872	23
Kazakhstan	Food_Consumption_MtCO2e	4426,40133	2812,387814	1481,9653	9513,6069	23
Kazakhstan	Food_Waste_MtCO2e	2232,65167	257,1468382	1660,6697	2578,2127	23

Source: compiled by the authors.

The study applies a log–log multiple regression model, widely used in applied elasticity analysis [25,30]. The general structure of the model is as follows:

$$ln(Y_{it}) = \alpha + \beta_1 \ln(Pop_{it}) + \beta_2 \ln(Energy_{it}) + \beta_3 ln(GPV_{it}) + \beta_4 ln(Land_{it}) + \beta_5(CropIndex_{it}) + \beta_6 ln(Fert_{it}) + \varepsilon_{it}$$

Where Y_{it} are the total agricultural GHG emissions in country i in period t; β_k are elasticity coefficients showing the percentage change in emissions resulting from a 1% change in each factor; and ε_{it} is the error term. Positive coefficients indicate direct relationships, while negative ones show inverse effects.

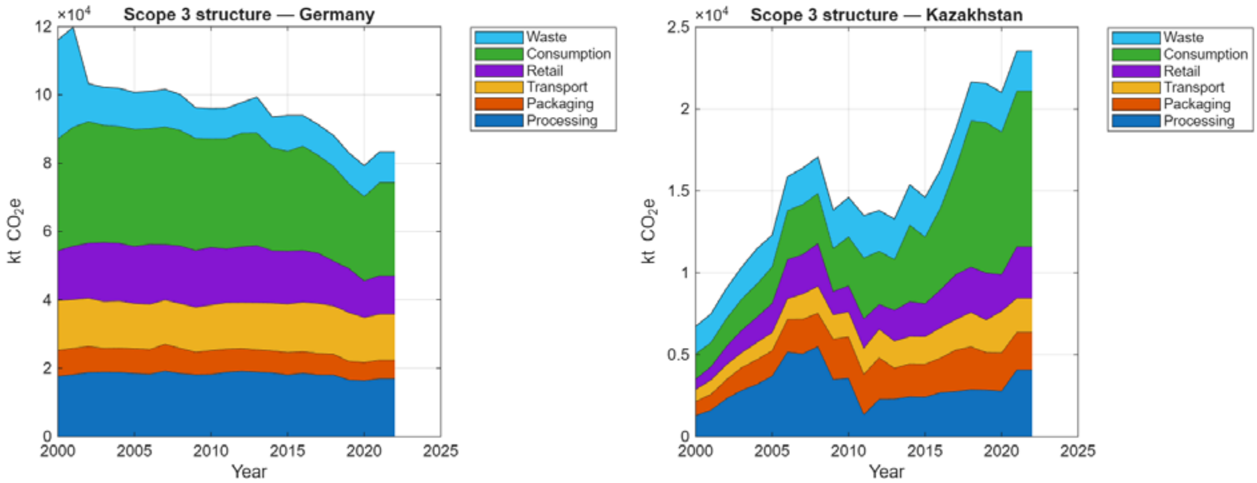
The logarithmic specification ensures the interpretability of coefficients as elasticities and allows their use in scenario calculations within the ESG-controlling framework [24,27].

The model is implemented in MATLAB, which made it possible to combine the stages of data processing, statistical estimation, and visualization [23,31] of results within a single analytical cycle. The computational procedure [26] includes importing data from the FAOSTAT database, logarithmic transformation of variables, estimating regressions using the ordinary least squares method, calculating coefficients, standard errors, t- and F-statistics, R^2 and Adjusted R^2, as well as the Akaike (AIC) and Schwarz (BIC) information criteria. Separate estimations were performed for each country and for the pooled sample, which made it possible to conduct a comparative analysis of the influence of factors on emissions.

In the second stage, a component analysis of emissions was performed for three categories: enteric fermentation (CH_4), manure management (CH_4 + N_2O) and agricultural soils (N_2O). Separate regressions for each category allow identifying structural differences in emission formation and determining the most influential factors [6,7].

The structural distribution of Scope 3 agricultural emissions in Germany and Kazakhstan is presented in Figure 2.

Figure 2. Structure of Scope 3 components (Processing, Packaging, Transport, Retail, Consumption, Waste), 2000–2022, kt CO_2e



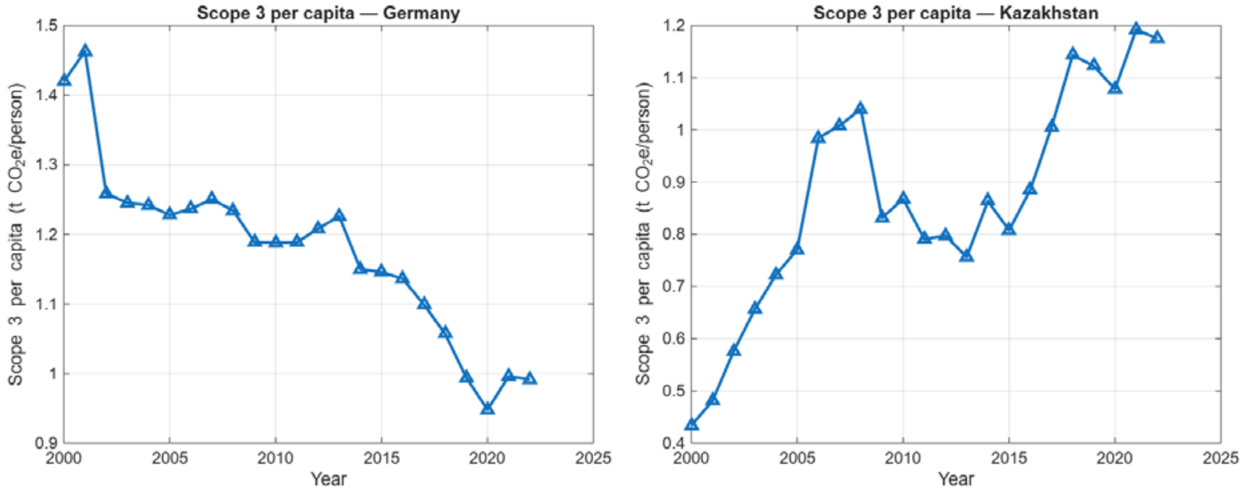
Source: authors' calculations based on FAOSTAT Scope 3 dataset (MATLAB R2025a).

