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Smart fertilizer recommendation through NPK analysis using Artificial Neural Networks

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SMART FERTILIZER RECOMMENDATION THROUGH NPK ANALYSIS USING ARTIFICIAL NEURAL NETWORKS

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Smart Fertilizer Recommendation through NPK Analysis using Artificial Neural Networks

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

Siva, Faith

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June 2019

Approval

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Abstract

Agricultural practices, tools and technologies have taken a new paradigm. Precision agriculture is essential to ensure that site-specific crop management is implemented, which includes soil nutrient remedies per crop requirement. Though fertilization is key in boosting productivity, there is need for analysis of the potentials and limitations of soil as a basis of recommending the correct type, quantities and application time of fertilizers to counter uncertainty in fertilizer use. The complexity of finding the optimal fertilization range greatly contributes to major inefficiencies like productivity losses, resource wastage and increased environmental pollution caused by farmers' use of intuition, trial and error, guesswork and estimation. With these, farmers cannot accurately predict what impact their decisions will have on the resulting crop yields and the environment. Some solutions implemented for soil fertility management such as use of mobile laboratories or imported equipment have had their share of challenges such cost of implementation, ease of use and adaptation to the local environment. Other available solutions including taking soil to laboratories for testing is tedious, time consuming and inconsistent. This study proposed development of an ANN model that predicts NPK nutrient levels and recommends the best fertilizer remedy and application time based on the weather forecast. This involved use of IoT, machine learning techniques and a weather API through RAD methodology and experimental research design. Historical data of temperature, PH and NPK from KALRO Library was used to train and validate the model. The developed model achieved an RMSE 0.5 with 75% of data used for training and 25% used for testing. This is in effort to encourage precise fertilizer production for particular areas of need.

Keywords: NPK, PH, Temperature, Sensors, Machine learning

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Acronyms and Abbreviations

ANN	Artificial Neural Networks
DAP	Diamonnium Phosphate
FAO	Food and Agriculture Organization
FAOSTAT	Food and Agriculture Organization Statistics
GDP	Gross Domestic Product
IoT	Internet of Things
KALRO	Kenya Agricultural and Livestock Research Organisation(Former KARI)
MEMS	Micro-Electro Mechanical System
NPK	Nitrogen, Phosphorus, Potassium (Complex Fertilizer)
PDA	Potash Development Association
PH	Scale of acidity from 0 to 14
RMSE	Root Mean Square Error
SDG	Sustainable Development Goals

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Dedication

To Victor, Albert, Florence, Sydney and Esther Wynn, the inspiration and continued support is much appreciated.

Chapter 1: Introduction

1.1 Background of Study

Nations prioritize agriculture as a sector for climate action as it faces challenges such as adaptation to climate change, emissions, reduction and achieving food security IFIA (2009). Apart from providing access to resources, many nations endeavour to assist in adaptation of proven best practices to sustain and improve production. As Kenya's food security mainstream, source of sustainability and economic growth, agriculture contributes to 26% of the GDP and 27% of the GDP indirectly through linkages to manufacturing, distribution and other service related sectors FAO (2018).

Some of Kenya's major cereals include maize, wheat, rice and sorghum among others. Sorghum is a drought tolerant crop that survives in arid and semi-arid areas which makes up almost 83% of Kenya. It has great impact in improving food security in Kenya despite its low production. It meets other needs from industries such as breweries, and fodder production. Its major health benefits include diabetes control, dietary options for celiac diseases, source of energy boost as well as improving digestive health Dietz, Foeken, Soeters & Klaver (2014).

Majorly, farmers' choice of crop, planting and fertilizing decisions are made based on mere reference, such as history of use or advice from friends, fellow farmers or extension officers when no consideration is made in regards to specific farm fertility analysis . The use of upgraded tools and precision farming techniques have influenced the yields in the recent years Burness Communications (2010). This dynamism calls for farmers to adapt to the changes in the sector; taking into consideration suitability of soil to sustain crop, weather changes, precautions in disease and fertilizer management among other aspects Karanja & Mariara (2007).

Agricultural productivity is affected by many factors among them soil fertility. Different factors influence soil fertility such as environmental, human or biotic, which affect the nutrient levels and influence crop health sustainability. Soil PH, soil temperature, microbial activity and moisture content influence nutrient release from fertilizers (Engeljord et al., 1997). Precise measures of the aforementioned elements therefore guide the amount of fertilizer to supplement and time of application to ensure maximum consumption. Weather plays a key role in deciding when to apply as rain or sunshine affects the nutrient flow in the soil.

These nutrients include macro and micro nutrients. The macronutrients include Nitrogen, Phosphorus and Potassium (NPK) while the micronutrients include Calcium, Magnesium, Manganese and Iron amongst others which constitute major fertilizers. NPK is a complex fertilizer that incorporates the named macro and micronutrients with different ratios of the nutrients. Soil fertility analysis is a basis of recommending correct type and quantities of fertilizers considering the complex fertilizers have different nutrient ratios that may be little or too much for the crops. KALRO's Gadam Sorghum manual document guides that 'Apply 2 bags per hectare or one bag per acre of NPK (20:20:20) during planting and when necessary to top dress with one bag (50kg) of CAN per acre.' It is important for the farmer to identify their 'necessary time' as this may vary and apply the correct ratio of fertilizer as it is important to ensure efficient soil nutrient management Bazzola, Smale & Falco (2016).

Various solutions have been proposed and implemented to help the farmer understand their farm needs. Some include use of agricultural laboratories tests, mobile laboratories tests, and smart systems other than home remedies. Each have their challenges making it difficult for the farmer to use. This research involves development of a model that checks NPK levels based on the temperature, and PH levels and recommend fertilizer to a farmer and best time to apply to avoid fertilizer burn, leaching, wash off, denitrification and volatilization which are caused by extreme weather conditions; specifically, sunshine and rainfall.

1.2 Problem Statement

Many farmers have a problem choosing the right fertilizer to apply to their fields KARI (2006). Farmers' fixated mind-sets, guesswork, trial and error and use of intuition are a bottleneck as most trust the fertilizer they think is right according to previous use or copied techniques. This can be caused by either lack of information on available solutions or lack of interest in the existing solutions. One's intuition and experiences vary, not all have the same judgment and this leads to inconsistency in decision-making in regards to fertilization.

The farmers' methods have been quite unstructured and unreliable. Sometimes application schedules are affected by errors committed by omitting other aspects of knowledge which if integrated would improve farmers' decision-making. Research laboratories where soil analysis can be done are not easily accessible for every farmer. Mobile laboratories were introduced to solve the inaccessibility issues though farmers still do not take the time to take up their soils for testing terming it as a waste of time hence their failure. Some imported equipment or techniques have proven unfit for the local problems Kamoni, P. (2019, January 25). Personal Interview.

Chimoita highlights that regardless of the abundant benefits of improved sorghum varieties and technologies, Kenya's production largely remained constrained by poor technology transfer, diseases and rainfall variability. The vulnerability in the arid and semi-arid areas in Kenya are because of recurring natural and emerging socio-economic challenges. The socio-economic challenges Kenyan farmers face include limited access to appropriate technologies, information as well as weak institutional support services. Lack of access to information on latest technologies escalates the challenge of strained produce further Chimoita (2017).

There is need for site-specific real time soil testing to replace the tedious, time wasting offsite soil testing practices. Most farmers may not go into this but instead take up other homemade solutions like use of litmus paper or bare observation where precision is questionable.

1.3 Objectives

1.3.1 General Objective

This research aimed at developing an NPK detection and fertilizer recommendation model for sorghum farming.

1.3.2 Specific Objectives

i. To evaluate challenges experienced by farmers in determining soil fertility levels for crop fertilizer use
ii. To review existing NPK testing and analysis tools and fertilizer recommendation models per crop requirement
iii. To design a model for NPK analysis and fertilizer recommendation for precision farming
iv. To develop the analysis and recommendation model
v. To validate the proposed model.

1.4 Research Questions

i. What challenges do farmers face in determining best fertilizer for maximum yield?
ii. What are the current techniques used in soil fertility analysis? What are the major classifications of crop fertilizers produced and how to meet crop requirements?
iii. How have the existing models, frameworks and architectures been used in soil testing and fertilizer recommendation?
iv. How will the proposed model be developed?

1.5 Justification

Precision agriculture has become an attractive topic globally with soil nutrients as one of the most important factors in estimating its development. Detection of nutrient contents more efficiently is one of the key issues as it informs well-structured schedules of boosting nutrient levels Liu et al. (2016).

Most fertilizers used in Kenya contained N and P with the assumption that Kenyan soil has an adequate supply of other essential nutrients. Earlier, the dependence on N and P was attributed to the fact that most fertilizers were donor sourced and we had little or no opportunity to suggest inclusion of other essential nutrients or speak out about effects of wrong dosages i.e.; Excessive application of N increases vulnerability of crops to diseases and pests and deterioration while in storage.

Various solutions such as use of research laboratories and further mobile laboratories have not been very efficient in assisting farmers effectively manage their soil fertility. Reasons such as lack of information and distance from their location to research laboratories are major hindrances to taking advantage of the advancements. Agriculture research centres have provided fertilizer conversion tables to guide on how different crops need to be fertilized though they are not site specific. Some imported solutions introduced have their major setback of not fitting local needs (Landon, 1984).

It is therefore prudent to develop a solution that facilitates real-time and accurate measure by the farmer and have a recommendation sent meeting what specifically is their need Kamoni, P. (2019, January 25). Personal Interview. Sorghum is categorized as the second most important cereal despite the low adoption and production rates, thus the need to address the yield gap by proposing solutions that can address the food security issues by coming up with sustainable solutions. Apart from having the right resources; tools, techniques, hybrid seeds, the farmers need to be advised on proper use of resources for optimal production as wrong use equally leads to production loses FAOSTAT (2015).

By providing the information on ways to determine deficiencies and remedies, the research tends towards reducing improper use of fertilizers. Improper use affects crop quality and causes wastage. Policy makers and agriculture stakeholders stand to benefit from the research because it provides information on production of fertilizers not generally, but as per crop and soil requirements depending on farmers' location Kamoni, P. (2019, January 25). Personal Interview.

1.6 Scope

As opposed to matching soil nutrient level to a crop that can grow on it, the research specifically focuses on sorghum and how monitoring of soil nutrient levels can give optimum sorghum growth requirements. The macronutrients studied are Nitrogen, Phosphorus and Potassium. These are entities considered at the pre-cultivation and growth stages of the crop. The model made use of IoT devices and machine learning tools to determine soil nutrient levels.

1.7 Limitations

Overcoming time constraint limitation, the research scope is limited to one crop; Sorghum. The data studied is accessible by the researcher and this can contribute to reasonable degree of success of the research.

Chapter 2: Literature Review

2.1 Introduction

The chapter discusses the importance of agriculture, challenges faced by farmers in maintaining soil fertility and solutions implemented on soil data mapping and look at how through machine learning and IoT techniques, integration can be applied to provide a package solution. A review of significant research and publications by accredited scholars helped understand the concept of precision agriculture and investigate the research problem.

2.2 Importance of Agriculture in the Society

Agriculture is Africa's growth engine. It accounts for almost a quarter of the continent's GDP and employs around two thirds of its labour force that largely constitutes small farm holders who practice subsistence or cash crop farming. This reflects Kenya's 26% contribution to agriculture while 27% as a result of indirect contribution of agriculture through processing industries such as breweries, food plants and manufacturing and other dependent industries. The fact that a majority of the population depend on agriculture a major source of live stream further emphasizes its importance. According to AGRA (2017), 70% of the population of Africa is involved in agriculture. Deloitte highlights that agriculture is the most prominent, important and dominant industry. As of 2015, the industry accounts for over 25% of the country's GDP, 20% of employment, 75% of the labour force, and over 50% of revenue from exports.

On the contrary, there is a mismatch between productivity levels of farmers in developing countries and size of agriculture labour forces as the agricultural sector is not performing as well as it should hence the strain in food production. There is little or no expectation that arable land will grow as much as population does thus the need to improve land productivity. Optimization of the production depends on techniques that minimize unwanted impacts such as acidification and efficient use of fertilizers FAO (2009).

As much as a bulk of the agriculture practice is informal an inefficient, the information technology sector recognizes the untapped potential in the sector by use of ICT to formalize the industry. Through knowledge discovery from data and dissemination to farmers, farmers learn how to embrace better farming practices and tap their potential to increase productivity. Sustainability is key in all these endeavours thus the need to put in place accessible, affordable and user-friendly tools. A way to ensure increased production is eliminating barriers that hinder the realization of improved productivity. It can be by eliminating the trouble farmers have to go through to have consistent soil tests, weather forecasts data amongst other data access that would inform their decision-making.

2.3 Precision Agriculture

Precision agriculture is a specialized methodology aimed at optimization of yields using modern technologies such as sensor technologies, GPS services, and big data optimization in a sustainable way to achieve both quality, quantity and financial gain. These allow a more precise understanding of a situation at grass root levels allowing better decisions to actualize maximum efficiency and reduced wastage of resources. These technologies used facilitate gathering and analysis of data to present the information in a way to initiate appropriate response. Use of sensors in agriculture makes it possible to implement the smart farming Ali (2013).

In order to optimize the growth environment of crop, various parameters such as the concentration of soil nutrients, consumption of water, and air temperature are measured Liu et al. (2016). As illustrated in figure 2.1, Food and Agricultural Organization of the UN predicts increase of global population to 8 billion people by 2025 and 9.6 billion people by 2050 FAO (2009).

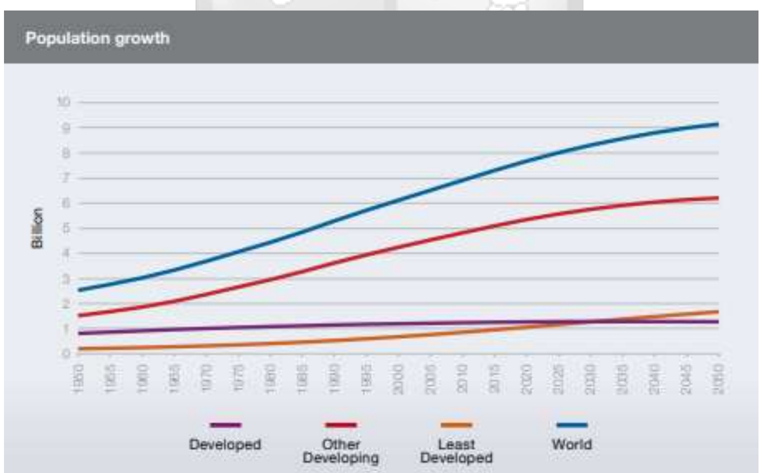

Figure 2.1: Population Growth Trend (Adapted from FAO (2009))

Food production must match the predicted growth by boosting production by 70% by 2050. There are several barriers to accomplishment of this imperative, which include limited availability of arable land demonstrated in figure 2.2, climate change, and go slow in productivity growth (FAO, 2009).

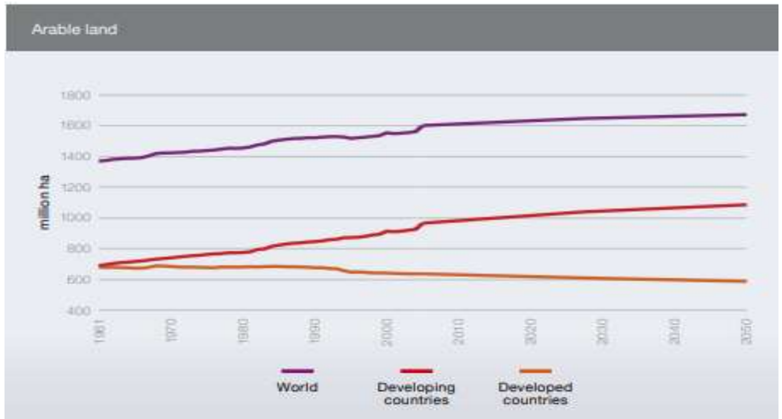

Figure 2.2: Arable Land Statistics (Adapted from: FAO (2009))

FAO recommends that all farming sectors get equipped with innovative tools and techniques for decision support systems backed up by real time data. Precision agriculture therefore takes centre stage in the quest to address challenges experienced in production optimization by ensuring precise solutions are provided to the specific problems experienced (FAO, 2018). This solution therefore leverages on Internet of Things (IoT) and weather API to allow an integrated multidimensional approach of farming activities for deeper understanding of considered how farming ecosystems work Cook et al. (2017).

2.3.1 Suitable indicators for Precision Agriculture

Soil sustainability has been changing based on the economic circumstances and technological advancements though land use has been on a large scale influenced by historical developments. Soil survey incorporating soil fertility experts is the only basis for optimal land use predictions. Vink (1963).

The right indicators are vital to achieving precision agriculture, to be able to assess the effects of use and management of soil health. Soil health as the ecological equilibrium and soil functionality and its capacity to maintain an ecosystem well balanced with high biodiversity. To understand and use soil health as a tool of sustainability, soil’s physical, chemical and biological properties are considered. Good indicators are attributes with rapid response to natural actions and the indicators selection is according to soil use and management, soil characteristics and environmental circumstances Elke et al. (2013).

Some of the considered chemical indicators included soil organic carbon, Nitrogen, phosphorus, Potassium, organic matter and PH. Physical indicators of soil health include texture, density, porosity and aggregate stability. Soil microbial activity and soil respiration have been used as bio indicators of soil health. Besides the constant monitoring and evaluation of the physical, chemical and biological processes, it is important to note that soil microorganism play a vital role in nutrient cycling and have complex interactions with plants. For these reasons, strategies that contribute to improved equilibrium of soil microorganism are able to result to a greater productivity and higher sustainability. This research supports this move by ensuring application of necessary mineral fertilizer to avoid wastage and interference with microorganisms' ecosystem. The proposed indicators include Temperature, PH, Nitrogen, Phosphorus and Potassium.

2.4 Challenges experienced by farmers

Some of the farmers' challenges in sorghum farming include information barriers, inadequacy of extension services, use of unstructured and unreliable traditional farming techniques, environmental constraints, institutional bottlenecks, policy impediments as well as lack of access to seeds in good time (Omoro, 2013). This therefore raises the question as to whether precision agriculture is irrelevant in developing countries.

A common explanation for minimum adaptation of precision agriculture is on cost benefit analysis. (Cook et. al., 2007) classify errors that occur into type I and type II errors. Type I errors occur when a farmer fails to act in potentially beneficial way i.e. failing to change a farming practice. Type II errors come about with farmers doing harmful or least beneficial things i.e. cultivating in a way that causes nutrient depletion, soil erosion and the likes. Common errors by farmers are type II errors, which cause short-term gain and long-term problems. As much as farmers wish to avoid the errors, they persistently fall victim, as they are unaware or uncertain that such errors would occur. They get into destructive and detrimental actions because of economic constraints. Use of DAP instead of NPK is a good example of type II Error where they insist on what they are used to; DAP but in the long run it causes a drop in PH Levels, a long-term effect (Cook et. al., 2007).

Solutions such as laboratory soil testing are viable but expensive and time wasting. A good representation of the farm would require greater sampling density to get a standardized measure. This takes both time and money and limits number of economically justified number of samples (Adamchuk, 2007).

The research wishes to help solve issues such as information barriers, inadequacy of extension services, and environmental constraint issues by providing service at the comfort of a farmer's home. With the proposed solution, a farmer would be able to minimize errors in decision making and uncertainty; evaluate their soil, be informed of the needs and apply remedies accordingly as the value of information is in the improved decision made.

