Final - A Comprehensive Report

Academic Research in the Field of Remote Sensing in Agriculture and AI

For the Implementation of Preliminary Research of an AI Proof-of-Concept

Title: Determining Soil Fertility for Agriculture with Water Saving Using Satellite Image and AI

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1 Introduction

The Hashemite Kingdom of Jordan is located in western Asia at approximately 31° 16' 47.50" N latitude and 37° 07' 47.08" E longitude. As a resource-poor, middle-income country, Jordan faces complex environmental challenges. The total budget for water use in all sectors is about (1286) million cubic meters, with agriculture consuming about (534) million cubic meters [19].

Jordan's landscape is predominantly desert (91%), characterized by arid and semi-arid regions and steep slopes. The altitude varies dramatically, ranging from below sea level at -392 m to 1,854 m at Mount Umm Dami. However, the total area of the slope is less than (6%) about (5,300 km^2), representing about 60% of the total territory of the Kingdom, and these areas occur in the plains of Irbid, Madaba, Karak, Shobak, tafilah, eastern desert, basalt plains in the North, basalt plateau in the northeast and the main lowlands such as Azraq, Jafr, DISA, Al-Ahasa, (Hafira - Jinz Depressions 31° 6'20.81" N and 36°11'34.22"E). The climate ranges from a semi-humid Mediterranean in the Northwest, where the annual rainfall is about (450-600 mm), to a desert climate with rainfall less than 50-100 mm to the East. Jordan has a total area of 89,318 km^2 and a population of 11,734,000 million [11]

Agriculture accounts for a staggering 69% of global freshwater consumption, underscoring the critical need for smarter water management. AI-driven precision agriculture is revolutionizing water utilization in farming, which is essential for addressing the pressing issue of water scarcity. This report presents a proof-of-concept program aimed at enhancing precision farming techniques, with a special focus on forecasting critical soil characteristics and improving irrigation timing in agricultural land management using the latest technology GeoAI-Geospatial Artificial Intelligence The program has two main objectives: first, to develop and train artificial intelligence models that accurately predict key soil characteristics—such as nitrogen (N), phosphorus (P), potassium (K), electrical conductivity (EC), pH, and soil moisture—tailored to Jordan's unique soil types and agricultural conditions; and secondly, determining the optimal timing of irrigation based on soil moisture levels, weather data, and crop requirements. By integrating artificial intelligence models with spectral data extracted from satellite images and utilizing drones for data collection, this initiative aims to improve resource efficiency, promote crop health, and support sustainable farming practices in Jordan's distinct environmental context.

Accurate soil characterization is essential for effective crop management and resource allocation, particularly in Jordan, where water scarcity, traditional soil analysis methods are limited in scale, and responsiveness, and soil degradation significantly hinder agricultural productivity. but integrating high-resolution multispectral and hyperspectral imagery from drones or satellites can offer real-time insights into soil variability. By combining traditional machine learning with advanced deep learning techniques, the project aims to enhance the accuracy and scalability of predictive models. However, challenges persist, particularly in accessing the high-quality and diverse datasets required for developing robust and reliable models.

2 Report Description

This comprehensive report outlines the requirements of a Proof of Concept (PoC) program designed to predict soil properties (NPK, EC, pH, and soil moisture) and optimize water irrigation timing for farmland. The program leverages a combination of satellite imagery, IoT sensor data, and AI/ML, and DL techniques, moreover, the report provides a detailed analysis and framework for implementing the PoC program in Jordan, utilizing advanced geospatial and AI-based technologies. It includes a review of global literature and technical advancements, an analysis of the local market, and an evaluation of technological and socio-economic factors. the research aligns with the Scope of Work (SoW) and focuses on the following key areas: Key objectives of the report include the Scope of Work(SoW):

1. **Literature Review and Evaluation:**

   - A thorough review of global research papers and technical information related to the PoC program, focusing on AI and remote sensing applications using satellite imagery, drones, and IoT.
   - Analysis and evaluation of selected studies on AI applications for predicting soil properties (NPK, pH, EC, soil moisture) and optimizing irrigation timing in Jordan, categorized into:
     (a) Traditional Machine Learning (2010-2015).
     (b) Deep Learning Revolution (2015-2020).
     (c) Hybrid Models with Transformers (2018-Present).
   - The availability of diverse data sources:
     (a) Satellite imagery
     (b) UAV data

   (c) Soil measurements (IoT, Lab)

- **Performance metrics:**
   (a) Accuracy
   (b) Cost
   (c) Accessibility
- Challenges such as data availability and overall expenditure.

2. **Data Availability and Cost Analysis:** An assessment of the availability and cost of relevant data sources,including:

   - Satellite Imagery: Evaluation of various satellite imagery options (for Research, such as PRISMA, open-source, such as Landsat and Sentinel, and commercial providers, such as Worldviews-3 and OHS), considering spatial and spectral resolution, revisit frequency, and cost.
   - IoT Sensor Data: Assess the availability and cost of IoT sensors for measuring soil moisture, temperature, humidity, and other relevant parameters.
   - Laboratories data, for available costs and the types of analyses how can the providers of these services to improve PoC project outcomes.
   - AI Model Selection and Evaluation: Exploration and evaluation of suitable AI/ML models for predicting irrigation timing, and soil property AI model considering factors such as accuracy, computational cost, and interoperability.
   - Technical and socio-economic: Analysis of the technical feasibility of implementing the PoC program, including the availability of necessary infrastructure (e.g., computing resources, data storage), and an evaluation of the potential economic benefits and return on investment.

3 Scope of Work

The impact of artificial intelligence (AI) has permeated numerous domains, with precision agriculture emerging as a significant beneficiary of these technological advances. Given the extensive body of research in this field, this review focuses on a curated selection of studies examining AI applications with satellite images in predicting soil properties and irrigation timing on farmland, with particular emphasis on water-scarce regions.

This comprehensive analysis encompasses recent scientific literature on AI models designed to predict key soil properties (NPK, pH, EC, soil moisture) and optimize irrigation timing on farmland. The review is structured into three primary categories: traditional machine learning approaches (2010-2015), deep learning revolution (2015-2020), and hybrid models incorporating transformers(2018-present).

A critical aspect of the analysis centers on the diverse data sources utilized by these AI models, including various types of satellite imagery, unmanned aerial vehicle (UAV)- drone data, and soil measurements. The evaluation framework considers multiple performance metrics, including accuracy and related statistical measures, along with implementation costs and accessibility considerations.

Data availability emerged as a significant constraint in this domain, as researchers face challenges in acquiring comprehensive datasets that adequately address their research objectives. The literature reveals two primary approaches to this challenge: utilization of open-source datasets or investment in commercial data sources.

A recurring theme across the reviewed studies is the substantial computational requirements such as using (GPU or TPUs) associated with processing large-scale agricultural datasets and implementing computationally intensive algorithms. This computational burden represents a significant consideration for the practical implementation of these technologies.

The emergence of the Internet of Things (IoT) in the farming field has introduced a paradigm shift in agricultural data collection and processing methodologies. The IoT infrastructure, comprising interconnected sensor networks, automated monitoring systems, and real-time data analytic platforms, has significantly enhanced the capability to gather data. This technological integration has facilitated more precise model training and validation processes, while simultaneously introducing new challenges in data management, standardization, and system interoperability across diverse agricultural settings.

3.1 Elaborate available research Papers

The prediction of soil property and optimization of irrigation timing has garnered significant attention in recent years, especially with the rapid advancements in artificial intelligence (AI) and remote sensing technologies. A comprehensive review of the available literature revealed a rich array of research papers that investigate different aspects of these themes through the lens of various methodologies. We will categorize the review papers into three stages as follows:

3.1.1 AI model prediction Soil Properties with satellite images

Research in soil property prediction has evolved through several stages, reflecting the progression of machine learning and deep learning techniques. Early studies predominantly employed traditional machine learning algorithms, focusing on establishing relationships between soil property, water timing, and various environmental factors. A comprehensive review of the existing literature, research papers, and technical resources related to the project was carried out, identifying the main gaps in the current understanding and classifying these gaps into three distinct periods: **Figure** 1

3.1.1.1 Traditional Machine Learning Approaches (2010-2015)

The early 2010s marked the foundation of computational approaches in soil property prediction. Initially, researchers primarily relied on conventional machine learning techniques, with Support Vector Machines (SVM) and Random Forests (RF) dominating the landscape. These methods demonstrated promising results in correlating spectral data with soil properties, though they were limited by their ability to handle complex, non-linear relationships in high-dimensional data by using remote sensing data and the VIC model, and comparison of SVM with ANN and MLR provides valuable insights into the relative strengths and weaknesses of different machine learning approaches for soil moisture estimation. [4]

This research paper reviewed the use of Remote Sensing (RS) techniques for determining soil properties in Precision Agriculture (PA), emphasizing their role in enhancing the efficiency and accuracy of soil mapping. The findings indicate that RS methods, such as satellite and aerial imagery, provide a cost-effective and rapid alternative to traditional grid sampling for gathering agricultural data. RS has been effectively applied to estimate various soil properties, including texture, organic matter, nutrients, moisture content, and pH. The visible and near-infrared regions of the electromagnetic spectrum are primarily used for these estimations. Techniques like Multiple Linear Regression (MLR), Principal Component Regression (PCR), and Partial Least Squares Regression (PLSR) are commonly employed for analyzing RS data to predict soil properties. Multiple Linear Regression (MLR) and Partial Least Squares Regression (PLSR) also played crucial roles during this phase, particularly in handling the high dimensionality of spectral data. These methods proved especially valuable when working with limited training datasets, which was often the case due to the cost and time constraints of soil sampling programs[20].

This research paper focuses on the critical need for accurate and high-resolution soil data to address global challenges like food security and soil sustainability.

to enhance the spatial resolution of soil moisture data from the AMSR2 satellite, downscaling it to 1 km using MODIS products. This research Two were employed machine learning models, Ordinary Least Squares (OLS), and Random Forest (RF), with RF outperforming OLS ($R^2 = 0.96$, RMSE = 0.06) due to its flexibility. Influential variables for downscaling included land surface temperature times Normalized Difference Vegetation Index and evapotranspiration. The study noted that the VUA-NASA AMSR2 algorithm might overestimate soil moisture at high elevations based on differing ground data. Overall, the research successfully improved satellite soil moisture data for localized applications [40].

The paper emphasizes the importance of integrating various data sources, including lab-based measurements, field observations, proximal sensors (e.g., handheld devices), and remote sensing data (e.g., satellite imagery, UAVs). The study utilized the STEP-AWBH model (Soil-Environmental Covariates) as a framework to integrate these diverse data sources. Also, the paper explores different approaches for fusing data from various sensors, including proximal sensors, remote sensors, and their combinations, to predict soil properties. The paper acknowledges the limitations and challenges associated with each data source and integration method, highlighting the need for careful consideration and evaluation [21].

3.1.1.2 Deep Learning Revolution (2015-2020)

After-2015s witnessed a paradigm shift with the introduction of deep learning architectures in soil science. This period saw the emergence of Convolutional Neural Networks (CNNs) as powerful tools for extracting features from spectral data. The breakthrough came with the ability to simultaneously predict multiple soil properties from a single spectral measurement. A significant advancement introduced a deep learning framework combining CNNs with attention mechanisms. This architecture could effectively process both hyperspectral data and auxiliary environmental variables, improving prediction accuracy by 15-20% compared to traditional methods.

The period also saw the development of specialized architectures:

- **1D-CNNs for Spectral Analysis:** Specifically designed to process continuous spectral signatures, these networks showed remarkable success in handling the sequential nature of spectroscopic data.

- **Residual Networks (ResNets):** Implementation of skip connections allowed for deeper architectures, enabling better feature extraction from complex soil spectra.

- **Ensemble Approaches:** Combining multiple deep learning models with traditional machine learning algorithms to leverage the strengths of both approaches.

To map the spatial distribution of key soil properties (organic carbon, pH, and electrical conductivity) in Bukkarayasamudrum Mandal, India, this study aimed to use a combination of field data, satellite imagery, and machine learning (Random Forest Model - RFM). Researchers collected 116 soil samples from various physiographic land units and high-resolution satellite imagery (IRS LISS IV), along with terrain attributes and vegetation indices (NDVI, EVI). The RFM was developed to predict soil properties based on this comprehensive dataset, chosen for its robustness and capacity to handle multiple predictors. Model performance was evaluated using R-squared and Lin's Concordance Coefficient, revealing reasonable accuracy, particularly for electrical conductivity. Key predictors identified included NDVI, EVI, and drainage characteristics[12] develop a method to predict soil properties (organic carbon, nitrogen, phosphorus, potassium) in an alpine grassland dominated by Stipa purpurea on the Qinghai-Tibet Plateau, using hyperspectral remote sensing data in this study. Hyperspectral data were collected from 67 sample points alongside corresponding soil samples for lab analysis. The researchers analyzed correlations between soil properties and spectral bands, developing stepwise regression models to predict soil properties from this data. The models showed relative RMSE values of 68.9%, 46.3%, 31.4%, and 45.5% for the respective soil properties, demonstrating the effectiveness of hyperspectral data for accurate soil property predictions. The enhanced spectral variables from satellite imagery yielded reasonable spatial distributions of the target soil properties[52] explores the use of Convolutional Neural Networks (CNNs) for predicting soil properties from diffuse reflectance infrared spectroscopy data, demonstrating their effectiveness in improving soil property mapping and monitoring. CNNs outperformed traditional methods like PLS and Cubist regression in predicting multiple soil properties simultaneously, with an 87% reduction in prediction error for soil organic carbon compared to PLS.

Representing spectral data as a 2D spectrogram significantly enhanced CNN performance. The research underscores the importance of large datasets for training effective CNN models. Access to high-quality datasets is crucial for successful model training and validation [48].

In Germany, soil moisture and temperature were estimated using both in situ measurements and hyperspectral imagery collected in Karlsruhe, in May 2017. A TRIME-PICO time-domain reflectometry (TDR) sensor recorded soil moisture at a depth of 2 cm, while hyperspectral images were captured with a Cubert UHD 285 camera, producing 50 x 50-pixel images with 125 spectral bands (450 nm to 950 nm) at a 4 nm resolution. The five-day field campaign provided valuable data, but the dataset lacks a coordinate system for the sample collection locations [37].

3.1.1.3 Current State-of-the-Art Models (2020-present)

This research demonstrates the potential of UAV-based remote sensing and deep learning techniques for optimizing fertilizer applications in agriculture. The high accuracy of the developed CNN model highlights the effectiveness of this approach in predicting soil macro-nutrient concentrations and identifying areas of nutrient deficiency or surplus. This technology has the potential to significantly improve fertilizer use efficiency, reduce environmental impacts, and enhance agricultural sustainability. The study successfully developed a Convolutional Neural Network (CNN)-based model to predict in-field NPKC (Nitrogen, Phosphorus, Potassium, and Carbon) concentrations in soil.

The advanced model achieved high accuracy with R-squared values ranging from 0.83 to 0.98, demonstrating its effectiveness in predicting soil macronutrient levels. The model can help identify areas of nutrient surplus or deficiency within the field, enabling more targeted and efficient fertilizer applications [28]

- Some papers to evaluate the accuracy of SoilGrids 2.0, a global soil database, this paper case study in the arid Thar Desert region of India. The paper compared SoilGrids 2.0 predictions of soil texture (sand, silt, clay) and pH with in-situ measurements. While SoilGrids 2.0 showed some discrepancies in predicting specific soil fractions, it demonstrated a general agreement with field observations, particularly in terms of soil texture classes. The study highlights the potential of SoilGrids 2.0 as a valuable tool for soil information systems, while also emphasizing the need for continuous improvement by incorporating more local soil data to enhance its accuracy in specific regions [10]

- To investigate the use of both Sentinel-2 and ZH-1 satellite data, along with machine learning algorithms (Random Forest and XGBoost), to map soil total Nitrogen (N) and Olsen-P content in agricultural fields. Satellite Performance: Sentinel-2 excelled in predicting total N, while ZH-1 showed better performance in predicting Olsen-P. Machine Learning Accuracy: Both RF and XGBoost algorithms demonstrated high accuracy in predicting soil nutrient content, with R-squared values exceeding 0.7 for both total N and Olsen-P, ZH-1 Advantage: ZH-1's higher spatial and spectral resolution likely provided more detailed information, leading to improved accuracy in predicting Olsen-P content [54]

- Computer vision techniques suggested for this paper, deep learning, have the potential to achieve high accuracy in identifying crop nutrient deficiencies. Early detection of nutrient deficiencies can enable timely interventions, potentially leading to significant cost savings in terms of fertilizer applications and reduced crop losses [44]

- Recent years have witnessed sophisticated approaches that integrate multiple data sources and advanced architectural innovations. The introduction of transformer models in soil science has revolutionized how temporal and spatial dependencies are handled.

- This paper highlights the promising potential of deep learning for predicting soil properties. While the MCA-CNN model demonstrates high accuracy, a comprehensive evaluation should consider factors like computational cost, data availability, and environmental impact for a complete understanding of its feasibility and sustainability.

- In this study the authors aimed to use a new convolutional neural network architecture (MCA-CNN) combined with visible and near-infrared spectroscopy for predicting soil properties (pH, (OC), (N), Clay, Salt, and Sand)[45]

  This study investigates the use of remote sensing data (Landsat 8 and Sentinel 2) and machine learning models (Random Forest, XGBoost, Decision Tree, and Support Vector Machine) to predict soil salinity (electrical conductivity) in a region of Northeast Iran. The study found that the Decision Tree model achieved the highest accuracy in predicting soil salinity, with high R-squared values and low RMSE and MAE. Key salinity indices derived from remote sensing data, such as Multi-resolution Valley Bottom Flatness, moisture index, and topographic indices (TWI and TPI), were identified as important predictors. Furthermore, time series analysis revealed a reduction in salinity and sodium levels in areas with drainage networks, demonstrating the effectiveness of such interventions [6]

- To address the soil salinization problem in Siwa Oasis, Egypt, and China, a novel deep learning-based approach was developed using a modified U-NET (MU-NET) architecture combined with Landsat 8 satellite imagery to accurately map and monitor the spatial and temporal dynamics of salinity and vegetation. The study highlights the increasing spatial distribution of salinity in the region, indicating accelerating soil degradation. The MU-NET model showed high accuracy in segmenting the salinity and vegetation zones, outperforming other methods, with accuracy exceeding 90% [16], [53], the other paper investigates the use of UAV-based multispectral remote sensing and deep learning techniques to accurately map and monitor soil salinity in sunflower fields along the southern bank of the Yellow River, a region heavily impacted by soil salinization. The research demonstrates the superior performance of the Transformer model compared to other machine learning models (BPNN, RF, PLSR) in predicting soil salinity content (SSC). The inclusion of the RE band significantly improved prediction accuracy. The study observed variations in model accuracy across different crop growth stages, with higher accuracy in the bare soil stage compared to the crop cover stage. [51], China, by developing a multi-indicator soil salinity monitoring model for GEE. The model integrates multiple predictors (spectral, salinity, composite indices, and topographic factors) and employs machine learning algorithms (RF, PLS, CART, SVM) to estimate soil salinity at different depths (0-20 cm and 20-40 cm). The Random Forest (RF) model demonstrated the highest accuracy, with R-squared values exceeding 0.7. Spatial analysis revealed significant changes in soil salinity over the study period (2002-2022), with an initial increase followed by a decline in recent years.[55]

The advanced approach using Landsat 8 images and geostatistical methods was used to accurately map soil salinity in Yichang Irrigation District, China. By addressing the scale mismatch between ground-point measurements and pixel-based remote sensing data, the study developed a group learning approach to improve soil salinity prediction.[7] To optimize mineral nutrition for grain crops in Kazakhstan through the efficient use of mineral fertilizers based on economic needs. Given the vast agricultural resources in the region, remote sensing tools were employed as an optimal solution for diagnosing essential plant nutrients. The research utilized remote sensing data analysis methods to predict nitrogen, phosphorus, and potassium (NPK) content in southern chernozems in Northern Kazakhstan [30].

