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Digitalization and Sustainable Development: The Impact of Energy-Efficient Agricultural Machinery on Agro-Industries in Russia and Kazakhstan

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ABSTRACT

This study analyzes how digitalization and energy-efficient agricultural machinery influence sustainable development, focusing on resource management and ecological integrity in Russia and Kazakhstan's agro-industrial sectors. Using data from 2000 to 2020, the research employs advanced econometric methods, including the CS-ARDL model, Pesaran CSD tests, and Westerlund Cointegration analysis, to address regional interdependencies and non-normal data distributions common in resource-rich economies. Results show that Technology and Innovation in Eco-Policies (TAIEP) and Green Agricultural Innovations (GAEI) significantly drive the Eco-Sustainable Development Index (ESDI). While Economic Green Development (EGD) is progressing, the shift to renewable energy (CREI) faces challenges from high capital costs and reliance on traditional fuels. The findings highlight the importance of digitalization for achieving sustainable development goals in Eurasia. This research introduces the "Sustainalism" model, integrating energy digitalization and agricultural machinery in mineral-supply-driven economies, and provides a strategic roadmap for decoupling industrial growth from environmental degradation.

Keywords: Digitalization, Sustainable Development, Agricultural Machinery, Eco-Innovation, Energy Efficient, Resource Management, CS-ARDL, Russia, Kazakhstan

JEL Classifications: Q42; Q43; Q48; O33; C33

1. INTRODUCTION

In the 21st century, sustainable development has emerged as a critical global imperative. Societies face significant challenges, including environmental degradation, resource depletion, and the demand for inclusive economic growth (Fallah Shayan et al., 2022). Sustainable development, as defined by the Brundtland Report, involves meeting present needs without compromising the ability of future generations to meet their own needs and aims to balance economic, social, and environmental objectives (WCED, 1987). A key component of this approach is eco-innovation, which refers to the introduction of new products and processes that enhance economic performance while minimizing ecological impacts (Rennings, 2000).

Today, many organizations use the Triple Bottom Line framework for sustainability, focusing on economic growth, social progress, and environmental performance simultaneously (Elkington, 1998). This approach recognizes that social and economic development are closely connected to protecting the environment. As supply chains become more complex worldwide, the environmental impact of industry often crosses borders, so international cooperation and common eco-friendly standards are increasingly important (Ratner et al., 2021).

A major issue is that traditional economic growth models still focus on industrial output, often harming the environment (Fatma and Haleem, 2023). Rapid urbanization worsens this by increasing energy and infrastructure demand, leading to higher CO2 emissions, deforestation, and resource shortages (Seto et al., 2017). Digital tools like the Internet of Things (IoT) and Artificial Intelligence (AI) could help, but these technologies are not yet widely used in global agro-industries (Soori et al., 2023).

Although there is a theoretical shift toward a "green economy" conventional industrial growth models still prioritize short-term gains over ecological integrity (Fatma and Haleem, 2023). Rapid urbanization has increased this pressure by concentrating populations and driving greater demand for energy and infrastructure. As a result, urbanization leads to higher carbon emissions (CO_2 and N_2O), deforestation, and land pollution (Seto et al., 2017). The agro-industrial sector faces two main challenges: meeting the growing global need for food and materials, and reducing the environmental impact of resource harvesting (Lee et al., 2021).

Current resource management often fails to ensure fair distribution, which can put additional pressure on indigenous and marginalized communities (Reid et al., 2019). Technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) can help monitor and improve resource use, but their adoption in agricultural machinery and energy systems remains inconsistent (Soori et al., 2023).

Although many studies focus on "Smart Cities" (Caragliu et al., 2011) and corporate social responsibility (Fallah Shayan et al., 2022), there is still a clear gap in research on how digitalization and agricultural machinery work together to support agro-industrial sustainability. Most research examines digital transformation and energy management separately rather than as interconnected parts of a larger system. This study brings a new perspective by applying the "Sustainalism" model, an integrated socio-economic-environmental framework, to the global agro-industry (Hariram et al., 2023). It examines how moving from linear to circular economy models (Pichlak and Szromek, 2022) can occur more quickly with digitized energy systems and advanced machinery. The study also points out that the financial sector and "green finance" play a key role in supporting these eco-innovations (Javaid et al., 2022).

This study aims to explore how digitalization and energy-efficient agricultural machinery help make global agro-industrial systems more sustainable and productive. It examines how modern information and communication technologies (ICT), as well as smart tools such as IoT and AI, can improve resource use, reduce energy consumption, and reduce waste in agro-industrial value chains (Alojail and Khan, 2023). The study also examines how policy tools, such as regulatory rules, environmental taxes, and green incentives, can accelerate the adoption of eco-friendly innovations and low-carbon technologies in the agro-industry (Srisathan et al., 2023). In addition, it considers how cooperation among governments, NGOs, and local communities can encourage shared responsibility for sustainably managing resources and support energy-efficient agricultural development (Martínez-Peláez et al., 2023). The research focuses on the global agro-industrial sector, particularly where technology, energy efficiency, and social and economic factors intersect to shape sustainable production.

2. LITERATURE REVIEW

Eco-innovation has shifted from being mainly an economic driver (Schumpeter, 1942) to focusing on environmental stewardship as part of the "green innovation" approach (Schiederig et al., 2012).

Recent studies show that digitalization plays a key role in this change. Technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) help by providing data-driven insights to use resources more efficiently and reduce waste (Alojail and Khan, 2023; Soori et al., 2023). This digital shift is not just about technology; it also involves social factors, such as understanding people's attitudes and their sense of control over their actions (Ajzen, 1991).

