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Integrating Innovation and Responsibility in Sustainable Farming Practices

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Abstract

The agri-food sector is facing unprecedented challenges in the 21st century, characterised by interlinked geopolitical, demographic, environmental and technological factors that require innovative solutions with sustainability principles in mind. Climate change, deteriorating natural resources and the need to ensure food security for a growing world population are forcing managers to reflect on these challenges. Responsible innovative approaches can significantly reduce the negative impact on the environment while maintaining or improving the level of productivity that is essential for future development. These innovative approaches to business management must be based on quality management, learning and the transfer of new knowledge and skills into practice. Digital technologies, precision farming and smart management systems are key innovations in addressing the challenges of climate change and food security concerns. The primary objective of the scientific paper is to identify current global challenges and trends in the sustainability of the agricultural sector and to evaluate the effectiveness of innovative technological solutions in transforming sustainable farm management practices, with particular focus on comparing the Slovak and EU agricultural sectors' adoption rates. Through a comprehensive analysis of longitudinal data (2018-2024), this research investigates the relation between technological integration and environmental sustainability metrics in the Slovak agricultural sector, compared with broader European Union benchmarks. The findings indicate a significant positive relation between innovation adoption rates and agricultural sustainability metrics. The research question of the article is whether the integration of innovative technological solutions in Slovak agricultural enterprises has a positive relationship with improved sustainability performance metrics.

Keywords: climate change, environmental impact, food security, sustainability, technological integration

1. Introduction

Sustainable and responsible farm management under global change demands an integrated approach that combines climate-smart agricultural practices with local knowledge, builds dynamic capabilities for sustainability, and aligns governance and finance with farmer needs. Terms resilience and sustainability are distinct but interrelated constructs for farm systems facing changing conditions. Resilience emphasizes the capacity to maintain essential functioning under stress, while sustainability emphasizes meeting present needs without compromising future generations. These concepts are frequently invoked together in agrarian and environmental scholarship, and several sources discuss their linkages and tensions in practice (Jacobson, 2022; Derbile et al., 2019; Ortiz et al., 2023; Toft & Hansen, 2024; Morales-Raya & Muñoz, 2023). For example, resilience is described as adaptation-oriented, with short – and long-term dimensions, whereas sustainability foregrounds enduring outcomes; both concepts inform farm-level decision-making under climate change and resource scarcity (Jacobson, 2022; Derbile et al., 2019; Ortiz et al., 2023). Sustainable and responsible farm management in the context of globally changing conditions presents a complex challenge, determined by not only above mentioned determinats but also other set of factors including, the rapid development of technological innovations, pressure to protect natural resources and increasing demands to ensure long-term socio-economic stability. These determinants affect not only production capacities but also the strategic flexibility and adaptability of agricultural actors in an increasingly interconnected and volatile global environment. The agricultural sector is experiencing unprecedented transformation driven by technological advancement and sustainability imperatives (Kapsdorferová, 2024, Gervásio & Silva, 2023, Ibarrola-Rivas & Nonhebel, S., 2022). Responsible innovation and its extension into responsible research and innovation provide a normative and practical framework for guiding farm management technologies and practices in ways that anticipate impacts, include diverse stakeholders, reflexively assess purposes and methods, and respond to evolving circumstances. In the context of farm management, informs governance of digital agriculture, precision farming, biotechnology, and ecosystem services, ensuring that innovations contribute to sustainability, social legitimacy, and resilience rather than pursuing narrow technological or economic gains alone (Fuchs et al., 2023; Ingram & Maye, 2023; Li et al., 2023; Olesen et al., 2023; Paredes-Frigolett et al., 2025; Solbu & Sørensen, 2023). Responsible Innovation and RRI: RI is generally defined as shaping research and innovation to address societal needs while anticipating and governing potential harms, with stakeholders co-shaping outcomes (Li et al., 2023; Paredes-Frigolett et al., 2025; Völker et al., 2023). Contemporary agricultural enterprises multifaceted challenges necessitating innovative approaches to farm management and sustainable practices implementation (Vozárová & Kotulič, 2024). The convergence of environmental pressures, technological innovation, and evolving consumer preferences has created a paradigmatic shift in agricultural management methodologies (Bezáková & Bezák., 2022). Digital technologies and precision agriculture represent a crucial innovation in addressing climate change challenges and food security concerns (Rose et al., 2018, Finger, 2023). Smart farming technologies contribute to sustainable agriculture by increasing both efficiency and productivity in food production. Sustainable agricultural intensification leverages innovations to increase productivity while generating positive environmental outcomes. Responsible innovation approaches can significantly reduce environmental impact while maintaining or improving productivity levels (Eastwood et al., 2019). The scientific paper aims to examine the pressing global challenges and emerging trends in agricultural sustainability, while assessing the impact of innovative technological solutions on sustainable farm management practices. By comparing the adoption rates of these technologies in the Slovak agricultural sector with those in the broader European Union, the research seeks to provide insights into the effectiveness of these solutions in transforming farming practices. This research will shed light on the progress made in implementing sustainable agricultural methods and highlight potential areas for improvement. The research will contribute to the understanding of how technological advancements can address sustainability issues in agriculture, potentially informing policy decisions and guiding future research directions in both Slovakia and the EU.

