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## Credit Default Risk and Client Segmentation in Agricultural Lending

Nidhal ZIADI<sup>1</sup>, Nihel ZIADI<sup>2</sup>, BEN AZOUZ Yazid<sup>3</sup>

### Abstract

*This study develops a predictive credit scoring model for the National Agricultural Bank (BNA) to improve the assessment and management of default risk among agricultural borrowers, who are highly exposed to financial vulnerability and environmental uncertainty. Using the CRISP-DM methodology, the research includes data preprocessing, exploratory analysis, and model comparison between Quadratic Discriminant Analysis, Random Forest, and XGBoost, followed by out-of-time validation. The proposed model integrates agriculture-specific financial indicators with ecological variables such as climate and regional temperature variability, which significantly influence rural credit risk. Findings reveal that XGBoost achieves the highest predictive accuracy and robustness, particularly in detecting high-risk clients. By combining financial and environmental dimensions, this approach strengthens BNA's credit risk management and supports sustainable lending practices in the agricultural sector. Additionally, the model enables strategic marketing applications by segmenting borrowers into distinct risk-based personas, facilitating the design of tailored financial products and communication strategies. These insights contribute to improved customer engagement and more inclusive agricultural finance, aligning with the bank's objectives of resilience and sustainability.*

**Keywords:** Climate variability, Credit risk Agricultural, finance, segmentation client Machine learning, Sustainable lending.

### 1. Introduction

Bank credit is essential for financing agricultural investment and production, yet it exposes financial institutions to significant credit risk the possibility that borrowers fail to meet repayment obligations which remain a major determinant of banking stability. In agriculture, this risk is intensified by climate variability, as droughts, floods, and other extreme events disrupt production, reduce income, and delay repayments, increasing default probability. To mitigate these challenges, banks must adopt innovative approaches that anticipate climate impacts on farmers' financial capacity, ensuring sound credit management. In Tunisia, the Central Bank has reinforced credit risk guidelines, and since the early 2000s, banks have progressively integrated advanced analytical tools, notably credit scoring models. With the advent of data science and machine learning, these models now offer enhanced predictive capabilities. This research aims to develop a credit scoring system tailored to the Tunisian agricultural sector, combining financial and ecological indicators to model default risk. The study evaluates multiple techniques and provides actionable insights to strengthen credit decision-making. Additionally, the model supports strategic marketing by enabling borrower segmentation and customized financial

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<sup>1</sup> Associate professor of Finance and Accounting, University of Tunis EL Manar, Faculty of Sciences of Tunis, LARIMRAF Laboratory Campus Universitaire Farhat Hached Tunis B.P. n° 94 - ROMMANA 1068, Tunisie, Email: [nidhal.ziadiellouze@fst.utm.tn](mailto:nidhal.ziadiellouze@fst.utm.tn)

<sup>2</sup> Associate professor of Marketing, Faculty of sciences of Tunis, University of Tunis El Manar, ERMA Laboratory, Tunis, Tunisia Campus Universitaire Farhat Hached Tunis B.P. n° 94 - ROMMANA 1068, Tunisie, Email: [nihel.ziadi@fst.utm.tn](mailto:nihel.ziadi@fst.utm.tn)

<sup>3</sup> Associate Professor of Marketing, University of Tunis EL Manar, Faculty of Sciences of Tunis Campus Universitaire Farhat Hached Tunis B.P. n° 94 - ROMMANA 1068, Tunisie, Email: [yazid.benazouz@fst.utm.tn](mailto:yazid.benazouz@fst.utm.tn)



products, fostering better client engagement and promoting inclusive, sustainable agricultural finance.

## 1 Conceptual framework and Literature review

The prediction of credit default risk using data science has been explored through various approaches in recent years (Sarder Abdulla Al Shiam et al., 2024). A comprehensive review of past studies in the field of credit risk management underscores the growing importance of automating risk evaluation processes through statistical, data mining, and machine learning models (Addo et al., 2018). Early approaches largely relied on traditional techniques such as logistic regression, which remains widely used due to its simplicity and efficiency (Dumitrescu et al., 2022).