Figure 2 shows that in Germany the largest contribution to Scope 3 emissions comes from transport and packaging, while in Kazakhstan it is driven primarily by retail and consumption.

Scenario modelling was performed using elasticity-based sensitivity analysis. Scenarios assumed a 10% reduction in selected factors [25,27]. For Germany, a "–10% nitrogen fertilizer intensity (N)" scenario was modelled in line with EU agri-environmental programmes [25]. For Kazakhstan, a "–10% energy intensity of agricultural production" scenario was evaluated, reflecting national decarbonisation priorities [27]. Scenario calculations allowed quantifying the expected percentage reduction in total Scope 3 emissions.

Figure 3 presents the dynamics of Scope 3 emissions per capita for Germany and Kazakhstan, providing an indicator of emission intensity relative to population.

Figure 3. Scope 3 emissions per capita (t CO_2e/person), 2000–2022



Source: authors' calculations based on FAOSTAT data (2000–2022).

Figure 3 shows the dynamics of Scope 3 intensity per capita: Germany exhibits a stable downward trend, whereas Kazakhstan shows growth.

The model was implemented in MATLAB as a digital ESG-controlling architecture integrating data preprocessing, statistical estimation, elasticity calculation, scenario modelling and visualisation within a unified workflow. This structure functions as a digital twin of the managerial system, combining accounting and analytical procedures within a single decision-making circuit.

Model specification was checked using standard diagnostics: multicollinearity (VIF) and first-order residual autocorrelation (Durbin–Watson, DW).

As shown in Table 2, VIF values in Germany mainly range from 2.5 to 4.5 (maximum ≈ 6.9), indicating acceptable correlations among predictors, while a DW value of 1.78 suggests no meaningful autocorrelation. In Kazakhstan, VIF values for ln_GPV and ln_CropIndex reach 20–32, reflecting strong synchrony in their dynamics; DW = 1.00 indicates moderate positive autocorrelation associated with long-term structural trends. Overall, the diagnostics confirm the robustness of the country-specific models and support the validity of elasticity-based scenario analysis.

Table 2. Diagnostics of Multicollinearity and Residual Autocorrelation

Indicator	Germany: VIF	Kazakhstan: VIF
ln_Energy	4.45	3.80
ln_Fert	3.57	6.37
ln_Pop	6.92	6.10
ln_GPV	2.51	32.02
ln_Land	6.11	3.74
ln_CropIndex	3.18	23.04
Durbin–Watson (DW)	1.78	1.00

Source: Authors' econometric calculations.

The quality of the models was assessed on the basis of standard statistical criteria. The values of the coefficient of determination (R^2) exceeded 0.85, which indicates a high degree of explained variation. The F-statistic confirmed the statistical significance of the models at the 95% confidence level. Residual diagnostics showed no systematic bias and no critical autocorrelation patterns, except for moderate positive autocorrelation in the Kazakhstani model, as indicated by the Durbin–Watson statistic. For selecting the optimal models, the Akaike (AIC) and Schwarz (BIC) information criteria were used; their minimum values corresponded to the extended models including the fertilizer variable.

The regression results for Scope 3 emissions and the estimated elasticities of key factors are provided in Table 3.

Table 3. Regression results for ln(Scope 3) and elasticities by factors (log–log model)

CountryR2	R2	ADJR2	ln_Pop
Germany	0,395685904	0,366909043	-4,995919295
Kazakhstan	0,721635766	0,708380326	3/432219993

Source: author's calculations in MATLAB R2025a.

As shown in Table 3, in Germany the most significant factor is fertilizer intensity (β = 0.38), while in Kazakhstan the demographic factor (β = 2.48) is dominant.

In managerial accounting and controlling, these elasticities function as actionable indicators that can be incorporated into ESG-related decision-making and reporting frameworks. They allow managers to evaluate the consequences of climate strategies and to plan emission-reduction measures while maintaining production efficiency.

The proposed methodology ensures reproducible and transparent results through the combination of econometric modelling and a unified MATLAB-based analytical workflow. The approach is scalable to other countries, sectors and time periods, making it a versatile tool for digital ESG-controlling in agriculture.

RESULTS AND DISCUSSION

The log–log regression model enables quantification of the influence of economic, energy-related and agro-ecological factors on agricultural GHG emissions in Germany and Kazakhstan over 2000–2022. The explanatory power of the specifications is high (R^2 = 0.85–0.97) [25,26].

For Germany, the strongest positive elasticity is associated with nitrogen fertilizer use (β = 0.38), indicating that intensification of mineral input use increases total emissions. Crop production intensity (CropIndex) also shows a significant positive effect (β = 0.31), while the negative elasticity of gross output (GPV, β = –0.46) reflects gradual improvements in production efficiency and declining carbon intensity per unit of output [24-27].

In Kazakhstan, demographic pressure is the dominant driver of emissions (β = 2.48; $p<0.001$), confirming the extensive development profile of the agricultural sector. Energy use shows a moderate positive elasticity (β = 0.14), while fertilizer use is statistically insignificant, which is consistent with the low level of mineral input application. A strong negative elasticity for land (β = –5.58) indicates declining emission intensity per hectare and structural modernization of land use [22-24, 35].