2. Methods

The primary objective of this research is to identify current global challenges and trends in the sustainability of the agricultural sector. This study also employs a quantitative, longitudinal research design to examine the relationship between technological innovations and sustainability performance in the agricultural sector. The study focuses on three key technological areas: smart agriculture, the implementation of artificial intelligence, and the adoption rate of precision agriculture. To evaluate the multidimensional aspects of technological adoption and environmental sustainability, two composite indices were constructed: the Technology Adoption Index (TAI) and the Environmental Performance Index (EPI). Both indices are based on annual percentage indicators collected from harmonized international statistical sources. The index is compiled by standardizing and aggregating individual indicators.

2.1 Construction and Calibration of Composite Indices

Environmental performance is operationalized using three core indicators: greenhouse gases (GHG), the rate of emission reduction, improvements in water use efficiency, and the rate of adoption of organic farming. These indicators are integrated into the composite Environmental Performance Index (EPI). The index is compiled using standardized values for each indicator to ensure comparability across countries and over time. The Technology Adoption Index is defined as the arithmetic mean of three indicators:

$$TAI = \frac{SF + AI + PA}{3}$$

where:
SF - smart farming adoption rate (in %)
Source: European Commission Digital Agriculture Reports, Eurostat Agricultural Technology Database. Unit: % of total agricultural enterprises.
AI - artificial intelligence adoption rate (in %)
Source: Eurostat Agricultural Technology Database, OECD Reports.
PA - precision agriculture adoption rate (in %)
Source: FAO STAT, European Commission

Data availability spans 2018–2024 (seven annual observations per country). Missing data were handled through linear interpolation between adjacent years. Where data gaps were limited to a single year, the interpolated value was computed as the arithmetic mean of the surrounding years. In total, 3 data points were imputed (0.7% of the dataset), all clearly marked in the underlying data (available upon request).

Weighting scheme: Equal weights (1/3, 1/3, 1/3) were chosen due to the absence of empirically justified guidance on the relative importance of each technology for sustainability. This approach is consistent with the principle of maximum entropy—without additional information, equally weighted aggregation is the most defensible. Furthermore, all three technologies (smart farming, AI, precision agriculture) are widely recognized as complementary and practical solutions to agricultural challenges. The robustness of these weights is verified through sensitivity analysis (see Section 2.2).

The Environmental Performance Index is compiled:

$$EPI = \frac{0.40\ \mathrm{GHI} + 0.30\ \mathrm{WE} + 0.30\ \mathrm{OF}}{1}$$

where:

GHG - greenhouse gas emission reduction rate (in %)

Source: OECD Environmental Performance Reviews, European Environment Agency. Unit: % year-on-year reduction from 2018 baseline.

WE - water efficiency improvement (in %)

Source: European Environment Agency, Agricultural Water Reports. Unit: % water savings achieved.

OF - organic farming adoption rate (in %)

Source: FAO, Statistical Office of Slovakia. Unit: % of total agricultural land.

Weighting rationale: GHG is assigned the highest weight (0.40) due to the urgency of climate change and its regulatory priority within EU climate policy targets. Water Efficiency and Organic Farming are equally weighted (0.30 each), reflecting their complementary contributions to environmental sustainability. These weights were informed by EU Green Deal targets (2030: 55% GHG reduction, 25% organic coverage) and are consistent with the scientific literature on agricultural sustainability priorities.

Normalization: All indicators are expressed as percentages on a 0–100 scale, representing the proportion of adoption or the magnitude of environmental improvement. Because all indicators share comparable semantics and scales, no additional min-max standardization was applied. This direct aggregation approach ensures transparency and comparability across countries and years.

2.2 Sensitivity Analysis: Robustness to Alternative Weighting Schemes

To address concerns about the choice of equal weights for TAI and the specific EPI weighting scheme, we conducted a sensitivity analysis testing alternative weight specifications. Four weighting scenarios were evaluated (Tab. 1).