With the rise of big data and increased computing power, financial institutions have progressively adopted more sophisticated machine learning techniques to enhance predictive performance and better identify at-risk profiles. Banks are increasingly turning to data-driven methods to manage credit risk, aiming to improve decision-making and reduce default rates. This evolution has led to the widespread adoption of credit scoring models, which quantify the creditworthiness of individuals or businesses using advanced analytical techniques. Credit scoring enables financial institutions to evaluate large volumes of loan applications efficiently. These models not only accelerate the decision-making process but also help reduce bad debts and improve portfolio performance. With the rise of artificial intelligence, modern scoring systems have evolved to incorporate complex algorithms such as decision trees, random forests, and discriminant analysis (Provenzano et al., 2020). In parallel, the field of agricultural finance has seen a growing number of studies assessing farmers' creditworthiness, accounting for seasonal income variations and environmental risks (Castro and Garcia, n.d.). Recent research has applied credit scoring techniques to agricultural loan portfolios to better anticipate default events, adjusting models to sector-specific variables such as weather conditions and natural disasters (Wang et al., 2024). Moreover, the integration of predictive analytics into agricultural finance opens new avenues for strategic marketing. By segmenting borrowers based on risk profiles and behavioral patterns, banks can design targeted financial products and personalized communication strategies. This marketing-oriented approach enhances customer engagement, improves service relevance, and supports inclusive financial development in rural areas. Overall, recent literature suggests a convergence towards combining high-performance predictive models with sector-specific insights to develop reliable, context-aware decision-support systems. This project aligns with this perspective by aiming to predict credit default risk in Tunisia's agricultural segment using advanced data analysis tools.

### Strategic Marketing and Segmentation of Agricultural Borrowers

Integrating the developed scoring model into a strategic marketing approach allows the National Agricultural Bank (BNA) to go beyond traditional credit risk assessment. By leveraging the model's outputs, BNA can segment its agricultural clientele into distinct personas based on financial behavior, ecological exposure, and vulnerability levels. This segmentation enables the design of tailored credit products that address the specific needs of each group. For instance, borrowers identified as high-risk may benefit from more flexible financial solutions, targeted training in financial management, or enhanced advisory services, while low-risk segments could

be offered loyalty incentives or bundled financial services. Such segmentation strategies have been shown to improve customer targeting and product relevance in agricultural finance (Miranda Colon, 2022; Fiechter & Ifft, 2019). Moreover, client segmentation contributes to profitability optimization and deeper client relationships, especially when combined with relationship management practices (Findev Gateway, 2015). This marketing-driven approach strengthens the relevance of financing decisions, improves customer relationships, and contributes to a more inclusive and sustainable agricultural finance system.

#### Problematic

In the agricultural sector, credit risk is particularly high due to unpredictable income, climate volatility, and market fluctuations. Banks face challenges in evaluating the reliability of farmers whose financial behavior often depends on seasonal factors. To address this, many institutions are turning to credit scoring models. These models enable banks to assess risk more objectively and adapt decisions to each client's profile. By integrating machine learning, banks can now generate personalized credit risk evaluations, anticipate potential defaults, and offer tailored financing solutions.

This personalization also opens the door to strategic marketing opportunities, allowing banks to segment agricultural borrowers into distinct profiles and design targeted financial products and communication strategies. By aligning credit decisions with client-specific characteristics, institutions not only improve risk management but also strengthen customer engagement and loyalty, contributing to a more inclusive and responsive agricultural finance system.

Advanced data science methods such as machine learning, statistical modeling, and credit scoring can be systematically applied to analyze the financial, transactional, and behavioral data of agricultural clients. These techniques allow for the identification of patterns and risk factors that are often nonlinear and context dependent. By leveraging these insights, banks can accurately predict the probability of credit default and proactively adjust their lending strategies. Moreover, these data-driven approaches support marketing segmentation by revealing client typologies based on risk behavior, financial resilience, and ecological exposure. This enables the design of personalized financial products and targeted outreach strategies, enhancing both risk control and customer satisfaction. In other words, effective credit default prediction in the agricultural sector requires not only robust analytical models but also a strategic integration of marketing intelligence to ensure that financial solutions are both accurate and client centric. The central issue explored in this study is: How can advanced data science techniques such as machine learning, statistical modeling, and credit scoring systematically applied to analyze the financial, transactional, and behavioral data of agricultural clients in order to accurately predict their credit default risk?

