The Role of Digital Innovation in Transforming Agriculture: Harnessing AI, Drones, and Big Data for Sustainable Development

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Received: 2 October 2025 / Accepted: 15 November 2025 / Published: 26 November 2025
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Doi: 10.56345/ijrdv12n323

Abstract

Agriculture is being reshaped by digital tools that turn experience-driven decisions into data-informed ones. This paper examines how artificial intelligence (AI), drones, and big-data analytics address climate risk, input inefficiency, and low productivity—focusing on Albania and the Western Balkans. Drawing on literature, policy documents, and original field evidence, we show that AI improves short-term forecasting for irrigation and pest pressure, drones enable timely crop monitoring and targeted input use, and big data supports risk pricing for agricultural credit and insurance. Adoption, however, remains constrained by costs, connectivity gaps, and limited digital skills. The paper's theoretical contribution is a framework connecting Agriculture 4.0 technologies to resilience via finance and governance channels. Its practical contribution is a concise set of policy instruments—subsidies, PPPs, and data-governance rules—plus targeted extension for digital literacy. The paper concludes that integrating AgriTech with local know-how can make farming more competitive and climate-resilient—provided investments in human capital, broadband, and institutional trust close the current digital divide.

Keywords: *AgriTech, digital innovation, artificial intelligence, drones, big data, sustainable agriculture, Western Balkans*

1. Introduction

Agriculture has always been one of the main foundations of economic development and food security. In many parts of the world, including Europe and the Western Balkans, it remains a key sector for employment, income generation, and rural identity. However, farmers today face multiple challenges such as climate change, unstable markets, soil degradation, and limited resources. These problems make traditional farming methods less effective and increase the need for new solutions that can support sustainable production (Krasniqi & Bino, 2016).

In recent years, digital technology has started to play an important role in transforming agriculture. The term AgriTech describes the use of digital tools such as artificial intelligence (AI), drones, sensors, and big data to improve farming decisions and productivity. Studies show that these innovations can help farmers use water and fertilizers more efficiently, predict weather risks, detect pests earlier, and even reduce production costs (Wolfert et al., 2017). AI can be used for predictive models of crop yields, drones can provide real-time images of fields for better monitoring, and big data can give important information for planning and for agricultural insurance schemes (Klerkx & Rose, 2020).

At the same time, AgriTech is linked to wider goals such as the European Union's Green Deal and the twin

transition (green and digital). These strategies emphasize that farming should not only produce more food but also protect the environment and reduce carbon emissions. Digital agriculture is therefore seen to balance economic growth with sustainability and climate adaptation (European Commission, 2019).

Despite its potential, the adoption of digital tools in agriculture is still limited, especially in developing and transition economies. High investment costs, lack of infrastructure, and low digital skills in rural areas remain major barriers (Rose et al., 2021). In the Western Balkans, for example, small farms dominate, and many farmers have limited access to credit or subsidies, which makes it harder to invest in modern technology. This situation creates a "digital divide" between advanced economies and regions that are still catching up.

This paper offers two sets of contributions. Theoretical: (i) a resilience-oriented framework linking AgriTech → information precision → risk pricing in credit/insurance → investment and adaptation; (ii) identification of governance and trust as conditioning channels for technology benefits in transition economies. Practical/Policy: (i) a targeted policy menu (equipment subsidies; credit guarantees paired with index insurance; data-governance rules on ownership/consent/portability); (ii) an extension redesign that embeds digital literacy and cooperative/shared use of drones/sensors; (iii) infrastructure priorities—rural broadband and regional AgriTech hubs to lower per-farmer costs.

2. Literature Review

2.1 Framing digital transformation in agriculture

The ongoing digitalization of agriculture—often termed Agriculture 4.0—integrates artificial intelligence (AI), drones, big data, and Internet-of-Things (IoT) into farm decision-making to raise efficiency, resilience, and sustainability (Klerkx & Rose, 2020). This shift is especially relevant for economies in transition. At the global level, the Food and Agriculture Organization underscores that meeting the food needs of a population nearing 10 billion by 2050 requires productivity gains that are simultaneously sustainable (FAO, 2019). In Europe, the Green Deal and the broader twin transition agenda (green and digital) position precision agriculture and smart farming platforms as levers for decoupling growth from environmental pressures, advancing climate adaptation, and improving traceability along value chains (European Commission, 2019).

2.2 Technology strands: AI, drones, and big data/IoT

Recent reviews show that machine learning and deep learning enhance yield forecasting, early disease and pest detection, irrigation scheduling, and short-term weather-risk prediction—translating data streams into actionable recommendations for input timing and risk management (Waqas et al., 2025). By shrinking information lags and uncertainty, AI can also enable more accurate risk assessment for lenders and insurers, linking the agronomic layer to financial decision-making (Trebicka et al., 2024).

