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Improving Water Allocation across Canal Outlets Using Irrigation Performance Indicators and Machine Learning Algorithm: Case Study of Koga Irrigation Scheme

Tadele, Menwagaw

BAHIR DAR UNIVERSITY

BAHIR DAR INSTITUTE OF TECHNOLOGY

SCHOOL OF RESEARCH AND GRADUATE STUDIES

FACULTY OF CIVIL AND WATER RESOURCES ENGINEERING

IMPROVING WATER ALLOCATION ACROSS CANAL OUTLETS USING IRRIGATION PERFORMANCE INDICATORS AND MACHINE LEARNING ALGORITHM: CASE STUDY OF KOGA IRRIGATION SCHEME

BY

Menwagaw Tadele Damtie

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Menwagaw Tadele Damtie

A thesis submitted to the school of Research and Graduate Studies of Bahir Dar Institute of Technology, BDU in partial fulfillment of the requirements for the degree of Master of Science in Engineering Hydrology, in the Faculty of Civil and Water Resources Engineering

Advisor Name: Seifu Admassu (Ph.D.)

Co-Advisor Name: Fasikaw Atanaw (Ph.D.)

February, 2020

Bahir Dar, Ethiopia

DECLARATION

I, the undersigned, declare that the thesis entitled " Improving Water Allocation Across Canal Outlets Using Irrigation Performance Indicators and Machine Learning Algorithm: Case Study of Koga Irrigation Scheme " comprises my own work. In compliance with internationally accepted practices, I have acknowledged and refereed all materials used in this work. I understand that non-adherence to the principles of academic honesty and integrity, misrepresentation/ fabrication of any idea/data/fact/source will constitute sufficient ground for disciplinary action by the University and can also evoke penal action from the sources which have not been properly cited or acknowledged.

Author's Name: Menwagaw Tadele Damtie Signature _____________

Date of submission: ________________

Place: Bahir Dar, Ethiopia

This is to certify that the above declaration made by the candidate is correct to the best of my knowledge.

Advisor Name: Seifu Admassu (Ph.D.)

Advisor's Signature: ______________________________

Bahir Dar University

Bahir Dar Institute of Technology-

School of Research and Graduate Studies

Faculty of Civil and Water Resources Engineering

THESIS APPROVAL SHEET

Student: **Menwagaw Tadele Damtie** ______ 20 - Feb, 2020

Name Signature Date

The following graduate faculty members certify that this student has successfully presented the necessary written thesis and oral presentation for partial fulfillment of the thesis requirements for the Degree of Master of Science in Engineering Hydrology.

Approved by:

Advisor: **Seifu A. Tilahun (PhD.)** ______

Name Signature Date

External Examiner Feleke Agide (PhD) ______ 19 Feb, 2020

Name Signature Date

Internal Examiner Abebech Abera ______ 26 Feb 2020

Name Signature Date

Chair Holder: Mulugeta Azeze (PhD) ______ 26 Feb, 2020

Name Signature Date

Faculty Dean: Temesgen Enku Nigussie (PhD) Faculty Dean ______ Feb 27, 2020

Name Signature Date

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ABSTRACT

An accurate flow rate measurement is crucial to improve the performance of irrigation systems by allocating the desired amount of irrigation water to the right irrigation system components. This study was aimed to develop alternative approaches to estimate the water delivered to quaternary canals in data scarce environments. It was conducted at Koga Irrigation Scheme at 6 blocks out of 12 available irrigation blocks namely; at Chihona, Kudmi, Adibera, Tagel, Andinet and Teleta irrigation blocks during the irrigation season of 2019.

An optical smartphone application device entitled 'DischargeApp' was evaluated on its applicability to measure canal flow rate in comparison to a 90-degree v-notch weir method at selected quaternary canals. Moreover, water delivery performance of quaternary canal outlets was assessed by using three performance indicators: adequacy (Pa), equity (Pe) and reliability (Pr) indicators. Finally, the application of seven Machine learning models to estimate discharge at quaternary canal outlets were evaluated using five input variables: water level per unit width(h), irrigated area ratio of outlets(a), distance of outlets from TC off-take(l), Manning roughness coefficient of TC canal(n) and ranking order of operated outlets along TC(r).

The Accuracy of the DischargeApp at field conditions with the flow rates range 15-60 l/s, was improved by changing the surface velocity correction factor. The mean discharge deviation and percent error were reduced from ±3.8 l to ±2.1 l/s and 11.5 to 7.1% respectively. The discharge observations lied within ±15 percent were also increased from 66 to 92.1 percent.

The water delivery performance at quaternary canals showed that there was a significant flow variation among quaternary canal outlets in terms of water supply adequacy, equity and reliability. On average, the water supply through head, middle and tail canal outlets were 2.08, 1.84 and 1.74 l/s/ha respectively. At block level, water supply adequacy performance of canal outlets was good (0.9 -1.1) at the two head reach blocks (Kudmi and Chihona) and one tail block (Andinet) while the two middle reach blocks (Adibera and Tagel) showed poor adequacy status (Pa<0.7&>1.1) because of surplus water use. Teleta, which is the most tail reach block scored fair adequacy performance (0.7-0.9). Despite of its adequacy problem, Tagel scored good equity (Pe<0.1) and reliability (Pr<0.1) performances whereas, Teleta block scored poor equity (Pe> 0.25) and good reliability performances.

Based on prediction performance and model equation interpretability, Multivariate adaptive regression splines (MARS) was selected to predict discharge at quaternary canal outlets. The performance of MARS at training and testing stages were (R^2 = 0.86 & RMSE=3.6) and (R^2=0.85& RMSE=3.48) respectively. Since the distance parameter was eliminated due to its zero regression coefficients, the developed MARS equation uses four variables to predict discharge.

Key Words: DischargeApp, Machine Learning, Water Delivery performance, MARS

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LIST OF ABBREVIATIONS AND ACRONYMS

ANN	Artificial Neural Network
App	DischargeApp
BFs	Basic Functions
Caret	Classification and Regression Training
CART	Classification and Regression Tree
DP:	Delivery Performance Ratio
KNN	K- Nearest Neighbors
MARS	Multivariate Adaptive Regression Splines
MLA	Machine Learning Algorithm
ML	Machine Learning
Pa	Adequacy Performance Indicator
Pe	Equity Performance Indicator
Pr	Reliability Performance Indicator
QC	Quaternary Canal
RF	Random Forest
RFE	Recursive Feature Elimination
SVM	Support Vector Machine
TC	Tertiary Canal
USBR	United States Bureau of Reclamation
XGBT	Extreme Gradient Boosting Tree

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1 INTRODUCTION

1.1 Background

Sustainable water management is currently a cross cutting issue in almost all aspects, due to the ever-increasing water demand and supply of the world community (Maher,et al.,2019). According to this report, effective management of the available water resource is the central idea to meet the increasing water demand.

Wheeler et al (2015) stated that agricultural activities consume by far the largest share of world water resource, contributing to water scarcity. This study also mentioned that agriculture accounts about 70 percent of all water withdrawals, and up to 95 percent in some developing countries. Despite the fact that agriculture is playing a vital role by solving food security problems, it is one of water use sectors contributing to water resources wastage (FAO 2017).

Adongo et al (2015) studied that large-scale irrigation schemes developed in the continent of Africa so far have serious management problems caused by infrequent maintenance of the designed canal capacity, absence of flow controlling gates in the canal distribution networks and operation of irrigation systems relying on traditional experience. These problems have greatly reducing the sustainability of irrigation schemes, and needs a great concern to identify which water planning and management system works good in community managed irrigation schemes functions better (Agide et al., 2016).

Assessing the performance of irrigation systems is a crucial point in ensuring sustainable agricultural development and improving the capacity of irrigation water management. The success of irrigation water management can be evaluated by how well water delivery meets the crop water requirements at irrigation fields. Therefore, assessing the existing conditions of irrigation schemes in accordance with the seated objectives is required, and remedial measures can then be taken to reduce the gap between the potential and actual performance of the irrigation schemes (Fan et al., 2018).

Koga irrigation scheme is one of the functioning projects in Ethiopia, that was developed to irrigate about 7000 hectares of land to improve the livelihood of the community in the project area (Eriksson et al., 2013).

Agide et al. (2016) found that one of the key constraints to distribute fair share of water in irrigation schemes is the absence of flow control structures, where flow is not adequately controlled and regulated. Quaternary canal outlets in Koga have no flow controlling structures, and due to the absence of water flow monitoring techniques at these irrigation sub-systems, the degree of flow uniformity and water supply sufficiency were not simply identified.

The relation between water level at the regulated canal head off-takes and other field information with water supplied to branched canals through outlet structures was not considered as an irrigation water management system.

The irrigation distribution network in Koga Irrigation Scheme is comprised of one main canal, 12 irrigation blocks (secondary canals) which distribute to tertiary canals, and tertiary canals distribute water to branching quaternary canals, which finally supply the crop water demand at the irrigation fields through field canals (Asres, 2018).

For effective irrigation water management, this water district required certain water measurement devices to simplify the operation problems at the ungated canal outlets. In such already developed irrigation systems, a permanent provision of intrusive flow measurement techniques would not be compatible to the varying range of can flow conditions. For instance, providing weirs and flumes at ungated canal systems would disturb the flow operation through backflow effects. Besides this, the intrusive flow measurement devices should be installed at many stations in the irrigation canal network, which require huge investment costs(Al-khateeb et al., 2019).