More specifically, how can data-driven scoring methods be leveraged not only to improve risk prediction in the agricultural sector, but also to support strategic marketing decisions by segmenting borrowers and tailoring financial products and services to their specific profiles?

#### Objectives and Hypotheses

The main objective of this project is to develop a credit scoring model to assess the default risk of agricultural clients at the Agricultural Bank. Through this model, the goal is to predict the probability of default based on clients' financial and sectoral characteristics, in order to improve credit risk management and loan profitability in the agricultural sector. Beyond risk prediction, the model also aims to support strategic marketing decisions by enabling

the segmentation of borrowers into distinct profiles. This allows the bank to tailor financial products and communication strategies to better meet the needs of each segment, enhancing customer engagement and satisfaction.

This study is structured around the following hypotheses:

A growing body of research highlights the importance of incorporating sector-specific variables particularly those tailored to agriculture into credit scoring models to enhance the prediction of credit default. Studies show that when additional financial indicators relevant to the agricultural context, such as operating margin, changes in return-on-equity, and growth measures related to assets and sales, are included alongside traditional variables, the accuracy of default prediction models improves substantially. For example, machine learning models like random forests achieved up to 87% accuracy when these complementary variables were added, compared to 69% for logistic regression and 50% for linear discriminant analysis using only standard variables (Barboza et al., 2017). Similarly, ensemble learning methods and hybrid models that integrate agricultural and financial features have demonstrated superior performance in predicting loan delinquency and credit risk among agricultural borrowers (Chen et al., 2021; Belhadi et al., 2021). These findings underscore that the integration of agricultural-specific variables provides a more nuanced and effective assessment of credit risk, supporting the development of more robust and accurate scoring models (Barboza et al., 2017; Chen et al., 2021; Belhadi et al., 2021).

H1: Adding agricultural-specific variables improves the accuracy of scoring models for predicting credit default.

**Advanced AI and Statistical Models Outperform Traditional Methods in Agricultural Credit Risk Management:** Recent research has increasingly focused on comparing advanced statistical and artificial intelligence (AI) techniques with traditional credit risk models in the agricultural sector. This literature provides strong evidence that machine learning (ML) and AI-based models generally deliver superior predictive accuracy and risk management capabilities.

**Performance Comparison: AI/ML vs. Traditional Models**

Multiple studies demonstrate that machine learning models such as random forests, boosting algorithms, deep neural networks, and ensemble methods consistently outperform traditional approaches like logistic regression and linear discriminant analysis in predicting credit default and managing risk. For example, ML models have shown up to 10–25% higher accuracy than traditional models, with ensemble and deep learning methods achieving the best results in both general and agricultural credit contexts (Barboza et al., 2017; Reis & Quintino, 2023; Chen et al., 2021; Ghahari et al., 2019; Mestiri, 2024; Belhadi et al., 2021; Zhang et al., 2021; Dastile et al., 2020; Bhattacharya et al., 2022; Tse et al., 2022; Munkhdalai et al., 2019). AI and advanced statistical models excel at handling complex, nonlinear relationships and large, heterogeneous datasets typical of agricultural finance. They offer improved recall and precision in identifying high-risk loans, enabling earlier and more accurate interventions (Reis & Quintino, 2023; Chen et al., 2021; Belhadi et al., 2021; Tse et al., 2022). However, these models can be less transparent (“black box” issue) and may require more computational resources and careful validation to ensure fairness and regulatory compliance (Robisco & Martínez, 2022; Reis & Quintino, 2023; Mestiri, 2024; Dastile et al., 2020). Recent studies have implemented structured frameworks to benchmark and validate the performance of AI/ML models against traditional methods, often using real-world agricultural loan data and a variety of performance metrics (accuracy, AUC,

recall, F1 score) (Robisco & Martínez, 2022; Reis & Quintino, 2023; Chen et al., 2021; Belhadi et al., 2021; Dastile et al., 2020). The evidence strongly supports that advanced statistical and AI-based scoring models outperform traditional methods in managing agricultural credit risk, though practical implementation requires attention to transparency, interpretability, and regulatory standards, Ziadi, N. and ZIADI, N. (2025).

