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AFRICAN CENTER OF EXCELLENCE IN INTERNET OF THINGS

**Research Thesis Title: Integration of IoT and Geospatial Techniques for Enhanced Nutrient Distribution Mapping in Maize Farming**

***A dissertation submitted in partial fulfilment of the requirements for the award of masters of science degree in internet of things: Wireless Intelligent Sensor Network***

Submitted By:

**Name: Doreen Thotho (Ref. No 221031679)**

**December, 2023**

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**Doreen THOTHO (REF.NO: 221031679)**

Supervised by:
-Dr. Said Rutabayiro NGOGA
-Dr. James RWIGEMA

**December, 2023**

## Declaration

I Doreen THOTHO, Master's student from African Center of Excellence in Internet of Things, at University of Rwanda. I declare that this research thesis is my own original work and it has never been presented before anywhere in the world.

Doreen THOTHO

Ref: 221031679

Date: 07/12/2023

## Bonafide certificate

This is to certify that this submitted Research Thesis work report is a record of the original work done by Doreen Thotho(**Ref. No:221031679**), MSc. IoT-WISNET Student at the University of Rwanda / College of Science and Technology / African Center of Excellence in Internet of Things, the Academic year 2021/2023.

This work has been submitted under the supervision of Dr. Said Rutabayiro Ngoga and Dr. James Rwigema.

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## Abstract

In the domain of agriculture, effective nutrient management practices serve as a fundamental pillar for achieving optimal crop yields while minimizing the adverse environmental impact. General fertilizer recommendations often lead to over or under fertilization and traditional soil testing methods fail to capture the spatial variability of nutrients in the field. This research aims to enhance maize farming practices through the integration of Internet of Things (IoT) and geospatial techniques for nutrient distribution mapping. It involves the design and implementation of an IoT-enabled handheld device for spatially referenced macronutrient measurements in maize fields and employing an interpolation technique, Inverse Distance Weighting (IDW) for data analysis and nutrient distribution map generation. These maps empower farmers with the invaluable insights to make informed decisions regarding the application of fertilizers allowing for the optimization of maize crop growth while minimizing resource wastage. The efficacy of this system is validated through field tests conducted on a maize farm. These nutrient distribution map has an accuracy percentage of 94.92, 92.99, 94.04 for nitrogen, phosphorus and potassium prediction for un sampled locations respectively. This study establishes the foundation for implementing more sustainable, efficient, and environmentally conscious maize farming practices by harnessing the power of IoT and geospatial integration, thereby contributing to global food security and responsible resource management.



*Keywords: Internet of Things (IoT), Global Positioning System (GPS), Inverse Distance Weighting (IDW), Geographic Information System (GIS)*

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## List of Acronyms

| | |
|---|---|
| **AI** | Artificial Intelligence |
| **API** | Application Programming Interface |
| **GIS** | Geographic Information System |
| **GPS** | Global Positioning System |
| **HTTP** | Hypertext Transfer Protocol |
| **IoT** | Internet of Things |
| **IDW** | Inverse Distance Weighted |
| **MQTT** | Message Queuing Telemetry Transport |
| **NPK** | Nitrogen Phosphorus Potassium |
| **SIF** | Solar induced chlorophyll fluorescence |
| **SSNM** | Site Specific Nutrient Management |
| **UAV** | Unmanned Aerial Vehicle |
| **VRT** | Variable Rate Technology |
| **VI** | Vegetation Indices |
| **VNIRS** | Visible and Near-Infrared Reflectance Spectroscopy |

# Chapter 1: Introduction

## 1.1 Introduction

Maize (corn), is a primary agricultural crop in Africa and its a main source of sustenance for a population of over 300 million people [1]. Corn provides feed source for livestock and plays a significant role in the production of various products, such as ethanol and corn oil. Its adaptability to a wide range of climatic conditions enables to thrive in regions that are too dry for rice cultivation and too wet for wheat. Maize is a valuable crop for small scale farmers due to its low labor demands and relatively short maturation period [2].

Despite its substantial prominence, maize yield in Africa is lower than the global average with a difference of 2.4 tons per hectare [3]. This is mainly attributed by ineffective agricultural methodologies, inadequate soil quality, and the detrimental consequences of climate change. Given the projected population growth to surpass 9.7 billion by the year 2050, the global food supply is faced with immerse pressure. In order to address the escalating demand and guarantee food security, it is imperative to achieve an annual growth rate of at least 2.2% in maize production [4].

The optimal growth of maize is dependent on the availability of several essential nutrients categorized into macronutrients and micronutrients. Macronutrients are of utmost importance in ensuring the optimal health and development of plants. Nitrogen fosters leafy growth, enhances photosynthesis, and promotes overall plant vigor. Phosphorus assumes a crucial function in the processes of root development, flowering, and fruit production. Potassium plays a significant role in enhancing the overall well-being of plants, bolstering their ability to combat diseases, and improving their capacity to withstand stressful conditions [5].

Fertilizer application is a critical aspect in crop farming as it provides essential nutrients that the soil might lack, promoting the growth and yield of the crop[6]. Traditionally, farmers apply fertilizers uniformly across the field and the decisions on the quantity of fertilizer to apply is based on mere reference, such as history of use, advice from fellow farmers or extension officers. However, this method can lead to over-application in some areas and under-application in others as the nutrient levels can vary significantly across the farm. This not only wastes resources but can also lead to water pollution due to runoff. Conversely, under-application can result in sub-optimal crop yield, affecting the economic viability of the farm[7].

The rapid advancement of technology, specifically in the field of Internet of Things (IoT), has opened numerous opportunities for enhancing nutrient management in agriculture. IoT makes it possible to collect soil parameters from the field using sensors. In this context, soil fertility can be monitored providing valuable data that can be used to tailor fertilizer application to the specific needs of the soil.

This research aims to develop a system which leverages IoT and geospatial techniques to generate a nutrient distribution map in a maize field which will provide a visual representation of the spatial variability of nutrients. The system will enable farmers to make informed fertilization decisions that enhance both crop yield and resource efficiency. Moreover, by reducing the environmental footprint of farming practices, this research contributes to sustainable and responsible agricultural development, which is of paramount importance in an era marked by increasing ecological awareness and the need to feed a rapidly growing global population.

### 1.2 Background and motivation

Several techniques have been developed and implemented to help farmers evaluate soil fertility for optimal fertilizer application. Agricultural laboratory testing, portable laboratory testing, and intelligent systems are examples of these methods[8]. However, each of these approaches has limitations that may prevent them from being widely adopted by farmers. As a result, the focus of this research is on developing an Internet of Things (IoT)-powered system and a geospatial model. The goal of this system is to provide a visual representation of nutrient spatial variability within a farm to enable variable fertilizer application.

Agriculture remains a pivotal sector in the global economy, contributing significantly to ensuring food security, generating employment opportunities, and fostering sustainable development. It has evolved over time, embracing scientific breakthroughs and technological innovations to boost productivity and efficiency. Precision farming, which involves the use of technology to make farming practices more accurate and controlled, has emerged as a cornerstone of modern agriculture. The efficient management of fertilizers is a critical component of precision farming[9].

Currently, the standard practice for soil testing is to collect samples from various parts of the farm and combine them into a composite sample that is then sent to a lab for analysis [8]. The soil is tested in these labs for various properties and nutrient contents, such as nitrogen (N), phosphorus (P), and potassium (K), all of which are essential for plant growth. However, the results of these tests do not depict the variability of nutrient levels across the field to help farmers in making informed decisions.

Traditional soil testing methods have been used in agricultural practices for many years, but they have limitations. Traditional soil testing is time-consuming, which is a significant disadvantage. Collecting soil samples, transporting them to a laboratory for analysis, and waiting for the results can take days, if not weeks. The fertility status of the soil can change significantly during this extended period due to the influence of various factors such as rainfall, temperature fluctuations, and microbial activity. As a result, by the time the test results are available, the nutrient profile of the soil may have changed, making the recommendations less accurate and potentially ineffective for guiding fertilizer application decisions.

### 1.3 Problem Statement

Farmers in Sub-Saharan Africa commonly rely on general fertilizer recommendations instead of conducting soil testing procedure [10]. This approach is flawed as the nutrient status of the soil keeps on changing over time and various factors such as diverse topography, soil types and climatic conditions can result in substantial variation in the nutrient levels [11]. Blanket fertilizer recommendation hence have serious consequences, including suboptimal crop yields, accelerated soil degradation, and environmental pollution.

Traditional soil testing methods fail to capture the intricate nutrient distribution within a field due to the constraints associated with composite sample analysis[12]. The fertilizer recommendations generated lack precision and fail to provide farmers with precise insights of nutrient distribution, leading to over- or under-fertilization in specific areas within the field. Moreover, the prolonged turnaround time for laboratory testing introduces the possibility of outdated information, as soil nutrients fluctuate dynamically due to environmental and biological factors [13].

These convergence of these challenges give rise to economic inefficiencies through over fertilizer application, low crop yields and environmental degradation , necessitating innovative and timely solutions that equip farmers with precise, up to date soil nutrient information and recommendations. The integration of IoT and interpolation techniques for spatial nutrient distribution analysis offers a promising solution. This approach enables the efficient mapping of nutrient distribution within a field.

## 1.4 Study Objectives

### 1.4.1 General objective

- To integrate IoT and geospatial techniques for nutrient distribution mapping system for maize farming.

### 1.4.2 Specific Objectives

- Design an IoT-enabled handheld device capable of measuring soil macronutrients, specifically nitrogen, phosphorus, and potassium.
- To employ geospatial techniques to analyze NPK nutrient levels at various sampling points within the agricultural field and create a nutrient distribution map.
- To design and implement a user-friendly interface that allows farmers to access the nutrient distribution map for their maize fields.

### 1.4.3 Research Questions

- What technical specifications and components are required to design an IoT-enabled handheld device capable of accurately measuring soil macronutrients, specifically nitrogen, phosphorus, and potassium?
- How can geospatial techniques be effectively employed to analyze and visualize the spatial distribution of NPK nutrient levels across multiple sampling points within an agricultural field and generate a comprehensive nutrient distribution map?
- What design principles and user interface features should be considered to create an intuitive and user-friendly platform that enables farmers to easily access and interpret nutrient distribution maps for their individual maize fields?

## 1.5 Hypothesis

The hypothesis of this study that utilizing a handheld IoT device to measure soil nutrients from different sample points within a maize field and using geospatial techniques to map the nutrient distribution in the maize field will enable the development of more precise and timely variable fertilizer recommendations.

### 1.6 Study scope

The study focus of this research includes:

- The design, development, and implementation of an IoT-enabled handheld device for the measurement of soil macronutrients, specifically nitrogen (N), phosphorus (P), and potassium (K).
- Additionally, the study includes the utilization of geospatial techniques to analyze NPK nutrient levels at various sampling points within an agricultural field and create a nutrient distribution map.
- Furthermore, the research involves the design and implementation of a user-friendly interface that allows farmers to access the nutrient distribution map for their maize fields.

The study is conducted within the context of maize cultivation, focusing on enhancing nutrient management practices and crop productivity in the agricultural sector.