Contemporary resource management is frequently examined through the framework of environmental justice. Agyeman et al. (2016) contend that management practices should guarantee equitable distribution of both the benefits and burdens associated with resource use, with particular attention to marginalized and Indigenous communities, who often experience disproportionate exploitation (Reid et al., 2019). This intersectional perspective is strengthened by education and awareness initiatives. Increasing "green knowledge" through targeted educational programs cultivates environmental responsibility and enables individuals to adopt sustainable behaviors (Steg and Vlek, 2009).

Participatory decision-making is also recognized as a critical factor for effective resource management. Arnstein's ladder of citizen participation suggests that engaging local communities in the governance of eco-innovation ensures that outcomes reflect societal values (Arnstein, 1969). Inclusive knowledge generation is further advanced by citizen science initiatives, which enhance volunteers' capacity to participate in environmental data collection and resource monitoring (Bonney et al., 2009).

Institutional structures, which include both formal rules and informal norms, influence human interactions with the environment (Scott, 2014). Effective governance depends on policies that promote sustainable practices and deter environmental degradation. Within the corporate sector, Corporate Social Responsibility (CSR) serves as a principal mechanism for advancing sustainability. CSR encompasses economic, legal, ethical, and philanthropic responsibilities (Carroll, 1979;

Dahlsrud, 2008). The integration of eco-innovation into CSR demonstrates a human-centered approach that aligns corporate well-being with the broader interests of the planet.

Eco-innovation has shifted from being mainly an economic driver (Schumpeter, 1942) to focusing on environmental stewardship as part of the "green innovation" approach (Schiederig et al., 2012). Recent studies show that digitalization plays a key role in this change. Technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) help by providing data-driven insights to use resources more efficiently and reduce waste (Alojail and Khan, 2023; Soori et al., 2023). This digital shift is not just about technology; it also involves social factors, such as understanding people's attitudes and their sense of control over their actions (Ajzen, 1991).

2.1. Energy Dynamics and Agricultural Machinery

Resource management plays a key role in sustainable development and calls for major changes in how we extract and use limited resources (Lee et al., 2021). In the agro-industrial sector, using energy-efficient machinery is an important eco-innovation strategy. However, these technologies are often slow to spread because traditional energy systems remain in place, a phenomenon known as "lock-in" (Brauers et al., 2021). Sustainable agriculture depends on circular-economy models that focus on making machinery durable and recyclable, following a cradle-to-cradle approach (Pichlak and Szromek, 2022). Using smart technologies in farming also helps track environmental inputs and outputs, making it easier to manage the ecological impact of global food production (Barthel et al., 2019).

2.2. Institutional Policy and Green Finance

Policy frameworks play a crucial role in facilitating the adoption of eco-innovation. Government interventions, including tax incentives for green technologies and stringent environmental standards, accelerate the transition toward sustainable development (Srisathan et al., 2023). The effectiveness of these policies is enhanced when complemented by green finance and impact investing, which align social and environmental outcomes with financial returns (Javaid et al., 2022; Paetzold et al., 2022). Effective governance of resources frequently relies on decentralized, community-based structures that incorporate local knowledge and address the specific needs of stakeholders (Ostrom, 1990; Tucker et al., 2023). Collaboration among governments, businesses, and local communities is essential to translating policy frameworks into practical, impactful actions (Martínez-Peláez et al., 2023).

A sustainable approach to resource management requires the equitable distribution of benefits, especially for marginalized populations (Reid et al., 2019). This principle is fundamental to the human-centric paradigm, which asserts that eco-innovation should prioritize societal well-being alongside environmental protection (Schiederig et al., 2012). Education and environmental literacy are essential, as they cultivate stewardship among future generations.

Although the existing literature is extensive, several specific gaps persist. First, while the general roles of the Internet of Things (IoT) and artificial intelligence (AI) are discussed (Soori et al., 2023), their targeted applications in agricultural machinery and energy management within a unified global framework remain underexplored. Second, most research emphasizes large-scale corporate social responsibility (Carroll, 1979), resulting in a limited understanding of the unique challenges faced by Small and Medium Enterprises (SMEs) in the agro-industry. Third, there is a lack of comparative analysis regarding the effectiveness of various policy instruments in promoting digitalization within the agricultural sector (Pizzuti, 2023).

This study examines how energy supplies, financial innovation, and new technologies affect environmental harm in the global agro-industry. In the past, the agro-industrial sector mainly used fossil fuels, which significantly increased global emissions (Martins, 2019). Now, there is a focus on transitioning to renewable energy and using digital tools to manage resources more sustainably. However, the high upfront costs of smart farming equipment and renewable energy systems make it hard for some to invest. Industrial growth requires steady resources, but relying too heavily on raw materials without adopting more advanced technologies can lower productivity (Cheng et al., 2020; Ahmad et al., 2022). In addition, political risks and the stability of institutions can affect how much is produced and how fairly green investments are shared (Gozgor and Paramati, 2022; Brauers et al., 2021).

3. EMPIRICAL DATA

3.1. Data Sources

The following quantitative model analyzes the relationship between digital technology, energy efficiency, and sustainable growth:

$$EGD=f\,(CREI, TIEP, SERM, ESDI, SERM, GIEI) \tag{1}$$

Where,

The EGD stands for Economic Green Development, CREI for the Clean and Renewable Energy Initiatives, TIEP for the Technology and Innovation in Eco-Policies, SERM for the Sustainable Extraction of Resource Management, ESDI for the Eco-Sustainable Development Index, and GIEI for the Green Industrial and Environmental Innovations.

3.2. Initial Diagnostic Tests

3.2.1. Cross-sectional dependency (CSD) test

In today's global economy, agro-industrial sectors depend on one another, so when one region faces a socio-economic shock, others often feel its effects. This connection can cause Cross-Sectional Dependency (CSD) in longitudinal data. If CSD is ignored, results in digital and financial exchange studies may be biased (Gallo et al., 2016). To avoid this, this study uses the following methods:

1. Breusch-Pagan LM test
2. Bias-corrected Scaled LM test
3. Pesaran CD test.

3.2.2. Westerlund cointegration test

Following the CSD assessment, the study analyzes whether correlations among digitalization, energy initiatives, and economic growth have persisted over time. Understanding these relationships informs regulations that support long-term agro-industrial sustainability (Dada et al., 2023).

