Received: 28.09.2025. Revised: 30.12.2025. Accepted: 12.02.2026. Published: 05.03.2026.

EKONOMIKA APK

https://doi.org/10.32317/ekon.apk/1.2026.10
Ekonomika APK, 33(1), 10-19

UDC 631.1:330.322:519.237(65)

ISSN: 2221-1055; E-ISSN: 2413-2322

Predicting farm investment success in semi-arid regions of Algeria: An asset-based policy tool

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▸ **Abstract.** The aim of this research was to develop a predictive model for agricultural investment success in Algeria's semi-arid cereal farming systems, with the view to guiding governmental policies on loan and subsidy allocation. The research focused on semi-arid regions, where cereal farming was fundamental for food security and strategic agricultural investment was crucial for enhancing outcomes and farm resilience. Utilising survey data from 198 farms in Setif-Algeria, it was built seven composite asset dimensions and established farm typologies via multiple variate analysis. A binary logistic regression model was developed to predict agricultural investment success. The logistic regression model demonstrated a practical overall classification accuracy of 79.8%, with a R^2 of 0.358 and R^2 of 0.486. Results indicated that "Technical Asset" was the strongest positive predictor of success (B = 0.728, OR = 2.072, p = 0.002). Some composite assets such as "Diversity of Farming", "Connectivity", and "Performance" were found to negatively predict investment success, suggesting complex dynamics such as over-diversification or higher-risk schemes by well-resourced farms. The results confirmed substantial structural differences between farm types, with large-scale farms demonstrating significantly higher levels of biophysical, human, and diversification assets, reflecting stronger resource capacity and adaptive potential. The developed predictive model showed strong explanatory and classification performance, confirming the key role of technical capacity as a decisive factor in achieving successful investment outcomes. The research gave a practical predictive framework for policymakers, enabling data-driven decisions to optimise resource distribution, reduce the risks associated with public financing and ultimately foster more successful agricultural investments, thereby strengthening sustainable cereal cropping and food security. These findings provided policymakers with a data-driven screening tool to optimise the allocation of agricultural subsidies and loans, directly strengthening food security in semi-arid regions

▸ **Keywords:** food security; farm typology; agricultural policy; predictive modelling; sub-arid

▸ Introduction

In Algeria, cereal production formed the base of national food security and was a core element of its sovereignty. This staple crop was deeply rooted in the Algerian diet and agricultural heritage, serving not only as a vital caloric source for the population but also as a key economic and social engine for rural communities. C. Baghdad (2022) documented how the Algerian agricultural sector remained structurally constrained by its limited contribution to economic diversification, with cereal farming simultaneously representing both a development priority and a vulnerability, given its heavy dependence on rainfall and public subsidies. Achieving self-sufficiency in cereal productivity was therefore a paramount national objective, aiming to reduce reliance on unpredictable international markets and to protect the country from global price fluctuations and supply chain disruptions. Algeria's food security remained approximately 70% dependent on cereal imports, with food imports providing for nearly 75% of the population's needs (Tanchum, 2021). This structural import dependency exposed the country to significant geopolitical and economic risks, making food autonomy crucial for ensuring socio-economic stability and preserving decision-making independence amidst climatic and political uncertainties.

▸ **Suggested Citation**: Rouabhi, A. (2026). Predicting farm investment success in semi-arid regions of Algeria: An asset-based policy tool. *Ekonomika APK*, 33(1), 10-19. doi: 10.32317/ekon.apk/1.2026.10.

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However, the vast semi-arid regions of Algeria faced significant challenges to sustainable cereal production. C. Ingrao *et al.* (2023) identified irregular rainfall patterns and substantial water scarcity as the primary biophysical constraints on agricultural productivity in dryland systems, noting that competition over freshwater resources between agricultural and non-agricultural users was intensifying across the Mediterranean and North African regions. S. Sharma *et al.* (2025) noted that this was compounded by the fact that agricultural water consumption already accounted for a disproportionately large share of total freshwater use, placing mounting pressure on already depleted water systems. B. Golla (2021) emphasised that frequent droughts further exacerbated the incidence of crop failure and rural poverty, particularly among smallholder farmers with limited adaptive capacity. A.R. Dzvene *et al.* (2025) conducted a comprehensive scoping review of climate change challenges in arid and semi-arid agri-food systems, concluding that the convergence of erratic weather patterns, urban encroachment onto agricultural land, and degraded soil conditions was progressively undermining the productive potential of dryland farming across Africa and the Mediterranean basin.

