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Integration of artificial intelligence technologies into financial risk forecasting in the agricultural sector

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ABSTRACT

Financial risk is also a constant menace to the agricultural industry in Ukraine. Still, a key problem with conventional banking methods is that they cannot reflect the risk dynamics specific to the area. This paper questions the prevailing belief that artificial intelligence (AI) is universal, in the sense that it outperforms conventional econometric models in predicting credit interest rate volatility across 25 administrative regions (2015-2020). We find an empirical paradox: under the comparatively constant national level, the simple Linear Regression model performed more effectively than elaborate algorithms, with an accuracy rate of 82.35, which confirms the effectiveness of the principle of parsimony when measured against macroeconomic conditions. Nevertheless, the benefit of AI will be high in economically complex regions. Deep learning (ANN) and gradient boosting models identified non-linear risk patterns that linear models overlooked in agricultural centers such as Kherson and Dnipropetrovsk, further enhancing predictive performance by as much as 10.6 percentage points. These findings are consistent with the Adaptive Markets Hypothesis, which posits that the utility of technology depends on market volatility. Therefore, we suggest a precision banking model: a hybrid model in which stable areas would maintain linear efficiency, whereas shock-affected areas would use AI-powered risk detection to maintain the stability of agricultural credit in the post-war period.

Keywords: Agricultural Finance, Artificial Intelligence, Deep Learning, Forecasting, Precision, Banking, Ukraine

1. Introduction

The agricultural industry is the foundation of the Ukrainian economy and is instrumental in ensuring and sustaining the food security and economic welfare of the population [1]. As one of the world's top food-producing countries, Ukraine's food production affects global food markets [2]. This impact is significant during crises, such as the ongoing war, which severely affects production and supply chains [3].

Not only does the industry sustain the rural population and boost the country's gross domestic product (GDP), but it also provides employment and stability [4]. Furthermore, as the agricultural industry output increases, the people in the country become better off [5], [6]. Regardless of the war, innovation and positive initiatives focused on sustainability are available, which help bolster productivity and enhance future export capacity [7], [8].

Still, there is fluidity and instability within the sector of the economy, including financial instability [9]. With the unpredictable nature of crop production, the financial aspect is the weak link [10]. Although the literature indicates the financial distress of a farmer due to all weather, market prices, and credit availability [11], sustainability frameworks within the discipline are still at an advanced stage because the predominant concern is historical data, which is somewhat inadequate because of the increasing frequency of so-called "black swan" events [12].

Adaptable measures used to manage risks in the agricultural sector, such as crop diversification, insurance, and technology adoption, are required to improve risk management capabilities [13]. However, these are not equitably distributed [14]. Moreover, traditional financial instruments often lack the flexibility to address the specific liquidity gaps faced by small-to-medium enterprises in volatile transition economies, making financial inclusion central to their economic viability [15].

With recent developments and innovations, artificial intelligence (AI) has been instrumental for financial risk detection and management in agriculture. AI, machine learning, and other predictive analytics enable stakeholders to process and analyze large volumes of data to manage better manage a variety of agricultural risks, such as climate change and pest outbreaks [16]. In a broader economic context, the integration of AI is increasingly viewed as a strategic necessity for achieving sustainable development goals within the legal and business spheres, provided that the reliability of information resources is maintained [17].

However, while scholars argue that these technologies enable the creation of tailored financial products and credit services, there remains debate over the interpretability versus accuracy of these models in regulatory contexts [18]. In addition, AI in agriculture helps simplify crop insurance risk processing and claims processing, making the services fairer. The opportunities of AI in precision agriculture to improve resource management provide the agricultural industry with a chance to survive the pressures of the modern financial environment and climate [19], [20].

AI in financial risk management has not yet been extensively researched, and its application in Ukraine's agricultural sector is no exception. Yet, the potential gains have been reported in the literature. The literature indicates that AI technologies can be used to finance agriculture through credit scoring and risk assessment, among other aspects of market decision-making [21] and management, within a climate-changing world [22]. The recent empirical research also shows the strong predictive ability of AI in providing financial transparency, i.e., its ability to identify anomalies in financial statements more accurately than conventional techniques [23].

