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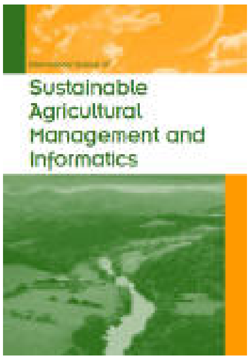

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Mirvari Kh. Gazanfarli

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How digitalisation affects agricultural progress in Azerbaijan: evidence from panel data approach

Mirvari Kh. Gazanfarli

UNEC Business School (MBA),
Azerbaijan State University of Economics (UNEC),
6 Istiglaliyyat, Baku, Azerbaijan
Email: gazanfarli.mirvari@unec.edu.az

Abstract: This study focuses on measuring the impacts of digital transformation on agricultural productivity in Azerbaijan. To realise the set goal, ICT characteristic indicators, including the infrastructural and human provision of ICT in agricultural enterprises, were identified, and 14 economic regions were investigated based on these factors in Azerbaijan within 2019–2021. Due to data structure, three static panel data models (POLS, REM, and FEM) were built for designing this process. Diagnostic tests analysis proved that the random effect model characterises these effects much more than others. The estimations and simulations concluded that the number of employees who used the internet in agricultural enterprises is associated negatively with the general product of agriculture in Azerbaijan. However, web page usage, software development, and the expenses of ICT infrastructure in the enterprises help to increase the productivity of the agricultural field of Azerbaijan's economy.

Keywords: agricultural enterprises; digital agriculture; economic regions; measurement indicators; diagnostic analysis; panel data analysis.

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Biographical notes: Mirvari Kh. Gazanfarli is a PhD in Economics (Econometrics, Economic Statistics), Lead Instructor, and Program Supervisor on the 'ICT and Data Sciences' at the UNEC Business School, Azerbaijan State University of Economics (UNEC). Her fields of scientific interest are quantitative and qualitative analysis of local economic processes and development issues, smart and sustainable development as well as the role of digitalisation, and digital transformation in the development of various economic fields with the main focus on the application of mathematical modelling (econometrics, optimisation modelling, fuzzy modelling, stochastic modelling, etc.). She has published more than 20 scientific papers proposing new approaches and methodologies in measuring and simulating economic activity by developing software using programming languages (Python, C#, JS) and programming platforms (visual studio (IDE), MATLAB, EViews).

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1 Introduction

Digitalisation effectively increases productivity and profits by giving firms and companies new technological tools to design their economic activity. The development of Industry 4.0 technologies causes to be created new fields of economy and raises dependencies on technological changes to provide economic growth. Since agriculture is the source of livelihood and supplier of raw materials to various industries, its improvement triggers the country's economic growth. Empirical estimation, implemented in India, proved that agriculture has long-run causal linkages with industry, services, and comprehensive economic growth (Khan et al., 2019). How digital agricultural transformations play a significant role in the income-increasing process (Luo et al., 2023), the improvement of rural areas (Chowdhury et al., 2023), the creation of opportunities for international trade (Jouanjean, 2019), providing sustainable development (Nitturkar 2021; Kashina et al., 2022; Lin and Li, 2023) and other effects have been analysed and estimated. Youm et al. (2022) investigated the influence of advanced technological usage in Korean agriculture and concluded that agricultural production and trade increased by 8.67% and 5.72%, respectively. Analysis proves that digital agriculture helps build a strong economy, besides ensuring effective agricultural activities. Therefore, numerous state regulations and strategic agendas were developed by different authorities (United Nations, 2015; Tkachev, 2017; 2018–2022 Public Administration Reform Strategy Action Plan, 2019).

Approximately €80 million was invested to support the deployment of advanced technologies in the EU agricultural sector under the projects of IoF2020 (€34 m), DEMETER (€17 m), ATLAS (€15 m), and SmartAgriHubs (€22 m). All these initiatives resulted in a 1.4% growth in Europe's gross domestic product (GDP) (FAO and ITU, 2020). However, the amount of investment reached $238 million in 2022 covering more than 80 agritech deals in African countries. This means a 127% increment in comparison with 2020.