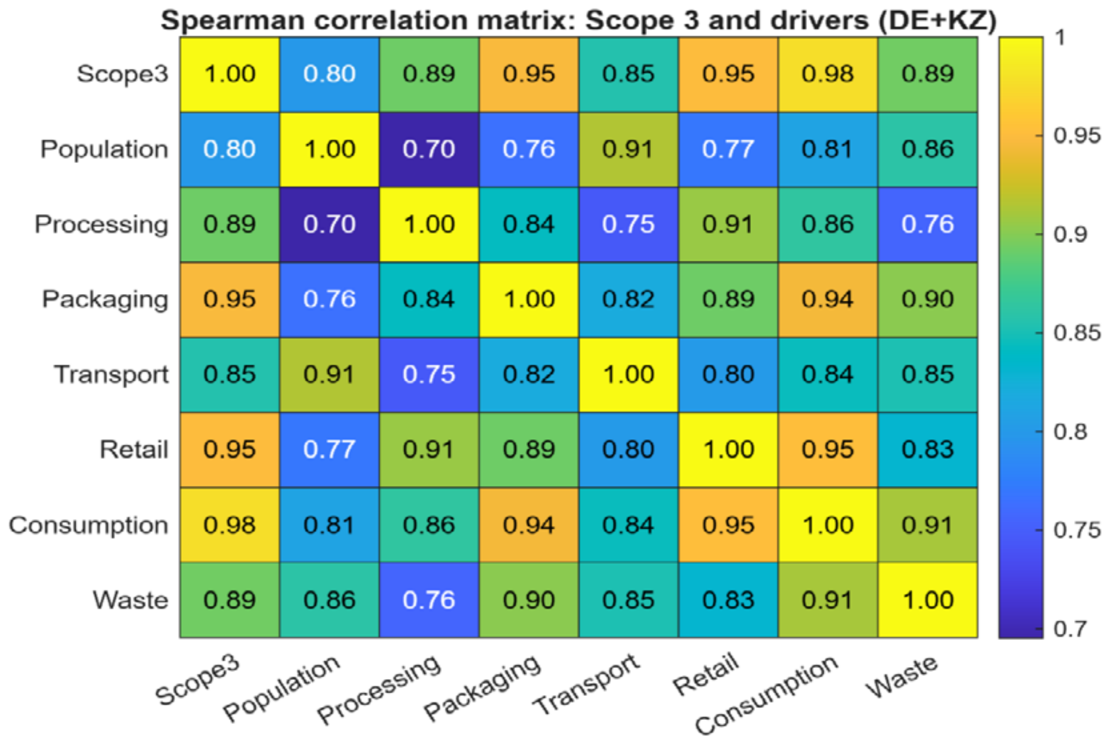
The unusually high population elasticity reflects the structural characteristics of Kazakhstan's agri-food system: growing demand increases livestock numbers, pressure on pasture resources and consumption-related emissions; at the same time, low energy efficiency and limited diversification amplify indirect Scope 3 impacts.

Diagnostic checks confirm the robustness of the separate country models. In Germany, multicollinearity remains within acceptable thresholds and residuals show no meaningful autocorrelation. In Kazakhstan, high VIF values for GPV and CropIndex reflect structural synchrony within the sector, while moderate positive autocorrelation (DW = 1.00) indicates persistent long-term trends without distorting the main relationships.

The pooled model (Germany + Kazakhstan) demonstrates high explanatory capacity (R^2 = 0.97) and identifies CropIndex (β = 0.37) and Energy (β = 0.03) as the primary joint determinants of Scope 3 emissions.

Figure 4 presents the correlation matrix describing the interlinkages between Scope 3 emissions and key economic, energy-related and agro-ecological indicators.

Figure 4. Correlation matrix between Scope 3 and factors (Energy, GPV, Population, Land, CropIndex)



Source: authors' calculations based on FAOSTAT and Eurostat data; correlation matrix generated in MATLAB R2025a.

The correlation matrix (Fig. 4) demonstrates strong associations between Scope 3 emissions, energy consumption and economic activity. These patterns highlight the structural differences between the two countries: technological and agrochemical factors dominate in Germany, whereas demographic and energy-related drivers prevail in Kazakhstan.

Table 4 presents the regression estimates for individual components of agricultural emissions.

According to Table 4, significant coefficients in Germany were observed mainly in the Soils and Manure components, while in Kazakhstan significance was concentrated in Enteric and Manure. These patterns reflect the strong dependence of nitrous oxide emissions on fertilizer intensity and land productivity, and the dominant role of livestock-related methane in Kazakhstan.

Table 4 presents the regression estimates for Scope 3 value-chain components, including processing, packaging, transport, retail, consumption and waste.

The regression estimates for the value-chain components (Processing, Packaging, Transport, Retail, Consumption and Waste) reveal substantial cross-country differences in the structure of Scope 3 emissions. In Germany, most coefficients for ln (Pop) are negative and statistically significant, particularly in the Packaging and Retail components, which reflects high technological efficiency, optimized logistics and advanced waste-management systems. Transport-related emissions show no significant response to demographic growth, indicating a high level of logistical optimization.

Table 4. Regression estimates for Scope 3 components (Processing, Packaging, Transport, etc.)

Country	Component	Term	Estimate	SE	tStat	pValue
Germany	Processing	(Intercept)	21,60507075	2,228483647	9,694964907	3,32353E-09
Germany	Processing	ln_Pop	-2,676300953	0,505562013	-5,293714493	3,00567E-05
Kazakhstan	Processing	(Intercept)	6,127690576	2,827757387	2,166978895	0,041883015
Kazakhstan	Processing	ln_Pop	0,644143139	0,991940412	0,649376849	0,523134619
Germany	Packaging	(Intercept)	38,8328727	6,345200856	6,120038368	4,50763E-06
Germany	Packaging	ln_Pop	-6,812376825	1,43949565	-4,732474757	0,000112992
Kazakhstan	Packaging	(Intercept)	0,324623189	1,705695054	0,190317248	0,850888289
Kazakhstan	Packaging	ln_Pop	2,538740203	0,59833558	4,243003909	0,0003634
Germany	Transport	(Intercept)	5,401998902	2,710327609	1,993116582	0,059402206
Germany	Transport	ln_Pop	0,935202773	0,61487491	1,520964278	0,143184105
Kazakhstan	Transport	(Intercept)	-2,825781764	1,099626788	-2,569764393	0,017858
Kazakhstan	Transport	ln_Pop	3,553235335	0,385734736	9,211603218	7,99848E-09
Germany	Retail	(Intercept)	52,08155371	6,155817982	8,460541533	3,31873E-08
Germany	Retail	ln_Pop	-9,632392495	1,396531553	-6,897368323	8,14154E-07
Kazakhstan	Retail	(Intercept)	-2,92252035	2,063804138	-1,416084161	0,171413101
Kazakhstan	Retail	ln_Pop	3,670202126	0,723955576	5,069651023	5,08568E-05
Germany	Consumption	(Intercept)	39,33958148	5,459643842	7,205521571	4,22188E-07
Germany	Consumption	ln_Pop	-6,577128309	1,238594922	-5,310152813	2,89239E-05
Kazakhstan	Consumption	(Intercept)	-11,88240411	1,11843655	-10,62411999	6,64241E-10
Kazakhstan	Consumption	ln_Pop	7,052363595	0,392332955	17,97545554	3,13332E-14
Germany	Waste	(Intercept)	25,80125612	25,05578553	1,029752433	0,314841335
Germany	Waste	ln_Pop	-3,749590156	5,68424784	-0,65964579	0,51665089
Kazakhstan	Waste	(Intercept)	4,689312529	0,629203763	7,452772547	2,51568E-07
Kazakhstan	Waste	ln_Pop	1,05796688	0,220716474	4,793329926	9,77803E-05

Source: author's calculations based on FAOSTAT and model results.