2.5 Sorghum Fertility Management

Adoption of proper and effective crop management practices are essential for higher yields. These strategies include appropriate cropping system, optimum planting time, precise fertilization and irrigation, integration of weed and pest management among others. This research focusses on optimizing soil nutrient levels and proper fertilization to improve the yields. This is by achieving the right soil status based on the deficiencies, and prescription of the correct fertilizer. Figure 2.3 demonstrates sorghum developmental stages which need optimum nutrients for proper growth.

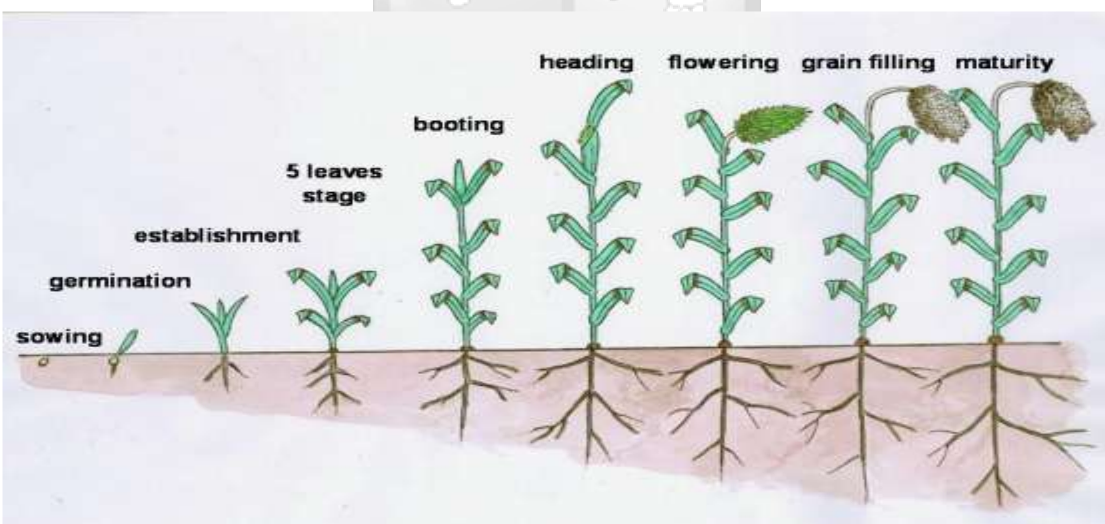

Figure 2.3: Sorghum Development Stages (Adapted from (Agropedia, 2011))

2.5.1 Soil requirements for Sorghum

Sorghum requires deep well drained fertile soils to enhance root growth and expansion for better uptake of moisture Hudo (2016). It is more tolerant to alkaline salts. Jean (2008) mentions that soils with a clay percentage between 10-30% are optimal for sorghum production. Fertile, well-drained loam soils realize high yields with high organic matter though Sorghum can grow in light sandy soils. PH directly influences Sorghum's production as it affects plant growth and development and affects nutrients solubility and availability. Prasad & Staggenborg mention that it generally grows in neutral pH to moderately alkaline. PH level below 5.7 and above 8.3 hampers, the development therefore recommends liming for levels below 5.7 to avoid aluminium toxicity. Similarly, in high pH soil or free lime, acidification takes place using acidifying fertilizers though causes deficiency of iron, and thus lowers the yields (Prasad & Staggenborg, 2010).

Presence of salts limits sorghum production though it is more tolerant to salinity compared to wheat and rice. Accumulation of excess salts i.e. in low rainfall regions decreases plant growth and development especially salts like Ca and Mg in form of chlorides and sulphates. Soil amendments is recommended to remove excess salts, as it is sensitive to salts in the germination and early vegetative growth. This amendment can be through leaching or chemical adjustments to adjust the acidity and enhance the nutrient levels to improve productivity in difficult soils (Prasad & Staggenborg, 2010).

Overtime, land evaluation assesses land's potential to support crop life. The evaluation incorporates analysis and interpretation of climatic characteristics, vegetation cover, soil health, terrain, social and economic factors and other factors like cropland use requirements. Soil samples testing in laboratories for physical and chemical compositions determine soil qualities. With this analysis, one is able to predict the crop suitable for the type of soil Senagi et al., (2017).

Food Organization Authority (FAO) of the UN categorizes suitability of the crop as highly suitable, moderately suitable, marginally suitable or unsuitable for a piece of land, which would ideally boost yields and support skill development for sustainable land use and soil management FAO (1976). This approach entails determining the type of crop to plant based on the soil suitability. This can differ in achieving the goals of improved yields by empowering a certain crop farmer become a better farmer with the crop of his choice. If a farmer grows sorghum, soil testing done against the sorghum requirements determines its nutrient needs and identify the remedy to its nutrient deficiency. With this, the right fertilizer can be determined and applied in correct ratios.

Sampling and testing of soil provides soil inventory of soil nutrients and other soil characteristics that influence its fertility such as pH and organic matter. Testing for plant available nutrients such as Nitrogen, Phosphorus and Potassium help determine nutrient needs, deficiencies and monitor management practices. Sampling depth and sampling timing are vital components of a well-designed sampling plan, which needs to be consistent and objective over time (Marssim, 2000). If soil tested is not representative enough i.e. for fertilization, fertilizer may be too much or little in

2.5.2 Effect of Soil Temperature and PH on NPK

The nutrients required for sorghum production include Nitrogen, Phosphorus, and Potassium, as macronutrients and Sulphur, Magnesium, Zinc and Calcium as micronutrients. Farmers are encouraged to apply NPK fertilizer, which has at least six combinations of the named nutrients. NPK fertilizers with ratios (N=20-24, P=9-11.5, k=4.5-7 including Sulphur Magnesium and Zinc give best combination ratio for production of sorghum.

Soil pH affects nutrient availability by changing the form of the nutrient in the soil. Adjusting soil pH to a recommended value can increase the availability of important nutrients. Soil pH of 6.5 is optimum for nutrient availability. Extreme pH values decrease the availability of most nutrients. Low pH reduces the availability of the macro and secondary nutrients, while high pH reduces the availability of micronutrients (except molybdenum), decreases bacterial activity hence nitrification of organic matter (Landon, 1984).

Figures 2.4 and 2.5 illustrate the correlation between PH and common soil elements including NPK being studied. Figure 2.5 further demonstrates how the specific elements react at different PH levels

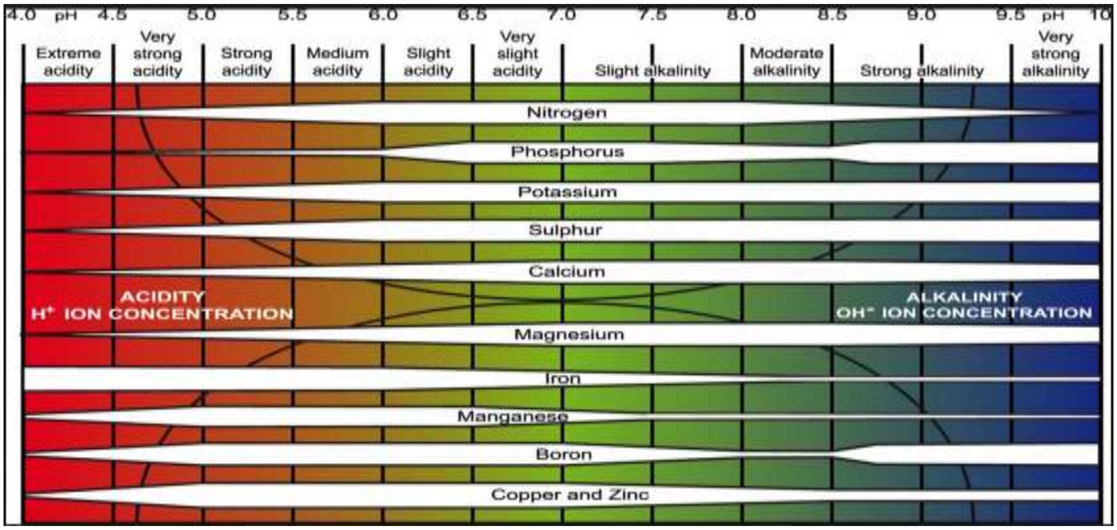

Figure 2.4: PH vs Soil Nutrients (Adapted from (PDA, 2019))

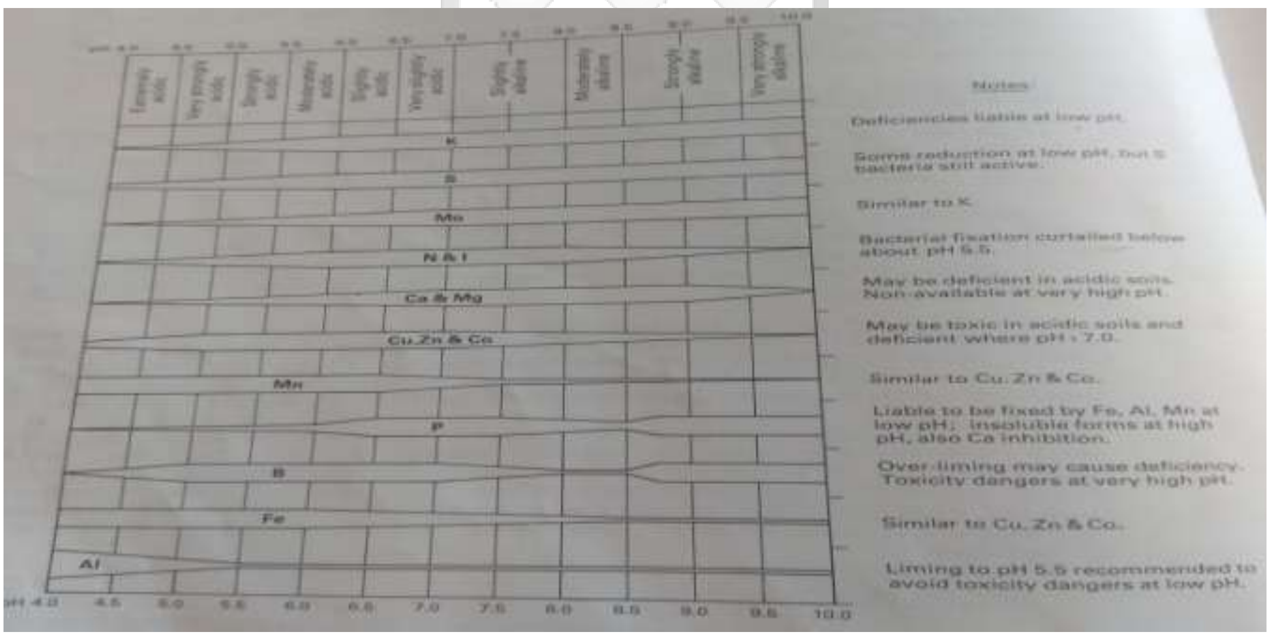

Figure 2.5: PH vs Soil Nutrients (Adapted from (Landon, 1984))

2.5.2.1 Nitrogen (N)

Nitrogen is the nutrient most often limiting in sorghum production. Sorghum utilizes it rapidly after the plants reach the five-leaf stage. Applications should therefore be timed so that N is in place for the rapid growth phase. At boot stage it takes up, 65-70% of N. (McClure, 2019).

Nitrogen is relatively mobile in the soil and Nitrate-Nitrogen (NO3-N) is the form most available to grain sorghum moves with water and can be readily brought to contact with crop roots for absorption. Nitrification- conversion from ammonium to NO3-N in the soil is most likely to occur when fields are arable. Waterlogging causes denitrification- conversion of nitrate to nitrogen gas and lost from the soil by volatilization. Ammonium-based fertilizers are more susceptible to volatilization losses when applied to the soil surface if no rain or irrigation occurs. Three key factors reduce the effectiveness of the surface applied N. This leads to volatilization losses, particularly when acting together. These are moist or wet soil, PH greater than 7 and increased temperature. Applying N prior to a predicted rain or scheduled irrigation is particularly advantageous. Volatilization occurs in waterlogged soil. Soil with low PH< 5.5 apply compound fertilizer. PH above this acidifying fertilizer like Diamonnium Phosphate and other sulphate fertilizers are used

Uptake of N increases with increase in soil temperature. There is reduced N availability in cold soils (Scarsbrook, 1965). Fertilization on cold soil therefore boosts the availability of the nutrient. Nitrogen boosting fertilizer application is best when soil is moist as it dissolves easily and moves down with water to the roots.

The root and stubble residues of sorghum leave excess amount of sugar in the soil causing vigorous multiplication of soil microorganisms. This microbial activity locks up the available Nitrogen for some time hence inducing N deficiency in the succeeding crop (Landon, 1984).

Nitrogen deficiency Occurs in soils with low organic matter, heavily leached soils, sandy soils or heavily cropped soils. Its deficiency causes pale green leaves (young) and pale yellow older leaves. Land fallowing recommended building organic N, land rotation with legumes.

2.5.2.2 Phosphorus (P)

Phosphorus is an immobile nutrient in the soil and are generally safe from leaching. Low and very low phosphorus levels, as indicated from soil tests, will likely show a response to applied phosphorus unless yield potential is restricted by insufficient moisture. Organic matter boosts water retention and this can be worm compost or garden compost. Mulching and removing of weeds also ensures moisture lasts. Yield response to phosphorous application tends to be erratic on medium testing soils and is unlikely on soils testing high and very high for phosphorus (McClure, 2019).

More fertilizer P is required at low soil temperature to ensure sufficient P uptake (Singh &Jones, 1977). When soil PH is greater than 8, some micronutrients and phosphorus become unavailable to the plants, biological activity reduces and soil becomes saline (Landon, 1991).

Phosphorus deficiency occurs in soils low in organic matter, long cropping times, and highly weathered soil, Iron rich soils, which makes Phosphorus less available or alkaline soils that makes Phosphorus insoluble and unavailable. Symptoms include stunted growth and purple pigmentation on leaves, sheath and stems.

2.5.2.3 Potassium (K)

Potassium is an immobile nutrient in the soil and are generally safe from leaching. Soils testing in a medium or higher range for potassium (K) generally do not show a yield response to added potassium fertilizer (McClure, 2019).

Sorghum's ideal PH range is 6.0 -7.5 with 6.5 considered optimum. Outside the range, nutrient efficiency deteriorates and liming is effective to raise the PH. Aluminium concentration increases with decrease in soil PH thus becoming toxic to the crop. Phosphates combine with toxic aluminium effectively reducing the concentrations in the soil.

Potassium deficiency occurs in soils with low organic matter or heavily cropped soils, soils formed from parent soils deficient of K, and soils textured lightly. Sorghum is highly sensitive to lack of Potassium. Some of the deficiency symptoms include Inter-venial and marginal necrosis, which occur in older leaves.

2.5.3 General Fertilizer Recommendations

Fertilizer use is vital in boosting food production and slowing down the environmental degradation rate. In the effort to overcoming food production challenges, efficient management of soil fertility must be highly considered alongside use of fertilizers and improved nutrient management strategies to achieve this efficiency. For soil depletion is a known effect of African agriculture, improved organic techniques of nutrient supply will undoubtedly affect the future soil health and productivity. Janssen (1993) mentioned that relying on recycling of nutrients however efficient would not cause restoration of the depleted soils. More nutrient mining and increased use of marginal land causes more inevitable consequences of low use of fertilizers than those anticipated from increased use of fertilizers (Evanson & Pingali, 2007).

In light of these considerations, there has been calls for increased fertilizer consumption compared to the developing countries where the use increased more rapidly. There are various reasons that influence a farmer's adoption and intensity of fertilizer use. These influence their decision to buy as well as the application rates. Some of the key influences include size of farm, access to credit, cooperative memberships and contact with extension workers, information access, and availability of inputs as well as distance to markets. It is important for a farmer to understand what their farm needs to align their remedies.

Fertilizers applied to boost these nutrients; both macro and micro depend on the soil PH levels. Acidic soils use alkaline fertilizers to raise the PH levels while alkaline soils use acidic fertilizers to lower the PH to recommended levels.

Fertilizers can either be compound or single nutrient fertilizers. Compound fertilizers like NPK take long to be absorbed in the soil; mostly used with acidic soils while fertilizers like DAP are absorbed first; crops respond first to them but in the end, they affect the soil as they lower the PH. Farmers may prefer DAP but should be aware of long-term effects. Leaching solves over fertilization problems because of rain but this is a waste of resources by a farmer Kamoni, P. (2019, January 25). Personal Interview. Sorghum fertilizers available include both basal and folia fertilizers; DAP, CAN, NPK as basal and Optimizer and Lavender as folia. (Green life, 2018).

A general guide for dry and high rainfall area is; in dry areas, fertilizer ratios of 40N:40P:35K kg per ha is used to fertilizer during the time of planting and additional 40kg/ha may be added 30 days after. In high rainfall regions, 60N:50:40K / ha is used when sowing and additional 60-70N 30 days after planting. The following guideline counters specific nutrient deficiency (Green life, 2018).

Figure 2.6 gives different PH level classifications while 2.7 gives a guideline on how different nutrient types are classified to facilitate analysis of potentials and limitations of soils as a basis or recommending fertilizer types and amounts (KALRO, 2019)

Table 3: Soil pH ratings and Hp

pH class	Name
< 4.5	extremely acid
4.5 – 4.9	strongly acid
5.0 – 5.9	moderately acid
6.0 – 6.4	slightly acid
6.5 – 6.9	near neutral
7.0 – 7.4	slightly alkaline
7.5 – 8.4	moderately alkaline
8.5 – 8.9	strongly alkaline
>8.9	extremely alkaline
*Hp > 1.0 me%	High (or toxic)

*= exchangeable acidity

Figure 2.6: Soil PH Ratings (Adapted from (KALRO, 2019))

Table 4: Soil fertility classes

MEHLICH METHOD				
Nutrient	**Deficiency level**	**Adequate level**	**Excessive/toxic level**	**Remarks**
Sodium, me%	None	0-2.0	> 2.0	excessive levels in saline & sodic soils
Potassium, me%	< 0.24	0.24-1.5	> 1.5	
Calcium, me%	< 2.0	2.0-15.0	> 15.0	
Magnesium, me%	< 1.0	1.0-3.0	> 3.0	
Phosphorus, ppm	< 30	30-80	> 80	Mehlich method
Manganese, me%	< 0.11	0.11-2.0	> 2.0	
TOTAL NITROGEN & CARBON				
Total nitrogen, %	< 0.27	0.27 - 0.40	> 0.40	0.133 – 0.27 moderate
Total organic carbon, %	< 1.33	2.70 - 4.00	> 4.00	1.33-2.70 moderate level
Extraction with 0.1 M HCl				
Copper, ppm	< 1.0			
Iron, ppm	< 10			
Zinc, ppm	< 5.0			
OLSEN METHOD				
Phosphorus, ppm	< 10	11.0 – 20.0	> 20.0	

Source: National Agricultural Research Laboratories ratings

Figure 2.7: Soil Fertility Classification (Adapted from (KALRO, 2019))

2.6 Related Works

ICT-enabled learning and knowledge exchange facilitates precision farming by giving farmers expert knowledge in the agricultural sector, conduct research, provide information on weather, fertilizers and advise on better farming practices. Various scientific groups have tried to detect the concentration of nutrition elements in soil based on basic electro-chemical methods. (Sudduth et.

al, 2003) have detected some major elements of soil nutrients by measuring the changes in the conductivity of soil samples. (Adamchuk et al., 2007) directly measured soil chemical properties by using ion-selective electrodes. (Liu et al., 2016) developed a miniaturized nutrient detection system, which was quite different in size and design compared to the previous ones.