It is obvious that agriculture is the third most important economic field of Azerbaijan (5.7% of GDP), and it has great potential for improving this sector in terms of natural and economic factors. Additionally, it must be mentioned that 37% of the population is employed in the agricultural sector. Therefore, developing this sector is one of the major priorities of our government. It is not a coincidence that for this purpose, numerous reforms and measures have been implemented in Azerbaijan. A decree on the 'Measures to improve governance in the agrarian field and accelerate institutional reforms' signed in 2014, Strategic Roadmap for 'The production and processing of agricultural products in the Republic of Azerbaijan' prepared in 2016 reflects the issues of expanding ICT services and actively applying digital technologies in the agricultural field economy. 'From Village to City' project, 2019, 'Vision for the Future: Transition to Digital Agriculture International Conference, 2022' and 'Application of the Electronic Agricultural Information System' are useful measures that allow for improving management and increasing productivity in the agricultural field of Azerbaijan economy. The top three agricultural startups were invested by the US with $7.9 billion, China with $3.5 billion, and India with $2.4 billion in Azerbaijan in 2018. The result of all measures resulted in the growth of more than two times within the last 10 years in the general product of the agricultural sector. The analysis of scholars' research and official working papers shows that despite the significant progress made in the field of digital transformation of agriculture, much remains to be done in Azerbaijan (Mustafayeva and

Jafarli, 2022; Temel et al. 2022). To reach the highest development through digital integration, the issue of 'how agricultural productivity and efficiency can be increased by digitalisation in Azerbaijan?' must be investigated and estimated. Therefore, our research is devoted to:

- analysing the level of ICT implementation in Azerbaijan
- defining the major indicators of digital agriculture in Azerbaijan
- assessing how digitalisation can affect the economic performance of the agricultural sector in Azerbaijan
- preparing recommendations for policymakers in providing effective agricultural activities in Azerbaijan.

2 Theoretical framework

Evaluating the digitalisation level of the agricultural sector requires the investigation of the adoption rate of technological changes in this field. There are numerous studies were devoted to defining the impact of the adoption level of technology on agricultural productivity in literature (Gebeyehu, 2016; Shita et al., 2019; Zegeye et al., 2022). The impact of digital inclusive finance (DIF) on agricultural green total factor productivity (GTFP) was measured in China. This research concluded that GTFP has an increasing trend and improvement through motivating agricultural technology innovation and industrial structure optimisation (Gao et al., 2022; Xiao et al., 2023). Klingenberg et al. (2022) analysed and measured the effects of digitalisation on value creation and its implications for value capture in the agricultural value chain. This estimation concluded that the digital transformation of agriculture would be as impactful as other revolutions the activity has undergone over time (Klingenberg et al., 2022). The adoption of advanced technologies and their impact on the Italian agricultural field were investigated, concluded that less awareness and the reduced average size of farms are the main barriers to adopting innovations (Bucci et al., 2019). The effects of ICTs on improving agricultural productivity were estimated in the case of African countries and concluded with the positive relations between them (Chibsa, 2020; Chowhan, 2020; Nkandu and Phiri, 2022).

A wide range of contributions related to studies of digital agriculture were dedicated to Industry 4.0. Technologies application. The application of Industry 4.0 technologies assists in raising the productivity and sustainability of farming, decreasing human labour and extreme expenditures (Patil and Shekhawat, 2019; Escamilla-García et al., 2020). Sharma et al. developed a cyber-physical agricultural systems (CPASs) framework, which is an intelligent integration of the internet of things (IoT), cloud computing (CC), cyber-physical systems (CPS), and big data with agricultural systems. The application of this system increased productivity (Sharma et al., 2020). Literature analysis shows that numerous smart agricultural applications and systems were developed and implemented in different countries. IoT-based smart agriculture monitoring system (Siddiquee et al., 2022), WebLog and UtafitiLog (Oteyo et al., 2020), and IoT-Based remote monitoring system (RMS) (Patil and Kale, 2016) are the samples of these types of systems. The swarm robots' mechanisations to implement agricultural processes were analysed systematically and evaluated comprehensively in terms of technology readiness level