H2: Scoring models based on advanced statistical techniques and artificial intelligence outperform traditional methods in managing agricultural credit risk. A structured methodological framework has been implemented to test the proposed hypotheses.

### 3. Methodology

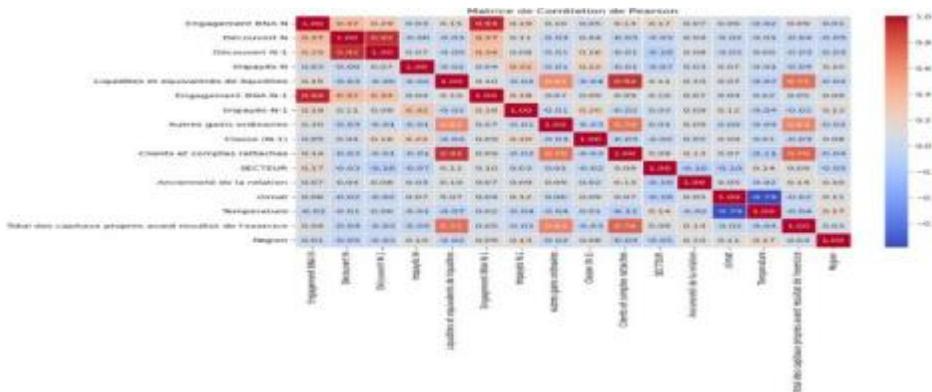
Businesses and organizations have come to understand that achieving strategic objectives requires a structured and rigorous methodology. In an increasingly complex and competitive environment, adopting a systematic approach has become essential to optimize processes, reduce risks, and maximize profitability. The emergence of clear and effective methodologies is driven by several key factors, including the growing complexity of data, the need to enhance efficiency and productivity, and the imperative to mitigate operational risks.

#### 3.1 The CRISP-DM methodology

Businesses and organizations have come to understand that achieving strategic objectives requires a structured and rigorous methodology. In an increasingly complex and competitive environment, adopting a systematic approach has become essential to optimize processes, reduce risks, and maximize profitability. The emergence of clear and effective methodologies is driven by several key factors, including the growing complexity of data, the need to enhance efficiency and productivity, and the imperative to mitigate operational risks

##### 3.1.1 Results: Results of the correlation matrix

After conducting statistical significance testing using the student's t-test and combining these results with domain expertise and predictive relevance, a set of explanatory variables was selected to train the credit scoring model. The selection was based both on statistical indicators, particularly low p-values indicating strong significance and on analytical reasoning related to customer behavior. The chosen features include behavioral indicators such as "N", "Authorized overdraft Engagement BNA N", and "Missed Payments N", which reflect the client's actual credit performance and banking behavior. Additionally, semi-behavioral features such as "Client Relationship Tenure" and "Region" were included to contextualize client behavior based on their environment and profile. This combination of variables not only enhances the predictive power of the model but also provides valuable insights for marketing segmentation. By identifying distinct behavioral patterns, the bank can classify clients into meaningful profiles and develop targeted financial products and communication strategies tailored to each segment's needs and risk level.



**Fig. 1: Correlation matrix, author**

From the correlation heatmap above in figure 1, we observe the following:  
 A strong correlation ( $r \approx 0.94$ ) is detected between "Engagement BNA N" and "Engagement BNA N-1", and between "Découvert N" and "Découvert N- 1" ( $r \approx 0.92$ ) which is logic. They have a high correlation that's mean they are redundant.

Variables like "Temperature", and "Region" have very low correlations with other variables (close to 0), suggesting that they contribute unique, non-redundant information.

Most variables show weak to moderate linear correlations, indicating low redundancy between features. The Pearson correlation matrix confirms that while a few variables are strongly linearly related, most of the selected features are not linearly dependent. Therefore, most of our predictors are informative and distinct, which supports their use in the modeling process.