### 1.7 Significance of the study

This study is significant because it has the potential to revolutionize agricultural practices and promote environmental sustainability by combining handheld IoT devices and geospatial techniques to assess soil nutrient levels and provide spatial nutrient distribution map of the field to guide farmers on optimal fertilizer application for maize cultivation. Several key points highlight the importance of this research:

- Enhancement of Precision and Efficiency: Modern fertilizer application practices frequently lack precision, resulting in suboptimal results. The proposed system promises precise and timely nutrient management, allowing farmers to apply fertilizers precisely where and when they are needed, optimizing crop growth.
- Environmental Protection: Excessive fertilizer use contributes to environmental degradation and water pollution. This study can mitigate the negative environmental consequences of traditional farming techniques by reducing fertilizer use, protecting local ecosystems and water bodies.
- Economic Advantages for Farmers: Inefficient fertilizer application can result in economic losses due to lower crop yields or higher input costs. The findings of the study have the potential to increase farmers' profitability by optimizing fertilizer utilization, increasing crop yields, and lowering production costs.

- Food Security: Increased crop yields from more efficient fertilizer application can play a critical role in advancing food security, particularly in regions where maize consumption is high. This research could help secure a more stable food supply to meet the needs of the world's growing population.
- Technological Advancement: Through the integration of IoT and geospatial techniques, this research fast-tracks the evolution of precision agriculture, laying the foundation for more innovative and sustainable farming practices in the future.

### 1.8 Organization of study

This study is organized into six distinct chapters, this first chapter is an introduction to the research which has discussed the background and motivation for the research, the research objectives and the significance of the study.

The second chapter provides literature review which has highlighted the significance of maize, its nutrient requirements and the role of fertilizers in increasing its yields. It further discusses the traditional soil testing methodologies, nutrient management techniques in precision agriculture and their limitations. The review has also analyzed geospatial methods which are used to generate nutrient distribution maps.

The third chapter has described in detail the research design that has been used for prototyping, data collection techniques and data analysis procedure to generate nutrient distribution map.

Chapter 4 provides the system's hardware components, power and energy requirements, embedded programming, data transmission protocols, API development, web application development, and database design.

Chapter 5 focuses on the assessment of field test results and subsequent analysis, aiming to offer comprehensive insights into the performance of the system, its implications for maize farming, and the tangible advantages it offers to farmers and agricultural practices as a whole.

Lastly chapter 6 gives a conclusion of the research and recommendation for future research directions.

### 1.9 Conclusion

In conclusion, this introductory chapter has highlighted the importance of optimizing nutrient distribution for precise nutrient management in maize farming, achieved through the integration of IoT and geospatial techniques. It has clarified the significance of maize in global agriculture, emphasizing the urgent need to increase production and the importance of responsible nutrient management. The integration of IoT and geospatial technology presents a potentially viable solution to the nutrient management challenges in maize cultivation, paving the way for a more efficient and sustainable approach to maize farming.

Subsequent chapters will delve into the methodology, system design, data analysis, and ultimately provide comprehensive conclusions while presenting practical recommendations for future research direction.

## Chapter 2: Literature Review

The literature review provides in depth knowledge of the fundamental aspects in maize production and its nutrient management. It discusses the significance of maize, its nutrient requirements, and its fertilizer for enhanced crop productivity. The review has also discussed traditional soil testing techniques employed to assess soil nutrient deficiencies, which is used in fertilizer recommendation. Precision agriculture is also discussed in the review, highlighting the technological advancements and methodologies used in modern farming practices for efficient nutrient management. Finally, the review discusses geospatial techniques used for interpolation to generate nutrient distribution maps. These maps play a crucial role in optimizing nutrient utilization within agricultural fields. The literature review will synthesize this wealth of knowledge to support the research's goals and contributions to maize cultivation and nutrient management.

### 2.1 Maize (Zea-mays)

Maize has been primary global agricultural crop for millennia. Its significance, adaptability, and substantial nutritional value have made it a pillar for global food security[14]. Maize cultivation is popular due to its versatility as a food source for humans, livestock feed, and industrial applications such as ethanol production. [2]. Furthermore, maize is a highly nutritious crop that contains a substantial amount of essential nutrients like carbohydrates, dietary fiber, vitamins, and minerals. Maize has the potential to produce high yields, particularly when managed properly.[15].

Maize adapts to a wide range of climatic conditions, flourishing in temperate regions with moderate precipitation and seasonal variations, as well as tropical and subtropical areas with adequate moisture. However, maize has a low tolerance for waterlogged conditions and requires well-drained soils to grow optimally [16]. Soil fertility is also important, with fertile soils rich in organic matter and essential nutrients ideal for maize production. A pH range of slightly acidic to neutral is preferred.

Maize production fluctuations in recent years can be linked to a number of factors, including climatic variability, pest and disease, and agricultural technological developments [17]. Nonetheless, modern agricultural practices have been critical in reducing these challenges and increasing maize yields in a variety of geographical areas. Adoption of improved seed varieties, precision agriculture techniques, and site-specific nutrient management (SSNM) approaches have all contributed to maize cultivation's overall success. With the projected doubling of the global population within the next three decades, there is an anticipated substantial surge in the demand for maize. This poses a significant challenge for farmers in their efforts to sustainably maintain maize production in order to meet the increasing demands of the growing population. Optimizing fertilizer application is one of the most pressing challenges in maize production. Conventional fertilizer application methods often prove inefficient and can lead to over-fertilization, polluting waterways and harming the environment [18].

### 2.1.1 Nutrient requirements of maize

In order to optimize maize plant yields and sustain their overall health and productivity, it is necessary to ensure the provision of essential nutrients throughout their entire life cycle. Maize necessitates substantial amounts of three crucial macronutrients, namely potassium (K), phosphorus (P), and nitrogen (N) [19]. Nitrogen is crucial for the growth and development of leaves and stems, as well as in the overall growth of plants. It also has crucial function in the synthesis of chlorophyll, a fundamental process for the occurrence of photosynthesis. Phosphorus promotes roots, flowers, and fruits development. Furthermore, it facilitates the process of energy transfer within the plant. A deficiency in phosphorus can lead to stunted growth and delayed maturity in maize plants. Potassium plays a crucial role in the regulation of nutrient transport, water absorption, and disease resistance. It has been observed to improve the vigor and stress tolerance of maize plants. Maize necessitates secondary macronutrients, specifically calcium (Ca), magnesium (Mg), and sulfur (S), in lesser proportions. Micronutrients such as manganese (Mn), boron (B), iron (Fe), zinc (Zn), copper (Cu), and molybdenum (Mo) are needed in trace amounts by maize[20]. Micronutrients play a crucial role in enzymatic reactions critical for maize plant health. They support essential metabolic processes and promote healthy growth and development.

Farmers employ various nutrient management strategies to effectively fulfill the nutritional requirements of maize. The practice of soil testing is essential to determine suitable strategies for fertilization and to evaluate the concentrations of nutrients.

## 2.2 Traditional soil analysis techniques

Traditionally, the common practice for soil testing in the laboratory is of two types namely; dry chemistry analysis and spectral soil testing.

### 2.2.1 Dry chemistry analysis

Dry chemistry soil testing is a time-honoured technique utilized to determine the composition and nutrient content of soil. The process entails the application of chemical reagents and procedures to extract and quantify a variety of compounds or elements present in a soil sample[21]. Titration, precipitation, heating, and dissolution in acid or other solutions are common operations used in these processes. Although its time-consuming, labor-intensive, and chemical-intensive, this method is very accurate.

### 2.2.2 Spectral analysis

Spectral analysis illuminates a soil sample with light and analyzes the reflected or transmitted light to determine the properties the soil properties. This is so as the composition of distinct compounds absorb, reflect, and emit light in different ways[22]. Infrared spectroscopy is a spectral technique that yields data pertaining to the abundance of minerals and organic matter within the soil. Visible and near-infrared reflectance spectroscopy (VNIRS) is an additional technique frequently employed to make estimations regarding soil characteristics such as nitrogen, organic carbon, and clay concentrations[23]. This method requires precise calibration models to link spectral data to soil parameters. These models are usually developed from a subset of samples analyzed using standard wet chemistry.

Maize farming requires fertilizer, but overuse can harm the environment and lower yields. Farmers have traditionally depended on sending soil samples in labs to determine soil properties and fertilizer recommendations. This method is accurate but has limitations. First, laboratory soil testing takes time, delaying results and recommendations. This information gap can delay fertilizer application decisions. Laboratory testing is expensive, making it less accessible for farmers, especially those with limited funds. Few laboratories serve a wide range of farmers in many regions. Over-reliance on laboratory testing hinders farmers' fertilizer application decisions and hinders widespread implementation in agriculture.[24].

## 2.3 Precision agriculture

Precision agriculture uses information and communication technologies to boost crop yield and sustainability. It involves collecting and analyzing environmental, crop, and soil data to make crop management decisions like pest control, fertilizer application, and irrigation [25]. Precision agriculture boosts crop yields, reduces environmental impact, boosts profitability, and improves sustainability [26].

Precision agriculture utilizes a variety of ICTs, including GPS, remote sensing, geographic information systems (GIS), yield monitors, the Internet of Things (IoT), and artificial intelligence (AI). Using these technologies, agricultural machinery can be directed to precise locations in the field, spatial data can be analyzed and visualized, and information about the environment, crops, and soil can be gathered [27].

Given its high value and susceptibility to nutrient levels and other environmental factors, precision agriculture is ideally suited for the cultivation of maize. The implementation of precision agriculture technologies enables maize farmers to customize their crop management strategies according to the distinct requirements of various sections of the field. This can result in substantial enhancements in both crop productivity and financial gain.

### 2.4 Technologies for nutrient management

Recent advancements in IoT and geospatial technologies have the potential to transform maize farming soil analysis and fertilizer recommendation. Internet of Things (IoT) is used to collect soil nutrient status and crop health data [25] while geospatial techniques are utilized in mapping soil nutrient distribution and other factors influencing crop growth [28]. This

can then be used to create and implement variable rate fertilization (VRT) plans that tailor fertilizer application to the specific needs of various sections of the fields.

Several studies have been conducted using various technologies to estimate crop nutrient requirements based on plant chlorophyll content or soil nutrient levels. This section will go over these technologies in greater detail, which have been divided into two categories: IoT sensor technology and remote sensing.

#### 2.4.1 Remote sensing

Remote sensing is a scientific discipline that collects data relating to objects or phenomena by detecting and analyzing electromagnetic radiation emitted or reflected by them[29]. This technology enables maize crop monitoring at various scales, from individual fields to entire regions. Remote sensing data is gathered from a variety of platforms, including aircraft, satellites, and unmanned aerial vehicles (UAVs). In addition to generating maps and images, this data can be used to estimate yields, identify pests and diseases, and assess crop health[30]. This comprehensive approach offers useful insights for improving agricultural practices and ensuring sustainable maize production.

Vegetation Indices (VIs) and Geographic Information Systems (GIS) are revolutionizing nitrogen fertilization efficiency in developed countries such as the US, Canada, and Sweden. Farmers can map soil characteristics, such as the composition of organic matter and chemical properties, with the use of GIS, a computer system designed to manage spatial data [31]. VIs offer information on crop development and nitrogen levels and are derived from multispectral data [27]. Precision fertilization strategies are guided by the synergy between GIS and VIs. Tractors with GIS capabilities and variable rate applicators are able to apply nitrogen fertilizer precisely where it is needed and in the right amounts, maximizing nutrient utilization and reducing the environmental impact.