DischargeApp is a non-intrusive smartphone application to measure water flow in open channels. It uses the available sensors in the smartphone device to calculates surface velocity of the channel flow based on surface structure imagery velocimetry technique (Maxcence et al., 2019).

The application of machine learning algorithms is recently very fundamental in the irrigation system for accurate prediction of water supply at locations where flow data is scarce (Atsalakis & Minoudaki, 2007). These models are used to estimate discharge using the available field information as predictor variables.

1.2 Statement of the Problems

Koga Irrigation Scheme is one of the foremost active irrigation projects used to irrigate about 7000 hectares of land to alleviate food problems in the project area (Eriksson et al., 2013). In this irrigation scheme, outlet structures at quaternary canals level were designed and constructed without controlling gates and water measurement techniques. The irrigation water is thus operated and controlled only at tertiary canal off-takes level. Agide et al. (2016) stated that the absence of such flow controlling structures is one of the key challenges in irrigation schemes, which lead to inadequate and inequitable water distribution among irrigation water users.

Though the operational strategy of Koga Irrigation scheme was to distribute adequate and fair share of water to each irrigation field throughout the whole irrigation period, there is no any mechanism to quantify where and when the actual water supply at quaternary canals level of the scheme are found. Water share disputes at this time are yet common in the scheme, due to irrigation flow variability and uniformity problems at spatial and temporal scales. Despite the fact that many overall Irrigation performance assessments have been done on Koga Irrigation Scheme, the studies masked and could not address water delivery performance of quaternary canal outlets.

The quantity of water supplied through a quaternary canal outlet is associated with water level released at tertiary canal off-take, its location and other field information. Thus, assessing water delivery performance of these canal outlets, and developing an empirical relationship between the outlet discharge and available information is necessary to improve scheme governance and efficiency. Applying machine learning models is central for accurate prediction of water supply at such irrigation sub-systems where water flow monitoring remains a challenge.

To quantify the actual amount of irrigation water supply, an accurate water flow measurement device is very essential at locations where water is not adequately controlled and regulated.

During the field works with IWMI and Bahir Dar University collaborative project Koga, a 90-degree notch thin plate weir was installed at selected quaternary canals. The notch weir was not adaptable with the canal flows, and conflicts with water users rise at some places, due to the interruption of canal flows by the weir barrage. This also led for demolishing of the installed notch weirs at some locations.

In addition to this, a permanent installation of notch weirs at several sites requires high investment cost for provision, installation and maintenance. Therefore, introducing a new non-intrusive and cost-effective flow measurement technique was ideal to solve water flow monitoring problems at the irrigation scheme. Evaluating the accuracy of an optical smartphone application device entitled 'DischargeApp', novel technology to measure channel flow rates was part of this study.

1.3 Research Questions

This study aims to answer the following research questions:

i) What is the accuracy of the discharge measurements when using the DischargeApp, a smartphone application device against a 90-degree notch weir?

ii) Does the discharge at the quaternary canal outlets vary as a function of its location along the tertiary canal?

iii) Which machine learning algorithm technique is most suitable to predict discharge at quaternary canal outlets in irrigation schemes?

iv) Can the discharge at the quaternary canal outlets be predicted based on available information from the tertiary canal?

1.4 Objectives of the Study

1.4.1 General Objective

The main objective of this study was to develop alternative approaches to estimate the water delivered to quaternary canals in data scarce environments.

1.4.2 Specific Objectives

- Evaluate the accuracy of using the DischargeApp for water flow measurements in irrigation canals
- Assess spatial and temporal variation of water delivery and overall performance at quaternary canal outlets

- Compare the performance of machine learning algorithms for predicting water supply through quaternary canal outlets
- Develop an empirical relationship which allows to predict the discharge delivery through a quaternary canal outlet as a function of its location, water level at tertiary canal and other field parameters.

1.5 Significance of the study

Since flow controlling and regulating mechanisms are absent at quaternary canals level in Koga, quantifying the actual amount of irrigation water at these outlets is very difficult. This leads to inequitable, unreliable and inadequate supply of water to the irrigation fields within and across irrigation blocks.

Assessing water delivery performance of quaternary canal outlets in space and time is vital to ensure equitable and timely water supply to farmers and support irrigated agriculture. Recently apps have been developed to help monitoring discharge in rivers and streams. In absence of weirs and other measurement infrastructure, these can provide low-cost solutions in measuring discharges in irrigation canals.

Furthermore, as there is no means to quantify the discharge at the respective outlet along the tertiary canal, there is a need to develop a relationship between the water released at the head of the tertiary canals and the respective outlets along the canal to improve equitable water supply within and between blocks. This can be done by using available information at the head of canal, other field information and machine learning algorithms.

This study aimed at understanding the variability in water delivery performance at outlets along the tertiary canals using different measurement techniques and machine learning algorithms with the aim to improve irrigation water management for Koga irrigation scheme.

2 LITERATURE REVIEW

2.1 Water Delivery Performance of Irrigation Schemes

In under developed regions of the world, freshwater resources are shrinking and expansion of irrigation systems are declining at their beginning (Malaterre & Baume, 2015). The study suggested that further development of irrigation at these regions would be unthinkable for the future unless the performance of existing irrigation systems is assessed and improved. Malaterre & Baume (2015) also believed that since the subject of irrigated agriculture is very complex, the performance could be improved by reducing the problems in the management systems in a holistic manner.

Arunkumar & Ambujam (2012) stated that a starting point in improving how the water is managed effectively within an irrigation system is by assessing the performance of the system. Their study described that there are some systems that perform well, but there are also many poorly performing irrigation systems, where performance improvements can be made. They finally conclude that the ultimate purpose of performance assessment is to achieve an efficient and effective use of resources in the irrigation system.

Tariq & Kakar (2010) explained that management of irrigation water is more important, as the new sources of irrigation supplies become scarce and new irrigation development work requires huge investment. Thus, optimum utilization becoming increasingly important to attain the maximum beneficial use. These researchers also expressed their thoughts as time may soon come, when the additional irrigation supplies will be only through the saving of water being lost.

Latif M. (1998) was tried to understand the factors that influence the performance of irrigation system. He had developed various analytical framework, criteria and indicators to quantify the water delivery performance and prescribing the management and physical interventions to improve the performance. The study also elaborates that the performance of irrigation schemes is influenced by many factors such as socio economics, environmental and technical. These factors are interlinked and may not be distinguishable. Physical effect may be easily identified, but their removal will not necessary to solve problems of underperformance (Latif M., 1998).

Hydraulic performance of an irrigation system refers that how much it is adequate to convey water to different locations, how efficiently it delivers and distributes irrigation water on spatial and temporal scales. Hydraulic performance of a system is measured against a set criterion, for which some indicators are established (Mirjat et al., 2017).

Mirjat et al (2017) states that the information on discharge measurements can be used to calculate various performance indices, such as an efficiency; a term from which comparative evaluations can be made for different years and among other irrigation systems. The performance assessment of irrigation systems must deal with operational assessment that provides required information to system managers and enable them to manage and operate the system.

The structured system in an irrigation project is the management of water distribution with regulated flow at the upper canal networks and a proportional division of water at the lower level canals based on a systematic operational plan (Adhikari, 2016). As per this study, upper level canals would run with continuous flow while lower level canals would run with intermittent supply. Adhikari (2016) also explained the irrigation water flow in lower level canals is maintained either at full supply level or at no flow condition for fixed days on a rotating interval. The system is equipped with water control gates at the upper canal networks up to the service area.

IDG (2014) revealed that modern schemes are those equipped with permanent irrigation infrastructure such as water diversion (head works), flow control structures, conveyance and distribution systems whereas, traditional schemes do not have permanent structures for water acquisition and flow control, and are made using local knowledge with local materials; including stones, soils, wooden logs, sand bags, etc.

2.1.1 Water Delivery Performance Indicators

Sanaee et al (2016) studied that due to the fact that many projects have failed to deliver the level of performance expected, assessing the performance of irrigation systems is an increasing concern in recent years. This demands for the evaluation of the water delivery performance in irrigation systems.

The study listed three indicators in defining water delivery performance of a system; the first one is delivery system's ability indicator, which can be defined as the ability of an irrigation system to meet the required amount of water.

The second indicator is, the spatial variability performance indicator (equity performance indicator) reflects the uniformity aspect of water delivery and measures the equity performance. The spatial variability performance indicator defines the variability in the delivery performance ratio over the time period of interest. The coefficient of variation of the delivery performance ratio over the time period is used to indicate the degree of this variability (Sanaee et al,2016).

The third indicator is reliability performance indicator, which is the reliability of water delivery in an irrigation system. The variation in the delivery performance ratio at any location of the delivery system and over time periods is the temporal flow variability performance indicator. The coefficient of variation of the average delivery performance over the systems is used to evaluate the temporal variability performance (Sanaee et al., 2016). The results of this study on the performance indicators in an irrigation district at Doroodzan Irrigation System in Iran, revealed that the physical system and the management could respond to the delivery of the intended supply. The indicators showed a better reliability performance than the equity performance in water delivery at the tertiary outlets. The results on this irrigation district also revealed that the system could not deliver water according to the real crop water requirements. The equity and reliability performance were illustrated by using the spatial and temporal variation of the expected overall efficiency at the district level.

Mangrio & Mirjat (2014) attempted to discuss performance indicators in large scale irrigation systems. This study stated that large irrigation command areas mostly suffer from inequitable water distribution and mismanagement in canal operation. The performance of such irrigation systems can be determined by indicators such as, water productivity, reliable supply and equity in water distribution within a canal command (Mangrio & Mirjat, 2014).

