
FACULTY OF ENGINEERING AND TECHNOLOGY

**DEPARTMENT OF AGRICULTURAL MECHANIZATION AND IRRIGATION
ENGINEERING**

**FINAL YEAR PROJECT THESIS
DEVELOPMENT OF A VEGETABLE IRRIGATION SCHEDULING TOOL USING
GIS, REMOTE SENSING AND SOIL MOISTURE MACHINE LEARNING
PREDICTIONS**

A case study of Busitema-Habuleke irrigation Scheme

BY

KUSEMERERWA JOSEPH

(BU/GS23/MID/6)

kujosoft@gmail.com

SUPERVISORS: Dr. KAVUMA CHRISH, Dr. BWIRE DENIS & Dr. KIMERA DAVID

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ABSTRACT

Water scarcity and poor irrigation timing continue to constrain vegetable yields in smallholder farming systems. This study developed a Python based irrigation scheduling tool for six vegetables at the Busitema Habuleke Irrigation Scheme that integrates GIS, remote sensing data, and machine learning (ML) soil moisture predictions. The study addressed the challenge of impractical and costly field-based monitoring for irrigation scheduling and the lack of packaged, data driven tools for smallholder farmers. The specific objectives were to (1) analyse spatial and temporal factors influencing root zone volumetric water content (VWC), (2) develop and compare ML models for VWC prediction, and (3) implement and validate an irrigation scheduling tool that generates trigger-based irrigation recommendations. For Objective 1, spatial and statistical analyses revealed that soil moisture distribution closely followed rainfall, evapotranspiration, and soil texture patterns. Higher VWC values were recorded in loam soils, while areas with sandy textures exhibited lower moisture levels. The mean VWC was 19.34% (SD = 5.86%), and rainfall, field capacity, bulk density, and available water content (AWC) were all recognised as significant contributors. Multiple regression explained 88% of the variance in VWC ($R^2 = 0.88$), with rainfall ($\beta \approx 0.305$) and AWC ($\beta \approx 0.295$) being the best predictors ($p < 0.001$). Sensitivity analysis showed that a 10% change in rainfall and AWC caused a 3% and 2.9% change in VWC, respectively. Under Objective 2, three ML models, Random Forest (RF), Long Short Training Memory (LSTM), and Extreme Gradient Boosting (xGBoost), were developed and compared using soil, climatic, and topographic data from 2010 to April 2025. XGBoost exhibited the best performance (NSE = 0.985, RMSE = 0.022, MAE = 0.017), followed by Random Forest (NSE = 0.954) and LSTM (NSE = 0.873). The superior accuracy of XGBoost was attributed to its strong ability to capture non linear relationships between soil moisture and environmental variables. For Objective 3, the validated irrigation scheduling tool produced irrigation recommendations. Seasonal gross requirements for tomatoes under drip ≈ 420 mm season total; green pepper sprinkler ≈ 540 –560 mm and event-level recommendations of carrots: start irrigation at VWC ≈ 0.22 –0.25 m^3/m^3 with 1.5–4 mm pulses were obtained. The tool schedules exhibited lower variability and greater alignment with reference evapotranspiration-based methods compared to farmer practice, leading to measurable improvements in yield consistency. Overall, the integration of in situ calibration, remote sensing, and ML models provides a practical, site specific tool for smallholder irrigation management. Future work should focus on adding offline functionality, expanding farmer trials, and performing uncertainty analysis to enhance operational reliability.

Key words: *Vegetable irrigation, Irrigation scheduling, GIS, Remote sensing, Soil moisture prediction, Machine learning, Smallholder farming.*

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DECLARATION

I, KUSEMERERWA JOSEPH of Registration Number BU/GS23/MID/6, declare that this thesis, titled "Development of a vegetable irrigation scheduling tool using GIS, Remote Sensing, and soil moisture Machine Learning predictions," is my original work and has not been submitted for a degree or diploma at any other university or institution of higher learning. Wherever the work of others has been used, it has been properly acknowledged and referenced. This study followed Busitema University's academic standards and ethical requirements.

Signature: _____

Date: _____

APPROVAL

The thesis was submitted to the Directorate of Graduate Studies, Research and Innovation through the Department of Agricultural Mechanization and Irrigation Engineering, Busitema University, with the approval of the following supervisors;

MAIN SUPERVISOR:

Dr. KAVUMA CHRISH (PhD),

Senior Lecturer,

Department of Agricultural Mechanisation and Irrigation Engineering.

Faculty of Engineering and Technology, Busitema University.

Signature:

Date:

CO-SUPERVISOR 1:

Eng. Dr. KIMERA DAVID (PhD),

Senior Lecturer,

Faculty of Engineering and Technology, Busitema University.

Signature:

Date:

CO-SUPERVISOR 2:

Dr. BWIRE DENIS (PhD),

Faculty of Engineering and Technology, Busitema University.

Signature:

Date:

DEDICATION

This thesis is dedicated to my dear wife and children, whose love, encouragement, and sacrifices have been my most important source of strength. I am sincerely grateful to my parents for their prayers, wisdom, and continuous support throughout my academic career. Specifically, I dedicate the writeup to Busitema University for believing in my dreams and giving me an opportunity to work as I study. Above all, I thank the Almighty God for giving me the wisdom, resilience, and grace to reach this milestone.

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LIST OF ABBREVIATION/ ACRONYMS

AIC	: Akaike Information Criterion
ANNs	: Artificial Neural Network
AWC	: Available Water Content
CD	: Critical depletion
CNN	: Convolutional Neural Network
DEM	: Digital Elevation Model
ET _o	: Reference crop evapotranspiration
ET _c	: Crop evapotranspiration
FAO	: Food and Agricultural Organization
FC	: Field Capacity
GIS	: Geographic Information System
GPS	: Geographical Positioning System
IDW	: Inverse Distance Weighting
K _c	: Crop Coefficient
LSTM	: Long Short-Term Memory
LULC	: Land Use/Land Cover
MAD	: Management Allowable Depletion
MAE	: Mean Absolute Error
ML	: Machine learning
MODIS	: Moderate Resolution Imaging Spectroradiometer
NDP III	: Third National Development Plan
NDVI	: Normalised Difference Vegetation Index
NSE	: Nash-Sutcliffe Efficiency
RF	: Random Forest
RMSE	: Root Mean Square Error
SAR	: Synthetic Aperture Radar
SDG	: Sustainable Development Goals
SPSS	: Statistical Package for the Social Sciences
SRTM	: Shuttle Radar Topography Mission

TDR	: Time-Domain Reflectometry
TP	: Trigger Point
UBOS	: Uganda Bureau of Statistics
UNEP	: United Nations Environmental Programme
VWC	: Volumetric soil moisture
WHC	: Water Holding Capacity
WSNs	: Wireless Sensor Networks
xGBoost	: Extreme Gradient Boosting

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