Some of the solutions used include:

2.6.1 Land Suitability GIS- AgriMaps

The agrinett project; by the University of West Indies aims at incorporating ICT into agriculture in Trinidad and Tobago. In alignment with United Nations SDGs, Agrinnet has developed mobile and web applications that provide users with features regarding an area based on GPS coordinates. It shares information in regards to physical features, roads and has a soil capability map to provide information on soil evaluation and recommender feature to guide a farmer how suitable their land is for a given crop. The applications and tools help farmers translate informed decisions into better field practices in quest to protect their agriculture landscapes (Agrinett, 2018).

The application incorporates detailed large-scale data and imagery and provides a bigger regional coverage of the landscape to aid watershed and conservation groups in developing protection plans and guide on land use initiatives (Agrinett, 2018). The application uses soil capability map to provide information on soil series and other observable characteristics as well as display proximity of water sources, access roads land physical features. From a planning edge, farmers benefit by being able to determine which crops best fit various farmlands across the country. A survey of land capability upon assessment along major land and geographic features is the basis of the application (Agrinett, 2018).

Although it may capture that an area contains a type of soil that supports a certain of crop, a consideration may be that the information is only a function of the map scale. This implies that soil delineation may occur where different areas on the map may have different soils not identified thus misguide a farmer’s decision. The maps give general soil survey data of dominant types and a distribution that occurs in a relative large area as such best used to make general comparisons of soil capabilities on a wide scale. They are therefore not reliable to make on farm decisions due to lack of detail that captures the variations of the farm. In addition to the limitation, maps indicate abrupt changes on the soil map while in reality, the soils transition from one type to another continuously. Data based on approximations interfere with the precision. Nature controls the real variability of soils not the maps and therefore it is necessary for a farmer time-to-time, check on their soil status to determine type and predict use, behaviour and remedies as uniform decisions fail to recognize actual variations and introduce error in decision-making.

Figure 2.8 illustrates how the agrinett application makes recommendations for choice of crop to be planted.

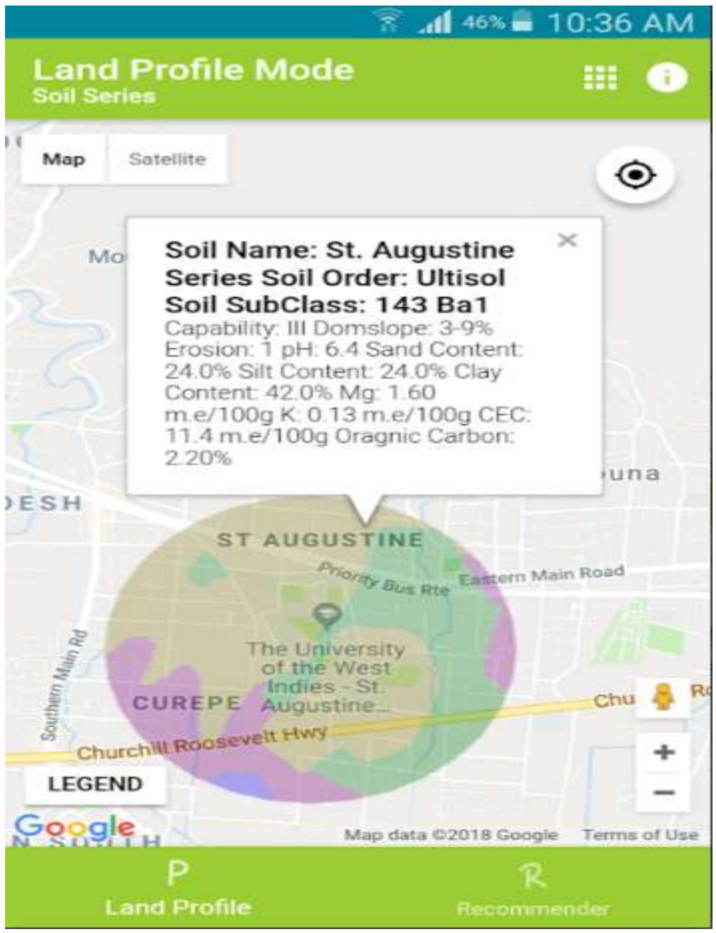

Figure 2.8: AgriMaps Application Module (Adapted from (Agrinett, 2018))

2.6.2 on-the Go Vehicle-Based Soil Sensors

Sensors able to measure variable soil properties on the go have been developed and can be used in conjunction with Global Positioning Systems (GPS). The soil properties collected generate base fields' maps used to advise farmers on land use and management. The number of measurement points vary depending on speed of travel, spacing between passes and sampling frequency. This gives a denser sampling compared to manual grid mapping and reduces the soil mapping costs (Adamchuk, 2002). This may be expensive for farmers, the need to acquire and maintain the tools ensemble. Some farms' terrain does not make it feasible to use. This is also not suitable with crops growing unless much spacing done in between crop rows to allow the lad vehicle to pass.

Figure 2.9 below is a sample of an on-the go machine.

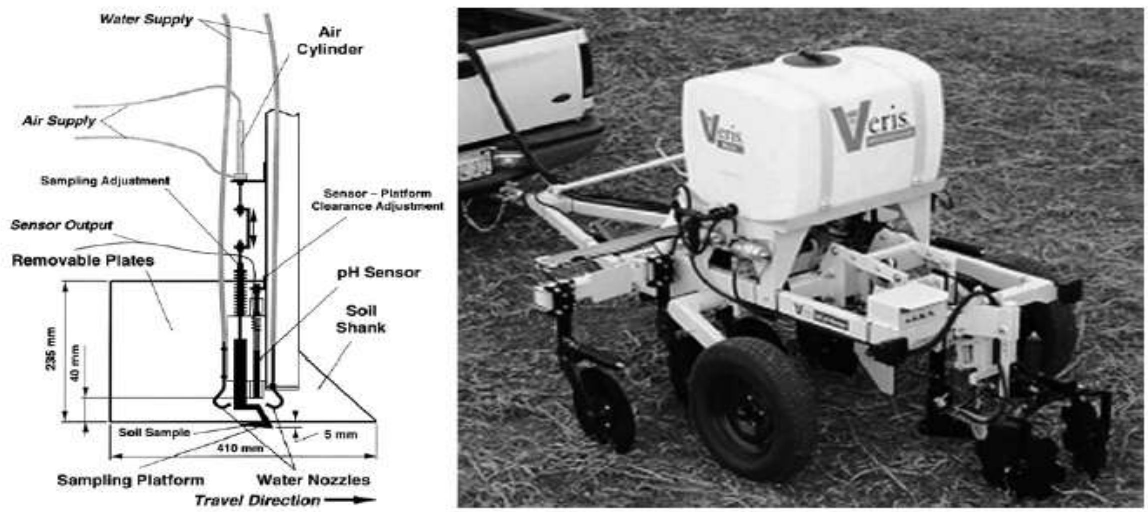

Figure 2.9: on -the-go machine (Adapted from (Adamchuk, 2002))

2.6.3 Agricultural Land Suitability Evaluator (ALSE)

ALSE was an intelligent system used to assess land suitability for different crops in the tropical and subtropical locations. Presented by (Elsheikh et al., 2013), the system used GIS capabilities in the digital map of a location using the FAO-SYS model. The system can suit the local environment, conditions for soil evaluation and supported expert knowledge. The system was able to detect crop specific conditions and systematically give spatial and temporary data with maximized potential. This facilitated complex decision-making in short times considering sustainability of the crop. Datasets used in the experiments were collected from West Malaysia and Terengganu and some of the attributes considered include rainfall, soil nutrient availability, rooting conditions, topology nutrient retention and soil workability. Figure 2.10 and 2.11 demonstrate how ALSE is structured. Fertilizer recommendation was not done at the point of analysis.

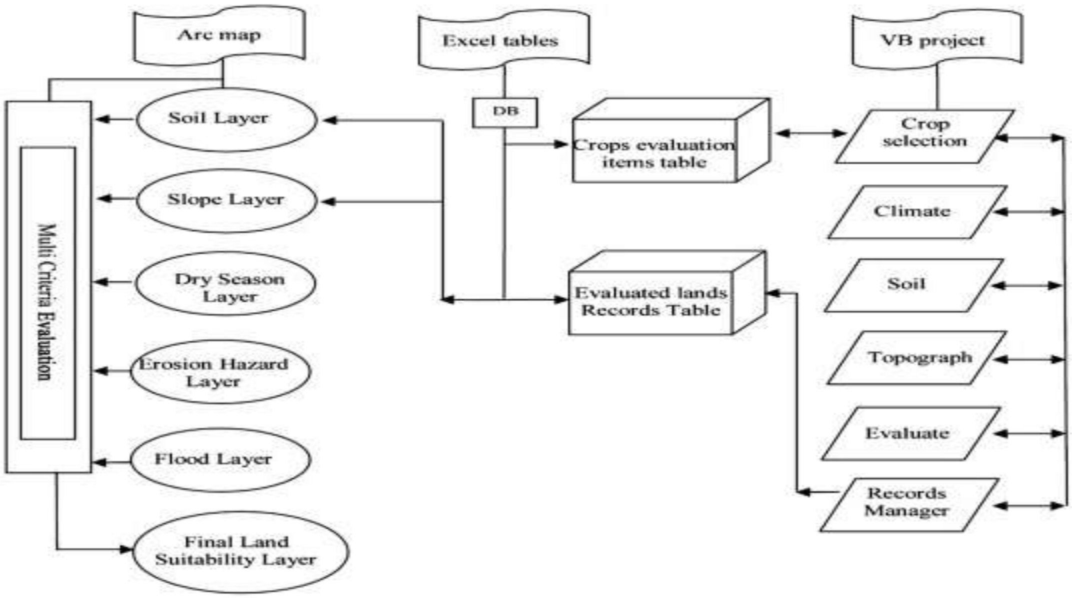

Figure 2.10: ALSE System Structure (Adapted from (ALSE, 2013))

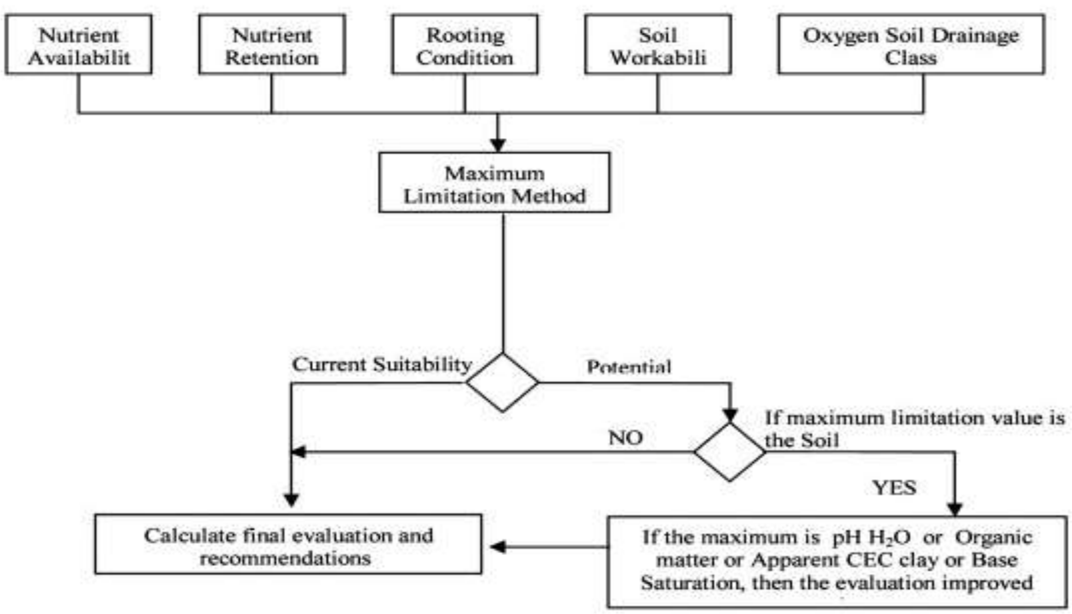

Figure 2.11: ALSE Flowchart (Adapted from (ALSE, 2013))

2.6.4 Involuntary Nutrients Dispense System (INDS) for Soil Deficiency using IOT

The aim of the project was to reduce fertilizer usage and work of the farmer by checking the PH and ensuring the right amount of NPK dispensed to the crops. Figure 2.12 illustrates how the PH sensor remotely monitors the nutrients and sends data to Raspberry Pi then displayed on LCD. Based on the values obtained, the farmers are able to visualize the data and switch on relay valves to connected nutrient tanks (See figure 2.13). Nutrient deficiency analysis depends on the PH value and the corresponding relay switched on as approved by farmer on a mobile application. Data obtained from the sensor is stored on the cloud (Brindha et al., 2017).

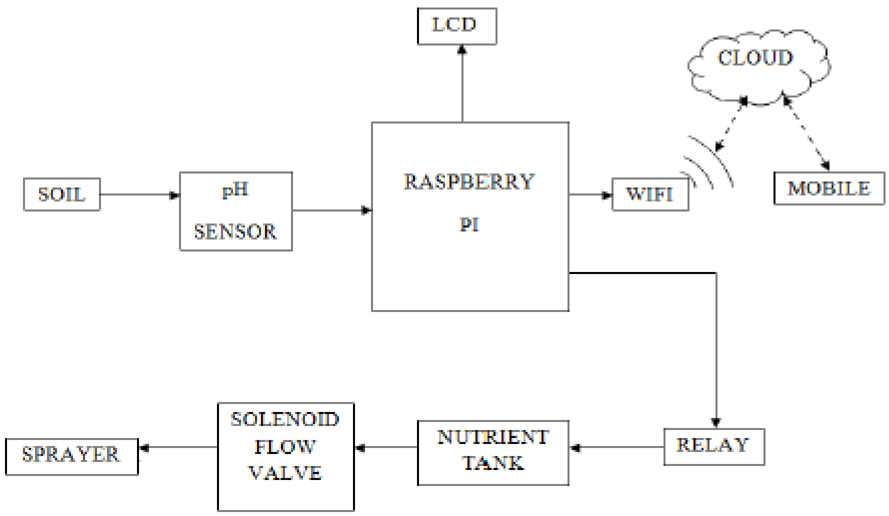

Figure 2.12: INDS Block Diagram (Adapted from (Brindha et al., 2017))

S.No.	Obtained NPK-pH Value	pH Value	Soil Nature	Nutrient	Relay 1 Status	Relay 2 Status	Relay 3 Status
1.	53	3.7	Acidic	Nitrogen	ON	OFF	OFF
2.	83	5.9	Acidic	Phosphorous	OFF	ON	OFF
3.	128	9.1	Basic	Potassium	OFF	OFF	ON
4.	98	7	Neutral	Phosphorous	OFF	ON	OFF
5.	63	4.5	Acidic	Nitrogen	ON	OFF	OFF
6.	122	8.7	Basic	Potassium	OFF	OFF	ON

Figure 2.13: INDS Experimental Values (Adapted from (Brindha et al., 2017))

The project heavily depended on efficient irrigation. This will not work in areas where automatic irrigation and nutrient dispensation is not set. Many farmers practicing informal agriculture have not set up such systems.

2.6.5 IOT Based Smart Agriculture and Soil Nutrient Detection System

The project provides an overview of soil monitoring system using sensors. Figure 2.14 demonstrates the working of the prototype where the information from the sensors is sent to an AD converter then to the cloud through Raspberry Pi. The information forms a basis to select suitable crops to grow given the soil parameter readings. The NPK sensor works by measuring the amount of NPK based on colour changes and the colour change sensed by colour sensor sends an electrical signal to a microcontroller (Chavan et al., 2018).

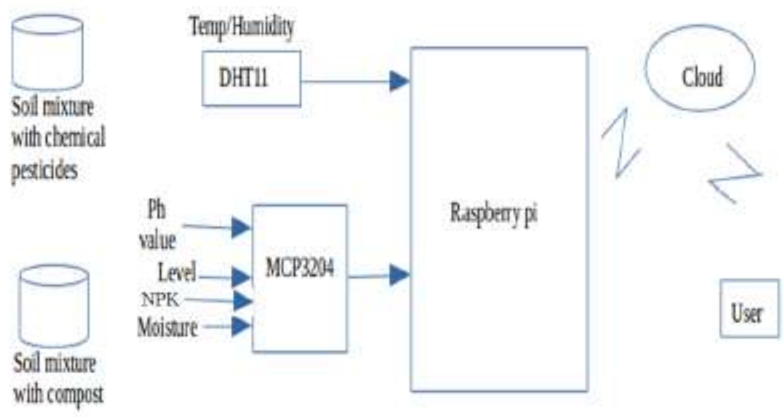

Figure 2.14: Soil Nutrient Detection System Block Diagram (Adapted from (Chavan et al., 2018))

From the above literature, it is worth noting that different implementations support techniques used in determining land suitability and nutrient detection for improved production. Building on this, this research encourages a crop farmer better their produce instead of changing crops per soil suitability. Once the nutrient levels are determined, the model recommends the boost based on the predicted weather patterns as supported by the weather API.

2.7 Technologies used in Developing Solutions

2.7.1 Nutrient Sensing Approaches

Smart farming has picked up with use of sensors placed on land to provide information needed on land effectiveness. The Internet Architecture Board defines Internet of Things as networking of smart objects that intelligently communicate in the presence of internet protocol, not directly operated by human being but exist as components in the environment. Also called a summation of services, data, networks and sensors (Bilal, 2017).

Wireless sensors have the capability to revolutionize soil ecology by facilitating soil measurements previously deemed impossible at temporal and spatial granularities. Figure 2.15 shows a demonstration of IoT enabled information collection from a farm. Terzis reiterates that wireless sensor networks promise low-cost and low impact rich data collection that is a better alternative to manual data logging or taking soil to the labs for testing. Sensors collect data from the environment and convert to useful data. (Terzis et al., 2009). Wireless sensor network platform preferred because of reduced size membrane durability, robustness, less output impedance and quick response, increased sensitivity and increased platform flexibility (Mayer, 2012)

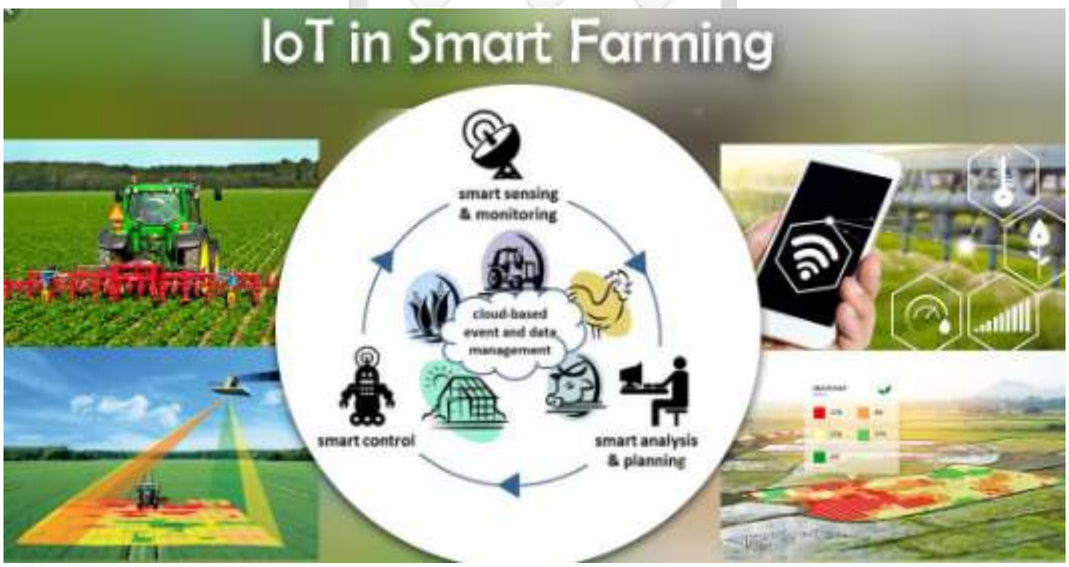

Figure 2.15: Demonstration of Smart Farming (Adapted from (Mizou Organic Project, 2019))

An extensive review of the sensors used to measure soil properties has it that the sensors are either optical or electrochemical. Optical sensing uses reflectance spectroscopy to detect energy level absorbed/reflected by soil particles and nutrient ions. Electrochemical sensors use ion-selective electrodes that generate a voltage or current output in response to the activity of ions selected (Sudduth et al., 2009).