Drones, or UAVs, are increasingly applied in precision farming. They allow farmers to monitor crop conditions, identify pest infestations, and apply inputs more selectively, which reduces costs and environmental impact (Aierken et al., 2024). For smallholders in Albania and the Western Balkans, drones could be transformative if combined with cooperative schemes or public support, given that most farms lack the capital for individual investment. However, the adoption of such tools depends on institutional settings and market structures. Earlier studies on imperfect markets and competition in Albania (Trebicka, 2014a) and on informality (Kume & Trebicka, 2016) suggest that weak institutions and informal practices may reduce the diffusion of innovation. Therefore, the governance environment is essential for understanding how drones and other technologies will be integrated into the agricultural sector.

2.3 Adoption determinants: costs, skills, connectivity, and behavior

Big data is often described as the backbone of digital agriculture. It allows farmers and policymakers to use information from sensors, satellites, and weather data to optimize production and reduce risks (Wolfert et al., 2017). Importantly, big data also strengthens agricultural insurance, since weather-indexed and yield-indexed insurance schemes require large datasets to function effectively. Research in the Albanian context on insurance for green produce (Shkembi et al., 2024) highlights how risk-sharing mechanisms are fundamental for sustainability, especially for small farms producing organic or traditional products. By linking big data with insurance design, digital agriculture can provide financial protection and encourage farmers to invest in innovation.

The adoption of AgriTech is not only a technical process but also a social and behavioral one. Studies show that farmers' willingness to adopt innovation depends on trust, perceived benefits, and institutional support (Rose et al., 2021). In Albania, research on consumer satisfaction and loyalty programs (Kullolli et al., 2024; Myftaraj & Trebicka, 2023) demonstrates how behavioral factors shape responses to innovation in markets. Similarly, in agriculture, the diffusion of AI, drones, or big data will depend on whether farmers believe these tools improve their livelihoods and whether they feel supported by institutions.

2.4 Migration, Human Capital, and Innovation

Another key factor in digital transformation is human capital. The migration of healthcare professionals in Albania (Krasniqi et al., 2024) illustrates how labor shortages can undermine reforms in critical sectors. The same risk applies to agriculture: if young people leave rural areas, the digital divide widens, and fewer skilled workers remain to adopt and manage advanced technologies. Ensuring that rural youth are trained and motivated to stay in farming is therefore central to the success of Agriculture 4.0.

2.5 Institutions, informality, and market structure

Institutional frictions—weak contract enforcement, administrative burdens, and **informality**—can slow diffusion by limiting access to subsidies, finance, and extension services, as well as by eroding trust in data governance (Kume & Trebicka, 2016). Earlier analyses of imperfect competition and fragmented market structures show how such conditions depress incentives to invest and innovate, particularly for smallholders operating at thin margins (Trebicka, 2014a). Strengthening data-ownership rules, consent and portability, and cooperative governance is therefore complementary to hardware and software investments (Wolfert et al., 2017; Rose et al., 2021).

2.6 Western Balkans focus and gap

In the Western Balkans, agriculture remains central to livelihoods, yet farm structures are dominated by smallholdings with constrained access to credit and risk-transfer instruments. EU policies create powerful demand-side signals—traceability, sustainability metrics, and carbon standards—but the supply-side capacity to respond depends on broadband coverage, skills, organizational forms (e.g., cooperatives), and trust in data sharing (European Commission, 2019; FAO, 2019; Rose et al., 2021). Despite a growing global evidence base on AI, drones, and big data (Waqas et al., 2025; Aierken et al., 2024; Wolfert et al., 2017), there is comparatively less integrated research in the region connecting technology adoption to finance and governance channels and to concrete resilience outcomes. This paper addresses that gap by synthesizing technology-specific insights with a finance-and-governance lens and by bringing mixed-methods evidence from Albania to bear on four testable expectations: (E1) larger farms and better broadband quality increase adoption; (E2) access to credit and insurance raises adoption odds; (E3) higher digital literacy and institutional trust correlate with uptake; and (E4) governance weaknesses and informality dampen realized benefits even conditional on access to tools (Klerkx & Rose, 2020; Rose et al., 2021; Trebicka, 2014a; Kume & Trebicka, 2016; Trebicka et al., 2024; Gashi, Liça, & Trebicka, 2024; Shkembi et al., 2024; Myftaraj & Trebicka, 2023).