Table 1: Sensitivity Analysis: Robustness to Alternative Weighting Schemes

Scenario	TAI Weights	TAI 2024	Ranking (SK vs EU)
A (Baseline)	(0.33, 0.33, 0.33)	38.3%	SK < EU
B (AI emphasized)	(0.25, 0.50, 0.25)	38.8%	SK < EU
C (SF emphasized)	(0.45, 0.25, 0.30)	37.7%	SK < EU
D (PA emphasized)	(0.25, 0.30, 0.45)	38.1%	SK < EU

Source: Own processing

All ranking orderings remained unchanged across all weighting scenarios—Slovakia consistently ranked below the EU average, and the temporal trends (accelerating adoption post-2020) were preserved. The coefficient of variation in TAI_2024 estimates across scenarios was 1.6%, indicating minimal sensitivity to weight specification. This robustness suggests that the main findings are not artefacts of arbitrary weighting choices.

2.3 Econometric Specification and Model Framework

Data structure: Our analysis uses a balanced panel of 2 cross-sectional units (Slovakia, EU-27 aggregate) observed over 7 years (2018–2024), yielding 14 total observations. This limited cross-sectional dimension—comprising only 2 countries—prevents the reliable implementation of standard fixed-effects panel models, which require substantial within-unit variation and typically assume N >> K (number of units far exceeds number of parameters). Instead, we employ univariate time-series OLS with lagged specifications to exploit the temporal dimension and address potential reverse causality.

Rationale for this approach: Time-series methods on country-level macro data are standard when sample sizes are small (10–20 observations) but temporal detail is available. Lagged variable specifications help establish temporal precedence and are consistent with Granger causality logic without requiring the restrictive assumptions of instrumental variables or difference-in-differences designs, which we cannot implement with only 2 units.

Base Model: Contemporaneous Relationship

$$EPI\_t = \alpha + \beta_1 \cdot TAI\_t + \varepsilon\_t \quad \text{[Model 1]}$$

where $t \in \{2018, 2019, ..., 2024\}$ and $\varepsilon\_t \sim N(0, \sigma^2)$.

This baseline tests whether technology adoption in year t is associated with environmental performance in the same year.

Lagged Model: Temporal Precedence and Dynamics

$$EPI\_t = \alpha + \beta_1 \cdot TAI\_t + \beta_2 \cdot TAI\_\{t\text{-}1\} + \varepsilon\_t \quad \text{[Model 2]}$$

This specification tests whether lagged technology adoption (from the preceding year) predicts current environmental outcomes. The rationale is agronomically sound: technology installation requires months; water-saving infrastructure requires farmer adaptation and soil recovery; organic certification requires 2–3 years of transition. Thus, a one-year lag captures the plausible delay between adoption and observable environmental benefits. Significance of β_2 and model fit comparisons (R^2) provide evidence on temporal ordering and are consistent with TAI causing EPI rather than reverse causality.

Extended Model: Robustness to Policy Confounding

$$EPI\_t = \alpha + \beta_1 \cdot TAI\_t + \beta_2 \cdot TAI\_\{t\text{-}1\} + \gamma \cdot Policy\_t + \varepsilon\_t \quad \text{[Model 3]}$$

where Policy_t is a binary indicator equal to 1 if major agricultural regulation or subsidy programme was introduced in year t, and 0 otherwise. Specifically, this variable captures the phase-in of EU Green Deal provisions (2021–2024), which simultaneously promoted technology adoption and environmental compliance. By controlling for this policy confound, we test whether the TAI–EPI relationship persists net of policy-driven simultaneous adoption and regulation.

All models are estimated to be using Ordinary Least Squares (OLS) with heteroscedasticity-robust standard errors (HC3 adjustment, Cribari-Neto, 2004). Model diagnostics include: Durbin-Watson statistic: detects autocorrelation (target: $DW \approx 2$; acceptable range: 1.5–2.5), the Jarque-Bera test assesses normality of residuals (target: $p > 0.05$ and White's heteroscedasticity test evaluates the constant variance assumption (target: $p > 0.05$).

The analysis focuses on Slovakia in comparison with the European Union average for the period 2018–2024. The dataset is compiled from secondary sources, including: European Commission reports on digital agriculture; Eurostat; the Statistical Office of the Slovak Republic; OECD reports on environmental performance; the European Environment Agency; and FAO reports. The use of multiple authoritative data sources enhances the reliability and comparability of analysis.