Precision fertilization for rice cultivation in large-scale cropland is studied in [32] using prescription maps from an enhanced nitrogen fertilizer optimization algorithm. Satellite and UAV imagery are combined with meteorological data. The study uses remote sensing and meteorological data to predict rice potential yield using in-season estimated yield index (INSEY). It improves grain nitrogen content (GNC) prediction with the Random Forest (RF) algorithm using vegetation indices and spectral features. The study uses enhanced NFOA to calculate rice's nitrogen demand and generate nitrogen fertilizer prescription maps from UAV multispectral images. The results show accurate yield and GNC predictions. These prescription maps are more precise and cost-effective than non-quantitative nitrogen fertilizer management methods, improving rice cultivation and field ecology.

G. Mohammed [33] and Yang [34] used solar-induced chlorophyll fluorescence (SIF) remote sensing to assess crop nitrogen status. Vegetation indices were less accurate than SIF. SIF measures plant chlorophyll fluorescence in response to sunlight. Non-photosynthetic chlorophyll fluorescence occurs when chlorophyll molecules absorb and re-emit light at a longer wavelength. A plant's chlorophyll fluorescence is directly related to its nitrogen status and chlorophyll content.

N. Lu [35] collected multispectral winter wheat images at critical growth stages using a UAV-mounted camera. Images from different angles were processed to create four vegetation indices. These indices assessed wheat canopy nitrogen nutrition under different nitrogen rate, variety, and planting density treatments.

Similarly, H. Zeng[36] used UAV-derived multispectral imagery to estimate plant nitrogen concentration in rice. However, it is important to note that multispectral imagery is limited to estimating nitrogen concentration and cannot assess other major nutrients.

In contrast, hyperspectral imagery is capable of predicting nitrogen content along with other nutrients. M. Borhan[37] used hyperspectral imagery of potato leaves to estimate chlorophyll content, which was then used to determine nitrogen content. Similarly, P. Pandey[38] used hyperspectral imagery to estimate nutrient contents in soybean and maize crops. Among the nutrients assessed, nitrogen prediction had the highest accuracy, compared to phosphorus, potassium, and various micronutrients.

The table below highlights the challenges of remote sensing technologies in monitoring soil nutrients and plant nutrients for optimized fertilizer recommendation.

| **Remote Sensing Technique** | **Limitations** |
| --- | --- |
| Geographic Information Systems (GIS) and Vegetation Indices (VIs) | Limited to determining nitrogen levels. Does not directly measure nitrogen content. Requires specialized equipment and expertise. |
| Solar-Induced Chlorophyll Fluorescence (SIF) | More accurate than VIs, but still indirect measure of nitrogen status. Requires advanced remote sensing techniques and data processing. |
| Unmanned Aerial Vehicle (UAV) Multispectral Imagery | Limited to estimating nitrogen concentration and cannot assess other major nutrients. Requires proper image acquisition and processing techniques. |
| Hyperspectral Imagery | Capable of predicting nitrogen content along with other nutrients. Provides more comprehensive nutrient assessment. Requires advanced data processing and analysis techniques. |

*Table 1: Limitations of Remote sensing technologies*

### 2.4.2 IoT sensor technology

The study by N. Othaman in [39] presents an Arduino MEGA microcontroller-based smart farming system that utilizes soil electrical conductivity (EC) measurements. The objective is to establish a correlation between the NPK (nitrogen, phosphorus, potassium) fertilizer levels necessary for optimal crop growth and the measured EC values. Higher EC values indicate greater nutrient concentration and soil salinity, whereas lower EC values indicate lower salt levels, according to the study. Moreover, EC values and total dissolved solids (TDS) provide a valuable instrument for precise nutrient management in agriculture by helping in the estimation of the required NPK fertilizer. The figure below is the hardware configuration of system in the study above.

Additionally, In another research[40] , the implementation of IoT-based fertigation systems has incorporated EC sensors to evaluate soil nutrients. These systems automatically adjust pH and EC levels by utilizing sensors, overcoming the issue of inaccurate fertilizer application amounts. These sensors are limited in that they cannot provide precise measurements of individual nutrient concentrations.

Soil reflectance sensors measure light reflected by soil to determine nutrient levels. In a study by M. Hasan [41], an IoT-based Site Specific Nutrient Management (SSNM) system is developed. SSNM measures soil solution color with a color sensor. The solution color reflects soil nutrient levels. The system then finds deficiencies using a soil nutrient database. NPK soil nutrients were detected by fiber optic sensor in [42]. The developed system reduces soil fertilizer waste, among other benefits. By accurately measuring nutrient levels, farmers can choose the right fertilizers to address field deficiencies.

Soil nutrient sensors are intended to directly measure nutrient levels in soil. These sensors use a variety of techniques to provide precise measurements of individual nutrient concentrations, such as ion-selective electrodes, spectroscopy, or chemical assays. Another study [43]explored the use of an NPK sensor to monitor nutrient content within the soil. NPK sensors provide accurate nutrient content when well calibrated. This approach highlights the diverse range of technologies being considered for nutrient management in agriculture. As research continues in this field, the development and refinement of these sensing technologies have the potential to enhance the accuracy and efficiency of nutrient management systems

### 2.5 Nutrients distribution mapping geostatistical methods

Farmland quality is intricately linked to soil nutrients, a factor influenced by both soil fertility and geographical location. Previous research has shown that soil fertility and nutrient concentration affect soil productivity [44]. Soil nutrients vary spatially due to pedogenic processes, parent material, topography, and human activities [45]. Given the spatial heterogeneity of soil nutrient content, composite soil samples are difficult to analyze. It's important to first assess these nutrients' spatial variability and then analyze their landscape distribution. Employing data-driven approaches becomes crucial for making informed decisions regarding fertilization strategies. The following sections discusses geostatistical techniques for mapping the distribution of soil nutrients.

### 2.5.1 Kriging

Kriging is a geostatistical technique which has been used to determine nutrient distribution in various studies. It does this by estimating nutrient values at unsampled locations based on spatial correlation and variability observed in sampled data [46]A study which was conducted in Croatia's Rasa River Valley [47] employed kriging and co-kriging geostatistical techniques to assess the nutrient variability. The soil properties which were being assessed in this study are: pH, EC, OM, AP, and AK. The study's findings uncovered notable patterns in the distribution of soil parameters, with pH, EC, OM, and AK registering high values in the northern and eastern regions of the study area. In contrast, AP concentrations were noticeably lower.

### 2.5.2 Inverse Distance Weighting (IDW):

IDW is an interpolation technique which is also used in nutrient distribution mapping. It assigns values to unsampled locations based on the weighted average of nearby sampled values[48]. Inverse Distance Weighting (IDW) method is more accurate for predicting the spatial distribution of soil nutrients[46]. This technique uses a moving weighted-average approach and works best when sampling points are distributed uniformly across the study area, avoiding clustering of sampling points. The IDW method presumes that an attribute value at an unsampled location is a weighted average of known data points in a local neighborhood surrounding the unsampled location[47]. It is written as follows:

$$\hat{z}(x_0) = \frac{\sum_{i=1}^{n} z(x_i) d_{ij}^{-r}}{\sum_{i=1}^{n} d_{ij}^{-r}} \tag{1}$$

Equation (1) predicts the value of $x0$, the point of interest, using the values of $xi$, the data points in the surrounding area. The weights ($r$) are determined by the distance between the point of interest and the data points, with closer data points having more influence.

The spatial distribution of vital plant nutrients (nitrogen, phosphorus, potassium, and silicon) in farmland soil was investigated in this study conducted in China's Pearl River Delta region [49]. The study examined 201 soil samples and discovered significant variation in these nutrients. For spatial analysis, the Inverse Distance Weighting (IDW) method was used, resulting in a uniform distribution of potassium and increasing nitrogen levels from northeast to southwest. This research contributes to the creation of farmland protection areas and land use planning policies.

## 2.6 Gaps from literature

Based on the comprehensive literature review, several notable gaps and opportunities can be identified in the context of developing an IoT handheld device for spatial nutrient distribution mapping in maize fields:

- Limited Accessibility and Affordability of Technology for Smallholder Farmers: Smallholder farmers, particularly in developing regions, face challenges in accessing affordable and user-friendly technology for soil testing and nutrient management. The existing literature underscores the pressing need for the development of portable and cost-effective IoT devices that can be readily operated by farmers with limited technical skills.
- Timely Availability of Soil Nutrient Analysis Results: Traditional soil testing methods are often characterized by time-consuming processes that may lead to delays in providing timely recommendations to farmers. This gap highlights the importance of streamlining the soil nutrient analysis process for more efficient decision-making in agriculture.
- Integration of IoT and Geospatial Technologies: Although there is a growing body of research focusing on IoT sensors and geospatial techniques as separate components, there exists a significant gap in studies that comprehensively integrate these technologies for the purpose of nutrient distribution mapping. The literature emphasizes the potential benefits of combining IoT data collection with geospatial analysis to offer a holistic solution for precision agriculture.

# Chapter 3: Research Methodology

This chapter discusses the research design employed for the study, the data collection procedure and detail the methods for data analysis and validation.

### 3.1 Study Area

The study area of this research is Kigali, the capital city of Rwanda. Kigali is an ideal setting due to its wide-ranging topography, which includes rolling hills and fertile valleys, contributing to spatial variability in soil nutrient levels across farms. This variation emphasizes the significance of our research, since variable fertilizer application to these varying conditions could have a significant impact on crop yields, resource utilization and environmental sustainability.

### 3.2 Research Design

This study is a prototype-driven research approach, a proof of concept of the system was developed for real-world demonstrations and testing of its functionality and feasibility. The system is then refined based on insights gained during this process, resulting in an improved system aligned with the research objectives. This approach allowed us to iteratively develop and refine the system while mitigating risks and controlling costs.

### 3.3 Data Collection

In this research an IoT device was designed and implemented specifically for soil nutrient assessment. The IoT device is equipped with a sensor capable of measuring spatially referenced Nitrogen (N), Phosphorus (P), and Potassium (K) levels in the soil. This is achieved by capturing the GPS coordinates for every sampling point.

#### 3.3.1 Sampling Technique

To collect accurate and representative data, a systematic soil sampling technique was employed:

- Grid Sampling: the study area was divided into a grid to ensure comprehensive coverage. Each grid cell represents a sampling point.
- Randomization: within each grid cell, multiple random sampling points were selected. Randomization minimizes bias and ensures that the dataset accurately reflects the spatial variability of NPK levels.

- Number of Samples: the number of samples collected was determined based on the size of the study area, the desired level of detail, and statistical considerations. A sufficient number of samples were collected to ensure statistical significance.

### 3.3.2 Data Transmission

The IoT device simultaneously transmits the data collected wirelessly to a central data repository for monitoring and analysis through Wi-Fi.