The study of Mangrio & Mirjat (2014) was made to evaluate the degree of equity and reliability in the selected area so as to develop some guidelines to improve the performance of the irrigation system in terms of equitable distribution among secondary canals.

Reliability of water supply at the head of distributaries and equity in water distribution was measured using Delivery Performance Ratio (DPR), Interquartile Ratio and coefficient of variation (CV). Delivery performance ratio is defined as the ratio of actual measured discharge to the design discharge.

It was calculated by using relation given by Murray-Rust et al (2000). These Authors and Molden & Gates (1990) defined the coefficient of variation as the standard deviation of the values divided by their average value.

2.1.2 Operational Performance of canal outlet structures

Since canal outlets are part of the irrigation system, the evaluation criterion of their water delivery performance is not differently seen.

Maatooq & Wahad (2018) define an outlet or offtake of a canal system as the hydraulic structure that withdraws the required discharge from a distributary canal to the inlet of a watercourse canal.

The outlet operational performance study of Maatooq & Wahad (2018) was at a secondary level irrigation canal using the SIC-model on Kifil- Shinafiya project along the Euphrates River. The study found that all outlets worked under a submerged flow and they were provided with a measuring weir at the downstream basin, but most of these had been damaged by farmers or had defects from the construction stage. In the damaged weirs, the head difference was out of engineering requirements, and all required reparation.

Tariq & Kakar (2010) also studied the effect of variability of discharges on equity of water distribution among outlets. They used to assess the canal outlets based on adequacy, equity and reliability performance indicators. The watercourses of the case study area are provided with non-adjustable outlet structures, designed on the basis of sanctioned duty and cultivable command area. These outlet structures were designed to provide proportional distribution of irrigation supply to the watercourses.

The study of Tariq & Kakar (2010) concluded that relative negligence of design and operational factors are the central problems for the gap between the potential and actual performance of irrigation system. The average delivery performance ratio of head pipe outlets was varied between 1.0 and 1.6, whereas at middle pipe outlet, the DPR was 0.70 and at tail open flume outlets it was varied between 0.6 and 0.90. the results clearly show that head outlets are withdrawing more than design discharge, while tail outlets suffer the most. In fact, equity is not improved even if the minor discharge rose more than the design discharge. Variability in discharges also increases from head to tail outlets (Tariq & Kakar, 2010).

Most Irrigation Engineering books such as, Sharma (2016) outlines that it is essential to design an outlet in such a way that it is reliable and be also robust enough such that it is not easily interfered with. Further the cost of an outlet structure should be low and should work efficiently with a small working head, since a larger working head would require higher water level in the parent channel resulting in high cost of the distribution system.

Sharma (2016) generally classified the module of outlets into three types; namely; non-modular outlet, semi modular outlet and module outlet. Non-modular outlets operate in such a way that the flow passing through them is a function of the difference in water levels of the distributing channel and the watercourse. Hence, a variation in either affects the discharge. These outlets consist of regulator or circular openings and pavement.

According to Sharma (2016), the discharge through Semi modular outlets depend on the water level of the distributing channel but is independent of the water level in the watercourse so long as the minimum working head required for their working is available. The discharge through modular outlets is independent of the water levels in the distributing channel and the watercourse, within reasonable working limits. This type of outlets may or may not be equipped with moving parts. Though modular outlets, like the Gibb's module, have been designed and implemented earlier, they are not very common in the present Indian irrigation.

2.2 Canal Flow Measurement Methods at Irrigation Schemes

Boman & Shukla (2016) explained that effective irrigation water management begins with accurate water measurement. Water measurement is required to determine both total volumes of water and flow rates supplied. Flow rate measurements help to ensure that the irrigation system is operating properly. The study also defines that measurement accuracy is the difference between the true flow and the flow measured with a meter. The measured flow should be as close as possible to the actual amount of water flowing in the canal.

Most irrigation meters should have an accuracy of ± 2.0% of the actual amount. The accuracy for a meter may be specified as a percentage of actual rate or as a percent of full scale. In most instances, flowmeters with rate accuracy should be selected. If a flowmeter is operated above or below its recommended range, the accuracy may be reduced (Boman & Shukla, 2016).

The most commonly known open channel flow measurement devices operate by producing critical depth through a control section of known dimensions. Sharp crested weirs, broad crested weir and a wide variety of flumes are examples of critical flow devices (ILRI, 2001).

Water measurement manual of USBR (2001) well states that several site-specific factors and variables that have to be considered during selecting the proper water measurement devices for a particular site. Before selecting the measurement devices for a particular site, dealing on the unique operational requirements of the site, governmental laws and compact agreements are the major concern. The manual also widely discusses the first five standard water measurement devices that are commonly used by Irrigation system operators. These devices are; weirs, flumes, submerged orifices, current meters and acoustic flowmeters. The selection of the measuring devices is mainly influenced by factors such as, accuracy requirements, cost, legal constrains, range of flow, head loss, adaptability to the site and variable operating conditions, maintenance requirements, etc.

a) The 90-degree notch thin plate weir

Since many of the intrusive open flow measurement techniques rely upon some empirical coefficients, a reliable technique is required to obtain new accurate physical data.

Thin-plate weirs are commonly used as measuring devices in channels, enabling an accurate discharge measurement with simple instruments.

Halefom (2018) used a thin plate notch-weir to assess water flow at minor irrigation canals. The researcher explained that when several forms of weirs or flumes might be used, the thin plate notch-weir is often preferred because of its greater accuracy at low flows or its lesser sensitivity to approach-channel geometry and velocity distribution.

The water management manual of USBR (2001) reinforces the explanations of Halefom (2018) by affirming a 90-degree v-notch thin-plate weir as an accurate flow measurement device particularly suited for small flows. The Cone equation is commonly used for 90-degree v-notch weirs. This equation is reliable for small, fully contracted weirs generally in measuring water for irrigation.

Wang (2016) expressed that thin plate weirs are commonly used as measuring devices in flumes and channels, enabling an accurate discharge measurement with simple instruments.

The discharge calibration of a large 90-degree notch thin plate weir was performed using an unsteady volume per time technique. The v-notch weir was initially closed by a fast-opening gate. The sudden opening induced an initial phase of the water motion followed by a gradually-varied flow phase. The findings of this study showed that the unsteady discharge calibration of the v-notch weir yielded similar results to a more traditional calibration approach based upon steady flow experiments (Wang, 2016).

b) DischargeApp, a smartphone Application flow measurement method

In most recent years, optical methods for water level measurement have been investigated more widely in the world. A non-intrusive, optical flow measurement device which are suited for natural water streams, irrigation furrows and water channel flow measurements have been developed.

Discharge app is one of those smartphone devices used to measure surface water flows. It was first used by the experts' group in Photrack Ltd found in Zurich, Switzerland. The app is fully integrated in the web platform 'discharge.ch'.

The Surface flow velocity of smartphone devices was initially estimated in the app by using an extended algorithm of Particle Image Velocimetry, which is called Surface Particle Image Velocimetry (Diego et al., 2014). In particle image velocimetry (PIV), the fluid motion is made visible by adding small tracer particles and from the positions of these tracer particles at two instances of time to infer the flow velocity field.

DischargeApp uses a Large Particle Image Velocimetry (LPIV) technique called Surface Structure Image Velocimetry (SSIV) algorithm, which is suitable for optical flow measurement with no need of particles called tracers on the channel flow.

The performance of SSIV method was assessed by João P. et al (2018) in comparison to the mean velocity measured by a conventional sensor array. The study found that the SSIV had a percentage error of 1.7% compared to the conventional flow sensors. The study results also reflect that the SSIV method is sensitive to light conditions. The study of João P. et al (2018) finally suggested that infrared lighting could be used to increase the accuracy of measurements in night or no sunlight conditions.

The ISO standard EN ISO 748:2007 and the physical model called mixing length model, which uses the roughness of the channel bed as a boundary condition are used to calculate the vertical mean velocity from the surface flow velocity. For the current works, DischargeApp uses the ISO standard method for mean velocity calculations.

Before performing measurements using DischargeApp, field set up is required by placing four markers on the two banks of the channel, two markers at each bank. The channel geometry, offshore distances of markers and roughness of the channel bed are necessary to be inserted in the app. Short movie recording and video processing can then be performed with time less than two minutes (http://www.photrack.ch/dischargeapp.html).

2.3 Application of Machine Learning Algorithms

2.3.1 Background of Machine Learning

Many of the machines in the world are developed using software programming, and are controlled by computers. Though the computers are explicitly programmed for high quality performance, creating such programs is tiresome and requires skillful experts. A machine learning model of these programs can be used to support software programing beginners and to foster the reuse of knowledge from successful programs (Weimer et al., 2009). The main difference between machine learning and programming is that there is no coding or programming involved in machine learning, while programming is about giving the machine a set of instructions to perform.

Weimer et al (2009) define machine learning as it is the process of building a model from data, and the data used for training the machine is called training data. Machine learning is applied to address the wide range of field research problems where manual coding of programs is difficult and inconvenient.

Divya et al (2018) explained that machine learning is simply training a model with data and then using the model to predict any new data. To solve the targeted problems in the specified circumstances, sufficient data has to be fed to train the machine. After the training, the machine can perform automatically and can also learn to fine-tune itself and the training process of the machine is called machine learning. Divya et al (2018) also elaborates that machine learning experiences information preprocessing, learning, and assessment stages.