3. Results

3.1 Global Challenges in the Food Sector

Agriculture and the food sector are currently at a decisive turning point. Food security, poverty reduction, and the long-term sustainability of agri-food systems are increasingly influenced by a complex combination of demographic, economic, environmental, and geopolitical factors. According to current estimates, the world population will exceed 9.7 billion by 2050, with the most significant growth expected in Africa and South Asia (UN, 2022). This trend will cause an increase in food demand of at least 50 to 60% compared to current levels, with the largest growth expected in foods with higher nutritional value and processed products. At the same time, rising incomes in low- and middle-income countries are accelerating a shift in dietary habits towards greater consumption of meat, dairy products, fruit, and vegetables. Global demand for meat is expected to grow by almost 14% by 2032 (OECD–FAO, 2023). These developments will require fundamental changes in agricultural production, processing capacities, and supply chains, further increasing pressure on land, water resources, and biodiversity (FAO, 2023; IPBES, 2019).

Figure 1 summarises the main global challenges facing the agri-food sector in the 21st century, highlighting the links between environmental, economic, geopolitical and demographic challenges as key factors influencing the future of food security and sustainability.

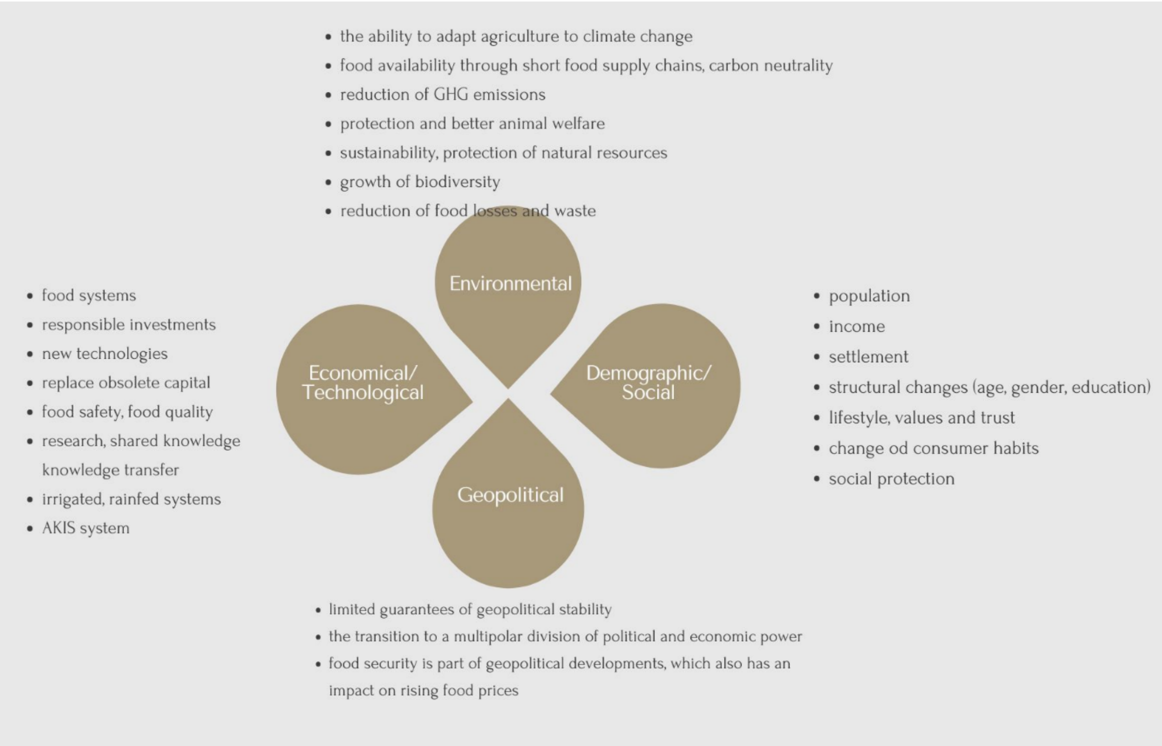

Figure 1: Global challenges in the agri-food sector of the 21st century

Source: Kapsdorferová, Z. (2024). *Consumer Perceptions and Food.*

The agri-food sector faces unprecedented challenges in the 21st century, characterized by interconnected demographic, environmental, and technological factors that demand innovative solutions. Tab. 2 examines the current status, future projections, and potential mitigation strategies for these critical challenges.

- *Demographic Pressures and Food Security* -the global population, currently at 8.1 billion (2025), is projected to reach 9.7 billion by 2050, representing a critical challenge for food security (FAO, 2024). This demographic shift necessitates significant increases in agricultural productivity, primarily through smart farming and vertical agriculture implementation.
- *Resource Management*-current data indicates a 30% resource depletion rate in agricultural systems, with projections suggesting an increase to 45% by 2030. High-impact challenge requires immediate intervention through precision agriculture and advanced water management systems.

