Predicting the Profitability of Agricultural Enterprises Using Area-related Ratios

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Abstract: This study investigates the predictive ability of financial and area-related ratios in forecasting future asset profitability. The predictive modelling was conducted using the Random Forest algorithm. The analysis encompassed both conventional financial ratios and their modified counterparts. Specifically, the following indicators were examined: profit-to-assets ratio, profit per hectare, sales-to-assets ratio, sales per hectare, debt-to-assets ratio, debt per hectare, fixed asset ratio, assets per hectare, and labour productivity. Empirical results indicate that profitability ratios, particularly the profit-to-assets ratio, exhibit strong predictive performance. Furthermore, area-related variants—such as profit per hectare and debt per hectare—demonstrated enhanced accuracy in certain scenarios. Nonetheless, the practical applicability of these area-related indicators is constrained by challenges related to data availability and consistency.

Keywords: financial analysis, Area-related ratios, profitability prediction, agricultural enterprises.
JEL Classification: G32, G33, Q14

1Introduction

Attempts to predict future developments in corporate financial health date back to the 1960s. Beaver (1966) analysed the financial statements of 79 companies that failed and 79 that survived between 1954 and 1964. He examined more than 30 financial indicators and assessed their ability to individually distinguish between healthy and troubled firms.

The first multivariate method introduced was Altman's Z-score (1968), which used discriminant analysis to construct a predictive model based on five financial indicators. Later, Ohlson (1980) applied logistic regression to forecast bankruptcy.

With the advancement of computer technology, the range of predictive methods has expanded significantly. These now include Logit/Probit models, decision trees and random forests, neural networks, and other machine learning techniques. The scope of predicted phenomena has also broadened: Altman (1968) focused on bankruptcy, Beaver (1966) on bankruptcy and insolvency, Gurčík (2002) on achieving a desired level of profitability, and Neumaierová and Neumaier (2025) on financial health, company value growth, and the attainment of a positive EVA (Economic Value Added).

Due to the specific characteristics of agricultural enterprises, models reflecting the peculiarities of this sector were soon developed. Agricultural models can be considered Gurčík's G-index (Gurčík, 2002); the Index of the Operational Programme Rural Development and Multifunctional Agriculture (Rosochatecká & Řezbová, 2004); and the CH-index (Chrastinová, 1998).

The adaptation and testing of existing models for agricultural applications have been addressed by several authors, including Purves et al. (2015), Rajin et al. (2016), and Stojanović and Drinić (2017). Further validation of model reliability was conducted by Kopta (2009), Soukal et al. (2024), Srebro et al. (2021), and Karas et al. (2017). These studies consistently reported low predictive accuracy of the tested indicators, which was attributed to both the inappropriate selection of category boundaries and the use of unsuitable indicators. Another frequently cited issue is the high interannual volatility of financial data (Karas et al., 2017).

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Another way to enhance predictive reliability is by integrating non-financial indicators into forecasting models. The potential of such indicators has been explored by Jones et al. (2017), Liang et al. (2016), and Doumpos et al. (2017), with Purves et al. (2015) also investigating their relevance in the context of agricultural enterprises.

The goals of this study are based on these foundational insights and seek to further investigate the predictive power of financial and area-related indicators in the agricultural sector. The primary objective of this study was to identify financial and area-related indicators that most effectively predict the future performance of agricultural enterprises.

2 Methodology

Data: The Albertina database was used to identify suitable agricultural enterprises. Enterprises that provided complete data for the period 2019–2023 were selected. This dataset was further enriched by linking it to the State Agricultural Intervention Fund (SZIF) database of subsidy recipients, which provided information on the size of the farmed area. Only enterprises farming more than 500 hectares were included in the analysis. In total, data on 437 enterprises were obtained. Of these, 101 enterprises were classified as unprofitable in 2023, while 336 enterprises were classified as profitable.