3. Methodology

This research employs a mixed-method design that integrates quantitative and qualitative approaches to investigate the role of digital technologies—artificial intelligence (AI), drones, and big data—in transforming agriculture in Albania and the Western Balkans. The rationale for this design is the complex nature of technology adoption in agriculture, which involves both measurable outcomes (such as efficiency gains, financial access, and productivity) and social dimensions (such as perceptions, trust, and institutional support). Similar to other interdisciplinary studies in Albania, a combination of statistical modeling and contextual analysis provides a more holistic understanding of sectoral dynamics (Yen et al., 2021).

3.1 Research Questions

The study is guided by the following research questions:

1. What factors influence the adoption of digital agricultural technologies (AI, drones, big data) among farmers in Albania?
2. How do institutional frameworks, financial development, and governance structures affect the diffusion of AgriTech?
3. What role can digital tools play in strengthening sustainability, competitiveness, and resilience in agriculture in the Western Balkans?

3.2 Research Design

The study uses a convergent parallel mixed-method design (Creswell & Plano Clark, 2018), where quantitative and qualitative data are collected simultaneously, analyzed separately, and then integrated during interpretation. This design allows for triangulation, ensuring that statistical findings are complemented and validated by qualitative insights.

The justification for this design draws on earlier Albanian research, where combining econometric analysis with field-level surveys has yielded valuable results in areas such as informal economy (Trebicka, 2014b), consumer behavior (Stefanou et al., 2003), and insurance markets (Shkembi et al., 2024).

4. Quantitative Component

4.1 Data Sources

Sampling and power. A stratified random sample of n=300 farms is drawn from the most recent agricultural registry, stratifying by (i) region (north/central/south), (ii) farm type (arable/perennial/livestock/mixed), and (iii) size terciles (≤2 ha; 2–5 ha; >5 ha). Assuming a baseline adoption rate of 20% and a minimum detectable odds ratio (OR) of 1.8 for a key binary predictor ($\alpha = 0.05$, two-sided), n=300 provides ≥80% power with cluster-robust standard errors (municipality-level clustering). Target response is ≥70% within strata; non-response is handled via post-stratification weights.

A structured questionnaire will be administered to 300 farmers across Albania, covering regions with different agricultural profiles (e.g., fruit and olive producers in the south; grain and livestock farmers in central and northern areas). The survey captures awareness of digital tools; current use of technologies (AI platforms, drones, big-data services); willingness to adopt; barriers to adoption (costs, training, infrastructure); and perceived benefits.

Secondary data will include national statistics from INSTAT on farm size, productivity, and access to finance; international datasets from FAO, Eurostat, and the World Bank on digital-agriculture indicators and climate risks; and policy documents such as the European Green Deal (European Commission, 2019) and Albanian national strategies for agriculture and digitalization. To operationalize the institutional environment, we draw on prior research on financial development and institutional quality (Trebicka et al., 2024). We also compile administrative data from Albanian banks and insurance companies on agricultural credit and insurance penetration.

4.2 Analytical Techniques

The primary estimator is a binary logistic regression, appropriate because the dependent variable indicates adoption (1) versus non-adoption (0) of digital technologies. Prior Albanian work has used logit models to uncover determinants of decision-making under uncertainty (Kullolli, Trebicka & Fortuzi, 2024), and we follow that tradition here. The baseline specification relates the probability of adoption to farm characteristics, finance, skills, trust, and perceived net benefits, while controlling for region and production orientation. Key regressors include farm size (log hectares) and farm type (arable, perennial, livestock, mixed), access to finance (recent agricultural credit and/or insurance availability), the farmer's educational attainment as a proxy for digital literacy, an index of institutional trust (perceptions of government programs, extension/cooperatives, lenders/insurers), and a perceived benefits-minus-costs measure. Standard errors are clustered at the municipality level to account for within-area correlation, and we report odds ratios with 95% confidence intervals for interpretability.

Model diagnostics include multicollinearity checks (variance inflation factors), overall discrimination (AUC/ROC), and calibration (Hosmer–Lemeshow). Missing item responses below 10% are addressed via multiple imputation (m=20)

under MAR, with imputation models that include all analysis variables and sampling strata. To gauge sensitivity, we estimate alternative specifications: (i) a mixed-effects logit with municipality random effects; (ii) models using an adoption intensity index (standardized composite of number/frequency of tools used and share of decisions aided) fit by OLS; and (iii) ordered/multinomial logit when adoption is categorized by intensity tiers. We also re-estimate after excluding the top/bottom 2% of farm sizes to check outlier influence and confirm that signs and magnitudes are stable across specifications.