However, these applications have not been studied in Ukraine. For example, the sooty tern optimization algorithm, an attention-based long short-term memory model, is one of many intelligent modeling approaches and has been shown to adapt to and predict the financial risks of agricultural enterprises. Additionally, AI enhances the timeliness and accuracy of risk assessment in crop insurance, an area where traditional approaches fall short [24]. The lack of AI risk management applications in Ukraine suggests an understanding of these technologies that has not been adequately explored. Clearly, it is a gap that needs to be filled.

To close these gaps, this study is the first of its kind to focus on the use of machine learning models in artificial intelligence [25] to predict financial risks in the agricultural sector. It will benchmark these machine learning models against traditional econometric models to assess their predictive accuracy. It seeks to determine the most effective econometric model for predicting risks, thereby reducing sectoral uncertainty. This also makes the study the first to examine the application of these models within Ukraine's agricultural sector.

2. Research method

2.1. Research design and data curation

To substantiate the risk of volatility in finance about the agricultural sector in Ukraine, this research approach will use a time series of monthly data on regional interest rates on loans to firms in the Ukrainian agricultural sector. The interest rate is a key indicator for determining financial risk, as it reflects the cost of capital and therefore the financial risks of the agricultural sector. The data derivation encompasses 25 administrative units of Ukraine and the city of Kyiv over 6 years (2015-2020). The data points were obtained from official statistical databases and rounded to meet the standards of the particular region.

To ensure appropriate model training and assessments that avoid overfitting, a systematic approach was taken to partition the aggregate collection of records into January 2015 to December 2019 and January 2020 to December 2020 intervals. This provided enough records (60 per geopolitical region) for model training, while leaving 12 records per geopolitical region (for the testing set) to evaluate the model's predictions after training was complete. Considering what has been described, the purpose of the sample period training data set from January 2015 to December 2019 is to train the model on the attributes of the data and extrapolate them to the future sample period of January 2020 to December 2020 to partition the data for training vs. testing purposes.

Indicator variables were built to ensure the sequence of each calendar year's observations were flagged; and, for each time period t, the data set was supplemented with a limited history of immediate observation

$(R_{t-1}, R_{t-2}, R_{t-3})$ to lock in observations that were temporally contiguous and a seasonal history (R_{t-12}) to guarantee cyclicality in the calendar year period and were included to facilitate the expected seasonality that is typical in agricultural financial cycles.

2.2. Econometric and machine learning models

This research compares classical econometrics with modern AI to determine the most suitable forecasting methodology for different regions.

2.2.1. Traditional baseline: linear regression

As a baseline for forecasting the future, we incorporated a simple linear regression model. This technique considers the relationship of the independent variable (time) and the dependent variable (interest rate) as linear, and is represented as:

$$y = \beta_0 + \beta_1 x + \epsilon, \tag{1}$$

where y is the interest rate, x is the index of time, and ϵ is the error term. This model is the most classical explanation of forecasting through long-term prediction.

2.2.2. Machine learning: random forest regressor

To incorporate potential non-linearities in the data set, we employed the Random Forest Algorithm, an ensemble learning technique in which a random subset of the data is selected to construct many decision trees during training. The prediction is obtained by averaging across each tree.

The overfitting of single decision trees is examined. The model was configured with 100 estimators. The node split was performed using mean squared error to capture the non-linear relationships in the dataset, and tight assumptions about the dataset's distribution were not required.

To incorporate potential non-linearities within the dataset, we employed the random forest algorithm, a bagging ensemble technique. The model constructs K independent decision trees during the training phase using bootstrapped subsets of the data. The final prediction $\hat{y}$ is obtained by averaging the output of individual trees:

$$\hat{y} = \frac{1}{K}\sum_{k=1}^{K} f_k(x), \tag{2}$$

where K is the total number of trees (set to 100 estimators in this study) and $f_k(x)$ represents the prediction of the k-th decision tree given input vector x.

The node splitting criterion within each tree is determined by minimizing the mean squared error (MSE):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2, \tag{3}$$

This ensemble approach mitigates the overfitting often associated with single decision trees and allows the model to capture complex nonlinear relationships without imposing strict assumptions on the data distribution.