## 3.4 Data processing and Analysis

Following the completion of data collection, the next crucial step was data preparation, involving careful data cleaning and processing. The objectives of this step were to identify, remove and correct anomalies to ensure the integrity of the dataset. Subsequently, the data underwent in-depth analysis using descriptive statistics, which included metrics such as minimum, maximum, mean, and coefficient of variation. These statistics provided valuable insights into the nutrient concentration patterns within the dataset.

The study uses spatial interpolation, specifically Inverse Distance Weighting (IDW), after descriptive analysis. The IDW was used to estimate values at unsampled locations in the maize field. This enables the generation of a nutrient distribution maps, which show the spatial variability of nutrients in the research field.

## 3.5 System Validation

In spatial analysis, validation points was used to assess the accuracy and reliability of a nutrient distribution map. The nutrient distribution map is used to estimate nutrient levels at these predefined validation points, which are strategically selected throughout the field. The estimated values were then compared to the actual measured nutrient concentrations, enabling a direct and targeted evaluation of the map's performance. Validation points acted as ground truth references, allowing the map's accuracy to be quantified and any disparities or discrepancies to be identified.

To evaluate the accuracy of the nutrient distribution map generated by the integrated IoT and geospatial techniques, three key error metrics were employed: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Accuracy Percentage. These provided quantitative measures between the interpolated nutrient values and the true (observed) values obtained from field sampling.

- *Root Mean Square Error (RMSE):* RMSE assessed the dispersion of errors between the interpolated nutrient values and the ground truth values. It quantifies the square root of the average squared differences between the two datasets. The formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\text{ TrueValue }_i - \text{ InterpolatedValue }_i)^2} \tag{2}$$

Where N= total number of sampled points

- *Mean Absolute Error (MAE):* MAE determined the average absolute differences between the interpolated and true values. The formula for MAE is as follows:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | \text{ TrueValue }_i - \text{ InterpolatedValue }_i | \tag{3}$$

- *Accuracy Percentage*: Accuracy percentage expresses the closeness of the interpolated values to the true values and is expressed as a percentage. It provides an intuitive measure of accuracy, with higher percentages indicating better accuracy. The formula for calculating accuracy percentage is as follows:

$$\text{Accuracy (\%)} = \left(1 - \frac{RMSE}{\text{MeanTrueValue}}\right) \times 100\% \tag{4}$$

# Chapter 4: System Analysis and Design

This chapter discusses the system architecture and design. It details hardware components used, power and energy requirements of the IoT device, embedded programming for the IoT device, data transmission protocols employed, API development, web application development, and database design of the IoT-based nutrient distribution mapping system. This provides a thorough understanding of the system's functionality and technological fundamentals.

## 4.1 Layered System Architecture

The architecture of this IoT system is made up of four layers whose functions are to collect, transmit, process, and analyse soil nutrient data, enabling user-friendly interaction and providing a comprehensive precision agriculture solution. The diagram presented below presents the system architecture.

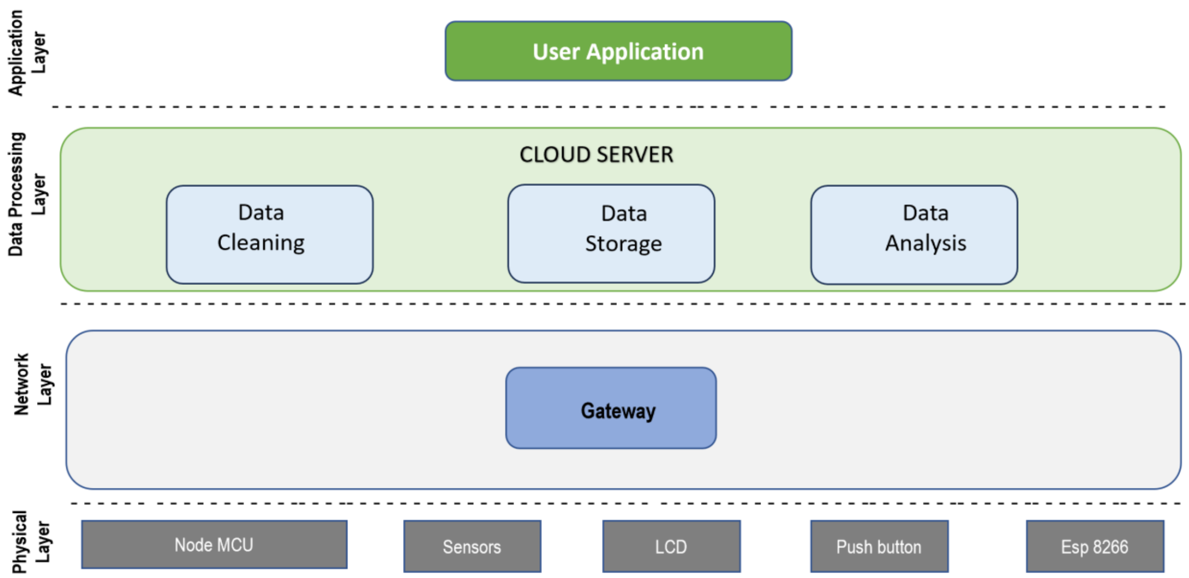



*Figure 1: System architecture*

### 4.2.1 Physical Layer

This layer collects spatially referenced soil NPK levels data using the IoT device. The IoT devices equipped with sensors to measure soil nutrient levels (Nitrogen, Phosphorus, and Potassium) and collect GPS coordinates representing the precise locations of these soil nutrient measurements.

### 4.2.2 Network and Communication Layer

The Network Layer enables seamless connectivity and data transfer within the IoT system. It uses Wi-Fi for data transmission to the central processing unit which in this case is the server. A gateway serves as an intermediary, ensuring secure and reliable data exchange between devices and the broader internet.

### 4.2.3 Data Processing and Analysis Layer

The Data Processing and Analysis Layer processes the raw data collected from IoT devices and stores the data in a database. The processed data is utilized to generate nutrient distribution maps using geospatial techniques to depict the spatial variability of soil nutrient levels across the agricultural field.

### 4.2.4 User Interface and Application Layer

The User Interface and Application Layer interact directly with end-users. It provides user-friendly interfaces and functionalities through mobile applications, web portals, and other user interfaces. These interfaces empower users, including farmers, agronomists, and researchers, to access the nutrient distribution maps, make informed decisions, and tailor fertilizer recommendations based on the spatial variability of soil nutrients.

## 4.2 Embedded hardware components

The hardware components of the IoT-based nutrient distribution mapping system include sensors, microcontrollers, and communication modules for data collection, processing, and transmission. The figure below is a block diagram for the system. The block diagram of the IoT-based nutrient distribution mapping system visualizes its hierarchical structure, data flow, and component interconnections

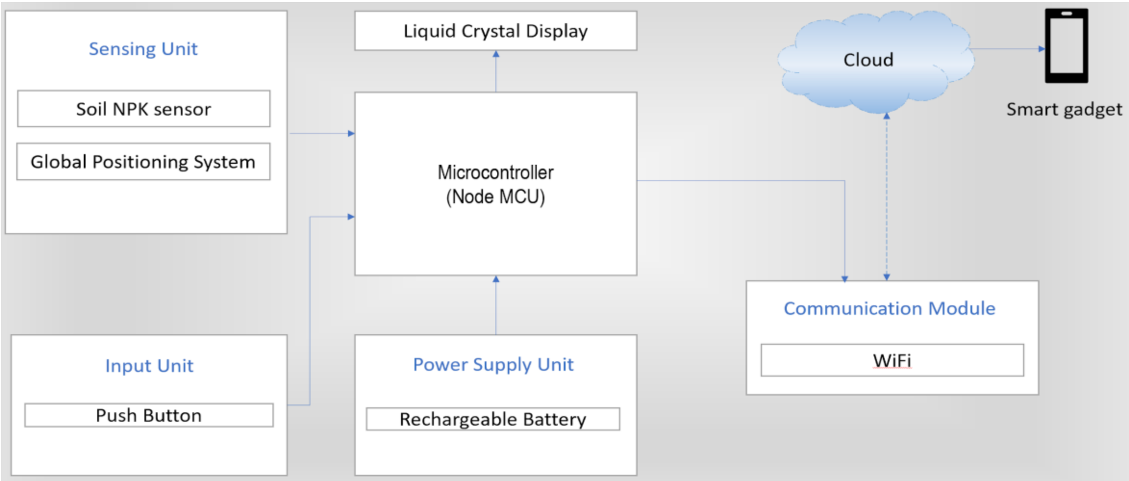



*Figure 2: System block diagram*

The IoT device utilized for this research project incorporates a range of hardware components, each with specific functions and specifications.

| **Component type** | **Specifications** |
|---|---|
| NodeMCU | • Microcontroller: ESP8266<br>• Connectivity: Wi-Fi 802.11 b/g/n<br>• Processing: 32-bit Tensilica L106<br>• GPIO Pins: 11 digital pins, 1 analog input<br>• Power Supply: 3.3V DC |
| Soil NPK sensor | • Power supply: 5-30VDC<br>• Maximum power consumption: ≤0.15W<br>• Operating temperature: -40~80°C<br>• Range: 0-1999 mg/kg(mg/L)<br>• Resolution: 1 mg/kg(mg/L)<br>• Precision: ±2%FS<br>• Response time: ≤1S |
| GPS Module (NEO-6M-0-001) | • Position Accuracy: Up to 2.5 meters<br>• Number of Channels: 50<br>• Update Rate: 1 Hz<br>• Interface: UART/TTL |
| OLED display | • Display Type: OLED (Organic Light-Emitting Diode)<br>• Resolution: 128x64 pixels |

| | |
|---|---|
| | • Interface: I2C<br>• Screen Size: 0.96 inches |

*Table 2: Embedded components selection*

### 4.2.6 Schematic diagram of IoT device

The schematic diagram for an IoT device shown below visually depicts the device's electronic components and their connections. It is an essential tool for designing, building, and troubleshooting the device. It provides a clear blueprint of the device's electrical design, making development and maintenance easier.

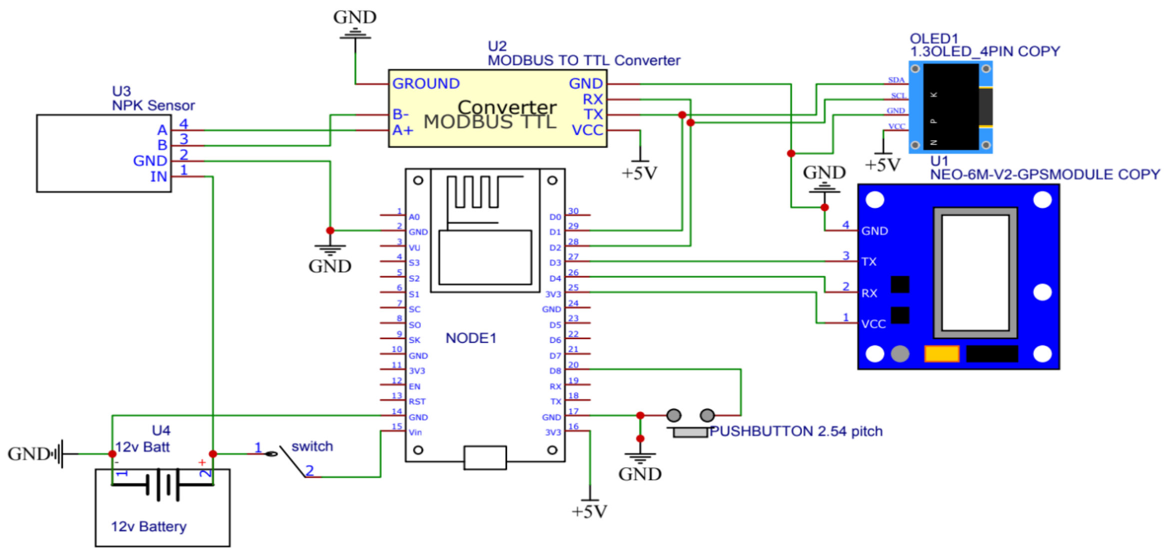



*Figure 3: IoT device schematic diagram*

### 4.3 Power and Energy Requirements of IoT device

The power and energy requirement determines how efficiently the device uses its electrical energy. This data is critical for designing power-efficient IoT devices, estimating overall energy consumption, sizing batteries, and optimizing power management strategies.