This study explores the use of short-wavelength visible and near-infrared spectroscopy (450-1050 nm) combined with machine learning algorithms (kNN, adaboost, and random forest) to predict nitrogen (N), phosphorus (P), and potassium (K) contents in tropical dry agricultural soils from Aceh Province, Indonesia. The study found that the kNN algorithm with minimum and maximum normalization achieved the highest prediction accuracy, with an RPD (ratio of performance to deviation) value exceeding 4.1 for all three elements. These results demonstrate the potential of this approach for rapid, accurate, and cost-effective soil analysis in tropical dry agriculture.[35]

another advanced AI method that study utilizes open-source remote sensing imagery and ground truth data from Punjab to estimate nine soil nutrients and textures, including Nitrogen and phosphorus. By applying DOS1 atmospheric correction and comparing it with raw data using four ensemble machine learning methods (GB, XGB, RFR, ADA), the results revealed that the raw dataset generally outperformed the corrected data. Additionally, the study highlighted varying correlations between multispectral images and specific soil parameters, demonstrating an effective approach for estimating soil texture and nutrient content.[13]

Another machine learning technique (Linear Regression and Deep Neural Networks - DCN) uses spectral data to predict soil nutrient content (N, P, K) in four Indonesian provinces. The research collected 145 soil samples and analyzed their spectral properties to develop predictive models. While the DNN model showed promise, the simpler Linear Regression model generally outperformed DNN in predicting key nutrients like N-Total, P-Total, and K-Total.[41]

These models excel at capturing long-range relationships in spectral data and have shown particular promise in processing time-series satellite imagery for soil property monitoring.

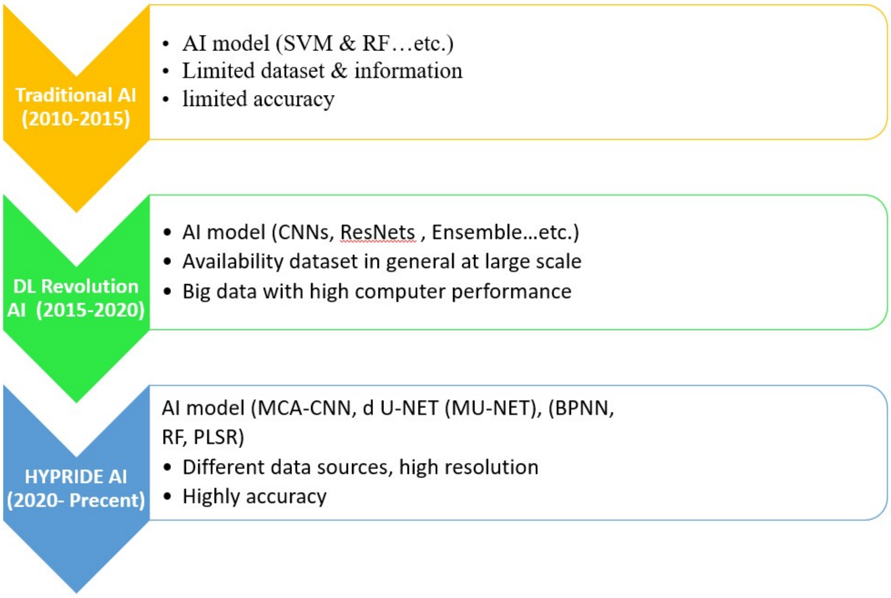


Figure 1: AI Model for Soil Property Prediction Evolution for Three Categories

3.1.1.4 Hybrid Models and Multi-Task Learning

Contemporary approaches frequently employ hybrid architectures that combine different neural network types:

- **CNN-LSTM Hybrids:** These models effectively process both spatial and temporal aspects of soil data, particularly useful when working with time-series satellite imagery [34].
- **Graph Neural Networks (GNNs):** Recently introduced for modeling spatial relationships between soil samples, GNNs have shown promising results in capturing local and regional soil property variations [32].
- **Multi-Task Learning Frameworks:** Modern systems often predict multiple soil properties simultaneously while sharing learned features, improving overall accuracy and computational efficiency [56].

3.1.1.5 Methodological Advances

Recent developments have also focused on addressing key challenges:

1. **Transfer Learning:** Pre-trained models on large spectral databases have shown remarkable success in adapting to new geographical regions with limited training data [47].

2. **Uncertainty Quantification:** Modern architectures incorporate Bayesian approaches or ensemble methods to provide confidence intervals for their predictions.

3. **Interpretability:** Development of attention mechanisms and visualization techniques has improved our understanding of model decision-making processes.

4. **Model Efficiency:** Lightweight architectures and model compression techniques have enabled deployment on edge devices for real-time soil analysis in the field.

These advancements have collectively transformed soil property prediction from a laboratory-based activity to a dynamic, real-time capability that can support precision agriculture and environmental monitoring at unprecedented scales.

3.1.2 Irrigation Timing AI Models

Recent research in agricultural technology has shown a significant focus on integrating Artificial Intelligence (AI) and Machine Learning (ML) techniques for optimizing irrigation systems. This review synthesizes findings from multiple studies examining the implementation and impact of AI-driven irrigation solutions, with particular emphasis on water efficiency.

Michael Abramov In Australia, the KOALA project Precision Irrigation: How AI Can Optimize Water Usage in Agriculture, the impact of AI on farming is profound. achieved a 20% increase in irrigation efficiency. This advancement not only conserves water but also enhances crop yields by 20 to 30%. It's a significant win for both farmers and the environment[2].

Smart irrigation systems are central to this agricultural transformation, these AI-powered systems gather real-time data on soil moisture and weather patterns, they use this information to predict crop water needs accurately, reducing water usage by up to 25

Moreover, these systems monitor plant health, detecting diseases and pests early. this approach minimizes the use of chemical treatments and ensures healthier crops. Additionally, it reduces the need for human monitoring, leading to substantial cost savings for farmers.

3.1.2.1 IoT Core Technologies and Methodologies

1. Data Collection Systems The majority of recent research emphasizes the fundamental role of data collection through IoT sensors [38]. Key components include:
   - Real-time sensor data collection for temperature, humidity, and soil moisture
   - Weather data integration
   - Historical irrigation records
2. AI and ML Implementation Approaches Research indicates several prevalent AI/ML approaches:
   - Linear Regression models for prediction
   - Decision Tree algorithms for optimization
   - Sensor fusion techniques for data integration
3. Key Implementation Factors
   (a) **Data Requirements**: Studies consistently emphasize the crucial nature of high-quality data for successful AI/ML implementation [50], including:

- Real-time sensor data
- Comprehensive weather information
- Historical irrigation patterns
- Crop-specific characteristics

(b) **Primary Methods of Irrigation Scheduling**: Research identifies four primary methods for irrigation scheduling [22]:

- Evapotranspiration and water balance (ET-WB)
- Soil moisture status monitoring
- Plant water status assessment
- AI-enhanced predictive modeling

4. System Integration and Challenges

(a) **Integration Challenges** Several studies highlight significant challenges in implementation [17]:

- Infrastructure integration complexity
- Hardware and software investment requirements
- Data quality and reliability concerns
- System maintenance and calibration needs

(b) **Technical Implementation** Successful implementations typically involve [29]:

- Cloud platform integration for data processing
- Automated alert systems for farmers
- Real-time monitoring capabilities
- Decision support system integration

5. Demonstrated Benefits and Outcomes

(a) **Efficiency Improvements**: Research demonstrates significant improvements in agricultural efficiency [31]:

- 20% increase in irrigation efficiency
- 20-30% boost in crop yields
- Up to 25% reduction in water usage
- Enhanced plant health monitoring capabilities

3.1.2.2 Compared seven machine learning methods to infer soil moisture from the images

This research uses machine learning and drone imagery to analyze soil moisture in vineyards for precision irrigation, promoting sustainable practices. A fast plant growth simulator generated synthetic images for testing various moisture conditions. Among seven machine learning methods, a deep convolutional neural network (CNN) achieved the best performance, with a 3.4% error in soil moisture estimation. This CNN-based system could reduce water consumption by up to 52% compared to traditional methods while remaining effective despite application errors. [49]

3.1.2.3 Advanced Root-Zone Irrigating Systems

This section examines a sophisticated methodology developed by researchers for monitoring root-zone soil moisture at the field scale through the integration of remote sensing and simulation modeling. The proposed framework combines multiple data sources, including:

- Field measurements (crop characteristics, soil properties, and meteorological data)
- High-resolution satellite imagery (open source, as Sentinel-2)
- Soil-Water-Atmosphere-Plant (SWAP) modeling system

The applied methodology employs inverse modeling techniques and data assimilation protocols to optimize model parameters and enhance the accuracy of both surface and root-zone soil moisture estimations. Empirical validation across diverse field conditions and crop varieties demonstrates the system's robustness, achieving:

- Low Root Mean Square Error (RMSE) values
- High coefficient of determination (R^2) metrics

3.1.2.4 Technical Advantages

The system demonstrates several significant technical achievements:

1. **Precision Performance**: Consistently high accuracy in soil moisture estimation across varied agricultural conditions
2. **Enhanced Resolution**: Superior spatiotemporal resolution enabling precise field-scale irrigation management
3. **Economic Viability**: Cost-effective implementation through utilization of readily available data sources

3.1.2.5 Implementation Considerations

Critical factors affecting system deployment include:

1. **Model Calibration Requirements**
   - Necessity for precise calibration protocols
   - Expertise requirements for accurate parameterization
2. **Data Infrastructure**

- Continuous satellite imagery availability
- Consistent meteorological data quality
- Robust computational resources for data processing

3. **System Adaptability**

- Model transferability across diverse agricultural environments
- Adaptation requirements for varying soil compositions and water irrigation timing on farmland
- Calibration needs for different cropping systems

The majority of research papers that dealt with irrigating scheduling models focused primarily on acquired data from IoT sensors, and based on that data, several AI models have been developed and implemented to monitor irrigation timing.

This study develops a precision irrigation scheduling framework using IoT sensors, machine learning (ML) models (Linear Regression and Decision Tree), and sensor fusion techniques to optimize water use in agriculture. This research demonstrates the significant potential of integrating IoT technologies, machine learning, and sensor fusion techniques for optimizing irrigation schedules and improving water use efficiency in agriculture. While the initial investment may be significant, the potential for significant water savings and improved crop yields makes this approach a promising avenue for sustainable agriculture.[38]

This research paper investigates the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques in optimizing irrigation scheduling for sustainable agriculture. to emphasize the potential of AI/ML to enhance water use efficiency, improve crop yields, and increase the resilience of agricultural systems to water scarcity and climate change. must Access high-quality data, including real-time sensor data, weather data, and historical irrigation records, which is crucial for the successful implementation of AI/ML models.[50]

A critical research paper explores the critical role of effective irrigation scheduling in modern agriculture, emphasizing the need to optimize water use while minimizing environmental impact. It focuses on the integration of Artificial Intelligence (AI) and Machine Learning (ML) techniques to enhance irrigation scheduling practices. Four primary methods as Evapotranspiration and water balance (ET-WB), Soil moisture (0) status, Plant water status The study involves a comprehensive review of relevant research literature to gather information on existing irrigation scheduling methods and the application of AI/ML techniques in this domain. Provide stakeholders with a better understanding of AI/ML applications in irrigation scheduling to facilitate informed decision-making. [22]

This research paper explores the applications of Artificial Intelligence (AI) in precision irrigation. It examines how AI technologies, such as machine learning and deep learning, are being used to optimize water management in agriculture. The paper covers key areas like soil moisture monitoring, weather forecasting, and real-time decision-making in irrigation. The paper using improve weather prediction accuracy, which is crucial for irrigation scheduling. AI can be used to develop real-time decision-making systems for irrigation, considering factors like soil moisture, weather conditions, and crop stage.

Integration Challenges: Integrating AI systems with existing irrigation infrastructure and farming practices can be challenging, requiring significant investment in hardware and software. Data Requirements: Accurate and reliable data, including weather data, soil moisture data, and crop information, is crucial for training and validating AI models.[17]

This research proposes a smart irrigation system that utilizes a Decision Tree machine learning algorithm to optimize water usage in agriculture. The system integrates IoT sensors to collect real-time data on temperature, humidity, and soil moisture from the field. This data is then transmitted to a cloud platform where the Decision Tree algorithm analyzes the information and predicts the optimal water requirements for the crops. The system then sends alerts to farmers via email, enabling them to make informed irrigation decisions and optimize water usage.

In this paper Utilizes IoT sensors for real-time data collection, enabling continuous monitoring of environmental conditions, and Employs a Decision Tree algorithm for accurate prediction of water requirements to apply Data-Driven Approach insights to optimize irrigation schedules and improve water use efficiency.[29]

The paper highlights a successful AI project in Australia (COALA) that achieved a 20 % increase in irrigation efficiency, accompanied by a 20-30% boost in crop yields. This exemplifies the win-win scenario of AI in agriculture, benefiting both farmers and the environment.

The core of this transformation lies in smart irrigation systems. These AI-driven systems leverage real-time data on soil moisture and weather patterns to precisely predict crop water needs, leading to significant water use reductions (up to 25%). Additionally, these systems contribute to improved plant health by enabling early detection of diseases and pests, ultimately reducing reliance on chemical treatments and human monitoring, while lowering costs for farmers.[31]

3.2 Survey the Current Market in Jordan

This section addresses the following topics, here will list them briefly, and then will delve into each topic and sub-topic in depth:

1. Similar commercial products/services (of determining or predicting soil properties) and their price/cost.
   (a) IoT
   (b) Lab
2. Available data, technologies, equipment and their cost required for the Poc

(a) Satellite images (either multi-band or hyperspectral)

(b) Drone-based multi-band/hyperspectral camera (as a service or rental) table

(c) Soil property data in Jordan (either open source or commercial), tables and techniques

(d) Soil property analysis service, Soil property measurement equipment, Soil property monitoring post (IoT-based or with data storage)

(e) Existing AI models for similar purposes

Note: here the reply massege for we don't have standard satellite solutions or products (e.g. imagery) for sale, they are rather custom projects.

3.2.1 Similar Commercial Products and Services Available

Within this section, we will list the available commercial products and services that are used to determine or predict soil properties and will state their prices and costs respectively, whether this product is IoT or lab-dependent.

An in-depth research was conducted to review and make contacts to obtain information and data available in the Jordanian and international market in terms of IoT data collection devices of all kinds and their cost, and to communicate with stockholders in the Directorate of Laboratories Jordan Valley Authority (JVA) and the Agricultural Research Center website (NARC), we found many noteworthy options available in the market, whether sensors or the cost of analyzing soil element data in accredited laboratories in Jordan.

Below is a breakdown of some of the key products, their functions, and an overview of their pricing structures where available. An in-depth research was conducted to review and make contacts to obtain information and data available in the Jordanian and international market in terms of IoT data collection devices of all kinds and their cost, and to communicate with stockholders in the Directorate of Laboratories Jordan Valley Authority (JVA) and the Agricultural Research Center website(NARC)[36], we found many noteworthy options available in the market, whether sensors or the cost of analyzing soil element data in accredited laboratories in Jordan.

The providers for all the laboratories in Jordan for more information Below is a breakdown of some of the key products, their functions, and an overview of their pricing structures where available. Among the existing facilities we have quoted:

1. **Royal Scientific Society**: Well-equipped but lacking background in soil analysis. The Royal Scientific Society acquisition of analysis material and an internal electronics maintenance team are available for repairs. Their brochures include price lists for analysis of water, industrial wastewater, pesticide nature, and content, lubricants, and building materials. They are interested in performing soil analysis, and though they have the necessary material, they lack experience in the field.

2. **University of Jordan**: rather well-equipped with a good staff but more used to research work than production of a large number of results on an industrial basis in soil related only for teaching there are a few soil chemistry and fertility specialists, and t this team is involved in teaching full-time. Soil analysis is performed in their laboratory by students and a few permanent technicians. The price they quoted for doing so was 6 to 10 times higher than in European laboratories.

3. **National Agricultural Research Center (NARC)**: The National Agricultural Research Center facility of the Ministry of Agriculture is well-staffed but lacking some of the equipment related to soil analysis, staff is not qualified for mass production of results. An analysis is conducted by highly ranked researchers; analysis only carries out tests according to international standards **Figure ??**.

4. **Jordan Valley Authority (JVA)**: Well-equipped and well-staffed used to performing

	Name of analysis (soil sample)	Analysis Fee (JOD)	
		Farmers	Other sectors
Fee of Service	Soil pH	1.5	5
	Electric conductivity	1.5	5
	Available phosphorus	2.5	10
	Available potassium	2.5	10
	Calcium Carbonate	1.5	5
	soil texture	4	12
	Organic matter	5	15
	Nitrogen	5	20
	Moisture (%)	3	10
	Rare items per item	3	12
	Heavy items per item	4	15
	Bulk density	3	10
	Phenols	6	25
	Boron	-	20
	Cations and Anions		
	Calcium	2	5
	Mg	2	5
	Sodium	3	10
	'Potassium.	3	10
	Chlorine	2	5
	Carbonate	2	5
	HCO3	2	5
Time to Complete the Service	3 to 7 business days		

Figure 2: NARC-soil analysis

significant numbers of analyses per month (150 water and 150 completed soil analyses per month). The laboratory facilities became operational at end of 1984. In addition to storerooms for chemicals, glassware, and samples, there are four different laboratories, as well as two preparation rooms soil and plant samples. The laboratory

minstry of water
jordan valley authority

عدد | sample cost

customer name ....

total price	samples	test No.	price	إسم التحليل	
0.00			4.50	sample preparation	soil sample
0.00			3.00	ECe dS/m	
0.00			3.00	pH	
0.00			5.00	Total calcium carbonate	
0.00			7.00	available phosphorus	
0.00			7.00	available potassium	
0.00			9.00	Total nitrogen	
			7.00	available boron	
0.00			14.00	soil texture	
			7.00	soil particles	
0.00			8.00	organic matter	
			6.00	specific density	
			8.00	Field capacity	
			7.00	gypsum	
			5.00	soil moisture	
			5.00	saturation percentage	
0.00			14.00	cation excahnge capacity	
0.00			6.00	cation excahnge /(Ca,Mg,K,Na)	
0.00			8.00	extarction by DTPA	
0.00			10.00	Trace element (Cu,Mn,Fe,Zn,Mo)	
			8.00	digestion by acid/sample	
0.00			10.00	) heavy metals	
			3.00	ECe dS/m	
			3.00	pH	
0.00			4.50	Calcium	water/soil extraction
0.00			4.50	magnesium	
0.00			4.50	sodium	
0.00			4.50	potassium	
0.00			4.50	carbonate	
0.00			4.50	bicarbonate	
0.00			4.50	chloride	
0.00			4.50	sulphate	
0.00			8.00	Total suspended solid	
0.00			5.00	nitrate	
0.00			10.00	Total dissolved salt/drying	
0.00			4.50	turbidity	
0.00			6.00	ammounia	
0.00			28.00	Total coliforms	
			7.00	available phosphorus	
			7.00	boron	

Figure 3: JVA Soil Analysis

can be used for a wide range of activities. The JVA have the ability to adjust the cost **Figure** 3.

3.2.1.1 IoT Soil Properties Sensors:

These devices continuously monitor soil conditions and provide real-time analytics. Typical sensor data can include moisture readings, EC, pH, NPK, and weather conditions as temperature profiles, IOT sensors we have tow options here:

- High professional soil analysis system such as delta, METER, and stevenswate Table **??**
- Limited properties samples for the soil analysis system such as comWinTop [1] which utilizes buried sensors to measure critical variables like moisture and temperature. These sensors collect and transmit data to a cloud platform, allowing farmers to monitor soil conditions remotely. The costs of these systems depend on the configuration and scalability of the solution. **table** 1.