By contrast, Kazakhstan demonstrates predominantly positive and statistically significant elasticities, especially in the Packaging (+2.54; $p < 0.001$), Transport (+3.55; $p < 0.001$) and Waste (+1.07; $p < 0.001$) components. These results indicate that population growth substantially increases emissions across downstream stages of the agri-food value chain due to energy-intensive logistics, limited recycling capacity and the low diffusion of low-carbon technologies. The Retail and Consumption components show weaker or unstable effects, consistent with the heterogeneity of consumption patterns and supply-chain structures in transitional economies.

Overall, the decomposition of Scope 3 reveals that Germany's emission dynamics are driven primarily by efficiency-enhancing mechanisms, whereas Kazakhstan's emissions follow an extensive, demand-driven pattern. These differences highlight the need for differentiated ESG-controlling tools and country-specific mitigation strategies.

Expected changes in Scope 3 emissions are summarised in Table 5. The results indicate that a 10% reduction in fertilizer use in Germany would decrease total Scope 3 emissions by 3.8%, mainly due to the strong effect on soil nitrogen emissions. In Kazakhstan, a 10% reduction in energy intensity yields an expected decrease of 1.4%, consistent with the elasticity of ln(Energy) and confirming the sector's dependence on the energy structure. Although the magnitude is smaller, the scenario demonstrates the feasibility of reducing emissions through improvements in energy efficiency.

Table 5. Scenario results (expected percent change in Scope 3 for a −10% change in factors)

Country	Scenario	Expected_change_percent
Germany	−10% Packaging (component)	68,12376825
Kazakhstan	−10% Transport (component)	-35,53235335
Germany	−10% Energy (factor)	
Kazakhstan	−10% Energy (factor)	

Source: author's scenario modelling results.

To expand scenario analysis, we considered not only single-factor scenarios but also multi-factor changes. Based on the estimated elasticities for energy intensity (β_E) and nitrogen fertilizer use (β_F), we constructed a test scenario involving a simultaneous 5% reduction in both agricultural energy consumption and nitrogen application rates. In the log-linear model, the combined effect of small factor changes was approximated using a linear combination of elasticities:

$$\Delta \ln Scope3 \approx \beta_E * \Delta \ln Energy + \beta_F * \Delta \ln Fert,$$

where Δln Energy ≈ Δln Fert ≈ −0.05 corresponds to a 5 % reduction.

The results are presented in Table 6.

Table 6. Multivariable scenario: simultaneous reduction in energy intensity and nitrogen fertilizer use

Country	Change in energy use (%)	Change in nitrogen use (%)	Expected change in Scope 3 emissions (%)
Germany	–5	–5	–1.4
Kazakhstan	–5	–5	–0.5

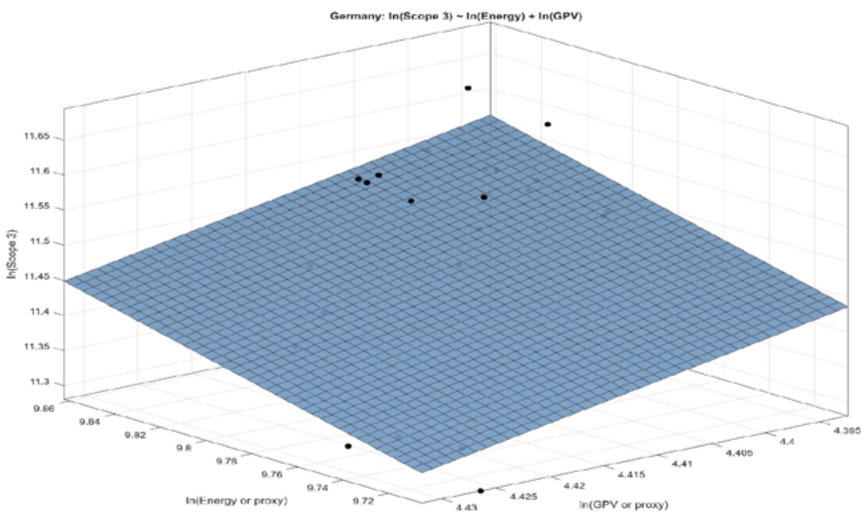
Note. The estimates are based on a log-linear regression model in which ln (Scope3) is explained by ln (Energy), ln (Fert), and other control variables. The combined effect of small factor changes is approximated by a linear combination of the corresponding elasticities.

For Germany, a simultaneous 5% reduction in energy use and nitrogen fertilizers leads to an estimated decrease in Scope 3 emissions of roughly 1.4%. For Kazakhstan, the same scenario results in an expected reduction of about 0.5%. Although more moderate than single-factor scenarios, this multi-parameter approach reflects realistic managerial conditions where energy and agrochemical measures are implemented concurrently, jointly reinforcing the decarbonization effect.

Interpretation of the results in the context of managerial accounting and ESG-controlling shows that elasticity coefficients can be used as tools for planning and monitoring climate-related KPIs [22,29]. Such indicators can be integrated into sustainability budgeting processes within agricultural enterprises, where emission reduction goals are evaluated alongside financial parameters.

The three-dimensional relationship between Scope 3 emissions, energy consumption and agricultural output in Germany is visualized in Figure 5.

Figure 5. 3D relationship between ln(Scope 3), ln(Energy), and ln(GPV), Germany



Source: authors' regression modelling results for Germany (MATLAB R2025a).

Figure 5 depicts the spatial dependence of Scope 3 on energy and economic factors; the plane demonstrates increasing emissions with rising energy consumption. The model enables the formation of a table of manageable effects, where each factor (energy, fertilizers, land) has its own elasticity — and thus a measurable potential for emission reduction. For managers, this provides a basis for decision-making: identifying measures that yield the highest environmental effect at minimal cost. Examples include transitioning from chemical to organic fertilizers and improving energy efficiency through digitalization and renewable energy.