In the learning system, it comprises of four design choices; namely, choosing the training data, the target function, the representation and the learning algorithm.

In machine learning, the data is the only input provided and the model is based on the algorithm that have decided to use. The algorithm to be used is based on various factors of the data: the features (or independent variables), the type of dependent variables, the accuracy of the model, and the speed of training and prediction of the model (Venkateswaran, 2017).

Based on their learning style, machine learning algorithms can be mainly divided into supervised and unsupervised leaning algorithms. In supervised learning all the data is labeled and the prediction of the output is learned from the input data. In unsupervised learning the output label does not exist which means that the algorithm does only depend on input variables with no corresponding output values (Marinósdóttir, 2019).

The study of Dasgupta & Nath (2016) classifies machine learning into three broad categories: namely; supervised learning, unsupervised learning and reinforcement learning. In supervised machine learning technique, the machine is fed with paired sets of inputs and outputs, which are called labeled datasets whereas, in case of unsupervised machine learning, the machine is given a dataset without the output sets. In this case, the main goal is to find a good internal representation of the inputs in the absence of output pairs. The third type of machine learning is reinforcement, which is more applicable to interactive problems where the learner is able to learn using its own experience. It learns a policy of how to act given an observation of the world without knowing whether it has reached the goal or not.

Mohri et al (2012) studied that supervised machine learning algorithm are typically categorized as linear regression, nonlinear regression and classification types. Linear regression models are statistical models to evaluate the linear relationship between an output variable and one or more predictor variables. Ordinary Linear Regression, Partial Least Squares Regression and Penalized Regression are typical examples of linear regression models in supervised machine learning. Mohri et al (2012) also discussed the nonlinear regression models, which include Multivariate Adaptive Regression Splines, Support Vector Machines, Artificial Neural Networks and K-Nearest Neighbors. The other regression supervised machine learning technique is a regression tree which includes models such as, Decision Tree, Bagging Tree, Random Forest and Boosted Tree.

A classification type of supervised machine learning technique deals with qualitative outputs. The method that performs classification is referred to as a classifier. These machine learning techniques includes logistic regression, linear and quadratic discriminant analysis. More advanced classifiers, such as classification trees, boosting and deep learning are also currently used. Instead of numeric data, classification training works with qualitative data (Ahmed, 2014).

2.3.2 Application of Machine Learning Models in Irrigation Studies

Machine learning, together with big data analysis technologies and high-performance computing has emerged to create new opportunities to understand data intensive processes in agricultural operational environments, and the learning process gives machines the ability to learn without being strictly programmed (Liakos et al., 2018).

Hans et al (2010) tried to compare the performance of different machine learning methods implemented and applied to irrigation prediction. and they finally recommend a possible technique for the same based on its superior results in other such time series analysis tasks.

Gu et al (2017) used genetic algorithm (GA)-back propagation (BP) neural network prediction machine learning algorithm to develop the yield-irrigation water model for predicting the corn yield for different irrigation systems under subsurface drip irrigation. The model with this algorithm gave accurate predictions of the yield. The average error is only 0.71%. The model was used to design irrigation systems under subsurface drip irrigation more accurately.

Huang & Fipps (2009) studied water distribution network models, which are required to prioritize and analyze various rehabilitation options, and also to quantify irrigation water demands, usages, and losses, and to help manage gate automation. However, commercially available software packages were limited in applications due to their high cost and operational difficulty. Due to these reasons, Huang & Fipps (2009) recommended to use predicting models in irrigation distribution networks rather than other distribution network models.

Haghiabi et al (2018) studied machine leaning models such as, multivariate adaptive regression splines (MARS), artificial neural network (ANN), and support vector machine (SVM) for prediction of discharge coefficient (Cd) of lateral intakes the irrigation and drainage networks.

The experimental data pertaining to dimensionless parameters on Cd were collected to develop the models. The results indicated that the MARS model outperforms the ANN and SVM models.

The tangent sigmoid and radial basic functions were found to be the most efficient transfer and kernel functions for ANN and SVM respectively. Evaluation of the performance of applied models in term of developed dispersity ratio index shows that the minimum data dispersity is related to the MARS model.

a) Multivariate Adaptive Regression Splines (MARS):

It was first presented by Friedman (1991) , and recently it is actively used in most fields of the engineering especially in hydraulic engineering. Its technique has been successfully applied for predicting the energy dissipation and scour depth at the downstream of the spillways, river discharge forecasting, rainfall-runoff modeling, etc. It is a flexible procedure to organize relationships between a set of input variables and the target dependent that are nearly additive or involve interactions with fewer variables. The nature of the MARS features breaks the predictor into two groups and models relationships between the predictor and the outcome in each group. Specifically, given a cut point for a predictor, two new features are “hinge” functions of the original. The “left-hand” feature has values of zero greater than the cut point, while the second feature is zero less than the cut point (Kuhn & Johnson, 2013).

Rezaie (2018) describes MARS as a nonparametric statistical method based on a divide and conquer strategy in which the training data sets are partitioned into separate piecewise linear segments (splines) of differing gradients (slope). It makes no assumptions about the underlying functional relationships between dependent and independent variables.

In general, the splines are connected smoothly together, and these piecewise curves (polynomials), also known as basis functions (BFs), result in a flexible model that can handle both linear and nonlinear behavior. The algorithm is available in the unified caret package with the ‘earth’ library in R programming.

b) Artificial Neural Network (ANN)

ANN is a nonlinear regression machine learning model which works in the principle of biological neural networks. It a family of powerful nonlinear models, which are capable of solving a wide variety of problems where the relationships may be quite nonlinear (Xiao, 2015).

Obaid & Hassan (2019) also studied that a neural network contains three fundamental layers which are named, input layer, hidden layer and output layer. The input layer takes in the predicting parameters and the output layer shows the prediction based on the input.

They iterate through each training data point and generalize the model by giving and updating the weight on each node of each layer. The trained model then uses those weights to decide what units to activate based on the input. There are several types of neural networks but one of the most used at the moment is called a multi-layer perceptron (MLP). It can be described as combination of many perceptron.

The network of the layers works similar to the perceptron where it takes an input vector including all the independent variables and produces an output vector which refers to the dependent variable (Maier et al.,2000).

c) Support vector machine (SVM)

SVM is a supervised machine learning model with associated learning algorithms used to examine data for both regression and classification analysis. First the algorithm was only intended and applied to classification tasks but later it was extended to handle regression problems as well. The SVM algorithm was developed in the early 1990s and was a promising addition to other machine learning algorithms at that time (Marinósdóttir, 2019).

d) K-Nearest Neighbors (KNN)

KNN model is one of the simplest of all machine learning models, whose construction is fundamentally depended on the K-closest individual samples from the training dataset. To predict the value of a new input for regression, KNN have to find out the K nearest neighbors in the dataset space. The predicted output is the mean (or the median) of the observed values of the K nearest neighbors. The basic idea of the above KNN model is based on the definition of the distance between different data points(Xiao, 2015).

e) Classification and Regression Training (CART)

CART is a simple self-explanatory algorithm, which can be used for both classification and regression. It usually known as decision tree, and it makes decisions based on values of all the relevant input parameters after training. It uses entropy to select the root variable, and based on this, it looks towards the other parameters' values.

It has all the parameter decisions arranged in a top-to-down tree and projects the decision based on different values of different parameters (Quinlan, 1990). The methodology of CART was developed in 1980s by Breiman and his colleagues, in their paper entitled Classification and Regression Trees.

f) Extreme Gradient Boosting Tree (XGBT)

This machine learning method, which is based on the gradient boosting decision tree, is a promising classification and regression model. It is an iterative decision tree algorithm comprising multiple decision trees, with the sum of the results of all decision trees constituting the final result. It is frequently applied to solve classification and regression problems. In the process of gradient boosting machine model operation, the objective of every iteration is to reduce the residuals of the previous iteration. In order to eliminate the residual, the gradient boosting machine model builds a new model in the direction of the gradient of residual reduction (Jin et al., 2019).

g) Random Forest (RF)

It is a model that uses multiple base models on subsets of the given data and makes decisions based on all the models. As cited by Ahmed et al (2019), the base model of random forest is a decision tree, carrying all the pros of a decision tree with the additional efficiency of using multiple models. One of the main advantages of the algorithm is that it can be used for both classification and regression. The algorithm is an ensemble method based on constructing combinations of many decision trees. The concept ensemble learning method refers to the idea of aggregating multiple methods with goal of improving model performance. The algorithm was first introduced by Tin Kam Ho which used the random subspace method where a sample of features is randomly selected from the entire set of features (Ahmed et al., 2019).

3 MATERIALS AND METHODS

3.1 Description of the study Area

Koga watershed is located in the upper source of the Blue Nile, Ethiopia having a total area of 266 square kilometers and elevation ranges from 1800 m at the gauge station ($11^0$22’12’’N latitude and $37^0$02’15’’E longitude) to 3000 m above sea level (Gebrehiwot et al., 2010). Koga Irrigation scheme is specifically located near Merawi town in the Mecha Woreda, West Gojjam Zone Amhara regional state (Tesfai, et al.,2011). Tesfai et al (2011) also stated that the reservoir of Koga has a capacity to store about 83 106 m^3 of water, which can able to irrigate 12 irrigation blocks covering a total of 7,000 ha reaching more than 10000 beneficiaries.