2.7.1.1 A Miniaturized On-Chip Colorimeter for Detecting NPK Elements

Based on MEMS technology and Beer-Lambert's Law, Liu created a novel chip- level colorimeter to detect the NPK elements. MEMS technology ensured a less voluminous chip as compared to other colorimeters with an advantage of low costs, fewer testing samples and high level of precision. Figure 2.16 below depicts the major subsystems of the components, which include the sensors, the circuitry, and the display or transmission module Liu et al. (2016).

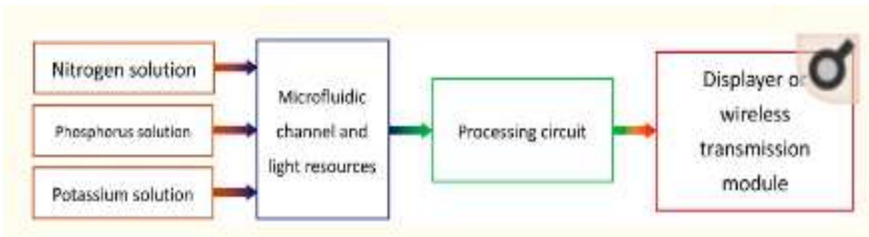

Figure 2.16: NPK Colorimeter Components (Adapted from (Liu et. al, 2016))

2.7.1.2 Measurement of NPK using NPK Micro sensor

Figure 2.17 is a picture of a micro sensor by Progis and SEA partners (2012). It is integrated into farm equipment, automatically to produce NPK values and automatically produce NPK maps. They use Ion Selective Field Effect Transistors (ISFET). It requires samples in small volumes with NPK ions targeted. The micro sensor assists in spatial data collection, precision irrigation and supplying data to farmers. This sensor has not been made available for use by the developers and it is worth noting that other developers such as Teralytic launched the first wireless NPK sensor in February 2019 with limited number of the soil probes released (Teralytic, 2019).

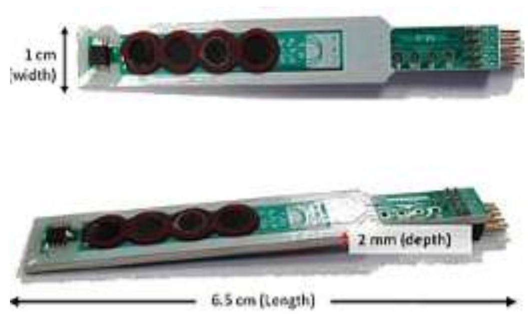

Figure 2.17: NPK Micro Sensor (Adapted from (Mayer, 2012))

2.7.1.3 Measurement of NPK from PH Value

The objective of the research by Khakal, Deshpande & Varpe (2016) was to develop a "Measurement of NPK from PH value". This is by use of a PH Sensor. The system has a measure capable of detecting the level of temperature, Element contents in soil (N, P, K), Humidity and Soil moisture. This was built based on the correlation between PH and the NPK availability in the soil. Figure 2.18 below is a picture of the micro-sensor used. Building on their research, this study implements this approach to detect the NPK levels, as NPK sensors were not available for use. An NPK sensor made available by an organization in Austria was going for 4960 Euros, which is very expensive to acquire for prototyping, not considering the implementation costs.

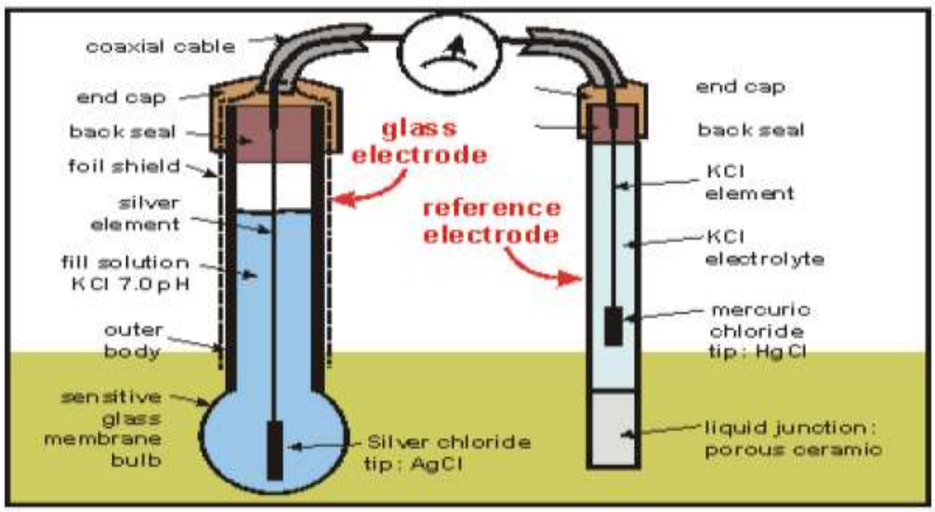

Figure 2.18: NPK Microsensor-phec 04 (Adapted from (Khakal et al., 2016))

2.7.1.4 Remote Sensing and GIS Integration- Assessment of Land suitability

AbedelRahman, Natarajan & Hegde carried out scientific analysis in 2016 identifying the main limiting factors for agricultural production and help decision makers to develop crop management strategies that improve land productivity. A GIS based approach used to match crop suitability in Chamarajanagar district Karnataka, India and soil suitability and capability maps developed to illustrate the degree of suitability and do spatial representation of the soil. Data used in the study was Remote sensing satellite (IRS P-6) LISS III and LISS IV sensor data with slope degree derived from Shuttle Radar Topography Mission (STRM and Topographic maps. Digital image processing techniques, ENVI 5.0 and GIS 10.1 for RS and GIS integration as well as land evaluation classification according to FAO standards implemented to assess the suitability (AbedelRahman, Natarajan & Hegde, 2016).

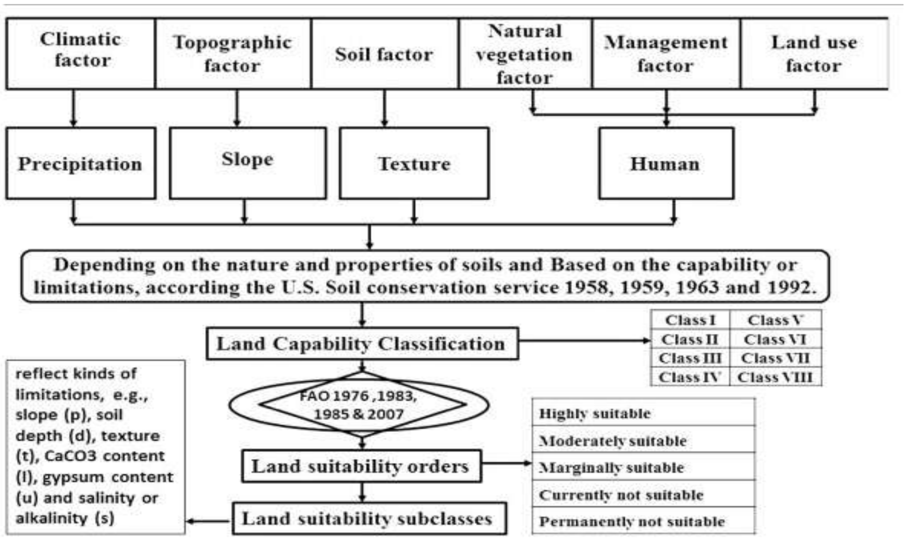

Figure 2.19: Remote sensing and GIS Flow chart (Adapted from (AbedelRahman et al., 2013))

Land suitability order	Percentage of area
Highly suitable (S1)	10.53
Moderately suitable (S2)	3.4
Marginally suitable (S3)	62.52
Currently not suitable (N1)	11.77
Permanently not suitable (N2)	0.43
Rock land (N2)	11.34

Figure 2.20: Land Suitability Order- Chamarajanagar district (Adapted from (AbedelRahman et al., 2013))

2.7.2 Machine Learning Models

Various machine-learning models for prediction or classification are built using different algorithms. Some of these include:

2.7.2.1 Artificial Neural Networks (ANN)

Artificial Neural networks have been used to create models for soil suitability checks and recommendations. Anitha and Acharjya (2017) came up with a model aimed at predicting crops that could grow in an area. This was by coming up with a hybridizing of rough set on fuzzy approximation space and ANN. They used datasets containing 2193 objects and attributes totalling to 15 collected from Vellore district between 2007 and 2014. The soil attributes used were 26 including soil pH, soil organic matter, and availability of phosphorus, potassium, water, nitrate, calcium, copper, magnesium, zinc, iron, manganese and moisture. 55 % of the data used for training while 45% used to test. The experiments developed in R achieved an accuracy of 93.2% with a Mean Square Error of 0.2436 (Anitha & Acharjya, 2017).

The algorithm has self-learning capabilities that enables it give better results as more data is input. An adaptive system restructures given information flowing through the network during the learning stage. It goes through a learning phase where it recognizes patterns in data and it contrasts its actual output with the desired output. It is taught what to look for and what the output should be in this supervised phase, using the information flowing in its structure (Dey, Bhoumik & Dey, 2016).

There are three interconnected layers in ANN. The first layer is the input while the second and third, output. ANN is made up of nodes that receive a series of entries to produce an output. Weight interconnects the nodes and the weight is adjusted until it achieves a desired output of the training dataset. Below is an illustration of Neural Networks.

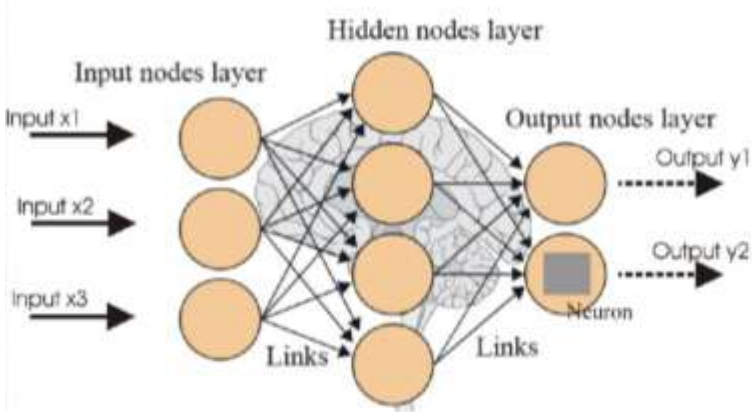

Figure 2.21: Structure of ANN (Adapted from (Brinda & Pushparani, 2016))

2.7.2.2 Support Vector Machine (SVM)

Fereydoon created an SVM- Two class model used to analyse wheat production in Iran. 22 soil profile representatives with each profile having 10 features were broken down in the following groups: climatic, topographic and soil related features. Design and testing of the model on MATLAB 8.2 while implementation on non-linear class boundaries. 80% data was for training while 20% for testing. All randomly, selected. Upon evaluation, they had a RMSE of 3.72 AND R2 of 0.84 (Fereydoon et al., 2014).

SVM is a supervised machine learning method. It has two classifications, linear where classifiers are separated using hyper plane and nonlinear SVM, which does not use hyper planes. The dataset informs SVM of classes the algorithm can classify new data. It maximizes on margin maximization that is the distance between the various classes included in the classification. SVM is considered accurate and most suitable for stock market predictions and forecasting by financial institutions as it offers best classification performance (Manoja, & Rajalakshmi, 2014).

SVM algorithm finds an optimal separating hyper plane based n Kernel Function. It is designed to create a model based on the available training dataset.

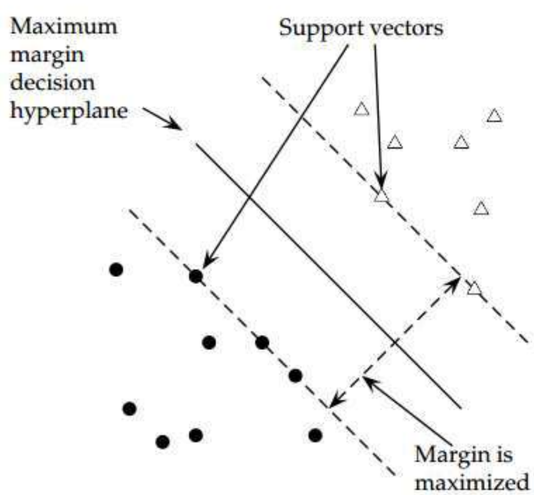

Figure 2.22: Support Vector Machine (Adapted from (Mundada & Gohokar, 2013))

2.7.2.3 Parallel Random Forest

Parallel Rand Forest is an ensemble machine-learning algorithm. Learning a dataset is through a divide and conquer approach. Its optimization based on a hybrid approach combining data-parallel and task parallel optimization. In a research by Spark M Lib, PRF shows superiority of the algorithms over in terms of classification accuracy, performance and scalability (Chen et al., 2018)

Senagi, Jouandeau and Kamoni, justified use of an optimized algorithm for prediction of land suitability for crop production in 2017. They used soil properties and had experiments using Linear Discriminant Analysis, Linear Regression, Parallel Random Forests, Gaussian Naïve Bayesian, KNN and Support Vector Machines. Upon evaluating experiments across 10 cross fold validation, parallel random forest had better accuracy of 0.96 and 1.7 seconds of execution. The goal of the research was to save time and improve on land evaluation accuracy levels. With these, they would be able to predict land suitability for cop production without use of soil experts (Senagi et al., 2017).

2.7.3 Expert Systems

Agriculture has evolved into a complex business that requires knowledge accumulation and integration from diverse resources. For competitive purposes, a farmer depends on different specialists to assist in decision-making but unfortunately, they are not always available when needed. In effort to alleviate the problem, expert systems act as powerful tools with information, great potential in agriculture information integration (Prasad, 2008).

An expert system is limited to a specific domain of expertise, able to reason with uncertain data and can explain trail of reason. The need for the expert system is necessary to do diagnostic tests on soil, as the human expertise is scarce. General classification of soil needs to be specific i.e. establishing precise recommendation to measured deficiency. Skilled practitioners rely on knowledge and intuition. For expert systems take advantage of experimental knowledge with intuitive reasoning, they combine the specialized knowledge and aid the farmer make best decisions for their crops. An example of an expert system developed to support agriculture management is Weiping Jin Expert system that adopted measures in managing crops such as irrigation, fertilization and spraying, built on fuzzy phenomena, as there was a lot of fuzzy crop states analysis (Prasad et. al., 2006). Expert systems

2.8 Conceptual Framework

Figure 2.24 below illustrates how the prototype works. Data from the sensor is fed into the model. The model recommends the fertilizer suitable for use. An incorporated weather API gives a weather prediction, which guides whether to fertilize, or not. KALRO Library is the source of historical data used for model training.

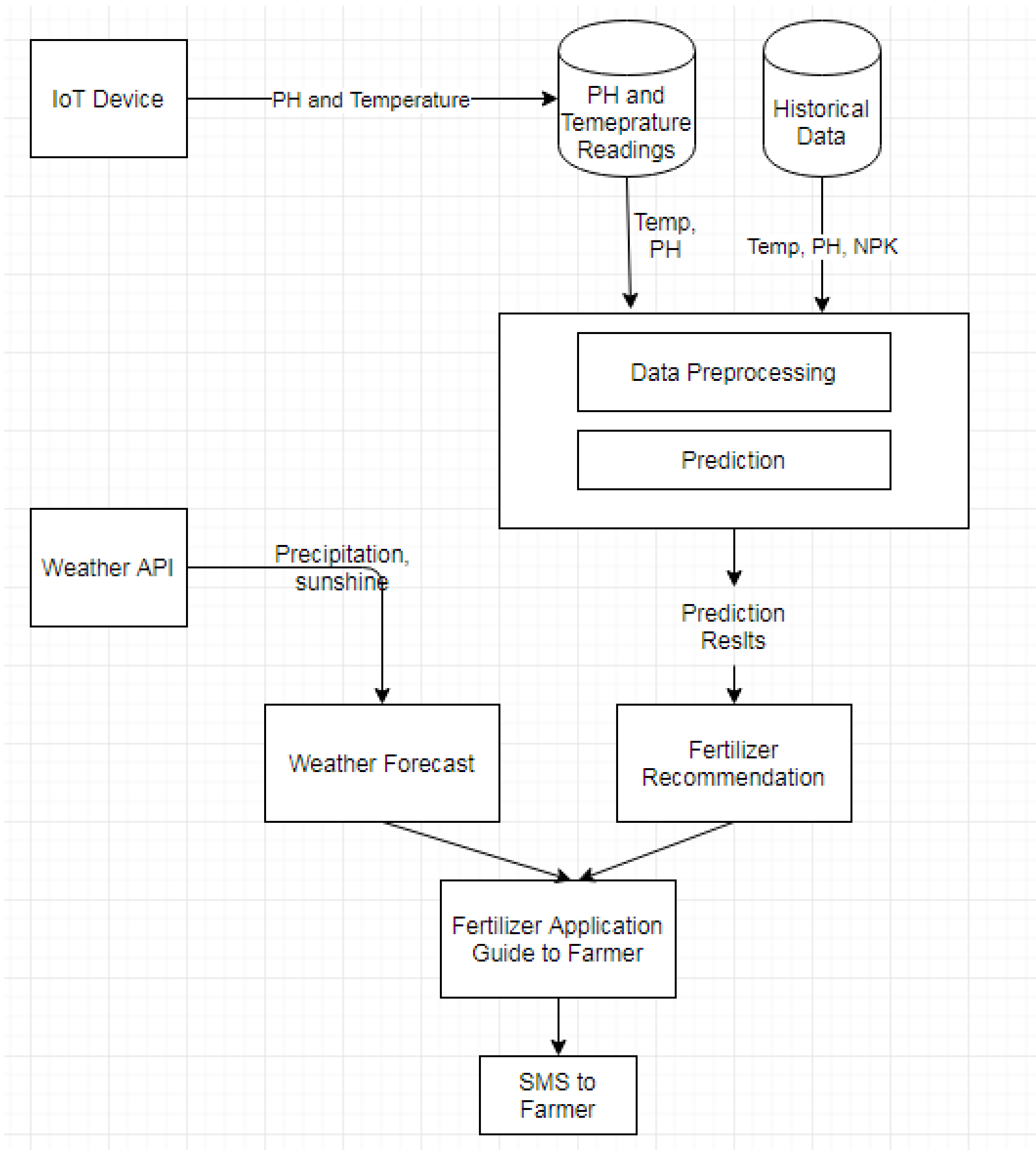

Figure 2.23: Conceptual Framework

Chapter 3: Research Methodology

3.1 Introduction

Methodology is the analysis of approaches or principles of methods applied in carrying out a study (Kumar, 2005). It is the process of systematically solving problems or considered as the science of doing research. This research was guided by objectives proposed to be met and was greatly informed by the nature of the problem under study.