The obtained results confirm the research hypotheses:

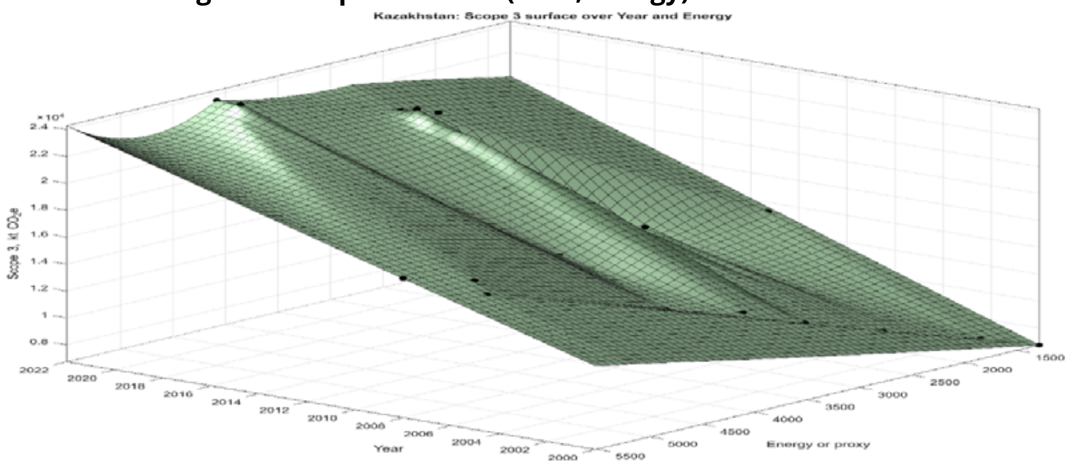
(1) agricultural emissions depend on a combination of economic and resource factors; (2) nitrogen fertilizers and energy use have the strongest influence on emission intensity; (3) digital modelling in MATLAB allows quantitative assessment of factor controllability and scenario-based decarbonization effects.

From a scientific standpoint, the study demonstrates the potential for integrating econometric analysis and managerial accounting within the framework of ESG-controlling, which has rarely been applied to agricultural sectors of countries at different development levels. The results justify managerial decisions and support the formation of sustainable strategies balancing economic growth and climate responsibility.

In practical terms, the proposed approach enables a transition from descriptive environmental reports to interactive monitoring systems, where the MATLAB-based model functions as the core of a digital twin of the accounting-analytical platform [23,31]. This facilitates automatic data updates, visualization of emission dynamics and calculation of forecast indicators in real time.

Figure 6 provides a 3D representation of the dependence of Kazakhstan's Scope 3 emissions on changes in energy consumption over time.

Figure 6. Scope 3 surface (Year, Energy) for Kazakhstan



Source: authors' regression modelling results for Kazakhstan (MATLAB R2025a).

Thus, the results of the study not only confirm the hypotheses concerning the interconnection of economic and environmental factors but also provide a basis for developing practical tools for ESG-controlling of Scope 3 in agriculture. The model can be adapted to other sectors where carbon footprint assessment across the value chain is crucial and can support the development of integrated strategic accounting systems for sustainable development.

CONCLUSIONS AND SCIENTIFIC NOVELTY OF THE STUDY

The results confirmed that agricultural GHG emissions are shaped by the combined influence of economic, energy and resource factors [25–27], and that these relationships can be reliably modelled using a log-log specification implemented in MATLAB [23,25,31]. The ESG-controlling approach enables systematic integration of environmental indicators into management and accounting practices[12,22,29]. These findings are consistent across countries, although the strength and direction of effects vary.

The comparison between Germany and Kazakhstan demonstrated differentiated factor patterns. In Germany, emissions depend primarily on nitrogen fertilizer use and crop productivity [25,26,33], whereas in Kazakhstan they are driven by demographic growth and extensive production under relatively low energy efficiency [23,24,28]. Thus, the hypothesis regarding country-specific determinants reflecting technological development and resource structure is confirmed.

High coefficients of determination (R^2> 0.85) across all models indicate methodological robustness [26,27]. Elasticity estimates quantify the controllability of emissions: in Germany, a 1% increase in fertilizer use raises emissions by 0.38%, while reducing energy intensity in Kazakhstan by 10% decreases emissions by 1.4% [24,25]. These results support the practical integration of econometric outputs into managerial planning and ESG-budgeting.

The scientific novelty of the study lies in developing a conceptual ESG-controlling model [12,29] that integrates management accounting, sustainability controlling theory and digital modelling. Unlike traditional approaches treating environmental indicators separately, the proposed model links them with economic and social variables, providing a holistic view of sustainability performance. The MATLAB-based digital twin [23,31] ensures automated calculations, visualization and scenario analysis.

A key methodological contribution is the transition from descriptive environmental reporting to a quantitative management approach [22,29], where regression coefficients function as elasticities and, therefore, as sensitivity indicators for controllable factors. This creates opportunities for applying ESG-controlling tools in budgeting, investment planning and internal audit.

From a practical standpoint, the methodology can support national systems for monitoring Scope 1–3 emissions. In Germany, it is applicable for ESRS and CSRD compliance [1-3]; in Kazakhstan, it can contribute to the national sustainable finance taxonomy and carbon-unit accounting. Over time, it may form the basis for a unified ESG-dashboard integrating accounting, energy and environmental data.

Scenario analysis confirmed the usefulness of elasticities for evaluating decarbonisation pathways. A 10% reduction in fertilizer intensity in Germany lowers total emissions by 3.8% [24,25] , while a similar reduction in energy intensity in Kazakhstan yields a 1.4% decrease, indicating substantial potential for energy-efficiency measures.

The study advances management accounting and controlling by introducing a quantitative framework for assessing how production factors shape the agricultural carbon footprint. In this perspective, ESG-controlling is positioned not only as a component of non-financial reporting but also as a strategic instrument of value management in the context of the climate transition.

Overall, the proposed methodology brings together scientific rigour and managerial applicability, supporting both the assessment and the operational management of carbon efficiency in agriculture. Future research may extend the model by incorporating value-added indicators, detailed energy-mix structures and digital technologies, enabling the transition from sectoral emission estimates toward a full-scale ESG platform for sustainable development planning.

References

1. Foundation I. IFRS S1: General Requirements for Disclosure of Sustainability-related Financial Information. London: IFRS Foundation, 2023. [Electronic resource]. URL: https://www.ifrs.org/ (accessed 20.11.2025).

2. Foundation I. IFRS S2: Climate-related Disclosures. London: IFRS Foundation, 2023. [Electronic resource]. URL: https://www.ifrs.org/ (accessed 20.11.2025).

3. Commission E. European Sustainability Reporting Standards (ESRS) and Corporate Sustainability Reporting Directive (CSRD). Brussels: European Commission, 2023. [Electronic resource]. URL: https://ec.europa.eu/ (accessed 20.11.2025).