### 4.3.1 Assumptions

- Operating Voltage: The operating voltage for NodeMCU is assumed to be 3.3 volts (V), while the operating voltage for Soil NPK Sensor, OLED LCD, and RS485 is assumed to be 5 volts (V).
- Active Current: This is the current consumed by each component when it is actively performing its function.

- Sleep Current: This is the current consumed by each component when it is in a low-power sleep or idle state.
- Duty Cycle: The duty cycle represents the percentage of time each component is active during the device's operation.
- Device Active Time: It is assumed that the device is operational for 12 hours in a day.
- Energy Calculation: Energy consumption is calculated using the formula Energy (Wh) = Power (W) x Time (hours).

### 4.3.2 Calculations

NodeMCU: Power (W) = 3.3 V x 80 mA / 1000 = 0.0528 W

Energy (Wh) = 0.0528 W x 12 hours = 0.6336 Wh

Soil NPK Sensor: Power (W) = 5.0 V x 15 mA / 1000 = 0.075 W

Energy (Wh) = 0.075 W x 12 hours = 0.009 Wh

GPS Module: Power (W) = 3.3 V x 40 mA / 1000 = 0.132 W

Energy (Wh) = 0.132 W x 12 hours = 0.03168 Wh

OLED LCD: Power (W) = 5.0 V x 20 mA / 1000 = 0.2 W

Energy (Wh) = 0.2 W x 12 hours = 0.024 Wh

Push Button: Power (W) = 3.3 V x 2 mA / 1000 = 0.0066 W

Energy (Wh) = 0.0066 W x 12 hours = 0.0792 Wh

RS485: Power (W) = 5.0 V x 30 mA / 1000 = 0.15 W

Energy (Wh) = 0.15 W x 12 hours = 0.018 Wh

Total Energy Consumption = Σ Energy (Wh) for all components

Total Energy Consumption =( 0.6336 + 0.009 + 0.03168 + 0.024 + 0.288 + 0.018 ) Wh

Total Energy Consumption ≈ 1.00428 Wh

The total energy consumption for the IoT device, considering the specified operating voltages and a 12-hour active period, is approximately 1.00428 watt-hours (Wh) per day. The table below shows the power requirements of the components of the IoT device.

| Component | Operating Voltage (V) | Active Current (mA) | Sleep Current (mA) | Duty Cycle | Power (W) | Energy (Wh) |
|---|---|---|---|---|---|---|
| NodeMCU | 3.3 | 80 | 0.1 | 20% | 0.0528 | 0.6336 |
| Soil NPK Sensor | 5.0 | 15 | 0.005 | 5% | 0.075 | 0.009 |
| GPS Module | 3.3 | 40 | 0.01 | 10% | 0.132 | 0.03168 |
| OLED LCD | 5.0 | 20 | 0.02 | 2% | 0.2 | 0.024 |
| Push Button | 3.3 | 2 | 0.001 | N/A | 0.024 | 0.288 |
| RS485 | 5.0 | 30 | 0.005 | 5% | 0.15 | 0.018 |
| **TOTAL ENERGY** | | | | | | 1.00428 |

*Table 3: Power requirements for IoT device*

### 4.3.3 Battery sizing

To determine the optimal battery capacity for the IoT device, the subsequent steps were carried out

- The first step was to determine the runtime of the device before replacing or recharge the batteries. In this case a duration of 24 hours was considered
- Secondly, calculation of the required battery capacity (in Wh) to support the desired runtime while considering efficiency losses was made.

  Battery Capacity (Wh) = Total Energy Consumption (Wh) / Battery Efficiency

  Battery Efficiency is typically in the range of 80% to 90% for many lithium-ion batteries. Assuming an efficiency of 85%.

  Battery Capacity (Wh) = 1.00428 Wh / 0.85 ≈ 1.1837 Wh (rounded up)

- The battery voltage was selected in consideration of the highest operating voltage of the device’s components and margin of safety.

  Battery voltage > Highest voltage required by any component in the device + Margin of safety

  The highest voltage required by any component in the IoT device is 5V, with a margin of safety of 1V, then a battery voltage of 6V will be required.

- The next step was to calculate the battery capacity in ampere hour

  Battery Capacity (Ah) = Battery Capacity (Wh) / Battery Voltage (V)

  Battery Capacity (Ah) = 1.1837 Wh / 6 V ≈ 0.197 Ah (rounded up)

A battery with a capacity of approximately 0.197 Ah at 6V will be required to power the IoT device for 24 hours, considering the calculated energy consumption and efficiency.

### 4.4 Embedded programming

The microcontroller used in this project for the IoT device was programmed using C++ within the Arduino IDE environment. Several libraries were employed to enhance the functionality of the IoT device:

- SoftwareSerial Library: This library was utilized to establish a software-based serial communication interface on digital pins of the Arduino. It enabled seamless communication between the Arduino and devices that rely on serial communication, such as the Modbus module integrated into the project.
- TinyGPS++ Library: The TinyGPS++ library played a pivotal role in parsing NMEA GPS data. Its purpose was to simplify the interaction with GPS modules, facilitating the extraction of vital location information crucial for the device's operations.
- Adafruit_GFX and Adafruit_SH110X Libraries: These libraries were instrumental in interfacing with the OLED display (Adafruit_SH1106G) and handling graphics rendering. They offered a user-friendly means of displaying data on the OLED screen, including text, shapes, and graphics.
- SPI and Wire Libraries: The SPI library was employed for communication with SPI devices, such as certain sensors and displays. Meanwhile, the Wire library served as the communication bridge for I2C-enabled devices. These libraries were selected to

streamline the interaction with various sensors and display modules, simplifying low-level communication and data parsing tasks.

The code begins with a setup() function that initializes serial communication, configures the GPS module, sets up the OLED display, and configures pins for the soil nutrient sensor. Within the main loop(), data is continuously collected from three soil nutrient sensors and displayed on an OLED screen. Additionally, if GPS coordinates are available, they are also displayed on the screen. Nutrient sensor functions are specifically designed to communicate with the soil nutrient sensor, ensuring accurate data collection. The smartdelay_gps() function efficiently handles GPS data updates by reading and decoding GPS information from the NEO-6M module using the TinyGPS++ library. This code effectively combines data from soil nutrient sensors and a GPS module, presenting it on an OLED screen and providing serial output for monitoring and data logging in agricultural applications.

### 4.5 Data transmission methods and protocols

In this research, Wi-Fi is used to transmit data from the IoT device to the server, HTTP protocol is used to send sensor data from the IoT device to the centralized database and retrieve data from the user interface. Sensor readings are sent to the centralized database as HTTP POST requests. This method efficiently transmits and stores IoT device data in the database for analysis. Users interact with the system via an easy-to-use interface. Users use HTTP GET requests to access centralized database data. The system retrieves and displays data for these requests through the interface.

HTTP, a popular internet data transfer protocol, is crucial to this process. It streamlines data exchange between the IoT device, database, and user interface.

HTTP data transmission has many benefits. It is a trusted protocol that protects data during transfer. Its compatibility with web technologies makes it suitable for data integration into the user interface, improving accessibility.

### 4.6 Database design

The three main entities in the database for this research project are "User," "Field," and "npk data." The data structure is defined by the interactions between these entities, which represent the fundamental components of the system. The entity "User" refers to any individual who uses the system, including farmers, farm managers, and agricultural specialists. These users are in charge of managing their fields and accessing the functionalities of the system. Different agricultural land owned or managed by users are represented by the "Field" entity. A one-to-many relationship between users and fields is established by each user's ability to manage multiple fields. Information about soil nutrients for each field is specifically intended to be stored in the "npk data" entity. Precise nutrient management strategies depend on this data. The field-npk data relationship follows a one-to-many pattern, just like the user-field relationship. The foundation of the database is made up of these three fundamental entities and their interactions, which allow for methodical data organization and retrieval. This methodical approach makes it easier to store, manage, and analyse data effectively, which in turn helps to optimize the distribution of nutrients in maize farming.

In the context of this research project, a SQLite database schema has been designed to effectively store and manage the critical data required for optimizing nutrient distribution in maize farming using IoT and geospatial techniques. The database schema encompasses three main tables: "User," "Field," and "npk_data," each with its respective structure and relationships.

User Table

- *id*: This auto-incremented integer column serves as the primary key, uniquely identifying each user.
- *username*: A text column for storing usernames, ensuring uniqueness and non-emptiness.
- *password*: A text column for securely storing passwords, marked as non-null to enhance data integrity.

Field Table

- *id*: An auto-incremented integer column acting as the primary key.
- *user_id*: An integer column storing the user's ID, ensuring its non-null nature and creating a link to the "users" table.
- *name*: A text column recording the name of each agricultural field
- *FOREIGN KEY (user_id) REFERENCES users (id)*: This establishes a foreign key constraint, guaranteeing that the "user_id" in the "fields" table corresponds to an existing "id" in the "users" table, maintaining referential integrity.

npk_data Table

- *id*: An auto-incremented integer column functioning as the primary key.
- *field_id*: An integer column storing the associated field's ID, marked as non-null and forming a relationship with the "fields" table.
- *nitrogen_content, phosphorus_content, potassium_content*: These REAL (floating-point) columns capture the NPK content values, ensuring they are non-null.
- *Latitude, Longitude*: These REAL (floating-point) columns hold coordinate values, marked as non-null.
- *FOREIGN KEY (field_id) REFERENCES fields (id)*: This foreign key constraint guarantees that the "field_id" in the "npk_values" table aligns with an existing "id" in the "fields" table, preserving data consistency and integrity.

This well-structured SQLite database schema enables efficient storage, retrieval, and management of crucial data related to soil nutrient levels and geographical coordinates. It forms the backbone of the IoT and geospatial-based nutrient distribution optimization system, ensuring that data is accurately associated with specific fields and users, thus facilitating precise nutrient management in maize farming.