3.2 Research Design

It is the structure research follows in terms of collection, measurement and analysis of data in effort to get answers to research questions. Wanjugu further reiterates that the research design should bring out the relevance of the research with the economy in procedure (Wanjugu, 2015). This study implemented an experimental design approach involving identifying research objectives and building an ANN model to prove the concept. Iterations made were to the interest of the best performing model.

3.3 Model Development

The model development took the following steps.

i. Data Collection
ii. Data Pre-processing
iii. Model Training
iv. Model Testing and Validation

3.3.1 Data Collection

Soil data and fertility analysis rules from KALRO Libraries were the main source of data. These came in form of soil records from the laboratories and nutrient management guides from agricultural publications. Fertilizer recommendation rules in figure 2.7, NPK fertilizer ratios per deficiency by Landon (1984) and dataset of 1233 entries with soil PH, Temperature and NPK values were collected for the study. Consultation and further discussion with the soil experts facilitated understanding of the data and soil analysis rules currently used.

Use of scientifically verified internet resources were vital to gather relevant information to the research area from researchers, seasoned industry players in the field as well as reviews and documentations by organizations such as KALRO, CYYMIT or FAO. Other sources like documentation of similar projects done on the same also contributed immensely in information collection. This aided identification of gaps the research could fill.

3.3.2 Data Pre-processing

The data obtained was extracted from the documentations i.e. organization logs and stored in a simple excel documents. Data cleaning helped identify the data needed and get rid of noisy and irrelevant information especially captured variables not considered in this project. Complete data saved for training, testing and model validation. This process was key in producing valid and reliable models.

3.3.3 Model Training

Training involves feeding inputs to the model for processing and training on the input data and expected output. The machine-learning algorithm used is Artificial Neural Networks. The data sets were split into 75% training data and 25% testing data in order to determine the possibility of determining precise fertilizer doses. The inputs soil temperature, PH and NPK values were used with an expected output of NPK soil levels for fertilizer recommendation.

3.3.3.1 Evaluation metric (RMSE)

This is a measure of how well the model performed. RMSE measures the difference between predicted values against the values observed in the real environment. It is also the standard deviation of residuals otherwise referred to as prediction errors. RMSE is a measure of how spread out these residuals are telling one how concentrated the data is around the line of best fit

3.3.4 Model Testing and Validation

Different experiments done determined the best combinations of the Temperature, PH and NPK inputs. ANN was used in the experiments and this was settled for as the sole algorithm considering the nature of inputs and expected output. ANN was best fit for its ability to learn and model nonlinear and complex relations, which in this place would be the complex relationship of different soil nutrients with PH considering different temperature levels. It is also working best with capturing associations or capturing regularities, which in this case comes in the relationship between nutrient availability and PH levels in soil. These are also affected by temperature. It captures many kinds of relationships, which PH, NPK and temperature have.

3.4 System Development Methodology

Rapid Application Development (RAD)

To develop a flexible and iterative model, there was need for a methodology that would facilitate that (flexibility) as the model is set up in a dynamic environment prone to change thanks to technology advancements. The model was able to accommodate change and be inclusive enough to assure cooperation between the users.

To factor in the time constraint, RAD is preferred as it holds more emphasis on development. The planning is in the first phase of the project and the remaining stages of development done iteratively. RAD combines CASE tools, techniques and strict delivery time for quality finished systems in less build-up time. It takes maximum advantage of powerful development software that has evolved recently (Martin, 1990).

As RAD takes advantage of automated tools to restructure process of development. Its iterative nature allows adjustments in reaction to knowledge gained as the project progresses. With its flexibility to changes, in a tight period it facilitates project development comfortably to meet the objectives of the project.

The following activities took place iteratively following the methodology demonstrated in figure 3.1 to satisfy the efficiency of working with it.

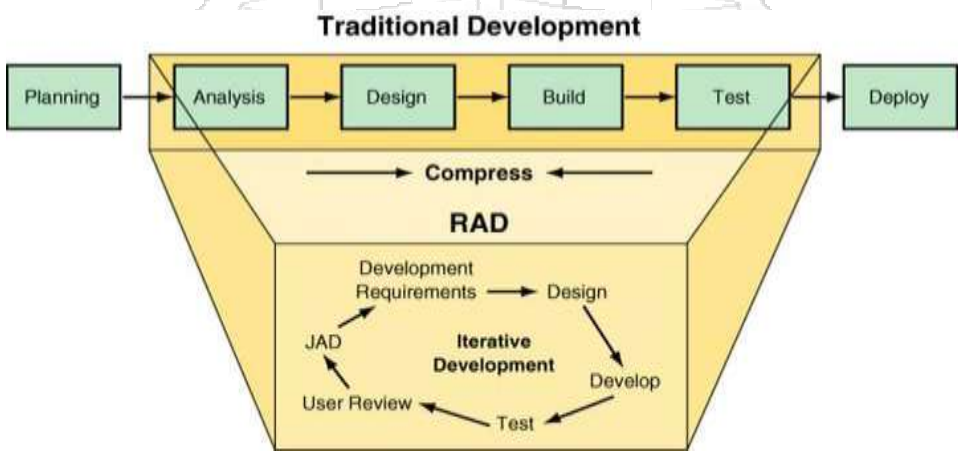

Figure 3.1: RAD vs Traditional Models (Adapted from (Karthiksangi, 2014))

Planning

Identification of area of research and problem to tackle. With these, the study objectives were set and research questions derived to provide a guidance on work to do.

Analysis

This laid emphasis on investigation of the problem identified and its requirements. To meet the study objectives, literature by scholars in the area of study was critiqued making the problem identified and objectives set more precise. Guide by KALRO soil scientists was critical in understanding the research problem and identify feasible solutions that fit local problems. This was by understanding how and why previous solutions failed and how to differently approach the issue considering nutrient management concepts, implementation feasibility and cost, and ease of use.

Design and Development

A conceptual solution that would fulfil the requirements and deign diagrams that depict the system behaviour and interactions were designed using software modelling tools. The building was then implemented using specialized hardware and software. These includes the IoT devices, database system, weather API, Messaging platform and machine learning tools.

Testing

This was done to ascertain if the proposed model performed its functions as intended under the condition specified. The testing verified if the model met the users functional and non-functional requirements in terms of Accuracy of recommendation, timeliness ease of use among others.

3.5 Ethical Considerations

The researcher did seek consent to do the research and ensured that information shared was solely used for the research purposes maintaining confidentiality. Credit was given to works of other authors and researchers in the area of research avoiding plagiarism.

Chapter 4: System Design and Architecture

4.1 Introduction

The chapter explores system design and architecture of the model using UML diagrams. The diagrams illustrate interactions and interconnection of the system components.

4.2 Requirement Analysis

Requirement analysis reviewed user expectations for the model ensuring it takes care of all stakeholders needs. In line with the set objectives, the section below discusses the functional and non-functional requirements of the model developed in the project.

4.2.1 Functional Requirements

The functional requirements specify what the system should do to support tasks, activities or goals through function, behaviour input and output. The functional requirements of the model include:

i. The system should allow the administrator to register a farmer
ii. The system should be able to retrieve environmental soil parameters (temperature and PH)
iii. The system should accurately classify the nutrient remedy using an ANN model and use forecasted weather to recommend whether to fertilize or not.
iv. The system should send the recommendation message to the farmer based on the results of the classification and anticipated weather

4.2.2 Non-Functional Requirements

These requirements describe general attributes of a system. They are qualities the system must have. Failure of these non-functional requirements causes detrimental results. The non-functional requirements include:

i. Availability; Describes the degree of dependability of the system at all times. The system should be available at all times.
ii. Reliability: Describes the extent to which the system consistently performs its functions without fail.
iii. Accuracy: The remedy recommendation and weather prediction should meet certain accuracy threshold, done with minimal error rate. With accuracy comes objective decision making in regards to efficient fertilizer use.

iv. Usability: Describes the ease of learning and operating the system functions.

v. Maintainability: Describes the ease of finding faults and errors in the system and fixing them to meet the user requirements.

vi. Response time: System should have a maximum response time from the time the recommendation is made to the time the message is sent out to the farmer

4.3 System Architecture

The system architecture addresses how various system components interact to achieve the system functionality. System architecture gives an understanding of how the system design, structure and user requirements must be supported by the system. Figure 4.1 below illustrates the subsystems and interconnections between them in the fertilizer recommendation model. The components in the proposed system architecture include users, IoT tools (temperature, PH Sensors and Arduino), weather API, database or server and the machine-learning model.

The IOT Nodes (temperature, PH Sensors) are placed in the farm to retrieve soil parameters that are sent to the database, which feeds the machine-learning model. The machine-learning component comprises of the pre-processor and an ANN classifier. Pre-processing takes place and the data fed to the classifier, which provides a classification of the type and quantity of fertilizer to use. Based on the fertilizer recommended and forecast data from the weather API, the model recommends whether to fertilize or not. This information is sent to the farmer

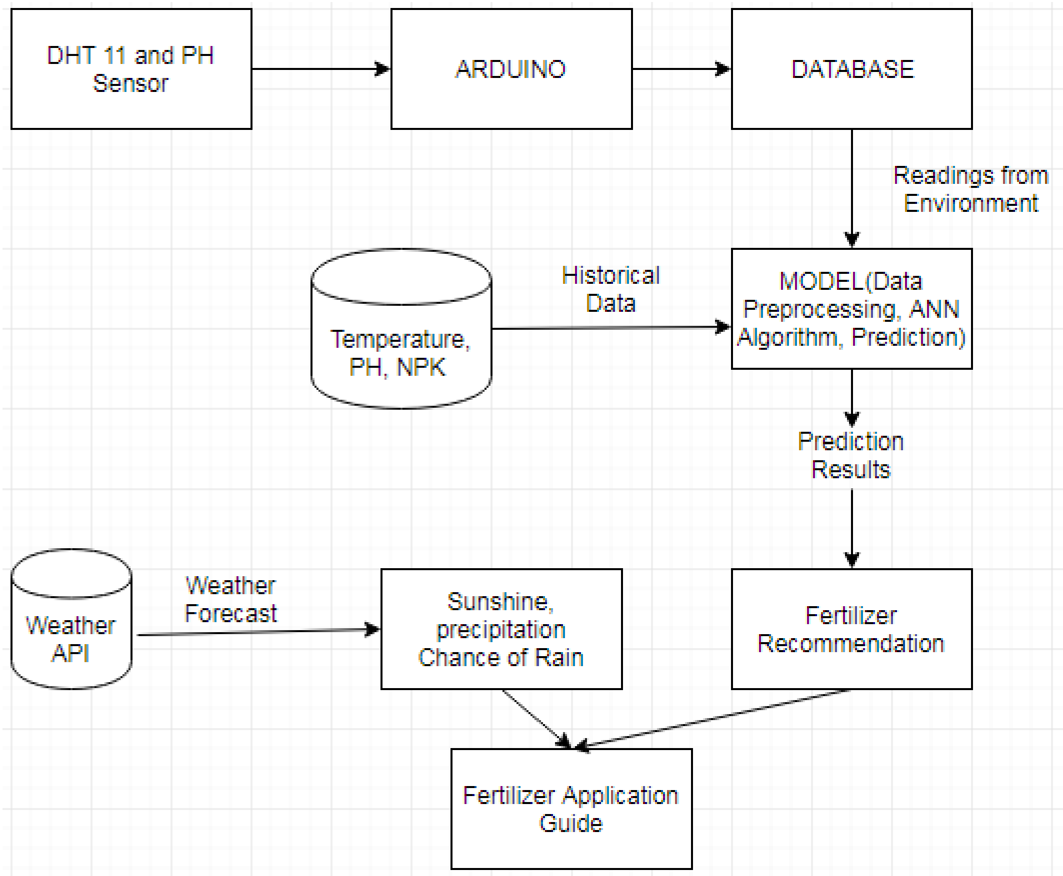

Figure 4.1: System Architecture

4.4 System Behavioral Modeling

This is an effective method of modelling the system and user requirements. A Use case diagram shows sets of actors, their use cases and relationship associated with them.

4.4.1 Use Case Narration

A textual representation of the proposed system events encountered when the actors interact

Use Case:

Registration of farm- farmer details

Primary Actor:

Soil Expert

Precondition:

i. Farmer must have sorghum farm
ii. Farmer must have a phone which can receive notification

Post Condition:

i. Farmer and farm details must be successfully uploaded to the system database
ii. Uploaded details of farmers (contacts and location) must be confirmed to be accurate

Main Success Scenarios

Table 4.1 : Registration of farm- farmer details

Actor Intention	**System Responsibility**
1. Soil Expert initiates farmer registration – Name, ID Number, Location, contacts	2. System stores farmer details for future communication
	3. System confirms user registration to the System Administrator and farmer
4. User exits the system	

Use Case:

Retrieve Soil Parameters (Temperature and PH)

Primary Actor:

Farmer, IOT Device

Precondition

i. User must have the soil sensors
ii. Farm and farmer details must be correctly registered
iii. The sensors should be correctly placed in the farm

Post Condition

Real time data on soil parameters successfully retrieved

Table 4.2: Use Case: Retrieve Soil Parameters (Temperature and PH)

Actor Intention	**System Responsibility**
1.Farmer initiates prediction and recommendation by setting up soil sensors in the farm	2. System retrieves soil environmental parameters (temperature and PH)
	3. System sends parameters to the database
4. Farmer views real-time parameters from the farm	5. System uses soil parameters and historical data to identify deficiency and recommend fertilizer
	6. System uses the fertilizer recommendation and weather API input to give the application guide
	7. System generates feedback to be sent out to farmer; name of fertilizer to apply and when.
8. Farmer receives the fertilizer application guide.	

Extensions or Alternative Flows:

At any time, the system fails to retrieve soil parameters, the farmer must be informed to check the setting up process in the soil

Use Case:

Send feedback to registered farmer

Primary Actor:

Farmer

Precondition:

i. Successful recommendation of the remedy and application guide by the system

Post Condition:

i. System to give a recommendation on the best fertilizer and time of application
ii. System to send out application guide to the farmer

Table 4.3: Send feedback to registered farmer

Actor Intention	System Responsibility
1. Soil Expert registers farmer information in the system	2. Soil Expert registers farmer information in the system
	3. System sends notification to farmer
3. Farmer views application guide	

Extensions or Alternative Flows:

Soil Expert checks and/or restart system in case the notification is not sent out.

Use Case:

Log real-time soil sensor data, Implement ML classification algorithm, predict NPK deficiency, and generate fertilizer remedy.

Primary Actor:

i. System

Precondition:

i. The soil parameters (temperature, and PH) were successfully logged and stored on the database

Post Condition:

i. Successful nutrient deficiency detection and fertilizer recommendation

Main Success Scenario

i. The soil sensors retrieve soil parameters (temperature and PH) and the information is transmitted to the database

ii. Based on the available information i.e. soil parameters, historical information on nutrient availability; the system uses ANN to predict the deficiency and recommend the best fertilizer

iii. Accuracy tested using the test data after prediction

iv. System generates a fertilizer to remedy deficiency depending on the information available in the internet server and that collected by the sensors.

Use Case:

Generation of fertilizer application guide based on fertilizer recommended by the model and forecast weather data from weather API

Primary Actor:

i. Model
ii. Weather API

Precondition:

i. The fertilizer remedy is accurately identified based on the deficiency detected

Post Condition:

i. Successful fertilizer application guide based on the weather predicted

Main Success Scenario

i. The fertilizer remedy is identified based on the deficiency detected.
ii. Weather forecast data is available from the weather API

iii. Based on the fertilizer recommendation and forecast weather the application guide is given

iv. The system sends the application guide to the farmer

v. System generates a fertilizer to remedy deficiency depending on the information available in the database and that collected by the sensors.

4.4.2 Use Case Diagram

Figure 4.2 illustrates the proposed system's use case diagram. The actors include the system administrator, the farmer and the system with the proposed use cases.

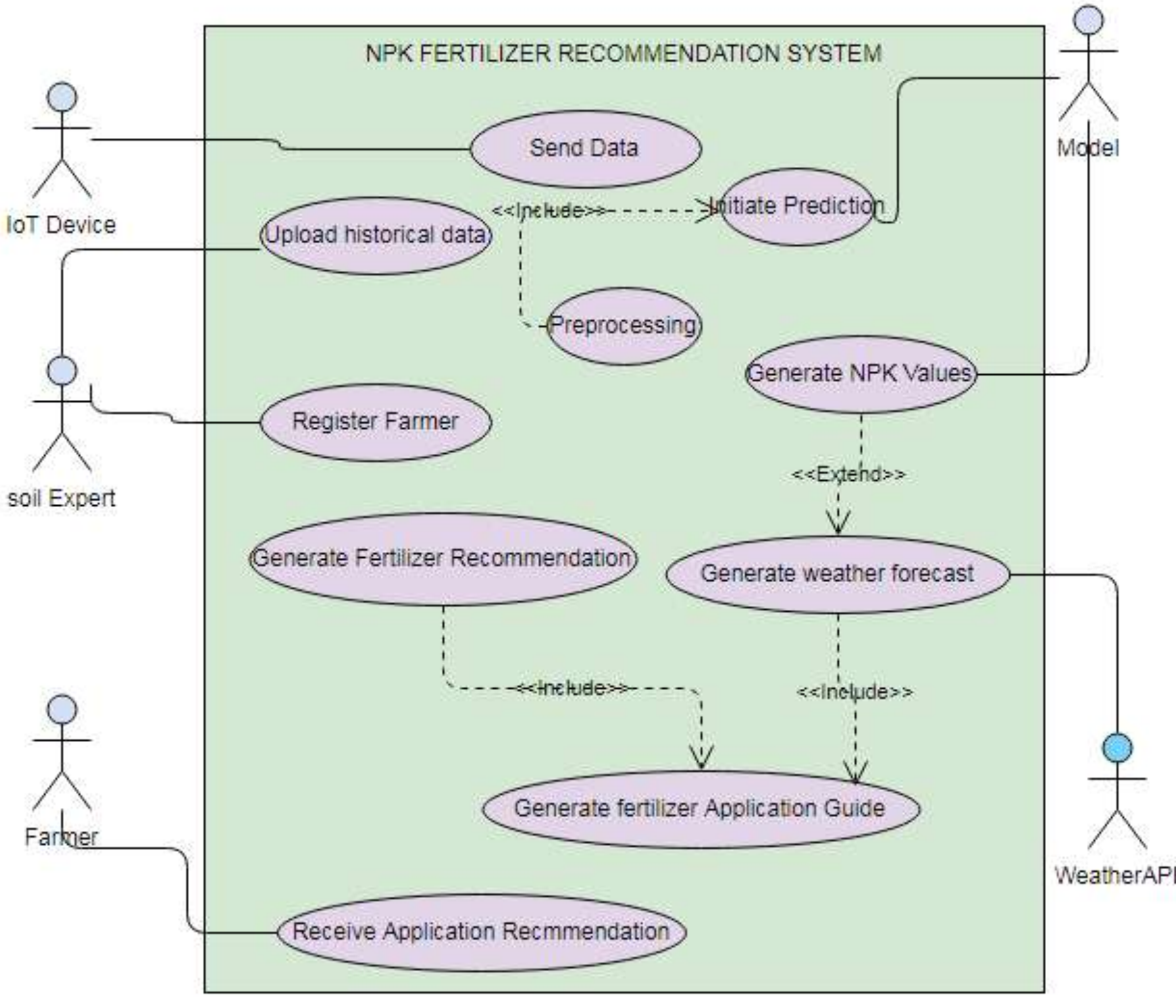

Figure 4.2: Use Case Diagram

4.4.3 Sequence Diagram

This is an interaction diagram that diagram depicts time ordering of messages between different system objects. The sensors are set up in identified farms. The farmer's details are registered in the system. Historical information on nutrient availability is stored. The soil parameters are collected using sensors and sent to the internet server. The collected parameters together with the historical data in the system are pre-processed and used in the prediction of nutrient availability and fertilizer recommendation based on forecast weather. The results are shared with the farmer in form of an application guide. The proposed system's sequence diagram is illustrated in figure 4.3 below.