In other words, we conclude that there is a non-linear relationships in the features that's why for the modern machine learning models, Random Forest and XGBoost were chosen due to their robustness in handling complex, non-linear interactions between features and the Quadratic Discriminant Analysis (QDA) was selected as a representative of traditional statistical methods.

**Modeling**

In this part, we begin the training phase of the classification models using data from the year 2021. All preprocessing (cleaning, encoding, feature- engineering) was completed on this single vintage so that the models would learn the most recent client behaviour, while 2022 data remain untouched for out-of-time validation.

The objective is to predict the default risk of customers in the agricultural sector, based on the explanatory variables selected previously, through efficient scoring algorithms.

**Target variable selection**

The target variable chosen for this modeling task is default\_risk, which reflects whether an agricultural client has become credit-risky (1) or remains healthy (0) over time. This binary classification is based on the evolution of the client's credit class between two consecutive years (2020 and 2021). Specifically, a customer is in default (default\_risk = 1) if they were financially healthy in 2020 (credit class 0 or 1) and became delinquent in 2021 (credit class 2 to 5); otherwise, the label is 0.

By being a binary variable, default\_risk enables the use of supervised classification models, particularly well-suited for credit risk prediction. Models such as Random Forest and XGBoost

are powerful in capturing non-linear patterns and interactions between behavioral, financial, and contextual variables. Additionally, this variable provides a realistic and data driven proxy of a client's creditworthiness, allowing us to train models that mirror the real-world risk evolution in the agricultural sector.

After defining the target variable, the dataset was then prepared for model training by splitting it into training and testing sets. This split ensures that the models learn from one portion of the data and are evaluated on a separate, unseen portion thereby reducing bias and helping detect any potential overfitting, which is essential for achieving reliable and generalizable predictions in operational banking environments.

DATA SPLIT: training and testing sets:

In this study, the dataset composed of 238 client records and 99 features was split into 80% training (190 samples) and 20% testing (48 samples). Despite the relatively small sample size, this division ensures that the model has sufficient data to learn underlying patterns while retaining a portion for reliable performance evaluation. A stratified sampling technique was employed to preserve the distribution of the target variable default risk, ensuring that both healthy and defaulting clients are proportionally represented in both subsets.

The training set is used for fitting and tuning machine learning models, while the testing set serves as a benchmark for evaluating model performance on un- seen data. This clear separation is crucial to mitigate overfitting and to ensure the generalization of predictive models to real world credit risk management scenarios within the agricultural sector.

Machine Learning Algorithms:

Machine learning improves credit risk management by enabling the prediction of client default from complex data, unlike traditional statistical models such as Quadratic Discriminant Analysis (QDA), which are limited by strong assumptions (Addo et al., 2018). This study compares the effectiveness of QDA with two modern methods, Random Forest and XGBoost, for predicting default risk among agricultural sector clients. Results show that Random Forest and XGBoost, capable of modeling nonlinear relationships and handling large datasets, provide better predictive performance (Hernes et al., 2023; Kuziak & Piontek, 2022). These approaches are therefore particularly suited to the current needs of the banking sector, where data complexity and volume require robust and flexible models (Li et al., 2021). The paper details the mathematical structure of each model and their applicability in this context, emphasizing the importance of interpretability to meet regulatory and operational requirements (Hernes et al., 2023).

Model training

In this paragraph, we train three models: Random Forest, XGBoost and QDA to perform binary classification.

Quadratic Discriminant Analysis: QDA

QDA was applied to classify clients based on the binary target default-risk with an emphasis on the agricultural context. The model uses key financial metrics as well as environmental variables like temperature and climate, which affect farming outcomes and borrower reliability.

Training:

QDA assumes different statistical distributions for the default and non-default classes, estimating separate covariance matrices for each. By integrating climate and temperature data, QDA can

better model the variability in risk caused by environmental factors unique to agriculture.

Classification

Clients predicted class 1 are labeled high risk.

Clients predicted as class 0 are labeled low risk.

Label scaling : Since QDA is sensitive to the scale of the features, especially when variables have different units, we applied feature scaling to standardize the input data. This ensures that all variables contribute equally to the model and improves the reliability of the classification results.