Agricultural investment in such environments was therefore both urgent and inherently complex. R.B. Pickson *et al.* (2024) demonstrated that in developing agricultural economies, private and public investment in farming activities can serve as a powerful mechanism for enhancing productivity and building long-term rural resilience, but only when investment decisions were aligned with the specific resource endowments and constraints of target farming systems. In semi-arid smallholder contexts across North Africa, the success of agricultural investments was strongly conditioned by pre-existing farm asset structures, institutional support, and access to technical knowledge; factors that vary considerably across farm types and agroecological zones. Despite these inherent constraints, semi-arid lands also offered genuine prospects. Their vast area provided a foundation for large-scale cereal cultivation, and with strategic investments in climate-resilient farming practices, these zones possessed the capacity to boost national food reserves and reduced Algeria's chronic dependency on cereal imports. P.K. Thornton *et al.* (2018) demonstrated that in water-scarce environments, the interaction between human capital (knowledge and skills), social capital (networks and institutions), and natural capital (land and water resources) created synergistic effects that significantly influenced investment outcomes. R.B. Pickson *et al.* (2024) demonstrated that agricultural investment was a crucial catalyst for sustainable development, not only generating employment and improving rural infrastructure but also driving technology adoption and increasing agricultural productivity. Their cross-regional analysis showed that targeted private-sector investment, when complemented by strong institutional support, yields the most sustained improvements in food security outcomes.

However, agricultural investments in such environments carry risks and should be supported. For governmental bodies and financial institutions, making informed agricultural investment decisions was crucial but complex (Blandford, 2007). The ability to predict investment success ex-ante was a critical missing link for efficient resource allocation and effective policy design, as evidence-based agricultural policies require careful scientific knowledge transfer in governmental processes (El Benni *et al.*, 2023). Academic work frequently examined isolated factors influencing agricultural performance, such as credit access or farmer education. Based on this theoretical framework, the study hypothesises that farms with higher composite asset scores across multiple dimensions will demonstrate significantly greater agricultural investment success compared to farms with concentrated asset portfolios, and that the interaction between human and technical asset dimensions will have a stronger predictive effect on investment outcomes. This study aimed to develop a predictive model of agricultural investment success in semi-arid Algerian cereal farming using a multi-dimensional asset-based approach. Specifically, the objectives were: 1) to construct seven composite asset dimensions capturing the key resource and capability profiles of cereal farms in Setif province; 2) to establish farm typologies based on these asset dimensions using multivariate analysis; 3) to develop a binary logistic regression model predicting investment success and identifying the most influential asset predictors

▸ Materials and methods

Study area, sample, and data collection

The study was conducted in the Setif province of Algeria, located on the high plateaus of the Northeastern part of Algeria, a region strategically vital for national cereal production in spite of its thought semi-arid climate. Setif province was characterised by an average annual rainfall of 458 mm (Rouabhi *et al.*, 2019) with significant inter-annual variability. Its agricultural landscape was dominated by rainfed cereal cultivation, primarily durum wheat, combined with some livestock breeding. Figure 1 illustrated the geographical distribution of the seven municipalities: Ain Sebt, Maouia, Dehamcha, Beni Aziz, Guelta Zerga, El Eulma, and Bazer Sakra; from which the 198 farms were sampled. The sampled municipalities were clustered in two distinct geographical zones, reflecting potential variations in agro-ecological conditions and agricultural practices. The Northern cluster included Ain Sebt, Maouia, Dehamcha, and Beni Aziz. This cluster might exhibit different climatic and topographic characteristics with mountainous reliefs indicating a small scall farming. The Southern cluster comprised Guelta Zerga, El Eulma, and Bazer Sakran municipalities. The proximity of these municipalities suggested a shared agro-ecological zone, characterised by vast plains conducive to large-scale cereal production. The distinct grouping of these municipalities allowed the study to capture potential regional variations in farm asset endowments and investment behaviours, which might be influenced by localised environmental conditions. This geographical distribution ensured that the sample reflected the heterogeneity of farming systems within the broader semi-arid cereal-producing landscape in Setif. A structured survey was run to a randomly selected sample of 198 farms primarily engaged in cereal production. The sampling frame was derived from the Sétif Provincial Agricultural Directorate registry of active farms (Setif province, n.d.), ensuring a diverse representation of farm sizes and operational characteristics. The data collection was conducted in April-May 2021. A limitation of this study lain in the fact that this period corresponded to a key stage in the agricultural cycle, when farmers were actively engaged in production activities and were able to provide accurate and up-to-date information on farm operations and investment decisions. The data collection instrument was a comprehensive questionnaire comprising 56 questions across seven main sections, including socio-demographic characteristics, farm structure and land tenure, technical practices and equipment, access to information and connectivity networks, performance indicators, and details on agricultural investment activities (including type, and perceived success or failure).