According to Asres (2018), the irrigation system comprises of 19.7 km of lined main canal, 52 km of lined secondary canals, 156 km of tertiary canals, 905 km of unlined quaternary canals and 11 Night Storage Reservoirs. The main canal is designed to provide irrigation water for 24 hours during irrigation period. There are 12 secondary canals, here after called blocks designed for 12 hours irrigation supply, each covering an area of irrigated land ranging from 220 ha to over 1000 hectares. Likely, tertiary canals are designed for 12 hours irrigation supply to distribute water to quaternary canals, which have a capacity of irrigating 8–16 ha of land while field canals serve an area of 2.0 ha within the quaternary unit and the maximum field canal design capacity is 30 l/s (Asres, 2018).

Quaternary canals have pre-casted concrete turnouts, hereafter named as outlets, with free open buried pipes, which are categorized as a semi-modular type of canal outlets. There is no mechanism to monitor water supplied to these outlets. Quaternary canals are managed and operated by group leaders so called water fathers.

In Koga Irrigation scheme, rotations were designed among quaternary canals. However, in most cases of the existing condition, water managers allow to release water in all quaternary canal outlets along a tertiary canal and the rotation is among farmer fields within a quaternary canal.

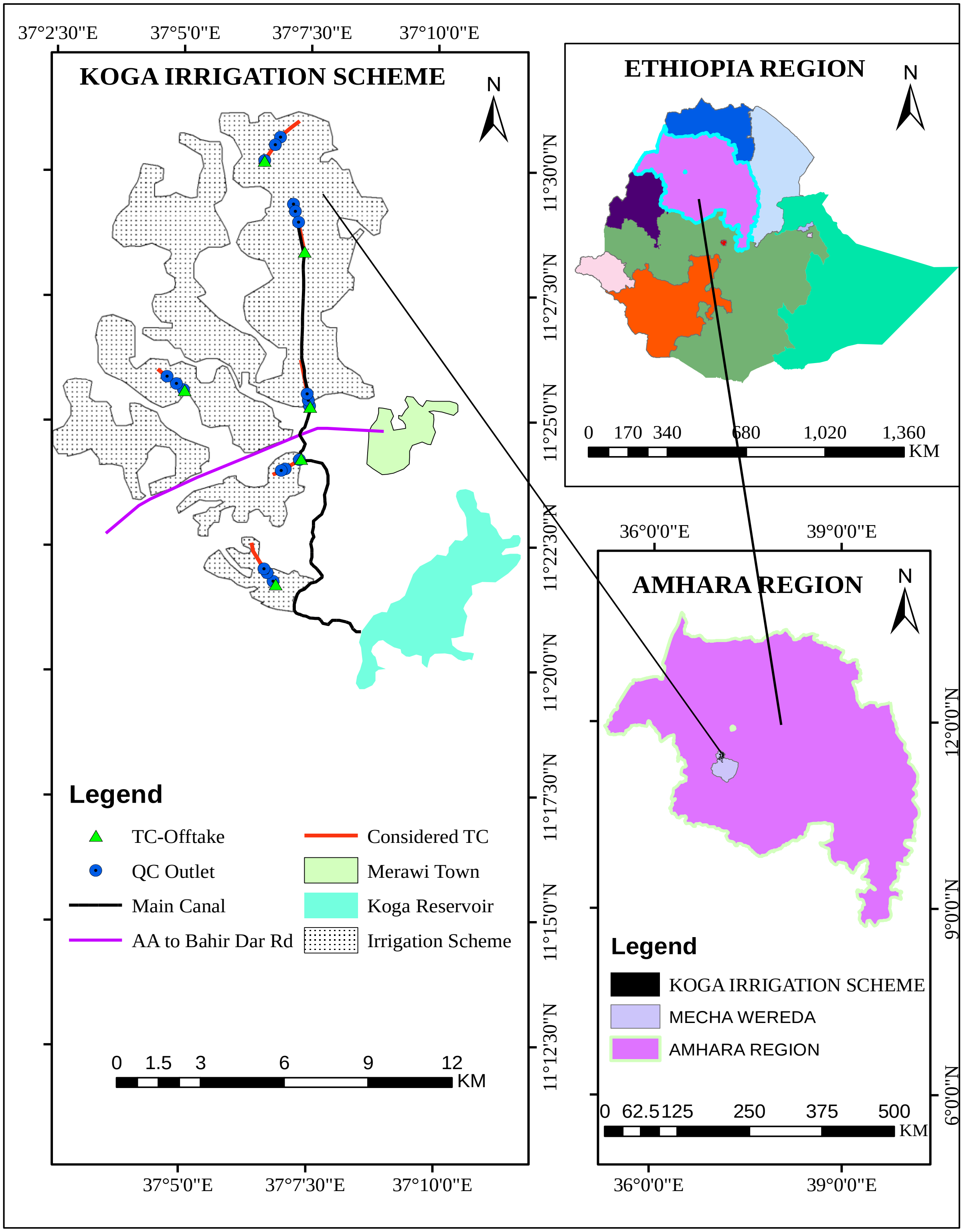

Figure 3-1: Location of the Study Area

3.2 Field Design and Setup

In this study, 6 blocks out of 12 available canal blocks in the scheme were selected in the field design, namely: Kudmi, Chihona, Adibera, Tagel, Andinet and Teleta blocks. The selection was by using a systematic sampling technique included from different reaches; two blocks from each head, middle and tail reaches of the scheme. A total of 6 tertiary canals, one tertiary canal from each block and 18 quaternary canal outlets, three outlets from each tertiary canal were selected. The field setup was appropriately planned well at different sections of the scheme to observe the spatial and temporal variability of water supply through canal outlet structures. The actual irrigated command area of quaternary canals, which were identified in the study varied between 6.7-16.5 ha, which is a bit different from the study of (Asres, 2018).

3.3 Data collection and Methods

This study was carried out during the irrigation season of 2019 at Koga Irrigation Scheme, from January to May 2019. The data collection was done by the researcher with the assistance of data collectors who were collecting immense irrigation data for a project named 'Closing Water Productivity Gap Project'. The project was carried out by Bahir Dar University in collaboration with International Water Management Institute (IWMI) with fund of Food and Agriculture Organization (FAO).

The primary data collection, such as discharge data, canal cross section, canal outlet distance, water level, fixed concrete weir size and other field observations were done by direct measurements. The secondary data such as, intended canal discharge, irrigated command area, rating curve equations of tertiary canal off-takes and other designed features of the irrigation scheme were collected from Koga Dam and Irrigation Scheme project office.

3.3.1 Discharge Measurement and Implementation of the Methods

Discharge measurements at tertiary and quaternary canal offtakes were made at a weekly basis in all selected sites during the irrigation season of 2019. A 90-degree thin plate v-notch weir, smartphone based non-intrusive application device here after called 'DischargeApp', and fixed concrete weirs at tertiary canal offtakes were used to collect water flow data concurrently.

a) Flow measurement using Notch Weir

A thin plate 90^0 v-notch weir is a standard method to measure water levels both in laboratories and small channels, and gives the most accurate results when measuring relatively low flows. It is particularly suitable for flows with significant velocity distribution and unregularized channel geometries, due to its less sensitivity to these features. In addition, it is relatively easy to manufacture from readily available materials and convenient to use. For this study, 90-degree triangular notches were designed after taking field observations by checking canal cross sections and investigating peak water supply demands in quaternary canals. The weirs were designed and manufactured from a 3mm thick metal sheet with standard dimensions. This v-shaped notch in a vertical thin plate were installed perpendicular to the sides and bottom of a straight channel. The line which bisects the angle of the notch was sat vertical and at the same distance from both sides of the channel. (Ibrahim, 2015).

The notch weirs were installed with a notch height(p) ranged from 2-5cm, to remove side flows due to backwater flow effects of the weir blockage. Since water courses have slightly horizontal slopes, water users were also claimed to reduce notch height to zero. The installation of standard dimensional notches was done at 18 selected quaternary canals, just near to the respective canal outlets throughout the irrigation season.

The general formula for 90-degree v-notch weir is described as,

$$Q = \frac{8}{15} * (2gCd)^{1/2}\ H^{2.5} \qquad \text{Eq. 3. 1}$$

Where, Q is the discharge in m^3/s; g is the acceleration due to gravity ($9.81 m/s^2$); Cd is a coefficient of discharge; and, H is effective water head at weir in meters.

The water management manual of USBR(2001) recommends Cone formula for 90-degree v-notch weirs. Cone formula is mostly used and reliable for small, fully contracted weirs generally encountered in measuring water for irrigation. Discharge is calculated by cone formula as,

$$Q = 2.49 * H^{2.48} \qquad \text{Eq. 3. 2}$$

where, Q = discharge over the weir (ft^3/s) and H = head in the weir (ft)

For an open channel flow measurement with thin plate weirs, equation 3.2 was converted to SI unit system by Skrenter, (2001) as $Q = 1.38 * H^{2.5}$ where, Q is outlet discharge(m^3/s),h is effective water head at weir(m).