### 4.7 Application Programming Interface(API) development

The Representational State Transfer (REST) API development for this project was executed using the Python Flask framework, known for its simplicity and adaptability. Flask's lightweight nature made it a fitting choice, aligning with the project's scale and requirements. To complement the Python-based development, an SQLite database was integrated, benefiting from direct support via the sqlite3 package and its lightweight, zero-configuration attributes, which facilitated rapid prototyping. The defined endpoints within the API and their respective functionalities include

*GET / (Home):*

- When a user is logged in, it renders a dashboard template displaying the username.
- In the absence of a logged-in user, it redirects to the login page.

*GET/POST /login (Login):*

- Renders the login page for a GET request.
- Processes a POST request containing the provided username and password.
- If the credentials are valid, it establishes the user's session and redirects to the dashboard.

- In case of invalid credentials, it presents an error message.

*GET /logout (Logout):*

- Logs the user out by terminating their session and redirects to the login page.

*GET/POST /signup (Signup):*

- Renders the signup page upon a GET request.
- Processes a POST request to create a new user with a username and password.
- Ensures username uniqueness; if successful, redirects to the login page.

*GET/POST /field/new (Create New Field):*

- Renders the page for creating a new field during a GET request.
- Processes a POST request to generate a new field for the logged-in user.

*GET /dashboard (Dashboard):*

- Displays a dashboard tailored to the logged-in user.
- Fetches and showcases the user's fields.

*GET/POST /field/update/int:field_id (Update Field):*

- Renders the page for updating an existing field upon a GET request.
- Processes a POST request to modify the name of a field associated with a given field_id.

*POST /field/delete/int:field_id (Delete Field):*

- Deletes a field with the specified field_id.

*POST /npk/new (Add NPK Data):*

- Handles both GET and POST requests.
- Permits the addition of NPK data to the database for a specific field.
- Returns a JSON response upon successful data addition.

This REST API, complemented by the SQLite database, forms the backbone of the system, facilitating seamless user interactions, data management, and nutrient distribution analysis.

### 4.8 User Interface development

The user interface was designed using the Flask framework's conventions, which state that HTML files should be treated as templates, while styling files are considered static assets.

HTML 5 was used to create dynamic templates to ensure a modern and visually appealing user experience, CSS 3 facilitated comprehensive styling, and Bootstrap was integrated to maintain a consistent and responsive design across various devices and screen sizes.

The Flask application's structure was designed to maximize code modularity and maintainability. Routes handled user interactions and rendered templates, static folders held CSS and other static assets, and a templates directory held HTML templates for dynamic web pages. This method simplified user interface development and ensured a consistent user experience by separation of concerns.


*Figure 4: User Interface development*

### 4.9 Data analysis software development

Python-based data analysis software conducts nutrient mapping for the agricultural field within the specified shapefile bounds . Spatial data from the shapefile is loaded using Geopandas. Python is used for data manipulation, random point generation, interpolation, and visualization. The SciPy library's Rbf (Radial Basis Function) function estimates nutrient values at grid points using Inverse Distance Weighting (IDW) interpolation. The Matplotlib library creates contour plots of the nutrient interpolation map to show distribution.

### 4.10 Unit Testing

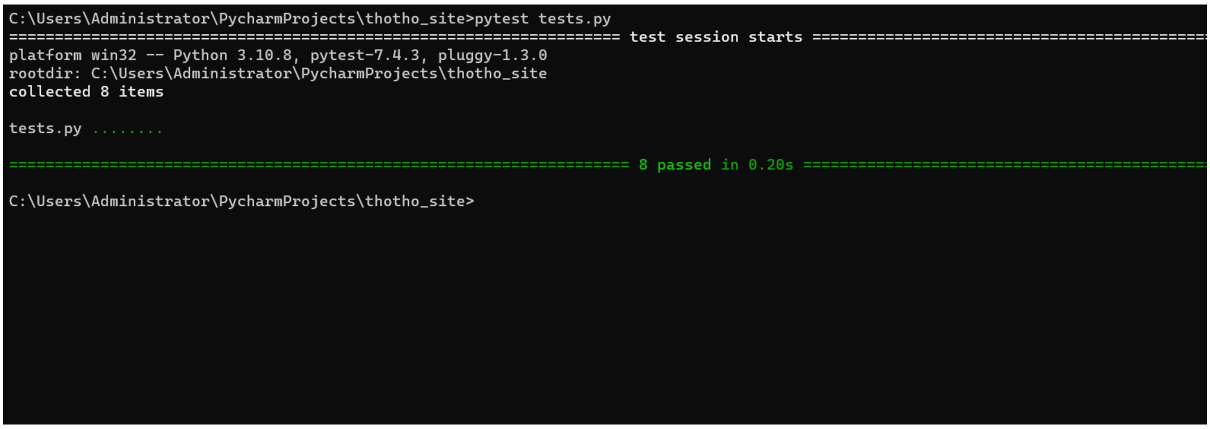
We used Pytest and Flask's built-in testing utilities to implement a comprehensive unit testing strategy in the development of our Flask web application. This method was critical in ensuring the integrity and functionality of each component of our application when used in isolation. Pytest was chosen as our testing framework because of its ease of use and powerful features, which allows efficient writing of  a wide range of test cases.

To isolate the Flask application from the production environment, it was configured to run in a dedicated testing mode, which was distinguished by setting app.config['TESTING'] = True. We also created a separate test database, which was critical for avoiding interference with production data and ensuring controlled, isolated testing conditions. A pytest.ini file was also created to customize Pytest settings specific to our application's needs.

Pytest fixtures handled resource management within tests by managing setup and teardown processes for the application context and the test client. These fixtures were critical in keeping each test case in a clean testing state. The tests focused on each Flask route, with the Flask test client simulating HTTP requests and asserting responses. We were able to test the behavior of each route using this method.

We used mocking for external dependencies such as APIs and databases to ensure the tests remained focused solely on the application's internal logic. This was especially important for routes that required authentication, as we simulated login and logout processes to effectively test session management and access control.

A screenshot of the test run is shown below:



# Chapter 5: Results and Analysis

The research on the on the integration of IoT and geospatial techniques for nutrient distribution mapping in a maize farm was done as explained in the methodology chapter of this document. This study was motivated by three specific objectives which are were:

- Design an IoT-enabled handheld device capable of measuring soil macronutrients, specifically nitrogen, phosphorus, and potassium.
- To employ geospatial techniques to analyze NPK nutrient levels at various sampling points within the agricultural field and create a nutrient distribution map.
- To design and implement a user-friendly interface that allows farmers to access the nutrient distribution map for their maize fields.

A field test was conducted in a maize field in Nyamirambo, Kigali, to assess the system's real-world applicability and effectiveness. This test consisted of several key steps. Initially, GPS coordinates were meticulously recorded along the perimeter of the field, laying the groundwork for precise field mapping. Following that, 42 strategic sampling points were chosen, each of which provided invaluable data including GPS coordinates and corresponding NPK nutrient values. This data was sent to the system's server where its was used to map the perimeter of the field and the data was further analyzed using inverse distance weighting technique a spatial interpolation method used in geostatistics and geographic information systems (GIS) to estimate values at unmeasured locations based on values observed at nearby locations. The inter

In this chapter, we delve into the field test results and analysis in order to provide robust insights into the system's performance, its implications for maize farming, and the tangible benefits it provides to farmers and agricultural practices in general.

### 5.1 Data collection

The data which is comprised of GPS coordinates and NPK soil content was collected using the IoT device which was designed and implemented and this data is transmitted to the sever using Wi Fi.

The NPK soil sensor was inserted into the soil at a depth of 10 cm to read more accurate NPK values.

*Figure 5: Data collection at a maize field in Nyamirambo*


*Figure 6: GPS coordinates being captured by the IoT device*

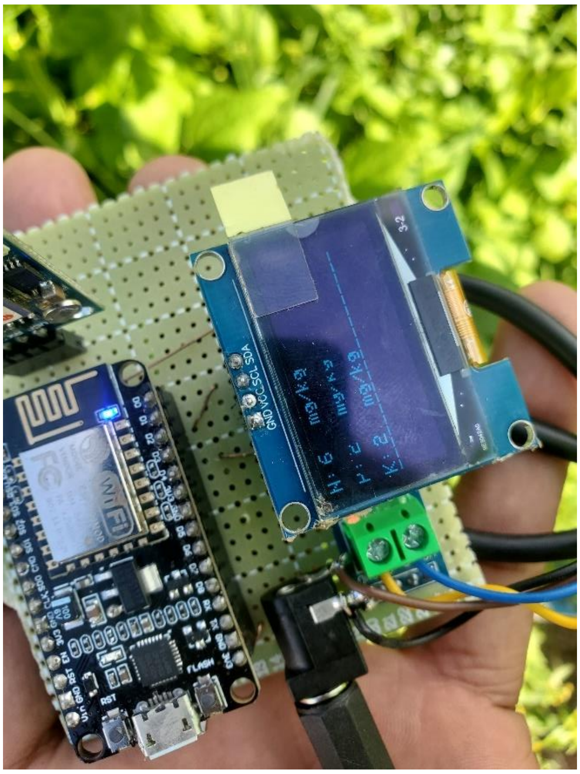



*Figure 7: IoT device capturing NPK values*

The figure below illustrates the data collected from the maize farm, which is stored in a server database.

Table: npk_values Filter in any column

| | id | field_id | nitrogen_content | phosphorus_content | **potassium_content** | coordinate_easting | coordinate_northing | node_type |
|---|---|---|---|---|---|---|---|---|
| | Filter | Filter | Filter | Filter | Filter | Filter | Filter | Filter |
| 1 | 1 | 1 | 3.0 | 2.0 | 2.0 | 30.0635 | -1.9703 | 0 |
| 2 | 2 | 1 | 3.0 | 3.0 | 4.0 | 30.0637 | -1.9703 | 0 |
| 3 | 3 | 1 | 4.0 | 3.0 | 2.0 | 30.0635 | -1.9705 | 0 |
| 4 | 4 | 1 | 5.0 | 4.0 | 3.0 | 30.0637 | -1.9704 | 0 |
| 5 | 5 | 1 | 5.0 | 4.0 | 4.0 | 30.0642 | -1.9704 | 0 |
| **6** | 6 | 1 | 6.0 | 4.0 | 3.0 | 30.0645 | -1.9704 | 0 |
| 7 | 7 | 1 | 6.0 | 4.0 | 4.0 | 30.0648 | -1.9704 | 0 |
| 8 | 8 | 1 | 9.0 | 2.0 | 5.0 | 30.0652 | -1.9704 | 0 |
| 9 | 9 | 1 | 3.0 | 2.0 | 2.0 | 30.0636 | -1.9705 | 0 |
| 10 | 10 | 1 | 4.0 | 2.0 | 3.0 | 30.0641 | -1.9705 | 0 |
| 11 | 11 | 1 | 5.0 | 4.0 | 3.0 | 30.0646 | -1.9705 | 0 |
| 12 | 12 | 1 | 6.0 | 3.0 | 4.0 | 30.0652 | -1.9705 | 0 |
| 13 | 13 | 1 | 4.0 | 2.0 | 2.0 | 30.0637 | -1.9708 | 0 |
| 14 | 14 | 1 | 5.0 | 3.0 | 4.0 | 30.0643 | -1.9708 | 0 |
| 15 | 15 | 1 | 7.0 | 4.0 | 6.0 | 30.0647 | -1.9708 | 0 |
| 16 | 16 | 1 | 3.0 | 2.0 | 3.0 | 30.0641 | -1.9709 | 0 |
| 17 | 17 | 1 | 4.0 | 3.0 | 2.0 | 30.0644 | -1.9709 | 0 |

*Table 4: NPK and GPS coordinates captured from the maize farm*

### 5.2 Data analysis and visualization

Out of the 40 sample points collected, 30 were employed for the interpolation process to generate a nutrient distribution map. The remaining 10 sample points were reserved for the validation of the generated map. The resulting nutrient distribution map, depicted in the figure below, was generated using these data points. The NPK values were compared against the recommended NPK optimal requirements for maize farming, which are as follows: Nitrogen (N): 60-100 Kg/Ha, Phosphorus (P): 60-35 Kg/Ha, and Potassium (K): 15-25 Kg/Ha.

