

A smart model for reducing Gharar in agricultural Salam contracts: using artificial intelligence and geographic information systems in islamic finance

Un modèle intelligent de réduction du gharar dans les contrats de Salam agricole : intégration de l'intelligence artificielle et des systèmes d'information géographique en finance islamique

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Abstract:

The Salam contract represents one of the principal Sharia-compliant financing instruments for agricultural production. However, assessing agricultural land before harvest remains a major source of uncertainty for Islamic financial institutions. Furthermore, existing research generally addresses either the jurisprudential aspects of Salam contracts or the application of Artificial Intelligence and geospatial technologies, without providing an integrated framework that combines legal, economic, and technical dimensions to support financing decisions. This study proposes an integrated decision-support framework combining remote sensing, Geographic Information Systems (GIS), climate data, and Artificial Intelligence to assess agricultural land quality for Salam financing. The empirical analysis is based on 420 spatial observations collected from an agricultural area located in the Casablanca–Settat region of Morocco during the period January 2024 to June 2025. Environmental indicators derived from Sentinel-2 Normalized Difference Vegetation Index (NDVI) imagery and CHIRPS precipitation data were integrated into a geospatial database and analyzed using the K-Means unsupervised clustering algorithm. The results show that K-Means successfully identifies three distinct environmental profiles corresponding to different levels of agricultural land quality. These environmental profiles are subsequently interpreted as financing risk categories, providing an objective basis for Salam financing decisions without relying on predefined classification thresholds or manually assigned labels. The proposed framework therefore contributes to a more transparent and evidence-based assessment of agricultural land while avoiding methodological circularity.

The findings should nevertheless be regarded as preliminary, since they are based on a single study area and a limited observation period. Future research should validate the proposed framework using additional agro-climatic regions, longer time series, and independent agricultural production data in order to assess its robustness and generalizability.

Keywords: Salam contract; Islamic finance; Artificial Intelligence; K-Means clustering; Remote sensing; Geographic Information Systems; NDVI; CHIRPS; Agricultural land assessment.

Classification JEL : G23, Q14, O16

Paper type : Empirical Research

Résumé :

Le contrat de Salam constitue un instrument majeur de la finance islamique destiné au financement de la production agricole. Toutefois, l'évaluation du potentiel productif des terres avant la récolte demeure une source importante d'incertitude pour les institutions financières islamiques. Par ailleurs, la littérature existante traite généralement séparément les dimensions juridiques du contrat de Salam et les applications de l'intelligence artificielle et des technologies géospatiales, sans proposer un cadre intégré de prise de décision. Cette étude propose un cadre d'aide à la décision combinant la télédétection, les Systèmes d'Information Géographique (SIG), les données climatiques et l'intelligence artificielle afin d'évaluer la qualité des terres agricoles dans le cadre du financement par Salam. L'analyse repose sur 420 observations spatiales issues d'une zone agricole de la région Casablanca–Settat (Maroc), couvrant la période janvier 2024 à juin 2025. Les indicateurs environnementaux, notamment le NDVI dérivé des images Sentinel-2 et les précipitations CHIRPS, ont été intégrés dans une base de données géospatiale puis analysés à l'aide de l'algorithme non supervisé K-Means. Les résultats montrent que l'algorithme identifie trois profils environnementaux distincts correspondant à des niveaux différents de qualité des terres agricoles. Ces profils sont ensuite interprétés comme des catégories de risque de financement permettant de soutenir les décisions relatives aux contrats de Salam sans recourir à des seuils de classification prédéfinis. Cette approche fournit ainsi une base objective pour l'évaluation environnementale des terres agricoles tout en limitant la circularité méthodologique. Les résultats obtenus doivent toutefois être considérés comme préliminaires, dans la mesure où ils reposent sur une seule région d'étude et une période d'observation limitée. Des validations supplémentaires sur d'autres zones agro-climatiques, des séries temporelles plus longues et des données indépendantes de rendement agricole seront nécessaires afin d'évaluer la robustesse et la généralisabilité du cadre proposé.

Mots-clés : Salam ; Finance islamique ; Intelligence artificielle ; K-Means ; Télédétection ; SIG ; NDVI ; CHIRPS ; Évaluation des terres agricoles.

JEL Classification : G23, Q14, O16

Type du papier : Recherche empirique

1. Introduction

Agriculture plays a fundamental role in economic development, food security, and rural livelihoods, particularly in developing countries where it represents a major source of employment and income (Mathenge et al., 2023). However, agricultural production is increasingly exposed to climate variability, environmental degradation, water scarcity, and extreme weather events, all of which increase production uncertainty and consequently the risks associated with agricultural financing. These challenges have intensified the need for more objective and reliable approaches to assessing agricultural production potential before financing decisions are made.

Within this context, Islamic finance offers several Sharia-compliant financing instruments designed to support productive economic activities. Among these instruments, the Salam contract occupies a distinctive position because it enables farmers to obtain financing before the production season in exchange for the future delivery of agricultural products under predetermined contractual conditions. Previous studies have highlighted its potential to improve farmers' income and support agricultural development (Sifa & Wiryono, 2023). As one of the oldest Islamic financing mechanisms, Salam contributes to improving farmers' access to liquidity while supporting agricultural development and food security.

From a jurisprudential perspective, Salam is defined as a forward sale contract in which the purchase price is fully paid at the time of contracting, whereas the delivery of the specified commodity is deferred to an agreed future date (Ibn Qudamah, 1997; Usmani, 2002). Its legitimacy is established by the Prophetic tradition and unanimously recognized by classical Muslim jurists (Al-Bukhari, 1997; Muslim, 2000). To minimize excessive uncertainty (*gharar*), Islamic jurisprudence requires that the price be paid in advance, the commodity be clearly specified in terms of quantity and quality, and the delivery date be precisely determined (Al-Zuhayli, 2006). While these legal principles remain unchanged, their practical implementation has become increasingly challenging in modern agricultural financing, particularly under conditions of climatic uncertainty.

In recent years, the rapid development of Islamic FinTech and geospatial technologies has created new opportunities for improving agricultural financing decisions. Artificial Intelligence (AI), Geographic Information Systems (GIS), remote sensing, and Earth observation technologies provide objective environmental information capable of supporting agricultural assessment through satellite imagery and climate data (Kamilaris & Prenafeta-Boldú, 2018; Xue & Su, 2017). These technologies have significantly improved agricultural monitoring, crop assessment, and environmental analysis, thereby offering promising tools for reducing uncertainty and strengthening transparency in financing decisions.

Despite these technological advances, an important research gap remains. Previous studies have generally examined Salam contracts from jurisprudential or economic perspectives, whereas research involving Artificial Intelligence, Geographic Information Systems, and remote sensing has primarily focused on agricultural monitoring and environmental assessment (Kamilaris & Prenafeta-Boldú, 2018; Binte Mostafiz et al., 2021). Although these research streams have developed independently, very few studies have integrated them into a unified decision-support framework specifically designed for Salam financing. Furthermore, most existing approaches rely on predefined classification criteria or supervised learning models, whereas little attention has been given to unsupervised Artificial Intelligence techniques capable of objectively identifying agricultural land profiles directly from environmental data. Consequently, Islamic financial institutions still lack an integrated framework that combines Sharia principles, geospatial intelligence, and Artificial Intelligence to support objective agricultural land assessment and financing decisions.