The USBR (2001) water measurement manual recommends that the discharge range of the 90-degree notch has to be between 0.05 and 4.25 ft^3/s for accurate measurements.

b) Field Implementation of the DischargeApp

The goal of using the app in this study was to introduce a novel ICT technology for improving irrigation water management through estimating water delivery to ungated canal outlets with no requirements of field installations. This app is a non-intrusive device which is fully integrated in a web platform. It requires an android device with version 4.1 and above. Any user can easily access it from a google play store, but it needs to create an account and get permission rights from organizations or developers' team.

c) DsichargeApp Measurement Procedures

In this study, the following procedures were used to measure canal discharge using the DischargeApp device:

Step 1. Create a user's account: The application was first downloaded from google play store and the user created an account on the android device which met the requirement of the application discharge.
A Huawei Media Pad M3 Lite 10 tablet with specification of android 7 and 1200x1920 pixels resolution was used for the study. The user was then registered to the DischargeApp to see the available organizations and existing measuring sites of which the user needs to request permission for measurements. In this study, the user had got permission rights by the International Water Management Institute.
Step 2. Create new measurement sites**:** After getting permission from organization, the user can create a new site either by presenting at the actual site and filling detailed canal information using direct measurements, or by filling previous field information wherever the site creator is located.

Positioning four reference markers at a known cross-sectional profile is the next task before taking measurements. Two reference markers should be placed at each shore side and distance from the shores shall be defined.

The reference markers were placed at a quaternary canal having nearly uniform cross section just downstream of the installed 90-degree v-notch weir to avoid canal water level rising due to the weir at the upstream side.

In addition to canal profile and place marks, the manning-Strickler roughness coefficient, Kst for stationary and uniform flow is user defined. The app has a roughness menu to guide the user to choose Kst values for the considered canal bed types. Bed roughness for natural streams, manmade earth channels, rock channels, cemented channels, channels with brick walls, steel channels, tunnels and cement pipes are available in the app with reasonable range values.

The user can also insert the roughness values which are obtained from soil test results for the channel bed. The bed material for earthen quaternary canals in the study area falls under fine gravel with ca.10/20/30mm and manmade shores. The value of roughness coefficient, Kst for such bed types is about 45 $m^{1/3}/s$, which is used for the present study.

Step 3. Record videos for calculating discharge: The reference markers must be inside of the camera view and clearly visible by the smart-phone camera at the chosen resolution. Once the observer stands at one side of the shore between the two markers, the camera preview screen of the app is accessed by clicking the camera icon of the site view.

When the observer clearly viewing the four markers and the moving water, the camera icon can be clicked for recording the video that takes about five seconds. After completing the video record, the camera view is calibrated by moving the appeared blue hairs over the placemarks. The water column is picked by moving the blue line to the actual water level of the canal. For the study, at least two video records were taken at both sides of the shore, to check the reliability of the records.

Step 4. Process the videos and upload results to cloud: The video processing starts by pressing a ‘process video’ icon and velocity vectors are plotted after execution video processing. The calculated surface velocity, discharge and water column are also be appeared.

The site video can also be uploaded using a 'send site video' button on the application. The quality and speed of video processing are dependent on the pixel resolution. For instance, a resolution default value of 1080p has better quality than the value of 480p. The video processing is much faster for the reduced resolution, and if the signal is strong enough, the accuracy for the velocity measurement will be significantly affected.

For this study, a resolution value of 1080p was used to get a better quality of the data processing. The measurements can be saved and successfully uploaded to the cloud by clicking on the 'upload results' button. The app enabled the user to download the measurements and also edit site features from the discharge.ch platform (www.discharge.ch/help).

d) Water level Measurement Using TC Off-take Weir

In Koga Irrigation Scheme, concrete weirs were constructed at all tertiary canal off-takes and at the preferred locations along these canals. The upstream corners of the vertical and parallel side walls are known to have a significant influence on both contraction of the weir flow and the boundary layer displacement thickness of the side walls.

Both effects make it impossible to apply the basic two-dimensional head-discharge equation to the full width of the control section unless the upstream corners of the side walls are dimensioned in such a way that the combined effects of lateral contraction and side-wall boundary layers are counterbalanced. A discharge passing over the fayoum weir without bottom opening uses the general formula for rectangular broad crested weir is described as,

$$Q = CLH^{n} \qquad \text{Eq.3.3}$$

Where, Q is the flow rate(m^3/s), C is discharge coefficient or contrast for the specific weir structure, L is width of the weir, H= height of water head over the weir's crest and n is structure variant, usually 3/2 for horizontal weir (Mohammed et al 2016). The exit weir structures of the tertiary canals were used in the place of the inlet gate to measure water level. The latter is not convenient to take measurements at many sites because of floating debris clogging the graded staff readings.

The width of the weirs, B at the selected tertiary canals varies between 0.56m and 0.67m, and only water level measurements were taken at these structures.

Quaternary Canal Outlet Structures: They are structures at the head of a water course or field channel. Water supply distribution to water courses (Quaternary canals) are highly dependent on outlet structures. Hence it is essential to design an outlet structure to be reliable and be also robust enough not easily demolished. These outlets must be constructed in a way that they should be operated at the minimum water level in the distributary canal.

In Koga, the quaternary canal outlets are buried pipes with the exit end free on air to the quaternary. The pipes are placed horizontally and at right angles to the center line of the tertiary canal. These types of outlets are categorized into semi-modular outlets. Because unlike non-modular outlets, the discharge through these outlets depend only on the water level of the tertiary canal but is independent of the water level in the quaternary canal so long as the minimum working head required for their working is available. However, in rare cases, there are also outlets whose pipe exit fully submerged by the water level at the quaternary canal.

Due to this the outlet discharge depends both on water level at tertiary and quaternary canals. These were faults during construction, and water users at these sites tried to solve the faults by reducing exit elevation through excavation.

3.3.2 Materials and Software Used

Materials used: the materials and devices used for the study are; a 90-degree notch thin plate weir, DischargeApp for measuring discharge at quaternary canals and TC off-take concrete weir for water level measurement at tertiary canal head.

Software and Packages used: R is the software environment used for data analysis and model developments, and RStudio is an Integrated Development Environment for R. It is an open source and freely accessible from the General public License (GPL). Version 3.6.1 of the R-software was used for this study. The Caret package (Classification and regression training) is a unified interface that attempts to streamline the process for developing machine learning models in R.

The applied machine learning models were trained and compared using a resampling technique in the Caret package with R programming. The package has basic tools for data splitting, pre-processing, feature selection, model tuning using resampling and variable importance estimation. Microsoft Excel 2016 was also used for data analysis to assess water delivery performance of canal outlets.

3.4 Data Analysis and Interpretation

3.4.1 Evaluation of discharge data measured by the DischargeApp

DischargeApp is a non-intrusive optical flow measurement technique used to measure quaternary canal flows in the present study. Before introducing the app to the water governors, it primarily needs to be evaluated with standard open channel flow measurement methods. A series of discharge measurements were made at quaternary canals using both the discharge application device and the 90-degree triangular notch weir at the same time, aiming to evaluate the accuracy of the DischargeApp at field conditions. The accuracy of the app was evaluated by Maxence et al (2019) under a controlled environment with laboratory flumes.

The surface flow velocity of the app is estimated by using an image sequence algorithm known as Surface Structure Image Velocimetry (SSIV), which is suitable for optical flow measurement with no need of particles called tracers on the channel flow. The vertical flow velocity distribution is estimated from the surface velocity fields using different approaches such as, a mixing length approach, which uses the roughness of the canal bed as a boundary condition and based on ISO standard recommendations. According to ISO standard EN ISO 748:2007, the average velocity of vertical section is calculated as,

$$\overline{\mathrm{V}} = \left(\frac{n_i}{n_i+1}\right) * \mathrm{Vs} \qquad \text{Eq.3.4}$$

Where, $n_i = \frac{\mathrm{Ndi}^{1/6}}{A*g}\left(\frac{2Ag}{Ag+\mathrm{Ndi}^{1/6}} + 0.3\right)$, N=Manning roughness coefficient of canal bed ($m^{1/2}$/s),

di = canal water depth(m), A= canal cross-sectional area (m^2), g = 9.81m^2/s, $\overline{\mathrm{V}}$ = average vertical flow velocity(m/s) and Vs = surface flow velocity(m/s).

The ISO standard recommends the value of the velocity coefficient factor, which is the average cross-sectional velocity and average surface velocity ranges between 0.8 and 1 for a given channel type. The current version of the DischargeApp uses constant velocity coefficient factor with a value of 0.8 for all types of channels.

Significance of regression relationship: From the total field discharge measurements by made by the app, only 76 observations were successfully uploaded to the discharge.ch web platform, and the same number of concurrent notch weir discharge observations were taken for the comparative study. These observations were not part of the 453 number of discharge datasets measured by the v-notch on a weekly basis.

A simple linear regression was used for the statistical analysis. Since the statistical analysis is between one predictor variable (App discharge) and one quantitative response (notch discharge), simple linear regression is the best approach. Mathematically, the linear relationship between the notch and app discharge data is described as,

$$Q_{vn} = ß_0 + ß_1 * Q_{app} + \varepsilon \qquad \text{Eq. 3.5}$$

where, Q_{app} is app discharge (l/s), Q_{vn} is notch discharge (l/s), ε is error term, $ß_0$ & $ß_1$ are coefficients representing the intercept and slope terms of the linear function respectively. Eliminating the intercept would give meaningful estimations. Because, for a nonzero intercept, the notch discharge estimated would have non-zero flows at zero flows when using the app.