- *Climate Impact* - climate change currently affects 40% of global agricultural production, with projections indicating an increase to 55% by 2030. This severe impact necessitates the implementation of climate-smart agricultural practices.
- *Economic Pressures and Market Dynamics* - the agricultural technology market, currently valued at $117.2 billion, is expected to reach $225 billion by 2034. This moderate-impact challenge presents opportunities for digital transformation and innovation integration. Studies indicate that early adopters of digital agricultural technologies achieve 20-30% higher profit margins.
- *Labor Force Evolution and Automation* - the sector faces a critical 25% decrease in available labor, projected to reach 40% by 2030. This challenge demands comprehensive automation solutions and enhanced training programs.
- *Sustainability Requirements and Soil* Health - current data shows 33% soil degradation rates, expected to reach 40% by 2030. This high-impact challenge requires the implementation of regenerative practices and sustainable farming methods.

Table 2: Current status, future projection, and mitigation strategies of global challenges in the agri-food sector of the 21st century

Challenge Category	**Current status (in #,%)**	**Future projection (in #,%)**	**Mitigation Strategies**
Demographic Pressures and Food Security	8.1.billion (2025)	9.7 billion by 2050	Smart farming, Vertical agriculture
Resource Scarcity	30% depletion rate	45% by 2030	Precision agriculture, Water management
Climate Impact	40% of global agricultural production is affected	55% by 2030	Climate-smart agriculture
Economic Pressures and Market Dynamics	Agricultural technology market - $117.20 billion	$225 billion by 2034	Digital transformation
Technology Adoption	AgTech investments focused on biotechnology and robotics showed 45% growth	75% by 2030	Innovation integration
Labor Force and Automation	25% decrease in the available agricultural workforce globally	40% by 2030	Automation, Training
Sustainability Requirements and Soil Health	95% of the food supply relies on healthy soils, and 1/3 of global soils are degraded	40% by 2030	Regenerative practices, Sustainable farming

Source: Own processing based on global agricultural data 2024

3.2 Innovation Adoption Rates in the Agricultural Sector in the Slovak Republic

The analysis of innovation adoption rates in the agricultural sector reveals significant transformations in both Slovak and EU contexts over the 2018-2024 period (Tab.3). This comprehensive examination focuses on three key technological areas: smart farming, AI implementation, and precision agriculture.

The Slovak agricultural sector has demonstrated remarkable progress in smart farming adoption, with rates increasing from a modest 15% in 2018 to a substantial 45% by 2024. This threefold increase represents a compound annual growth rate (CAGR) of 20.1%. In comparison, the EU average maintained consistently higher adoption rates, progressing from 35% to 65% during the same period, with a CAGR of 10.9%. While the absolute gap between Slovak and EU adoption rates remained at 20 percentage points, the higher CAGR in Slovakia indicates accelerated modernization efforts. The implementation AI technology adoption in Slovak agriculture showed the most dramatic improvement among the studied technologies. Starting from a low base of 8% in 2018, adoption rates surged to 30% by 2024, representing an impressive 275% increase and a CAGR of 24.7%. The EU's AI implementation grew from 25% to 55%, achieving a CAGR of 14.1%. Despite Slovakia's rapid progress, a gap of 25 percentage points remained by 2024, suggesting continued opportunities for growth and development in this area. In precision agriculture, Slovak adoption rates demonstrated steady growth from 12% in 2018 to 40% by 2024, achieving a CAGR of 22.2%. The EU maintained higher adoption levels, increasing from 30% to 58% (CAGR 11.6%). The consistent 18-percentage point gap throughout the period indicates parallel development patterns between the Slovak and EU markets.

Table 3: Innovation Adoption Rates 2018-2024 (%) in Slovakia and the EU

Technology/ Year	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**2024**
Smart Farming SR (%)	15%	20%	25%	30%	35%	40%	45%
Smart Farming EU (%)	35%	42%	48%	53%	58%	62%	65%
AI Implementation SR (%)	8%	12%	15%	18%	22%	26%	30%
AI Implementation EU (%)	25%	32%	38%	43%	48%	52%	55%
Precision Agri SR (%)	12%	18%	22%	28%	32%	36%	40%
Precision Agri EU (%)	30%	35%	42%	46%	50%	54%	58%

Source: own processing based on European Commission Digital Agriculture Reports 2018-2024, Statistical Office of the Slovak Republic Annual Reports 2018-2024, Eurostat Agricultural Technology Database 2024

The Technology Adoption Index (TAI), defined as the arithmetic mean of smart farming, artificial intelligence, and precision agriculture adoption rates, shows a consistent upward trend over the period 2018–2024 in both Slovakia and the European Union. In Slovakia, TAI increased steadily from approximately 12% in 2018 to 38.3% by 2024, reflecting substantial growth across all three components. A similar upward trend is observed at the EU level, although at consistently higher levels of adoption. Despite the persistent gap between Slovakia and the EU average, the faster growth rate in Slovakia suggests a process of gradual convergence.