This study addresses these limitations by proposing an integrated decision-support framework that combines remote sensing, Geographic Information Systems, climate data, and Artificial Intelligence for Salam financing. The proposed framework applies the K-Means clustering algorithm, an unsupervised machine-learning technique, to identify homogeneous agricultural land profiles based on satellite-derived NDVI and CHIRPS precipitation data. Unlike conventional approaches based on predefined thresholds or manually assigned land-quality classes, the proposed methodology identifies natural environmental clusters directly from the data and subsequently interprets them as financing risk categories, thereby avoiding methodological circularity while improving the objectivity of financing decisions.

This study makes three major contributions to the literature.

First, it provides a theoretical contribution by bridging Islamic jurisprudence, Islamic financial engineering, Artificial Intelligence, Geographic Information Systems, and remote sensing within a unified analytical framework for Salam financing.

Second, it offers a methodological contribution by introducing an unsupervised machine-learning approach based on K-Means clustering for agricultural land assessment. Unlike supervised classification methods, the proposed methodology does not require predefined land-quality labels, thereby reducing classification bias and improving methodological consistency. Third, it makes a practical contribution by providing Islamic financial institutions with an objective decision-support framework capable of assessing agricultural land quality, classifying financing risk, reducing information asymmetry and *gharar*, and supporting transparent, evidence-based, and Sharia-compliant financing decisions.

Accordingly, the objective of this study is to investigate whether the integration of Artificial Intelligence, Geographic Information Systems, remote sensing, and environmental indicators can improve agricultural land assessment and support financing decisions in Salam contracts. More specifically, the study applies the K-Means clustering algorithm to classify agricultural land according to similarities in NDVI and precipitation characteristics and proposes a financing decision-support framework based on the environmental profiles identified through the clustering process.

Based on this objective, the study addresses the following research question: *How can the integration of Artificial Intelligence, Geographic Information Systems, remote sensing, and environmental indicators improve agricultural land assessment and support financing decisions in Salam contracts while maintaining compliance with Sharia principles?*

To answer this research question, the following hypotheses are proposed:

H1. Environmental indicators derived from satellite imagery (NDVI) and climate data (CHIRPS precipitation) enable the identification of distinct agricultural land profiles through unsupervised machine learning.

H2. The environmental clusters identified by the K-Means algorithm provide an objective basis for differentiating agricultural land quality and financing risk in Salam contracts.

H3. The proposed Artificial Intelligence-based decision-support framework contributes to reducing information asymmetry and *gharar* by supporting transparent, objective, and evidence-based Salam financing decisions.

The remainder of this paper is organized as follows. Section 2 reviews the literature on Salam contracts, Islamic financial technology, Artificial Intelligence, Geographic Information Systems, remote sensing, and agricultural land assessment. Section 3 presents the research methodology, data sources, and analytical framework. Section 4 reports the empirical results. Section 5 discusses the findings and their implications for Islamic agricultural finance. Finally, Section 6 concludes the paper, outlines its limitations, and proposes directions for future research.

2. Literature Review

This section reviews the theoretical and empirical literature relevant to the present study. It first examines the role of Salam financing and the challenge of managing gharar in Islamic agricultural finance. It then discusses recent developments in Artificial Intelligence, Islamic FinTech, remote sensing, and Geographic Information Systems (GIS) for agricultural assessment. Finally, it reviews the application of machine-learning techniques to agricultural land classification and identifies the research gap that motivates the proposed integrated framework for Salam financing.

2.1 Salam Financing and the Challenge of Gharar

Salam is one of the earliest Islamic financing contracts designed to support agricultural production by allowing advance payment for goods that will be delivered at a future date (Usmani, 2002). It constitutes an important financing mechanism for farmers by providing liquidity before harvest while complying with Sharia principles. Nevertheless, because delivery occurs in the future, Salam contracts remain exposed to production uncertainty resulting from climatic conditions, environmental variability, and agricultural risks.

From an Islamic jurisprudential perspective, the main challenge associated with Salam financing lies in the management of gharar (excessive uncertainty). Gharar refers to uncertainty regarding the existence, quality, quantity, or delivery of the contracted asset and is prohibited because it may generate information asymmetry, disputes, and unfair outcomes between contracting parties (El-Gamal, 2006; Kahf, 1996). Although Salam is exceptionally permitted under specific Sharia conditions, reducing uncertainty remains essential to ensure its effective implementation and compliance with Islamic commercial law.

Several recent studies have emphasized the importance of strengthening risk management in Salam financing. Atah et al. (2019) argued that improving agricultural risk assessment could enhance the sustainability of Salam financing. Similarly, Mulyany et al. (2021) proposed an operational framework for Salam implementation within Islamic banks.

However, these studies mainly focus on jurisprudential, institutional, or contractual aspects and rely primarily on qualitative analyses. They do not incorporate objective environmental indicators capable of evaluating agricultural production potential before financing decisions are made. Consequently, although they contribute to understanding Salam financing, their practical applicability for financing risk assessment remains limited.

2.2 Artificial Intelligence in Islamic Finance

Artificial Intelligence (AI) has become an important driver of digital transformation within the financial sector. Recent studies demonstrate that AI improves decision-making, risk assessment, fraud detection, and financial forecasting while reducing operational costs (Firmansyah & Anwar, 2022).

Within Islamic finance, AI applications have expanded considerably during recent years. Recent studies suggest that artificial intelligence, machine learning, and financial technologies can improve decision-making processes, risk assessment, and financial service innovation while supporting Sharia-compliant financial practices (Firmansyah & Anwar, 2022; Rabbani et al., 2021).

Despite these advances, existing studies mainly investigate AI applications in Islamic banking, credit assessment, customer services, or financial technology. Very limited attention has been devoted to agricultural financing under Salam contracts, particularly to the integration of environmental information derived from satellite imagery into financing decision-making.

2.3 Remote Sensing and Geographic Information Systems for Agricultural Assessment

Remote sensing and Geographic Information Systems (GIS) have become essential technologies for agricultural monitoring. Satellite-derived vegetation indices, particularly the Normalized Difference Vegetation Index (NDVI), provide reliable indicators of vegetation vigor and crop conditions (Xue & Su, 2017).

Numerous studies have demonstrated that combining NDVI with precipitation data significantly improves agricultural land assessment (Kamilaris & Prenafeta-Boldú, 2018). Similarly, Mathenge et al. (2023) showed that GIS facilitates the integration of environmental information for spatial agricultural analysis.

More recently, Varzakas & Smaoui (2024) demonstrated that machine-learning algorithms applied to remote sensing data can accurately classify agricultural land according to environmental characteristics.

Nevertheless, these studies focus primarily on agronomic evaluation and land management. None explicitly addresses financing decisions or incorporates Islamic financial principles into agricultural land assessment.

2.4 Artificial Intelligence for Agricultural Land Classification

Machine-learning techniques have become increasingly popular for environmental classification because they automatically identify patterns within multidimensional datasets. Among these techniques, K-Means clustering, originally introduced by MacQueen (1967), represents one of the most widely used unsupervised learning algorithms for identifying homogeneous groups without requiring predefined labels. The algorithm partitions observations into clusters by minimizing intra-cluster variance and maximizing inter-cluster similarity (Jain, 2010; Talukdar et al., 2020).

Compared with supervised classification methods, K-Means reduces subjective intervention since observations are grouped according to their natural similarities. This characteristic makes the algorithm particularly suitable for environmental datasets in which objective classifications are unavailable (Jain, 2010).

Previous studies have successfully employed K-Means for land-cover mapping, vegetation monitoring, and agricultural zoning. However, these applications remain essentially agronomic and have not been extended to financing risk assessment in Islamic finance (Talukdar et al., 2020; Binte Mostafiz et al., 2021).