2.2.3. Deep Learning: Artificial Neural Network

The study's first approach to assessing the applicability of deep learning was to use a multi-layer perceptron (MLP) regressor. It is a feedforward artificial neural network composed of an input layer, one or more hidden layers that perform feature abstraction, and an output layer. The mathematical operation for a single neuron j in a hidden layer is defined as:

$$h_j = \emptyset\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right), \tag{4}$$

where x_i are the input features (lags and calendar indices), w_{ij} are the synaptic weights connecting input i to neuron j, b_j is the bias term, and $\emptyset$ is the activation function.

For this study, the architecture used had two hidden layers, each with 100 and 50 neurons, respectively. The hidden layers used Rectified Linear Units (ReLUs) to introduce nonlinearity, allowing the model to learn complex patterns.

$$\emptyset(z) = max(0, z), \tag{5}$$

The optimizer for the model was the Adam solver, with a maximum of 1000 iterations to ensure convergence. Before model training, all input features were subjected to Z-score normalization to improve the efficiency of gradient descent.

$$z = \frac{x-\mu}{\sigma}, \tag{6}$$

where μ is the mean and σ is the standard deviation of the training set.

2.2.4. Alternative machine learning models

The study also included Gradient Boosting Regressor, Support Vector Regression (SVR), and K-Nearest Neighbors (KNN) to diversify the machine learning models used in the benchmarks, enabling a thorough assessment and robust results [26].

Each of these models can serve as an alternative by varying aspects of the data, thereby modeling the particular local adaptabilities that an individual AI approach might overlook.

2.3. Evaluation of forecasting performance

An evaluation of the forecasting performance was completed using a recursive window approach on the test set. For each month in the 2020 testing window, the model forecasted the interest rate using historical data or previous predictions, mimicking a scenario in which predictions are made into the future.

As quantifying model performance on various regions with different interest rate baselines and metrics was required, the models used Mean Absolute Percentage Error (MAPE) to measure accuracy on an absolute scale. The accuracy is defined by:

$$Accuracy\ (\%) = 100\ x\ (1 - MAPE), \tag{7}$$

where *MAPE* is generated by averaging the absolute percentage errors of the actual values against the forecasted values over the testing window.

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y_i}}{y_t} \right|, \tag{8}$$

where n is the number of observations in the testing set ($n=12$), y_t is the actual interest rate at time t, and $\hat{y_1}$ is the forecasted interest rate at time t.

3. Results and discussion

3.1. Results

3.1.1. Aggregated national performance

An assessment was conducted for each of the six models to evaluate their performance at the national level, starting the analysis. The findings of the study show a ranking of these studies, as displayed in Table 1. This finding is contrary to the prediction that all AI systems have a starting position advantage. In the results, the Simple Linear Regression (LR) model was the strongest predictor across the datasets, with an accuracy of 82.35% (MAPE = 17.65%).

The results have shown a contradiction to the predictions made for the more modern types of machine learning, and deep learning is expected to outperform SVR and KNN, with accuracies of 74.58% and 74.34%, respectively, which are below the linear base. The ANN model, which is an average of 25 regions, posed a challenge to theorists, who predicted an average accuracy of 71.37% (MAPE = 28.63%).

Table 1. Comparative model performance (national aggregate)

Model Architecture	Average Accuracy (%)	Mean Absolute Percentage Error (MAPE)	Performance vs. Baseline
Linear Regression (Baseline)	82.35%	17.65%	—
Support Vector Regression (SVR)	74.58%	25.42%	-7.77 pp
K-Nearest Neighbors (KNN)	74.34%	25.66%	-8.01 pp
Random Forest (RF)	71.57%	28.43%	-10.78 pp
Gradient Boosting Regressor	71.45%	28.55%	-10.90 pp
Artificial Neural Network (ANN)	71.37%	28.63%	-10.98 pp

3.1.2. Regional heterogeneity and model adaptability

Even though the linear model had the highest average performance, a more granular, regional examination reveals performance divergence across models. The models' performance was regionalized. This was based on the region's particular financial conditions.

To visualize this heterogeneity, Figure 1 shows the analysis of forecasts for four selected regional archetypes. The left-side panels (Lviv and Chernihiv) show homogeneous markets in which the Linear Regression model (blue line) follows the deterministic decreasing trend of the market.