Firstly a new field was created and the data from the device was sent to the field id of the field created.

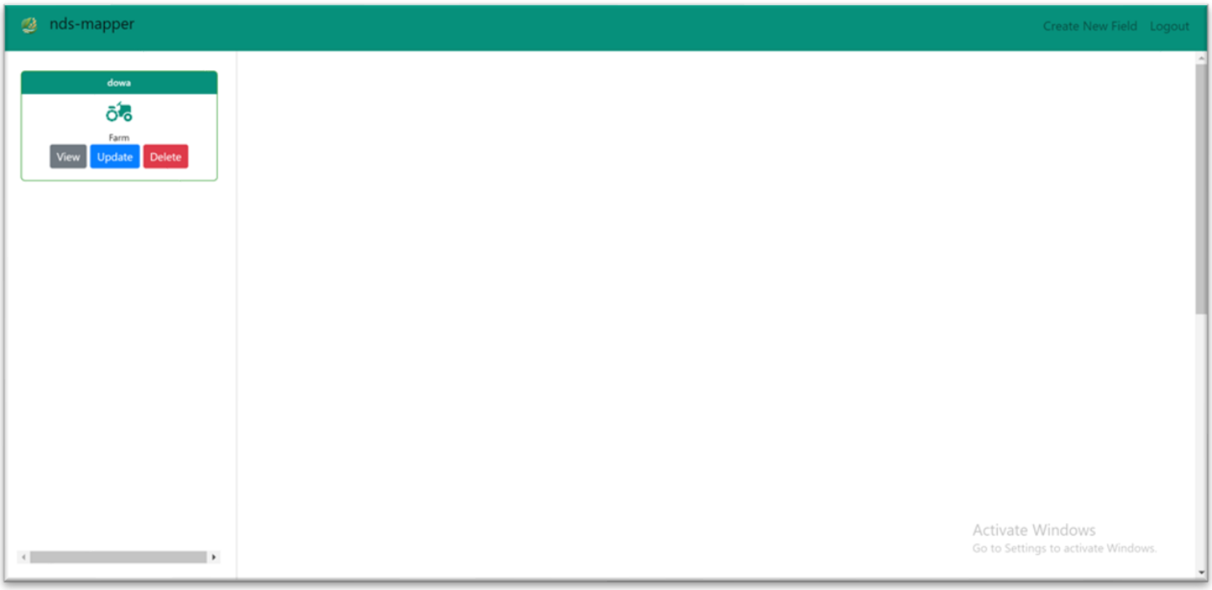



*Figure 8: Creating new field*

Then when the view button is clicked it displays the map and highlights the perimeter of the field as shown in fig 20 below.

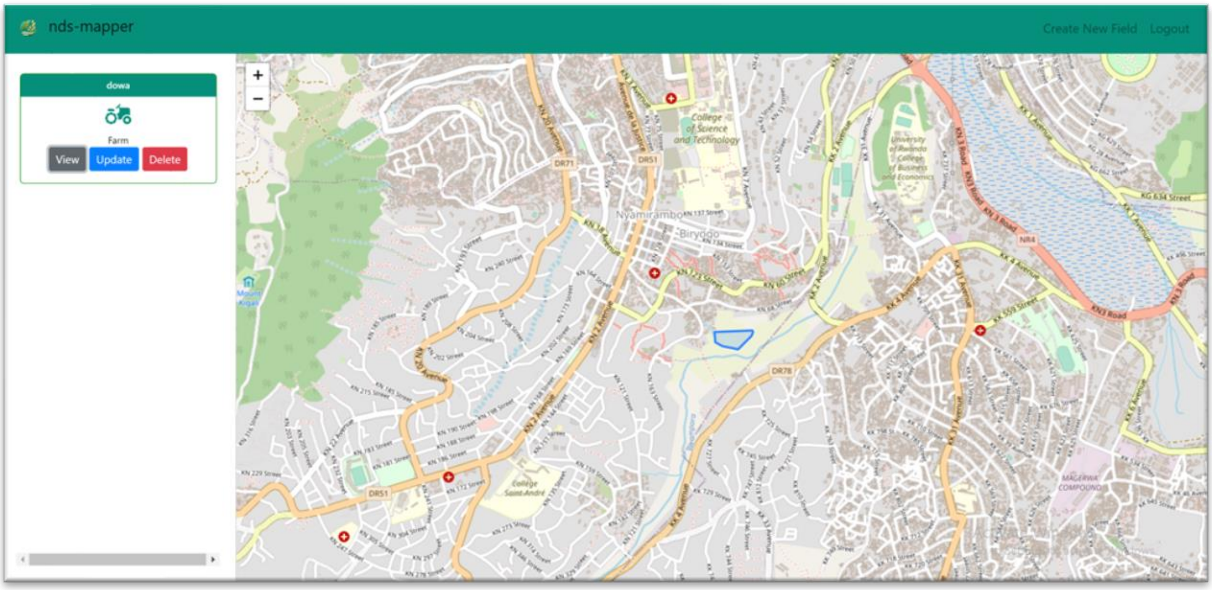



*Figure 9: Mapping the perimeter of the field.*

Phosphorus nutrient distribution mapping of the field is displayed below from the data that was collected.

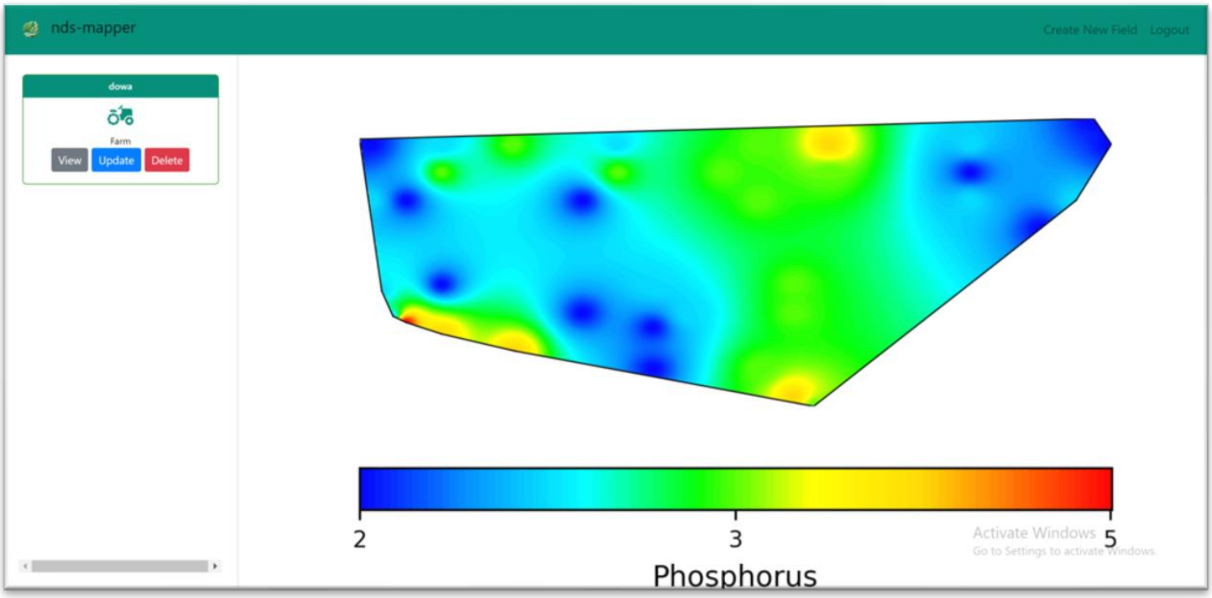



*Figure 10: Phosphorus nutrient distribution*

Nitrogen nutrient distribution mapping of the field is displayed below from the data that was collected.

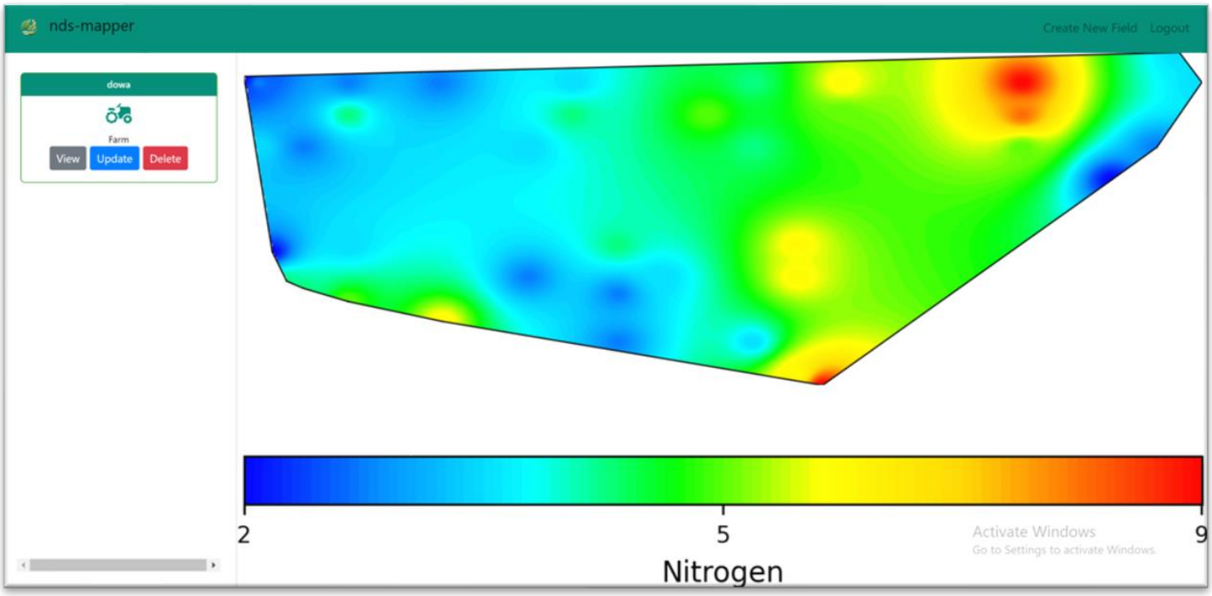



*Figure 11: Nitrogen nutrient distribution mapping*

Potassium nutrient distribution mapping of the field is displayed below from the data that was collected.