2.5 Critical Review of Previous Studies

Although previous research has significantly advanced the fields of Islamic finance, remote sensing, and Artificial Intelligence, several methodological limitations remain.

Studies focusing on Salam financing mainly rely on conceptual or institutional analyses and generally lack objective environmental indicators capable of supporting financing decisions before contract implementation. Consequently, their external applicability for agricultural financing remains limited.

Research dedicated to remote sensing and machine learning has demonstrated the effectiveness of NDVI, precipitation data, and Artificial Intelligence for agricultural land assessment. However, these investigations are restricted to agronomic applications and do not incorporate financial decision-making or Sharia-compliant financing mechanisms.

Similarly, recent studies on Artificial Intelligence in Islamic finance concentrate on digital banking, customer services, and credit evaluation rather than agricultural financing.

Overall, existing research remains fragmented into three largely independent streams : Islamic jurisprudence and Salam financing, Artificial Intelligence in Islamic banking, and remote sensing for agricultural assessment. The absence of an integrated framework combining these three dimensions represents an important methodological limitation in the current literature.

Table 1. Comparative Review of Previous Studies

Study	Objective	Methodology	Main Findings	Limitations
Atah et al. (2019)	Improve Salam financing for agriculture	Conceptual framework	Proposed a secured Bay-Salam model to mitigate agricultural financing risks	No integration of environmental indicators or AI techniques
Mulyany et al. (2021)	Salam implementation in Islamic finance	Conceptual and institutional analysis	Developed an operational framework for Salam financing	Limited consideration of environmental and technological factors
Firmansyah & Anwar (2022)	Review Islamic FinTech development	Literature review	FinTech enhances efficiency, decision-making, and innovation in Islamic finance	Does not address agricultural financing or Salam contracts
Rabbani et al. (2021)	Islamic FinTech and financial innovation	Literature review	Digital technologies support financial inclusion and risk management	No application to agricultural financing
Xue & Su (2017)	Review vegetation indices in remote sensing	Literature review	NDVI is a reliable indicator of vegetation conditions and crop health	No financing perspective
Kamilaris & Prenafeta-Boldú (2018)	AI applications in agriculture	Literature review	AI improves agricultural monitoring and environmental assessment	No integration with financial decision-making
Mathenge et al. (2023)	GIS-based spatial analysis for food security assessment	Spatial analysis	GIS facilitates the integration of environmental information for spatial decision-making	No application to Islamic finance
Varzakas & Smaoui, (2024)	Remote sensing and machine learning for environmental assessment	Review study	Machine-learning techniques improve environmental classification and monitoring	Does not address financing decisions
Talukdar et al. (2020)	Machine learning for land-use and land-cover classification	Literature review	Machine-learning algorithms improve environmental classification accuracy	Restricted to environmental applications
Binte Mostafiz et al. (2021)	Agricultural land suitability assessment	Remote sensing and GIS analysis	Satellite-derived indicators improve agricultural land evaluation	No financing or Islamic finance dimension

Source: Authors.

As shown in Table 1, previous studies have generally focused on one of three distinct research streams: Salam financing, Artificial Intelligence and Islamic FinTech, or remote sensing and agricultural land assessment. While each stream provides valuable insights, none integrates Sharia principles, Artificial Intelligence, Geographic Information Systems, remote sensing, and environmental indicators within a unified decision-support framework for Salam financing. This gap motivates the present study, which seeks to bridge these fragmented strands of literature through an integrated and data-driven approach.

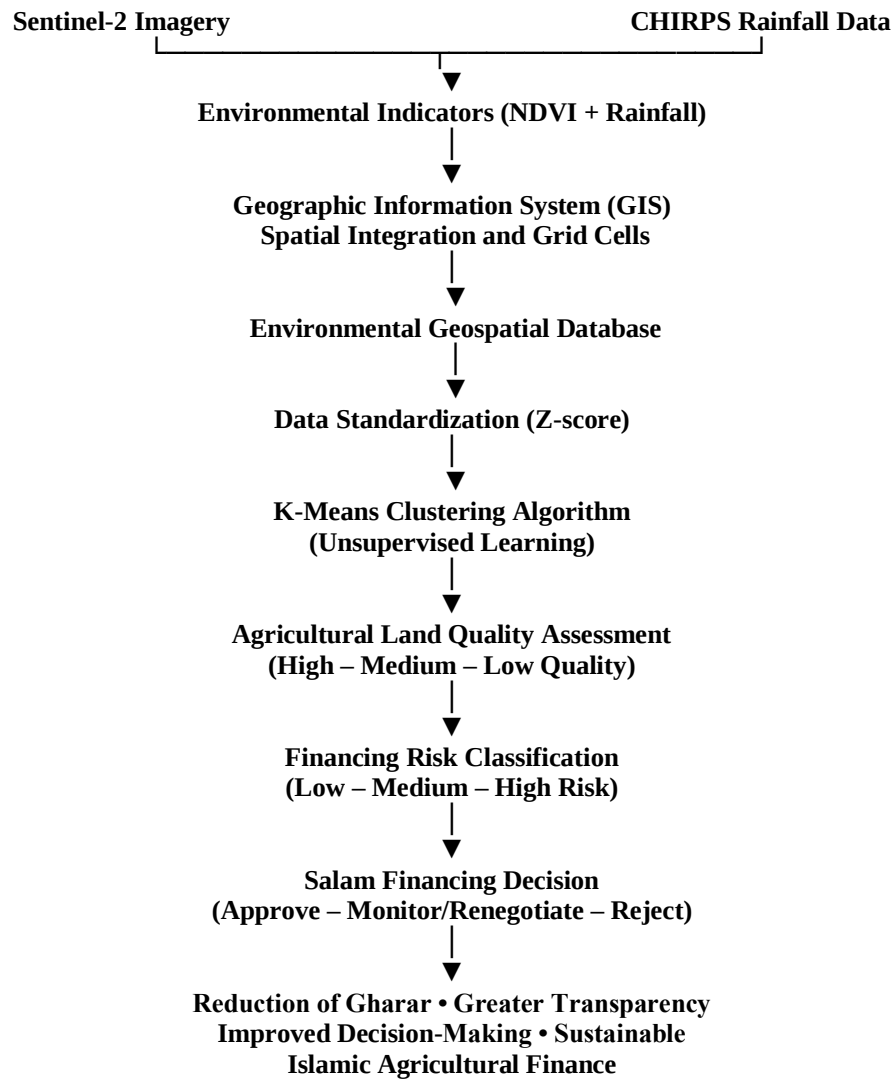
2.6 Research Gap

A critical examination of the existing literature reveals that research has developed along three largely independent directions. The first focuses on the jurisprudential and institutional dimensions of Salam financing, the second examines Artificial Intelligence applications in Islamic banking and financial services, while the third investigates remote sensing and machine-learning techniques for agricultural monitoring.

To the best of our knowledge, no previous study has integrated these three dimensions into a unified decision-support framework for Salam financing. In particular, the literature lacks an approach combining satellite-derived environmental indicators, Geographic Information Systems, climate information, and unsupervised machine learning to support financing decisions while reducing information asymmetry and uncertainty (*gharar*). The present study

addresses this gap by proposing an integrated framework that combines Sentinel-2 imagery, CHIRPS precipitation data, Geographic Information Systems, and the K-Means clustering algorithm to classify agricultural land according to environmental characteristics. The identified clusters are subsequently interpreted for financing risk assessment, thereby providing a transparent, objective, and Sharia-compliant decision-support framework for Salam contracts.