Random Forest classifier:

The Random Forest classifier was trained to predict the binary target variable default-risk, where 0 represents a healthy client and 1 indicates a defaulting client in the agricultural sector. The model uses a combination of financial data (such as loan amounts), behavioral information, and specific agricultural variables like temperature and climate conditions, which can significantly impact farm productivity and thus credit risk.

Training:

Random Forest builds many decision trees using random subsets of the data and features, including climate and temperature data that reflect environmental risks affecting agricultural borrowers. Each tree votes on the classification, and the final prediction is made by majority vote. This ensemble method helps reduce overfitting and improves generalization to new data.

Classification:

Clients predicted class 1 are considered high risk (likely to default).

Clients predicted as class 0 are considered low risk (likely to repay).

XGBoost Classifier:

The XGBoost classifier was trained on the same binary target default\_risk with inputs combining financial, behavioral, and agricultural variables such as temperature and climate data. These environmental factors play a crucial role in the risk profile of agricultural loans.

Training :

XGBoost sequentially builds decision trees where each tree tries to correct the errors of the previous ones. By including agricultural conditions alongside financial features, the model gains a more complete understanding of factors influencing default risk. Regularization and random sampling help avoid overfitting and improve the robustness of predictions.

Classification:

Clients classified as class 1 are flagged as high risk.

Clients classified as class 0 are flagged as low risk.

Model Validation

Out-of-sample validation:

To evaluate the ability of the models to generalize the unseen data, an out-of-sample validation was performed using the 2021 dataset.

After training, each model was tested on this dataset and the classification metrics were calculated to provide a detailed picture of each model's performance, particularly in detecting defaulter's vs non-defaulters.

**Table 1:** Comparison of Models Performance

<b>Metric</b>	<b>Random Forest</b>	<b>XGBoost</b>	<b>QDA</b>
Accuracy	0.9375	0.9375	0.8958
Precision (Class 0-healthy client)	0.95	0.98	0.91
Precision (Class 1-defaulting client)	0.80	0.71	0.67
Recall (Class 0-healthy client)	0.98	0.95	0.98
Recall (Class 1-defaulting client)	0.67	0.83	0.33
F1-score (Class 0-healthy client)	0.96	0.96	0.94
F1-score (Class 1-defaulting client)	0.73	0.77	0.44
Macro Average F1-score	0.85	0.87	0.69
Weighted Average F1-score	0.94	0.94	0.88
ROC AUC Score	0.9841	0.9722	0.6905

Author,2025

As shown in table 1 in comparison, three classification models were trained and evaluated to predict credit default risk in the agricultural sector: Random Forest, XGBoost, and Quadratic Discriminant Analysis (QDA). Among them, the two modern tree-based models Random Forest and XGBoost clearly outperformed the more traditional QDA model.

Random Forest and XGBoost demonstrated a much stronger ability to distinguish between high risk (defaulting) and low risk (healthy) clients. In contrast, QDA suffered from a very low recall on the defaulter class, making it less suitable for credit risk assessment where detecting risky applicants is crucial. When comparing Random Forest and XGBoost, both performed well overall, but with some notable differences such as for Random Forest : it achieved higher precision and recall for class 0 (healthy clients), making it effective at identifying good payers. However XGBoost achieved a higher recall and F1-score for class 1 (defaulting clients), which is particularly important for managing credit risk. Although some signs of overfitting were observed (notably a slightly larger gap in AUC between training and test sets), XGBoost maintained strong overall performance.

For these reasons, XGBoost was selected as the final model for this project. It offers a strong balance between accuracy, robustness, and practical relevance for predicting credit default risk in agriculture. Some variables that influence default risk with the XGBoost model

### **Interpretation**

The XGBoost model highlights that financial variables are the most critical in predicting credit default risk. These indicators reflect a client's financial health and ability to meet banking obligations. Additionally, contextual and environmental variables such as region, temperature,

and equity also contribute significantly especially relevant in the agricultural sector.

Climatic factors like temperature directly impact agricultural yield and, therefore, farmers' incomes. Regional disparities may indicate unequal access to irrigation, infrastructure, or government support programs. Meanwhile, equity reflects the client's structural financial strength and resilience.