Selection of independent variables: The independent variables were categorised into two groups. The first group comprised financial analysis indicators, including return on assets, return on sales, return on fixed assets, asset turnover, turnover of fixed assets, turnover of current assets, cost of output consumption, personnel cost ratio, depreciation cost ratio, debt ratio, current liquidity, and the acid test ratio. Each indicator was calculated in two variants: the first based on the current annual value, representing the indicator in the year immediately preceding the prediction; the second based on the average value of the indicator over the four years prior to the prediction. The second group consisted of area-related indicators, specifically profit per hectare, revenue per hectare, assets per hectare, debt per hectare, and labour productivity, measured as revenue per employee.

Statistical methods: Differences in the mean values of the ratios between profitable and unprofitable companies were statistically tested. Additionally, the Spearman correlation coefficient was calculated to assess the relationship between each independent variable and the future level of profitability. The core part of the predictive analysis was conducted using the Random Forest method.

3 Results

Table 1 presents the overall reliability of the model in distinguishing between profitable and unprofitable enterprises. The model demonstrates higher accuracy in identifying profitable farms. In contrast, its performance is less reliable for loss-making enterprises, with 18% of unprofitable farms incorrectly classified as prosperous.

The overall performance of the model is reflected in two key metrics: the coefficient of determination (R^2), which reached 87.29%, and the mean absolute error (MAE), which was 0.0136. The R^2 value indicates how well the independent variables explain the variability of the dependent variable—in this case, future profitability. A value of 87.29% suggests that the model accounts for a substantial portion of the variance in the data, demonstrating strong predictive power. The MAE represents the average magnitude of errors between predicted and actual values, without considering their direction. A low MAE value, such as 0.0136, indicates that the model's predictions are very close to the actual outcomes, further confirming its reliability.

Table 2 presents the reliability matrix based on ROA quartiles. The model demonstrates the highest accuracy in the middle range of ROA, where the prediction error is nearly zero. At the extremes—both low and high ROA—the model tends to underestimate or overestimate profitability. Nevertheless, the model proves to be highly reliable, especially for enterprises with average performance.

Table 1 Classification error rate

	Correctly classified		Missing classified	
Positive profitability (336 total)	318	94.64%	18	5.36%
Negative profitability (101 total)	75	74.25%	26	25.75%
Overall success rate (437 total)	393	89.93%	44	10.07%

Source: Albertina database, own calculations

Table 2 Reliability matrix by ROA quartiles

Quartile (ROA category)	Average actual ROA	Average predicted ROA	Average residual	Standard deviation of the residual
I.	–0.0475	–0.0280	–0.0194	0.0232
II	0.0144	0.0142	0.0001	0.0105
III	0.0358	0.0317	0.0040	0.0092
IV	0.0832	0.0660	0.0172	0.0165

Source: Albertina database, own calculations

3.1 Selecting appropriate indicators

Among the classical financial analysis indicators, profitability proved to be the most decisive. All applied methods confirmed the strong predictive power of return on assets (ROA). High Spearman correlation coefficients suggest that agricultural enterprises tend to maintain their relative positions in the dataset over time. This finding aligns with previous research, such as Klepáč and Hampel (2017), who also emphasised the critical role of profitability in successful prediction models.

Other profitability indicators, such as return on sales (ROS) and return on equity (ROE), exhibited lower predictive ability, primarily due to their higher volatility. In contrast, the indicator profit per hectare demonstrated superior predictive performance compared to traditional ROA measures. Its relative importance in the Random Forest model reached 0.240, whereas ROA achieved only 0.147. A similar pattern was observed in the correlation coefficients: Spearman's correlation for profit per hectare was 45%, while the classic profitability ratios were 10 to 15 percentage points lower.

Interestingly, the Labour Costs/Sales indicator showed unexpectedly high predictive power, despite being rarely used in prediction models. The correlation between this indicator and profitability was negative (-24%), indicating that a lower share of labour costs is strongly associated with higher profitability.