In fact, the line matches the observed data perfectly. In these markets, the AI models (red line) exhibit spurious fluctuations, a hallmark of overfitting. In turn, the right-side panels show (Dnipropetrovsk and Zaporizhzhia) volatile markets with structural breaks.

In these, the linear trend line cannot capture periods of recovery, and the AI models (mainly gradient boosting and ANN) follow interest rate changes rather than replicating the linear line; thus, the AI models performed better in these markets.

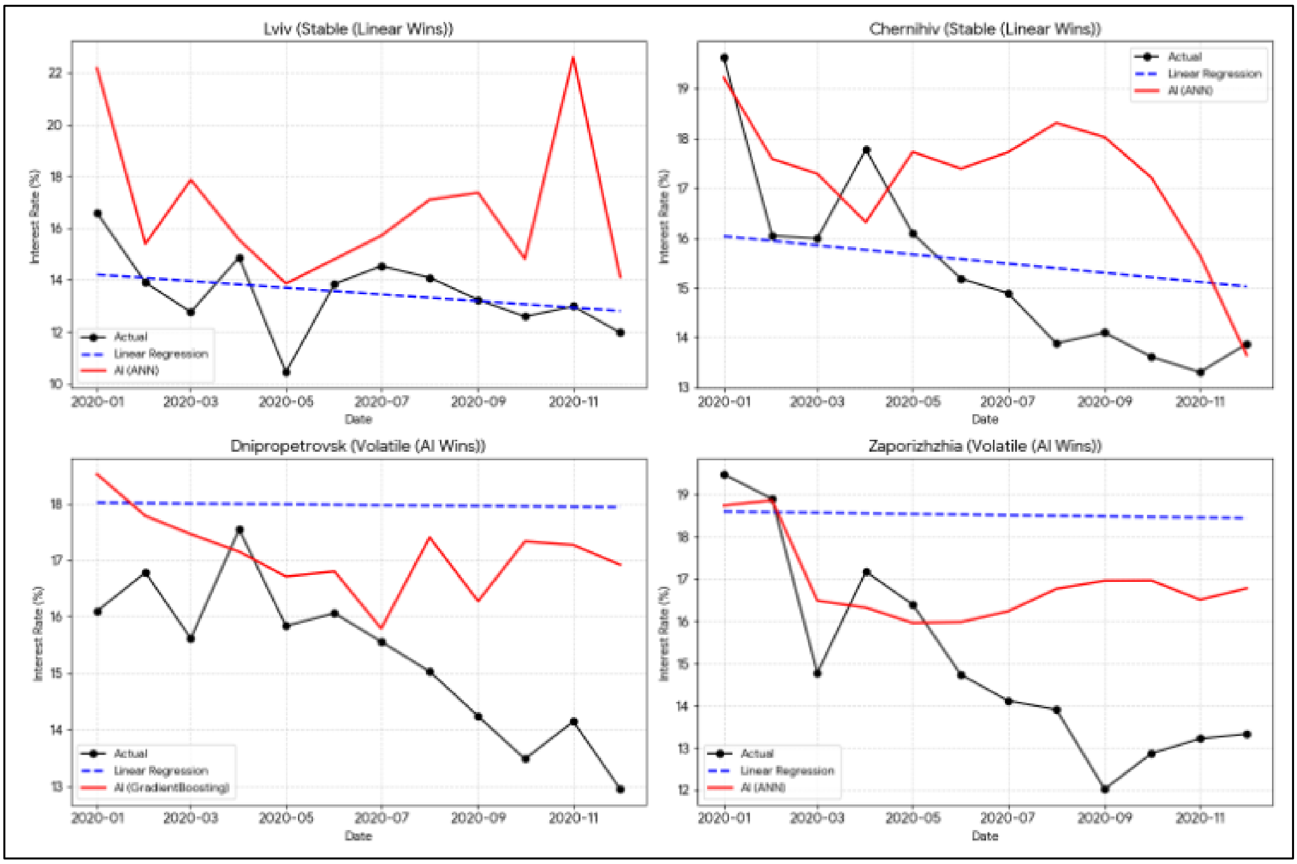

Figure 1. Comparative forecast analysis (stable vs. volatile regions)

Table 2 adds details to this divergence with respect to regions in stable areas of Luhansk, Lviv, and Chernihiv, where the predicted output of linearity is above 92%. The financial risk in these areas was predictably deterministic, so no sophisticated models or AI were needed.

