BUSITEMA UNIVERSITY
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P.O. Box 236, Tororo, Uganda
Gen: +256 - 45 444 8838
Fax: +256 - 45 4436517
Email: info@adm.busitema.ac.ug

www.busitema.ac.ug

FACULTY OF ENGINEERING

DEPARTMENT OF MINING AND WATER RESOURCES ENGINEERING

FINAL YEAR PROJECT REPORT

DEVELOPMENT OF A MACHINE LEARNING ALGORITHM FOR SOIL MOISTURE PREDICTION.

(A CASE STUDY OF KIBIMBA IRRIGATION SCHEME, BUGIRI DISTRICT)

BY

LUTALO WYCLIFF HENRY

BU/UP/2018/3640

wycliffpcb@gmail.com

0776774608/0700590582

COSUPERVISOR: MS. HOPE NJUKI

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May the good Lord reward you all!

DECLARATION

I, **LUTALO WYCLIFF HENRY,** here by certify and confirm that the information I have written in this project proposal is a result of my own effort, research and has not been submitted before to any university or institution of higher learning for any academic award.

LUTALO WYCLIFF HENRY

Signature: .... Date: ....

APPROVAL

This proposal on the development of a machine learning algorithm to predict soil moisture has been written under the supervision of;

Name: **Ms. Hope Njuki**

Signature:

Date: 03/06/2023

Abstract

This study investigated soil moisture content with real data measured from cropped farm areas especially irrigation schemes. Soil moisture content is important in irrigation scheduling (when to irrigate and how much to irrigate), which is key in the growth and development of the agricultural sector. In order to aid farmers, get real time soil moisture predictions, we have designed a locally hosted web application using a maize farmland dataset obtained from Kaggle.com. the application can be used to predict soil moisture to a tune of 80% accuracy. This application can be used round the clock. In building the model, 5 machine learning techniques were used and these were Random Forest Algorithm, Gradient Boosting regressor, the lasso regressor, elastic net regressor and the ridge regressor. With this application, farmers can obtain soil moisture readings without the need for soil moisture probes.

LIST OF ACRONYMS

ML – Machine Learning

AI – Artificial Intelligence

RFA – Random Forest Algorithm

NDP III – National Development Plan 3

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CHAPTER 1: INTRODUCTION

1.1 Background of study

Agriculture across many regions in the global south, such as Africa, Latin America, and South Asia, depend mainly on rainfed agriculture for their staple food production. In Africa over 95% of agriculture is rainfed, contributing to 65% of the employment and 35% of the gross domestic product on the continent. Agriculture employs over 70% of Uganda's population and contributes most to Uganda's gross domestic product (GDP) which increased by 3.4 % in 2020-2021 from 17.8 in 2019-20. In 2020, the contribution of agriculture reached as high as 9715 UGX billion(Bwambale & Mourad, 2022). With a 3% annual growth rate, the demand for agricultural products for household consumption is increasing and hence more people are getting involved in agriculture due to the readily available market.

Irrigated agriculture contributes about 40 percent of the global food production from an estimated 20% of agricultural land, or about 300 million hectares globally (McGuire, 2015). Irrigated farmland typically generates three times the production of an equivalent area farmed under dry-land systems.

The Government in its Vision 2040 and in the NDP III (2016-2020) appropriately lists irrigation investment as a high priority along with agricultural value-chain development. The National Agricultural Policy (NAP, Ministry of Agriculture, Animal Industry and Fisheries, MAAIF, 2010), which stipulates the sectoral approach to the NDP, emphasizes the need for rehabilitating public irrigation schemes, transferring the management responsibility of irrigation schemes to the lowest appropriate levels and establishing new irrigation schemes.

Soil moisture Is an important factor in effective irrigation in that determining soil moisture content provides for a means to determine how much water to irrigate and when to irrigate. Knowing the soil moisture content of a soil at 2 different dates enables for calculation of the crop water consumption between those dates, when such measurements are continued for a year or more, it is possible to calculate annual crop water requirement. The amount of water a soil is able to hold from an irrigation can also be determined from the same measurements. Soil moisture measurements can as well be used to detect problems that may exist due to water in the root zone(Marsh, n.d.)

Traditionally, field-based measurements of SM have been limited to in situ recordings using SM probes. This implies that for large irrigation fields, to have SM measurements from various fields of

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