Table 3a: Independent variables, their characteristics and predictive power

Independent variable	Profitable farms	Unprofitable farms	Standard deviation: Profitable farms	Standard deviation: Unprofitable farms	p-value of the difference
ROA	5.35%	4.68%	3.22%	4.87%	0.1037
Profit/hectare	5.22	3.28	4.09	4.20	0.0000
ROE	5.80%	4.66%	5.96%	9.03%	0.1394
ROS	7.29%	5.34%	5.96%	6.05%	0.0043
Labour costs/Sales	0.21	0.23	0.07	0.08	0.0014
Asset turnover	0.57	0.64	0.19	0.26	0.0030
Sales per hectare	75.35	55.95	58.11	31.44	0.0014
Turnover of fixed assets	3.33	1.21	42.46	0.78	0.6165
Turnover of current assets	1.96	1.68	4.80	0.63	0.5633
Debt ratio	32.49%	33.71%	0.19	0.22	0.5905
Debt per hectare	49.04	31.29	87.46	29.74	0.059
Long-term debt/assets	18.06%	19.20%	0.14	0.16	0.037
Short-term debt/assets	13.78%	14.37%	0.12	0.12	0.033
Current liquidity	6.32	5.55	12.07	7.78	0.046

Source: Albertina database, own calculations

Table 3b: Independent variables, their characteristics and predictive power

Independent variable	Spearman's coefficient	Spearman's coefficient: p-value	Point-biserial correlation	Point biserial p-value	Mean Decrease in Impurity
ROA	36.40%	0.0000	7.79%	0.104	0.147
Profit/hectare	45.93%	0.0000	19.50%	0.000	0.240
ROE	31.32%	0.0000	7.08%	0.139	0.047
ROS	34.38%	0.0000	13.64%	0.004	0.034
Labour costs/Sales	-24.08%	0.0000	-15.27%	0.001	0.089
Asset turnover	-11.37%	0.1074	-14.15%	0.003	0.046
Sales per hectare	30.01%	0.0000	15.24%	0.001	0.096
Turnover of fixed assets	-11.83%	0.1304	2.40%	0.617	0.047
Turnover of current assets	2.06%	0.6677	2.77%	0.563	0.040
Debt ratio	-3.79%	0.4288	-2.58%	0.591	0.037
Debt per hectare	16.85%	0.0004	9.56%	0.046	0.059
Long-term debt/assets	-1.34%	0.7801	-3.38%	0.481	0.037
Short-term debt/assets	-9.06%	0.0583	-2.13%	0.658	0.033
Current liquidity	3.95%	0.4097	2.90%	0.546	0.046

Source: Albertina database, own calculations

The predictive capabilities of activity indicators proved to be weak, and in most cases, the correlation with future profitability was negative. This finding is somewhat surprising, given that this ratio indicators are commonly included in prediction models. One possible explanation is offered by Lososová and Zdeněk (2013), who demonstrated a relationship between the altitude at which an enterprise operates and its activity indicators. Altitude appears to influence activity indicators more significantly than it affects overall business success. Another explanation is provided by Boďa and Úradníček (2019), who evaluated various prediction models in agriculture and attributed the low predictive power of activity indicators to their high volatility.

Indicators based on yields per hectare showed slightly better predictive performance than traditional activity ratios, with a relative importance score of 0.096. Moreover, a notable positive correlation was observed between yields per hectare and achieved profitability (30.01%).

For this indicator, the difference between prediction results calculated per hectare (sales per hectare) and those calculated per assets (sales per assets) was the most pronounced. The authors of this study do not yet have a definitive explanation for this discrepancy. One possibility is the influence of production focus and intensity. A more likely explanation, however, may lie in the limitations of Czech national accounting practices. Among other issues, the accounting treatment of land value is particularly problematic. While the adjusted indicator reflects the actual cultivated area, the traditional asset-based indicator fails to account for leased land (which constitutes the majority of agricultural land in the Czech Republic) or values it at historical prices, which are disconnected from current economic realities.