(TRL), adaptability, dependability, motion ability, perception ability, and decision autonomy (Albiero et al., 2020). In order to assess the impacts of agricultural mechanisation on intrahousehold labour allocation, a picture-based smartphone app called time-tracker was developed to record data in real-time to avoid recall biases in Zambia (Daum et al., 2018). Artificial intelligence (AI), machine learning (ML), and deep learning (DL) algorithms are also efficient ways to improve agriculture, especially the food industry (Crane-Droesch, 2018; Kamilaris and Prenafeta-Boldú 2018; Ayed and Hanana, 2021). It is obvious that the application of the IoT resulted in gathering real-time data on various parameters, generating a massive amount of streaming data, often referred to as 'big data'. Theoretical analyses of big data applications in smart farming show that its usage provides anticipating insights into farming operations, drives to make real-time decisions, and redesigns business processes (Wolfert et al., 2017). The joint application of IoT, Big Data, and AI in the agricultural field creates new opportunities for data analytics, farmers, food processors, and other stakeholders (Misra et al., 2020). The futuristic IoT with a blockchain model was prepared to provide lower energy consumption and network stability. The model simulation results showed that the proposed protocol network stability is 23% higher compared to the low-energy adaptive clustering hierarchy protocol (Awan et al., 2021). Blockchain is another crucial technology that assists in increasing agricultural productivity by building accurate food supply chains and providing trust relationships between consumers and producers (Xiong et al., 2020).

The above literature analysis proves that digital transformation and technology applications have a crucial role in improving the agricultural field. However, digitised agricultural activity has some difficulties and cons, and ICT application is not enough to provide sustainable agricultural development. Some indicators used to characterise digital agricultural activity are costly and have negative consequences. Numerous scientific investigations confirm the negative impact of ICT in this sector (Ogutu et al. 2014; Ma and Wang, 2020). Kante et al. (2016) revealed that the effect of ICT usage on agricultural activity is positive in developing countries, while the ICTs' high service expenditure negatively impacts their use. Nguyen and Do (2022), Nguyen et al. (2022) showed that internet usage enhances income inequality among rural populations. Shrivastava et al. (2016) investigated internet usage at workplaces and its impact on working style in India. This study concluded that internet addiction is a growing problem that ruins lives and decreases productivity by causing mental disorders and attention deficit hyperactivity disorder. Studies of the above approaches and estimations reveal that the negative impact of ICT in agriculture mostly happens due to inefficient usage of the Internet, energy, and high costs.

The literature was analysed systematically taking into consideration review and methodological aspects of digital agriculture. Consequently, it can be mentioned that digitalisation is the key factor that leads to the development of agriculture as well as economic growth and this process requires enhancing the indicators that have significant effects. Therefore, our research focuses on defining the main indicators of digital agriculture and estimating the impact it has on the agricultural sector and the entire economy in Azerbaijan.

3 Materials and methods

3.1 Research methodology

From the previous literature and conceptual framework analysis, it can be concluded that measuring the impact of digitalisation on agriculture requires studying ICT adoption indicators such as the usage rate of digital tools, computer software, application of information systems, and building effective infrastructure in this field. This analysis has helped us to define indicators that characterise the digital agricultural sector of Azerbaijan's economy. Therefore, the economic model that expresses the linkage between digital integration and the productivity of the agricultural sector will be defined as below:

$$GP = f(ICTC, IE, IC, CE, CQ, EC, WP) \tag{1}$$

Since this analysis involves the 14 regions of Azerbaijan within the 3 years, the model specification will be expressed as follows:

$$\begin{aligned} lnGP_{it} &= \alpha_0 + \alpha_1 lnICTC_{it} + \alpha_2 lnIE_{it} + \alpha_3 lnIC_{it} + \alpha_4 lnCE_{it} + \alpha_5 lnCQ_{it} \\ &\quad + \alpha_6 lnEC_{it} + \alpha_7 WP_{it} + e_{it} \end{aligned} \tag{2}$$