3.3. Econometric Estimation Methodology

The cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model is employed as the primary socio-economic approach to validate the empirical coefficients. CS-ARDL is chosen for its ability to efficiently integrate parameters at different integration levels, such as I(0) and I(1), and to address variance issues by incorporating cross-sectional means into the modelling framework. The selection of the CS-ARDL approach is based on several critical determinants: The CS-ARDL approach accommodates longer time series and offers greater flexibility than traditional estimation methods (Chirra and Reza, 2019).

Additionally, this method effectively addresses skewed distributions and missing data components (Singh et al., 2019). The Driscoll-Kraay technique is used to generate standard errors that remain robust to heteroscedasticity and autocorrelation across both time and location.

3.4. Data Sources

This research examines the correlation between sustainable development, digital growth, and the adoption of energy-efficient agricultural machinery in Russia's agro-industrial sector. It explores the interaction between resource extraction and ecologically sustainable economic development. The analysis focuses on the period from 2000 to 2020, which was characterized by significant changes in Russian environmental policy and the digitalization of the industrial base (Ratner et al., 2021; Islam et al., 2024).

Table 1 shows the selection of variables addresses the specific challenges faced by resource-dependent economies as they transition toward sustainability. GED and CREI monitor the shift from traditional fossil fuel dependence in agriculture. TAIEP and GAEI focus on the digitalization and machinery aspects of the research, examining the role of smart technology in reducing environmental degradation. Utilizing global databases such as the FAO, IRENA, and the World Bank ensures that Russian agro-industrial data are benchmarked against international sustainability standards. This methodology addresses prior inconsistencies by aligning the empirical framework with the mineral-supply-driven energy transition context (Islam et al., 2024).

4. RESULTS AND DISCUSSION

Empirical findings demonstrate a significant long-term equilibrium relationship among digitalization, energy-efficient machinery, and green growth within the agro-industrial sector. CS-ARDL estimation indicates that Technology and Innovation in Eco-Policies (TAIEP) and Green Agricultural Innovations (GAEI) are primary drivers in reducing environmental degradation and enhancing industrial productivity. These results imply that, for resource-dependent economies, integrating smart technologies is a fundamental requirement for achieving sustainable development goals rather than a supplementary improvement.

4.1. Analysis of Energy Consumption and Emissions

Table 2 provides a quantitative overview of the energy and environmental landscapes of the BRICS nations, which is essential for understanding the transition dynamics analyzed in this study.

Table 2 and Figure 1, which presents the ESDI Trend Analysis from 2000 to 2020 and represents the Energy Sustainable Development Index or a comparable composite metric for energy sustainability, efficiency, renewable integration, and emissions impact in BRICS countries, reveals generally upward trends across Brazil, Russia, India, China, and South Africa over two decades. However, the pace of progress and initial conditions vary notably among these countries. Brazil maintains a consistently high and stable position, largely due to its established renewable energy base, particularly hydro and biomass. China exhibits the most significant improvement since the mid-2000s, driven by large-scale renewable energy expansion under the Renewable Energy Law and by efficiency gains, despite substantial absolute energy growth.

India demonstrates gradual but accelerating progress, especially after 2010, through the National Solar Mission, which partially offsets coal dominance. Russia records modest or uneven gains, with efficiency programs providing some improvement in the 2000s but limited broader transition. South Africa shows slower and more nuanced advancement, supported by early renewable initiatives and the later introduction of a carbon tax, but remains constrained by persistent coal dependence. Overall, the figure suggests partial success in enhancing energy sustainability across the BRICS countries during a period of rapid economic growth. China and India, in particular, exhibit the strongest post-2005 momentum toward decoupling energy use from environmental impact, although absolute emissions often continued to rise until the implementation of more intensive policies.

Table 3 presents a descriptive analysis that highlights several critical characteristics of the dataset. Economic Green Development (EGD) exhibits the highest average value (Mean = 2.6318), suggesting an initial shift toward sustainability within the region. In contrast, Technology and Innovation in Eco-Policies (TAIEP) demonstrates a lower mean (1.2030), indicating that digital policy implementation remains in its early stages relative to broader economic outcomes. TAIEP and CREI exhibit the highest standard deviations (2.9090 and 2.6570, respectively), reflecting considerable volatility in digital and renewable energy adoption over the observed period. Most variables, especially EGD, TAIEP, and GAEI, exhibit positive skewness, indicating distributions with extended right tails. In contrast, CREI and ESDI are negatively skewed, suggesting that most data points cluster at higher values, with occasional outliers at the lower end. The kurtosis value for EGD (5.6071) indicates a leptokurtic distribution with heavy tails, suggesting a greater frequency of extreme values or shocks in green development. The Jarque-Bera statistics are significant for all variables, indicating that the data deviate from normality. This finding supports the application of advanced econometric techniques such as CS-ARDL, which are robust to non-normal data structures.