Figure 1. Conceptual Framework of the Proposed Financing Decision-Support Framework for Salam Contracts



Source: Authors' own elaboration based on the reviewed literature.

3 Méthodologie de recherche

To investigate the potential contribution of Artificial Intelligence, remote sensing, and Geographic Information Systems (GIS) to Salam financing decisions, a comprehensive methodological framework was developed. The methodological approach adopted in this study combines satellite-derived environmental indicators, climate data, geospatial analysis, and unsupervised machine learning to assess agricultural land quality and support financing risk evaluation. The following subsections present the research design, data sources, analytical procedures, and Artificial Intelligence techniques employed in the study.

3.1 Research methodology

This study adopts a quantitative analytical research design integrating remote sensing,

Geographic Information Systems (GIS), climate data analysis, and Artificial Intelligence to support financing decisions in Salam contracts.

Sentinel-2 satellite imagery and CHIRPS rainfall data, accessed through Google Earth Engine (GEE), were processed to derive environmental indicators describing agricultural land conditions. The study area was subdivided into 420 spatial grid cells, each representing one analytical observation. For every grid cell, the mean Normalized Difference Vegetation Index (NDVI), monthly precipitation values, and geographic coordinates were extracted and integrated into a unified geospatial database.

The resulting dataset was subsequently analyzed using the K-Means clustering algorithm, an unsupervised machine-learning technique that automatically groups observations according to similarities in their environmental characteristics. Unlike supervised classification methods, K-Means does not require predefined class labels or manually established thresholds, thereby avoiding methodological circularity between the explanatory variables and the classification outcome.

After the clustering process, the environmental characteristics of each cluster were examined by comparing their centroid values, particularly the average NDVI and precipitation levels. Based on these environmental profiles, the clusters were interpreted as representing high-, medium-, and low-quality agricultural land. Finally, the interpreted clusters formed the basis for a financing risk assessment framework designed to support objective, transparent, and Sharia-compliant decision-making in Salam contracts.

3.2 Data sources

This study integrates three complementary data sources to assess agricultural land quality and support financing decisions in Salam contracts.

Sentinel-2 satellite imagery (January 2024–June 2025). Sentinel-2 multispectral images were acquired through the Sentinel Hub EO Browser platform (Sinergise) to derive the Normalized Difference Vegetation Index (NDVI). NDVI was calculated using Band 8 (Near Infrared, NIR) and Band 4 (Red) following the standard vegetation index formula. To ensure data reliability, only images with minimal cloud cover were selected throughout the study period.

CHIRPS rainfall data (January 2024–June 2025). Monthly precipitation data were extracted from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) dataset through Google Earth Engine (GEE). With a spatial resolution of approximately 0.05° (≈ 5 km), CHIRPS provides consistent rainfall estimates that were used to characterize climatic variability and complement the information obtained from satellite-derived vegetation indices. Spatial data and GIS processing. The study area was delineated in QGIS and subdivided into 420 regular spatial grid cells, each representing one analytical observation. Geographic Information Systems (GIS) were used to integrate NDVI values, monthly precipitation data, and geographic coordinates into a unified geospatial database. This integrated environmental dataset served as the input for the subsequent Artificial Intelligence analysis aimed at identifying homogeneous agricultural land conditions and supporting financing risk assessment within the Salam financing framework.

3.3 Analysis tools

3.3.1 Remote sensing technology

The study area is located in the Casablanca-Settat region of Morocco and was delineated using a polygon defined by the following geographic coordinates:

- Latitude : 33.311950 to 33.358560 north
- Longitude : from -7.343670 to -7.227120 west

The study area was delineated as a polygon for spatial analysis, and satellite images were downloaded from the Sentinel-2 platform, part of the European Copernicus Open Access Hub, for two time periods :

- January to June 2024
- January to June 2025

To ensure data quality, only images with minimal cloud cover were selected using the cloud probability filtering option available on the Sentinel Hub EO Browser platform.

Figure 1: Sentinel-2 satellite image of the study area on February 20, 2024



Source: European Space Agency (ESA) – Copernicus program.

Following image acquisition, the Normalized Difference Vegetation Index (NDVI) was calculated to evaluate vegetation conditions across the study area. NDVI is a widely used remote sensing indicator that measures vegetation vigor and biomass from the spectral reflectance recorded in the near-infrared (Band 8) and red (Band 4) wavelengths. The resulting NDVI maps provided objective information on the spatial variability of agricultural land conditions.

Within the proposed framework, remote sensing contributes to:

- Assessing the productive potential of agricultural land before financing decisions are made;
- Providing objective environmental indicators for agricultural land evaluation;
- Supporting evidence-based agricultural land assessment;
- Reducing information asymmetry and uncertainty (*gharar*) through transparent environmental information.

3.3.2 Geographic Information Systems (GIS)

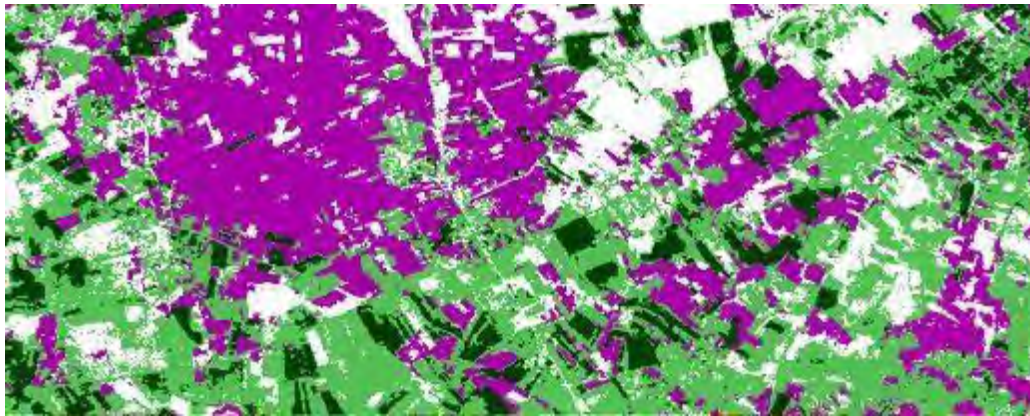
The spatial analysis was conducted using QGIS, an open-source Geographic Information System widely used for processing satellite imagery, spatial analysis, and map production (Sherman, 2008). Sentinel-2 images were imported into QGIS to calculate the Normalized Difference Vegetation Index (NDVI) from Band 8 (Near Infrared) and Band 4 (Red) using the standard equation:

$$\frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})} = \text{NDVI}$$

Where:

- NIR (Near-Infrared) : Band 8 in Sentinel-2
- RED (Red) : Band 4 in Sentinel-2

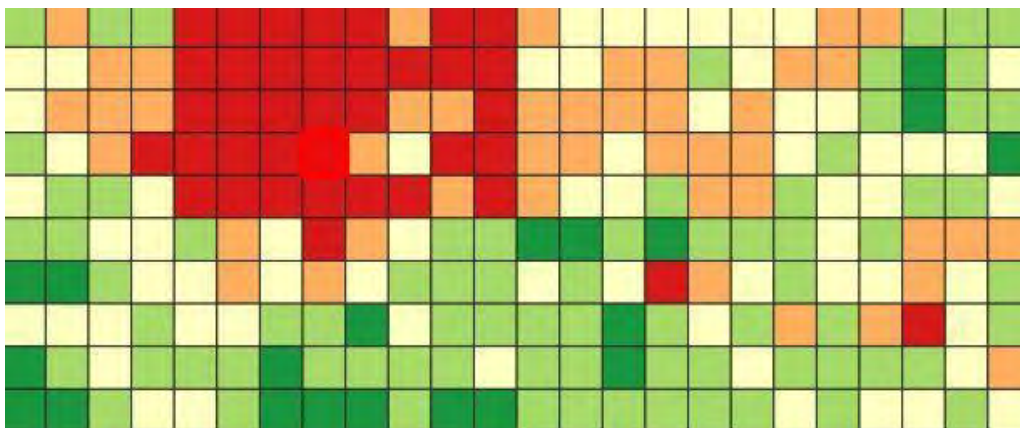
Figure 2. NDVI map of the study area derived from Sentinel-2 imagery (20 February 2024).