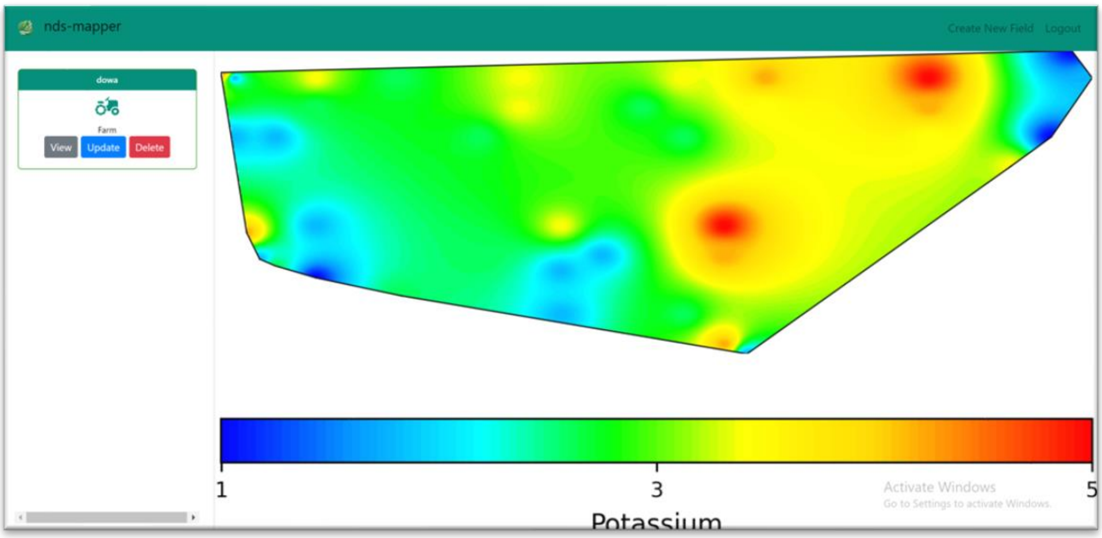



*Figure 12: Potassium nutrient distribution*

### 5.3 Validation

The table presented below displays both the actual NPK values and the interpolated NPK values for a set of 10 sample points, which were utilized to assess the accuracy of the nutrient distribution map.

| northing | easting | n | p | k | | n_interpolated | p_interpolated | k_interpolated |
|---|---|---|---|---|---|---|---|---|
| -1.971 | 30.0637 | 4 | 3 | 2 | | 3.76 | 3.3 | 1.78 |
| -1.9703 | 30.0655 | 6 | 2 | 1 | | 5.54 | 2.4 | 0.87 |
| -1.9707 | 30.0652 | 5 | 3 | 3 | | 4.67 | 3.01 | 2.71 |
| -1.9707 | 30.0642 | 4 | 4 | 4 | | 4.08 | 3.97 | 4.22 |
| -1.9707 | 30.0647 | 5 | 3 | 3 | | 5.11 | 3.33 | 2.88 |
| -1.9709 | 30.0641 | 3 | 4 | 5 | | 2.87 | 3.87 | 5.3 |
| -1.9709 | 30.0647 | 4 | 2 | 4 | | 4.02 | 1.8 | 3.91 |
| -1.9709 | 30.0638 | 3 | 4 | 2 | | 2.99 | 4.23 | 1.92 |
| -1.9705 | 30.0647 | 4 | 3 | 4 | | 4.15 | 2.9 | 4.1 |
| -1.9705 | 30.0652 | 5 | 4 | 3 | | 5.2 | 3.85 | 3.12 |

*Table 5:Validation dataset*

The graphs below were plotted for the True NPK values and Interpolated NPK values of the 10 sample points.


*Figure 13: True and Interpolated Nitrogen graph*

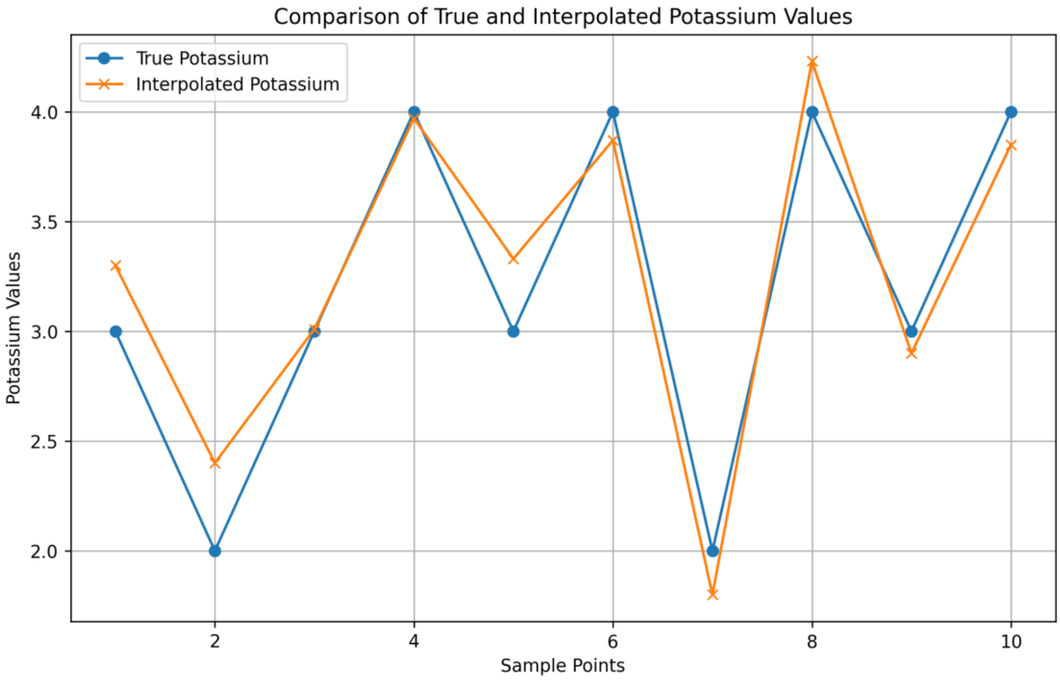



*Figure 14: True and Interpolated Potassium graph*

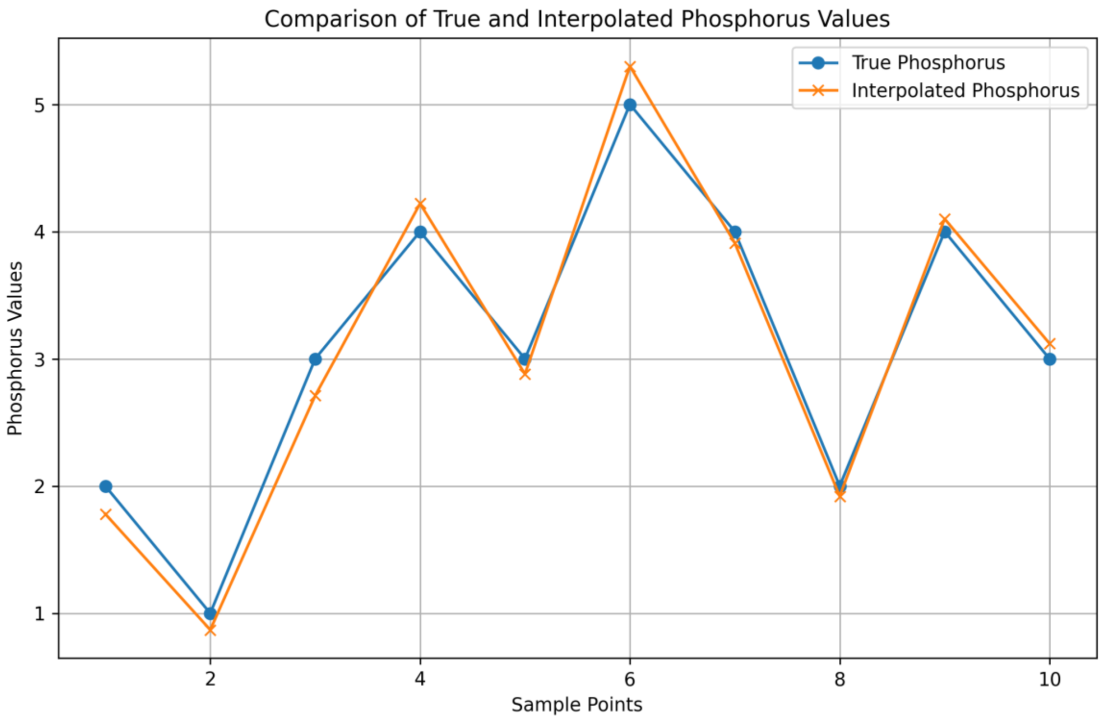



*Figure 15: True and Interpolated Phosphorus graph*

### 5.3.1 Calculation of Error Metrics

The table below shows the error metrics values for the nutrient distribution map

| Nutrient | RMSE | MAE | Accuracy % |
|---|---|---|---|
| Nitrogen | 0.21829 | 0.17300 | 94.92 |
| Potassium | 0.22409 | 0.18799 | 92.99 |
| Phosphorus | 0.18468 | 0.16699 | 94.04 |

*Table 6:Nutrient distribution map error metrics*

## Chapter 6: Conclusion and Recommendations

This research successfully developed and implemented system for nutrient distribution mapping in maize farming that integrates IoT technology and geospatial techniques. The study met its specific objectives, which included developing an IoT-enabled handheld device for soil macronutrient measurement, analyzing NPK nutrient levels using geospatial methods, and developing a user-friendly interface for farmers to access nutrient distribution maps.

The field test results for the nutrient distribution mapping system proved its effectiveness in providing precise and reliable nutrient information for maize farming. Three error metrics were calculated these included: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Accuracy Percentage. The accuracy percentage for NPK was 94.92%, 94.04% and 92.99% respectively.

These results underscore the system's potential to improve nutrient management in maize farming, providing farmers with a tool for optimizing fertilizer application, boosting crop yields and environmental conservation. The user-friendly interface ensures ease of use and adoption for farmers, facilitating informed decision-making and promoting efficient resource utilization. As precision agriculture continues to gain prominence, the findings of this research highlight the system's significance in promoting both agricultural sustainability and food security, positioning it as a promising solution for the contemporary challenges faced by maize growers.

To enhance the system's effectiveness and real-world applicability, several recommendations have been put forth. First and foremost, there is a strong suggestion to explore the adoption of a wireless sensor network as an alternative to the current handheld device. Recognizing that the handheld device, while valuable, can be physically demanding during field operations, transitioning to a wireless sensor network can alleviate the physical strain on farmers and streamline data collection for improved efficiency.

Furthermore, collaborative research endeavors involving agronomists, soil scientists, and agricultural experts hold the potential to adapt the system to diverse crop varieties and agricultural regions, thus broadening its scope and impact.

Additionally, to unleash the system's full potential, comprehensive training and ongoing user support are paramount. The development of user-friendly manuals, video tutorials, and easily accessible helplines is indispensable in enabling users to effectively harness the system's capabilities.

Incorporating these recommendations not only contributes to advancing precision agriculture but also addresses practical challenges, enhances user experiences, and facilitates the widespread adoption of innovative technologies for sustainable and efficient farming practices.

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