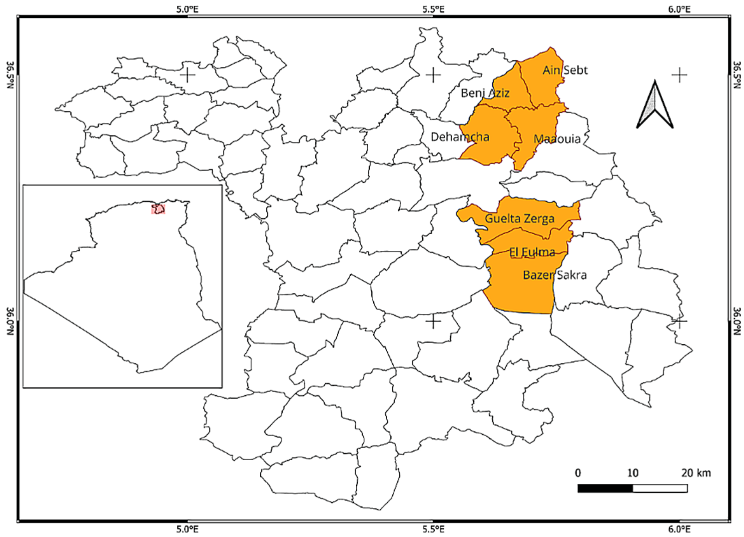

Figure 1. Map of sampled municipalities in Sétif province, Algeria
Source: developed by the author

Variables of operationalisation and composite dimension descriptions

The primary dependent variable, "Agricultural Investment Outcome", was operationalised as a binary variable. It was coded as "Success" (1) if the farmer reported having undertaken an agricultural investment and perceived it as having met or exceeded expectations, and "Failure" (0) if the investment was undertaken but perceived as having failed to meet expectations or resulted in a loss. Only farms that reported agricultural investment activity (n = 84) were included in the predictive modelling phase, focusing the analysis solely on the determinants of success among investing farms. Seven independent composite metrics (assets) were systematically constructed to capture distinct dimensions of farm resources and capabilities. Each composite was formed by aggregating relevant standardised individual variables from the survey, ensuring conceptual coherence and equal weighting of underlying components. The "Biophysical Asset" aggregated land area and livestock holdings to reflect the farm's natural productive base. The "Human Asset" combined education, training, and labour variables to represent the household's knowledge and management capacity. The "Diversity Asset" aggregated indicators of engagement in multiple productive activities, reflecting the degree of income diversification. The "Connectivity Asset" captured institutional integration through variables measuring access to advisory services, administrative relationships, and associative membership. The "Technical Asset" reflected agronomic sophistication, drawing on variables related to soil preparation, fertilisation, crop rotation, and equipment mastery. The "Performance Asset" aggregated yield, economic outcomes, and resource potential indicators to represent baseline farm viability. Finally, the "Constraint Asset" combined variables related to water deficit, soil degradation, land fragmentation, and tenure issues to quantify the structural risk burden faced by each farm. Together, these seven composites form the independent variable set used in the multivariate analyses and the binary logistic regression model.

Given the mixed nature of the dataset, a general overview of descriptive statistics and t-test comparisons were done to highlight the most important bodies of variation. A standard Principal Component Analysis (PCA) was performed on 198 farms. Then a Mixed Factorial Analysis (MFA) was conducted on 84 farms having invested in a new agricultural activity. MFA was suited for analysing datasets containing both quantitative and qualitative variables organised into distinct groups. Finally, a binary logistic regression model was developed with the binary Agricultural Investment Outcome (Success/Failure) as the dependent variable with the 7 composite metrics as independent variables. This model was selected for its suitability in modeling dichotomous outcomes and its capacity to produce interpretable Odds Ratios (OR) quantifying each asset's contribution to success probability. Model fit was assessed using the Hosmer Lemeshow (HL) test, where a non-significant result ($p > 0.05$) indicated adequate fit, while predictive performance was evaluated through overall classification accuracy, and pseudo-R^2 coefficients (Cox & Snell, 1989; Nagelkerke, 1991). The study was conducted in accordance with the norms of The Declaration of Helsinki (2013), statistical analyses were done by the free RStudio software V.2024.12.1.