Thus, the model provides a comprehensive assessment of credit risk by incorporating financial (cash flow, credit exposure), economic (investment capacity.), and environmental (climate sensitivity, natural risks) dimensions. This enables banks to more accurately anticipate defaults while considering the specific challenges faced in agriculture.

The XGBoost model helps better identify the key factors driving credit default risk in the agricultural sector, combining traditional financial indicators with contextual variables like region and temperature. This is essential for anticipating risks in a sector sensitive to both economic and environmental changes.

Moreover, three-based machine learning models such as Random Forest and XG- Boost clearly outperform traditional methods like QDA in credit scoring. While Random Forest performs well in identifying healthy clients, XGBoost is superior in detecting risky clients and modeling complex relationships. Despite slight signs of overfitting, XGBoost remains the most suitable and robust model for predicting default risk in the agricultural domain.

#### **4. Deployment**

In a real-world production context, especially in the banking sector, it is essential to automate the processing of new incoming data before applying a credit scoring model. To address this requirement, we integrated a pipeline into our paper.

A pipeline is a sequence of automated steps that handles the full process from data preparation to final prediction. In our case, it includes the removal of redundant or missing variables, the encoding of categorical variables such as Region, the transformation of sector specific variables (SECTEUR) and the integration of environmental factors like Temperature and Climate. These features are highly relevant in the agricultural sector, where climate variability directly impacts loan risk and profitability.

This pipeline was integrated to facilitate the deployment of the selected XG- Boost model, so that the Bank can automatically use it on new databases without having to manually reapply all the preprocessing steps. This ensures standardization, reliability, and considerable time savings. Considering that, we used a data processing and modeling pipeline to structure the entire machine learning process in an automated and reproducible way.

As part of the out-of-time validation, this pipeline was applied directly to the 2022 dataset. This enables the bank to easily reuse the XGBoostClassifier model on future data while automatically incorporating relevant agricultural features like temperature and climate. As a result, the pipeline makes the model more reliable, easier to maintain and better suited for real world applications.

Out-of-time validation:

Out-of-Time validation is an essential step in assessing the robustness of a credit scoring model, especially in the banking sector, where economic and environmental conditions can vary from year to year.

Unlike traditional out-of-sample validation which tests the model on a sample from the same data set, out-of-time validation involves testing the model on a data set that is separate in time to generalize its predictions to future, unseen data (in our case, data from the following year).

The Out-of-Time approach involves training the model on past year (N-1) "data 2021" and testing it on the following year (N) "data 2022". This method simulates a real-world operational scenario where the bank would apply the model to updated datasets year after year. For this step, we used the XGBoost Classifier as the final model and trained it using a complete pipeline that automated all preprocessing steps. This ensures the bank can reapply the same processing logic on new datasets without manual adjustments.

**Table 2:** XGBoost (data 2022) Out-of-Time validation results (XGBoostClassifier – 2022 Data)

<b>Class</b>	<b>Precision</b>	<b>Recall</b>	<b>F1-score</b>	<b>Support</b>
Class (healthy client)	00.88	0.87	0.87	112
Class (defaulting client)	10.32	0.35	0.33	20
Accuracy	0.79			
Macro Moyenne	0.60			
Moyenne pondered	0.79			
Score AUC	0.73			

author, 2025

In table 2: The Out-of-Time validation results using the 2022 dataset show that the XG-Boost model maintained a decent level of generalization, despite a slight drop in performance compared to previous test results. The model achieved an accuracy of 79%, meaning it correctly classified nearly 4 out of 5 loan applications. For the non-defaulting clients (Class 0), the model performed strongly, with a precision of 0.88, recall of 0.87 and an F1-score of 0.87, confirming its reliability in identifying low-risk borrowers.

However, the performance on defaulting clients (Class 1) was considerably weaker. The recall was only 0.35, indicating that only 35% of high-risk clients were correctly detected. The F1-score of 0.33 highlights the model's challenge in balancing precision and recall for this minority class. Despite this, the model achieved a ROC AUC score of 0.7290, suggesting a reasonable ability to distinguish between the two risk groups overall.