In contrast, the linear model performed much worse in economically active, more unstable, and higher-volatility areas.

Table 2. Comparative accuracy by selected regions (top performing vs. volatile regions)

Region	Linear Regression Accuracy (%)	Best AI Model Accuracy (%)	Best AI Model
Stable Regions			
Luhansk	94.13	88.98	Random Forest
Lviv	92.53	77.28	SVR
Chernihiv	92.22	85.23	ANN

Region	Linear Regression Accuracy (%)	Best AI Model Accuracy (%)	Best AI Model
Stable Regions			
Volatile / Complex Regions			
Kherson	85.06	92.47	ANN (Deep Learning)
Donetsk	87.99	88.11	KNN
Dnipropetrovsk	81.43	86.81	Gradient Boosting
Zaporizhzhia	73.49	84.09	ANN (Deep Learning)
Vinnytsia	77.54	83.90	ANN (Deep Learning)

3.1.3. AI superiority in high-volatility contexts

The main contribution of this study is to show that certain regions with nonlinear financial patterns exhibit superior performance of Artificial Intelligence models. In particular, the ANN and Gradient Boosting models outperformed the traditional baseline by a significant margin in high-performing agricultural and industrial regions.

Forecasting results for the Kherson region are depicted in Figure 1. Although the Linear Regression model (Blue Line) underestimated the localized dips and plateaus in interest rates during the backtracking of time, which was late 2020, the ANN model (Red Line) adeptly adjusted to that nonlinear situation, achieving 92.47% accuracy compared to the baseline linear model's 85.06%.