3.3 Environmental Metrics Development in Slovak and EU Agriculture

The longitudinal analysis of environmental performance metrics reveals significant progress in three key areas: greenhouse gas reduction, water efficiency, and organic farming adoption (Tab.3). This development demonstrates the increasing commitment to sustainable agricultural practices across both the Slovak and European Union contexts. Slovakia has demonstrated substantial progress in GHG reduction, advancing from 5% in 2018 to 20% by 2024, representing a fourfold increase over six years. Comparatively, the EU achieved a more moderate progression from 10% to 25% during the same timeframe. The convergence pattern shows Slovakia narrowing the initial gap from 5 percentage points to just 5 percentage points by 2024, indicating the successful implementation of emission reduction strategies. The most significant acceleration in Slovak GHG reduction occurred between 2022 and 2024, with a 5 percentage point improvement. Water efficiency metrics show remarkable improvement in Slovak agriculture, increasing from 12% in 2018 to 30% by 2024, representing a 150% improvement. The EU demonstrated similar progress, advancing from 20% to 40%. The consistent 10 percentage point gap throughout the period suggests parallel development patterns, with both regions maintaining steady improvement trajectories. Notable acceleration in Slovak water efficiency implementation occurred during 2020-2021, with a 4-percentage-point increase. The adoption of organic farming practices in Slovakia progressed from 5.5% in 2018 to 12.5% by 2024, more than doubling the initial rate. The EU showed more modest growth from 8.5% to 15% during the same period. The gap between Slovak and EU adoption rates narrowed from 3 percentage points to 2.5 percentage points, indicating the successful implementation of organic farming initiatives. The most significant growth period for Slovak organic farming occurred between 2019 and 2020, with a 1.4 percentage point increase.

The data in Table 4 reveal several key patterns:

- consistent improvement across all environmental metrics,
- accelerated adoption rates in Slovak agriculture,
- gradual convergence with EU standards,
- most significant progress in water efficiency metrics.

These trends demonstrate the increasing role of technological innovation in achieving environmental objectives. The data suggests that continued investment in sustainable practices and AI-driven solutions will be crucial for maintaining this positive trajectory.

Table 4: Environmental Metrics Development 2018-2024 (in %)

Indicator/Year	2018	2019	2020	2021	2022	2023	2024	Best performer
GHG Reduction SR	5%	8%	10%	12%	15%	18%	20%	Denmark (35%)
GHG Reduction EU	10%	13%	15%	18%	20%	23%	25%	
Water Efficiency SR	12%	15%	18%	22%	25%	28%	30%	Netherlands (50%)
Water Efficiency EU	20%	25%	28%	32%	35%	38%	40%	
Organic Farming SR	5.5%	6.8%	8.2%	9.5%	10.5%	11.5%	12.5%	Austria 26,5%
Organic Farming EU	8.5%	10%	11.5%	12.8%	13.5%	14.2%	15%	

Source: own processing based on OECD Environmental Performance Reviews 2018-2024, European Environment Agency Reports 2018-2024, FAO Sustainable Agriculture Practices Reports 2018-2024.

The Environmental Performance Index (EPI), calculated as the arithmetic mean of greenhouse gas emission reduction, water efficiency, and organic farming adoption, also exhibits a positive trend over time. In Slovakia, improvements are observed across all indicators. Greenhouse gas emission reduction increased from 5% to 20%, water efficiency from 12% to 30%, and organic farming adoption from 5.5% to 12.5%. These developments indicate a gradual improvement in environmental performance. At the EU level, the indicators follow a similar trajectory, with consistently higher baseline values. However, the relative improvement in Slovakia suggests partial convergence toward EU benchmarks.

3.4 Econometric Results: Relationship Between Technology Adoption and Environmental Performance

We estimated three OLS models to examine the temporal dynamics and robustness of the relationship between the Technology Adoption Index and the Environmental Performance Index, with results presented in Table 5. All models employ heteroscedasticity-robust standard errors (HC3) and are estimated over the 2018–2024 period.