Source : Prepared by the authors using QGIS.

To facilitate spatial analysis, the study area was divided into a regular grid using the Grid Cells tool in QGIS. Each grid cell represented an individual spatial observation and was assigned a unique geographic location. Zonal statistics were subsequently applied to calculate the mean NDVI value for each cell, and the resulting dataset was exported in GeoJSON format to preserve both the environmental attributes and the geographic coordinates.

Figure 2. NDVI map of the study area derived from Sentinel-2 imagery (20 February 2024).



Source : Prepared by the authors using QGIS.

The GIS database subsequently integrated NDVI values, precipitation data, and spatial coordinates into a unified geospatial dataset describing the environmental characteristics of each observation.

Within the proposed decision-support framework, GIS contributes to:

- Integrating environmental indicators with spatial information;
- Generating homogeneous spatial units for environmental analysis;
- Supporting objective agricultural land assessment;
- Providing geospatial information for financing risk evaluation;
- Reducing information asymmetry and uncertainty (*gharar*) in Salam financing.

3.3.3 Precipitation data (Google Earth Engine – CHIRPS)

Monthly precipitation data were obtained from the Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) through the Google Earth Engine (GEE) platform. CHIRPS combines satellite observations with in situ weather station measurements to provide precipitation estimates at a spatial resolution of approximately 0.05° (≈ 5 km) (Funk et al., 2015).

The same study area polygon used for the NDVI analysis was imported into GEE to ensure spatial consistency across all environmental variables. Monthly cumulative precipitation was extracted for each spatial grid cell from January 2024 to June 2025.

Precipitation values were subsequently integrated into the GIS database, allowing each grid cell to be characterized by its mean NDVI value, monthly precipitation amount, and geographic coordinates. This unified geospatial database constituted the environmental dataset used for the subsequent Artificial Intelligence analysis.

The integration of satellite-derived vegetation and precipitation indicators provides an objective basis for evaluating agricultural production potential and supports transparent, data-driven financing decisions while contributing to the reduction of uncertainty (*gharar*) in Salam contracts.

3.3.4 K-Means Clustering

Agricultural land quality was assessed using the K-Means clustering algorithm, an unsupervised machine-learning technique that automatically identifies homogeneous groups of observations without requiring predefined class labels. This approach eliminates the need for manually assigning land-quality categories and avoids methodological circularity between the input variables and the classification outcome.

The input dataset consisted of the environmental variables extracted during the previous stages, namely the Normalized Difference Vegetation Index (NDVI) and monthly CHIRPS precipitation values for each of the 420 spatial grid cells. Prior to clustering, all variables were standardized using z-score normalization to ensure comparable measurement scales and prevent variables with larger numerical ranges from dominating the clustering process.

The number of clusters was fixed at $k = 3$, corresponding to three homogeneous groups intended to represent different agricultural land conditions within the proposed Salam financing framework. This choice was made to obtain an interpretable classification distinguishing agricultural land with relatively favorable, intermediate, and unfavorable environmental characteristics.

The K-Means algorithm iteratively assigned each observation to the nearest cluster centroid using the Euclidean distance metric. Cluster centroids were updated until convergence was achieved, defined as the point at which no significant changes occurred in centroid positions or cluster membership between successive iterations.

Unlike supervised classification methods, K-Means does not rely on previously labeled observations. Instead, it discovers the natural structure of the environmental dataset by grouping observations with similar NDVI and precipitation characteristics. Consequently, the resulting clusters were interpreted only after the clustering process through an examination of their centroid values and environmental profiles, ensuring that the land-quality categories emerged from the data itself rather than from predefined thresholds.

3.3.5 Financing Risk Assessment

Following the K-Means clustering process, the environmental characteristics of the three identified clusters were analyzed by examining their centroid values, particularly the average NDVI and monthly precipitation levels.

The cluster exhibiting the highest average vegetation density (NDVI) together with the most favorable precipitation conditions was interpreted as representing high-quality agricultural land and was therefore associated with low financing risk. Conversely, the cluster characterized by the lowest vegetation density and the least favorable rainfall conditions was interpreted as low-quality agricultural land and associated with high financing risk. The remaining cluster represented intermediate environmental conditions and was consequently classified as moderate financing risk.

This interpretation was performed after the clustering process and was based exclusively on the environmental characteristics of the identified clusters rather than on predefined thresholds or manually assigned land-quality labels. Consequently, the proposed framework avoids methodological circularity while providing an objective and data-driven basis for agricultural land assessment.

Based on these three financing risk levels, the proposed decision-support framework recommends the following financing decisions:

- Low risk: Financing approved.
- Moderate risk: Financing approved subject to additional monitoring or contractual adjustments.
- High risk: Financing rejected or renegotiated.

By integrating remote sensing, Geographic Information Systems (GIS), climate data, and Artificial Intelligence, the proposed framework provides a transparent and objective approach for assessing agricultural land conditions and supports Sharia-compliant financing decisions while reducing information asymmetry and uncertainty (*gharar*) in Salam contracts.

4 Résultats

The empirical analysis generated a set of environmental clusters derived from the integration of NDVI and CHIRPS precipitation data using the K-Means algorithm. These results provide insights into the environmental heterogeneity of the study area and constitute the basis for the proposed financing risk assessment framework. The following subsections present the characteristics of the identified clusters, their spatial distribution, and their implications for Salam financing decisions.

4.1 K-Means Clustering Results

The integrated environmental dataset, comprising 420 spatial observations characterized by the Normalized Difference Vegetation Index (NDVI) and monthly CHIRPS precipitation values, was analyzed using the K-Means clustering algorithm, with the number of clusters fixed at $k = 3$. As an unsupervised machine-learning technique, K-Means automatically partitioned the observations into three homogeneous clusters according to similarities in their environmental characteristics, without relying on predefined class labels or manually established thresholds. Following the clustering process, the environmental characteristics of each cluster were examined by calculating the average NDVI and precipitation values. The interpretation of the clusters was performed after the clustering process and was based on their environmental profiles rather than on predefined classification rules. The cluster characterized by the highest average vegetation density (mean NDVI = 0.487) together with favorable precipitation conditions (mean precipitation = 42.14 mm) was interpreted as representing high-quality agricultural land. The second cluster exhibited intermediate vegetation conditions (mean NDVI = 0.273) despite relatively low precipitation (mean precipitation = 4.93 mm), suggesting that factors other than rainfall also influenced vegetation development, and was interpreted as medium-quality agricultural land. The third cluster presented the lowest vegetation density (mean NDVI = 0.124) despite moderate precipitation (mean precipitation = 37.49 mm), and was therefore interpreted as low-quality agricultural land.

The environmental profiles of the clusters reveal substantial differences in both vegetation condition and precipitation. In particular, the relatively low NDVI values observed in the third cluster despite moderate rainfall suggest that precipitation alone is insufficient to explain vegetation conditions. Other environmental factors, such as soil characteristics, irrigation practices, crop management, or local environmental conditions, may also influence vegetation development.