Results and Discussion

Composite means by region and investment level. Multivariate analysis and farm typology

The comparative analysis of composite asset means revealed distinct profiles among farms, influenced by their regional location and tendency to invest. Farms in El Eulma, Guelta Zerga and Bazer Sakra municipalities with large scale farming showed significantly superior "Biophysical Assets" (average 81.07 vs. 18.80, $p < 0.001$) compared to those in small scale farming, in Ain Sebt, Beni Aziz, Dehamcha and Maaouia municipalities, generally characterised by a mountainous landscape (Table 1). This substantial difference underscored the intrinsic advantages of peri-urban zones, likely benefiting from more fertile lands and better water access, crucial for cereal production in semi-arid. Simultaneously, "Diversity Asset" score was higher in large-scale farming (average 3.17 vs. 1.72, $p < 0.001$), suggesting greater engagement in diverse agricultural activities, which can enhance resilience (Nicol *et al.*, 2015). "Human Asset" also showed a significant advantage for large-scale farming (average 12.71 vs. 10.01, $p < 0.01$), indicating potentially higher education or more skilled labour. However, "Connectivity Asset", "Technical Asset", "Performance Asset", and "Constraint Asset" do not significantly differentiate these two regional farm types, implying these attributes might be shaped by factors beyond geographical scale.

Table 1. Scores of composite assets by region and t-test equality of means

		Biophycal	Human	Diversity	Connectivity	Technical	Performance	Constraint
Small scale farming	Ain sebt	16.29	10.29	2.07	4.14	7.93	41.29	4.78
	Beni aziz	21.75	9.67	2.30	3.87	6.77	37.80	5.99
	Dehamcha	20.15	8.33	1.52	3.50	7.35	39.22	4.70
	Maouia	17.00	11.78	1.00	4.56	7.56	30.33	3.92
	Average	**18.80**	**10.01**	**1.72**	**4.02**	**7.40**	**37.16**	**4.85**
Large scale farming	El-Eulma	63.51	14.74	2.53	3.74	8.21	31.32	6.91
	Guelta-Zerga	90.25	10.65	2.96	3.70	7.93	32.63	9.62
	Bazer-Sakra	89.45	12.74	4.03	3.82	7.38	47.21	5.37
	Average	**81.07**	**12.71**	**3.17**	**3.75**	**7.84**	**37.05**	**7.30**
	Sig. (2-tailed)	***	**	***	**ns**	**ns**	**ns**	*
Investment undertaking	No	51.46	10.34	2.02	3.82	7.67	35.04	5.47
	Yes	53.45	11.26	3.16	3.71	7.36	41.47	7.46
	Sig. (2-tailed)	**ns**	**ns**	***	**ns**	**ns**	***	**ns**

Note: levels of significance – *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$, ns – not significant
Source: developed by the author

When examining farms according to whether or not they have undertaken (Yes/No), the "Diversity Asset" emerged as a highly significant discriminator, with investing farms demonstrating higher diversification (average 3.16 vs. 2.02 for non-investors, $p < 0.001$). Diversification acts as a safety shield, particularly for small farms, by ensuring self-sufficiency and reducing reliance on single crops or livestock (Kurdyś-Kujawska, 2016). This reinforced the notion that diversified income streams provided the financial stability necessary to undertake new investments. Similarly, "Performance Asset" was significantly higher among investing farms (average 41.47 vs. 35.04 for non-investors, $p < 0.001$), indicating that current economic success and productivity were strong enablers of future investment. Z. Ahmadirad (2024) noted that the integration of technology and financial innovations was reshaping investment landscapes and became a critical factor in future investment decisions. The other composites, including "Biophysical Asset", "Human Asset", "Connectivity Asset", "Technical Asset", and "Constraint Asset", do not show significant differences between investing and non-investing farms, suggesting that, although important, they were not the main distinguishing factors in the decision to invest or not. PCA was conducted on the seven composite asset dimensions to identify underlying patterns and reduce data dimensionality. The eigenvalues indicated that the first three dimensions were the most significant, with eigenvalues of 2.397, 1.517, and 1.035, respectively (Table 2).