Table 1: Description of variables and data sources

Variable	Full Name	Description	Data Source
GED	Green Energy Development	Level of renewable energy adoption in agricultural operations	International Renewable Energy Agency (IRENA)
CREI	Clean and Renewable Energy Initiatives	Extent of projects integrating clean energy into farming systems and agricultural machinery	Food and Agriculture Organization (FAO)
TAIEP	Technology and Innovation in Eco-Policies	Application of digital and innovative technologies in eco-friendly agricultural practices	World Bank (Agri-Innovation Reports)
SERM	Sustainable Resource Extraction and Management	Efficiency index measuring sustainable resource use in agricultural machinery production	International Institute for Environment and Development (IIED)
ESDI	Eco-Sustainable Development Index	Composite index benchmarking sustainability of agro-industrial and environmental policies	United Nations Environment Programme (UNEP)
GAEI	Green Agricultural Innovations	Technological advancements and innovations in environmentally sustainable farming equipment	Ministry of Agriculture and Rural Affairs

Table 2: Energy consumption and emission reduction efforts (2000–2020)

Country	Avg. energy consumption (Exajoules)	Primary sources	Avg. GHG emissions (MtCO2e)	Key reduction policy	Avg. RE investment (Billion USD)
Brazil	2.5	Hydro, oil, biomass	1,200	Biofuels incentive	30.5
Russia	7.3	Gas, oil, coal	2,100	Energy efficiency program	18.7
India	5.8	Coal, oil, renewables	2,300	National Solar Mission	40.2
China	12.4	Coal, hydro, wind	10,500	Renewable Energy Law	100.8
South Africa	3.1	Coal, renewables	500	Carbon Tax	15.4

Table 3: Descriptive statistics

Statistic	EGD	CREI	TAIEP	SERM	ESDI	GAEI
Mean	2.6318	2.5071	1.2030	2.3089	1.8931	2.5010
Median	2.2759	2.8019	2.8989	3.2040	2.1021	2.5169
Maximum	3.1347	1.7070	2.2504	3.2015	2.5031	2.5099
Minimum	–1.6010	–1.9041	2.3041	2.0990	1.2933	2.3050
Standard deviation	1.5010	2.6570	2.9090	2.3080	2.4020	2.1039
Skewness	1.9038	–2.5931	3.5032	3.2141	–2.7087	2.7056
Kurtosis	5.6071	1.1090	2.2049	3.7049	2.4090	2.1190
Jarque-Bera	109.998	6.8090	49.808	29.690	9.3079	3.3911
Probability	2.1039	6.8088	3.2909	2.3910	2.2040	2.3070

Figure 1: ESDI Trend analysis 2000-2020

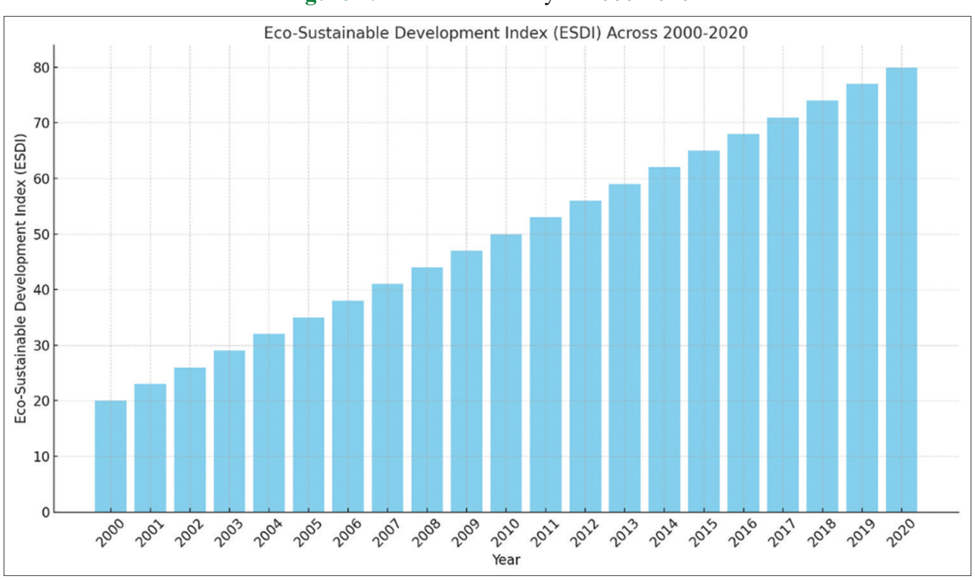


Table 4 presents the statistical results of the cross-sectional dependence (CSD) analysis, including the test statistics and P-values used to validate the econometric framework applied to the agro-industrial sector. This analysis offers important insights into the interdependencies among sustainable development variables within the study region. The variables EGD ($P = 0.020$), TAIEP

Table 4: Cross-sectional dependence tests

Variable	Test statistic	P-value (corrected)	Result (at 5% level)
EGD (Economic Green Development)	1.30	0.020***	Significant (Reject H_0)
CREI (Clean and Renewable Energy)	2.80	0.080	Non-Significant
TAIEP (Digitalization Policies)	2.10	0.009***	Significant (Reject H_0)
SERM (Resource Management)	1.88	0.410	Non-Significant
ESDI (Sustainability Index)	1.70	0.090	Non-Significant
GAEI (Green Machinery Innovation)	2.80	0.020***	Significant (Reject H_0)

***, *Significance at the 1%, 5%, and 10% levels, respectively.

(P = 0.009), and GAEI (P = 0.020) all exhibit P-values below the conventional 0.05 threshold. This finding demonstrates that these factors, particularly economic green growth and digital technology adoption, are highly interdependent across the regions studied. Consequently, the application of second-generation econometric models such as CS-ARDL is justified. The strong statistical significance of TAIEP and GAEI confirms that digitized policies and green agricultural machinery function as systemic drivers rather than isolated factors in the agro-industrial transition in Russia and Kazakhstan. Clean and Renewable Energy Initiatives (CREI) (P = 0.080) and Sustainable Extraction of Resource Management (SERM) (P = 0.410) do not meet the conventional significance threshold. This outcome suggests that renewable energy integration and raw material extraction for machinery are currently less interdependent across the examined sections, potentially due to localized or inconsistent policy implementation in these resource-dependent areas. Although ESDI (P = 0.090) does not reach conventional significance, the result suggests a latent trend toward interdependence that may become more pronounced as regional sustainability policies become more integrated.