Overall, these results demonstrate that the K-Means algorithm successfully identified distinct environmental patterns within the study area based on the natural similarities of the environmental variables, thereby providing an objective basis for the subsequent financing risk assessment without introducing methodological circularity.

Table 1. Environmental characteristics of the identified clusters

Cluster	Mean NDVI	Mean precipitation (mm)	Environmental profile
Cluster 1	0.487	42.14	High-quality agricultural land
Cluster 2	0.273	4.93	Medium-quality agricultural land
Cluster 3	0.124	37.49	Low-quality agricultural land

Source: Authors' calculations based on the K-Means clustering results.

4.2 Spatial Distribution of Agricultural Land Quality

The K-Means algorithm classified the **420 spatial observations** into three homogeneous clusters representing different levels of agricultural land quality. The distribution of observations among the identified clusters is presented in Table 2.

Table 2. Distribution of observations among the identified clusters

Cluster	Number of observations	Percentage (%)	Interpretation
Cluster 1	159	37.86	High-quality agricultural land
Cluster 2	90	21.43	Medium-quality agricultural land
Cluster 3	171	40.71	Low-quality agricultural land
Total	420	100.00	

Source: Authors' calculations based on the K-Means clustering results.

The results reveal considerable spatial heterogeneity across the study area. This spatial variability confirms the ability of the K-Means algorithm to identify naturally occurring environmental patterns without imposing predefined classification thresholds. Approximately 37.86% of the observations were classified as high-quality agricultural land, while 21.43% corresponded to medium-quality land and 40.71% to low-quality land. This distribution reflects the variability of vegetation and rainfall conditions within the study area and highlights the ability of the K-Means algorithm to identify homogeneous environmental patterns without requiring manually defined thresholds.

4.3 Financing Risk Assessment

Following the clustering process, the environmental characteristics of the three identified clusters were interpreted in terms of financing risk for Salam contracts. This interpretation was performed after clustering by examining the average NDVI and precipitation values associated with each cluster, rather than by applying predefined classification thresholds.

The cluster characterized by the highest vegetation density and favorable rainfall conditions was associated with low financing risk, reflecting a higher agricultural production potential. Conversely, the cluster presenting the lowest NDVI values was interpreted as high financing risk, indicating less favorable environmental conditions for agricultural production. The remaining cluster represented intermediate environmental characteristics and was therefore associated with moderate financing risk.

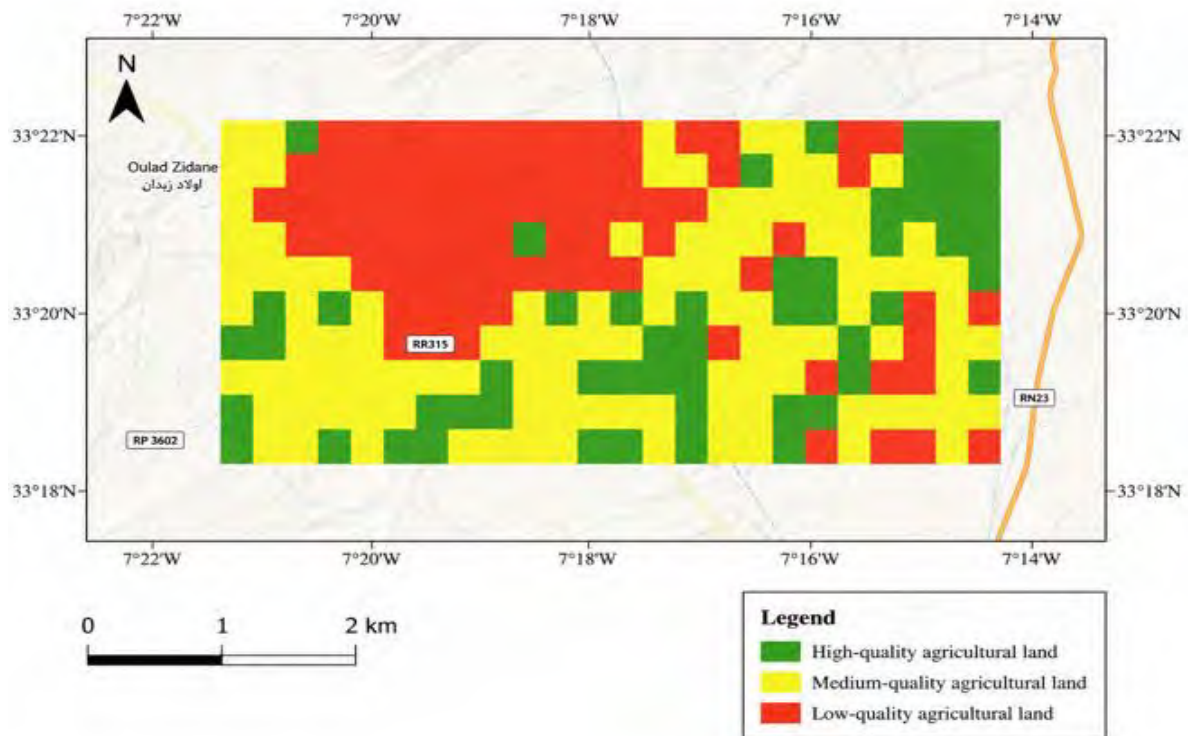
This interpretation provides an objective basis for financing decisions while avoiding methodological circularity between the explanatory variables and the classification outcome. Based on these three financing risk levels, the proposed decision-support framework recommends the following financing actions:

- **Low financing risk:** Financing approved.
- **Moderate financing risk:** Financing approved subject to additional monitoring or contractual adjustments.
- **High financing risk:** Financing rejected or renegotiated.

4.4 Spatial Classification Map

To visualize the spatial distribution of agricultural land quality, the clustering results obtained from the K-Means algorithm were integrated into the Geographic Information System (GIS) environment. Figure 4 presents the spatial distribution of the three clusters identified from the combined NDVI and CHIRPS precipitation dataset.

Figure 4. Spatial distribution of agricultural land quality obtained from K-Means clustering based on NDVI and CHIRPS precipitation data.



Source: Prepared by the authors using Sentinel-2 imagery, CHIRPS rainfall data, Google Earth Engine, and QGIS.

The map illustrates the spatial organization of agricultural land according to the environmental similarities identified by the K-Means algorithm. Areas displayed in green correspond to the cluster interpreted as high-quality agricultural land, characterized by relatively high vegetation density and favorable environmental conditions. Yellow areas represent medium-quality agricultural land, reflecting intermediate environmental characteristics, whereas red areas indicate low-quality agricultural land, associated with less favorable vegetation and climatic conditions.

The observed spatial distribution reveals substantial heterogeneity across the study area, highlighting the existence of distinct environmental zones with different agricultural production potentials. Unlike conventional threshold-based classification methods, the proposed approach identifies these zones through unsupervised machine learning by grouping observations according to their natural similarities in NDVI and precipitation values.

From a practical perspective, the spatial classification map provides an effective decision-support tool for Salam financing. It enables Islamic financial institutions to visualize areas presenting different levels of agricultural potential and financing risk, thereby facilitating more objective, transparent, and evidence-based financing decisions. By integrating remote sensing, Geographic Information Systems, climate information, and Artificial Intelligence, the proposed framework contributes to reducing information asymmetry and uncertainty (*gharar*) while supporting Sharia-compliant financing decisions.