Table 1: **Soil Sensor Models and Specifications**

Company Name	**Model**	**Price ($/JD)**	**Measuring Items**	**Accuracy**
ComWinTop	`CWT-Soil-DL-4G(E)`	99.6$ 70.62 JD	Temperature	±0.5℃
			Humidity	3% within 0-50%RH, 5% within 50-100%RH
			Conductivity (EC)	0-10000 us/cm range is ±3%; 10000-20000 us/cm range is ±5%
			PH	±0.3PH
			NPK	1 mg/kg(mg/L)
ComWinTop	RS485	32.3$ 22.923 JD	Temperature	±0.5℃
			Humidity	2% within 0-50%RH, 3% within 50-100%RH

Table 1 – Continued from previous page

Company Name	**Model**	**Price ($ / JD)**	**Measuring Items**	**Accuracy**
			Conductivity (EC)	0-10000 us/cm range is ±3%; 10000-20000 us/cm range is ±5%
			PH	±0.3PH
			NPK	±2%FS

We provide you with additional details about the specifications and costs of IoT sensors, based on the technical and financial offer submitted by a local company **Agri. logistic**, as shown in the figure 4

- **IoT requirements - Advantages and disadvantages with differences between IoT and Lab Analysis :** IoT requirement's have basic requirements:

  1 - Technical Specifications :

  - Sensor Type: measuring soil moisture, pH, temperature, EC, and NPK.

  - Connectivity: wireless communication (e.g., Wi-Fi, LoRa, Zigbee, or cellular).

  - Power Supply: Sustainable power options like solar panels, rechargeable batteries, or low-energy consumption technologies.

  2 - Data Management:

  - Data Processing Unit: Local processing capabilities to filter and analyze data before transmission.

  - Cloud Connectivity: Integration with cloud platforms for data storage, analysis, and access- check with MODEE.

  3 - Durability and Resilience:

  - User Interface based on:

AgriLogistic

Agrilogistic Co. Ltd.

Total Fertigation Solutions

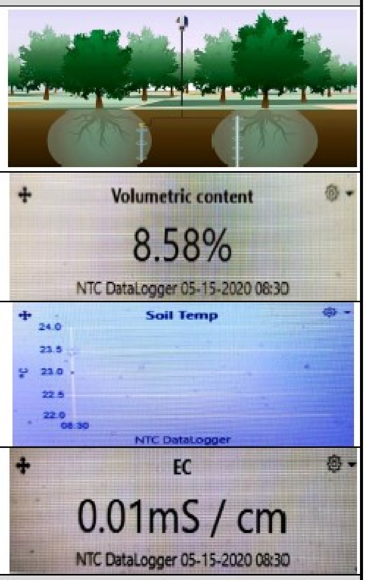
Amman Sport City
Tel.: 00962 6 5656528
Mob.:00962 79 6816600
Fax: 00962 6 5656548
P.O. Box 213858 code 11121
e-mail: info@agrilogistic.com

EXTRA OPTIONS:

- **Soil / substrate sensors**

Appropriate **moisture**, **temperature** and **electrical conductivity** (EC) conditions at the root level cause an increase and improvement in the quality of the production. Moreover, the information about the movement of the water and the salts in the soil is very valuable for preventing the loss of water and fertilizers due to deep percolation and, therefore, to prevent the contamination of the subsoil. (**VWC**, **EC** and **Temp**) sensors provide an accurate measurement of temperature, volumetric water content, and electrical conductivity (EC) at different depths along the soil profile, **including:**

1- Soil Depth: 60 Cm (6 Reading Levels Every 10 Cm).
2- Soil Humidity (Tensiometer).
3- Soil Salinity (E.C.).
4- Soil Temperature.



Total Cost	**1,750**
Lease cost:	**840JD/Y (70JD/M)**

Terms & Conditions:
- All price in JOD
- Payment 100% in advanced (3years lease, payment Yearly)
- Validity 60 days
- Delivery within 3-4 weeks from payment.

With our sincere appreciation

Agrilogistic Co. L.L.C
Eng. Sufian Albess, G.M.

Figure 4: agri.logistic-company technical and financial offer -IoT-soil property

- Mobile/ Web Application: A user-friendly interface for users to access real-time data, alerts, and insights regarding soil conditions.

- Analytics Dashboard: Tools for visualizing data trends and generating actionable insights for irrigation and fertilization management.

4 - Installation:

- Ease of Deployment: Simple installation procedures that require minimal technical expertise. – Scalability: The ability to add or remove sensors easily to fit different farm sizes or monitoring needs.

- **Advantage and disadvantages with differences between IoT and Lab Analysis:**

The figure 5 highlights the trade-offs between using IoT sensors for real-time, continuous monitoring and laboratory analysis for detailed, precise soil assessments. Each method has its strengths and weaknesses, making them suitable for different applications depending on the specific needs of soil monitoring and analysis.

1. IoT Sensors offer real-time, continuous soil monitoring with immediate feedback, making them cost-effective and easy to deploy for large-scale use, though they may lack accuracy and require maintenance.

2. Laboratory Analysis provides highly accurate, detailed soil assessments with established methodologies, ideal for comprehensive evaluations, but it is time-consuming and more expensive per sample.

3. IoT sensors are better for tracking trends and specific parameters like moisture, while lab analysis excels in identifying complex soil interactions and nutrient compositions.

4. IoT sensors are prone to technical issues and require expertise for data interpretation, whereas lab analysis offers static snapshots without real-time capabilities.

5. Both methods have distinct advantages, with IoT sensors suited for ongoing monitoring and lab analysis for in-depth, periodic assessments.

Aspect	IoT Sensors	Laboratory Analysis
Advantages	- Real-time data collection	- Comprehensive analysis of soil properties
	- Continuous monitoring of soil conditions	- High accuracy and precision
	- Immediate feedback for timely decision-making	- Established methodologies and standards
	- Cost-effective for large-scale monitoring	- Detailed nutrient and chemical composition
	- Easy to deploy and scale	- Can identify a wider range of soil issues
Disadvantages		
	- Limited accuracy compared to lab analysis	- Time-consuming process (waiting for results)
	- May require calibration and maintenance	- Higher costs per sample analysis
	- Data interpretation may require expertise	- Samples represent a static condition
	- Vulnerable to technical issues and failures	- Cannot provide real-time monitoring
Differences		
	- Provides continuous and immediate data	- Offers in-depth analysis at specific intervals
	- More suitable for monitoring trends	- Ideal for comprehensive assessments
	- Focuses on specific parameters (e.g., moisture)	- Can analyze complex interactions in soil

Figure 5: IoT requirement's -advantage and disadvantages with differences between IoT and Lab Analysis

Recommendations: An analysis of one soil sample with the required characteristics can be performed to determine the correlations between the two options between all the results.

3.2.1.2 Soil and Water Sample Analysis in JVA and NARC laboratories

Soil and water sample analysis is vital for sustainable agriculture. It provides essential data for effective resource management and environmental protection.

laboratories such as JVA (Jordan Valley Authority) and NARC (National Agricultural Research Center)[36] are instrumental in conducting detail and reliable analyses of soil and water samples. These analyses help farmers and researchers understand the nutrient composition, pH levels, and overall health of the soil, as well as the quality of water resources used for irrigation. Soil analysis is a vital component of agricultural productivity, and its quality directly influences crop yields. The AJV and NARC laboratories specialize in various soil tests, including:

- **Nutrient Content Assessment**: Measuring essential nutrients such as NPK, determine soil fertility.
- **pH Testing**: Evaluating soil acidity or alkalinity, which affects nutrient availability and microbial activity.
- **Soil Texture Analysis**: Assessing the proportion of sand, silt, and clay to understand drainage and retention capabilities.

The costs for these analyses vary based on the type of tests conducted. As per the information available from the departments and their websites.

3.2.2 Available data, Technologies, Equipment and their cost required for the PoC:

According to the PoC the Available data, technologies, equipment, and their cost required and utilizing advanced technologies like satellite imagery, IoT sensors, and machine learning, tools facilitate data-driven decision-making that enhances crop yields and supports sustainable farming practices. Satellite image and drone with cost availability, based on the minimum requirements of the satellite imagery are as more than 10 multi-band or hyperspectral ranging from near ultra-violet to near infra-red, spatial resolution 50 m or less, revisiting cycle 1 week or less, cover target PoC sites in Jordan, as in the following details

3.2.2.1 Satellite Images (either multi-band or Hyperspectral)

Based on the minimum requirements of the satellite imagery areas more than 10 multi-band or hyperspectral ranges from near ultra-violet to near infra-red. spatial resolution 50 m or less, revisiting cycle 1 week or less, cover target PoC sites in Jordan, as in the following details in the table:

According to these requirements, the available satellite data was divided into three categories:

1. for research: used for research and other must-paid purposes and may have limited commercial availability. They often have medium 30m spectral resolution and may have longer revisit times.
2. Commercial hyperspectral: these sensors provide high-resolution hyperspectral images for commercial applications. They usually have shorter revisit Times and higher costs compared to the search category.

3. Open source / free: these sensors provide freely available images, making them valuable for a wide range of applications. They may have a lower spatial or spectral resolution compared to commercial sensors.

The **table** 2 highlights a variety of remote sensing data (satellite images) available, ranging from highly specialized satellites like WorldView-3 and Hyperscout-2, which are geared toward commercial applications, to freely available options like Sentinel-2A and Landsat 9 for research purposes.

The data reflects advancements in remote sensing technologies, providing a range of options for different applications, from agricultural monitoring to environmental assessments. The comparison of spectral ranges, bands, and resolutions allows researchers and practitioners to select the most suitable platform based on their specific needs and budget. the table provides a valuable overview of the various satellite imaging options available, allowing users to choose the most suitable sensor for their own needs and budget

Table 2: Overview of available Satellite Providers and Specifications

Satellites Providers	**Spectral Range**	**Spectral Bands**	**Spatial Resolution**	**Repeat Cycle**	**Price /100 Sq Km**
Variable For Research					
PRISMA	400–2500 nm	VNIR, SWIR	30 m	13 days	For research
DESIS	400–1000 nm	1-20 (VNIR) & 20-60 (SWIR)	30 m	3 days	For research
EnMAP	420–2450 nm	14 bands (from VNIR to SWIR)	30 m	27 days	For research
Hyperspectral Commercial					
HISUI	400–2500 nm	256 bands (VNIR, SWIR)	Hyperspectral: 30m Multispectral: 5m	1-2 days	Commercially
WorldView-3	400–2500 nm	31 Bands	0.31 m	7-8 days	$8000
OHS	460–940 nm	32	10 m	3-5 days	Minimum order size 2,500 sq km/ per Sq Km: $1.50
Open Source / Free					
Sentinel-2A	400–2480 nm	13 bands (RGB, NIR, SWIR)	10, 20, and 60 m	5 days	Free
Sentinel-1A (SAR)	C-band Frequency of 5.405GHz	polarization (VH and VV)	20m	6-12 days	Free
Landsat 9	433–2200 nm	11 bands (visible to thermal)	30 m	16 days	Free

Note: some companies reply us via-email about there servises for hyperspectral satellite images "That said, we don't have standard satellite solutions or products (e.g. imagery) for sale, they are rather custom projects" .

Recommendation for satellite imagery availability:

To identify the most appropriate satellite technology for accurately predicting soil properties and irrigation timing on farmland using AI models derived from imagery, it is crucial to utilize multiple narrowband images. The predictive accuracy is directly enhanced by an increased number of narrow spectral bands within a given image. However, this approach faces challenges due to the limited availability of hyperspectral options and the higher costs associated with hyperspectral satellite imagery compared to multispectral alternatives.

As a viable solution, the use of high-resolution multispectral images which include model parameters requirements and open-source images can yield beneficial results. Recent advancements in algorithms and technologies enable improved accuracy through the integration of data from multiple satellites with available dataset sources, these datasets can be processed and analyzed using cutting-edge deep learning techniques, which significantly reduce costs related to acquiring various narrowband images.

Given the limited budget for the proposed proof of concept (PoC), relying on costly hyperspectral satellites is not recommended. Instead, focusing on more accessible multispectral and integration with open-source imagery including open datasets offers effective alternatives while still providing dependable predictions for soil properties and irrigation timing, so We recommend the following:

1- The development of an advanced model with high accuracy to predict soil fertility, can not rely on a single source of high-resolution satellite images, because the construction of the model depends on several inputs, so the use of multi-band satellite data from **WorldView 3**, along with other open source data sources for Complementary input models, is necessary because it serves as the primary data provider for many contracted companies. This data can be obtained directly through Grotech in Jordan.

2- Through a technical team specialized in remote sensing and AI (GeoAI), more than one data source can be integrated and thus provide the model-building requirements

3- Growtech local Company has promising experience in this field and has developed and trained a soil properties prediction model as attached

3.2.2.2 Drone-based multi-band/hyperspectral camera (as a service or rental)

Drones have become essential data collection and analysis tools, particularly when equipped with advanced multispectral cameras or Hyperspectral, that capture high-resolution images across various spectral ranges. This capability enables researchers to efficiently assess critical soil properties—including NPK, pH, EC, and soil moisture—over extensive agricultural areas.

One primary advantage of using drones in the Verification Commission's work is their ability to gather real-time data, which is crucial for making accurate predictions and timely irrigation decisions. In contrast to traditional methods that often depend on ground sampling and laboratory analysis—which can be both time-consuming and limited in spatial coverage—drones facilitate rapid data collection that reflects the variability of soil characteristics.

This swift data acquisition allows for the formulation of more precise irrigation schedules by pinpointing areas that require specific water management interventions based on current soil conditions. Furthermore, integrating drones with artificial intelligence models significantly enhances the predictive accuracy of soil assessments. Combining drone-collected imagery with satellite data improves the precision of soil property evaluations and enables regional analyses that inform broader agricultural practices.

By searching for Drone Imaging Service Providers in the local Jordanian market, all imaging companies were contacted and asked for technical and other technical offers about the characteristics of their cameras with the cost according to the requirements and objectives of the PoC. However, after consulting with relevant regarding the purchase or rental of drones, it has become evident that there are limitations. Currently, no company in Jordan can provide hyper-spectral bands due to the high costs associated with imaging and the other requirements involved. the available cameras provide Multispectral, RGB, Thermal, and LiDar.

Most companies in Jordan operate using visible spectral bands and near-infrared (NIR) imaging. The primary challenges facing the use of drones in this context include the high costs, the availability data the lack of necessary resources to develop advanced models.

the latest hyperspectral in drone imaging, the FS-60C company. This advanced camera, priced at 34,000 dollars is compatible with DJI M300/350 drones. This information provide us by Email.[14]

In figure?? have the main type drone in Jordan with the specification and cost

- Bureaucracy and preparing document administration and permission take a long time
- Availability limitation material, types of equipment, and time
- Cost: its expensive cost
- Most important is that the providers haven't the hyperspectral camera and other specifications needs required for the PoC program.
- The drone images need specific pre-processing take more time and storage

Recommendation: using the drone faces the following challenges:

Recommendation:

Providers	Drone Model	Spectral Bands	Spatial resolution	Cost/ JD
JETX	DJI 3 pro AI DJI MAVIC 2	multispectral (RGB, NIR, Red Edge) & RGB	1- 3.5 c m	5000 per 40 donum
Sager	MicaSense RedEdge-P &Trinity& Sony RX1RII DJI-P1	RGB & multispectral (RGB, NIR, Red Edge)	1- 5 cm 7.7 cm	62,700 JD Amount is Tax Exclusive
MARSROBOTICS	DJI Matrice 300 RTK RedEdge-P Thermal H20T	multispectral (RGB, NIR, Red Edge) & RGB	7.7 cm	1000/ day
RJGC	RedEdge-P + DLS 2	multispectral (RGB, NIR, Red Edge) & RGB	2cm	750 JD / per km2

Figure 6: Main type drone in Jordan

Using drones equipped with hyperspectral imaging to develop AI models for predicting soil properties (NPK, EC, pH, and soil moisture) and irrigation timing on farmlands AI models we not be recommended: - The costs of operational training, data processing, and flight operations are prohibitively high for small—to medium-scale farmers. - Hyperspectral data acquisition requires specialized knowledge and skills to operate the drones effectively and interpret the data accurately, and additional costs for training personnel to handle and analyze hyperspectral data. - Drones can be negatively affected by environmental conditions such as poor weather (rain, fog), which can impede their ability to gather accurate data. - Uneven crop distribution and variability in soil properties may result in mixed signals when collecting data from a height, affecting model accuracy.

3.2.3 Soil Properties and Data Availability Evaluation In Jordan

1. **The Historical Context of Soil Surveys and Land Specifications in Jordan**: We reviewed the outputs of several projects also in addition to some relevant sources such as the World Soil Survey Archive and Index; which includes a summary of the archived materials for Jordan in historical chronology; as well as the report on the development of the current Jordanian Soil Resources Information System (JOSCIS).

Also, review the outputs of the time series of soil survey and land use classification projects in Jordan from the 1950s to the present time, below the brief of output and time series of soil studies. All existing soil information collected to characterize or map soils from the previous projects mainly landscape and site descriptions, soil profile morphological descriptions, laboratory analysis of the main chemical, physical, and biological soil properties, Soil maps, Geophysical/geotechnical surveys as well as the other maps such as climate, geology, land use, topographic maps and reports.

We hope that these previous soil data reviews will add value to the POC project through comparison with the soil analysis results that will be obtained by using satellite imagery and sensors and will help achieve the objectives of the PoC project so that we can determine to match the soil types with the suitable crop, moreover, the soil test result can also be used to decide on the most suitable crop matching for the nutrients available in the soil types. (1950s) Soil mapping and classification started in Jordan in the (1950s) at a scale of (1:1,000,000), using the US soil classification system of (1938) with twelve great soil groups being recognized, the most common of which being grey desert soils, alluvial soils developed under desert climate, yellow soils developed under steppe conditions, and yellow and red Mediterranean soils developed where annual rainfall exceeds (250) mm. During the (1960s), the soils of Baqa'a Valley were at a scale of (10,000) using the U S Soil Taxonomy (7th Approximation). The area covered by this study was about (6,700) ha. The dominant taxonomic units encountered were the groups Xerochrepts and Chromoxerets, usually these soils were located on gentle slopes and flat topography. Xerorthents were also identified in that area. However, their distribution was limited and they only occurred on the eroded slopes.

The soil survey was extended during the (1970s) to the Irbid and Karak regions.

A detailed survey was carried out for (2,500) ha, and a semi-detailed survey for (70,000) ha in the Irbid region. Similar soil studies were conducted also in different parts of the country. An estimated (80,000) ha area was mapped at a scale of (1:50,000) in Balqa. Land Regions for Jordan were defined by Mitchell (1975) and the interpretation of (1:250,000) scale LANDSAT MSS imagery to refine these units provided the basis for the soil mapping program of the National Soil Map and Land Use Project (NSM and LUP) (1989-1995). This study, conducted on behalf of the Jordanian Ministry of Agriculture by Hunting Technical Services Ltd. (UK) in association with Cranfield University's Soil Survey and Land Research Centre (UK) led to the production of a national soil map and land use database for Jordan. (1989-1995) The National Soil Map and Land Use Project (NSMLUP) was identified by staff of the Ministry of Agriculture the project is carried out at three different levels of intensity. The Level 1 soil survey, a broad reconnaissance of the soils of the whole Kingdom with mapping at (1:250,000) scale, was the first part of a three-level study:

(a) The level I Report consists of three volumes:
    - Volume 1- Summary Report in Arabic.
    - Volume 2- The Main Report.
    - Volume 3- Representative Profile and soil analyses. Map Album Consists: 7 Sheets at scale 1:250.000

(b) Level 2 involved semi-detailed soil survey and production of soil, land use, and land suitability maps of (9000) km2 at (1:50,000) scale. Level 2 Report consists of three volumes
    - Volume 1 - Summary Report in Arabic.
    - Volume 2 - The Main Report.

- Volume 3 - Representative Profile and soil analyses.

Map Album Consists: 84 Sheets which includes: 28 Sheet/Soil map. 28 Sheet/ Land Cover map. 28 Sheet/ Land Suitability map at scale 1:50.000.