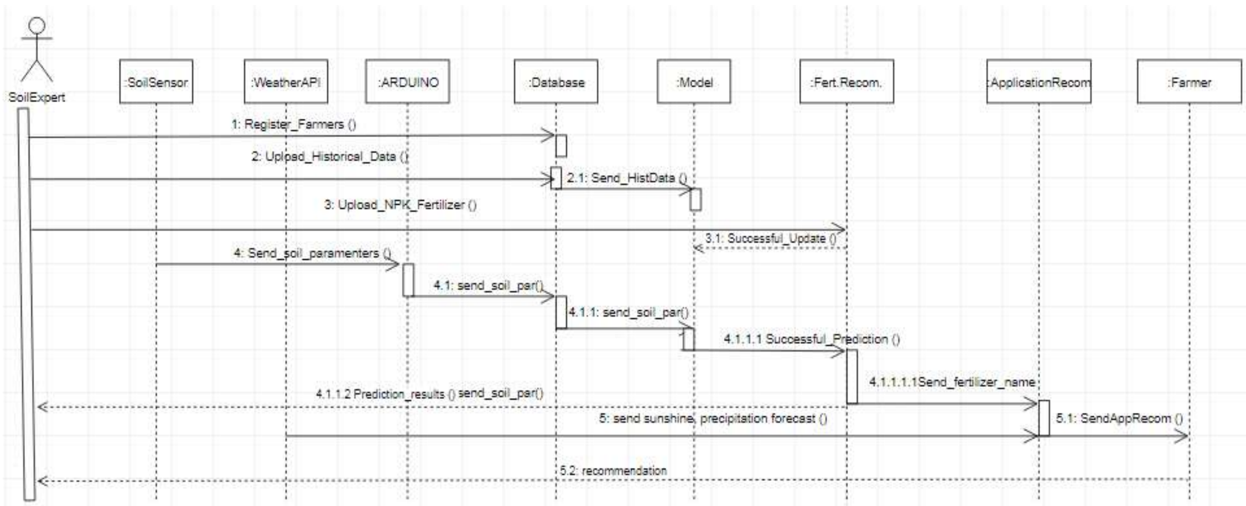

Figure 4.3: Sequence Diagram

4.5 Process Modelling

4.5.1 Context Diagram

The context diagram in figure 4.4 demonstrates the interaction of the model with the immediate external entities and how messages are exchanged. The main entities include farmer, Soil Expert, sensors and the model. The diagram defines the system boundaries.

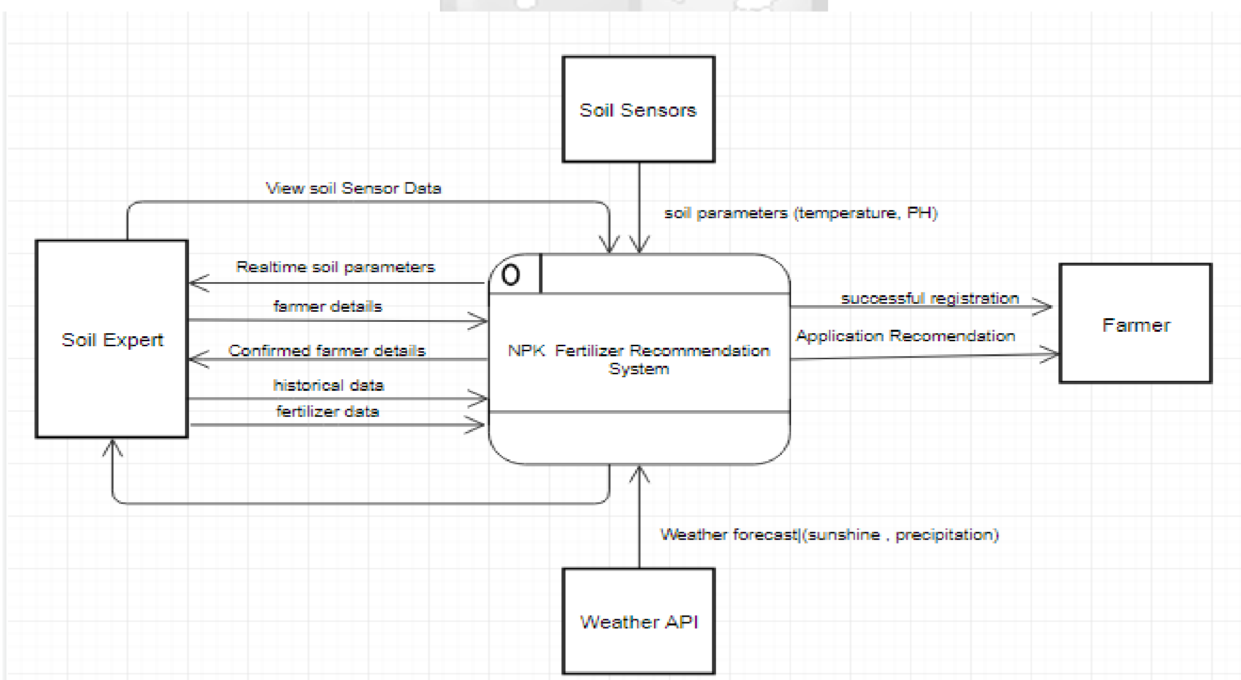

Figure 4.4: Context Diagram

4.5.2 Level 1 Data Flow Diagram

The diagram in figure 4.5 gives a breakdown of the aforementioned context diagram. It shows the second level processes of the model. Addition of data stores and data flows between the system processes help elaborate the main entities processes and their interaction in the system. Process one entails registration of the farmer (location and contact details) used when sending the fertilizer application recommendation. The NPK and temperature historical information the NPK levels together with the collected PH and temperature parameters are used in the prediction and recommendation process. The weather API gives information about the weather that guides on the application process to ensure optimum absorption; minimized wastage, which may be caused by either fertilizer burn or wash off. The fourth process entails keying in PH and Temperature parameters from the sensors into the database. The collected parameters are fed to the neural network model to perform predictions. The results are used to recommend the best fertilizer needed and the application guidance is given with information from the weather API.

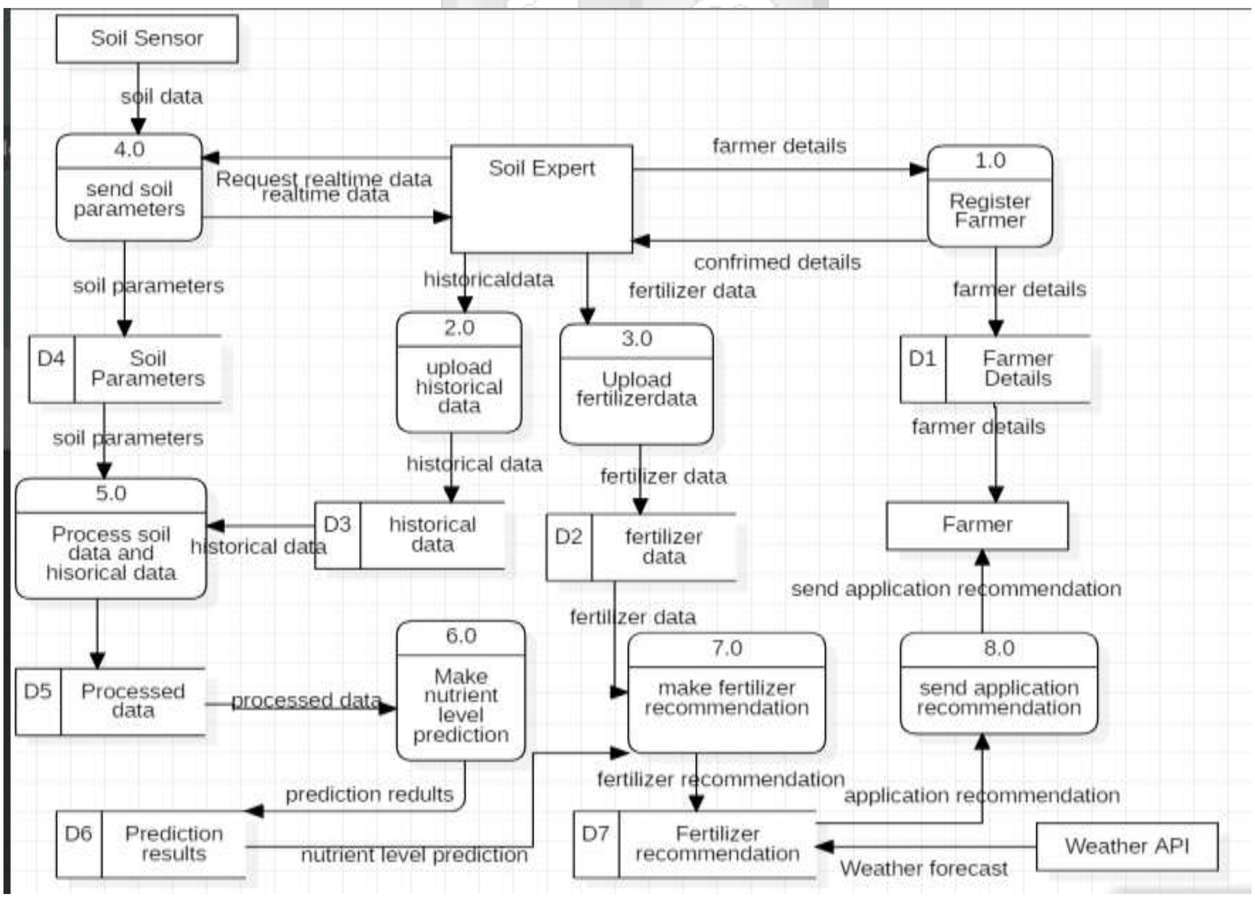

Figure 4.5: Level 1 Data Flow Diagram

4.6 Partial Domain Model

The figure 4.6 below illustrates a domain model with conceptual classes of the proposed system. It comprises of conceptual classes, their attributes and associations between them. The classes include sensors, soil parameters, ANN Model, fertilizer recommendation farmer and weather API. The classes interact from farmer registration, sensors retrieving soil parameters, data processing by the ANN model, fertilizer recommendation and fertilizer application recommendation which is finally sent to the farmer via SMS.

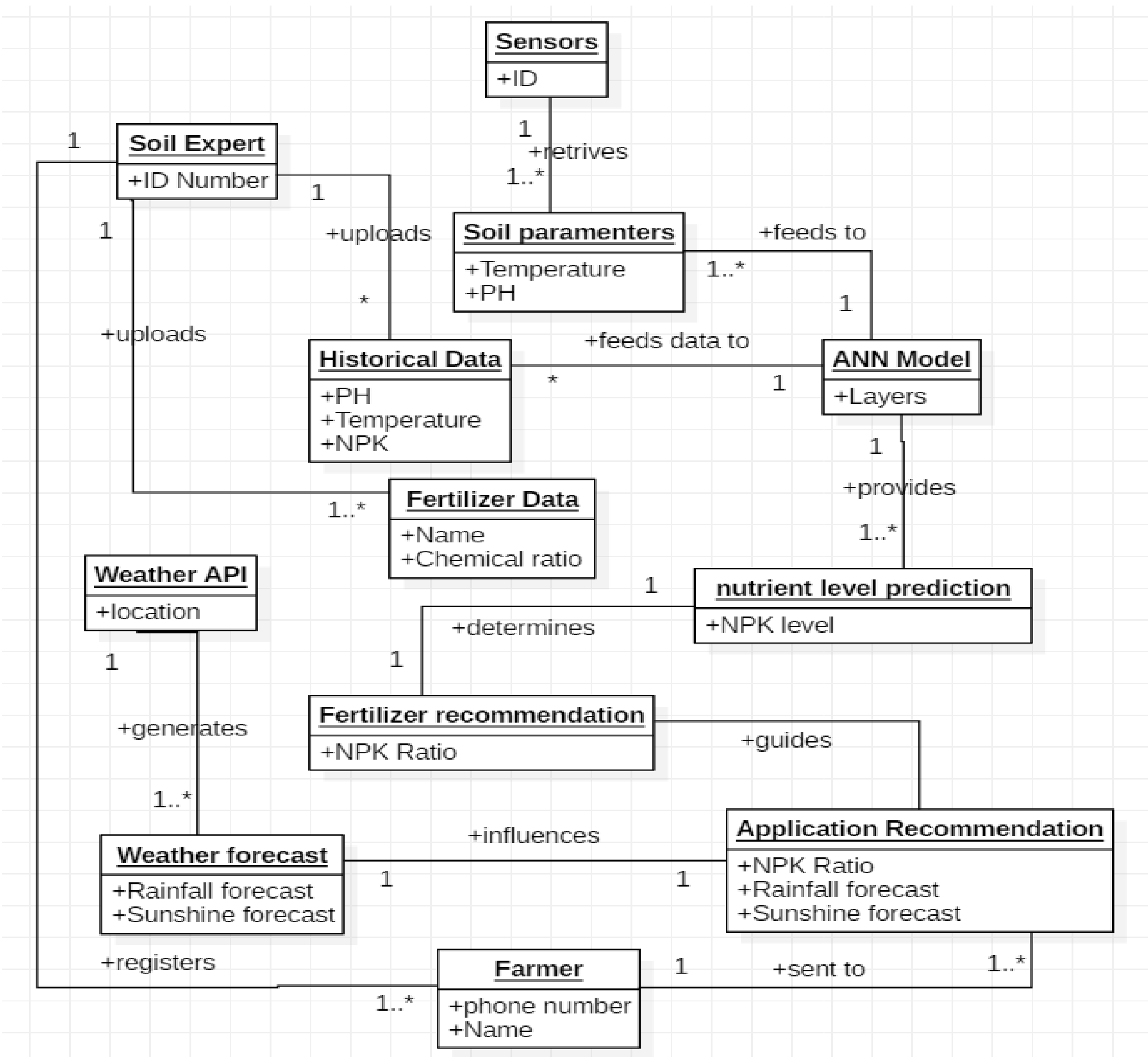

Figure 4.6: Partial Domain Model

Chapter 5: System Implementation and Testing

5.1 Introduction

This chapter delves into the actual implementation of the system. The PH and Temperature sensors were deployed in the soil to capture the PH and temperature levels. The Sensors were connected to the Arduino and parameters' readings sent to the database then fed to the model. Artificial Neural Network algorithm was used with the parameters collected to provide prediction of nutrient levels in the soil. Based on these results, the suitable remedy; fertilizer is recommended. Weather forecast from the weather API comes in to guide on whether to fertilize or not based on the forecast weather. This fertilizer application recommendation is sent to the farmer as an SMS.

5.2 Components of the Prediction Model

5.2.1 IoT System Components

These include the PH and Temperature sensors and the Arduino. The IoT components used include.

Analog PH Meter – The sensor in figure 5.1 retrieves the PH readings from the soil. It has a module power of 5.00V, measuring range of between 0 and 14, measuring temperature between 00 and 600with an accuracy of ± 0.1pH (25 ℃). Its response time is ≤ 1min.

Figure 5.1: PH Electrode (Adapted from Robotshop, 2019))

DHT 11- Sensor in figure 5.2 that retrieves temperature readings made capable by a thermistor (an NTC temperature sensor). Has a basic chip able to do analog –digital conversions and send out digital signal to the Arduino.

Figure 5.2: DHT 11Sensor (Adapted from (Adafruit (2019))

Arduino picture in figure 5.3 is able to read inputs from the PH Meter and temperature sensor.

Figure 5.3: Arduino (Adapted from (Arduino (2019))

5.2.2 ANN Model

The model was developed using Artificial Neural networks. Inputs to the model included the temperature and PH collected by the sensors deployed in the soil. The algorithm has three layers discussed below.

Input Layer

Provides outside world information to the network. No computation is done in this layer, only passes information to the hidden layer. The inputs in this study are temperature and PH readings from the database.

Hidden Layer

They are referred to as hidden layers as they have no connection to the outside world. Computations are performed here and desirable output transferred to the output nodes.

Output Layer

Responsible for some computations as well. Receives data from hidden layer, have computations done then transfer information to the outside environment.

5.2.3 Server Side Application

Node Red was used to wire together the sensors, weather API and SMS platform as part of Internet of things. Data from the sensor through the Arduino is uploaded to the localhost.

5.3 Implementation of the Prediction Model

The section discusses actual implementation of the system using the aforementioned components.

5.3.1 Data capture by the PH and Temperature Sensors

The sensors collect data of temperature and PH, which influence availability of NPK nutrients. The Arduino is connected to the analog PH sensor to get PH values and DHT sensor to capture the temperature readings. The figure 5.4 below illustrates the set up and connection of the IoT components to the laptop. Figure 5.5 shows how the readings relayed to the Arduino are displayed on COM3. NodeRed was used to wire the sensors and API together on one platform and figure 5.6 illustrates how the nodes interface to facilitate communication from the sensor to Arduino, through NodeRed to the database as well as from the weather API to the ANN Model.