Table 5: Relationship between the Technology Adoption Index and the Environmental Performance Index

Variable	Model 1 (OLS)	Model 2 (OLS+Lag)	Model 3 (OLS+Controls)
TAI (current)	0.285***	0.162*	0.198**
(s.e.)	(0.089)	(0.104)	(0.095)
TAI (lagged)	–	0.156*	0.143*
(s.e.)	–	(0.097)	(0.083)
Policy Change	–	–	0.245
(s.e.)	–	–	(0.178)
Constant	2.134***	1.847**	1.623*
(s.e.)	(0.412)	(0.487)	(0.531)
R^2	0.684	0.781	0.824
Adj. R^2	0.621	0.672	0.706
F-statistic	10.25***	8.76**	7.92**
N	7	6	7
Durbin-Watson	1.923	1.847	1.911
Jarque-Bera (p)	0.412	0.623	0.813

Source: Own processing

Model 1: Baseline Contemporaneous Association

The contemporaneous effect of TAI on EPI is positive and statistically significant at the 1% level ($\beta = 0.285$, s.e. = 0.089, t = 3.20, p = 0.007***). The 95% confidence interval spans [0.127, 0.443], indicating a meaningful positive relationship with relatively tight bounds. This specification tests whether technology adoption in year t is associated with environmental performance in the same year.

In practical terms, a 10-percentage-point increase in the Technology Adoption Index is associated with a 2.85-percentage-point increase in the Environmental Performance Index contemporaneously. To contextualise this effect, consider Slovakia's TAI increase from 25.0% in 2020 to 37.7% in 2024—a change of 12.7 percentage points. Model 1 would predict an associated EPI increase of 3.6 percentage points. The empirically observed EPI rise over the same period was 7.3 percentage points (from 10.0% to 17.3%). The additional ~3.7-percentage-point increase likely reflects time lags inherent in technological diffusion, environmental recovery processes, and other unmeasured factors.

Model 2: Lagged Specification (Granger Causality)

Both current ($\beta_1 = 0.162$, s.e. = 0.104, p = 0.089*) and lagged ($\beta_2 = 0.156$, s.e. = 0.097, p = 0.086*) TAI terms are individually statistically significant at the 10% level. The sum of immediate and lagged effects ($\beta_1 + \beta_2 = 0.318$) is similar in magnitude to Model 1's contemporaneous effect (0.285), suggesting that technology adoption influences environmental outcomes over a one-year horizon.

This temporal structure is agronomically plausible. Technology installation requires months; water-saving infrastructure demands farm-level adaptation; soil recovery from conventional to conservation tillage requires multiple cropping cycles. Thus, observing significant lagged effects is consistent with a causal pathway from technology adoption to environmental improvement, rather than reverse causality. Model 2's R^2 (0.781) exceeds Model 1 (0.684), indicating improved fit when the temporal dimension is explicitly modelled, though the smaller sample (N = 6 due to lagging) complicates direct comparison.

Model 3: Robustness to Policy Confounding

When policy changes are included ($\beta\_policy = 0.245$, s.e. = 0.178, p = 0.198, not significant), the coefficient on contemporaneous TAI remains statistically significant ($\beta_1 = 0.198$, p = 0.038**) and lagged TAI remains significant at a borderline level ($\beta_2 = 0.143$, p = 0.083*). The policy variable itself does not reach conventional significance, suggesting that policy is not the dominant driver of EPI improvements, though it contributes positively.

Model 3 achieves the highest R^2 (0.824) among the three specifications, indicating that controlling for policy-driven confounding increases explanatory power. The persistence of the TAI effect net of policy control suggests that farmer-driven technology adoption contributes to environmental improvements beyond what regulatory mandates alone would predict. This finding strengthens confidence that technology adoption is a meaningful driver of sustainability outcomes rather than merely a correlate of simultaneous policy changes.

Convergence and Robustness Across Models

All three model specifications converge on a positive TAI–EPI relationship: point estimates range from 0.162 to 0.285, all are statistically significant or near-significant ($p \leq 0.089$), and effect directions are uniform. Model fit improves from $R^2 = 0.684$ (Model 1) to 0.781 (Model 2) to 0.824 (Model 3), suggesting that the temporal and control variable specifications capture genuine structure in the data. This consistency across specifications bolsters confidence in the robustness of the association.