(c) Level 3 presents Soil, land cover, and land suitability maps at a (1:10,000) scale of about (800) km2 based on a detailed soil survey. Level III Detailed Survey: Scale 1:10.000 - Cover 1000 ha level III Report consists of Six Volumes:

- Volume 1 - Summary Report in Arabic.
- Volume 2 - The Main Report.
- Volume 3 - Appendices.
- Volume 4 - Soil Physics
- Volume 5 - Thin section Studies
- Volume 6 – Soil map legends.

Map Album Consists: 36 Sheets which include a soil map. Land Cover map. Land Suitability map at scale 1:10.000.

(1993-1995) The Jordan Soil and Climatic Information System, JOSCIS, concluded in 1993, was established as an integral part of the National Soil Map and Land Use Project[24, 23]. The Terms of Reference for this project suggested that a country that does not already have a national geo-referenced database should seriously consider implementing such a system during its first major mapping operation'. The intention was that national resource surveys such as the National Soil Map and Land Use Project should benefit from establishing an appropriate geo-referenced database to facilitate the results being fully utilized in planning the sustainable use of land.

1996-1998: Project of the Jordanian Arid Zone productivity (JAZZP).

2012: The Global Soil Partnership (GSP) was established with the mission to position soils at the national and regional to promote sustainable soil management, hosted by the Food and Agriculture Organization of the United Nations FAO, to improve soil governance to guarantee productive soils toward food security, climate change adaptation and mitigation, and sustainable development.

2. **Previous Legacy Data Constraints and Limitations**: Documentation has vast gaps, most of the original authors are not available, the data is scattered and mostly paper-based, and it is very difficult to make harmonization issues, Quality errors, One of the most difficult things the data is not having Georeferencing, lack and un-clear/difficult to do projections Map units (proportions, classes, impurities), Classification (names, taxonomy, ref. properties), Uniformity issues (sampling, depth, units, etc. . .).

3. **Methodology for preparation of data deliverables** The process of preparing the data deliverables for this work has involved several stages, Figure 7.

   The process of preparing the data deliverables for this work has involved some stages, (Figures. . . .). Firstly, the data sources for Jordanian soils and related environmental information available to the Ministry of Agriculture (MoA) were assembled and reviewed, this primarily related to data sources linked to JOSCIS and the subsequent previous projects. For each project, we held several computer media data stores and backups. These were each located and sorted through to identify a combined listing of data sources available and which file to use in the case of duplicates. This point is important as the filesets we hold do not represent a 'definitive and final' set of data for JOSCIS, but rather several projects' working filesets, backups, operator-specific filesets, and other outputs (digital and non-digital). In many cases, it was found that we held multiple versions of files representing staged backups in the process of their construction and editing. In all these cases, we have to ascertain which file represented the 'latest state' which would become the basis for the later transformation and inclusion in the deliverable outputs.

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Figure 8 the summary of output data requirements and sources, electrical conductivity (EC), pH, Soil Moisture content, Water Holding Capacity (AWHC) NPK total and Available, Filed Capacity Soil Data including information such as: 1. Profile ID 2. Latitude and Longitude 3. Depth Range (start and end of each Horizon) which is a basis for the case study.Figure**??** Number and distribution of point data consist of all the data collected by the soil scientists in the field and are stored in the DMS at National Soil Map and Land Use at Land and Irrigation Department /MoA, total points data is (3739) Profiles [33, 24, 26], unfortunately only (1780) profiles from the total table 3 with coordinates It also does not contain all the analyses needs. But I think what has been obtained is sufficient to understand the characteristics soil of Jordanian soil at each site with georeferenced, profile description and in addition, chemical analyses from representative soil profiles DSM simple processing of the

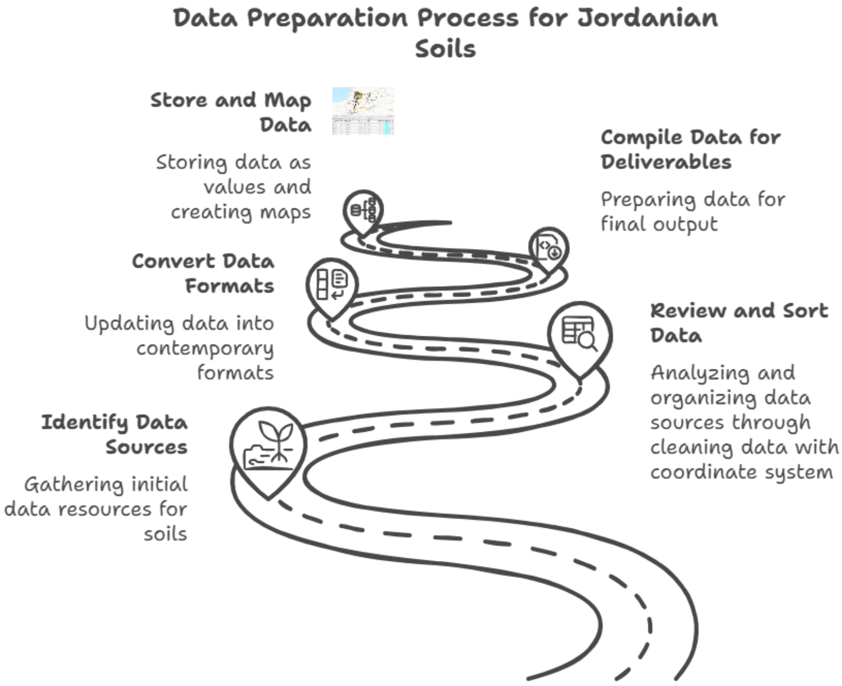


Figure 7: Data Preparation Process for Jordanian Soils

individual information sets into a map, the density of one observation site every 15.5 sq.km. Figure 8

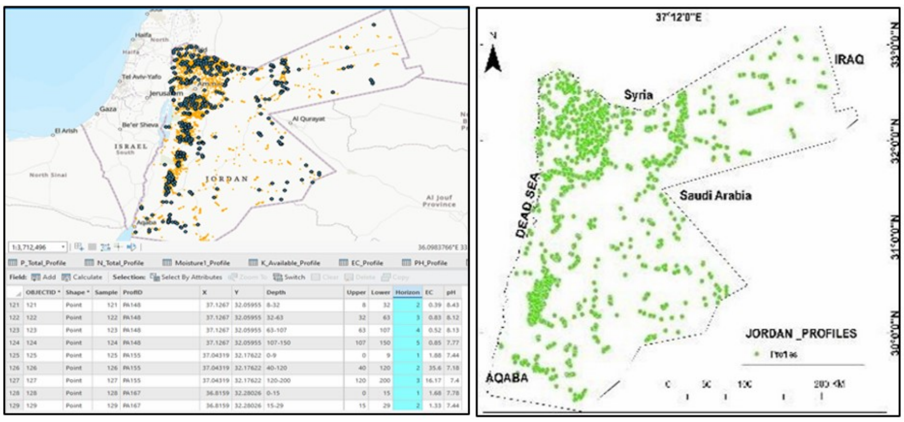


Figure 9: Number and distribution of all data available

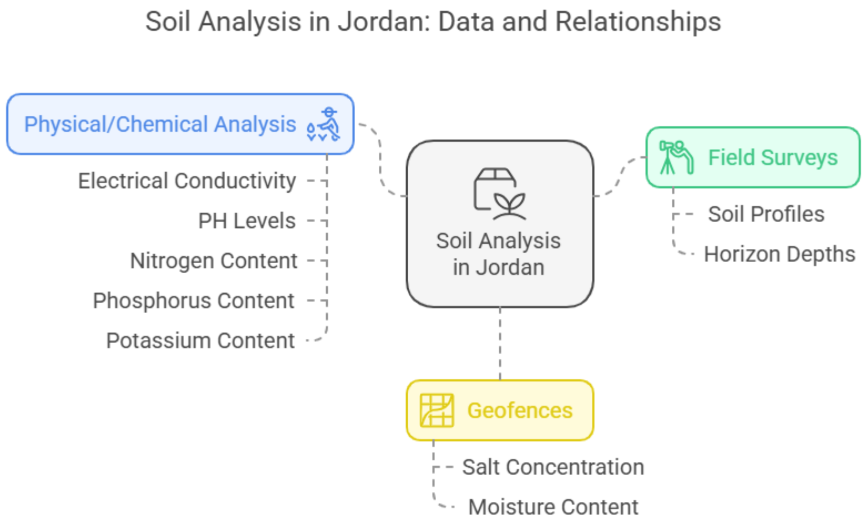


Figure 8: soil analysis output

ID	Property	No_Profile
1	N_T	268
2	P_T	250
3	P_Available	267
4	K_Available	7
5	EC	583
6	Moisture	45
7	pH	556
Total		1,976
Horizon		1.780

Table 3: Summary of Soil Properties

Table 4: Soil Properties AI Model - Satellite Images Requirements

NO	**ISRIC Dataset (250 m)**	**Sentinel 2A** (10m and 20m)	**AI Models**	**Sentinel 1A** (10m)	**SRTM** (30m)
1	Total Nitrogen	Blue / 496.6nm	GB	VV	DEM
	NPK	Green / 560nm	XGB		
	V NIR, SWR1	Red / 664.5nm	RF		
	ECE	Red Edge1 / 703.9nm	RADA		
	Silt	Red Edge 2 / 740.2nm	regression analysis		
	Clay	NIR / 835.1nm			
	Sand	SWIR1 / 1613.7nm			
2	EC - Salinity	G, R, NIR (560 - 835 nm)		VH	Slope
3	Soil Moisture	NIR / 835.1nm			Aspect

Continued on next page

Table 4 – Continued from previous page

NO	ISRIC Dataset	Sentinel 2A	AI Models	Sentinel 1A	SRTM
4	pH	SWIR1 / 1613.7nm		VV	DEM

4. **Soil Distribution and Soil Formation:** Soil types and their distribution reflect the overlap between climatic factors, geology and long-term periods of moisture and drought, especially in the desert areas, which constitute 91% of the Jordanian lands, The soils of Jordan have been classified according to the criteria and definitions of the USDA's Soil Taxonomy (1975) and the 1990 keys to Soil Taxonomy, contained in SMSS Technical Monograph Nol9. In this report, there follows a brief description of the great groups which have been recognized during the course of this study. in Jordan [25, 26, 23] Six orders have been recognized all over the country.

   (a) **Aridisols**: Widespread occurrence in the country within the aridic Moisture Regime, which represents approximately 75% of the total area, and is an important constituent of Regions Wadi Arabah, Wadi Arabah Escarpment, Arabah Hills Dissected Basement Plateau, - Disi-Ram Highlands, South Jordan Dissected Sandstone Plateau the eastern part of Region – Jordan Highlands Plateau, Jafr Basin, East Jordan Limestone Plateau, Hafira-Jinz Depressions, - North-east Jordan Basalt Plateau and – North-east Jordan Limestone Plateau. They occur on a wide range of parent materials The dominant soil subgroups are, Which occur in association with Camborthids and Gypsiorthids and to a lesser extent with Torriorthents especially in Regions Arabah Hills Dissected

Basement Plateau and – Disi-Ram Highlands, and Torrifluvents in wadis. Coarse textured Calciorthids occur in Region Arabah Hills Dissected Basement Plateau in colluvial and alluvial fans but are dominantly fine–loamy and fine–silty in texture in the other Regions, with varied content of stones and gravel depending on the parent material and slope position however, Salorthids, most of the soils of the arid regions are saline except in wadi beds and channels, and evaporites occur on the surface of some basins as flood water evaporates. However, the Salorthid great group with its requirement of a water table within two meters is of very limited occurrence. They are found in limited areas near the much-reduced Azraq pools, around the Dead Sea, especially in the Ghor Safi area, and in limited spring-fed sabkhas in Wadi Arabah; limited sandy Salorthids occur behind the Aqaba beach.

(b) **Entisols**: Occupied 10% and consists from mean soils subgroup; Torrifluvents, Ustifluvents, Xerofluvents, Ustorthent, and Xeropsamments These are generally layered soils with a very mixed particle size class. They occur in recent alluvia of Wadi channels; most contain numerous gravel layers. these soils are calcareous but do not contain visible calcium carbonate. Meanly all these are non-saline, reflecting their youth, coarse texture, and occasional leaching by flash floods. occurs in most of Arabah Hills Dissected Basement Plateau, - Jafr Basin, East Jordan Limestone Plateau, Hafira-Jinz Depressions, North Jordan Basalt Plateau, North-east Jordan Basalt Plateau and – North-east Jordan Limestone Plateau.

Ustifluvents, this great group is limited to Wadi channels in the Jordan Valley, Region which flow off the escarpment and in parts of the Zor. They are non-saline and coarse-textured, often with numerous bands and lenses of gravel. They also occur in recent alluvium of the lower reaches of the Zarqa River and other major, deeply incised wadis.

Xerofluvents, these soils are of very limited extent and occupy narrow wadis in the more highly dissected areas of Regions Northern Highland Dissected Limestone Plateau, Central Highlands Dissected Limestone Plateau, Southern Highlands Dissected Limestone and Jordan Highlands Plateau; in Region Highlands Plateau their xeric moisture regime is maintained by occasional wadi flow. The soils are generally coarse-textured, and are non-saline, and have no visible secondary carbonate.

Ustorthent, this great group is associated with Ustochrepts mainly in a narrow zone in the middle and lower part of the escarpment to the Jordan Valley. They are associated with young colluvium on steep slopes, or are very shallow to rock: a few occur on extremely gravelly terraces within the ustic moisture regime. Most have a loamy–skeleted particle size class. The soils are calcareous and non-saline. Xeropsamments, this great group is found in one small area where sand from the sandstones of Region Disi-Ram Highlands has been blown up onto the high-level edge of the Ras en Naqb – Jebel Petra escarpment. They occur at the very limits of the xeric moisture regime.

(c) **Inceptisols**: Xerochrepts Soils of this great group occupy extensive areas of Jordan (7%) where rainfall exceeds 200mm, or where additional moisture is received from run-on in depressions, wadi channels, etc in more arid areas. And meanly is dominant in Regions of Northern Highland, Central Highlands Plateau, Southern Highlands Ajlun Highlands Plateau. these soils have developed in alluvial and colluvial mantles derived from calcareous rocks, directly on limestone, and aeolain deposits of the plateaux and depositional basins. Xerochrepts occur in a wide range of topographic positions, from the long steep colluviated slopes to the nearly level plains of Irbid. Madaba, Karak, and Tafila. The texture varies from fine-loamy to clayey, and the steep Xerochrepts colluvial mantles normally contain a high stone content.

The Xerochrepts vary from strong to non-calcareous; the level of free CaC03 depends partly on rainfall. Xerochrepts are associated with Vertisols in the higher clay areas of Regions Northen highland and central highland, organic-rich Haploxerolls in high rainfall areas in Regions Northen highland, Ajloun highland, s on hill crests, and steep slopes, very stony colluvium. To the east, they grade towards the Camborthids and Calciorthids of the more arid Regions. The Xerochrepts are the most important soils agriculturally, supporting rainfed cereal and summer cropping, tree crops, and irrigated horticulture. This group of soil very limited extent and meanly occurs on the escarpment to the Jordan Valley and Jordan Valley Escarpment in association with soils of the Ustochrept great group, i.e. in the narrow zone where rainfall exceeds 250-300mm and annual soil temperature exceeds 22°C. Moreover, Haplustolls, the limited area of Haplustolls on the escarpment soils are moderately to strongly calcareous and non-saline, they often contain a few calcium carbonate concretions.

(d) **Vertisols**: Chromoxererts occur in regions northern Highland Plateau and Central Highlands, and have very limited occurrence in Regisouthern highland and Ajloun highland. The largest area of the Chromoxererts occurs in the Irbid plains and Yarmuk basalt plateaux, also these cracking clay soils are found in limited areas in the northern part of the Jordan Valley in gently sloping alluvial deposits. This soil group has characteristic swelling and shrinking in the summer, the soil cracks very widely, with surface cracks of between 5cm and 10cm common, and extend downwards for up to 100cm, including well-developed wedge-shaped aggregates and extensive slickensides, the Chromoxererts very limited drainage which restricts leaching of calcium carbonate and maintains alkalinity, the clay content of the Chromoxererts is usually more than 45% and non-saline. Xerochrepts are associated with Chromoxererts. This gradation includes of with some of the vertisols characteristics. Vertisols are generally calcareous and a few have calcic horizons. Chromoxererts and Xerochrepts are important for cereal production and, locally, for tree crops.

(e) **Andisols**: Only very limited areas of this order have been recognized, they are associated with cindery parent materials of volcanic cones, mainly occur in regions north Jordan Basalt plateau and north-est Jordan basalt plateau, also in very areas in region Jordan Highlands Plateau. Two great groups have been recognized: Vitritorrands and Haploxerantds in the arid region North-east Jordan Basalt Plateau and Haploxerands in the northern parts of the region – North Jordan Basalt Plateau and the moistest parts of the region – Jordan Highlands Plateau. Both groups are very stony with a loamy textured matrix and are often shallow to basalt rock.

(f) **Molisols:** Haploxerolls These soils occur in regions of Northern Highland Dissected Limestone Plateau and Ajlun Highlands Dissected Limestone Plateau where rainfall is high and can sustain vigorous vegetation growth. They occur most commonly under trees, dense scrub, and grass vegetation.

The Haploxerolls are largely confined to steeper slopes that are either uncultivated or under tree crops. Thus, there is a high proportion of shallow and moderately deep soils (25-80cm). The soils are mainly fine-loamy in texture, with a few clayey examples. They normally have a high stone content. Mycelia of calcium carbonate commonly occur in the Haploxerolls, but they are usually only weakly to moderately calcareous; a few are non-calcareous and non-saline.

Soil Moisture Regime: Soil of Jordan is divided into the five-soil moisture regime the most dominate is aridic occupied (82.50%) which equal (73583.6 km sq) from the total land, Xeric (8.18%) equal (7292.4) km sq, Transition Aridic -xeric (7.6150%) equal (6785.8) km sq, Transition Aridic- ustic (0.69%) equal (619.2) km sq, Ustic (0.43%) equal (397.3) km sq.

Figure 10 [39] The Water Holding Capacity (AWHC), and moisture contents at tensions: (1-15 bar): show volume% of AWHC for the texture, Silty clay loam, Silty loam and Sandy clay loam are slightly less (13.0- 15.0 volume%) while the values of the texture of Silty clay, Sand clay and fine Sandy clay are (16.0-17.9) volume.

A summary of soil moisture analysis from available data shows that the soil's moisture-holding capacity, intake rate, and depth are the principal criteria affecting the type of system selected. Sandy soils typically have high intake rates and low soil moisture storage capacities. They may require an entirely different irrigation system, timing, and strategy (south Jordan sandy stone plateau, Disi, Muddwarra, wadi Arabah and Jafer, hafira, and east Jordan plateau). The deep clay soil with low infiltration rates but high moisture-storage capacities meanly occurs in North Jordan Valley, North Highland, central and part of Karak Shoubak and Tafila) region. Sandy soil requires more frequent, smaller applications of water whereas clay soils can be irrigated less frequently and to a larger depth. Other important soil properties influence the type of irrigation system to use. The physical, biological, and chemical interactions of soil and water influence the hydraulic characteristics and filth. The mix of silt in soil influences crusting and erodibility (Steepe region) should be considered in each design. The soil influences crusting and erodibility and should be considered in each design (Badiya) desert. The distribution of soils may vary widely over a field and may be an important limitation on some methods of applying irrigation water.