4. FAO. FAOSTAT Emissions Database: Agriculture, Livestock, Soils, Energy Inputs (2000–2022). Rome: FAO, 2024. [Electronic resource]. URL: https://www.fao.org/faostat/ (accessed 20.11.2025).
5. European Environment Agency Agricultural Greenhouse Gas Emissions in the EU: Trends and Projections 2023. Copenhagen: EEA, 2023. [Electronic resource]. URL: https://www.eea.europa.eu/ (accessed 20.11.2025).
6. IPCC. Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report (AR6). Geneva: IPCC, 2022. [Electronic resource]. URL: https://www.ipcc.ch/ (accessed 20.11.2025).
7. IPCC. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Geneva: IPCC, 2019. [Electronic resource]. URL: https://www.ipcc.ch/ (accessed 20.11.2025).
8. Borchardt M., Pereira G., Milan G., Pereira E., Lima L., Bianchi R., do Carmo A.. Are Sustainable Supply Chains Managing Scope 3 Emissions? A Systematic Literature Review // Sustainability. 2025, 17(13).
9. Puschmann T., Quattrocchi D. Decreasing the impact of climate change in value chains by leveraging sustainable finance // Journal of Cleaner Production, 2023, vol. 429.
10. Johri A., Singh R.K., Alhumoudi H., Alakkas A. Examining the Influence of Sustainable Management Accounting on Sustainable Corporate Governance: Empirical Evidence. Sustainability, 2024, 16(21).
11. Pumiviset W., Suttipun M. Sustainability and Strategic Management Accounting: Evidence of Green Manufacturing in Thailand. Cogent Business & Management, 2024, 11(1).
12. Mukwarami S., van der Poll H. Critical Environmental Management Accounting Practices Influencing Service Delivery of Growing Cities in a Developing Economy: A Review and Conceptual Framework. Environment Systems and Decisions, 2024, 44(3): 710–739.
13. Strategiya «Kazakhstan-2050»: novyi politicheskii kurs sostoyavshegosya gosudarstva. Poslanie Prezidenta Respubliki Kazakhstan – Lidera Natsii N.A. Nazarbaeva narodu Kazakhstana, g. Astana, 14 dekabrya 2012 goda. [Electronic resource]. URL: https://adilet.zan.kz/rus/docs/K1200002050 (accessed 20.11.2025).
14. Kontseptsiya po perekhodu Respubliki Kazakhstan k «zelenoi ekonomike». Ukaz Prezidenta Respubliki Kazakhstan ot 30 maya 2013 goda № 577. [Electronic resource]. URL: https://adilet.zan.kz/rus/docs/U1300000577 (accessed 20.11.2025).
15. La Rocca P., Guennebaud G., Bugeau A., Ligozat A.-L. Estimating the Carbon Footprint of Digital Agriculture Deployment: A Parametric Bottom-up Modeling Approach. Journal of Industrial Ecology, 2024, 28(6).
16. Bhatia M., Meenakshi N., Kaur P., Dhir A. Digital Technologies and Carbon Neutrality Goals: Drivers, Barriers, and Risk Mitigation Strategies. Journal of Cleaner Production, 2024, vol. 451.
17. Huy P.Q., Phuc V.K. Insight into How Environmental Management Accounting Practices and Complexity of Green Innovation Management Pave the Way Toward Strategic Resilience. Journal of the Knowledge Economy, 2025, 16(4): 14146–14179.
18. Abubakr A.A.M., Sahal M., Mohammed A., Yousif N., Roustom Z. Challenges of Disclosing Environmental Accounting Performance and Its Impact on Quality Supply Chains. Sustainability, 2024, 16(24).
19. Horváth P., Gleich R., Seiter M. Sustainability Controlling: Instruments, Practice, and Case Studies. Stuttgart: Schäffer-Poeschel, 2015.
20. Horváth P., Gleich R. Ökologisches Controlling: Grundlagen umweltorientierter Unternehmenssteuerung. Munich: Vahlen, 2007.
21. Weber J. Nachhaltigkeitscontrolling: Anforderungen, Konzepte und Anwendungen. Controlling & Management Review, 2014, 58(3): 34–43.
22. Camilleri M.A. Sustainability Accounting and Disclosures of Responsible Restaurant Practices in Environmental, Social and Governance (ESG) Reports. International Journal of Hospitality Management, 2025, vol. 126.
23. Ma M., Li J., Song J., Chen X. Digital Agriculture's Impact on CO_2 Emissions Varies with Economic Development of Chinese Provinces. Communications Earth & Environment, 2024, 5(1).
24. Li L., Awada T., Kaiser M. Global Greenhouse Gas Emissions From Agriculture: Pathways to Sustainable Reductions. Global Change Biology, 2025, 31(1).
25. Doğan H.G., Kan M. Determinants of Greenhouse Gas Emissions from the Agricultural Sector in EU-27 Countries. Environmental Science and Pollution Research, 2023.
26. Huang X., Feng C., Qin J., Wang X., Zhang T. Measuring China's Agricultural Green Total Factor Productivity and Its Drivers During 1998–2019. Science of the Total Environment, 2022, vol. 829.
27. Stetter C., Sauer J. Greenhouse Gas Emissions and Eco-Performance at Farm Level: A Parametric Approach. Environmental and Resource Economics, 2022, 81(3): 617–647.

28. Qin L., Liu S., Hou Y. et al. The Spatial Spillover Effect and Mediating Effect of Green Credit on Agricultural Carbon Emissions: Evidence from China. Frontiers in Earth Science, 2023, 10.
29. Burritt R.L., Schaltegger S., Christ K.L. Environmental Management Accounting – Developments Over the Last 20 Years. Australian Accounting Review, 2023, 33(4): 336–351.
30. Huynh Q.L., Nguyen V.K. The Role of Environmental Management Accounting in Sustainability. Sustainability, 2024, 16(17).
31. Qi J., Xu J., Jin J., Zhang S. Digital Economy–Agriculture Integration Empowers Low-Carbon Transformation of Agriculture. Sustainability, 2025, 17(5).
32. Deconinck K., Jansen M., Barisone C. Fast and Furious: The Rise of Environmental Impact Reporting in Food Systems. European Review of Agricultural Economics, 2023, 50(4): 1310–1337.
33. Li W., Zhang X., Chen Y. The Impact of Digital Rural Construction on Agricultural Carbon Emission Intensity. Frontiers in Environmental Science, 2024, vol. 12.