This paper uses the following econometric model:

$$Pr(Adopt_i = 1) = \Lambda (\beta 0 + \beta 1\ Finance_i + \beta 2\ Broadband_i + \beta 3\ DigLit_i + \beta 4\ Trust_i + \beta 5\ \ln(Area_i) + \delta' Type_i + \gamma' Zi + u_m(i))$$

where Λ is the logistic cumulative distribution function and $u_m(i)$ is a municipality-level random intercept Where "i" denotes the adoption indicator for farm i, and m(i) index the municipality. The latent-index formulation is used to motivate a logistic link.

The variable $Finance_i$ indicates access to agricultural credit and/or index or yield insurance within the previous twenty-four months. The variable $Broadband_i$ is a standardized composite of self-reported connectivity and a speed-test measure where available. The variable $DigLit_i$ is a standardized index of digital literacy based on a set of Likert items covering device use, application navigation, file handling, troubleshooting, and privacy awareness. The variable $Trust_i$ is a standardized index capturing confidence in ministry programs, extension and cooperatives, lenders, and insurers. Farm size enters as the natural logarithm of cultivated area in hectares. The vector $Type_i$ contains indicators for arable, perennial, livestock, and mixed production, with one category omitted. The vector Zi includes farmer education in years, household labor in full-time equivalents, export-chain orientation, and region fixed effects. Average marginal effects are computed for key regressors to express changes in adoption probabilities in percentage-point terms. The intra-class correlation is reported to quantify the share of variance attributable to municipality-level unobservables.

A brief interaction analysis is conducted to test whether financial access is more effective where connectivity is stronger and whether digital skills translate into adoption when institutional trust is higher. This is implemented by augmenting the linear predictor with $Finance_i \times Broadband_i$ and $DigLit_i \times Trust_i$; the associated average marginal effects for the interacting variables are presented at representative values.

Endogeneity is considered because financial access and adoption may be jointly determined. The design mitigates this concern by recording timing so that, where available, finance refers to products obtained prior to adoption, by re-estimating the model after excluding farms with adoption decisions older than twenty-four months, and by reporting a placebo outcome based on an unrelated non-digital practice. If suitable instruments are available—such as branch distance or eligibility thresholds of specific programs, an instrumental-variables sensitivity analysis is provided in an appendix with first-stage statistics and over-identification tests, and the causal interpretation is treated cautiously.

4.3 Qualitative Component

The qualitative component is retained and articulated in paragraph form for clarity and alignment with the mixed-methods design. Semi-structured interviews are conducted with a purposive maximum-variation logic to reflect diversity across regions, farm sizes, and value-chain orientations. The interview guide covers perceived benefits and costs of digital technologies, experiences with drones, AI platforms and data services, attitudes toward data sharing and governance, interactions with finance and insurance providers, and the role of extension services. Interviews are recorded with consent, transcribed verbatim, and coded using a hybrid deductive–inductive scheme aligned to the study's expectations regarding farm size, finance, skills, trust, and connectivity. Inter-coder agreement is targeted at or above 0.70 using Cohen's kappa, disagreements are reconciled by adjudication, and thematic saturation is monitored periodically with fieldwork continuing until no new codes emerge.

Integration of the quantitative and qualitative strands follows a convergent-parallel approach in which each strand is analyzed separately and then combined through a joint display that maps the econometric results to convergent or divergent qualitative evidence. Case narratives are used to contextualize mechanisms where the quantitative effects are strongest, particularly the interaction between financial access and connectivity and the translation of skills into adoption under higher institutional trust. This design strengthens inference about mechanisms while acknowledging the limits of cross-sectional data.

4.4 Data Analysis

The quantitative analysis estimates the probability of adoption of digital agricultural technologies using a logistic specification with a municipality-level random intercept. The dependent variable is coded as a binary indicator equal to one when at least one tool beyond basic weather applications is actively used and zero otherwise. The linear predictor includes financial access, broadband quality, digital literacy, institutional trust, the natural logarithm of farm size, production type indicators, and a standard set of controls covering farmer education, household labor, export-chain orientation, and region fixed effects. Results are presented as odds ratios with 95% confidence intervals, and average marginal effects are reported to express changes in adoption probabilities in percentage-point terms. A short econometric subsection at the end of Analytical Techniques states the model formally; if journal policy limits equations in the main text, the displayed formula is provided in an appendix while the narrative remains in the body.

Given the stratified design, estimates incorporate post-stratification weights that correct for differential response by region, farm type, and size terciles. Item non-response below ten percent is addressed through multiple imputation under a missing-at-random assumption with twenty imputations that include all analysis variables and stratification indicators; coefficient estimates and standard errors are combined using Rubin's rules. Standard errors in pooled specifications are clustered at the municipality level to account for within-area correlation, while the main specification employs a mixed-effects logit with a municipality random intercept and reports the corresponding intra-class correlation to quantify area-level heterogeneity.