Herein *ln* is the natural logarithm, *i*, $i = \overline{1.14}$ denotes regions of Azerbaijan Republic, *t*, $t = \overline{1,3}$ denotes time.

GP gross product of agriculture (with actual prices of the respective years, measured in thousand manats)

ICTC expenditures for ICT in agricultural enterprises (thousand manats)

IE the number of employees who used the internet in agricultural enterprises

IC the number of computers with internet access in agricultural enterprises

CE the number of employees who used computers in agricultural enterprises

CQ the number of computers in agricultural enterprises

EC the number of agricultural enterprises using computers

WP the number of agricultural enterprises with a web page on the internet.

In our estimation, *GP* is the explained variable, $ICTC_{it}$, IE_{it}, IC_{it}, CE_{it}, CQ_{it}, EC_{it}, WP_{it} are explanatory variables; e_{it} is an error term that consists of both region-specific and time-specific effects, α_0 – intercept, α_j, $j = \overline{1,7}$ – elasticities of general product concerning regressors. Except the WP all other data has been transformed into natural logarithms for standardising measurements and reducing heteroskedasticity.

The main goal of this research is to estimate the effects of digital characteristics of agriculture in Azerbaijan, taking into account its regions on agricultural improvement. For this purpose, three years of statistical data covering 14 regions are utilised. Since the short length of time-series data of regions of Azerbaijan, the dynamic such as the Arellano-Bond estimator or the generalised method of moments (GMM) will be inappropriate. With this in mind, the static panel data methods, namely pooled ordinary least squares (POLS) fixed effects model (FEM), and random effects model (REM) have been applied, and results have been validated using diagnostic analysis.

The main reasons for applying the panel data model FEM and REM are considering heterogeneity for individuals, controlling unobserved factors, investigating time-varying effects, and making efficient usage of panel data (Baltagi, 2013).

Having individual specific intercepts α_{0i}, $i = \overline{1,14}$ that each of them can be understood as the fixed effect of regions characterises fixed effect model. Therefore, the fixed effect model specification will be expressed as below:

$$\begin{aligned} lnGP_{it} &= \alpha_1 lnICTC_{it} + \alpha_2 lnIE_{it} + \alpha_3 lnIC_{it} + \alpha_4 lnCE_{it} + \alpha_5 lnCQ_{it} \\ &+ \alpha_6 lnEC_{it} + \alpha_7 WP_{it} + \alpha_{0i} + e_{it} \end{aligned} \tag{3}$$

Since the REM makes a precise fixed effect model by selecting individuals (regions) randomly in the panel, their characteristics will also be random, and model specification will be as follows:

$$\begin{aligned} lnGP_{it} &= \alpha_1 lnICTC_{it} + \alpha_2 lnIE_{it} + \alpha_3 lnIC_{it} + \alpha_4 lnCE_{it} + \alpha_5 lnCQ_{it} \\ &+ \alpha_6 lnEC_{it} + \alpha_7 WP_{it} + \overline{\alpha}_0 + \delta_{it} \end{aligned} \tag{4}$$

where

$$\alpha_{0i} = \overline{\alpha_0} + u_i; \ \delta_{it} = u_i + e_{it} \tag{5}$$

δ_{it} error term that incorporates both individual specifics as well as the initial regression error term.