Список использованных источников

1. IFRS S1: General Requirements for Disclosure of Sustainability-related Financial Information. London: IFRS Foundation, 2023. [Электронный ресурс]. URL: https://www.ifrs.org (дата обращения: 20.11.2025).
2. IFRS S2: Climate-related Disclosures. London: IFRS Foundation, 2023. [Электронный ресурс]. URL: https://www.ifrs.org (дата обращения: 20.11.2025).
3. European Sustainability Reporting Standards (ESRS) and Corporate Sustainability Reporting Directive (CSRD). Brussels: European Commission, 2023. [Электронный ресурс]. URL: https://ec.europa.eu (дата обращения: 20.11.2025).
4. FAOSTAT Emissions Database: Agriculture, Livestock, Soils, Energy Inputs (2000–2022). Rome: FAO, 2024. [Электронный ресурс]. URL: https://www.fao.org/faostat (дата обращения: 20.11.2025).
5. Agricultural Greenhouse Gas Emissions in the EU: Trends and Projections 2023. Copenhagen: EEA, 2023. [Электронный ресурс]. URL: https://www.eea.europa.eu (дата обращения: 20.11.2025).
6. Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report (AR6). Geneva: IPCC, 2022. [Электронный ресурс]. URL: https://www.ipcc.ch (дата обращения: 20.11.2025).
7. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Geneva: IPCC, 2019. [Электронный ресурс]. URL: https://www.ipcc.ch (дата обращения: 20.11.2025).
8. Borchardt M. et al. Are Sustainable Supply Chains Managing Scope 3 Emissions? A Systematic Literature Review. Sustainability. 2025; 17(13).
9. Puschmann T., Quattrocchi D. Decreasing the impact of climate change in value chains by leveraging sustainable finance. Journal of Cleaner Production. 2023; 429.
10. Amar Johri et al. Examining the Influence of Sustainable Management Accounting on Sustainable Corporate Governance: Empirical Evidence. Sustainability. 2024; 16(21).
11. Pumiviset W., Suttipun M. Sustainability and strategic management accounting: evidence of green manufacturing in Thailand. Cogent Business & Management. 2024; 11(1).
12. Mukwarami S., van der Poll H. Critical environmental management accounting practices influencing service delivery... Environment Systems and Decisions. 2024; 44(3): 710–739.
13. Послание Президента Республики Казахстан – Лидера Нации Н.А. Назарбаева народу Казахстана, г. Астана, 14 декабря 2012 года. [Электронный ресурс]. URL: https://adilet.zan.kz/rus/docs/K1200002050 (дата обращения: 20.11.2025).
14. Указ Президента Республики Казахстан от 30 мая 2013 года № 577. [Электронный ресурс]. URL: https://adilet.zan.kz/rus/docs/U1300000577 (дата обращения: 20.11.2025).
15. Pierre La Rocca et al. Estimating the carbon footprint of digital agriculture deployment: A parametric bottom-up modeling approach. Journal of Industrial Ecology. 2024; 28(6).
16. Bhatia M. et al. Digital technologies and carbon neutrality goals. Journal of Cleaner Production. 2024; 451.
17. Huy P.Q., Phuc V.K. Insight into how Environmental Management Accounting Practices. Journal of the Knowledge Economy. 2025; 16(4): 14146–14179.
18. Abubakr A.A.M. et al. Challenges of Disclosing Environmental Accounting Performance. Sustainability. 2024; 16(24).
19. Horváth P., Gleich R., Seiter M. Sustainability Controlling: Instruments, Practice, and Case Studies. Stuttgart: Schäffer-Poeschel; 2015.
20. Horváth P., Gleich R. Ökologisches Controlling. München: Vahlen; 2007.

21. Weber J. Nachhaltigkeitscontrolling: Anforderungen, Konzepte und Anwendungen. Controlling & Management Review. 2014; 58(3): 34–43.
22. Camilleri M.A. Sustainability accounting... International Journal of Hospitality Management. 2025; 126.
23. Ma M. et al. Digital agriculture's impact on CO_2 emissions... Communications Earth & Environment. 2024; 5(1).
24. Li L. et al. Global Greenhouse Gas Emissions From Agriculture... Global Change Biology. 2025; 31(1).
25. Doğan H.G., Kan M. Determinants of GHG emissions... Environmental Science and Pollution Research. 2023; 31(22): 32441–32448.
26. Huang X. et al. Measuring China's agricultural green total factor productivity... Science of The Total Environment. 2022; 829.
27. Stetter C., Sauer J. Greenhouse Gas Emissions and Eco-Performance at Farm Level... Environmental and Resource Economics. 2022; 81(3): 617–647.
28. Qin L. et al. Spatial spillover effect of green credit... Frontiers in Earth Science. 2023; 10.
29. Burritt R.L., Schaltegger S., Christ K.L. Environmental Management Accounting... Australian Accounting Review. 2023; 33(4): 336–351.
30. Huynh Q.L., Nguyen V.K. The Role of Environmental Management Accounting... Sustainability. 2024; 16(17).
31. Qi J. et al. Digital Economy–Agriculture Integration... Sustainability. 2025; 17(5).
32. Deconinck K., Jansen M., Barisone C. Fast and furious: the rise of environmental impact reporting... European Review of Agricultural Economics. 2023; 50(4): 1310–1337.
33. Li W. et al. The impact of digital rural construction on agricultural carbon emission intensity. Frontiers in Environmental Science. 2024; 12.