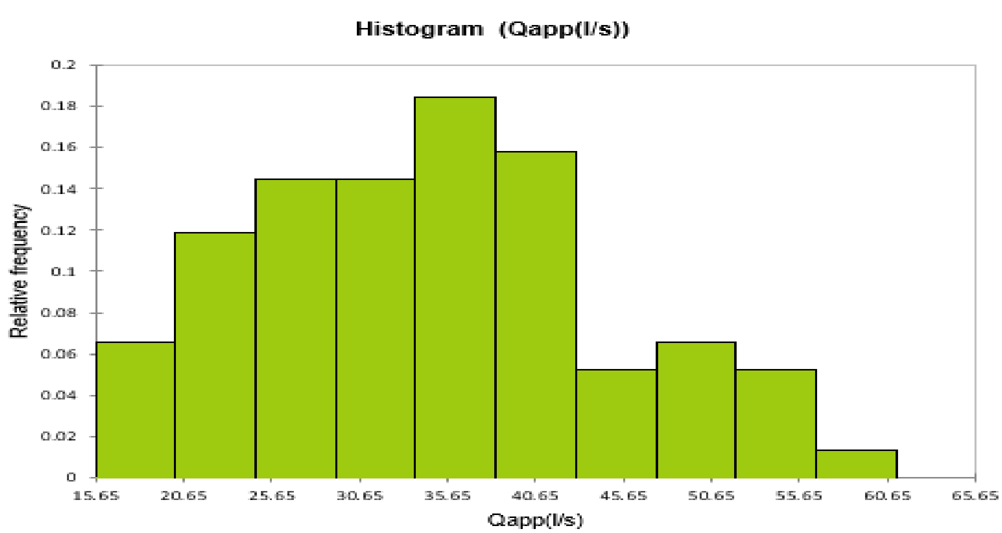

Figure 3-2: Relative frequency of app discharge

Figure 3.2 indicates that the relative frequency of the app discharge is high for observations between 25-40 l/s.

Hypothesis test: Before developing the linear relationship between the pairs of datasets, a hypothesis test for the significance of the association has to be made. Hypothesis tests on the coefficients were performed by using standard errors. The tests are:

Ho: null hypothesis, there is no relationship between Qvn and Qapp ($ß_1 = 0$) and

Ha: alternative hypothesis, there is some relationship between Qvn and Qapp ($ß_1 \neq 0$)

If the coefficient $ß_1 = 0$, then equation 3.5 is reduced to Q_{vn}= $ß_0$+ ε and there is no any association between the predictor and response variables.

Calculating t-statistics and P-value: the p-value at 95% significance level has to be smaller than 0.05 to reject the null hypothesis.

Measuring the strength of the regression: After rejecting the null hypothesis, the quality of the linear regression fit has to be evaluated through the root mean square error (RMSE) which is known as residual standard error, and coefficient of determination (R^2).

The RMSE describes the measure of the lack of fit for the model to the dataset. A small RMSE indicates that the predicted by the regression model is close to the actual values and the model fits the data very well. Coefficient of determination (R^2) is interpreted as how much of the variability of the response variable (notch discharge) is explained by the predictor variable (App discharge). R^2 is estimated as,

$$R^2 = 1 - \frac{\sum_{k=0}^{n}(\text{Qvn}-\text{Qapp})\text{ \^{}}2}{\sum_{k=0}^{n}(\text{Qvn}-\overline{\text{Q}}\text{app})\text{\^{}}2} \qquad \text{Eq.3.6}$$

where, Qapp is the app discharge (l/s), Qvn is the notch discharge (l/s) and $\overline{\text{Q}}$app is the average value of App discharge (l/s). It is an alternative measure of fit for the model over the RMSE. The RMSE is also calculated as,

$$\text{RMSE} = \sqrt{\frac{\Sigma(Qvn-Qapp)^{\wedge 2}}{n-1}} \qquad \text{Eq.3.7}$$

Where, n is number of observations. The RMSE has no clear sets to what it constitutes for the good fit whereas, the value of R^2 range between 0 and 1 and a value of R^2 close to 1 implies that large proportion of the variability of the notch discharge is well explained by the regression model.

Other statistics, like Akaike Information Criterion and Bayesian information criterion were also used to describe the quality of the regression model. However, it is advisable to use such performance criterions when the performance of two or more models need to be compared.

Accuracy of the App: The accuracy of the app discharge is well described by the percentage of the errors. The lower the percentage error, the higher is the accuracy of the app discharge. The percentage error indicates the deviation of the app discharge from the notch discharge, and it is calculated as,

$$\%\ \text{Error} = \frac{\text{Qapp}-\text{Qvn}}{\text{Qvn}} * 100 \qquad \text{Eq.3.8}$$

Where, % Error is the percent error, Qapp is the app discharge (l/s) and Qvn is the notch discharge (l/s).

3.4.2 Assessing Delivery Performance of Quaternary Canal Outlets

a) Existing Conditions of the Irrigation System

The outlet structures at quaternary irrigation canals were designed to supply a manageable discharge of 30 l/s, irrigating 2 ha of land for 12 hours operational time in each day. The field irrigation pattern was planned with a rotation among the users in a quaternary canal. The two parallel buried semi modular pipe outlets have same diameters of 0.15m and expected to deliver 15 l/s each. However, the measured discharge by the thin plate 90-degree v-notch weir, just downstream of these outlets show a significant spatial variation ranging between 2.4 to 47.6 l/s with average discharge measurement of 27.2 l/s.

On the other hand, the irrigated area in each quaternary canal varies between 6.7 and 16.5 ha. Thus, comparing the measured discharge with the intended flow is not meaningful unless the discharge is changed to irrigation duty (Qa) in l/s/ha, which makes sense to evaluate the spatial and temporal flow variability in terms of equity, adequacy and reliability across and within quaternary canals outlet structures.

Irrigation duty is the amount of discharge applied for a unit area of farm field. It therefore is estimated by dividing the outlet discharge in l/s by the irrigated area (ha) under the outlet.

The mean intended irrigation duty is also calculated by considering the 30 l/s discharge supplied by the parallel outlets, applied at 2 ha and operated for 12 hours with eight average days in an irrigation event.

The intended irrigation duty(Q) is therefore calculated as, Qd =30 l/s*1 day/2ha*event/8days, which is equivalent to 1.88 l/s/ha.

b) Evaluating Irrigation water supply variability at quaternary canal outlets

Based on the availability of secondary and measured water supply data, this study aimed at evaluating outlet structures of quaternary canals in terms of irrigation water supply equity, adequacy and reliability for same cropping season. To meet this goal, a total of 453 discharge and water level measurements were collected at 18 quaternary canal outlets and six tertiary canal off-taking points respectively, on a weekly basis throughout the irrigation period.

The weekly observations were then converted to the average monthly value to see the seasonal variation of water supply at different crop development stages. Three indicators were used to evaluate the water delivery performance of the Quaternary canal outlets; namely, Adequacy (Pa), Reliability (Pr) and Equity (Pe) performance Indicators.

Adequacy Performance Indicator (Pa): For this study, Pa can be defined as the ability of the outlet structure to supply the planned irrigation water to the water course (quaternary canal). For each measurement date and per outlet location, Pa is defined as the ratio of actual measured discharge to the intended discharge, which is called Delivery Performance Ratio (DPR). This was calculated based on Murray-Rust et al (2000) as,

$$DPR = Q_a/Q_d \qquad \text{Eq.3.9}$$

Where, DPR is the monthly delivery performance ratio at the outlets (dimensionless), Q_a is monthly average of measured water supply through the outlet (l/s/ha) and Q_d is the intended monthly average water supply through the outlet structure (l/s/ha). The monthly average of measured water supply was calculated at each outlet for months of January, February, March and April.

The adequacy performance indicator, Pa at each canal outlet was calculated by averaging monthly delivery performance ratio over the four months. A value of Pa close to unity implies that on average, the outlet structure was supplying the intended amount of irrigation water whereas a value of Pa less than unity shows inadequate or insufficient water supplied related to the planned amount. A value of Pa greater than one means surplus water supplied through the outlet structure.

Equity Performance Indicator (Pe): This is a spatial variability performance indicator which defines the variability in the delivery performance ratio over the time period. The coefficient of variation (CV) is used to evaluate the degree of this variability. The CV of the DPR over the months at each outlet is the spatial coefficient of variation. The spatial CV values are used to compare the flow uniformity across the outlets. The equation described by Sanaee et al (2016), was used to calculate Pe at a block level as,

$$\mathrm{Pe} = \mathrm{std.dev\ of\ DPR/Average\ of\ DPR} \qquad \mathrm{Eq.3.10}$$

Where, Pe is the equity performance indicator, std.dev of DPR is the standard deviation of the delivery performance ratio between the months and the average DPR is the average of the delivery performance ratio over the four months.

When the value of Pe is close to zero, the degree of spatial uniformity in water delivery is higher and indicates that there is fair share of water in the system.

As suggested by Murray-Rust et al (2000), the minimum discharge at distributary canal outlets should not be less than 70% and not more than 30% of design discharge value.

Reliability performance indicator (Pr): The variation in the delivery performance ratio at any location of the delivery system and over time periods is in fact the temporal variability performance indicator. The coefficient of variation of the DPR for a specific season over the outlets, either at blocks levels or overall scheme is the temporal coefficient of variation. It is used to compare the reliability of flow over the irrigation months. The Pr value is calculated by the coefficient of variation of the DPR over the block outlets to evaluate the temporal variability performance.

$$\mathrm{Pr} = \mathrm{DPR}_{\mathrm{std.dev}}/\mathrm{DPR}_{\mathrm{avg}} \qquad \mathrm{Eq.3.11}$$

Where, Pr is the reliability performance indicator, DPRstd.dev is the standard deviation of delivery performance ratio between the block outlets and DPRavg is the average of the delivery performance of the outlets in the block. The indicator Pr is a reliability performance measure and the closer the value of this indicator comes to zero, the more reliable the water delivery becomes over time.