3.2 Data employed in the empirical analysis

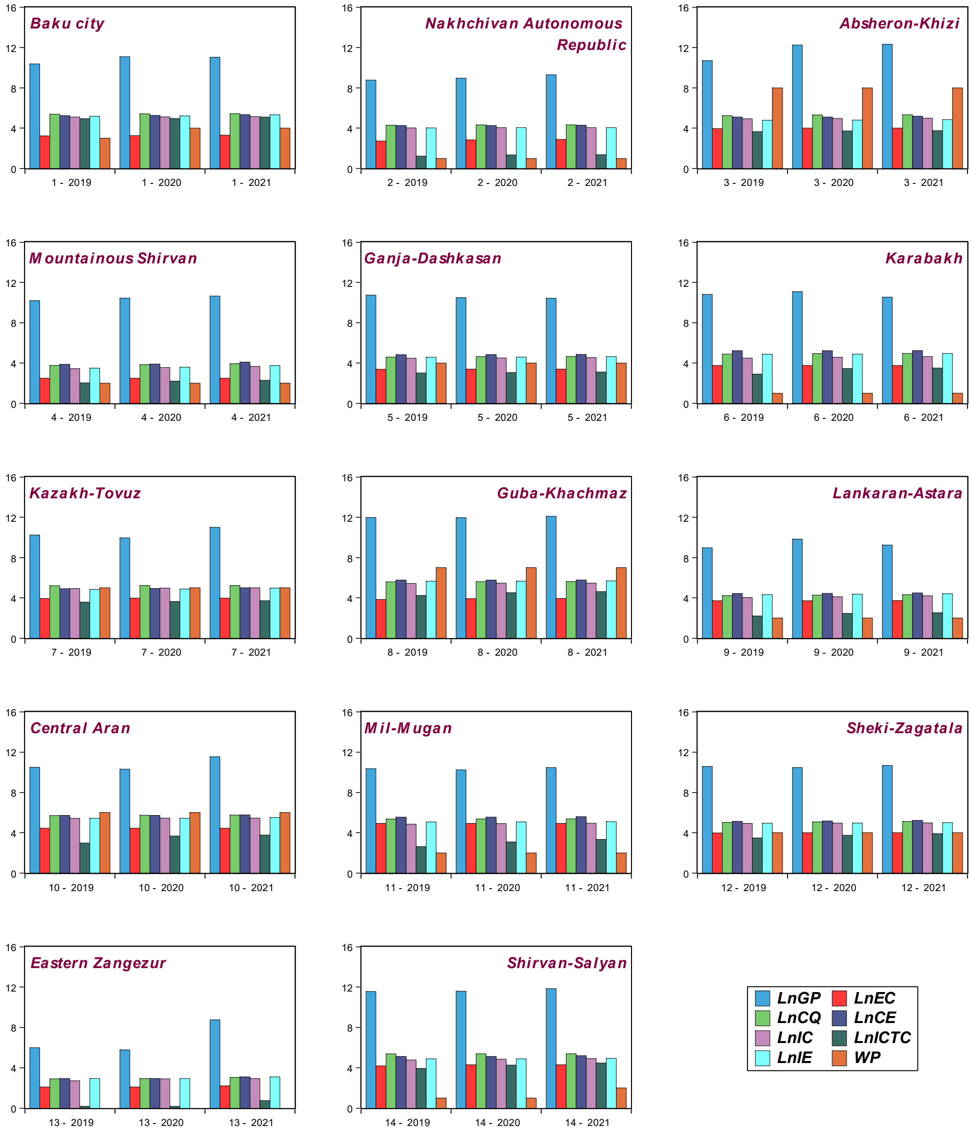
In this analysis, a balanced panel sample of 14 regions of Azerbaijan covering the period 2019, 2020, and 2021 are utilised. Important data was obtained from the State Statistical Committee of the Republic of Azerbaijan by applying an official letter No. 3-34/2-343-02-2/2023. The visual representation of utilised data is given in Figure 1. To improve the accuracy and interpretability of the model, explanatory variables except WP were transformed into natural logarithms. Table 1 provides the descriptive statistics for all studied variables.