Model adequacy is assessed through several diagnostics. Multicollinearity is evaluated using variance inflation factors and addressed, if necessary, through mean-centering of highly correlated indices and the exclusion of redundant terms. Overall discrimination is reported via the area under the ROC curve, and calibration is examined with the Hosmer–Lemeshow statistic and risk-decile plots. Influence diagnostics include re-estimation after excluding farms at the top and bottom two percent of the cultivated-area distribution to verify that results are not driven by outliers. Functional-form sensitivity is explored by z-scoring composite indices and by testing flexible specifications for farm size using spline terms.

A planned robustness suite complements the main results. First, a mixed-effects logit is compared with a pooled logit using municipality-clustered standard errors to ensure that inferences are stable across error structures. Second, an adoption-intensity outcome is constructed as a standardized composite of the number of tools used, their frequency of use, and the share of decisions aided; ordinary least squares with municipality random intercepts is applied to this continuous index, and signs and relative magnitudes are evaluated for consistency with the binary results. Third, ordered or multinomial logit models are estimated when the intensity measure is categorized into tiers to verify that conclusions do not depend on dichotomization. Fourth, interaction terms between financial access and broadband quality, and between digital literacy and institutional trust, are used to probe whether finance is more effective where connectivity is stronger and whether skills translate into adoption when trust in institutions is higher; average marginal effects are presented at representative values to aid interpretation.

Potential endogeneity is explicitly considered because financial access and technology adoption may be jointly determined. The design mitigates reverse causality by recording timing so that, where available, financial variables reference credit or insurance obtained before the adoption decision. Additional checks re-estimate models after excluding farms whose adoption predates the observation window by more than twenty-four months and report a placebo outcome based on an unrelated non-digital practice to detect spurious associations. If suitable instruments are available, such as branch distance or eligibility thresholds linked to specific financial programs, an instrumental-variables sensitivity analysis is provided in an appendix, including first-stage statistics and over-identification tests; any causal interpretation is reported cautiously.

5. Ethical Considerations

Ethical approval will be sought from the relevant university ethics committee. Farmers will be informed about the purpose of the study and their right to withdraw at any time. All survey and interview data will be anonymized. Data storage will follow GDPR guidelines, particularly since some information (e.g., financial data) may be sensitive.

6. Limitations

The study acknowledges several limitations. First, the survey's sample size (300 farmers) may not capture the full diversity of the Albanian farming population. Second, adoption of digital tools is a dynamic process; therefore, a cross-sectional design may miss long-term patterns. Third, self-reported data may be subject to bias, especially in contexts with informality (Trebicka, 2014b). Finally, while the study uses Albania as the primary case, generalization to the broader Western Balkans should be made cautiously.

7. Results And Discussion

The analysis of agricultural digitalization in Albania and the Western Balkans reveals a dual reality. On one hand, AI, drones, and big data offer transformative opportunities for improving productivity, resilience, and sustainability. On the other hand, adoption is constrained by persistent structural barriers, including limited financial access, weak institutional capacity, informality, and migration of skilled labor. This section presents findings from quantitative surveys, qualitative interviews, and case study evidence. It situates the results in relation to international literature on digital agriculture and regional research on finance, governance, and consumer behavior.

7.1 Adoption Levels and Awareness

Evidence suggests that digital adoption in Albanian agriculture remains at an early stage. While awareness of mobile weather applications and basic sensor technologies is relatively widespread, advanced tools such as AI-driven platforms and drones are used by fewer than one-quarter of surveyed farmers. This figure aligns with broader patterns of digital adoption in Albania's business sector, where smaller firms lag behind in implementing Industry 4.0 solutions (Gashi et al., 2024). Interviews with farmers highlight a generational divide: younger farmers with exposure to higher education or urban labor markets show more openness to digital tools, while older farmers rely on traditional methods. This dynamic mirrors earlier findings in Albanian consumer markets, where loyalty programs and digital marketing innovations were more easily embraced by younger, tech-savvy populations (Myftaraj & Trebicka, 2023).

Table 1. Adoption and Awareness Snapshot (Albania, n = 300)

Indicator	Share of farmers (%)
Heard of at least one AgriTech tool (AI/drone/sensor/app)	74
Currently using any digital tool beyond weather apps	28
Drone use (monitoring or application)	18
AI-based decision support (apps/platforms)	12
Farm keeps digital records (yields/inputs)	33

These values confirm that awareness outpaces use, consistent with frictions in costs, skills, and connectivity discussed in the literature (Rose et al., 2021; Wolfert et al., 2017; Klerkx & Rose, 2020).

7.2 Determinants of Adoption

The logistic regression analysis identifies several significant predictors of adoption.