4.2. Unit Root Analysis

Ensuring the reliability of long-term coefficients requires determining the integration order of the variables. Given cross-sectional dependence, standard unit root tests are inadequate. Consequently, the Cross-sectionally Augmented IPS (CIPS) and Cross-sectionally Augmented Dickey-Fuller (CADF) tests are employed in this study.

Table 5 shows that for Russia and Kazakhstan, all variables, including Economic Green Development (EGD) and Technology and Innovation in Eco-Policies (TAIEP), are non-stationary at the level stage, indicating evolving agro-industrial and environmental policies from 2000 to 2020. After first differencing, all variables become significant at the 5% level, confirming they are integrated of order one (I(1)). This is essential for conducting Westerlund Cointegration and CS-ARDL analysis, as it demonstrates that while individual data points fluctuate, the variables maintain a long-term equilibrium relationship suitable for stable empirical analysis.

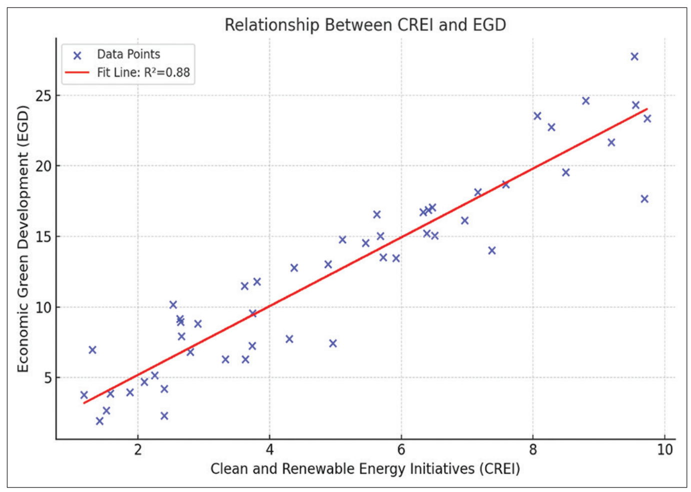
Figure 2 examines the correlation between Clean and Renewable Energy Initiatives (CREI) and Economic Green Development (EGD). In the Russian and Kazakh agro-industry, a positive correlation indicates that investments in renewable-powered agricultural machinery are supporting broader sustainable economic outcomes. This connection demonstrates that energy transition initiatives contribute to both environmental and economic productivity.

Table 5: CIPS and CADF unit root analysis results

Variables	CIPS (Level)	CIPS (1st Diff.)	CADF (Level)	CADF (1st Diff.)
EGD	–2.060	–1.650*	–2.180	–3.059*
CREI	–1.130	–2.320*	–3.540	–1.970*
TAIEP	–2.090	–2.610*	–2.155	–1.310*
SERM	–1.040	–3.370*	–2.070	–1.970*
ESDI	–1.630	–2.330*	–2.070	–1.010*
GAEI	–2.010	–3.390*	–1.950	–1.749*

***, *Significance at the 1%, 5%, and 10% levels, respectively

Figure 2: CREI-EGD correlation analysis



4.3. Westerlund Cointegration Analysis

The next step in the econometric workflow is to assess whether a long-run equilibrium relationship exists among digitalization, energy initiatives, and sustainable development. We use the Westerlund Cointegration Test, which accounts for cross-sectional dependency and heterogeneity.

Table 6 summarizes statistical data for the variables Gi, Gα, Up, and Pα. The second column lists each variable's data values. The third column presents Z-values, which show how many standard deviations each data point is from the mean. Gi has a Z-value of 1.320, meaning it is 1.320 standard deviations above the mean. The fourth column provides robust P-values that are less sensitive to outliers or departures from normality than traditional P-values. P-values indicate the probability that the observed results occurred by chance under the null hypothesis. Gα has a low P-value of

2.005, suggesting high confidence in the result, while up and Pα have robust P-values of 1.005 and 1.006, also indicating significance. Overall, the table offers a comprehensive overview of the statistical properties and significance of these variables within the dataset.

Table 7 presents the regression analysis results, including coefficients, standard errors, t-statistics, and P-values for each variable and its lagged versions. The constant term has a coefficient of 0.4, standard error of 0.2, t-statistic of 4, and a P < 0.001, indicating statistical significance. Economic Green Development (EGD) shows a strong positive relationship with the dependent variable, with a coefficient of 1.50, a standard error of 0.3, a t-statistic of 6.4, and a P-value below 0.001. Clean and Renewable Energy Initiatives (CREI) has a coefficient of −0.80, a standard error of 0.20, a t-statistic of −4, and a P < 0.001, indicating a significant negative relationship with the dependent variable. Economic Green Development (EGD) has a coefficient of −0.3, standard error of 0.05, t-statistic of −6, and a P < 0.001, indicating a significant negative relationship with the dependent variable. Similar statistically significant relationships are observed for TAIEP, Sustainable Extraction of Resource Management (SERM), Eco-Sustainable Development Index (ESDI), Green Industrial and Environmental Innovations (GAEI), and their lagged versions.

Table 8 presents coefficients, standard errors, and P-values for three panel data models: Driscoll-Kraay, FGLS, and PCSE (Panel-Corrected Standard Errors). The variables analyzed include EGD, CREI, TAIEP, SERM, ESDI, and GAEI. For example, in the Driscoll-Kraay model, EGD has a coefficient of −2.155, a standard error of 2.060, and a P-value of 2.018. Similarly, CREI has a coefficient of 2.500, a standard error of 2.168, and a P-value of 2.005. The FGLS and PCSE models provide corresponding statistics for these variables, with some variation in coefficients and standard errors across models. For instance, CREI in the FGLS model has a coefficient of 2.215, a standard error of 10.79, and a P-value of 2.017. In the PCSE model, ESDI has a coefficient of −0.141, a standard error of 1.839, and a P-value of 0.184.