Table 1 Summary of descriptive statistics (42 observations)

Variables	*Mean*	*Std. dev.*	*Min.*	*Max.*
LnGP	10.39	1.37	5.77	12.33
LnEC	3.65	0.75	2.08	4.93
LnCQ	4.86	0.76	2.89	5.75
LnCE	4.89	0.74	2.94	5.78
LnIC	4.59	0.72	2.71	5.46
LnICTC	3.13	1.22	0.18	5.10
LnIE	4.68	0.71	2.94	5.69
WP	3.36	2.39	0.00	8.00

Source: Author's own elaboration

Figure 1 The development of digitalisation in regions' agricultural activity (see online version for colours)

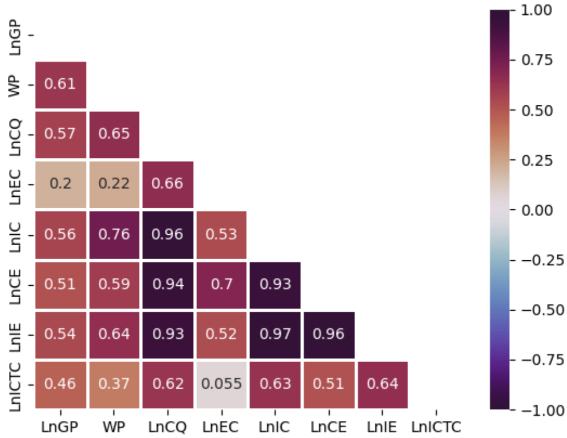


Source: Author's own elaboration using EViews-10 based.

4 Results

Before the model building, in order to measure this impact by providing the accuracy of the model some correlation analysis must be implemented (Figure 2). The results show that CQ and IC severely correlated with each other and with other explanatory variables such as CE and IE.

Figure 2. Correlation analysis (see online version for colours)



Source: Author's own elaboration using Python programming

Therefore, regressors that highly correlated and negatively impacted other explanatory variables' significance, were eliminated, and the model was built in the participants of four explanatory variables: CE, IE, ICTC, and WP. The results of three statics panel data methods are given in Table 2.

Table 2 Estimation results of three static panel methods

Variables	*POLS*	*REM*	*FEM*
LCE	3.532***	3.419***	5.863
	[0.000]	[0.0010]	[0.3703]
LIE	–3.804***	–3.629***	0.525
	[0.0001]	[0.0023]	[0.9318]
LICTC	0.915***	0.902***	0.395
	[0.000]	[0.0001]	[0.4342]
WP	0.121**	0.115*	–0.055
	[0.0253]	[0.0911]	[0.9061]
Intercept (c)	7.647	7.437	–21.811
	[0.000]	[0.000]	[0.0517]

Notes: ***, **, and * denote the significance at the 1, 5, and 10% levels, respectively.
Figures in [.] are the p-values.

Source: Author's own elaboration using Python programming

The results express that while the effects of all variables using POLS and the REM are significant, the impacts of variables using fixed effect are insignificant (Table 2) at the all-percent level. Results indicate that Null hypotheses for LCE, LIE, and LICTC are rejected at 1% significance level in the case of both POLS and REM. However, the Null hypothesis for WP is rejected at 5% and 10% significance level in the estimating of POLS and REM, respectively.

According to POLS and REM, only the number of employees who use the internet in agricultural enterprises hurts the gross product of agriculture. Fixed effect model analysis shows that only web page usage has the opposite, others have positive impacts.

After checking the significance of model parameters, the next step consists of the diagnostic analysis of the models to check the validity of the developed model by using various ways (Table 3).