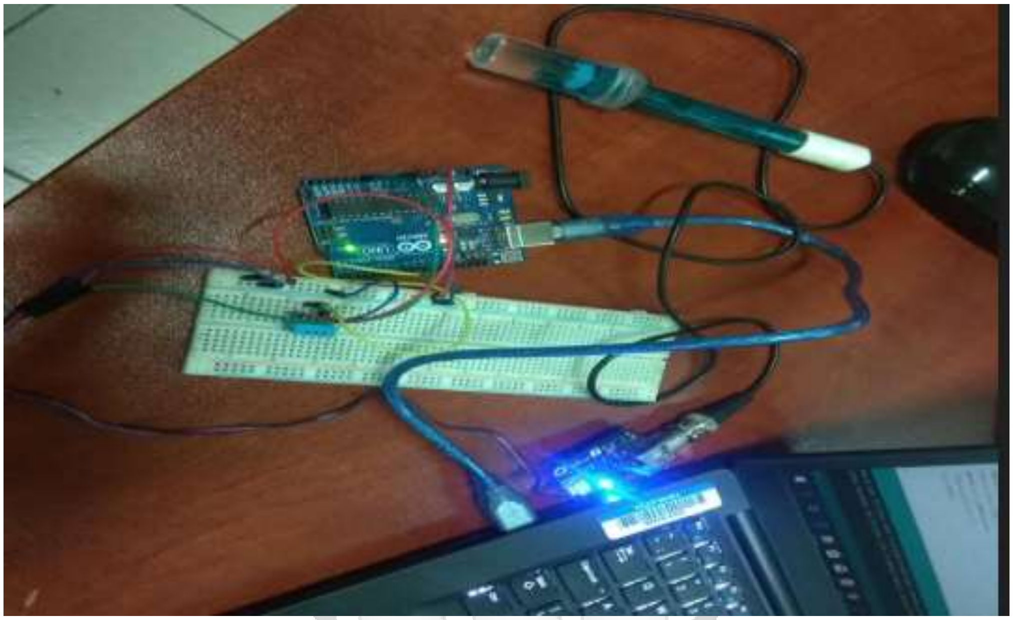

Figure 5.4: Sensor Setup

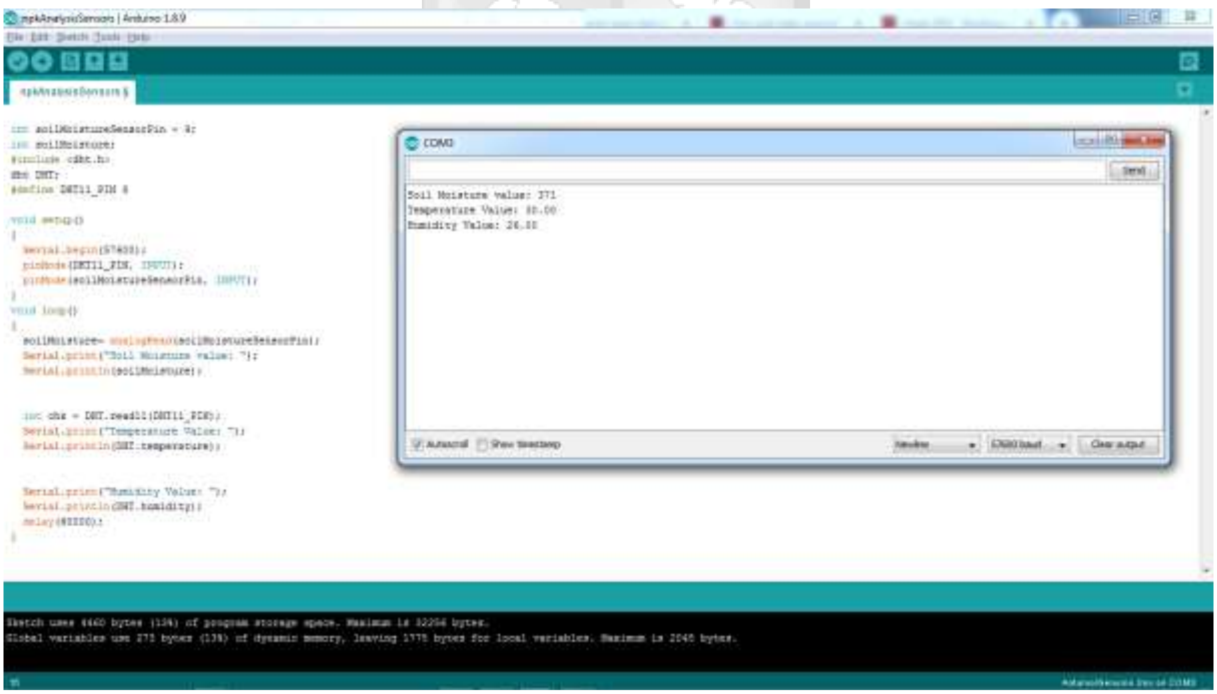

Figure 5.5: Arduino connection code and display on COM3

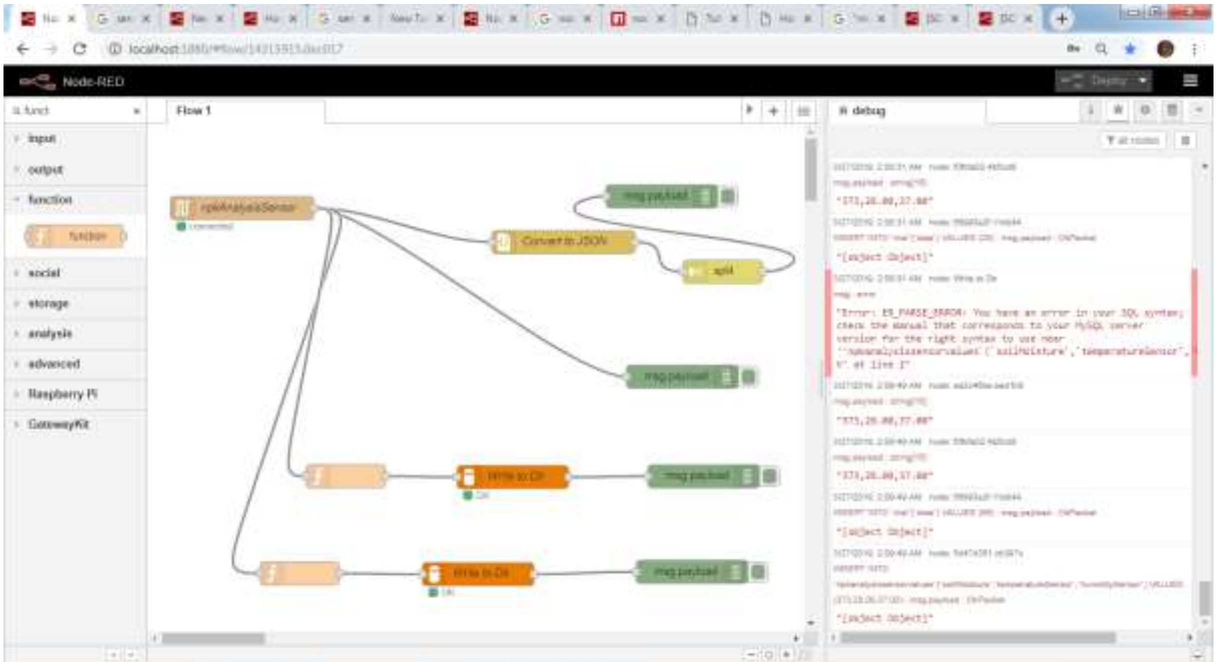

Figure 5.6: NodeRed Implementation (Sensor, Localhost connection)

5.3.2 Storage of the sensor read parameters; PH and Temperature

The data from the Arduino through NodeRed is sent to the database for storage as illustrated in figure 5.7.

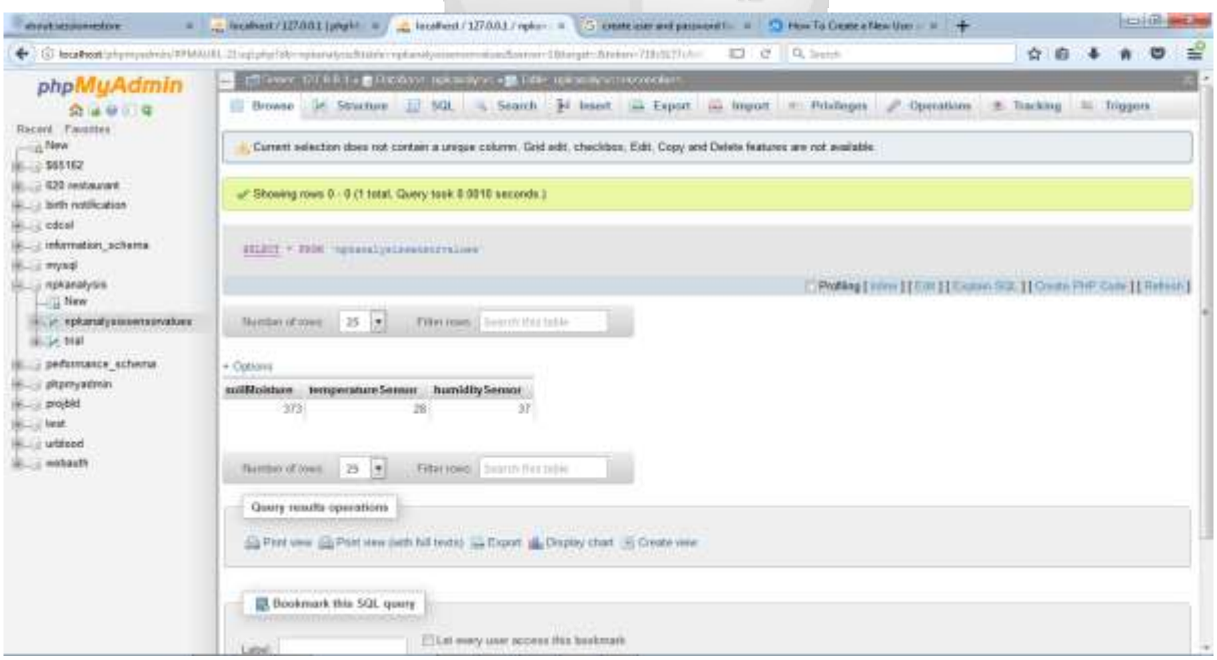

Figure 5.7: Parameters values storage

5.3.3 Database-Model Connection

The model gets data from the database and this is used in predicting the NPK Level. Once the recommendation is done, a farmer receives a text of their application guide via Twilio.

Below is a snippet of the code that enables connection of the database to the model.

```
import mysql.connector

from mysql.connector import Error

connection = mysql.connector.connect(host='localhost',

                    database='npkanalysis',

                    user='root',

                    password='')

mycursor = connection.cursor()

mycursor.execute("SELECT * FROM npkanalysissensorvalues")

myresult = mycursor.fetchall()
```

5.3.4 Modelling and Implementation of the ANN Model

The system used artificial neural networks algorithm to predict the nutrient levels of NPK in the soil. Once the nutrients available are noted, fertilizer is recommended based on the soil need. Forward propagation ANN was used to generate NPK level predictions given the temperature and PH of the soil. The input layer receives the Temperature and PH readings and passes to the hidden layer where the computations are done. The output layer use hidden layer node to make the predictions. An epoch is done such that the temperature and PH dataset are learnt.

5.3.5 Weather API Input

The weather influences fertilizer absorption. This determines either its optimum take in or wastage. Too much sunshine, causes fertilizer burn while too much rain causes waterlogging which causes nitrification; loose of Nitrogen in the soil or all fertilizer wash off. The farmer therefore needs to fertilizer at optimum condition to ensure they do not end up wasting because of wrong alignment with the weather patterns. The weather API was roped in using Node Red as illustrated in figure 5.8 below.

Figure 5.8: Weather API Implementation on NodeRed

5.3.6 SMS Notification to Farmer

The system sends a farmer a notification, which is the fertilizer application guideline. Twilio was used as the SMS platform. Based on the results, a sample of the SMS content is in figure 5.9.

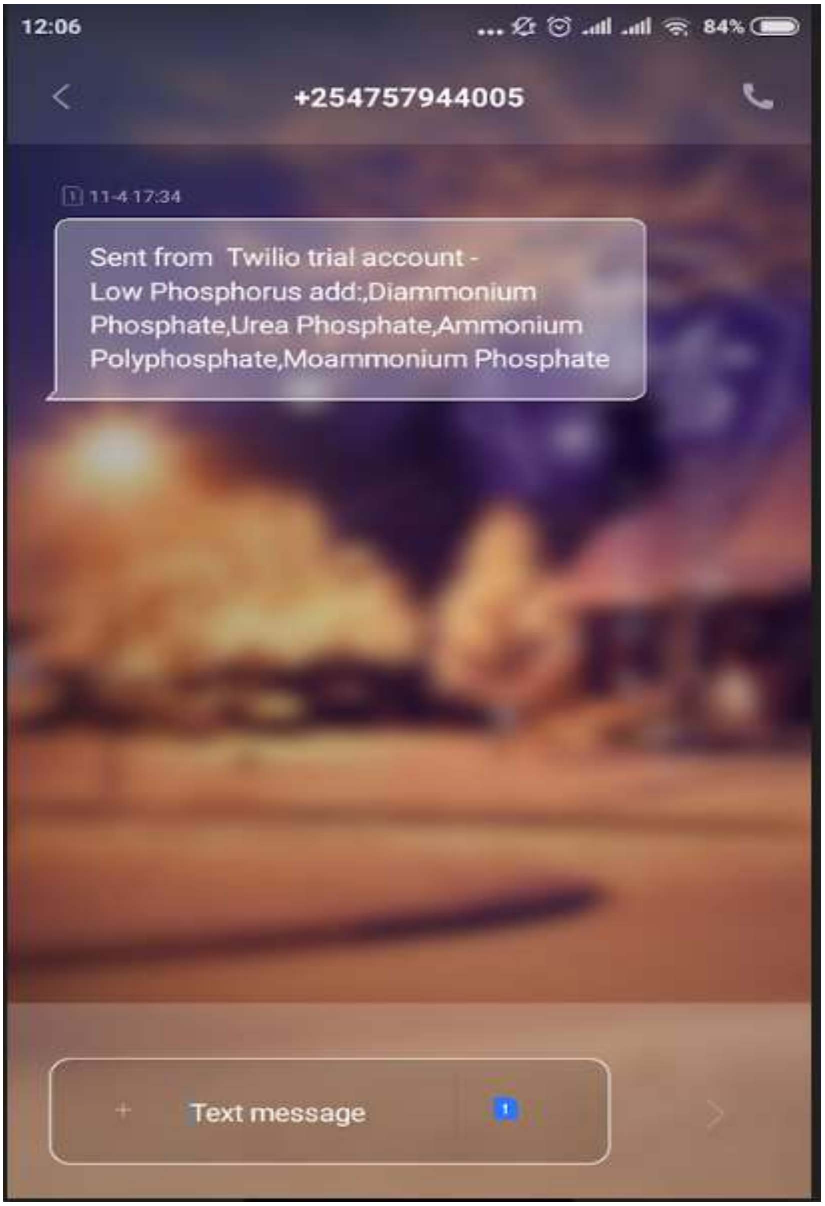

Figure 5.9: Sample SMS

5.4 Model Training

Experiments were done to compare how the model performed with various inputs; PH, Temperature, N, P and K values gotten from KALRO Research Laboratory.

5.4.1 Model Experimentation 1

The inputs consisted of Soil PH and NPK values. 75 % was used for training while 25% used for testing. The data was used as presented and no normalization done. The mean square error was

357.1804533241052 while the mean absolute error was 5.724771949061643 for the y test predictions.

Below is a python code snippet demonstrating how the training and testing environment were set up on Jupyter notebook.

```
import numpy
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
from keras.utils import np_utils
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error,mean_absolute_error
from sklearn.preprocessing import MinMaxScaler
```

Building of the ANN Regression Model

```
# define baseline model
def ph_model():
    # create model
    = Sequential()
    model.add(Dense(3, activation='relu', input_shape=(1,)))
    model.add(Dropout(0.5))
    model.add(Dense(9))
    model.add(Dropout(0.5))
    model.add(Dense(6))
    model.add(Dense(3))
    model.compile(loss="mae", optimizer='adam', metrics=['mae'])
    return model

model = ph_model()
trained_model = model.fit(X_train_, y_train,epochs=100000, batch_size=200, verbose=2)
```

5.4.2 Model Experimentation 2

The inputs consisted of Temperature, Soil PH and NPK values. 75 % was used for training while 25% used for testing. The temperature values were normalized using the equation 5.1below.

$$z = \frac{x \; - \min(x)}{\max(x) \text{ - } \min(x)}$$

Equation 5.1: Normalisation Equation

The mean square error was 6.5499164361463516 while the mean absolute error was 0.7736487456041057 for the y test predictions.

The inclusion of the second input made the model have a better performance with less error.

A snippet of the code with inclusion of normalized temperature values;

```
# define baseline model
def ph_model():
    # create model
    model = Sequential()
    model.add(Dense(2, activation='relu', input_shape=(2,)))
    model.add(Dropout(0.5))
    model.add(Dense(4))
    model.add(Dropout(0.5))
    model.add(Dense(4))
    model.add(Dense(3))
    model.compile(loss="mae", optimizer='adam', metrics=['mae'])
    return model

model = ph_model()
trained_model = model.fit(X_train_, y_train,epochs=100000, batch size=100, verbose=2)
```


5.4.3 Model Experimentation 3

Building on experiment 2, the Nutrients inputs; NPK were normalized as well. This yielded an RMSE of 0.5 and further iterations and inclusion of more inputs such as soil moisture did not make a difference in the results. The model and database were connected with PH and temperature values used to make predictions using the model created. Figure 5.10 below illustrates how the picks values from the database to be used for prediction of NPK values and recommendation of fertilizer to be applied.

```
In [ ]: !pip install pymysql
        ! pip install sqlalchemy
        !pip install mysql-connector-python
```

```
In [7]: import mysql.connector
        from mysql.connector import Error
        connection = mysql.connector.connect(host='localhost',
                                             database='npkanalysis',
                                             user='root',
                                             password='')
```

```
In [8]: mycursor = connection.cursor()

        mycursor.execute("SELECT * FROM npkanalysissensorvalues")

        myresult = mycursor.fetchall()

        for x in myresult:
          print(x)

        (373, 28, 37)
        (298, 28, 37)
        (299, 28, 37)
        (296, 28, 37)
        (372, 28, 37)
        (299, 28, 37)
```

Figure 5.10: Database-Model Connection code snippet

Prediction test

The code below illustrates the prediction test of the model given PH values in the arrays below.

```
array([[ 5., 20.],
    [ 2., 23.]])

m = open('model.json', 'r')

model= m.read()

m.close()

model = model_from_json(model)

# load weights into new model
```

```
model.load_weights("model.h5")

print("Loaded model from disk")

results = model.predict(prediction_test)

last_one = results[-1]

last_one

array([0.09236324, 0.79424584, 0.4954729 ], dtype=float32)

n, p, k = last_one

next_one_wk = True
```

Fertilizer recommendation

```
def n_decider(n):

    if n < 0.27:

        print("Apply Fertilizer any of the following")

        for fert in sulphates_low:

            print(fert)

    elif n>=0.27 and n<4.0:

            for fert in sulphates_medium:

                print(fert)

    elif n>4.0:

        for fert in sulphates_high:

            print(fert)

    if(not next_one_wk):

    p_decider()

    k_decider()

    n_decider()
```

```
else:

    print(" Low Phosphorus, Apply Urea")
```

5.5 Model Testing

Various tests were carried out as shown in table 5.1 to determine whether the system developed satisfied the proposed requirements. The sample test cases below illustrate how the developed system matched the proposed requirements.

Table 5.1: Model Testing

Test Case	Importance	Test Results
Does the application successfully capture temperature and PH values from the soil?	High	Soil temperature and PH were captured by soil sensors
Does the application successfully upload sensor data to the server?	High	data successfully uploaded to the server
Does the application provide real-time data to the administrator?	Medium	The administrator is able to access real-time data on temperature and PH readings on Node red dashboard
Does the weather API send the weather forecast to the system?	High	Forecast weather successfully sent to the system and used in the application guide
Is the weather forecast considered in the application recommendation	High	Weather forecast successfully integrated in the recommendation process.
Does the application send out an SMS notification to the to farmers	High	Farmer successfully received the SMS via Twilio.