5. **Soluble Salts**: We reviewed the salinity data in cooperation with staff at the Land and Irrigation department/ MoA has greatly helped to assist a more comprehensive

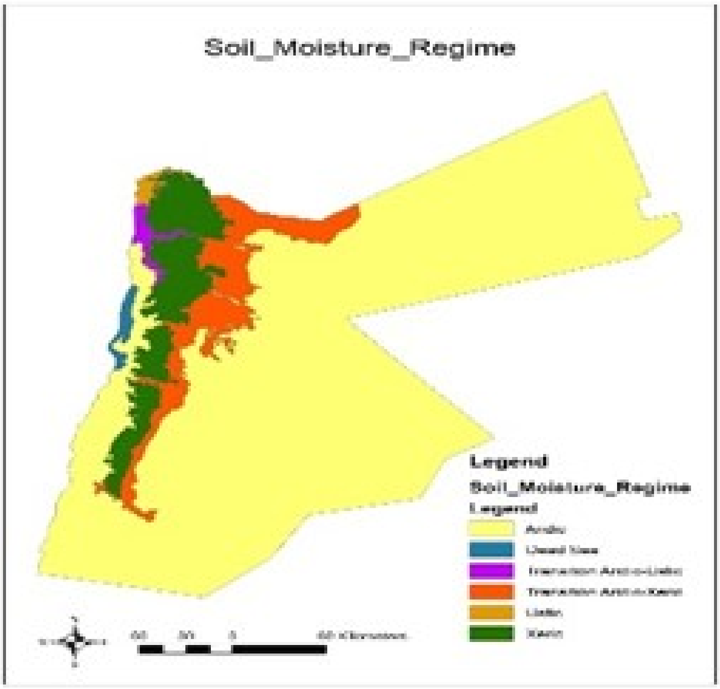


Figure 10: soil moisture regime

picture of the exact area of lands affected by salinity and its percentage and distribution which in turn made our task more feasible and accessible to link the many factors causing salinity in each area such as the physical environment, soil formation (genesis) and several agricultural improper activities farming practices such as irrigation, fertilizing. Jordan has been divided into eighteen physiographic regions. (Mitchell C.W 1975). The major factors considered in defining the 18 Land Regions outlined in (Figure 2) are: Climate, Vegetation, Land Use, geology and geomorphology, Topography, hydrology, and Landsat imagery characteristics. The soil salinity was measured on depths top soil from 0-30cm and 30-100cm where we used the following Soil indicators of salinity: ECe ms/cm, PH, ECe: Electrical conductivity is measured with a standard EC meter on an extract from the saturated paste.

Generally, with decreasing rainfall, Badia contains a large number of soluble salts, the sources of salt in the Jordanian soil are as follows:

(a) Natural salinity, in this case, salinity arises naturally by weathering of the materials constituting the parent material, and in this case, primary salinity is formed mainly in the east and northeast. And south of the deserts and south of Jordan, Valle,y and Wadi Araba. In fact, the salt content could be a residual fact of soil erosion on the rocks. The remains mainly occur on hilltops and on steep hillsides where erosion is active which encourages salinity; In most cases, these are shallow soils, and another group of erosion soils remains on a gently sloping limestone plateau, but even here, aeolian matter likely contributed to the salt build-up, in arid soils where average rainfall is lower 50 mm salt containing moderate to strong 8 to 15 dS/m1 (table 2,3. . . . . . .,) and extreme salinity >15ds/m this level found in mostly dominant arid soil such as Gypsiorthids Calciorthid, and Salorthids.

(b) if the salts accumulate in the soil profile as a result of poor land management,

SALINITY 0-30 CM				
Id	Legend	Salinity area	Most Common	SOC/ tonnes. ha-1
1	NE Basalt Plateau	9697.9699830000	Slight Salinity	10
2	N Lava Flows	2700.6444600000	Moderate Salinity	14
3	Northern Highland (high prec)	209.55820400000	None	46.5
4	NE Plateau	13976.204021000	Strong Salinity	10
5	Central Highlands	363.03745200000	None	38
6	Arabah Hills	983.59537300000	Slight Salinity	15
7	E Plateau	19763.404704000	Slight Salinity	8.5
8	Dead Sea	529.06067700000	Slight Salinity	23.5
9	Highland Plateau	4729.8172100000	Slight Salinity	19
10	Hafira-Jinz	3298.3280700000	Slight Salinity	19
11	S Sandstone Plateau	2938.9800230000	Slight Salinity	5
12	Rum - Disi	3821.4856990000	Slight Salinity	15
13	Wadi Arabah	1912.5875520000	Slight Salinity	13
14	Southern Highlands	149.78984300000	None	28
15	Wadi Arabah Escarpment	1472.0725950000	Slight Salinity	27
16	Jordan Valley	542.34253500000	Slight Salinity	13
17	Jafr Basin	10677.8759510000	Extreme Salinity	19
18	N Highlands	2308.82964900000	Slight Salinity	49
19	Jordan Valley Escarpment	1275.79624900000	Slight Salinity	46

Figure 11: Soil Organic Carbon (SOC) in 0- 30 cm depth

this an example of secondary salinity usually found in desert highlands, and were groundwater is extensively used which increases problem high salinity especially if groundwater has high-level salts, furthermore high temperature also contribute to the formation secondary salinity this is observed in dissected eastern south limestone plateau desert with annual total evapotranspiration of 2427mm in the south and 2325mm, in east Rewashed, south Jordan Valley moving from north to south salinity increases more severely on the Dead Sea coast and Aqaba. in the northeast basalt and limestone plateau, west and north earthen parts of the central highland of Jordan where the rainfall is more than 300 mm mostly soil is non-saline. [23, 27]. In the area south of Azraq, the soils become saline Towards the south around Disi, Mudawwra fairly serious increasing salinity and sodicity problems Figure11 , 12.

Mean Values of Salt-Affected Areas: The averages and ranges of salinity ECe $>$ 4.0 ds/m, and PH 8.3-8.9, in many soils of southern, eastern and south of Jordan Valley to Aqaba increases indicating insufficient and quality of water irrigated to leach the Salts to depth in profile, for the major soil have been given and Average

SALINITY 30-100 CM				
Id	Legend (Land Regions)	Salinity area	Most Common	**SOC/** tonnes. ha-1
1	NE Basalt Plateau	9771.020202000	Moderate Salinity	10
2	N Lava Flows	2712.45055600	Moderate Salinity	14
3	Northern Highland (high prec)	182.2566070000	None	46.5
4	NE Plateau	13978.41766400	Strong Salinity	10
5	Central Highlands	476.6711260000	None	38
6	Arabah Hills	1035.247043000	Slight Salinity	15
7	E Plateau	19826.86247000	Moderate Salinity	8.5
8	Dead Sea	529.0606770000	Slight Salinity	23.5
9	Highland Plateau	5683.159462000	Slight Salinity	19
10	Hafira-Jinz	3492.390773000	Moderate Salinity	19
11	S Sandstone Plateau	2940.455785000	Moderate Salinity	5
12	Rum - Disi	4366.779758000	Slight Salinity	15
13	Wadi Arabah	2096.319921000	Strong Salinity	13
14	Southern Highlands	174.8777970000	None	28
15	Wadi Arabah Escarpment	1773.865924000	Slight Salinity	27
16	Jordan Valley	540.8667730000	Slight Salinity	13
17	Jafr Basin	10765.68379000	Extreme Salinity	19
18	N Highlands	2333.179722000	Slight Salinity	49
19	Jordan Valley Escarpment	1432.964902000	Slight Salinity	46

Figure 12: Soil Organic Carbon (SOC) in 30- 100 cm depth

values of ECe exceed 30 mS/cm'1 in regions wadi Arabah and Disi-Ram, wadi Arabah escarpment, Arabah hills dissected basements plateau, Jafer Basin, East and south limestones plateau where the dominant soil subgroups occur (Calciorthid, Cambortids, Gypsiorthid, and Salorthids, and values over ECe16ds/ m'1 occur The salinity levels in the soils of the arid regions are high for crop production without leaching. Given the weak-developed structure of the majority of the arid soil, permeability is not likely to hinder leaching. However, where water availability is limited and the opportunity cost high, the high salinities of most arid zone soils constitute a serious impediment to development. (Figure 4,5) lists the salinity map units of the arid regions which contain moderate to low contents of salts. These less saline soils occur either in coarse-textured parent materials such as the sandstone-derived alluvium and aeolian sands of regions wadi Arabah and Disi-Ram, or occur in broad wadi lines where the upper soil profiles consist of young alluvium and aeolian material, and there is occasional flow in these wadis which is lent to leach out most of the soluble salts and maintain the salt balance at a relatively low level, these areas represent the best available land for irrigation develop within the arid zone since the use of scarce water for reclamation is minimized.

Successful irrigation of sandy alluvial soils is already carried out in the Mudawwara and Disi areas. (Mean EC, PH Realization in figure. . . . . . ,).

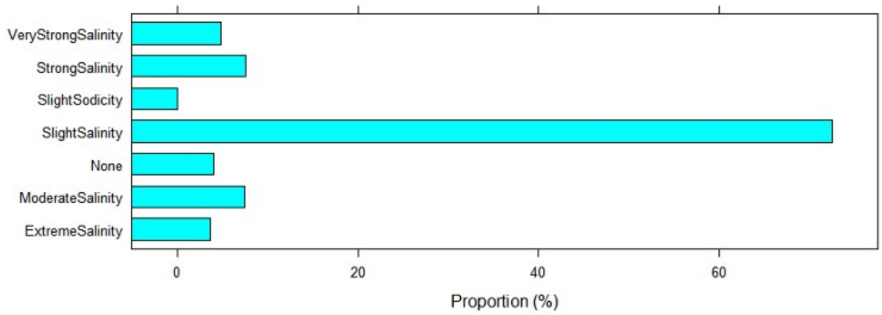


Figure 13: Salt-Affected Soils of Jordan 2019

Generally, most of the arid lands in Jordan on the topsoil at depth (0-30 cm) are slight to moderately saline associated with strong patchy saline, seen clearly in south-eastern areas neighboring KSA and Iraq, while the Jafer mudflat is considered an extreme salinity area and surrounding areas to it considered strongly saline, transitional zones show lightly salinity, while the north and central highland none saline. (Figure,4). Study Results have demonstrated that slightly saline land area is significantly larger at (30-100 cm) depth suggesting that salinity increases with an increase in depth, on the other hand, moderate saline land area has grown in desert and transitional zones especially the soil under irrigated agriculture which can be seen at Mafraq, Disi, Modawarra, Jordan valley and Aqaba figure 13

6. **PH**: The pH of Jordanian soil commonly in ranges from 7.3 to 8.5 occasionally increases with rising alkalinity in very small areas. According to analysis, we can divide the PH into 4 classes Neutral 6.8–7.5, Slightly alkaline 7.5–7.8, Moderately alkaline 7.9–8.4, Strongly alkaline more than 8.5

   Calculation pH: The concentration in the samples is calculated by comparison of the reading of the sample with the reading of the standard solution. Concentration in standard is 10 me Cl/1 (a) Average reading for a standard solution is (b) The dilution factor for the samples is (c) The chloride concentration in the sample can now be calculated as follows: Conc.CI (me/I) =(axc)/(b) or =(10Xc)/(b).

Agro ecological Systems	Ece ms/cm 26-60	PH 26-60cm	O.M% 0-10cm	CaCo3% 26-60cm	Gypsum % 20-80
Jordan Valley	2.5-5.8	7.7-8.0	1.47	18	5.0
Highland	2.6	6.9-7.8	1.13	13	-
Steppe Zone	25.3	7.6-8.2	1.21	37	03
Badia	60.1	7.8-8.4	0.37	25	15.2

Figure 14: Main Chemical Soil Characteristics

Generally value of pH 8 presents no problem to adapted crops up Thereafter both phosphate and nitrogen become much less available, and above pH 8.6 there are major limitations, restricting severely the choice of cropping or requiring expensive fertilizers or ameliorants to be applied.

7. **Main Chemical Soil Characteristics**: Calcium Carbonate, majority of soils is calcareous, Sources are Aeolian dust Calcic horizons occur in the dry steppe and desert 63% of soil content $>$ 18% CaCo3. Clay Content, moderate to high clay content and decrease from north to south, and from west to east highest content in an alluvial Soil derived from basalt in the arid northeast Jordan, 55% clay, PH varies 7.2 - 8.4, Organic Matter, Low content and wide C/N ratio.1.13% - 1.71% in highland rainfed.1.47% in J.V irrigated. Main Chemical Soil Characteristics Figure14

8. **Nutrients Availability NPK**: In general, soils of Jordan are considered poor in organic matter content, ranging from 1 to 3%, and the percentage does not exceed 0.1-0.03% in desert soils, and 1% in transitional areas, while it increases in the northern Jordan Valley regions to reach 2.5-3%, however in the Jordanian undulating plains 0.99-1.7%.The mean total phosphorus in most soils in Jordan Valley is 1099 ppm and available 11 ppm, the total and available ranges in highlands are 1479 ppm and 6 ppm respectively. The average total values and available phosphorus in Steppe Zone are (1300 ppm) and 9 ppm for typical dry Camborthids soils within the transitional moisture regime, while in desert (Badia) total and

available ranges are 1706ppm and 5 ppm NPK: Generally, the average values for available phosphorous represent the lower levels of adequacy in most of the Typic Camborthids and xerochreptic Camborthids soils in the soil such as Xerochrepts, Calcixerollic Xerochreps, Vertic Xerochreps and Vertisols

Soil fertility generally varies from one soil order to another. The most fertile soils are those of the Inceptisols and Vertisols, due to their high clay content and high caption exchange capacity. However, these soils suffer from low organic matter and nitrogen contents, and sometimes iron, zinc, and phosphorus deficiency due to high carbonate content. The Vertisols induce physical stress on plant roots due to cracking which is driven by swelling and shrinking due to moisture variations., Aridisols in the dry regions pose various problems for cultivation that result from high carbonate, gypsum or salt contents. Entisols are difficult to cultivate as well because they are dominated by sandy, gravelly, stony, or shallow substrate.

However, in Hydrocarbon Possibilities, the soil of Jordan is divided into 4 classes the dominant is low ware occupied 30.44% equal (27153.4) km sq, Fair classes 25.79% (23002.3) km sq, good classes 22.20% (19798.7) km sq, very poor (non) 21.57% (19235.7) km sq.

The average total nitrogen content is between 0.05-0.02%. Total phosphorus in arid, sandy, and alluvial soils is 580-950 total, and the available 2-7 ppm while potassium is 0.75, 0.6,7, and 0.60% total potassium.

In most cases, it is water availability that is many times more limiting than nutrient availability, per season though often crops suffer from nutrient deficiency because of the drying out of the nutrient-rich topsoil. Nutrients Availability figure 15

9. **Techniques for linking soil properties data with satellite images:**

   - **Machine learning**: Techniques such as random forests, support vector machines

Agro ecological Systems	Tot N% 10-25	Available N% 25-60cm	Tot P ppm 0-10cm	Available P ppm 25-60cm	Tot K % 10-25	Available K % 25-60
Jordan Valley	0.09-0.1	NR	1099	11	0.75,	NR
Highland	0.05-0.060		1479	6	0.64	
Steppe Zone	0.032-0.050		1300	9	0.62	
Badia	0.02-0.041		1706	5	0.70	

Figure 15: Agro-ecological Systems-NPK

and neural networks can be used to train models that predict soil properties based on satellite images and other relevant data.

- **Remote sensing**: Techniques such as spectral indicators and radar backscatter analysis can be used to derive information on vegetation cover, soil moisture and other soil properties from satellite images.
- **Geo-statistics**: Techniques such as kriging can be used to extrapolate soil properties data from point measurements to create continuous spatial maps.
- **Data fusion**: Combining data from multiple sources, such as satellite imagery, ground measurements, and climate data, can improve the accuracy and spatial resolution of soil characteristic maps Table 5.

Table 5: Soil Properties Analysis Dataset Requirements

No.	**ISRIC & MoA Data**	**Sentinel-2A Bands**	**AI Models**	**Sentinel-1A**	**SRTM**
1	- Total Nitrogen - NPK - ECE - Silt - Clay - Sand	- Blue (496.6nm) - Green (560nm) - Red (664.5nm) - Red Edge 1 (703.9nm) - Red Edge 2 (740.2nm) - VNIR, SWIR1	- GB - XGB - RF - RADA - Regression - SVM - CNN - MCA	- VV - VH	- DEM - Slope - Aspect
2	EC	G, R, NIR (560-835 nm)	–	–	–
3	Soil Moisture	NIR (835.1nm)-SWIR	–	VV/VH	–
4	pH	SWIR1 (1613.7nm)	–	VV/VH	DEM

3.2.3.1 Soil property analysis service, Soil property measurement equipment, Soil property monitoring post (IoT-based or with data storage):

Understanding soil properties—such as moisture content, pH, EC, and NPK —is essential to maximize crop yields, manage resources efficiently, and mitigate environmental impacts. The Poc Soil Property Analysis Service exemplifies how technology can facilitate the assessment and monitoring of soil properties through advanced measurement equipment IoT-based solutions and satellite images. In this overview, we will explore various tools and techniques available for soil property measurement and monitoring, ensuring that land managers and farmers have access to the information necessary to make informed decisions.

3.2.3.1 Soil Property Measurement Equipment: - Soil Moisture Sensors: to measure the volumetric water content in soil for irrigation management.

- Time-Domain Reflectometry (TDR) Sensors: Measure the reflection of a pulse from the soil, offering high accuracy.

- pH meters assess the soil's acidity or alkalinity, influencing nutrient availability, these can be handheld for field use or used in laboratory analyses to ensure precision.

- EC meters measure soil salinity and nutrient levels, helping farmers understand soil fertility. important for managing soil health in irrigated areas.

- soil samples and Spectrometers analyze soil composition by examining how soil reflects or absorbs light.

IoT-based monitoring systems and data analytics, allow for real-time insights that lead to informed decision-making.

- Soil Property Monitoring Post (IoT-based or with Data Storage)

- Deploying a network of interconnected sensors in the field and transmitting data in real-time.

- Using IoT technology (e.g., Wi-Fi, LoRaWAN,) to send collected data to cloud storage or a local server for processing and analysis.

- Creating user-friendly dashboards for stakeholders (farmers, land managers, researchers) to access real-time data.

Data Collection: Gathering soil samples and records from various locations for initial analysis.

Analysis Techniques: Utilizing both traditional laboratory analysis (e.g., chemical tests) and advanced techniques (e.g., spectroscopy) to determine soil properties such as pH, and NPK.

Integration with Technology: Combining soil data with satellite images and IoT sensor data for a more robust understanding of soil health across landscapes.

Table 6: High-End Professional Soil Analysis Systems

Provider	Model	Parameters	Connectivity	Price Range (USD)
Sentek	Drill & Drop	Moisture, Temperature, Salinity	4G/LoRaWAN	2,000-3,500
Stevens Water	HydraProbe	Moisture, EC, Temperature	RS-485/SDI-12	1,500-2,500
METER Group	TEROS 12	VWC, EC, Temperature	SDI-12/USB	1,200-2,000
Delta-T	WET-2	Water, EC, Temperature	RS-232	2,500-3,800

Table 7: NPK Specific Sensors

Provider	Model	Measurement Depth	Accuracy	Price Range (USD)
Libelium	Smart Agriculture	0-30cm	±2% NPK	3,500-4,500
Stenon	Diagnostic	0-40cm	±1.5% NPK	4,000-5,000
AgroCares	SoilCares	0-20cm	±2% NPK	2,800-3,500
Teralytic	Soil Probe	0-45cm	±1% NPK	5,000-6,000

Commercial Sensor Solutions

3.2.4 Existing AI models for similar purposes:

Integrating AI models with satellite imagery, drone technology, and IoT sensors offers an effective way to predict soil properties and optimize irrigation timing in agriculture.

Table 8: IoT-Enabled Complete Soil Monitoring Systems

Provider	Solution	Parameters	Platform	Price Range (USD)
CropX	Pro	NPK, Moisture, EC, pH	Cloud-based	8,000-12,000
Monnit	ALTA	NPK, Moisture, Temperature	IoT Platform	6,000-9,000
Sensoterra	Pro Series	Moisture, EC, Temperature	Web/Mobile	4,000-7,000
Soil Scout	Underground	Moisture, Temperature, EC	Cloud Analytics	7,000-10,000

These innovations support precision farming, which not only boosts productivity but also helps save resources.