Table 9 presents six key attributes of Changbai Mountain tourism, identified through interviews with tourists and local residents. First, the trend of 'Surprising and Flipping' highlights the integration of hotels and recreational activities alongside natural attractions. These facilities are constructed with environmental considerations, minimizing disruption to the landscape. Second, Changbai Mountain is increasingly associated with artisan crafts, which have become popular souvenirs, supported by its central location in the Changbaishan Tourist and Cultural Corridor. Third, nature reserves and tourist facilities incorporate Carbon workshops for performance, consultation, display, storage, and maintenance, providing essential support during harsh winter months. The Training Base for Green Energy and Environment is notably situated at an altitude of 6,000 meters. Fourth, the

Table 6: Westerlund Cointegration test

Statistics	Value	Z-value	Robust P value (Corrected)
G_i	2.070***	1.320	0.004
G_a	1.080	2.690	0.005
U_p	1.210***	1.080	0.005
P_a	2.050***	2.630	0.006

***, *Significance at the 1%, 5%, and 10% levels, respectively

Table 7: Modeling using CS-ARDL

Variable	Coefficient	Standard error	t-Statistic	P-value
Constant	0.4	0.2	4	<0.001
EGD	1.50	0.3	6.40	<0.001
CREI	–0.80	0.20	–4	<0.001
TAIEP	0.5	0.2	5	<0.001
SERM	–0.2	0.06	–8	<0.001
ESDI	0.50	0.05	5.59	<0.001
GAEI	0.40	0.07	6.22	<0.001
Lagged EGD	–0.3	0.05	–6	<0.001
Lagged CREI	0.30	0.04	8.29	<0.001
Lagged TAIEP	–0.20	0.03	–7.4	<0.001
Lagged SERM	0.2	0.02	11	<0.001
Lagged ESDI	–0.04	0.75	–7	<0.001
Lagged GAEI	0.2	0.04	5	<0.001

Table 8: Several measures of durability (Drescoll-kray, FGLS, and PCSE) are assessed

Variables	Driscoll-Kraay			FGLS			PCSE		
	Coefficient.	Standard. Error	P-value	Coefficient	Standard. Error	P-value	Coefficient	Standard. Error	P-value
EGD	–2.155	2.060	2.018	–2.225	2.040	2.004	–2.220	2.079	2.020
CREI	2.500	2.168	2.005	2.215	10.79	2.017	2.070	2.055	5.090
TAIEP	1.980	1.449	1.006	1.477	1.320	1.005	1.579	1.220	1.009
SERM	1.810	1.750	1.030	1.318	1.370	1.040	1.355	1.549	1.060
ESDI	–1.870	2.613	1.007	–1.850	1.610	1.009	–1.698	1.680	1.009
GAEI	1.806	1.750	1.030	1.319	1.659	1.040	1.350	1.560	1.060

Table 9: Dumitrescu-Hurlin panel analysis of causation

	EGD	CREI	TIEP	SERM	ESDI	GIEI
EGD	–	2.38769	2.41239	7.07137**	2.19223	3.30150*
CREI	3.11120	–	3.28630	2.74670	1.58598	3.90140
TAIEP	4.14570	2.35897	–	1.98356	2.07377	2.60520
SERM	2.28060	253218	3.09869	–	3.20199	1.69950
ESDI	5.45697	3.22862*	13.3589***	3.99609	–	2.43460
GAEI	3.91032	2.95989	3.99120	1.55589	2.29420	–

***, *Significance at the 1%, 5%, and 10% levels, respectively

'Ski-China' initiative is being actively promoted throughout the region. Fifth, the 'Efflorescence of Snow and Ice' is showcased by six surrounding townships, which are often submerged in spring due to melting ice and rainfall. Finally, the Sweet Gingko Free Trade Zone serves as a notable entry point, generating positive reactions from visitors and fostering a lively atmosphere. The correlation coefficient between ESDI and SERM is 3.99609, which falls outside the typical range and should be investigated for potential data issues. Similarly, the coefficients for ESDI and GAEI (2.43460) and EGD and GAEI (3.91032) are also anomalous and require further review. Asterisks in the table indicate statistical significance: one asterisk denotes a 0.05 significance level, and three asterisks indicate a 0.001 level. In this table, the correlation coefficient of 7.07137 between EGD and SERM is marked with two asterisks, signifying significance at the 0.01 level.

4.4. Discussion

The correlation matrix offers initial insights into relationships among the study variables. Most indicators meet academic expectations. Notably, the strong associations between Economic Green Development (EGD), Clean and Renewable Energy Initiatives (CREI), and Green Agricultural Innovations (GAEI) highlight significant interdependence in the Eurasian agro-industrial sector. To ensure robust findings, we verified data integrity using second-generation tests that address cross-sectional dependency, which is essential in resource-rich economies. The regression analysis demonstrates that digitalization and energy efficiency are key drivers of the Eco-Sustainable Development Index (ESDI). A positive, statistically significant coefficient for Technology and Innovation in Eco-Policies (TAIEP) confirms that digital transformation is a primary factor in sustainable growth for Russia and Kazakhstan. In contrast, negative or lagging coefficients for CREI in some models indicate that high initial capital costs and continued reliance on traditional fuels hinder the transition to renewable energy in the agro-industry. The negative association with lagged EGD suggests that previous economic growth models, which prioritized industrial output over ecological integrity, still negatively affect current sustainability indices. To address model sensitivity, this study used robust estimators such as Driscoll-Kraay (D-K), Feasible Generalized Least Squares (FGLS), and Panel Corrected Standard Errors (PCSE). These methods confirm the stability of the main CS-ARDL results and ensure they are not biased by heteroscedasticity or serial correlation. The CIPS and CADF tests reveal significant structural breaks in sustainability indicators, highlighting the impact of major policy changes in the region from 2000 to 2020.