Chapter 6: Discussions

6.1 Introduction

This chapter discusses the results of the solution developed as compared to the objectives and research questions set in chapter one. The main objective was to develop a model for prediction of NPK levels in soil, recommend the best fertilizer remedy and application in alignment with the weather. The model used ANN algorithm to predict the macronutrient levels. The inputs from the soil sensors included temperature and PH.

As discussed in the problem statement, this model responds to the challenges faced by farmers in identifying the best fertilizer and improving existing frameworks used in determining soil suitability levels and fertilizer recommendation. The developed model fills the gap by enabling a farmer to identify their farm's deficiency and applying the right remedy in time avoiding errors in fertility management and the tedious time consuming process of taking the soil to the soil laboratories for testing and awaiting results. This also takes care of the guesswork and intuition or mere farmer to farmer inconsistent reference when it comes to fertilizer recommendation. This justifies the reason for change of fertilizer regimes to match crop and region needs and also take care of the ecosystem reducing environmental pollution by caused by fertilizer wastage.

The study established that sorghum required PH of averagely 6.5, temperature between 24^0 and 30^0 and NPK ranges of N (100-180), P (20-45) and K (35-80) to optimally grow. The temperature and PH influenced the availability of nutrients further affecting the absorption of the macronutrients.

6.2 Results of the Study

Historical data used in the experiments were obtained from the KALRO Library. In the live experiments, the sensors were deployed in soil to capture temperature and PH levels. The data is processed and fed to the NN algorithm that gives predictions based on various computations. The recommendations sent to the farmer via SMS. Section 5.4 discusses how the experiments were done, comparing how the inputs were iterated to achieve the lowest RMSE. An RMSE of 0.5 was achieved after the third experiment done using an ANN model. The aim of the experiments was to identify the best inputs based on the NPK and environment relationship and ones chosen were normalized to achieve the best training for the prediction. Building on a previous studies and recommendations on the best algorithm to use considering the kind of data, attribute relationships and need from the model, ANN was considered the best algorithm to use hence no comparative analysis was done.

6.3 Validation of the System

This is a task to find out if the system created represents the proposed system and to what extent. The system met its proposed functional requirements as it was able to retrieve soil parameters, send the data to the database which was interfaced with the model and make an application recommendation based on the weather. The system was reliable to perform its function and it was easy to identify error and fix them though the accuracy of the prediction was not perfectly achieved as demonstrated by the RMSE of 0.5.

6.4 Validity of the Proposed Systsem

Several systems and solutions have been developed for precision agriculture- fertilizer management. In Kenya, Mobile laboratories were introduced to save the farmers the trouble of finding agriculture labs but this failed, as farmers were not willing and or available to avail themselves. Most trust their intuition and past experiences and fertilizers use. Wrong fertilizer use continues to destroy our soil profiles, continually depleting a certain nutrient or boosting some to unnecessary levels. This causes reduction in produce and endangers food security. The cheap available solutions continually kill our potential due to lack of knowledge on the same or proper systems to help mitigate the wrong use of fertilizers.

On the other hand, developed countries have solutions that do not fit our problems. Most work in controlled farms that have systems set for automatic farm management. Also, some solution developed by them have not been made available for use. For example, a company in Austria has a direct NPK sensor that is able to give direct NPK reading but it costs 4960 Euros. This is too expensive to think of. Progis Company also developed an NPK sensor to measure the macro nutrient levels though it is not available for use. This informed the need to get a solution that works for non-automated farm systems, cheap, available and easy to use. The proposed solution employs use of IoT tools that are able to pick data from the farms and use it for the recommendation process. These can be made available for use and the whole process advises the farmer using collected information where they are not required to participate in the decision-making. With this system, the farmers receive accurate information about their farms and the specified fertilizer that accurately meets their needs.

6.5 Research Limitations

The developed solution had several confines;

i. Fertilizer management is key for all plant species though the study focused on sorghum, which happens to be a key crop that can alleviate food deficiency though it is gown in marginalized areas; less care taken for it can survive tougher conditions compared to other crops.
ii. The research concentrated on NPK fertilizers that have NPK, the macronutrients that form the major components of compound fertilizers.
iii. The research assumed that not all farmers are tech-savvy or rather have access to smartphones. The administrator therefore interacts with the system i.e. for registration and update of farmer details as well as observing sensor readings
iv. This study used environmental available samples from KALRO Library which consisted of the temperature, PH and NPK values which greatly influenced the prediction results of the model

Chapter 7: Conclusions, Recommendations and Future Works

7.1 Conclusions

There is a direct mismatch between farmers' efforts and their produce as Kenyans still suffer from hunger. Kenya imports food from countries like Egypt that have implemented strategies to improve their farming conditions We have the power to manage our farms and improve the production to reduce the hunger strikes, reduce food importation and produce food for Kenyans, while creating businesses and employment in the long run. As the government and other agencies go bench making in countries that have gotten it right, there is need to understand that local fit solutions will work best as some copied strategies have failed terribly by not meeting the farmers' challenges and needs. Currently, the solution is use of agriculture field officers and tabulated recommendations whose challenge is that they are not enough to reach out to all farmers while the tabulated solutions to do fit all farms as each farms nutrient is influenced by the surrounding rocks (weather to form soil), weather and farming practices. Cheaper farmer fit solutions will work best allowing farmers to be informed and able to monitor their farmers.

This study has presented a model that involves use of sensors that collect data used in macronutrient level prediction for fertilizer recommendation. This ensures that the precise remedy is applied at the right time for optimum weather. This is ensured by alignment of fertilization schedules with the weather patterns. The use of IoT sensors allow the administrator, farmers and agricultural agencies i.e. KALRO to have information regarding the nutrient levels and fertilizers needed.

7.2 Recommendations

Based on the study, the researcher recommends:

i. Use of several sensors at different points in the farms to get a good representation of the farm nutrient status.
ii. Other sensors can be incorporated to give different environmental readings that influence the availability of nutrients moisture, humidity, and measure of soil texture among others to increase the accuracy of the prediction results.
iii. Soil data i.e. PH should be collected periodically and shared with the policy makers and manufacturers so that the production aims at fulfilling needs of a particular area.

7.3 Future Work

The proposed system looked into fertilizer recommendation for sorghum. Future studies can enhance the model and incorporate other needs:

i. The developed model could be enhanced to incorporate analysis of other environmental factors results, soil statuses and fertilizer use to advise fertilizer produces on fertilizers to produce instead of general fertilizers and wholly take care of the ecosystem.
ii. Future studies can consider elements in the soil that cause deterioration of the nutrients needed and come up with ways of ensuring a comfortable environment is not created for their occurrence i.e. Aluminium and Sodium and how irrigation and leaching can help get rid of excess nutrient elements or the said dangerous elements
iii. Future studies can focus on post-harvest nutrient management and farm management to ensure a boost in nutrients before next planting schedules.
iv. Natural fertilizer recommendation can be considered i.e. compost manure apart from chemical fertilizers

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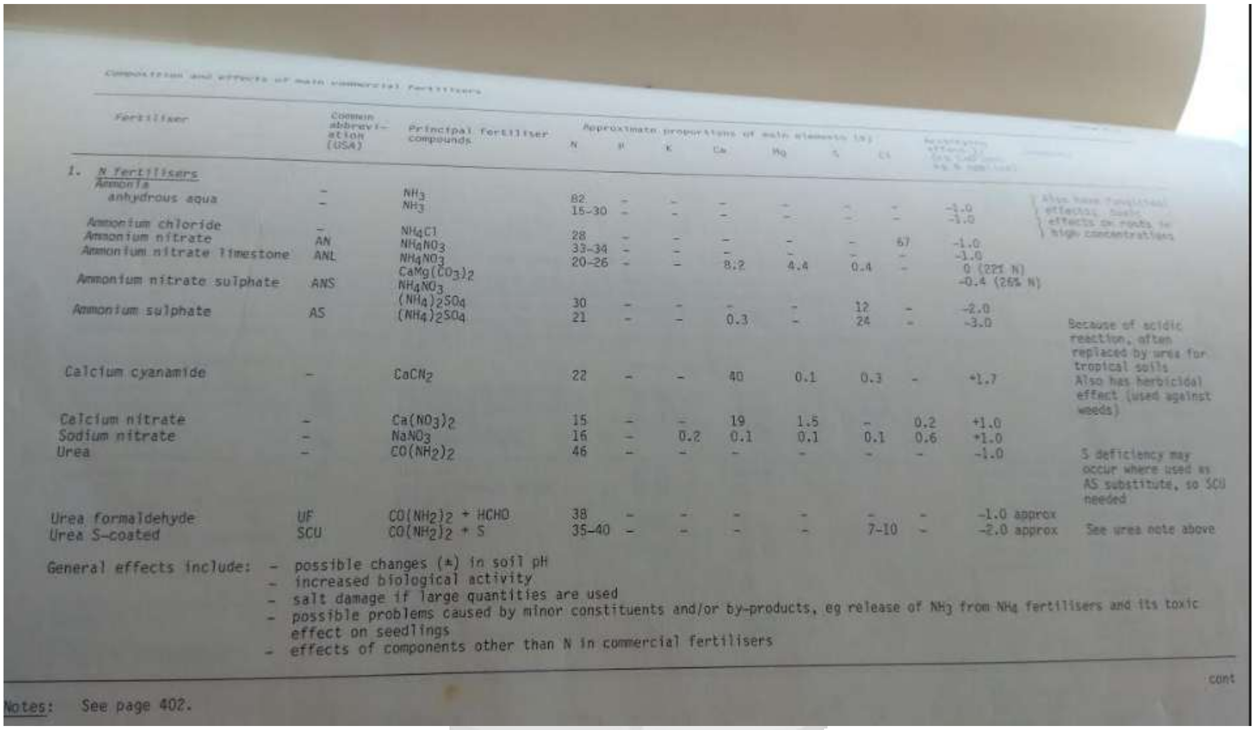
Appendices

Appendix I: Fertilizers recommendation sample (Landon, 1984)



Composition and effects of main commercial fertilisers

Fertiliser	Common abbreviation (USA)	Principal fertiliser compounds	N	P	K	Ca	Mg	S	Cl	Acidifying effects	Comments
1. *N fertilisers*											
Ammonia											
anhydrous	–	NH_3	82	–	–	–	–	–	–	-1.0	Also have [illegible] effects; [illegible] effects on roots in high concentrations
aqua	–	NH_3	15–30	–	–	–	–	–	–	-1.0	
Ammonium chloride	–	NH_4Cl	28	–	–	–	–	–	67	-1.0	
Ammonium nitrate	AN	NH_4NO_3	33–34	–	–	–	–	–	–	-1.0	
Ammonium nitrate limestone	ANL	NH_4NO_3 $CaMg(CO_3)_2$	20–26	–	–	8.2	4.4	0.4	–	0 (22% N) -0.4 (26% N)	
Ammonium nitrate sulphate	ANS	NH_4NO_3 $(NH_4)_2SO_4$	30	–	–	–	–	12	–	-2.0	
Ammonium sulphate	AS	$(NH_4)_2SO_4$	21	–	–	0.3	–	24	–	-3.0	Because of acidic reaction, often replaced by urea for tropical soils
Calcium cyanamide	–	$CaCN_2$	22	–	–	40	0.1	0.3	–	+1.7	Also has herbicidal effect (used against weeds)
Calcium nitrate	–	$Ca(NO_3)_2$	15	–	–	19	1.5	–	0.2	+1.0	
Sodium nitrate	–	$NaNO_3$	16	–	0.2	0.1	0.1	0.1	0.6	+1.0	
Urea	–	$CO(NH_2)_2$	46	–	–	–	–	–	–	-1.0	S deficiency may occur where used as AS substitute, so SCU needed
Urea formaldehyde	UF	$CO(NH_2)_2$ + HCHO	38	–	–	–	–	–	–	-1.0 approx	
Urea S-coated	SCU	$CO(NH_2)_2$ + S	35–40	–	–	–	–	7–10	–	-2.0 approx	See urea note above

General effects include:
- possible changes (*) in soil pH
- increased biological activity
- salt damage if large quantities are used
- possible problems caused by minor constituents and/or by-products, eg release of NH_3 from NH_4 fertilisers and its toxic effect on seedlings
- effects of components other than N in commercial fertilisers

cont

Notes: See page 402.

Caption showing different fertilizers with different nutrient content levels. This can be used to map the specific deficiencies to the best fertilizer to use ie, Most deficient mapped to fertilizer with the highest level of nutrient to raise the nutrient levels to the optimum required.

Appendix II: Code

Arduino Code

Reading values of PH and Temperature from the sensors. The values are then sent to the database for storage. When making predictions the model picks the latest value of PH and temperature to predict the NPK Value at an RMSE of 0.5 to recommend the best fertilizer to apply based on the weather forecast.

```
#define SensorPin 0          //pH meter Analog output to Arduino Analog Input 0

unsigned long int avgValue;  //Store the average value of the sensor feedback
```

```
float b;

int buf[10],temp;

String temperature;

String humidity;

#include <dht.h>

dht DHT;

#define DHT11_PIN 7

void setup()

{

 pinMode(13,OUTPUT);

 //Serial.begin(9600);

 Serial.begin(57600);

 pinMode(DHT11_PIN, INPUT);

}

void loop()

{

 for(int i=0;i<10;i++)       //Get 10 sample value from the sensor for smooth the value

 {

  buf[i]=analogRead(SensorPin);

  delay(10);

 }

 for(int i=0;i<9;i++)        //sort the analog from small to large

 {

  for(int j=i+1;j<10;j++)
```

```
 {
   if(buf[i]>buf[j])
   {
     temp=buf[i];
     buf[i]=buf[j];
     buf[j]=temp;
   }
 }
}
avgValue=0;
for(int i=2;i<8;i++)                     //take the average value of 6 center sample
  avgValue+=buf[i];
float phValue=(float)avgValue*5.0/1024/6; //convert the analog into millivolt
phValue=3.5*phValue;                      //convert the millivolt into pH value
//phValue = phValue.toInt();
char buffer[10];
dtostrf(phValue, 4, 2, buffer);
//charBuf
//Serial.print("Soil Moisture value: ");
//Serial.print(soilMoisture+soilMoisture);
int chk = DHT.read11(DHT11_PIN);
temperature = DHT.temperature;
//Serial.print(phValue + "," + temperature);
//Serial.print("pH:");
```

```
  Serial.print(phValue,2);

  Serial.print(",");

  //Serial.print("Temp:");

  Serial.println(temperature);

  //Serial.println(" ");

  delay(6000);

}
```

Weather API Connection to Model

The model used an averaged 3-day forecast to determine the suitability of fertilizer application in effort to avoid wastage caused by extreme rainfall (wash off) or extreme sunshine (fertilizer burn).

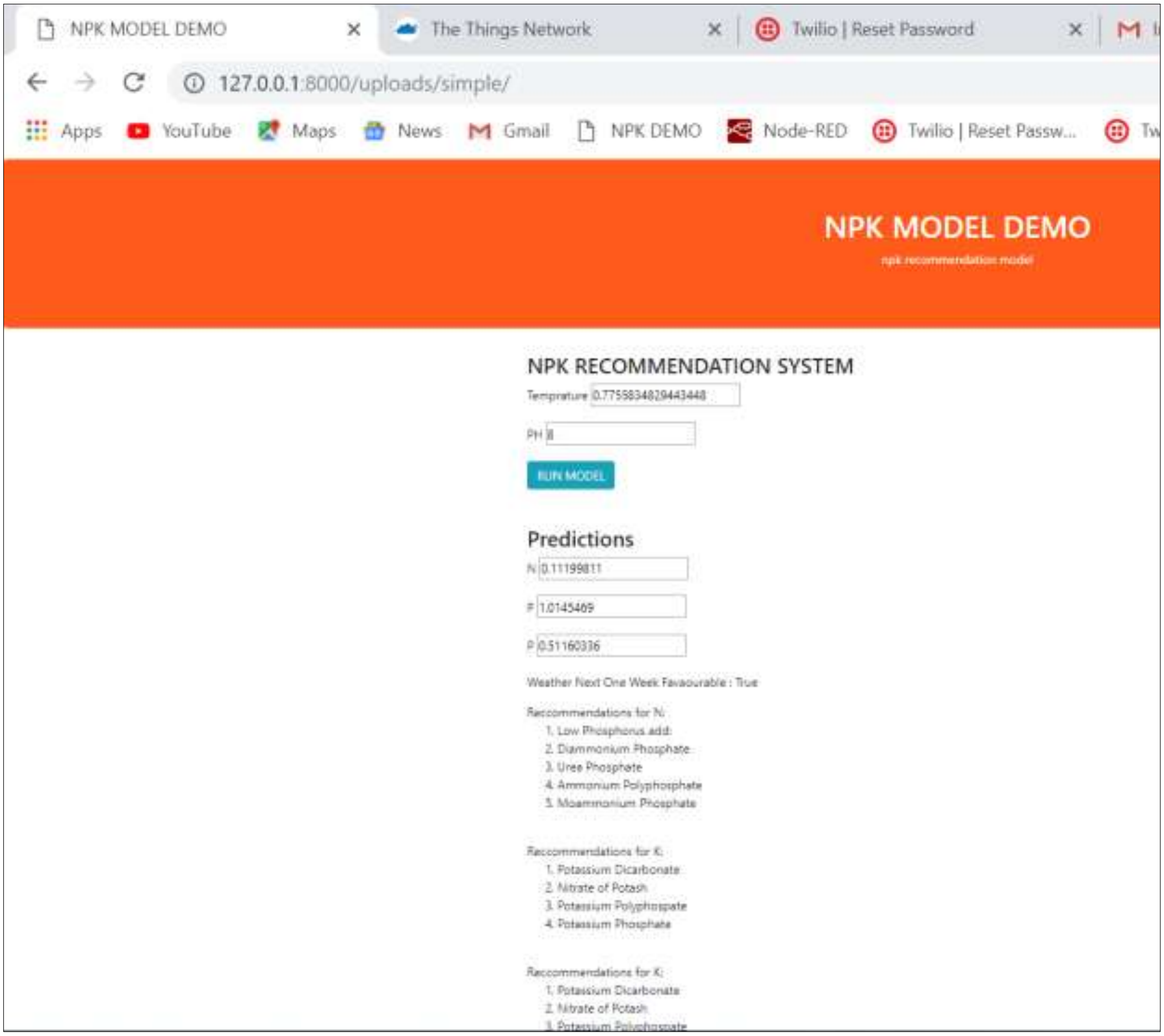
```
# importing the requests library

import requests

from collections import defaultdict

# api-endpoint

URL = "http://api.worldweatheronline.com/premium/v1/weather.ashx"

#?key=&q=Nairobi&format=json&includelocation=yes

# location given here

q = "Nairobi"

key = "198217c5f587480ca7c212321192803"

format ="json"

includelocation = "yes"

# defining a params dict for the parameters to be sent to the API

PARAMS = {"q":q,"key":key,"format":format,"includelocation":includelocation}

# sending get request and saving the response as response object

r = requests.get(url = URL, params = PARAMS)
```

```
# extracting data in json format

data = r.json()
```

Normalization Code

```
def normalise_me(max,min,x):

    normalised = (x-min)/(max-min)

    print(normalised)

    if x > 30:

        normalised = 1

    if x < 7.72:

        normalised = 0

    return normalised
```

Appendix III: Sample UI



Running the model on the UI gives the predicted NPK values, which depict the deficiency level of the soil tested. This is based on the latest data, PH and Temperature from the database. The model then recommends the best fertilizer nutrients to supplement.