3.2.4.1 Satellite Imagery Analysis:

1. Machine Learning Models: (e.g., RF, SVM) can correlate spectral data from satellite imagery with soil characteristics like NPK levels, pH, and moisture content.

2. Artificial Neural Networks (ANN): Can model complex non-linear relationships and have shown promising results in predicting soil properties from multi-spectral and hyperspectral imagery.

3. Gradient Boosting Machines (GBM): Ensemble learning methods that combine multiple weak learners to create a strong predictor. Effective for handling complex relationships and improving model accuracy.

4. Deep Learning Models: as (CNNs) to extract features from high-resolution satellite images, enabling the prediction of soil properties across large areas, for learning

complex patterns in the data that relate to soil health indicators.

5. Recurrent Neural Networks (RNNs): Suitable for time-series data, RNNs can be used to model temporal variations in soil properties and incorporate historical data into predictions.

6. Input Data: open sources such as Sentinel-2, and Landsat imagery (spectral bands like NIR, SWIR, RED for NDVI, NDWI, etc.).

7. **Output:** Predicts NPK, pH, EC, and soil moisture.

3.2.4.2 Drone-Based Hyperspectral Imaging

1. Hyperspectral Cameras: Drones equipped with hyperspectral cameras (as FIGSPEC), then data can be processed using AI models to assess soil properties and moisture levels.

2. AI Algorithms for Image Processing: as Deep Learning (e.g., U-Net, ResNet) Algorithms can be trained on hyperspectral data to predict soil properties by correlating spectral signatures with known soil characteristics.

3. Output: High-resolution maps of NPK, pH, EC, and soil moisture

3.2.4.3 IoT Sensors and Data Integration, Real-Time Soil Monitoring:

1. Model: Time-series models (e.g., LSTM, GRU) or regression models (e.g., XGBoost, LightGBM).

2. Input Data: IoT sensor data (soil moisture, temperature, humidity, EC, pH).

3. Output: Real-time predictions of soil properties.

4. Data Fusion Models: AI models that integrate data from various sources (satellite, drone, and IoT sensors) can provide comprehensive insights into soil health and irrigation needs, and can utilize ensemble learning techniques to improve prediction accuracy.

3.2.4.4 Predictive Analytics for Irrigation Timing:

1. Evapotranspiration (ET) and Soil Moisture Prediction from WaPOR by FAO for water productivity[18]:
2. Model: Regression models or CNNs for predicting ET and soil moisture.
3. Input Data: open source as Sentinel-1 (SAR for soil moisture), Sentinel-2 (optical for NDVI, NDWI), and weather data.
4. Decision Support Systems: AI-driven decision support systems can analyze historical data and real-time sensor inputs to recommend irrigation timing that maximize water efficiency and crop yield.
5. Output: Optimal irrigation timing.
6. Long Short-Term Memory (LSTM) networks: Effective for handling time-series data and can capture long-term dependencies in weather patterns and crop growth.
7. Reinforcement Learning: Can be used to develop an agent that learns the optimal irrigation policy over time by interacting with the environment (farmland) and receiving rewards for successful irrigation decisions.

3.2.4.5 Key Considerations:

1. Data Quality: The accuracy of predictions heavily relies on the quality and quantity of data.

2. Model Training and Validation: Rigorous training and validation procedures are essential to ensure model accuracy and reliability.

3. Computational Resources: Training and deploying deep learning models often require significant computational resources.

4. Data Privacy and Security: Appropriate measures must be taken to ensure the privacy and security of sensitive data.

3.2.5 The Irrigation Timing Model

3.2.5.1 Irrigation timing data in Jordan (either open source or commercial) tables – techniques

According to the MoA, Noting that the Ministry of Agriculture does not have real data on irrigation timing in terms of quantities and dates followed in each farm According to the MoA.

After reviewing the available scientific research AI to predict the model for the timing of irrigation on selected agricultural land we were able to determine the open source growth requirements and commercial requirements.

Data Sources:

1. **Historical Irrigation Records on farmland:** past irrigation timing data on farmland are valuable to developing and training the AI Model, it is effectiveness in different irrigation strategies.

2. Real-time Sensor Data commercial (IoT):

   - Temperature and Humidity: These factors directly influence evapotranspiration rates, which is crucial for determining water needs for optimizing irrigation schedules.

- Soil Moisture: to help determine when and how much water to apply.
- **Water Balance**: accounting of water inputs (rainfall, irrigation) and outputs (evapotranspiration, runoff, deep percolation) provides a comprehensive understanding of the water dynamics within the field.

3. **Crop-specific Information**: Different crops have varying water requirements and sensitivities to water stress. Incorporating crop-specific data allows for more precise irrigation scheduling.

4. **Satellite images spectral values**:

- **Thermal bands (Landsat 9)**: thermal images provide information on the surface temperature. This is critical for estimating evaporation, as warmer surfaces generally indicate higher transpiration evaporation rates.
- **VRGB bands**: these bands are sensitive to the health and activity of plants. Changes in the reflection of vegetation in these ranges can indicate water tress, which allows early detection of moisture deficiency.
- **SWIR1 (shortwave infrared 1)**: this tape is particularly sensitive to soil moisture content.
- Changes detection can be used to estimate soil moisture levels.
- Red-edge 1 and 2: these bands are located at the edge of the red part of the visible spectrum. They are sensitive to the content of plant chlorophyll, which is an indicator of Plant Health and water stress.

3.2.5.2 Water Irrigation Timing Techniques on Farmland Data with Satellite Images:

The AI model uses a multifaceted approach to predicting the optimal irrigation timing. By integrating historical data, real-time sensor measurements, satellite images and advanced machine learning technologies, the model aims to improve water use efficiency, reduce water waste, and enhance crop yields.

There are several we can AI models implemented in this area, such as :

- Decision tree algorithms: these algorithms use a series of rules to make decisions. In this context, they can be used to classify conditions (for example, high, medium and low water stress) and determine the optimal watering timing based on the input data.
- Regression techniques: to predict the amount of water required for irrigation based on input data.
- Sensor fusion technologies: by combining data from multiple sensors and data sources (satellite images, weather stations, soil moisture sensors), an AI model can improve the accuracy and reliability of its forecasts.

Table 9: Water Irrigation Timing Analysis Requirements

Input Data	**Sensor Systems**	**Analysis Methods**	**Spectral Bands**	**SAR Data**
• Historical irrigation records • Water balance • Soil moisture • Crop status • Real-time sensor data: - Temperature - Humidity - Evapotranspiration	• IoT sensors • Thermal bands (Landsat9) • Cloud platform integration for data processing	• Decision Tree algorithms • Regression • Sensor fusion techniques	• Red (664.5nm) • Red Edge 1 (703.9nm) • Red Edge 2 (740.2nm) • NIR (560-835nm) • SWIR1	• VV polarization • VH polarization

3.2.5.3 Review of Commercially Available AI Applications for Soil Property Prediction and Irrigation Optimization

Commercially available AI applications are revolutionizing precision agriculture by predicting soil properties such as NPK, pH, EC, and soil moisture while optimizing irrigation timing. Key features, use cases, and market positioning of leading AI applications in this space are highlighted in the review for the features analysis, cases, and Technology. Some of the key Commercially Available AI Applications: **A. Soil Property Prediction:**

1. **CropX:**

- Features: Analyzes soil data (moisture, temperature, EC) using in-field sensors and satellite imagery.

- Use Case: Provides real-time soil insights and recommendations for irrigation and fertilization.

- Technology: Combines IoT sensors, satellite data, and machine learning models.[9]

2. **Taranis:**

- Features: Uses high-resolution satellite imagery and AI to monitor crop health, soil conditions, and nutrient levels.

- Use Case: Identifies nutrient deficiencies (NPK) and soil variability across fields.

- Technology: AI-powered image recognition and data analytics.[46]

3. **SoilWeb :**

- Features: Provides detailed soil property maps (pH, EC, organic matter) using satellite and geospatial data.

- Use Case: Helps farmers understand soil variability and plant nutrient management.

- Technology: Integrates remote sensing and GIS technologies.[43]

4. **Agrible:**

- Features: Predicts soil moisture and nutrient levels using weather data, satellite imagery, and AI models.

- Use Case: Offers actionable insights for irrigation and fertilization scheduling.

- Technology: Machine learning algorithms and predictive analytics.[3]

B. Irrigation Timing Optimization:

1. **Farmers Edge:**

- Features: Combines satellite imagery, weather data, and soil sensors to optimize irrigation schedules.

- Use Case: Reduces water usage while maintaining crop health.

- Technology: AI-driven decision support system.[15]

2. **AquaSpy:**

- Features: Monitors soil moisture and root zone conditions to recommend irrigation timing.

- Use Case: Improves water efficiency and crop yields.

- Technology: IoT sensors and AI analytics.[5]

3. **Cropio:**

- Features: Uses satellite data to monitor soil moisture and vegetation health, providing irrigation recommendations.

- Use Case: Helps farmers optimize water usage and reduce costs.

- Technology: Remote sensing and machine learning.[8]

4. **Sentera :**

- Features: Leverages drone and satellite imagery to monitor soil moisture and crop health for precision irrigation.

- Use Case: Provides real-time irrigation recommendations.

- Technology: AI-powered image analysis and predictive modeling.[42]

3.3 The PoC program's Requirements Identification:

This section highlights the sample area and evaluates the choice between using satellite imagery and drones, the specific type of satellite imagery required, the number of samples needed, and other relevant considerations.

3.3.1 Sample Area

The sample areas will be examined at a specified observation density using satellite imagery and IoT sensors per km^2. It is standard practice to survey these areas for key parameters such as EC, pH, NPK, and soil moisture, typically at four sites per km^2, depending on crop type and land use. Conducting an initial survey of the sample areas was deemed essential to gather critical information on the relationships between soil properties, water availability, and crop types. As a result, the survey of the sample areas was conducted as the first phase of the field study in each designated location. The sample areas were utilized to achieve the following objectives:

1. Verify Accuracy and Determine Requirements: Validate the accuracy of soil properties, assess crop suitability to soil conditions, evaluate irrigation water sustainability, analyze satellite imagery and IoT sensor data, and determine the number of soil samples needed for detailed analysis.

2. Understand Relationships: Provide sufficient data to understand the relationships between soil type characteristics, landforms, available water, and nutrient levels, enabling the determination of optimal storage and processing methods.

3. Establish Study Parameters: Define a study level for the sample areas to understand the range of soil types and nutrient variations and provide insights into IoT and irrigation water compatibility with specific crop types.

4. Extend Findings: Extend the insights gained from the sample areas to the broader region by selecting representative farms that align with the primary Proof of Concept (PoC) objectives.

5. Training and Standardization: Serve as an initial training ground for partners and establish uniform standards for data collection and analysis.

3.4 Choice of Sample Areas:

The selection of sample areas will begin with the interpretation of open-source satellite imagery to identify representative areas covering the main farm units. Four sample areas will be chosen across four agro-climatic zones within the country to ensure diverse and comprehensive data collection. Satellite images of these areas will undergo detailed interpretation to generate precise descriptions and identify suitable sites for soil sampling. This process ensures coverage of all major facets within the farms. Each sample area will span 5–10 square kilometers, with soil samples and IoT sensor sites selected based on the relationships between soil nutrients, soil moisture, and crop types.

3.4.1 Use of Sample Areas:

Data collected from the sample areas will play a crucial role in defining the following parameters:

- The range of EC, pH, NPK, and soil moisture levels.
- The variability within the broader farm units.
- The relationship between soil properties, irrigation timing, and suitable crop types.

The proportion of various soil properties in relation to nutrients, water irrigation extent, and crop types.

This information will be cross-checked against farm units delineated after final satellite image interpretation and field data collection. These units will be digitized into a GIS system, registering and displaying all sites within the farm unit, including those within or overlapping with the sample areas. The data will be combined to create the final farm units.

For each farm unit, a legend will provide detailed information, including soil proportions, brief descriptions linking soils to specific landscape features, and data on NPK, pH, soil moisture, and irrigation timing. In cases where sample area details were insufficient or observation sites were limited, estimates will be derived using satellite images. However, the determination of relationships between soil properties, soil moisture, nutrient levels, and land proportions will rely heavily on data from the sample areas, whether from detailed registers or the sample area surveys themselves.

(We successfully executed two sample areas studies in separate areas the full reports of both studies are available among the files previously sent to you, (North Ghor 100 km2 and Ruwaished 2 km2))

According to the protocols of agencies and companies that provide satellite imagery with varying types and characteristics, services are typically offered at two levels:

1. Archive Imagery: This option involves requesting pre-existing images from the provider's archive. The minimum area that can be requested is 25 km^2, and the cost is relatively lower.

2. Tasked Imagery: This option requires scheduling a new image acquisition at a specific time. The minimum area for such requests is 100 km^2, and the cost is significantly higher than that of archive imagery.

To identify the requirements for the (PoC) program aimed at developing and training an AI model to predict soil properties (NPK, pH, EC, and soil moisture) and water irrigation timing on farmland based on hyperspectral images in high-resolution the key elements to consider:

1. Satellite data helps in understanding historical trends and regional variations in soil properties.

2. **Satellite type**: Hyperspectral images, preferred composition with other sources as SAR images

3. **Resolution**: High-resolution satellite imagery (preferably Worldview-3) for (0.3cm - 5m for VNIR and SWIR groups) As well as compiling it with Multispectral (e.g., Sentinel-2, Landsat) and SAR backscatter for soil moisture (e.g., Sentinel-1).

4. **Spectral Bands**: Imagery that includes visible, near-infrared (NIR), and shortwave infrared grouping bands (SWIR) for the PoC required analysis.

5. **Frequency**: Regular updates (e.g., bi-weekly or less) are necessary to capture changes during critical growth periods.

6. satellite image samples for the soil properties (NPK, pH, and EC) hyperspectral images based on the growth stages of plants (entail early, mid, and end) need one time. Still, The most sensitive is the moisture content which plays rules in irrigation timing, according to this we clarify the following:

7. hyperspectral high resolution more expansive (worldview 3) need an image each day, week if available relevant to the growing season, ensuring coverage across different climatic conditions and crop types.

8. **Satellite Images Samples:**

   Temporal Resolution: For soil properties: 1-2 images during the growth stage.

   - **For irrigation timing:** Weekly or bi-weekly images to monitor soil moisture, climate condition, and crop conditions to ensure model accuracy. Building a soil fertility prediction model relies on historical and recent data to track changes in soil properties over time. Therefore, you may need:

   (a) To effectively evaluate crop requirements about soil characteristics using multiple images over several growing seasons (at least 2-3 years),

(b) based on the area the large area, you may need 10-20 images per season to ensure full coverage, depending on the spatial distribution of the fields. for temporal and spatial variations.

Iot Samples: Depending on the efficiency, capacity, and accuracy of the devices, we recommend using devices with an average cost that is acceptable to the project budget. In any case, the project needs many devices at the current stage(most of the providers recommended a site density between 25-30 sensors/ km2).

9. **Number of Samples for train AI model:** for traditional ML between 500-1,000 labeled samples for deep learning +10,000 labeled pixels.
10. **Model Development**: Train and validate the AI model(CNN, TensorFlow/PyTorch).
11. Validation: Compare predictions with ground truth data.
12. Deployment: Provide soil health maps and irrigation timing.

3.4.2 PoC Program Requirements for AI-Based Soil Property Prediction and Irrigation Timing Prediction:

These sections target the data sources for soil property prediction and model irrigation timing on farmland:

1. **Soil Property Prediction**: pH, EC, Soil Moisture, NPK.
2. **Irrigation Timing Prediction**: Optimal irrigation timing for farmlands Data Acquisition and Preparation

3.4.2.1 Data Sources for Soil Property Prediction

1. Satellite Imagery: High-resolution multispectral imagery or hyperspectral (e.g., world view 3, Sentinel-2, Landsat-8) with visible, near-infrared, and shortwave

infrared bands.

2. Ground Truth Data: Soil samples with measurements for pH, EC, soil moisture, and NPK content, accurately georeferenced.

3.4.2.2 Data Sources for Irrigation Timing Prediction:

1. **Weather Data:** Historical weather data (temperature, precipitation, humidity, wind speed, solar radiation).
2. **Soil Data:** Soil type, texture, depth, and water-holding capacity.
3. **Crop Data:** Crop type, planting date, growth stage, and water requirements.
4. **Irrigation History:** Historical irrigation records (dates, amounts, methods).
5. **Remote Sensing:** Satellite imagery (spectral indices) to monitor crop health and stress.
6. **Soil Moisture Sensors:** Real-time soil moisture data from in-field sensors.

3.4.3 AI Model Building for Soil and Irrigation

3.4.3.1 Data Preprocessing:

Image Processing: Atmospheric correction, geometric correction, cloud masking, and band selection for satellite imagery. Feature Engineering: Extract relevant features from satellite imagery (e.g., vegetation indices, texture measures, spectral indices), weather data (e.g., cumulative rainfall, evapotranspiration), and crop data (e.g., crop water stress indices).

1. **Data Cleaning:** Handle missing values, outliers, and inconsistencies in all datasets.

2. **feature engineer:** To enhance the performance of your AI models for predicting soil properties and irrigation timing, also combine domain knowledge with data-driven methods to create meaningful features that capture the underlying patterns in the data.

3. **Data Aggregation:** Aggregate data at appropriate time intervals (e.g., daily, weekly) for irrigation timing prediction.

3.4.3.2 Model Development and Training:

1. **Model Selection:** Soil Property Prediction: Choose appropriate machine learning algorithms (e.g., Random Forest, Support Vector Regression, Deep Neural Networks) based on the complexity of relationships between soil properties and satellite data.

2. **Irrigation Timing Prediction**: Choose suitable machine learning algorithms (e.g., time series models, recurrent neural networks, support vector regression). Training Data: Split datasets into training, validation, and testing sets.

3. **Model Training**: Train the selected models using the training data, fine-tuning hyperparameters for optimal performance.

4. **Model Evaluation**: Evaluate model performance using appropriate metrics:

   Soil Property Prediction: R-squared, RMSE, MAE Irrigation Timing Prediction: Accuracy, precision, recall, F1-score

3.4.3.3 Validation and Deployment

1. **Independent Testing**: Assess model performance on the held-out testing set to ensure generalizability.

2. **Uncertainty Quantification**: Estimate prediction uncertainty to provide a measure of confidence.

3. **Deployment**: Develop user-friendly interfaces (e.g., web applications, mobile apps) to allow users to input data and obtain predictions.

3.4.3.4 Model Key Considerations

1. **Data Quality**: Ensure high-quality and reliable data sources for both models. Model Interpretability: Choose models that provide insights into the factors influencing soil properties and irrigation timing.

2. **Real-time Updates**: Incorporate real-time weather forecasts and soil moisture data for improved irrigation timing predictions. User-friendliness: Design user-friendly interfaces that are easy for farmers and other users to use.

3. **Sustainability**: Develop sustainable data collection and model updating strategies.

3.5 The Potential Impact of PoC Technology:

This section will discuss the the potential impact of PoC technology including how it will benefit both governments and farmers, Propose to predict the soil and water property, applying in two pilot areas selected by MoA using open source satellite images and GeoAI methods that have been developed in the Growth-Jordan company (SPDT).

We believe that the application of the PoC using AI technologies has great potential for revolutionizing the planning, monitoring, and management of land and irrigation in Jordan. Moreover, we expect that AI—a model that learns from user inputs and experiences over time—combined with interpretability through AI holds great promise.

Furthermore, it will add great value to research and development in land sustainability and irrigation management, which may be better positioned as a result. If AI focused on applying such science to transdisciplinary problems such as water scarcity, land degradation, fertigation, and irrigated agriculture, it could achieve the optimal balance of economic, environmental, social, and institutional considerations.

The PoC project through soil properties and irrigation studies generates a very considerable volume of data, on soil and water irrigation. The data on the soil characteristics will be recorded and inputted into a computer. The data will be collected through the use of satellite imagery, within-field, and machine-mounted sensors, and the AI module will provide impetus for rapid development and will sift through the enormous data streams efficiently. The use of the AI module will permit the user to pose complex questions and request information on a very wide and comprehensive range of soil properties, irrigation timing, and Fertilization including, effective synthesis of such data.