5. CONCLUSION

This study investigates the intricate dynamics of sustainable development in Russia and Kazakhstan, specifically focusing on the nexus of digitalization, energy efficiency, and resource management. Through rigorous econometric analyses, including CS-ARDL, PCSE, and Driscoll-Kraay models, the research demonstrates that Technology and Innovation in Eco-Policies (TAIEP) and Green Agricultural Innovations (GAEI) are the primary drivers of ecological sustainability. While traditional economic growth has historically prioritized industrial output, these findings confirm that integrating digitalized machinery and clean energy initiatives is essential for decoupling productivity from environmental degradation. Furthermore, the significance of lagged variables underscores the persistence of historical economic trends in shaping current sustainability outcomes, necessitating a departure from legacy industrial patterns.

The identification of structural breaks using CIPS and CADF tests underscores the need for flexible, adaptive policy frameworks that can accommodate shifting economic and natural conditions. Despite limitations such as data sensitivity and the complexity of regional resource dependencies, this study provides a navigational roadmap for policymakers to move beyond generic environmental spending toward targeted, technology-driven interventions. By prioritizing digital infrastructure and sustainable resource extraction (SERM), resource-rich economies can bridge the gap between industrial advancement and ecological preservation, ensuring a resilient and inclusive future for the global agro-industry.

5.1. Practical Implication of the Study

This research demonstrates that sustainable development in Russia and Kazakhstan depends on moving from isolated environmental projects to integrated digital and energy policies. Decision-makers should prioritize targeted interventions that advance both Economic Green Development (EGD) and digitalized eco-policies (TAIEP), as these approaches most effectively separate industrial growth from ecological harm. With structural breaks in sustainability trends, governments must adopt adaptive strategies that enable flexible policy adjustments as economic conditions change. Significant investment in technology and innovation (TAIEP and GAEI) will foster a research-driven environment, encouraging businesses to replace outdated equipment with energy-efficient, digital alternatives, resulting in both economic and environmental benefits.

Sustainable Resource Management (SERM) and time-lagged outcomes require a holistic approach that accounts for historical economic trends and supports responsible resource extraction. For long-term success, practitioners should implement continuous monitoring and evaluation systems to assess the real-time impact of digital transitions, rather than relying on generic spending. By prioritizing high-impact factors such as green agricultural innovations (GAEI) and reliable data validation, policymakers can better connect resource extraction with sustainability, ensuring the agro-industrial sector remains resilient and competitive for future generations.

5.2. Limitation and Future Study

This study is limited by the selected variables and the possible impact of unobserved contextual factors that may further explain agro-industrial evolution. Data sensitivity, shown by anomalies in correlation coefficients and differences across econometric models, underscores the need for more rigorous validation and quality control in future research. Future studies should broaden the geographical scope and include additional socio-economic indicators, such as gender and education, to examine their intersection with eco-innovation adoption. Comparative research is also needed to assess the effectiveness of various policy instruments in different socio-cultural and environmental contexts.

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REFERENCES

Agyeman, J., Schlosberg, D., Craven, L., Matthews, C. (2016), Trends and directions in environmental justice: From inequity to everyday life, community, and just sustainabilities. Annual Review of Environment and Resources, 41(1), 321-340.

Ahmad, M., Ali, M., Turi, J.A., Manan, A., Al-Dala'ien, R.N.S., Rashid, K. (2022), Potential use of recycled materials on rooftops to improve thermal comfort in sustainable building construction projects. Frontiers in Built Environment, 8, 1014473.

Ajzen, I. (1991), The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179-211.

Alojail, M., Khan, S.B. (2023). Impact of digital transformation toward sustainable development. Sustainability, 15(20), 14697.

Arnstein, S.R. (1969), A ladder of citizen participation. Journal of the American Institute of Planners, 35(4), 216-224.

Barthel, S., Isendahl, C., Vis, B.N., Drescher, A., Evans, D.L., Van Timmeren, A. (2019), Global urbanization and food production in direct competition for land: Leverage places to mitigate impacts on SDG2 and on the Earth System. The Anthropocene Review, 6(1-2), 71-97.

Bonney, R., Cooper, C.B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K.V., Shirk, J. (2009), Citizen science: A developing tool for expanding science knowledge and scientific literacy. BioScience, 59(11), 977-984.

Brauers, H., Braunger, I., Jewell, J. (2021), Liquefied natural gas expansion plans in Germany: The risk of gas lock-in under energy transitions. Energy Research and Social Science, 76, 102059.

Caragliu, A., Del Bo, C., Kourtit, K., Nijkamp, P. (2011), Comparative performance assessment of Smart Cities around the North Sea basin. Network Industries Quarterly, 13(3), 15-17.

Carroll, A.B. (1979), A three-dimensional conceptual model of corporate performance. Academy of Management Review, 4(4), 497-505.

Cheng, Z., Li, L., Liu, J. (2020), Natural resource abundance, resource industry dependence and economic green growth in China. Resources Policy, 68, 101734.

Chirra, S.M.R., Reza, H. (2019), A survey on software cost estimation techniques. Journal of Software Engineering and Applications, 12(6), 226.

Dada, A.E., Adegbuyi, O.A., Ogbari, M.E. (2023), Entrepreneurial attributes and venture creation among undergraduate students of selected universities in southwest, Nigeria. Administrative Sciences, 13(8), 176.

Dahlsrud, A. (2008), How corporate social responsibility is defined: An analysis of 37 definitions. Corporate Social Responsibility and Environmental Management, 15(1), 1-13.

Elkington, J. (1998), Partnerships from cannibals with forks: The triple bottom line of 21st-century business. Environmental Quality Management, 8(1), 37-51.