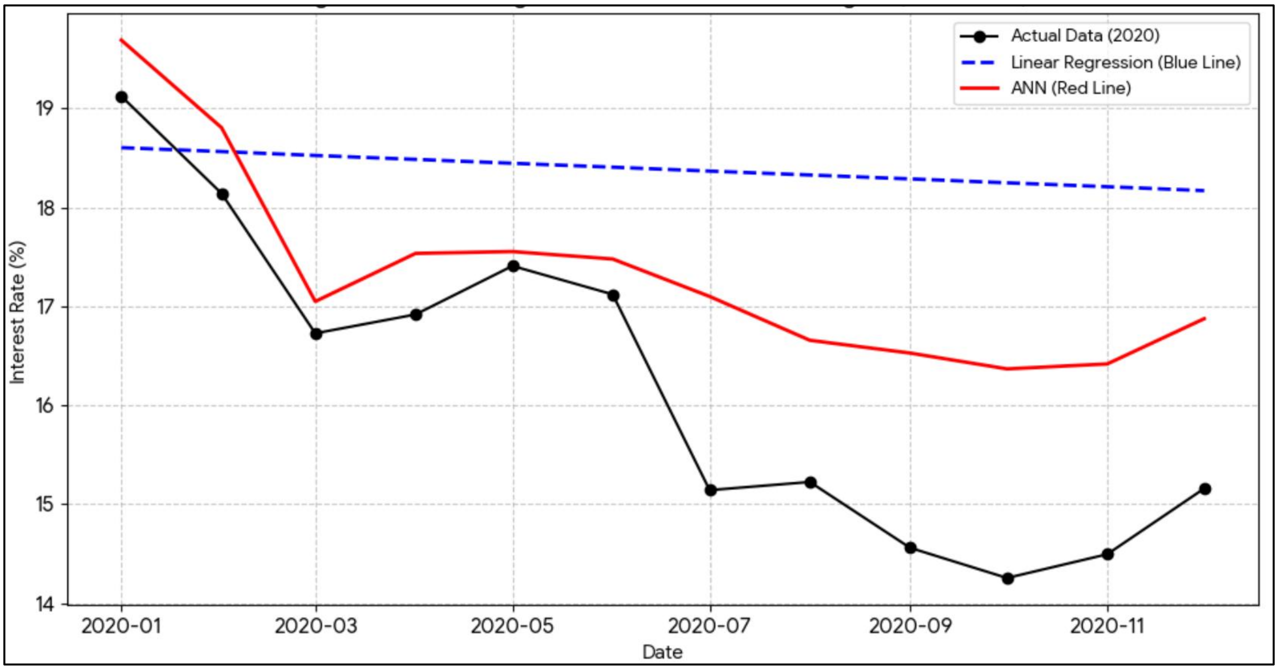

Figure 2. Forecasting performance in the Kherson region (ANN vs LR)

Also, in Dnipropetrovsk, a region with a mixed industrial-agricultural economy [27], the Gradient Boosting Regressor achieved the highest accuracy, 86.81%, with the smallest difference relative to a linear projection (81.43%). This suggests that while linear projection models are still accurate enough for general forecasting, AI models are indispensable in forecasting financial risk in turbulent, "black swan" events, and rapidly changing environments.

This empirical evidence directly answers the research question regarding the comparative effectiveness of forecasting tools, confirming that while linear projection models are sufficient for generalized forecasting, AI models are indispensable in forecasting financial risk in turbulent environments characterized by rapid structural changes.

3.2. Discussion

3.2.1. The parsimony principle: why traditional models prevail in stable markets

The results of this study showed contradictory outcomes regarding the current ‘AI hype’. The simplest Linear Regression model at the national average level was more accurate at predicting values than the advanced models using machine learning and deep learning. This can be explained using the Principle of Parsimony (Occam's Razor) of econometrics. The principle states that, in cases where data exhibit a deterministic trend, simpler models can extrapolate more accurate out-of-sample predictions than more complex models [28].

Gradual stabilization of the financial sector as a result of the National Bank of Ukraine's inflation targeting policy in Ukraine in the period from 2015 to 2020. This economic situation was associated with a strong positive linear correlation with declining interest rates [29]. Under nominal variability of the economic environment, advanced econometric models, such as Random Forest or ANN, tend to overfit the noise in the training dataset.

This is especially relevant to the 2020 dataset. They were observed to achieve lower predictive accuracy on the test dataset than a benchmark linear model, demonstrating that the benchmark displaced the noise. The underlying trend is clear economic growth. This is especially true in agricultural finance. When macroeconomic stability is evident, classical econometric models in the toolbox are much cheaper than competitors and offer the same accuracy and design stability. This observation explains a significant weakness of the presented AI solution: unless volatility or data complexity are sufficiently high, sophisticated algorithms can impose additional computational costs without performance improvement, which puts the relevance of the old-fashioned econometrics in stable markets once again into question [30], [31].

3.2.2. The "Black Swan" advantage: AI in high-volatility regions

However, the mere reliance on national averages masks the actual 'value add' of AI: the fine regional breakdown. The most significant regional economic disaggregation benefits the contribution of this study. It presents strong evidence that, in Kherson and Dnipropetrovsk, with high macroeconomic volatility and complexity, the ANNs and Gradient Boosted models are an order of magnitude superior to their classical econometric counterparts.

Kherson is an agricultural and irrigation-dependent region that faces unique risks, including climate vulnerability and seasonal cash-flow gaps that differ from the national industrial mean [32]. The better performance of the ANN model in Kherson (92.47% vs. 85.06% LR) indicates its ability to identify complex, non-linear relationships and interdependencies that purely linear models cannot capture. While linear regression, by design, predicts with a constant change, the ANN, being multi-layered, can model change with the presence of an equally significant structural change, or 'shock' that are common in the agricultural markets in response to weather or other significant price changes [33].

The same case in Dnipropetrovsk: the performance of Gradient Boosting implies the presence of a complex set of financial signals in the region, which has a thick blend of industrial and agricultural capital. In this case, the econometric model untangled the interlocking economic elements to yield better risk predictions. This, in turn, lends credence to the assertion that the market environment's volatility and complexity are positively correlated to the marginal value of AI [34].