The impact of accounting methods on financial health prediction has been discussed by Dvořáková (2015), while Sedláček (2010) highlights the differences between IFRS and Czech accounting standards. According to Sedláček, IFRS prioritises the accuracy and reliability of financial data, whereas Czech accounting emphasises formal compliance with rules and the principle of prudence.

The ability to predict future developments using debt indicators was generally low, which contradicts several studies that confirm the influence of debt on financial performance. For example, Klepáč and Hampel (2017) found a strong negative correlation between debt and profitability. Other studies report moderately strong or weak negative correlations (Gabrić, 2015; Maxim, 2021). One possible explanation for the low predictive power of debt indicators in this study is the influence of legal form. Aulová and Hlavsa (2013) demonstrated that legal form significantly affects debt levels.

On the other hand, the debt-to-hectare ratio emerged as a meaningful predictor. Again, the authors do not yet have a reliable explanation for this finding. It is possible that production focus and intensity play a role. Intensive farms specialising in livestock production typically manage fewer hectares but achieve higher profitability.

Liquidity indicators also showed low predictive ability. This finding is consistent with the assumptions of Střeleček et al. (2011), who identified a strong relationship between liquidity and the production focus of agricultural enterprises—specifically, that livestock-oriented farms tend to have higher shares of current assets and thus higher liquidity. In such cases, liquidity reflects production structure more than business success. The low predictive power of liquidity indicators is further supported by Saleem and Rehman (2011). However, Ehiedu (2014) found a positive correlation between ROA and liquidity, suggesting that the relationship may vary depending on context and methodology.

The assumption that area-related indicators can enhance predictive accuracy was confirmed. Indicators such as profit per hectare, sales per hectare, and debt per hectare showed stronger correlations with future economic performance than traditional financial ratios. Moreover, in the Random Forest model, these area-related variables demonstrated higher relative importance, further supporting their predictive relevance.

Using Area-Related Ratios reduces the impact of external influences and better reflects management performance, enabling more accurate benchmarking, particularly where accounting systems may distort financial results. The approach is valuable for policymakers when comparing business models or targeting support to vulnerable farms.

4 Conclusion

Among classical financial analysis indicators, return on assets (ROA) emerged as the most reliable predictor of future performance. Interestingly, and in contrast to previous studies, the ratio of personnel costs to company sales also proved to be significant. On the other hand, liquidity and asset turnover indicators contributed little to distinguishing between profitable and unprofitable enterprises. This may be because liquidity tends to reflect the production focus—distinguishing crop-oriented farms from livestock-oriented ones—rather than overall business success. Although asset turnover is traditionally included in prediction models, its limited usefulness in classification may be explained by its strong correlation with altitude (see Lososová & Zdeněk, 2013) or its high volatility in agricultural enterprises (see Boďa & Úradníček, 2019).

The assumption that classical ratio indicators could be effectively replaced by area-related indicators, where profit or sales volume is measured relative to the size of farmed land, was confirmed. These modified indicators demonstrated superior predictive performance compared to their unadjusted counterparts. However, it must be acknowledged that calculating modified indicators and obtaining the necessary data is more complex.

A key limitation of this study is that the classification of profitable and non-profitable enterprises is based solely on data from the fiscal year 2023. While this period was chosen for the primary validation of the proposed methodological framework, the limited temporal scope may not fully account for long-term economic fluctuations. This is further complicated by the inconsistent informativeness of accounting statements; for instance, varying proportions of leased assets and different accounting practices can distort activity indicators even among farms of comparable size and structure. Consequently, the validity and robustness of the current findings remain subject to further research, which will focus on longitudinal verification across broader time periods to confirm the stability of these indicators over time.

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