5. Discussion

The present study proposed an integrated framework combining remote sensing, Geographic Information Systems (GIS), climate data, and unsupervised machine learning to support financing decisions in Salam contracts. By classifying agricultural land according to its environmental characteristics rather than predefined thresholds, the proposed approach provides an objective basis for evaluating agricultural production potential while contributing to the reduction of information asymmetry (*gharar*) in Islamic agricultural finance. The discussion below interprets these findings in relation to previous research, highlights their practical implications, and identifies the main limitations of the proposed framework.

5.1 Interpretation of the Clustering Results

The K-Means clustering algorithm successfully identified three environmentally homogeneous groups representing different levels of agricultural land quality. The environmental profiles of the clusters reveal substantial differences in both vegetation condition and precipitation. The cluster characterized by the highest average NDVI values together with favorable rainfall conditions exhibited the greatest agricultural production potential, whereas the cluster presenting the lowest vegetation density was associated with less favorable environmental conditions.

These findings confirm the relevance of NDVI as a reliable indicator of vegetation vigor and agricultural performance, consistent with the conclusions of Xue and Su (2017), who highlighted the importance of vegetation indices derived from remote sensing for environmental monitoring and agricultural assessment. The results also support the observations of Binte Mostafiz et al. (2021), who demonstrated that satellite-derived environmental indicators can effectively differentiate agricultural land according to their productive potential.

Although precipitation contributed to distinguishing the environmental profiles of the identified clusters, the results indicate that rainfall alone cannot fully explain vegetation conditions. This observation suggests that vegetation dynamics are influenced by the interaction of multiple environmental factors, including soil conditions, irrigation practices, and local management systems. Such findings are consistent with previous studies emphasizing the multidimensional nature of agricultural ecosystems (Kamilaris & Prenafeta-Boldú, 2018).

Unlike conventional land evaluation approaches based on predefined thresholds, the proposed framework identifies natural structures directly from the environmental data through unsupervised learning. This data-driven approach reduces subjective intervention and avoids methodological circularity, thereby providing a more objective basis for agricultural land assessment.

5.2 Practical Implications for Salam Financing

The environmental clusters identified through K-Means clustering provide a practical decision-support framework for Salam financing. Since Salam contracts involve advance payment for future agricultural production, reducing uncertainty regarding production capacity is essential for protecting both contracting parties and ensuring compliance with Sharia principles.

The proposed framework enables agricultural land to be classified according to objectively measured environmental conditions before financing decisions are made. Agricultural areas characterized by favorable vegetation and climatic conditions can therefore be associated with lower financing risk, whereas areas presenting less favorable environmental conditions may require additional contractual safeguards or financing adjustments.

Rather than replacing expert assessment, the proposed framework should be viewed as a complementary decision-support tool capable of improving the transparency, consistency, and objectivity of agricultural land evaluation.

Table 5. Relationship between environmental clusters, financing risk levels, and financing decisions

Environmental cluster	Financing risk	Recommended financing decision
High-quality agricultural land	Low	Financing approved
Medium-quality agricultural land	Moderate	Financing approved with additional monitoring or contractual adjustments
Low-quality agricultural land	High	Financing rejected or renegotiated

Source: Authors' interpretation based on the K-Means clustering results.

5.3 Comparison with Previous Studies

The findings of this study complement and extend several strands of previous research discussed in the literature review.

Studies focusing on Salam financing, such as those of Atah et al. (2019) and Mulyany et al. (2021), emphasized the importance of improving risk management and financing procedures within Salam contracts. However, their analyses remained primarily conceptual and institutional, without incorporating objective environmental indicators capable of assessing agricultural production potential before financing decisions are made. The present study extends this literature by introducing a quantitative and data-driven framework based on environmental information derived from remote sensing and climate data.

Similarly, previous studies on Artificial Intelligence and Islamic finance highlighted the growing role of digital technologies in improving financial decision-making and operational efficiency (Firmansyah & Anwar, 2022; Rabbani et al., 2021). Nevertheless, these studies focused mainly on Islamic banking services and financial innovation rather than agricultural financing. The present research contributes to this emerging literature by demonstrating how Artificial Intelligence can be applied specifically to Salam financing through environmental risk assessment.

From an agronomic perspective, the results are consistent with the work of Xue and Su (2017), Kamilaris and Prenafeta-Boldú (2018), Talukdar et al. (2020), and Binte Mostafiz et al. (2021), who demonstrated the effectiveness of remote sensing and machine-learning techniques for environmental monitoring and agricultural land classification. However, unlike these studies, which were primarily concerned with agronomic evaluation, the present framework explicitly links environmental classification to financing decisions within an Islamic finance context.

Consequently, the main contribution of this study lies in bridging three research streams that have largely evolved independently: Salam financing, Artificial Intelligence in Islamic finance, and remote sensing-based agricultural assessment. By integrating these dimensions within a unified decision-support framework, the study provides a novel application of geospatial intelligence and unsupervised machine learning for Islamic agricultural finance.

5.4 Comparison with Conventional Agricultural Assessment

Compared with conventional agricultural land assessment procedures based mainly on field inspections and expert judgment, the proposed framework offers several operational advantages.

Table 6. Qualitative comparison between conventional agricultural assessment and the proposed framework

Criterion	Conventional assessment	Proposed framework
Data source	Field observations and expert reports	Sentinel-2, CHIRPS, GIS
Cost	Relatively high	Relatively low through open-access environmental data
Processing time	Several days or weeks	Rapid after data acquisition
Objectivity	Depends on expert judgement	Data-driven and reproducible
Spatial coverage	Limited	Large geographical coverage
Updating	Periodic field surveys	Regular updates using satellite imagery

Source: Authors' qualitative comparison.

The comparison presented in Table 6 is qualitative and is intended to illustrate the operational characteristics of the two approaches rather than to provide a quantitative benchmarking exercise. Future studies involving real-world implementations within Islamic financial institutions would enable a more rigorous quantitative comparison.

5.5 Contribution to Islamic Financial Engineering

The principal contribution of this study lies in the integration of Artificial Intelligence with remote sensing technologies to support financing decisions in Salam contracts.

By combining satellite-derived vegetation indices, precipitation information, Geographic Information Systems, and unsupervised machine learning, the proposed framework introduces a transparent and reproducible methodology for evaluating agricultural land quality. This approach contributes to reducing information asymmetry (*gharar*) by providing objective environmental evidence before financing decisions are made.

Although the proposed framework does not replace the expertise of agricultural specialists, it provides an additional analytical layer capable of supporting more informed and consistent financing decisions. From the perspective of Islamic financial engineering, this represents an innovative application of Earth observation technologies to agricultural financing while preserving compliance with the principles of Sharia.

5.6 Limitations and Future Research

Despite the contributions of the proposed framework, several limitations should be acknowledged. First, the empirical analysis was conducted within a single agricultural area located in the Casablanca–Settat region of Morocco and relied on environmental observations collected between January 2024 and June 2025. Although the study demonstrates the feasibility of integrating Artificial Intelligence, remote sensing, Geographic Information Systems (GIS), and climate data for Salam financing, the limited spatial and temporal scope may restrict the generalizability of the findings to other agricultural and climatic contexts.

Second, the analysis was based exclusively on two environmental indicators, namely the Normalized Difference Vegetation Index (NDVI) and CHIRPS precipitation data. While these variables provide valuable information regarding vegetation conditions and rainfall variability, agricultural productivity is also influenced by additional factors such as soil properties, irrigation practices, crop type, topography, and water availability. Incorporating such variables could improve the comprehensiveness of agricultural land assessment.

Third, although the K-Means algorithm provides an objective and data-driven classification of agricultural land without relying on predefined labels, the practical relevance of the identified clusters should be further validated. Future research should compare the clustering results with independent agricultural production indicators, such as crop yields, and complement the quantitative analysis with expert evaluations involving agronomists and Islamic finance practitioners.