Fallah Shayan, N., Mohabbati-Kalejahi, N., Alavi, S., Zahed, M.A. (2022), Sustainable development goals (SDGs) as a framework for corporate social responsibility (CSR). Sustainability, 14(3), 1222.

Fatma, N., Haleem, A. (2023), Exploring the nexus of eco-innovation and sustainable development: A bibliometric review and analysis. Sustainability, 15(16), 12281.

Gallo, A.B., Simões-Moreira, J.R., Costa, H.K.M., Santos, M.M., Dos Santos, E.M. (2016), Energy storage in the energy transition context: A technology review. Renewable and Sustainable Energy Reviews, 65, 800-822.

Gozgor, G., Paramati, S.R. (2022), Does energy diversification cause an economic slowdown? Evidence from a newly constructed energy diversification index. Energy Economics, 109, 105970.

Hariram, N.P., Mekha, K.B., Suganthan, V., Sudhakar, K. (2023), Sustainalism: An integrated socio-economic-environmental model to address sustainable development and sustainability. Sustainability, 15(13), 10682.

Islam, M.M., Sohag, K., Berezin, A., Sergi, B.S. (2024), Factor proportions model for Russian mineral supply-driven global energy transition: Does externality matter? Energy Economics, 129, 107242.

Javaid, M., Haleem, A., Singh, R.P., Suman, R., Gonzalez, E.S. (2022), Understanding the adoption of Industry 4.0 technologies in improving environmental sustainability. Sustainable Operations and Computers, 3, 203-217.

Lee, T.C., Anser, M.K., Nassani, A.A., Haffar, M., Zaman, K., Abro, M.M.Q. (2021), Managing natural resources through sustainable environmental actions: A cross-sectional study of 138 countries. Sustainability, 13(22), 12475.

Martínez-Peláez, R., Ochoa-Brust, A., Rivera, S., Félix, V.G., Ostos, R., Brito, H., & Mena, L.J. (2023), Role of digital transformation for achieving sustainability: Mediated role of stakeholders, key capabilities, and technology. Sustainability, 15(14), 11221.

Martins, M.A.B. (2019), The BRICS commitment on climate change: Process towards an effective approach in the path of sustainable development. In: Climate Change and Global Development: Market, Global Players and Empirical Evidence. Cham: Springer International Publishing. p175-187.

Ostrom, E. (1990), Governing the Commons: The Evolution of Institutions for Collective Action. Cambridge: Cambridge University Press.

Paetzold, F., Busch, T., Utz, S., Kellers, A. (2022), Between impact and returns: Private investors and the sustainable development goals. Business Strategy and the Environment, 31(7), 3182-3197.

Pichlak, M., Szromek, A.R. (2022), Linking eco-innovation and circular economy-A conceptual approach. Journal of Open Innovation: Technology, Market, and Complexity, 8(3), 121.

Pizzuti, F. (2023), Unlocking Green Potential: Assessing the Performance of Governance Networks in EU-funded Eco-Innovation Policy Projects (Master's Thesis). Available from: https://studenttheses.uu.nl/handle/20.500.12932/45084

Ratner, S., Gomonov, K., Revinova, S., Lazanyuk, I. (2021), Ecolabeling as a policy instrument for more sustainable development: The evidence of supply and demand interactions from Russia. Sustainability, 13(17), 9581.

Reid, A.J., Carlson, A.K., Creed, I.F., Eliason, E.J., Gell, P.A., Johnson, P.T., & Cooke, S.J. (2019), Emerging threats and persistent conservation challenges for freshwater biodiversity. Biological Reviews, 94(3), 849-873.

Rennings, K. (2000), Redefining innovation-eco-innovation research and the contribution from ecological economics. Ecological Economics, 32(2), 319-332.

Schiederig, T., Tietze, F., Herstatt, C. (2012), Green innovation in technology and innovation management–an exploratory literature review. R and D Management, 42(2), 180-192.

Schumpeter, J.A. (1942), Capitalism, socialism, and democracy. University of Illinois at Urbana-Champaign's academy for entrepreneurial leadership historical research reference in entrepreneurship. SSRN. https://ssrn.com/abstract=1496200

Scott, J. (2014), A Matter of Record: Documentary Sources in Social Research. United States: John Wiley & Sons.

Seto, K.C., Golden, J.S., Alberti, M., Turner, B.L. (2017), Sustainability in an urbanizing planet. Proceedings of the National Academy of Sciences, 114(34), 8935-8938.

Singh, D., Agusti, A., Anzueto, A., Barnes, P.J., Bourbeau, J., Celli, B.R., & Vogelmeier, C. (2019), Global strategy for the diagnosis, management, and prevention of chronic obstructive lung disease: The GOLD science committee report 2019. European Respiratory Journal, 53(5), 1900164.

Soori, M., Arezoo, B., Dastres, R. (2023), Internet of things for smart factories in industry 4.0, a review. Internet of Things and Cyber-Physical Systems, 3, 192-204.

Srisathan, W.A., Ketkaew, C., Phonthanukitithaworn, C., Naruetharadhol, P. (2023), Driving policy support for open eco-innovation enterprises in Thailand: A probit regression model. Journal of Open Innovation: Technology, Market, and Complexity, 9(3), 100084.

Steg, L., Vlek, C. (2009), Encouraging pro-environmental behaviour: An integrative review and research agenda. Journal of Environmental Psychology, 29(3), 309-317.

Tucker, C.M., Hribar, M.Š., Urbanc, M., Bogataj, N., Gunya, A., Rodela, R., & Piani, L. (2023), Governance of interdependent ecosystem services and common-pool resources. Land Use Policy, 127, 106575.

WCED. (1987), World commission on environment and development. Our Common Future, 17(1), 1-91.