Table 2. PCA eigenvalues, variance explained, and the quality representativenee of the most important dimensions

Eigenvalues	Dimension 1			Dimension 2			Dimension 3		
	2.397			1.517			1.035		
% of variance	34.24			21.67			14.79		
Cumulative % of var	34.24			55.91			70.70		
Asset	**loading**	**ctr**	**cos_2**	**loading**	**ctr**	**cos_2**	**loading**	**ctr**	**cos_2**
Biophysical	0.53	11.57	0.28	0.613	24.73	0.37	0.02	0.03	0.00
Human	0.759	24.04	0.58	-0.14	1.39	0.02	0.23	5.04	0.05
Diversity	0.51	10.96	0.26	0.698	32.07	0.49	-0.01	0.01	0.00
Connectivity	0.834	29.01	0.69	-0.32	7.15	0.11	0.01	0.02	0.00
Technical	0.754	23.74	0.57	-0.32	6.81	0.10	-0.13	1.55	0.02
Performance	-0.01	0.00	0.00	0.53	18.41	0.28	-0.584	32.99	0.34
Constraint	-0.13	0.68	0.02	0.38	9.42	0.14	0.790	60.36	0.62

Note: ctr – % of contribution, cos_2 – representativeness quality
Source: developed by the author

Cumulatively, these three dimensions explained 70.70% of the total variance. This significant cumulative variance indicated that a three-dimensional model effectively captures the primary data structure, allowing for a parsimonious summary of the asset relationships. This reduction was crucial for establishing robust farm typologies, as it focused on the most relevant aspects of farm asset profiles (Jolliffe, 2002). Dimension 1 (34.24% of variance) was primarily defined by high positive loadings from "Connectivity Asset" (0.834), "Human Asset" (0.759), and "Technical Asset" (0.754). This dimension can be interpreted as a "Technical-Connectivity Capacity" factor, highlighting farms with strong social integration and technical adoption. Dimension 2 (21.7% of variance) was strongly associated with "Diversity Asset" (0.698) and "Biophysical Asset" (0.613), suggesting a "Resource and Diversification" factor. This indicated that farms with better resources often pursue a wider range of activities. Dimension 3 (14.79% of variance) was dominated by "Constraint Asset" (0.790) and "Performance Asset" (-0.584). This factor differentiated farms based on their ability to manage limitations and achieve economic results, where higher constraints were inversely related to performance. Other asset categories have minimal influence on this dimension, indicating that it isolated the trade-off between performance and constraint assets. The biplot visually confirmed these relationships, showing clear groupings of variables along these principal axes, where three distinct variable clusters emerge. Constraint and performance assets followed a third dimension, represented on the two-dimensional biplot (Fig. 2).

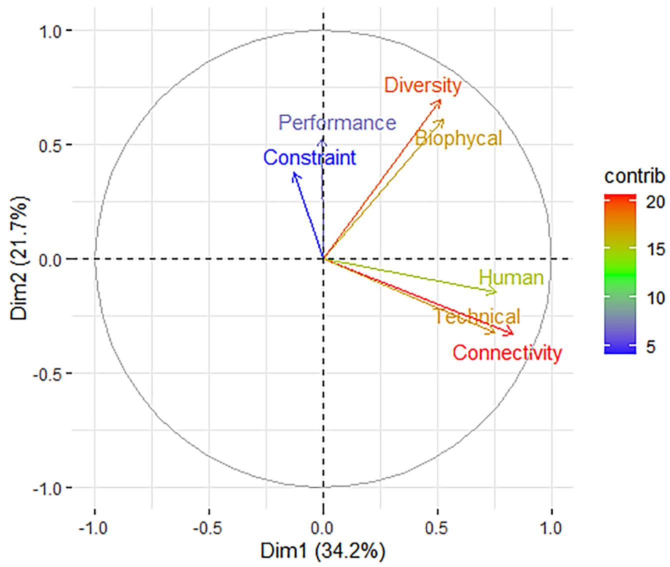

Figure 2. PCA factorial map showing the contribution of composite dimensions
Source: developed by the author

The clear variable separation with distinct contribution patterns validated the PCA approach, though the 55.9% explained variance suggested additional components might enhance comprehensive analysis.