Table 3 Diagnostic analysis

	POLS	*REM*		*FEM*
R-squared	0.8221	Weighted statistics	0.7198	0.9226
		Unweighted statistics	0.8217	
Adjusted R-squared	0.8028	0.6895		0.8677
F-statistic	42.735***	23.760***		16.818***
	[0.000]	[0.000]		[0.000]
Breusch-Pagan LM test	150.0274			
	[0.0001]			
Hausman test (REM vs. FEM)		8.874386		
		(0.0643)		
Redundant fixed effects tests				2.395793
				(0.0308)

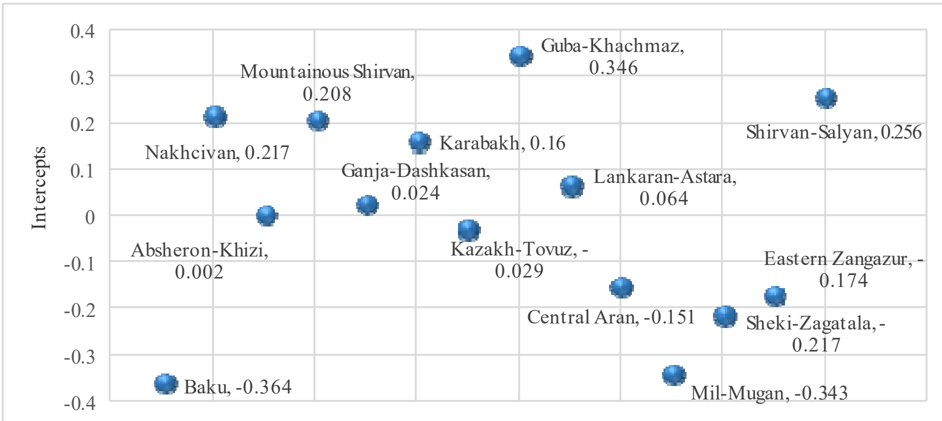
Notes: ***, **, and * denote the significance at the 1, 5, and 10% levels, respectively. Figures in [.] are the p-values.

Source: Author's own calculation

Results of three assessments show that regressors can explain 82% (POLS), 82% (REM), and 92% (FEM) of the total variation in the gross product of agriculture. Joint test analysis of all estimations, including POLS, REM, and FEM proves that the relationship between explained and explanatory variables is statistically significant, and our developed regression models provide a better fit to a dataset. The next steps consist of defining which model is more appropriate by using essential diagnostic tests to ensure the panel data regression analysis is reliable and valid. For this purpose, the Breusch-Pagan LM test was initially applied to the results of POLS and concluded that POLS is not appropriate based on the rejecting null hypothesis at the 5% significance level. Chow test (redundant fixed effects test) was used to choose the model of whether POLS or FEM is most relevant in assessing panel data. The outcome shows that FEM is much more appropriate in comparison with POLS (Table 3). These results drove us to check the Hausman Test, which helped to define the estimation method of FEM or REM that best fits the model (Table 3). Hausman test results (p-value and chi-square value analysis) prove that the null hypothesis cannot be rejected and both estimates (REM and FEM) are consistent, however, the coefficients of the random-effects model are also efficient. Therefore, REM is most appropriate.

As mentioned in equation (5), the intercept (7.437), which is estimated by REM is the mean of each region. Therefore, all intercepts of each region separately were assessed in Figure 3.

Figure 3 Random effect intercepts per region (see online version for colours)



Source: Author's own elaboration based on the calculated REM

It must be mentioned that assessments and simulations were implemented by using Python programming language in the visual studio code IDE, and EViews-10 software.

5 Discussion

Digitalisation accelerates innovative development, enables better use of resources, and helps the economic growth of various sectors of the economy. As in other sectors, digital technologies play a key role in the solution of challenges facing agriculture. The necessity of agriculture for Azerbaijan's economy was studied, and implemented reforms and measures were investigated in the above section. Taking into account this importance, our research was dedicated to analysing the role of digitalisation in the agricultural field, defining crucial indicators that characterise how digital changes integrate into agriculture, and estimating the impact of digital changes on agricultural development in the Azerbaijan Republic. Since digital (precision) agriculture is one of the new fields of the digital economy, its characteristics and components began to be measured in 2019. Therefore, only a 3-year database could be obtained from state authorities. However, taking into account the digital transformation based on 14 regions of Azerbaijan helped us to reduce this problem.