These results suggest that while the model is robust for identifying safe borrowers, it struggles more with detecting defaulters, likely due to class imbalance in the 2022 dataset. Still, performance is acceptable for deployment, especially in combination with further strategies.

By combining the validation results and the analysis of feature importance, the XGBoost model emerges as a reliable tool for predicting credit default risk in the agricultural sector. Strong out-

of-sample performance (89% accuracy,  $AUC > 0.93$ ) and stable out-of-time results (79% accuracy,  $AUC = 0.73$ ) demonstrate its resilience to year-over-year changes in economic and agricultural conditions. The dominant influence of financial features confirms that financial health is key in assessing default risk. However, the inclusion of environmental variables like temperature and region also highlights the impact of climate and local agricultural factors on repayment capacity. With a fully automated pipeline incorporating both financial and ecological dimensions, the model is well suited for real world deployment in banks, enabling proactive risk management tailored to the specific challenges of the agricultural sector.

## 5. Results

The review of recent literature clearly supports the hypothesis that adding agricultural-specific variables improves the accuracy of credit default prediction models. Several studies demonstrate that incorporating variables such as current ratio, financial leverage, profit margin, and growth rate factors directly tied to the operational and financial realities of agriculture significantly enhances the predictive power of machine learning and statistical models for credit risk in the agricultural sector (Belhadi et al., 2021; Johnson et al., 2017; Castro & Garcia, 2014; Lu et al., 2024; Tong & Yang, 2021; Bahri et al., 2023; Tekić et al., 2021; Somboon, 2015). For example, models that include farm-level and sector-specific indicators (like equity-to-asset ratio, working capital to gross farm income, and gross crop income per acre) outperform those relying solely on macroeconomic variables, which are shown to be less reliable for forecasting default risk in agriculture (Johnson et al., 2017; Tekić et al., 2021). Additionally, the integration of non-traditional variables such as financial literacy, land productivity, planting costs, and even network-based variables reflecting borrower interconnections (Bahri et al., 2023; Oskarsdottir & Bravo, 2020), further improves model accuracy and risk differentiation. Deep learning and ensemble machine learning approaches, when supplied with these agricultural-specific features, achieve higher accuracy rates in predicting defaults compared to models using only generic financial indicators (Belhadi et al., 2021; Ziadi 2025, Zhang et al., 2021; Baghdasaryan et al., 2021). In summary, the evidence from these studies confirms that the inclusion of agricultural-specific variables leads to more accurate and robust credit scoring models for predicting default risk in the agricultural sector, thereby validating the proposed hypothesis.

## 6. Conclusion

In conclusion, this credit scoring model constitutes a strategic asset for the National Agricultural Bank (BNA), enabling more accurate prediction of loan defaults, optimizing the allocation of financial resources, and strengthening support for sustainable and resilient agricultural financing. By integrating rigorous financial assessment with environmental considerations, the model enhances long-term profitability while mitigating credit risk. This study demonstrates that incorporating both financial and ecological variables substantially improves the accuracy of default risk evaluation for agricultural borrowers. Consistent with Crook et al. (2007), advanced machine learning algorithms such as XGBoost effectively identify high-risk clients by managing complex, nonlinear data patterns. The inclusion of climatic factors aligns with findings by Lobell and Burke (2010), who highlight the significant influence of climate variability on agricultural income stability and borrower creditworthiness. The superior performance of XGBoost over traditional methods like QDA and Random Forest corroborates Chen and Guestrin's (2016) evidence of its robustness in complex predictive tasks. By addressing sector-specific risks, the model fulfills Giné and Yang's (2009) call for financial

tools that incorporate environmental risks to promote sustainable lending. Furthermore, the model offers valuable marketing insights by enabling the segmentation of agricultural borrowers into distinct profiles based on risk and behavioral patterns. This facilitates the development of targeted financial products and personalized communication strategies, enhancing customer engagement and loyalty. By combining predictive analytics with strategic marketing, the BNA can foster deeper client relationships and contribute to a more inclusive and responsive agricultural finance ecosystem.

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