Mixed factorial analysis investment activities and outcomes

The two MFA factor maps provided insightful visualisations of how different agricultural investment activities and investment outcomes (success/failure) were positioned within the multidimensional space of farm characteristics. From the Figure 3, "Activity Investment" illustrated the centroids of various newly invested agricultural activities, while the right plot, displayed the centroids for investment success and failure. The shared dimensional axes (Dim. 1: 18.6% variance; Dim. 2: 14.1% variance) allowed for direct comparison and interpretation of associations. In the "Activity Investment" map, "Poultry" and "Cow Breeding" activities were positioned in the upper-left quadrant, suggesting they were associated with certain basic farm characteristics captured by negative Dim. 1 and positive Dim. 2. Conversely, "Fruit Plantation" and "Sheep Breeding" were located in the right-hand side. "Market Garden", "Beekeeping", and "Services" appeared closer to the centre, implying they were broadly distributed across farms. This spatial arrangement helped identify distinct investment profiles among farms. The "Invest" map clearly separated "Failure" and "Success" outcomes. "Failure" was predominantly located in the upper-left quadrant, aligning spatially with "Poultry" from the activity map. This visual overlap suggested a potential association: "Poultry" investments were predominantly associated with "Failure", accounting for 53% of all reported investment failures. This suggested that poultry farming might present significant challenges or higher risks for farmers in this context. S.U. Khan *et al.* (2023) that the productivity and profitability of poultry farms in Algeria were influenced by several interrelated factors, including disease prevention and optimal breeding practices. However, the bovine breeding faces several challenges, including environmental degradation, and resource constraints. Desertification was a significant issue affecting nearly 80% of Algeria's agricultural land, leading to a scarcity of forage resources and declining farming activities (Daoudi *et al.*, 2010). Also, financial constraints and lack of technical knowledge were barriers to adopting sustainable practices (Yulianti *et al.*, 2024). On the other side of the plot, "Success" centroid was located in the lower-right quadrant, suggesting a positive association with market-gardening, representing 40% of all successful investments. However, cow breeding contributed to both failure (31%) and success (23%), implying it's a high-risk, high-reward activity, for this purpose farmers tend to employ traditional extensive grazing systems, which helped to improve farm's incomes (Table 3).

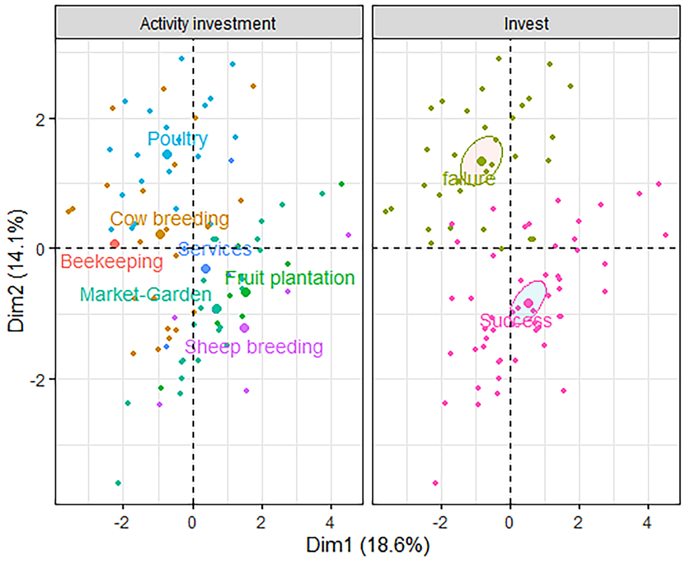

Figure 3. MFA factorial map

Notes: each dot represents an individual farm. In the left panel, dot colours indicate the type of agricultural activity invested in (blue: "Poultry"; orange: "Beekeeping", etc.). In the right panel, colours reflect investment outcome centroids (pink: "Success"; green: "Failure"). Farm positions along Dim. 1 (18.6% of variance) and Dim. 2 (14.1% of variance) reflect their composite asset profiles

Source: developed by the author

Table 3. Distribution of Agricultural Investment output by farming activity, %

Invest output		Activity investment							
		Beekeeping	Cow breeding	Fruit plantation	Market-gardening	Poultry	Services	Sheep breeding	Total
	Failure	3	31	0	6	53	6	0	100
	Success	0	23	15	40	6	6	10	100

Source: based on R. Meziane *et al.* (2024)

To identify the asset dimensions most predictive of investment success, a binary logistic regression model was applied to 84 farms that had undertaken an agricultural investment. The model demonstrated strong explanatory and predictive power. Prediction model showed enhanced explanatory power with R^2 of 0.358 and R^2 of 0.486, indicating that approximately 36-49% of variance in investment success was explained by the predictors (Cox & Snell, 1989; Nagelkerke, 1991). The HL test ($\chi^2 = 6.035$, $p = 0.643$) indicated excellent model fit, confirming that the logistic regression assumptions were adequately met. The predictive capability of binary logistic regression in classification accuracy was model selection, and data quality. The classification accuracy of 79.8% demonstrated strong predictive capability, with impressive sensitivity for successful investments (92.3% correctly classified) compared to moderate specificity for failures (59.4%) (Table 4). This pattern suggested the model was especially effective at identifying successful investments, which was valuable for investment decision-making. Logistic regression was noted for its robustness to linear dependencies and scaling issues, which can enhance accuracy without extensive pre-processing.