To implement the purpose of the research, panel data regression analysis was applied, three static panel models were estimated and crucial tests were checked to choose which was much more appropriate.

The above estimation and testing operations prove that the REM can explain the process properly. Therefore, the main findings of this research are as follows:

- 1% increasing the number of employees who use computers in agricultural enterprises will increase the gross product of agriculture by 3.4%;
- 1% increasing the number of employees who use the internet in agricultural enterprises will decrease the gross product of agriculture by 3.6%;

- 1% increasing Expenditures for ICT in agricultural enterprises will increase the gross product of agriculture by 0.9%;
- 1 unit increasing the number of agricultural enterprises with a web page on the internet will increase the gross product of agriculture by 12.2%.

Initial analysis showed that some parts of digital transformation are directly related to each other in the agricultural sector of the Azerbaijan Republic. Considering the usage and adoption of major technological tools based on the internet, it can be mentioned that this result is expected (Aker and Ksoll, 2016; Zheng et al., 2022). However, other factors, which are ICT infrastructure expenditures, computer and internet users of employees, and software applications play crucial roles and are useful for measuring the impact of digitalisation on agriculture. To the further estimation results, while employees who use computers can help raise the productivity of the agricultural sector, a lot of internet usage will reduce it. There are some reasons such as distractions and time consumption, inaccurate or unreliable information, cybersecurity threats, etc., that confirm the reliability of getting results about internet usage. Irrational usage of internet can also cause excessive electric consumption and additional costs for enterprises. The finding mentioned in the 'internet inclusion summit panel' puts the importance of electricity for internet nicely: 'Without electricity, internet is only a black hole'. Therefore, from the point of view of these issues, the irrational use of the Internet can negatively impact the performance of not only agriculture but also entire economic fields. Previous studies that characterise the feasible negative impact of the internet on the agricultural sector have also been analysed and estimated in the case of different countries (Shrivastava et al., 2016; Domguia and Asongu, 2022; Nguyen et al., 2022). Besides the opposite influence of the internet on agricultural productivity, the other components of ICT have significant and positive effects. This suggests the Internet has a negative impact if it is used irrationally, however, usage purposefully, such as web page activation, staff improvement, market investigation, and others, of the internet will help to develop agricultural productivity. Both human and software development require financial provision. Another significant finding is related to ICT expenditure that proves spending any amount on the improvement of ICT will result in efficient productivity in the same amount.

6 Conclusions

This study has some significant theoretical contributions to the literature. Initially, this paper analysed the theoretical background and detected the main trends and gaps in the literature related to the digitalisation of the agricultural sector covering numerous economies of the world. This analysis highlights that while there are some problems in the adoption and usage of advanced technologies in agriculture, the states have admirable achievements through the digitalisation of this sector. Secondly, the main indicators of digital agriculture were defined and a new approach was developed to measure the impact of digital changes on agriculture in Azerbaijan. It can be mentioned that this is the first methodology that estimates the relationship between ICT indicators and agricultural growth taking into account all different regions of the country by using the panel data model.

This research also provides several implications for practice. Firstly, investigating how the agricultural sector consists of an essential part of Azerbaijan's economy and ICT plays a crucial role in its development is a valuable tool for officials in the making decision process. Another significant finding is the defining useful ICT factors (such as CE, IE, ICTC, and WP) that assist in measuring the integration level of digitalisation in the Azerbaijani agricultural sector. Thirdly, this paper provides accurate estimations of how ICT indicators will affect the general product of Azerbaijani agriculture, based on an official database covering 14 regions. It is not a coincidence that analysing and measuring the interrelationships of macro indicators is of vital part of state policy. Since this paper revealed the main effects that lead to economic growth, all these significant results can be used for developing this field in the digital era by policymakers.

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