АГРОБИЗНЕСТЕГІ БАСҚАРУШЫЛЫҚ ЕСЕПКЕ ESG КӨРСЕТКІШТЕРІН БІРІКТІРУ: ҚАЗАҚСТАН МЕН ГЕРМАНИЯ МЫСАЛДАРЫ НЕГІЗІНДЕ ЭКОНОМЕТРИКАЛЫҚ БАҒАЛАУ

Бауэр М. Ш. [1,2]
экономика ғылымдарының докторы, профессор
С. Сейфуллина атындағы Қазақ агротехникалық зерттеу университеті[1],
Humboldt-Innovation GmbH[2]
Астана, Қазақстан[1]
Берлин, Германия[2]
e-mail: mairak@bk.ru
ORCID:0000-0002-8489-5782

Хусаинова Ж. С.
экономика ғылымдарының кандидаты, профессор
С. Сейфуллин атындағы Қазақ агротехникалық зерттеу университеті,
Астана, Қазақстан
e-mail: zhibekh11@mail.ru
ORCID: ORCID: 0000-002-2617-838X

Оразбаева А. С.* [1,2]
экономика ғылымдарының магистрі,
С. Сейфуллина атындағы Қазақ агротехникалық зерттеу университеті[1],
Humboldt-Innovation GmbH[2]
Астана, Қазақстан [1]
Берлин, Германия[2]
e-mail: a.orazbaeva@kazatu.kz
ORCID: 0000-0001-7685-1782

Алтайбаева Ж. К.
экономика ғылымдарының кандидаты, профессор
Инновациялық Еуразия университеті;
Павлодар, Қазақстан
e-mail: zhanat.ka@mail.ru
ORCID: 0000-0003-3058-6965

Аңдатпа. Бұл зерттеудің мақсаты ө ауыл шаруашылығы секторындағы ESG-контроллинг жүйесі шеңберінде 3-санаттағы парниктік газдар шығарындыларын бағалау және есепке алу үшін эконометриялық модель әзірлеу. Зерттеу ауыл шаруашылығындағы шығарындылар мен негізгі экономикалық факторлар арасындағы өзара байланыстарды айқындауға және орнықты даму көрсеткіштерін басқарушылық есепке енгізуге бағытталған. Әдістемелік негіз ретінде Германия мен Қазақстан бойынша 2000–2022 жылдар аралығындағы FAOSTAT және Eurostat деректеріне сүйенген лог–лог регрессиялық модельдеу және сценарийлік талдау қолданылды. Есептеулер MATLAB R2025a ортасында жүйелі панельдік деректер (малдардың ас қорытуынан бөлінетін метан — Enteric CH_4, көңнен бөлінетін N_2O, ауыл шаруашылығы топырағынан бөлінетін N_2O және 3-санат компоненттері — өндіру, тасымалдау, қаптау, тұтыну және қалдықтар) негізінде жүргізілді. Зерттеу нәтижелері энергия тұтынуы мен жалпы өнім құнына қатысты 3-санат шығарындыларының жоғары икемділігін көрсетті, бұл декарбонизация деңгейінің ресурстық тиімділікке тәуелді екендігін білдіреді. Сценарийлік модельдеу Қазақстанда ауыл шаруашылығының энергия қарқындылығын 10%-ға төмендету шығарындыларды 1,4%-ға азайтатынын, ал Германияда азот тыңайтқыштарын қолдану қарқындылығын 10%-ға төмендету жалпы шығарындыларды 3,8%-ға қысқартатынын көрсетті. Зерттеудің практикалық маңызы – 3-санат шығарындыларын басқарушылық есеп пен контроллингке енгізудің әдістемелік негіздерін қалыптастыру, ESG есептілігінің ашықтығын арттыру және ауыл шаруашылығы саласында орнықты бюджеттеуді енгізуді қолдау.

Түйін сөздер: ESG-контроллинг, басқарушылық есеп, 3-санат шығарындылары, ауыл шаруашылығы, парниктік газдар есебі, икемділіктер, сценарийлік талдау.

ИНТЕГРАЦИЯ ESG ПОКАЗАТЕЛЕЙ В УПРАВЛЕНЧЕСКИЙ УЧЁТ АГРОБИЗНЕСА: КОЛИЧЕСТВЕННАЯ ОЦЕНКА НА ПРИМЕРЕ КАЗАХСТАНА И ГЕРМАНИИ

Бауэр М.Ш.[1,2]
Доктор экономических наук, профессор
Казахский агротехнический исследовательский университет имени С.Сейфуллина[1],
Humboldt-Innovation GmbH[2]
Астана, Казахстан[1]
Берлин, Германия[2]
e-mail: mairak@bk.ru
ORCID:0000-0002-8489-5782

Оразбаева А.С. * [1,2]
магистр экономических наук,
Казахский агротехнический исследовательский университет имени С.Сейфуллина[1],
Humboldt-Innovation GmbH[2]
Астана, Республика Казахстан[1]
Берлин, Германия[2]
e-mail: a.orazbaeva@kazatu.kz
ORCID: 0000-0001-7685-1782

Хусаинова Ж. С.
кандидат экономических наук, профессор
Казахский агротехнический исследовательский университет им. Сакена Сейфуллина г. Астана,
Республика Казахстан
e-mail: zhibekh11@mail.ru
ORCID: 0000-002-2617-838X

Алтайбаева Ж. К.
кандидат экономических наук, профессор
Инновационный Евразийский университет
г. Павлодар, Республика Казахстан
e-mail: zhanat.ka@mail.ru
ORCID:0000-0003-3058-6965

Аннотация. Цель данного исследования - разработать эконометрическую модель для оценки и учета выбросов парниковых газов категории Scope 3 в рамках системы ESG-контроллинга в сельском хозяйстве. Исследование направлено на выявление взаимосвязей между выбросами и ключевыми экономическими факторами, а также на интеграцию показателей устойчивого развития в практику управленческого учета. Методологическая основа работы сочетает лог-лог регрессионное моделирование и сценарный анализ на базе данных FAOSTAT и Eurostat для Германии и Казахстана за период 2000–2022 гг. Расчеты выполнены в MATLAB R2025a с использованием панельных данных по выбросам от энтеральной ферментации (CH_4), навозоуправления (N_2O), почвенных процессов (N_2O), а также компонентам Scope 3 (производство, транспортировка, упаковка, потребление и отходы). Результаты показывают высокую эластичность выбросов Scope 3 по отношению к энергопотреблению и валовой продукции сельского хозяйства, что свидетельствует о зависимости уровня декарбонизации от ресурсной эффективности. Сценарные расчёты демонстрируют, что снижение энергоёмкости сельского хозяйства Казахстана на 10% приводит к сокращению выбросов на 1,4%, а уменьшение интенсивности применения азотных удобрений в Германии на 10% снижает совокупные выбросы на 3,8%. Практическая значимость исследования заключается в разработке методических принципов учета выбросов Scope 3 в управленческом учёте и контроллинге, повышении прозрачности ESG-отчетности и поддержке внедрения инструментов устойчивого бюджетирования в аграрном секторе.

Ключевые слова: ESG-контроллинг; управленческий учет; выбросы Scope 3; сельское хозяйство; учет парниковых газов; эластичности; сценарный анализ.