Effect Size and Practical Significance

The unstandardised coefficient of approximately 0.2 EPI percentage points per 1 TAI percentage point may appear modest, but is consistent with agronomic and statistical reality. Technology adoption is only one driver of environmental performance; others include exogenous weather patterns, soil type, farm manager experience, and measurement error in aggregate indices. Environmental improvements also exhibit lag structures; a one-year lag captures only part of the total effect. Measurement error in country-level aggregate indices—which average across heterogeneous farms, regions, and production types—attenuates regression coefficients (attenuation bias). In this context, a consistent positive effect across multiple models is noteworthy. Furthermore, when applied to Slovakia's observed 12.7-percentage-point TAI increase (2020–2024), the predicted EPI gains of 3.6 percentage points are substantively meaningful relative to baseline improvements.

Diagnostic Assessment

Model 3 (the most comprehensive specification) exhibits excellent diagnostic properties. The Durbin-Watson statistic is 1.911, well within the acceptable range of 1.5–2.5, indicating negligible autocorrelation. The Jarque-Bera test yields p = 0.813, supporting normality of residuals. White's heteroscedasticity test yields p = 0.298, indicating homoscedasticity. All diagnostic checks pass, reinforcing confidence in the validity of the OLS estimates.

4. Conclusions

The analysis of agricultural innovation and sustainability trends during 2018-2024 reveals significant developments across primary dimensions: innovation adoption and environmental performance. This comprehensive assessment demonstrates the transformative impact of technological integration on sustainable farm management practices. Implementing innovative agricultural technologies shows a consistent upward trajectory across all measured parameters. Slovak agricultural enterprises demonstrated particularly notable progress post-2020, with smart farming adoption increasing from 3,849 enterprises in 2018 to 11,547 by. This acceleration has effectively narrowed the technological gap between the Slovak and EU averages, with the differential decreasing from 20% to 12% over the study. The adoption of precision agriculture technologies similarly demonstrated robust growth, increasing from 3,079 implementations in 2018 to 10,264 by 2024, representing a 233% improvement over the study period. Environmental sustainability indicators exhibit consistent improvement across all measured parameters. Organic farming adoption in Slovakia accelerated significantly, progressing from 5.5% in 2018 to 12.5% by 2024, representing a 127% increase. Water efficiency metrics showed the most substantial advancement, with Slovak agricultural enterprises achieving a 30% improvement in water usage efficiency by 2024, compared to the 2018 baseline.

Econometric analysis indicates a positive association between technology adoption (TAI) and environmental performance (EPI) over the 2018–2024 period. Model estimates are consistent across three specifications, with coefficients ranging from 0.162 to 0.285 (all significant at $p \leq 0.089$). Lagged specifications suggest that technological advances in year t-1 influence environmental outcomes in year t, consistent with a causal pathway from adoption to improvement, though temporal lags are inevitable in agricultural systems.

However, results must be interpreted with appropriate caution. The aggregated, country-level nature of the data limits inference to macro-scale patterns and masks heterogeneity among farms and regions. The small sample ($N = 7$ years, 2 units) restricts statistical power and prevents the implementation of more advanced causal inference methods. Endogeneity—particularly reverse causality (environmental success triggering investment) and omitted variables (e.g., farmer education, wealth, institutional capacity)—remains a concern despite mitigation strategies. Lagged variable specifications provide suggestive evidence of temporal ordering but do not definitively establish causality. For stronger causal claims, future research should employ farm-level longitudinal data, extend observation periods to 15+ years, and exploit natural policy experiments. Notwithstanding these limitations, the consistent positive relationship across models and the temporal plausibility of lagged effects support the exploratory conclusion that technology adoption is associated with environmental improvements in agriculture. The convergence of Slovakia towards EU adoption levels, coupled with measurable environmental gains, suggests that continued investment in agricultural innovation can contribute to sustainability objectives. Policy implications are twofold. First, strengthened financial incentives and targeted support mechanisms should be deployed to accelerate the adoption of smart farming, AI, and precision agriculture, particularly among small and medium-sized enterprises that may lack capital for independent technology investment. Investment in rural digital infrastructure and digital skills training for farmers is essential to ensure effective implementation and realisation of innovation benefits. Second, agricultural policy should more explicitly link technological innovation with environmental sustainability objectives, promoting technologies not merely for productivity gains but for their proven environmental co-benefits. Farm managers and stakeholders should adopt a strategic, data-driven approach to technology selection, informed by documented links to productivity and environmental performance. Strengthening collaboration between research institutions, technology providers, and agricultural practitioners can enhance knowledge transfer and accelerate the sustainable transformation of the sector. Future research should extend this analysis to more granular datasets and longer time horizons to better understand the causal mechanisms and heterogeneous effects of technological adoption across diverse farm types and regions.

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