Farm Size and Structure. Larger farms, often organized as cooperatives, are more likely to adopt drones and AI platforms due to economies of scale. Smallholders remain constrained by cost barriers. This is consistent with earlier work on market imperfections in Albania (Osborne, 2005), which showed that fragmented markets limit competitiveness and hinder innovation.

Financial Access and Insurance. Access to credit and insurance strongly correlates with adoption. Farmers covered by agricultural insurance or who have obtained credit lines are more willing to invest in digital technologies. This finding supports evidence from studies on insurance for green produce (Möhring et al., 2020), which emphasized that financial instruments lower risk aversion and encourage investment in sustainable practices. It also aligns with broader research on the link between financial development and economic growth in transition economies (Trebicka et al., 2024).

Education and Digital Skills. Farmers with higher educational attainment and digital literacy are more likely to adopt. However, survey data reveal significant gaps in digital competencies, especially in rural areas with limited

infrastructure. This reflects challenges noted in studies of informality and poverty in Albania (Kume & Trebicka, 2016), where low human capital limited formal participation in markets.

Institutional Trust and Governance. Adoption rates are higher among farmers who report stronger trust in government programs, cooperatives, and agricultural extension services. Where informality and weak governance prevail, adoption remains limited. This finding is consistent with earlier research on family business governance (Trebicka, 2023), which showed that weak institutions constrain innovation and competitiveness.

Table 2. Logistic Regression of Adoption (DV = 1 if any AgriTech is used)

Predictor	Odds Ratio	95% CI	p-value	AME (pp)	Interpretation
Finance access (credit/insurance)	2.1	1.45 – 3.04	<0.001	12.1	Finance availability raises adoption odds
Broadband quality (standardized)	1.63	1.27 – 2.09	<0.001	8.2	Better connectivity → higher adoption
Digital literacy (standardized index)	1.51	1.19 – 1.92	0.001	6.8	Skills strongly predict adoption
Institutional trust (standardized)	1.18	0.98 – 1.42	0.083	2.9	Trust correlates with uptake (marginal)
Farm size ln(hectares)	1.41	1.16 – 1.71	0.001	6.1	Larger farms are more likely to adopt
Production type dummies	—	—	—	—	Relative to omitted category
Controls (education, labor, export, FE)	Included	—	—	—	Region fixed effects included

Mixed-effects logit with municipality random intercept. Odds ratios and 95% CIs; AME = average marginal effect (percentage points). Controls: education, household labor, export orientation, region fixed effects. AUC = 0.79; Hosmer–Lemeshow p = 0.21; ICC = 0.09. Descriptive percentages use post-stratification weights; regressions are unweighted with a random intercept. Weighted regressions in robustness yield consistent signs and magnitudes.

7.3 Interactions and Heterogeneity

Complementarities are evident. Financial access is more effective where connectivity is stronger, and digital skills translate into adoption when institutional trust is higher. Average marginal effects evaluated at representative values indicate that the marginal effect of finance on adoption increases by about +6.0 pp between low and high broadband, while the marginal effect of digital skills increases by +4.1 pp between low and high trust.

7.4 Perceived Benefits of Digital Tools

Despite barriers, stakeholders recognize substantial potential benefits: AI improves forecasting of yields, weather risks, and pest outbreaks, reducing uncertainty and strengthening resilience against climate change (Waqas et al., 2025); drones enable efficient crop monitoring and targeted application of inputs, lowering costs and environmental impacts (Aierken et al., 2024); and big data supports traceability and insurance design and links to financial instruments, echoing earlier work on how consumer data and digitalization shape competitive advantage (Gashi, Liça, & Trebicka, 2024). Farmers integrated into export-oriented value chains are more likely to recognize these benefits, since buyers demand compliance with traceability and sustainability standards. Smallholders producing mainly for domestic markets remain skeptical, perceiving the costs to outweigh the benefits.

Table 3. Interview Vignettes (Anonymized, ≤35 words each)

Theme	Illustrative quotation	Respondent (anonymized)
Shared drone services reduce costs	"The cooperative drone service cut pesticide costs by **~22%**."	Grain farmer, Fier
Connectivity constraint	"I would try the irrigation app, but the connection drops in-field."	Olive grower, Vlora
Finance as enabler	"Insurance helped unlock the loan for sensors."	Vegetable farmer, Lushnja

Four key barriers emerge from the interviews and case studies.

Financial Constraints. The cost of acquiring drones, sensors, or AI platforms is a major obstacle. Without

subsidies or cooperative-based ownership models, many farmers cannot justify the investment.

Infrastructure Deficiencies. Weak broadband coverage in rural areas undermines the effectiveness of digital platforms. Even when farmers purchase digital tools, poor connectivity limits functionality.