3.2.3. Implications for financial inclusion and risk pricing

According to the reports, the risk models used by financial institutions neglect a fundamental multi-regional aspect of risk within their firms [35]. Our assessment shows that this uniform approach across all geographies results in inefficient pricing, especially in credit risk, where prices are a bargain in high-credit-risk areas.

Take, for example, a bank that applies a linear model in Kherson, where financial risk, if any, is probabilistic across all high-risk regions. The bank may overestimate financial risk to the extent of imposing high collateral demands, excluding smallholder farmers, or creating a large volume of bad debt.

This translates into a strong case for financial institutions to embrace a 'Precision Banking' approach, in which they will continue to apply simple linear models to stable regions (e.g., Lviv). In contrast, in unstable ones, they will apply AI-driven dynamic risk pricing. For instance, in the southern agricultural hubs, the ANN forecasting models would provide better credit risk and credit score assessment. This also addresses the lack-of-credit problem that Klapper et al. [11] described. Hence, more inclusive financial services are offered to the farmers in high-risk situations [36].

3.2.4. Limitations and future research directions

Although such a study offers a solid benchmark, it is not free of limitations. The first is that the dataset is mainly based on interest rates as a measure of financial risk, which, although indicative, might not reflect the full range of operational risks faced by farmers. To develop a comprehensive, multi-faceted risk model for Agri-FinTech, future research should consider integrating multi-modal data, including satellite imagery to detect crop pathologies and real-time weather information. Second, the research covers the years preceding and including 2020. As the structural ruptures caused by the 2022 war are severe, future research should subject these AI models to stress testing on wartime data to understand how they perform under hyper-volatile conditions.

4. Conclusions

This work is the first to provide an empirical comparison of AI with the conservatism of econometrics and to give an example of forecasting the financial risks of regions in the Ukrainian agricultural sector. The research uses a sample of 25 administrative units spanning 2015-2020 to demonstrate that machine learning may be valuable in transitional economies.

The primary input of the study is to develop the limits of AI's applicability. The evidence presented in this study proves that AI is not always superior, as is often assumed. At the general national level, the Simple Linear Regression model was more robust (82.35% accuracy, MAPE=17.65 %) and more accurate than various deep learning models. The observation is in line with the Principle of Parsimony, according to which forecasting models that are cost-effective, especially when macroeconomic conditions are well-stabilized and inflation is under control, are linear. Nevertheless, AI models in the region outperformed traditional methods. They showed the highest value in the economically most complicated and agriculturally unstable areas, i.e., Kherson, Dnipropetrovsk, and Zaporizhzhia. In particular, the Artificial Neural Network (ANN) and Gradient Boosting algorithms improved accuracy by up to 10.60 percentage points over the linear baseline by effectively identifying non-linear risk and structural breaks. This fact supports the Adaptive Markets Hypothesis and shows that AI's utility depends directly on market complexity and volatility.

Based on these findings, we propose a model of "Precision Banking" for agricultural finance in Ukraine. We recommend that financial institutions and policymakers employ a Hybrid Modeling Strategy, in which a linear model approach is tailored to stable regions to reduce costs, and an AI model is used for dynamic risk pricing to safeguard financial inclusion and resilience to “Black Swan” events in the more volatile agricultural areas. While the focus in this case remains mainly on the war and interest rates, the prospects are considerably optimistic. Beyond the weaknesses of this study, some ideas for future research are evident. First, although in this analysis the interest rates are used as a proxy for financial risk, future studies ought to consider multi-modal datasets, i.e., combine real-time satellite images of crop health, global commodity futures, and climate data, to create a comprehensive index of Agri-FinTech risk. Second, since the current dataset ends in 2020, an urgent direction for future research is to stress-test these AI structures on wartime and post-war data (2022-present). Research into how machine learning models can quickly adapt to the drastic structural discontinuities caused by the conflict will be critical to the development of robust financial systems during the rebuilding of Ukraine. In the country's effort to get back on track, these advanced predictive technologies will be central to establishing an inclusive and strong agricultural economy.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: S. Stender, N. Petrukha: study conception and design; N. Petrukha, M. Huz, S. Petrukha: data collection; M. Huz, S. Petrukha, D. Nikolaienko: analysis and interpretation of results; D. Nikolaienko: draft preparation. All authors approved the final version of the manuscript.

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