Table 4. Classification model of the predicted investment output, %

Observed		Predicted		
		Investment output		Percentage correct
		Failure	Success	
Investment output	Failure	19	13	59.4
	Success	4	48	92.3
Overall percentage				79.8

Source: based on P. Komarek & A. Moore (2005)

From the binary logistic regression-built model, “Technical Asset” emerged as the strongest positive predictor (B = 0.728, p = 0.002, OR = 2.072), indicating that investments with higher farm technical skills were over twice as likely to succeed. This finding strongly aligned with contemporary research on technical innovation driving superior investment returns and competitive advantages (Brynjolfsson & McAfee, 2014). However, “Diversity Asset” showed a significant negative effect on investment success (B = -0.521, p = 0.027, OR = 0.594). This suggested that diversification may reduce success probability by approximately 41%. This counterintuitive finding contested traditional portfolio theory but may reflect over-diversification penalties or focus benefits in specific investment contexts (Goetzmann & Kumar, 2008). While diversification mitigated risk and provided alternative income, excessive engagement in too many activities might dilute management focus, spread resources too sparsely, and prevent the specialisation needed for high returns in any single project (Table 5).

Table 5. Binary logistic regression-built model for predicting investment success

Assets	B	Significance	95% C.I. for OR		
			OR	Lower	Upper
Biophycal	0.011	0.124	1.011	0.997	1.025
Human	0.016	0.775	1.016	0.911	1.134
Diversity	-0.521	0.027	0.594	0.375	0.941
Connectivity	-0.745	0.034	0.475	0.238	0.946
Technical	0.728	0.002	2.072	1.319	3.254
Performance	-0.073	0.005	0.929	0.883	0.978
Constraint	0.056	0.101	1.057	0.989	1.130
Constant	1.608	0.319	4.992	-	-

Note: B – unstandardised logistic regression coefficient; OR – Odds Ratio; 95% C.I. – 95% confidence interval for OR (lower and upper bounds)
Source: developed by the author

“Connectivity Asset” emerged as another significant negative predictor (B = -0.745, p = 0.034, OR = 0.475), this finding contradicted network theory expectations, but may reflect information overload, decision complexity, or systemic risk exposure in highly connected systems (Battiston *et al.*, 2012). The substantial negative coefficient indicated that each unit increase in connectivity reduces success odded by approximately 53%. A negative association with success might imply that high interconnectedness exposed farmers to information overload or even herd mentality, leading them to invest in popular but potentially unsuitable projects without thorough individual farm assessment. Alternatively, a strong reliance on external networks might reduce internal innovation or critical evaluation of investment opportunities.

“Performance Asset” showed a small but significant negative effect (B = -0.073, p = 0.005, OR = 0.929) on the investment success. A negative link to investment success could be due to already high-performing farms undertaking riskier, more ambitious investments. These ventures, while having higher potential returns, also inherently carry a greater chance of absolute failure. Investors often overestimate their knowledge and abilities, leading to risky decisions without adequate information (Xie, 2024). Such farms might be leveraging their strong performance to experiment with novel or large-scale projects, which were not guaranteed successes. This complex interplay highlighted that the factors driving the ability to invest were distinct from those guaranteeing investment success. This finding resonated with data of J. Lakonishok *et al.* (1994), who suggested that performance chasing can lead to suboptimal outcomes. The remaining assets – biophysical, human, and constraint showed non-significant effects, though their inclusion contributed to overall model performance.

Indeed, understanding agricultural investment through the lens of farm assets had become an increasingly prominent area of inquiry, within smallholder farming contexts. The theoretical foundation of this approach traces back to the sustainable livelihood’s framework introduced by F. Ellis (2000), which conceptualised agricultural outcomes as products of the dynamic interplay among different capital assets. R. Chambers & G.R. Conway (1992) further advanced this thinking by demonstrating that adaptive capacity in farming systems was shaped not by financial resources alone, but by the full spectrum of livelihood assets available to farm households. Complementing this view, A. Sen (2001) argued through the capability approach that what ultimately determined agricultural outcomes was the farmer’s ability to translate available assets into productive action. Subsequent empirical work had reinforced and extended these theoretical foundations. A. Bebbington (1999) showed that households managing diverse asset portfolios tend to display stronger resilience and a greater capacity for investment. Building on this, A. Khatri-Chhetri *et al.* (2017) provided more recent evidence that farms characterised by well-balanced asset endowments were better positioned to embrace new technologies and realise higher returns on their investments. Together, these studies lend robust support to a multi-dimensional understanding of agricultural investment success. Despite this growing body of knowledge, a significant gap remained. As F. Rosa *et al.* (2019) observed, farmers typically construct their production plans under conditions of incomplete information, which introduced systematic biases into decision-making. In summary, investment success was driven by technical competency, while diversification, connectivity, and current performance paradoxically reducd success odds. These findings contest simplistic assumptions about asset endowments and highlight the complexity of investment dynamics in resource-constrained environments.