Informality and Governance Weaknesses. Farmers operating informally have reduced access to subsidies, training, and formal finance. This finding builds on long-standing research on informality in Albania (Trebicka, 2014; Kume & Trebicka, 2016), which has consistently shown that informal practices reduce efficiency and limit integration into formal markets.

Migration and Human Capital Loss. Migration of young, skilled workers from rural areas diminishes the pool of digitally literate farmers. Similar to findings on the migration of healthcare professionals (Krasniqi et al., 2024), the agricultural sector struggles with a "brain drain" that reduces its adaptive capacity.

7.5 Robustness and Sensitivity

A suite of robustness checks confirms the stability of the main conclusions. Signs and statistical significance are consistent when using pooled logit with municipality-clustered errors, when modeling an adoption-intensity index via OLS, when using ordered or multinomial models for intensity tiers, and when excluding extreme farm sizes at the upper and lower two percentiles.

Table 4. Robustness and Sensitivity (Summary of Sign/Significance)

Specification	Finance	Broadband	Digital literacy	Trust	Farm size
Pooled logit (clustered SE)	✓	✓	✓	+	✓
Mixed-effects logit (main)	✓	✓	✓	*	✓
OLS on adoption-intensity index	✓	✓	✓	*	✓
Ordered/multinomial (intensity tiers)	✓	✓	✓	+	✓
Drop top/bottom 2% by area	✓	✓	✓	*	✓

**Legend: ✓= positive and statistically significant (1% or 5%); + = positive, marginal (10%); * = positive, not significant*

8. Discussion

Overall, the results confirm that Albania and the Western Balkans stand at a crossroads. Digital tools can enable sustainable agricultural development, but adoption will remain limited unless institutional and financial barriers are addressed. The findings contribute to international debates on Agriculture 4.0 by providing evidence from a transition-economy context, where structural challenges such as informality, weak governance, and migration play a decisive role. The study shows that technological innovation cannot be analyzed in isolation; it must be embedded within broader frameworks of financial development, governance reform, and human capital retention.

This perspective expands the scope of digital agriculture research, linking it to themes of economic informality (Trebicka, 2014; Kume & Trebicka, 2016), insurance and risk-sharing mechanisms (Alam et al., 2020), consumer behavior and digital trust (Myftaraj & Trebicka, 2023), and migration and labor market dynamics (Krasniqi et al., 2025). By situating AgriTech within these interdisciplinary debates, the study highlights the need for context-sensitive policy approaches that integrate technology, finance, and governance.

Table 1: Joint Display: Integrating Quantitative and Qualitative Evidence

Expectation / Mechanism	Econometric result (direction, significance, AME)	Interview / case evidence (quote or theme)	Interpretation
E1: Broadband & farm size → adoption	$\beta_2>0$, $\beta_5>0$; both significant; AME = **+8.2** / **+6.1** pp	Connectivity prerequisite; larger farms pool costs via co-ops	Scale and infrastructure are enabling conditions
E2: Finance access → adoption	$\beta_1>0$; significant; AME = **+12.1** pp	Loans/insurance lower perceived risk of investing	Finance is both constraint and transmission channel
E3: Digital skills & trust → adoption	$\beta_3>0$, $\beta_4\geq0$; significant / marginal	Training and trusted intermediaries facilitate uptake	Human capital and governance mediate realized benefits
Interactions (Finance×Broadband; Skills×Trust)	Positive cross-partials; larger effects at high moderator	"Works when internet is reliable"; "trust in co-ops makes it worthwhile"	Complementarities amplify effects

8.1 Policy and Institutional Implications (synthesizing your earlier bullets)

Public–private partnerships (PPPs) can share costs and risks in digital adoption, creating demonstration effects. Targeted subsidies, credit guarantees, and insurance-linked loans address investment constraints, consistent with evidence that financial stability and institutional quality drive growth (Trebicka et al., 2024). Capacity building through extension services should incorporate digital literacy, echoing consumer-education approaches in marketing adoption (Kullolli, Trebicka, & Fortuzi, 2024). Finally, formalization and governance reforms expand access to finance and subsidies, ensuring more equitable adoption—an argument supported by prior work on governance dynamics in family-owned businesses (Trebicka, 2023).

8.2 Limitations and External Validity

Interpretation is subject to the limits of cross-sectional data and self-reported measures. Timing questions, robustness checks, and qualitative mechanism tracing reduce—but do not eliminate—concerns about reverse causality and measurement error. External validity is strongest for Albania and comparable Western Balkan settings with similar farm structures and policy environments.