The promised output of the PoC project using AI techniques highlights the potential benefits of AI techniques in irrigation management. Overall, AI can provide several benefits for irrigation and sustainable land management (SLM), including, but not limited to, optimizing irrigation schedules, reducing water use, and improving crop production. The benefits of PoC are to support irrigation management systems. Moreover, the advantages of using these systems, including the use of AI techniques, could reduce the cost of irrigation, manpower, and time.

Moreover, the AI model can also, provide real-time monitoring of soil moisture, weather conditions, and crop health. By analyzing and operating these data, it can achieve optimal irrigation schedules, reducing water wastage and ensuring that crops receive the right amount of water at the right time, this valuable information can help farmers improve the efficiency of their irrigation systems and better management in soil and fertilizer. As well as to improve soil management by focusing on monitoring soil moisture and drainage conditions, and making adjustments to irrigation schedules as needed. This will help to prevent waterlogging and soil salinization, which can give negative results on crops and reduce yields. As aforementioned, one of the biggest output expectations of the PoC project and use of AI is cost reduction, Efficient water use and resource management results in cost savings for farmers especially small farmers. Reducing water and energy consumption contributes to economic sustainability in agriculture.

The objectives of the PoC project are fully consistent with the strategies plan of the Ministry of Water and Irrigation and the Ministry of Agriculture 2023-2040. The National Water Strategy 2023-2040 of Jordan indicates that on-farm water use efficiency does not exceed 55-60%, this will leave a significant challenge for improvement on the use of water irrigation and land sustainable management and subsequently, improve water use efficiency at the farm level through innovative technologies and improve irrigation water management, increasing, on the economic value of water for each crop.

The PoC, project will create a model for implementing accurate and flexible management that will facilitate and help the decision-makers in better planning sustainable irrigation water and soil properties management. It will also provide a greater opportunity for the exchange of data and information between partners at the national level, which will facilitate the achieve of the relevant strategic plans.

Moreover, Synergies regulations and standards or policies will allow systems to be flexible and comply with water usage, environmental impact, cost, and data privacy. Compliance ensures that AI-driven irrigation systems meet fiduciary standards and follow to the best practices. This requirement is essential for the government to ensure that nascent technology adheres to the necessary guidelines. The government should consider environmental and Public Policy priorities systems that promote water conservation, and energy efficiency, and minimize negative impacts on local communities and ecosystems. The need to balance the benefits of AI-driven irrigation systems and land management with the best potential environmental and social consequences is necessary. By considering these factors, policymakers can ensure that AI-driven irrigation systems contribute to sustainable agriculture and responsible resource management. Policymakers through the use of this project and AI-driven mechanisms will have the possibility to use technology on a broader scale to achieve their goals of sustainable agriculture and efficient resource management.

3.6 Pilot area – N.Jordan Valley and Rwished– open source:

GrowTech company developed and trained AI predictive models of soil and water properties. The use of satellite images for open-source data and data sets from various sources, the following are the results of the pilot area selected by the MoA

Table 16 illustrated data requirements, data collection, and preprocessing details on various data sources used to predict soil and water properties, focusing on the Northern Jordan Valley, and Rwished. It includes information on open sources of satellite data from Sentinel-1 and Sentinel-2, Shuttle Radar Topography Mission (SRTM) for elevation, and Soil Grid data for soil properties like clay, sand, and nitrogen content. Additionally, it mentions JEDIT 4 A Raster for aboveground biomass density and Open Land Map for soil pH. The data spans different spatial resolutions and dates, with measurements in various units. This information is crucial for precision agriculture and environmental monitoring.

3.6.1 Soil and water properties Prediction Results

1. **Soil Properties** (moisture stress, total soil moisture, and vegetation moisture) on 29/01/2025

   Using traditional ML methods as Random Forest (RF) algorithms were divided into two methods: **figure** 17 (classification- regression),divided the data that has been

Data source	Bands and products	Spatial resolution	Study areas	Date	Measurement Unit	Depth
Sentinel-1 SAR GRD	vertical transmit/vertical receive (VV)	10 m		30/01/2025	-	-
	vertical transmit/horizontal receive (VH)					
Sentinel-2A	Blue	10 m	N . Jordan Valley	29/01/2025	-	-
	Green	10 m				
	Red	10 m				
	Red Edge	20 m				
	NIR	10 m	Rwished	31/01/2025		
	SWIR1	20 m				
	SWIR2	20 m				
Shuttle Radar Topography Mission (SRTM)	Digital Elevation Model (DEM)	30 m		2000	m	-
Soil Grid (ISRIC)	Clay	250 m	N . Jordan Valley		%	0 – 5 cm
	Sand				%	
	Silt				%	
	Total Nitrogen				%	
	Bulk Density				(cg/cm^3)	
	Cation Exchange Capacity				(mmol/kg)	
	Soil Organic Carbon Content				(dg/kg)	
	Soil Organic Carbon Density				(hg/dm^3)	
	Soil Organic Carbon Stocks				(Ton/Hectar)	
GEDI L4A Raster	Aboveground Biomass Density (AGBD)	25 m		2019 - 2023	Mg/ha	-
Open Land Map	pH	250 m		1950 - 2018	-	0 – 5 cm

Figure 16: Data Sources: Pilot Study Area

used into two groups:

- **The Independent variables**: (i.e., Sentinel 1 polarization, Sentinel 2A bands, soil grid dataset, elevation, and slope).
- **The dependent variables**: (soil properties from the soil grid dataset, an open land map, and GEDI).

The training samples are generated depending on the area and the shape of the farm, as well as the methods that generated the samples (i.e., Randomly or stratified). the accuracy a bout 71%.

Figure 18 consists of six maps that display various soil properties. Each map uses color gradients to represent different spectral values which are extracted from satellite images providing a visual interpretation of soil characteristics.

It includes maps for Cation Exchange Capacity (CEC), Bulk Density, and Soil Organic Carbon Stock, highlighting nutrient retention, soil compaction, and carbon levels, respectively, Soil Organic Carbon Density and Biomass, indicating organic matter presence and productivity.

Figure 19 Soil property N .Jordan Valley (Soil Texture, clay, Sand, silt, Total. N, Ph, EC)

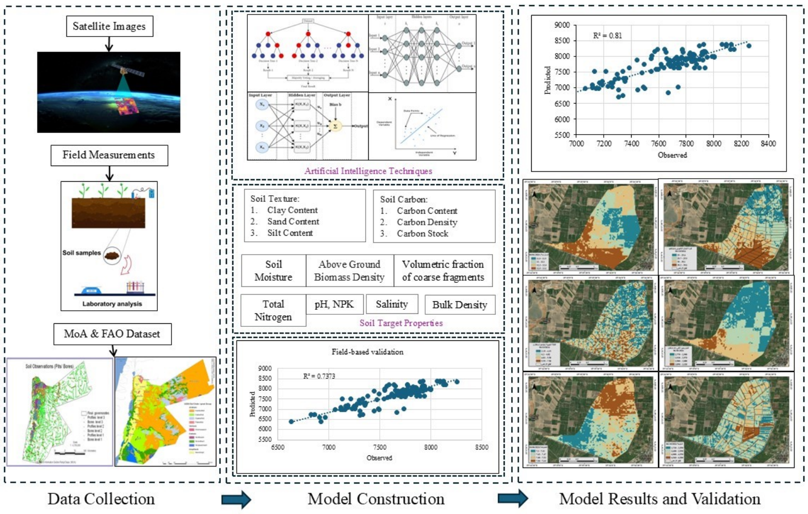


Figure 17: Soil Properties Predictive Models Workflow

2. **Water properties (moisture stress, total soil moisture, and vegetation moisture) on 29/01/2025:**

   Figure 20 outlines a workflow for analyzing water properties using satellite images and field measurements. It incorporates artificial intelligence techniques to assess vegetation moisture content, soil water content, and general moisture levels. The process involves data collection from sources like Moa and FAO datasets, followed by model construction. The final steps include generating model results and validating their accuracy. This approach is essential for precision agriculture and resource management and for PoC objectives.

3. **Water properties (moisture stress, total soil moisture, and vegetation moisture) on 29/01/2025:**

The results in figure 21 displays three maps illustrating different moisture metrics across the pilot area. soil moisture Stress, with spectral values, and total Soil Moisture, indicating the overall moisture content in the soil across the farms. Vegetation Moisture reflects moisture levels specifically in the vegetation.

- Pilot 2 - Soil and Water analysis for the Rwished area on 31/01/2025:

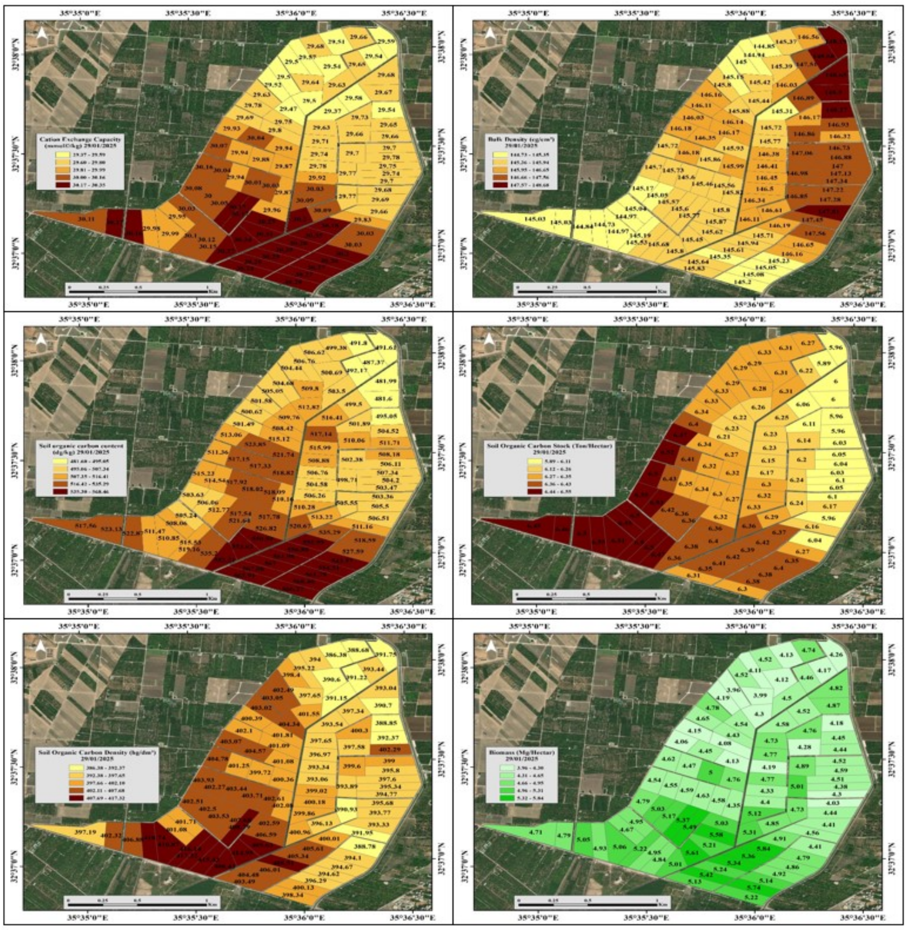
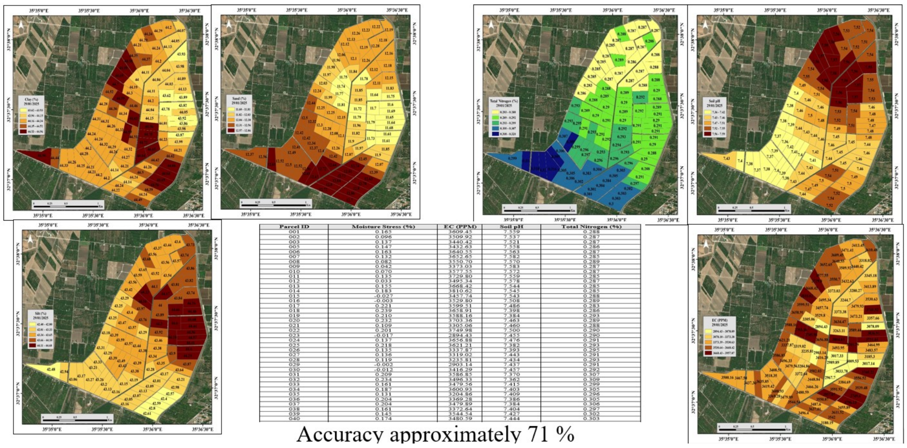


Figure 18: Soil properties -Clay, sand, CEC, SOC, bulk density, Biomass



Parcel ID	Moisture Stress (%)	EC (PPM)	Soil pH	Total Nitrogen (%)
001	0.165	3609.45	7.559	0.288
002	0.096	3509.92	7.537	0.287
003	0.137	3440.42	7.521	0.287
005	0.147	3432.63	7.558	0.286
006	0.163	3640.55	7.563	0.287
007	0.132	3652.65	7.582	0.285
008	0.082	3550.70	7.570	0.289
009	0.042	3373.03	7.583	0.287
010	0.070	3577.55	7.572	0.287
011	0.135	3729.80	7.559	0.285
012	0.033	3495.34	7.578	0.287
013	0.155	3668.42	7.544	0.285
014	0.183	3810.62	7.545	0.285
015	-0.027	3457.74	7.543	0.288
016	-0.003	3529.80	7.508	0.289
017	0.221	3599.51	7.486	0.283
018	0.239	3658.91	7.398	0.286
019	0.210	3588.16	7.384	0.293
020	0.232	3703.36	7.463	0.289
021	0.109	3305.06	7.460	0.288
022	0.201	3749.98	7.500	0.290
023	-0.017	2894.43	7.455	0.290
024	0.137	3656.88	7.476	0.291
025	0.218	3621.21	7.382	0.293
026	0.135	3337.87	7.393	0.295
027	0.136	3319.02	7.443	0.291
028	0.119	3235.81	7.434	0.293
029	-0.002	2903.14	7.437	0.291
030	-0.012	3416.29	7.457	0.292
031	0.209	3586.85	7.370	0.307
032	0.234	3496.33	7.362	0.309
033	0.161	3479.56	7.415	0.299
034	0.187	3600.93	7.403	0.305
035	0.131	3204.86	7.409	0.296
036	0.204	3369.28	7.386	0.305
037	0.204	3479.89	7.384	0.306
038	0.161	3372.64	7.404	0.297
039	0.145	3544.54	7.427	0.302
040	0.174	3480.59	7.444	0.303

Figure 19: soil property -soil texture-clay-sand- silt- total Nitrogen -pH, and EC

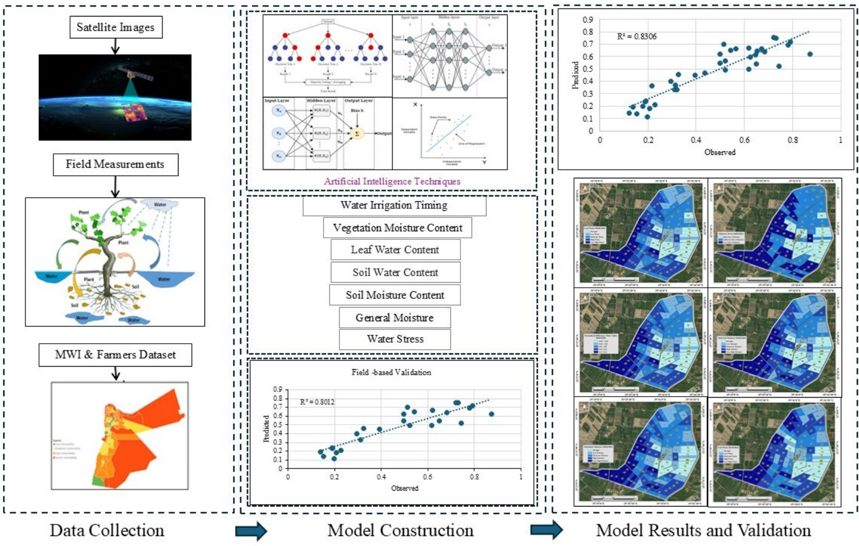


Figure 20: Water irrigation models Workflow

The figure22 illustrates four maps displaying various soil properties across the Rwished area. Total Nitrogen levels indicate different concentrations. Electrical Conductivity (EC), showing variations in soil salinity, and the soil pH, indicating acidity and alkalinity across the region. Finally, the moisture stress reflects water availability for plant growth.

The table 23 illustrates validation between prediction and observes soil properties, the model accuracy is about 80%.

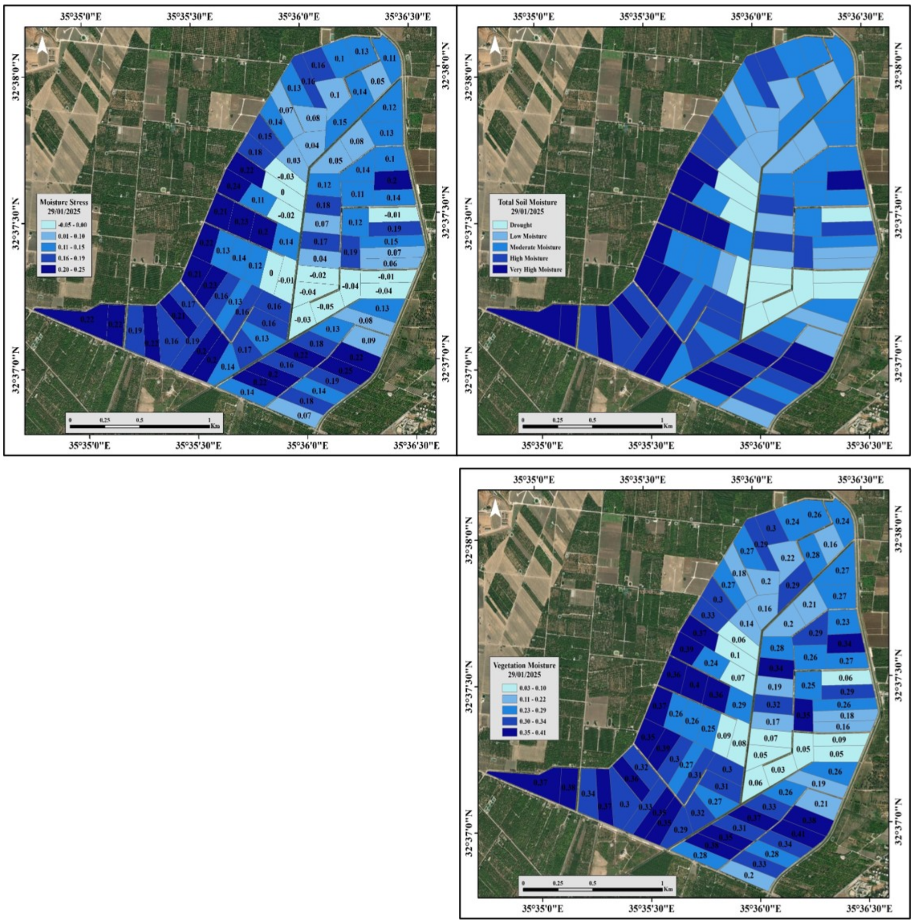


Figure 21: Soil Moisture with Spectral Values

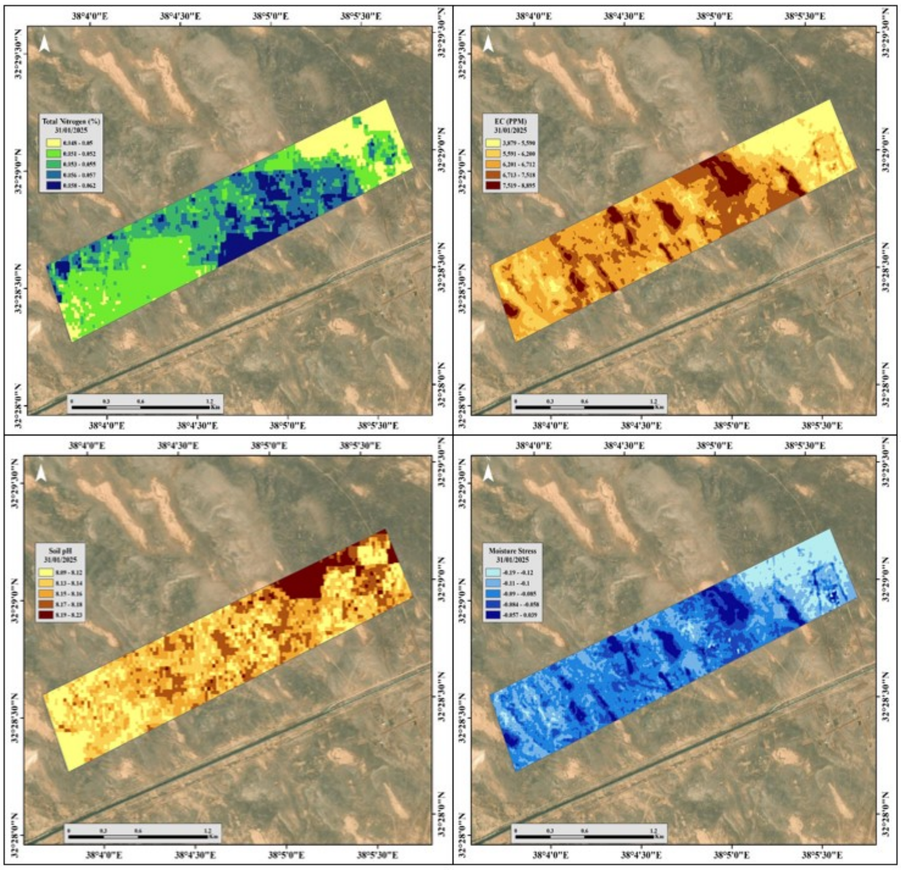


Figure 22: Soil and Water Prediction -Rwished

Selected soil and water	Mean Predicted Value	Mean Observed Value
pH	8.1	7.5
Soil Moisture (%)	-0.096	-
EC (PPM)	6432	5192
Total Nitrogen (%)	0.053	-

Accuracy approximately 80 %

Figure 23: Table illustrates validation between prediction and observes soil properties,

3.7 The Definition of the Expected Outputs

This section mainly outlines the expected outputs from the target PoC program at hand.