▸ Conclusions

Study underscored the critical importance of strategic agricultural investment for enhancing food security in Algeria's semi-arid cereal farming regions, where understanding the drivers of successful investment was paramount for national resilience. This research developed a robust predictive model based on seven composite asset dimensions, offering a practical framework for evidence-based agricultural policy design. The binary logistic regression model demonstrated strong predictive performance, achieving an overall classification accuracy of 79.8%, with a R^2 of 0.486, the model explains nearly half of the variance in investment outcomes. The HL test confirmed excellent goodness of fit ($\chi^2 = 6.035$), validating the reliability of the model's predictions across the full range of estimated probabilities. The model's results revealed that a farm's "Technical Asset" was the strongest and most significant positive predictor of investment success (OR = 2.072, p = 0.002), confirming that farms with higher technical competency were more than twice as likely to achieve successful outcomes. Three asset dimensions exert significant negative effects: "Diversity Asset" (OR = 0.594, p = 0.027), "Connectivity Asset" (OR = 0.475, p = 0.034), and "Performance Asset" (OR = 0.929, p = 0.005). These counterintuitive findings suggested that over-diversification, information overload from extensive networks, and risk-seeking behaviour among already high-performing farms may collectively undermine investment success. These insights offered a powerful tool for governmental policies, enabling a shift from reactive support to proactive, evidence-based allocation of loans and subsidies. By targeting farms with asset profiles associated with higher success probability, policymakers can optimise public spending and directly contribute to sustainable cereal production. The study acknowledged limitations related to its cross-sectional design and regional scope. Future research should prioritise longitudinal studies and broader geographical coverage to refine and generalise the predictive framework.

▸ Acknowledgements

I would like to acknowledge Benlaoukli Mouna and Mentasseur Tounes for their valued help.

▸ Funding

None.

▸ Conflict of interest

None.

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Прогнозування успішності аграрних інвестицій у напівпосушливих регіонах Алжиру: інструмент політики на основі активів

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▸ **Анотація.** Метою цього дослідження було розробити прогностичну модель успішності аграрних інвестицій в напівпосушливих зернових господарствах Алжиру з метою сприяння розробці урядових політик щодо розподілу кредитів і субсидій. Дослідження було зосереджено на напівпосушливих регіонах, де зернове господарство було основою продовольчої безпеки, а стратегічні аграрні інвестиції стали важливими для поліпшення результатів і підвищення стійкості господарств. Використовуючи дані опитування 198 фермерських господарств у Сетіфі (Алжир), було створено сім складених вимірів активів і визначено типи господарств за допомогою багатовимірного аналізу. Для прогнозування успішності аграрних інвестицій була розроблена модель бінарної логістичної регресії. Модель логістичної регресії показала практичну загальну точність класифікації 79,8 %, з $R^2 = 0{,}358$ та $R^2 = 0{,}486$. Результати показали, що «Технічний актив» був найсильнішим позитивним предиктором успіху (B = 0,728, OR = 2,072, p = 0,002). Деякі складені активи, такі як «Різноманітність фермерства», «Зв'язок» та «Продуктивність», виявилися негативними предикторами успіху інвестицій, що вказувало на складні динаміки, такі як надмірна диверсифікація або вищі ризики в господарствах з більшими ресурсами. Результати підтвердили значні структурні відмінності між типами господарств, при цьому великі господарства продемонстрували значно вищі рівні біофізичних, людських і диверсифікаційних активів, що відображало більшу ресурсну базу та адаптаційний потенціал. Розроблена прогностична модель показала високу пояснювальну та класифікаційну ефективність, підтверджуючи ключову роль технічної спроможності як вирішального фактору для досягнення успіху інвестиційних результатів. Дослідження надало практичну прогностичну основу для розробників політики, що дозволило приймати рішення на основі даних для оптимізації розподілу ресурсів, зниження ризиків, пов'язаних з державним фінансуванням, та в кінцевому підсумку сприяння успішнішим аграрним інвестиціям, що зміцнювали сталий розвиток зернових культур та продовольчу безпеку. Ці результати надали розробникам політики інструмент для відбору даних, що оптимізував розподіл аграрних субсидій та кредитів, безпосередньо зміцнюючи продовольчу безпеку в напівпосушливих регіонах

▸ **Ключові слова:** продовольча безпека; типологія господарств; аграрна політика; прогностичне моделювання; напівпосушливі регіони