Finally, future studies should extend the analysis to multiple agro-climatic regions and longer observation periods covering several agricultural seasons. Such a research design would make it possible to evaluate the stability and robustness of the identified environmental clusters under different climatic conditions. In addition, comparing K-Means with alternative unsupervised learning techniques, such as Hierarchical Clustering, Gaussian Mixture Models, and DBSCAN, could provide further evidence regarding the suitability of Artificial Intelligence methods for supporting transparent, objective, and Sharia-compliant Salam financing decisions.

5. Conclusion

This study proposed an integrated decision-support framework combining remote sensing, Geographic Information Systems (GIS), climate data, and Artificial Intelligence to support financing decisions in Salam contracts. By integrating satellite-derived NDVI and CHIRPS precipitation data within a K-Means clustering framework, the study demonstrated that unsupervised machine learning can objectively identify homogeneous agricultural land profiles without relying on predefined land-quality thresholds or manually assigned class labels.

The empirical results showed that the proposed framework successfully distinguished three environmental profiles corresponding to different levels of agricultural land quality. These profiles were subsequently interpreted as low-, moderate-, and high-financing risk categories, providing a structured basis for supporting financing decisions in Salam contracts. Unlike conventional assessment approaches that often depend on expert judgment or predefined decision rules, the proposed methodology relies on environmental similarities extracted directly from satellite observations and climate information, thereby improving the consistency and transparency of agricultural land assessment.

From a theoretical perspective, this research contributes to the literature by integrating Islamic financial engineering, Artificial Intelligence, remote sensing, Geographic Information Systems, and environmental analysis within a unified framework for Salam financing. Methodologically, it demonstrates the potential of unsupervised machine learning for agricultural land assessment while avoiding methodological circularity associated with supervised classification approaches. Practically, the proposed framework offers Islamic financial institutions an evidence-based decision-support tool capable of facilitating agricultural financing decisions through objective environmental assessment.

The findings also have broader implications for the governance of Islamic finance. The proposed framework may support Sharia supervisory boards, Islamic financial regulators, and standard-setting institutions by providing transparent environmental information that complements traditional financing assessment procedures. Although quantitative decision-support tools cannot replace Sharia governance or human expertise, they may contribute to strengthening transparency, consistency, and accountability in the evaluation of Salam financing applications.

Several limitations should nevertheless be considered when interpreting the findings. The study was conducted within a single agricultural region and relied on a relatively limited observation period and a restricted set of environmental indicators. In addition, the proposed classification framework has not yet been validated using independent agricultural production data or expert assessments. These limitations are discussed in greater detail in Section 5.6.

Future research should focus on validating the framework across different agro-climatic regions and longer observation periods while incorporating additional environmental and agricultural indicators. Comparative analyses involving alternative Artificial Intelligence techniques and collaborations with Islamic financial institutions would further strengthen the practical applicability and robustness of the proposed approach. Such developments may also contribute to the establishment of appropriate governance mechanisms for the responsible use of Artificial Intelligence in Islamic agricultural finance.

Overall, this study demonstrates that the integration of geospatial technologies and Artificial Intelligence can provide valuable support for agricultural financing decisions while remaining consistent with the principles of Salam contracts. By combining environmental intelligence with Sharia-compliant financial practices, the proposed framework represents a promising step toward more informed, transparent, and sustainable Islamic agricultural finance.

Références :

- (1). Mulyany, R., Indriani, M., & Indayani, I. (2021). Salam financing : From common local issues to a potential international framework. *International Journal of Islamic and Middle Eastern Finance and Management*, 15(1), 203–217. <https://doi.org/10.1108/IMEFM-01-2020-0008>
- (2). Al-Bukhari, M. I. (1997). *Sahih al-Bukhari*. Dar Ibn Kathir.
- (3). Al-Zuhayli, W. (2006). *Financial transactions in Islamic jurisprudence* (Vols. 1–2). Dar Al-Fikr.
- (4). Atah, U. I., Mohammed, M. O., Adawiyya, E. R., & Adeyemi, A. A. (2019). Proposed secured Bay-Salam model for financing agriculture by Islamic banks. *International Journal of Management and Applied Research*, 6(4), 181–195. <https://doi.org/10.18646/2056.64.19-013>
- (5). Binte Mostafiz, R., Noguchi, R., & Ahamed, T. (2021). Agricultural land suitability assessment using satellite remote sensing-derived soil–vegetation indices. *Land*, 10(2), Article 223. <https://doi.org/10.3390/land10020223>
- (6). El-Gamal, M. A. (2006). *Islamic finance: Law, economics, and practice*. Cambridge University Press. <https://doi.org/10.1017/CBO9780511753756>
- (7). Firmansyah, E. A., & Anwar, M. (2022). Islamic financial technology (FinTech): Literature review and future research agenda. *Sustainability*, 14(17), Article 10826. <https://doi.org/10.3390/su141710826>
- (8). Ibn Qudamah, A. M. (1997). *Al-Mughni* (Vol. 4). Dar Alam Al-Kutub.
- (9). Jain, A. K. (2010). Data clustering: 50 years beyond K-means. *Pattern Recognition Letters*, 31(8), 651–666. <https://doi.org/10.1016/j.patrec.2009.09.011>
- (10). Kahf, M. (1996). *Islamic economics: Notes on definition and methodology*. Islamic Research and Training Institute (IRTI), Islamic Development Bank.
- (11). Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90. <https://doi.org/10.1016/j.compag.2018.02.016>
- (12). MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations. In L. M. Le Cam & J. Neyman (Eds.), *Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability* (Vol. 1, pp. 281–297). University of California Press.
- (13). Mathenge, M., Sonneveld, B. G. J. S., & Broerse, J. E. W. (2023). Mapping the spatial dimension of food insecurity using GIS-based indicators: A case of Western Kenya. *Food Security*, 15(1), 243–260. <https://doi.org/10.1007/s12571-022-01308-6>
- (14). Muslim, I. A. H. (2000). *Sahih Muslim*. Darussalam.
- (15). Rabbani, M. R., Bashir, A., Nawaz, N., Karim, S., Abdullah, Y., & Rahiman, H. U. (2021). Exploring the role of Islamic FinTech in combating the aftershocks of COVID-19: The open social innovation of the Islamic financial system. *Journal of Open Innovation: Technology, Market, and Complexity*, 7(2), Article 136. <https://doi.org/10.3390/joitmc7020136>
- (16). Sifa, E. N., & Wiryono, S. K. (2024). How does Salam financing affect farmers' income? A system dynamics approach. *Journal of Islamic Accounting and Business Research*, 15(1), 119–135. <https://doi.org/10.1108/JIABR-02-2022-0042>
- (17). Talukdar, S., Singha, P., Mahato, S., Pal, S., Liou, Y. A., & Rahman, A. (2020). Land-use land-cover classification by machine learning classifiers for satellite observations—A review. *Remote Sensing*, 12(7), Article 1135. <https://doi.org/10.3390/rs12071135>
- (18). Usmani, M. T. (2002). *An introduction to Islamic finance*. Kluwer Law International.

- (19). Varzakas, T., & Smaoui, S. (2024). Global food security and sustainability issues: The road to 2030 from nutrition and sustainable healthy diets to food systems change. *Foods*, 13(2), Article 306. <https://doi.org/10.3390/foods13020306>
- (20). Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of Sensors*, 2017, Article 1353691. <https://doi.org/10.1155/2017/1353691>