The expected output of the PoC project is to use the new art of technology to address the key constraints in the irrigation sector and land management. The project aims to achieve results that can be interpreted in overall effective irrigation management facilitates increased crop yields, reduced water use, production efficiencies, reduced production costs and time, it will allow all the partners to exchange knowledge and information management in the field of algorithms of AI. Further, this project will improve environmental stewardship. Finally, the expected outputs from the target PoC program may alleviate poverty and increase food security while simultaneously promoting sustainable land management and irrigation through the assessment of water and soil resources and their use.

Furthermore, PoC will assist in better management and garner significant interest in irrigation procedures within and across fields, and AI systems will help expedite and refine agricultural decision-making, particularly in response to sustainable land management and in predicting shifts in crop phenology associated with irrigation timing and fertilizer. It is also expected that this program will help farmers make informed irrigation decisions and increase stabilization of agricultural production, enhance production and efficiency in irrigated agriculture suitable technologies to smallholder farmers, capacity building, and transfer the new art of technology AI to the beneficiaries. The PoC project by using AI can forecast data associated with the data on the landscape. AI studies can give an insight into the soil's nutrient content and therefore we can determine the suitable crop.

Finally, and not limited to: the different scenarios that will be collected and analyzed from the field studies of irrigation and soil properties management. Researchers can be assisted in making systems and models to support research in agricultural irrigation and development technologies and algorithms, precision agriculture, remote sensing, and predictive analytics. The Policymakers may use the results of the PoC project to promote a base data for a national strategic plan in water irrigation and land management.

3.8 Socio-Economic benefits of the PoC project:

We cannot Determine in advance what decisions the Jordanian Government will make based on information from the PoC.

The following estimates, based on vegetable production, simply illustrate how yields could be increased after the completion of various PoC projects.

3.8.1 The Implementation of AI Technology

Utilizing advanced techniques including AI throughout the PoC project would help gain a better knowledge of soil properties water irrigation and their climatic environment. Adapting farming practices to these advanced techniques conditions would lead to higher yields on the presently cultivated areas Yields could be increased by 0.1 ton/hectare, or a total of 10,000 tons/hectare, by using fertilizers adapted to the specific soil types and suitable schedules timing of irrigation. The economic benefits of the project thus involve both an increase in yields and a decrease in the random allocation of farming equipment, fertilizers, and other inputs moreover AI-based system can reduce water consumption by up to 30% compared to traditional irrigation methods.

Vegetables are currently an expensive commodity in Jordan, and the project would help increase the yield. However, the PoC project will also allow Jordanian farmers to grow a wide range of Mediterranean fruits. These fruits have a higher added value than vegetables, which would be even greater if processing took place locally. Thus, the above calculations are based on improvements in irrigation. Vegetable production is a conservative estimate when other commodities are taken into account. Irrigated agriculture has boomed, particularly in the highlands, with steady expansion year on year since the eighties. This growth is not sustainable without significant utilization of advanced techniques AI of water for irrigation. The economic value of irrigation water varies significantly based on the kinds of crops grown and irrigation practices used Jordan Valley has a 50% higher economic value for irrigation water than the highlands. Water security, food security, and utilizing advanced techniques are interdependent national priorities. Irrigated agriculture and sustainable land management rely on water supplies, which makes it imperative to ensure that these supplies are sustainable, effectively managed, and protected. Collaboration and alignment of activities between water and agriculture sectors are essential, combined with comprehensive governmental support, to enhance the stoical economic life of farmers and both a vibrant agricultural sector and water security.

3.8.2 Contribution to Jordan Economy

However, a project can also create new jobs and opportunities for workers to develop new skills. PoC utilization can change the structure of markets by introducing new products and services or changing the way existing markets are produced and delivered, improving carbon in soils and reducing waste, and increasing autonomous and remote-control requirements associated with training farmers and agricultural professionals on the proper use and maintenance of AI-driven irrigation systems, also add value to the financial potential benefits of AI-based irrigation it stems should also be taken into account. This includes improvements in water use efficiency, leading to reduced water consumption and costs and the potential for reduced labor costs due to automation of certain irrigation management tasks. Evaluating these benefits in relation to the associated costs can provide a clearer understanding of the overall economic value of AI-driven irrigation systems.Cost challenges are a key aspect of inclusivity across various socioeconomic backgrounds.

4 Conclusion and Recommendations

1. Jordan is an arid – semi-arid, located East Mediterranean country with (89,189) km^2. It has (11,630,323) million population in 2024. The highest and lowest population density is observed in Amman (5, 255) million and Tafilah Governorate (116.2) thousand. It has a typical Mediterranean climate, with dry summers, mild winters, and relatively short spring and autumn seasons. Almost more than 6% of the country is sloping and steep. Based on geo-climatic conditions and land use, Jordan is divided into four large regions: the Jordan Rift Valley, the Highlands, the Marginal Lands (steppe), and the Badia Zone (Desert). It is also well known for its rich geological characteristics.

   The Quaternary alluvial and colluvial sediments, fluvial and tertiary sediments-marl, shale, and clay dominate on the highland area and north and middle of Jordan Valley. While limestone, granite, and sandstone dominate in the south and southeast of Jordan.

   The annual amount of precipitation ranges between 50 and 500 mm with a snow cover on high mountains on occasion. Agricultural area of (2.7) million Dunums. However, the average irrigated area is about (one million Dunums), the Jordanian farmers grow citrus, banana, grapes, tomatoes, apples, vegetables, potatoes, and olives.

2. The Ministry of Agriculture (MoA) is hosting the national soil information. The dominant soil type in Jordan is Aridisols representing (75%) of the total area. Entisols occupy the second place (13%), Inceptisols have an area of (10%), Andisols (<1%), Vertisols (<1%) and Mollisols (<1%). The soil resources in the country witness several degradation factors like erosion, salinity, urban encroachment, land use change, land abandonment, and contamination.

3. Jordan began studying and surveying soil resources in the 1950s and culminated its efforts in soil studies and classification in the 1990s through the National Soil Survey and Land Use Classification Project. This project was carried out through cooperation and support between the MoA and international and regional donor organizations. The MoA actively participated in producing the Global Soil Organic Carbon Map and Global Salinity Affected Soil (SAS) map. moreover, soil protection has been recently put on the agenda of national priorities of the MoA with the LDN target-setting program, which concluded the need to adopt land management practices to keep sustainable land management (SLM), maintain soil fertility, and rationalize the use of irrigation water.

4. Farmers occasionally collect soil samples on their own and send them to soil laboratories for analysis, primarily to the National Agricultural Research Center (NARC) and the Jordan Valley Authority (JVA). However, the results they receive lack specific recommendations on nutrient and water management practices. This highlights a critical need to standardize soil sampling, handling, preparation, and analysis processes, as well as to improve access to extension services for small and medium-sized farmers. This is particularly important given that the MoA reported in 2023 that 80% of farmers did not receive any extension services, and the majority of those who did were supported by private companies. To address this gap, the PoC will develop a user-friendly application designed to provide farmers with daily assessments of optimal irrigation timing and best practices for soil and fertilizer management.

5. Water Irrigation timing and Soil protection were recently included in the MoA's national priorities list. The fully consistent target-setting program of the PoC concluded that water irrigation efficiency and soil property management practices must be adopted and enhanced to avoid water waste, reduce costs and manpower, and improve returns for small and medium farmers.

6. Endorsing and expanding JICA's partnership program in Jordan's agriculture sector, in collaboration with the Ministry of Agriculture and stakeholders, will promote advanced irrigation technologies and sustainable soil management. This initiative aligns with Jordan's 2025-2030 strategic plan to enhance water productivity and sustainable water use. It addresses water scarcity and strengthens long-term agricultural resilience.

7. The lack of integration of advanced technologies, such as AI for water irrigation timing and soil management, into national policies, coupled with high costs and limited farmer expertise, creates significant barriers to sustainable land and crop management, impeding agricultural productivity and food security planning in Jordan.

8. The National Soil Laboratory Network comprises several soil laboratories, with the National Agricultural Research Center (NARC) operating the largest network, strategically located across Jordan's main agro-climatic zones. However, these laboratories, while key players in soil data collection and analysis lack modern techniques for soil and water irrigation management and require upgrading the basic soil-related skills of their staff. To address these gaps and ensure the conservation and sustainable management of soil and water resources, the report recommends adopting state-of-the-art technologies, such as satellite image sensors and AI techniques. These advancements will help update and harmonize existing soil data, integrate it into a decision-support platform, revise current legislation, and improve its enforcement. Additionally, the report emphasizes the need to enhance coordination among soil and water information users, strengthen the science-policy interface to develop sustainable policies and practices and promote digital farming and precision agriculture. It also calls for disseminating good practices through living labs, monitoring soil health under various land uses, and aligning national soil and water irrigation priorities with broader resource development goals in Jordan.

9. Soil analysis laboratories: The only existing facilities are:

   - **Royal Scientific Society**: Well-equipped but lacking background in soil analysis
   - **The University of Jordan** is rather well-equipped with a good staff but more used to research work than the production of a large number of results on an industrial basis.
   - **Research and Extension facility of the Ministry of Agriculture**: well-staffed but needs equipment.
   - **Jordan Valley Authority**: well-equipped and well-staffed, used to performing significant numbers of analyses per month.
   - **The analysis**: It will be done in any laboratory chosen by the tenderer, but the choice of a Jordanian laboratory will be crucial.

10. To identify the necessary data requirements and achieve the PoC objectives, a comprehensive survey was conducted. This involved leveraging high-resolution and hyperspectral satellite images from satellites and drones, which are essential inputs for predictive models of soil fertility and AI-based irrigation timing. The survey included the following steps:

    (a) **Literature Review and Analysis:** Scientific papers were reviewed, analyzed, and categorized into three levels based on the evolution of AI algorithms from 2010 to the present time. Initially, traditional methods were dominant, followed by a major shift toward deep learning algorithms. Currently, advanced hybrid techniques that combine multiple algorithms and models are being used to predict soil fertility and optimize irrigation timing on farmland.

    (b) **Engagement with Technology Providers:** To meet the PoC requirements, consultations were held with both local and global providers of hyperspectral satellite imagery, IoT devices, and drones. Detailed technical and financial proposals were evaluated, focusing on the availability, cost-effectiveness, and accuracy of these services to ensure they align with the project's goals.

This approach ensures that the PoC leverages cutting-edge technologies and methodologies to deliver accurate and actionable insights for soil fertility and irrigation management.

11. According to the PoC requirements for multi-band or hyperspectral satellites, they have specific technical characteristics, including at least 10 spectral bands, a resolution of at least 50 meters, high image quality, and a suitable re-visit cycle, with coverage extending to Jordan.

    (a) Although hyperspectral imagery offers detailed insights, it comes with high costs and requires specialized processing by expert teams in remote sensing and artificial intelligence. Among the available options, **WorldView-3** stands out as one of the best choices, providing 32 spectral bands with resolutions ranging from 0.30 cm to 5 meters, including Shortwave Infrared (SWIR) bands.

    WorldView-3 satellite data is also the main provider for most of the companies contacted. The data can be obtained directly from the source through Growtech Company in Jordan, making it well-suited to meet the PoC requirements and support predictive AI models.

    (b) Since most high-resolution satellites are expensive, technical procedures exist to obtain data from different sources. These procedures allow the integration of high-resolution open-source data with high accuracy to complete the model-building requirements.

    (c) Possible require images capturing the full spectral bands and other necessary specifications for each season, aligned with the plant growth stages, to accurately predict soil properties.

12. **Drone data availability** -based multi-band/hyperspectral camera.

    (a) No companies provide hyperspectral cameras in the Jordan market.

    (b) Most drone providers offer multispectral imaging capabilities, including NIR or VNIR, along with a red-edge band, as well as RGB, thermal, and LiDAR technologies.

    After communicating via e-mail with many international companies, including (FS - 60C) company, it has advanced camera, priced at 34,000 USD compatible with DJM 300/350 drones

    Despite the high accuracy and detail achievable with drone imagery, their use in Jordan currently faces several limitations. The most significant challenges include the high rental or purchase costs, so we are not recommended for the following reasons:

    - The costs of operational training, data processing, and high-cost flight operations.
    - Obtaining hyperspectral data requires specialized knowledge and skills to operate drones effectively and interpret the data accurately, and additional costs for training personnel to handle and analyze hyperspectral data.
    - Drones are affected by environmental conditions such as bad weather (rain, fog, wind ... etc.) that can hinder their ability to collect accurate data.
    - The uneven distribution of crops and diversity in soil characteristics may lead to mixed signals when collecting data from a height, which affects the accuracy of the model.

13. **IoT requirements and availability:** IoT sensors offer significant advantages for soil monitoring in agriculture, including real-time data collection, continuous monitoring, cost-effectiveness for large-scale applications, and ease of deployment.

- Challenges such as limited accuracy compared to laboratory analysis, the need for regular calibration and maintenance, and potential technical issues must be addressed. Despite these drawbacks, the immediate feedback and adaptability of IoT sensors make them a valuable
- We surveyed the local and international markets and communicated with IoT sensor providers, and we received various technical and financial offers from them. Depending on the efficiency, capacity, and accuracy of the devices, we recommend using devices with an average cost that is acceptable to the project budget. In any case, the project needs many devices at the current stage(most of the providers recommended a site density between 25-30 sensors/ km^2).

14. **Soil property data in Jordan either open source or commercial and Measurement Equipment:** The ownership of soil legacy data in Jordan is hosted at the (MoA), and this data can be accessed through various open-source platforms on different scales. Moreover, the key sources include:

    (a) **ISRIC-Global Soil Information (FAO)**: Provides comprehensive data on soil properties such as organic carbon, texture, pH, EC, and soil moisture, accessible via their online platform or API.

    (b) **ISRIC-Global Soil Information (FAO)**: Provides comprehensive data on soil properties such as organic carbon, texture, pH, EC, and soil moisture, accessible via their online platform or API.

    (c) **FAO World Soil Map**: Aims to create a detailed global soil map at a 1:50,000 scale, offering insights into soil characteristics, land cover, and climate.

15. **We propose integrating soil properties data with satellite imagery using advanced techniques to enhance precision and accuracy:**.

- Machine learning hybrid methods, such as neural networks, MCA - CNN, and U-NET, can predict soil properties by combining satellite imagery with other datasets. Remote sensing techniques, including spectral indices and radar backscatter analysis, offer critical insights into vegetation health, soil moisture, and related characteristics.
- Geostatistical methods, such as kriging, can generate continuous spatial maps from point-based soil measurements. Integrating these techniques with other advanced methods enhances soil analysis, leading to more informed decision-making and the optimization of agricultural practices.
- Propose data fusion of diverse data sources, including satellite imagery, ground-based measurements, and climate data, to enhance the precision and detail of soil characteristic maps. This method strengthens model predictions and contributes to cost efficiency.

16. **We recommend developing and training models by ensuring a sufficient number of samples, particularly spectral values:**

    - For machine learning (ML) models, this requires 500 to 1,000 labeled samples, while for deep learning (DL) models, including hybrid and advanced methods, over 10,000 labeled pixels are necessary. The model development process should involve training and validating the AI model using frameworks like neural networks (NN) and tools such as TensorFlow in Python language.
    - Validation should be conducted by comparing model predictions with ground truth data to ensure accuracy, reliability, and robust performance.

17. **Soil Property Measurement Equipment:**

    - Soil moisture sensors measure volumetric water content for effective irrigation management.

- Time-domain reflectometry (TDR) sensors provide high accuracy by measuring pulse reflection from the soil.
- pH meters assess soil acidity or alkalinity
- nutrient (NPK) availability.
- EC meters measure soil salinity and levels to evaluate fertility.
- Soil composition is analyzed using spectrometers that examine light absorption and reflection, and core samplers extract soil samples at various depths.
- Remote sensing combines satellite data with ground measurements.

18. **Irrigation timing data in Jordan:** In Jordan, the MoA faces a lack of accurate and reliable data on irrigation timing. To address this gap, we recommend utilizing artificial intelligence to develop a predictive model for determining optimal irrigation timing. Key data sources analyzed is required to support this initiative include:

    - **Historical Irrigation Records**: Past irrigation timing data to establish baseline patterns and trends.
    - **Real-Time Sensor Data (IoT)**: Continuous monitoring of environmental and soil conditions to inform real-time irrigation decisions.
    - **Water Balance Data:** Information on water availability and usage to promote sustainable irrigation practices.
    - **Satellite Imagery Spectral Values**: Thermal bands, VNIR bands, water stress indices, SWIR1 (Shortwave Infrared 1), and (red edge 1, and 2 bands) to assess crop health and water requirements.
    - **Climatic Data:** Temperature, humidity and trans-evaporation.

19. **The Programming tool**: We recommend using Python as the main programming language to build predictive soil fertility models due to the following aspects:

- **Rich Libraries**: Python offers powerful libraries such as geopandas, TensorFlow and PyTorch, Scikit-learn ... etc, which facilitate the development of advanced models for predicting soil fertility.
- **Readable Architecture**: Its easy-to-read syntax promotes efficient coding and collaboration, which is essential for managing complex datasets.
- Integration with Visualization Tools: Python seamlessly integrates with data visualization tools, enabling clear interpretation of soil health and irrigation timing data.
- Rapid Prototyping: For the PoC, Python allows for quick modeling, testing, and iteration, ensuring efficient development before full-scale deployment.
- Strong Community Support: Python has a large, active community that provides extensive resources and troubleshooting assistance during the development process.

20. **To reduce costs and time**, while achieving the Proof of Concept PoC objectives, the project requires a professional, technically skilled management team with innovative and intelligent leadership. This team must be capable of keeping pace with advancements, overcoming challenges, and resolving issues swiftly and effectively.

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