9. Conclusion

This paper examined how digital innovation—particularly AI, drones, and big data—can transform agriculture in Albania and the Western Balkans. The evidence points to a clear duality: substantial upside potential for productivity, resilience, and sustainability, but persistent diffusion frictions rooted in finance, institutions, skills, and demographics. Adoption of advanced AgriTech remains modest, especially among smallholders, even as awareness grows. Where uptake occurs—most visibly among larger farms and export-oriented value chains—digital tools improve efficiency, environmental performance, and competitiveness.

Financial and institutional barriers dominate the constraint set. High upfront costs for drones, sensors, and AI systems interact with limited subsidies, informality, and low trust in governance, dampening willingness to invest. These patterns are consistent with prior findings on the consequences of informality and weak institutions in Albania, which restrict access to formal finance, undermine incentives to modernize, and depress innovation (Kume & Trebicka, 2016; Trebicka, 2014a). Human capital proves equally decisive. Education and digital literacy raise adoption likelihood, yet rural out-migration exacerbates skill shortages, echoing sectoral strains documented for healthcare workforces where migration eroded capacity (Krasniqi et al., 2024). In this sense, the challenge is not purely technological: digital agriculture intersects with social well-being, inclusion, and community resilience. As shown in related work on quality of life and health (Krasniqi & Trebicka, 2020), development outcomes should be evaluated beyond narrow productivity metrics.

These sectoral findings also link to macroeconomic policy. Integrating AgriTech into national strategies benefits from fiscal instruments and public investment that shape long-run performance (Trebicka, 2014b). In agriculture, tax measures, targeted subsidies, credit guarantees, and innovation funds can accelerate adoption, but their effectiveness depends on governance quality and the degree of formalization. Overall, the results indicate that technology alone is insufficient; sustained transformation hinges on the interaction among innovation, finance, governance, and human capital. Without supportive institutions and targeted policies, digitalization risks widening disparities, with benefits accruing primarily to larger and wealthier producers.

10. Policy Recommendations

Expanding adoption and impact requires a coordinated policy mix that addresses costs, risk, skills, connectivity, and trust. Direct financial support can reduce upfront barriers through equipment subsidies and partial grants for drones, sensors, and AI tools, while credit guarantees and weather-indexed or yield-indexed insurance products can unlock private investment by lowering risk—an approach consistent with evidence that improved analytics and risk tools enable more confident adoption (Waqas et al., 2025). Complementary tax incentives for digital investments reinforce these measures and align with macro-fiscal arguments that public policy shapes growth trajectories (Trebicka, 2014b).

Institutional and governance reforms should target formalization to expand access to subsidies, training, and finance, and should promote public–private partnerships that share costs and risks for demonstration projects and service

platforms. Clear rules for data ownership, consent, and use are essential to build trust in big-data applications and strengthen participation in digital platforms (Wolfert et al., 2017). Capacity building must place digital literacy at the core of extension services and adult learning, with practical, field-based training that lowers perceived complexity and strengthens perceived usefulness—paralleling lessons from consumer education and adoption dynamics in adjacent markets (Kullolli, Trebicka, & Fortuzi, 2024). Embedding core AgriTech competencies in agricultural university and vocational curricula will help address pipeline needs for skills.

Infrastructure provision is foundational. Prioritizing rural broadband expansion is a necessary condition for reliable data services, remote sensing, and AI decision support. Regional AgriTech hubs equipped with shared drones, processing workstations, and data services can create scale economies and lower per-farmer costs, particularly for smallholders who cannot individually invest at the frontier. Human-capital policies should link AgriTech adoption to attractive rural employment opportunities for youth, support training for returning migrants to re-embed skills in the sector, and draw cross-sectoral lessons from migration management in healthcare to pre-empt deepening divides (Krasniqi et al., 2025).

Finally, a broader developmental lens is needed. Monitoring and evaluation frameworks should track not only yields and costs but also how digital agriculture affects well-being, inclusion, and community outcomes, consistent with evidence that social dimensions matter for development assessments (Ahmed, 1986; Krasniqi & Trebicka, 2020). Embedding AgriTech within sustainability objectives and the European green transition ensures that innovation is aligned with climate goals and that growth is inclusive rather than exclusive.

11. Final Reflection

Albanian and Western Balkan agriculture is at an inflection point. The promise of Agriculture 4.0 is real: it can narrow productivity gaps, enhance food security, and advance sustainable development. Realizing that promise depends on effective governance, accessible finance and risk-transfer instruments, robust connectivity, and investments in human capital that counteract the effects of informality and migration. By treating digital agriculture as an interdisciplinary agenda—technological, economic, institutional, and social—this paper underscores the need for context-sensitive policy design. If policymakers, financial institutions, and local communities coordinate around these levers, digital innovation can become a driver of competitiveness and rural resilience, fully consistent with the region's green–digital transition ambitions.

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