For both spatial and temporal coefficient of variations, the lower the value of the CV is the higher the equity and reliability performances of the outlets respectively. The values of the CV less than 0.1, between 0.1-0.25 and greater than 0.25 are considered as good, fair and poor performances respectively to describe equity indicator whereas, allowable CV value for reliability performance is reduced from 0.25 to 0.2 (Molden & Gates,1990).

3.5 Development of Machine Learning Algorithms for predicting discharge

3.5.1 Data Description and Preparation for Machine Learning

a) Description of Parameters

The main objective of this study was to develop a predictive model for estimating the irrigation water supply at a quaternary canal outlet structure located at certain distance from the regulated off-take at the tertiary canal. Several parameters, which would affect the discharge at the outlet structures were investigated before developing the predictive model. These parameters were classified as geometric, hydraulic, distance and operational management factors.

The geometric factor includes type of the outlet structure (whether modular, semi modular or non-modular pipe outlet), the diameter of pipe outlet (d), type of distributary canal (lined or unlined), width of off-taking weir at tertiary canal head (B) and slope of buried outlet pipes (s). The hydraulic factor includes water level released at the regulated TC off-taking weir(H) and operational management factor contains the command area irrigated under each quaternary and tertiary canal, and number of outlets operated at a time along a tertiary canal. Distance of the outlet location from the tertiary off-taking head (l) was considered as a factor for estimating outlet discharge.

During field observations at Koga irrigation scheme, some parameters such as, type of outlet structure (semi modular), slope, and size (diameter is 15 cm) were found relatively uniform throughout the selected sites, and reduced after a rough model building stage from estimating discharge. Some parameters such as, irrigated command area (A) of a tertiary canal and of TC off-take weir (B) are repetitive terms in the quaternary canal outlets which are found in the tertiary canal. these parameters were combined with other parameters to make them a dimensionless term. The selected parameters involved for estimating discharge were:

$$Q \approx f(h, a, l, n, r) \qquad \text{Eq.3.12}$$

Where, Q= estimated discharge supplied by the QC outlet structure (l/s), h = water level per unit width at TC head weir($h = \frac{H}{B}$, dimension less), a = proportion of irrigated area under QC outlet from the total irrigated area under TC weir($a = \frac{A}{At}$, dimensionless), H = water level at TC off-taking weir(m), B= width of off-taking concrete weir structure(m), A= irrigated area under a QC outlet, At= total area irrigated under TC-off-taking weir(ha), l = distance of the outlet from the TC head (m), n = Manning roughness coefficient to represent TC canal type (dimensionless), and r = the ranking order of the operated outlets in ascending order along a TC (dimensionless) to describe the cumulative flow errors at the outlets u/s of the considered outlet. The width of rectangular TC head off-taking weirs at sites of koga scheme varies from 0.56m to 0.67m.

From the statistics of the variables on table 3.1, the range of values are extremely different from one variable to another one. Thus, the structure of the dataset requires to be transformed to an appropriate format.

Table 3-1: Statistical Summary of Variables

Variable	Unit	Number of Datasets	Minimum	Maximum	Mean	Std. deviation
Q	l/s	453	2.35	47.57	27.05	9.10
h	-	453	0.41	0.98	0.71	0.13
a	-	453	0.07	0.20	0.15	0.03
l	m	453	20.00	1734.64	665.19	517.26
n	-	453	0.02	0.03	0.02	0.00
r	-	453	1.00	7.00	3.51	1.85

b) Data Transformation

Data transformation is a data management process to change the structure of the set of data in the required format. The goal of transforming a set of data in machine learning is to facilitate faster learning of the algorithms. Unless the values of all variables have the same ranges, some machine learning algorithms like Artificial Neural Network would be malfunctioned to display the model performance criterion in the R programming.

Normalization is one of the simplest data transformation techniques, particularly used when seeking relationships in regression and multivariate analysis.

A maximum-minimum normalization technique was selected for this study to put the values of the variables in the predefined ranges between zero and one. The max-min normalization can be described as,

$$Xn = (Xi - Xmin /(Xmax-Xmin) *(b-a) + a \qquad \text{Eq.3.13}$$

Where, Xn is normalized data, xi is the observed values, Xmin and Xmax are the minimum and maximum values of the data respectively. The terms a and b are the predefined range values,0 and 1 respectively for the present study. After the predictions are performed, the variable values are denormalized to the original scale. The reason behind this is to develop the final model equation to directly estimate discharge based on the value of input variables.

c) Data partitioning

The data which contain 453 pairs of observations were split into training and testing data several times. The training and testing sets were partitioned into the percentage proportions of (70 ,30), (80,20) and (50,50) respectively.

3.5.2 Selection Criteria for Applied Predictive Models

Since there are several available models in the arena of machine learning, four basic criteria were used to select the candidate predictive models. The selection criteria were; accessibility of the algorithm, type of research problem to be addressed in the study, models performance and their interpretability.

Accessibility of algorithms: Caret (**C**lassification **a**nd **re**gression **t**raining) package is a unified interface of more than 238 packages to a single package for modeling and prediction of data. The Caret package is available in R software. The R environment has an immense number of packages for machine learning algorithms, which are designed with different naming. Since selection of models from several individually named machine learning algorithms is much difficult and time consuming, the caret package was selected to train and make comparisons of many algorithms at a time using a resampling technique. This was also the criteria to select R software, where caret is found, from other softwares such as, Matlab and Python.

Type of research problem: Since the aim of the study was to develop a predictive model which allow to estimate discharge at canal outlets using the available information, a quantitative output was required from the collected labeled data. Thus, the research problem was a multivariate supervised machine learning problem which required a regression model approach. There are also several regression supervised machine learning models which are further categorized into linear, nonlinear, and tree-based regression types. The nature of the available data structure was used to select the type of regression models. The input parameters in the dataset failed to show linearity trends with the output variable and the relationship was complex.

The nonlinear regression models, which include multivariate adaptive regressions, support vector machines, artificial neural networks and k-nearest neighbors, and tree-based regression models such as, decision tree, bagging tree, random forest and boosting were reviewed based on the aforementioned above criterion.

Model Prediction Performance: Pre-selection of machine learning models using this criterion was mostly literature based. Though prediction performance of a model is different based on the data type and the training method, some classic regression models performed high prediction quality in the recent Irrigation Engineering studies, which are nearly similar to the present study.

Several supervised machine learning models were reviewed in accordance to the targeted research problem. Artificial neural network was applied (Gu et al, 2017) to develop the yield-irrigation water model for predicting accurate corn yield in drip irrigations. Regression models such as, multivariate adaptive regression splines (MARS), artificial neural network (ANN), and support vector machine (SVM) were applied (Haghiabi et al, 2018) for prediction of discharge coefficient of lateral intakes the irrigation and drainage networks, and all models relatively gave high prediction performance.

Interpretability of Models: Though the models are developed to achieve high predictive performance, they should be interpretable as well. Interpretability of a model in the present study is defined by answering the questions such as, how does the model work? and what the predicted results tell us? The first question refers the level of model black-box ness, which is usually known as model transparency. Model transparency is the understandability of the model in the process of the desired predictions.

During running for prediction, some models are less complex as they give explanations for each modelling steps and outputs while other models have high computational complexity, even the explanations they give are not interpretable. The second question in model interpretability is used to answer the understandability of the model outputs, such as the developed model equations and computational results of model terms. Machine learning models such as, deep learning neural networks and tree-based classifiers lack to generate predictive equations whereas other models like, multivariate adaptive regressive splines develop prediction equations.

The degree of interpretability for the model results is different from one model to the other. The present study tried to optimize all the aforementioned model selection criteria to select the final model having prediction equations. Considering the first three model selection criteria, the selected and developed classic machine learning models are; Multivariate Adaptive Regression Splines (MARS), Artificial Neural Networks (ANN), Support Vector Machines (SVM) with radial basis, Random Forest (RF), K-Nearest Neighbors (KNN), Extreme gradient Boosting Tree (XGBT) and a basic decision tree called Classification and Regression Trees (CART).

3.5.3 Developing Machine Learning Predictive models

In this study, the motive behind applying predictive machine learning models was their strong ability to map and learn the input data to predict the desired output where other methods such as multiple linear regression could not perform the prediction well. Though linear regression method is easy to perform and simple to understand, the main target such studies is to achieve high prediction performance at the first hand and also easily understandable models in the second hand.

a) Methodology for Model Development

The task of developing a predicting model was started by loading the caret packages and related features for the candidate machine learning models. The following procedures were used to develop the final model for estimating canal outlet discharge:

Step 1. Load the package and dataset: this was the first step in the modelling process. The packages of the candidate models were first installed on the R software. Figure 3.3 describes the flow chart for model development procedures.

Step 2. Data preparation and pre-processing: In this step, the basic tasks are splitting the dataset into training and testing sets and transform the dataset to the required data structure.

Step 3. Visualize the importance of variables: After data preprocessing is completed, the data is visually examined how the predictors influence the response variable using feature plots.

Step 4. Feature selection using recursive feature elimination: This step is used to determine significantly important predictors in predicting discharge. Recursive feature elimination is best in selecting the important features using three important stages: the first stage is building a machine learning model on a training dataset and estimate the feature importance on the test dataset. The next stage is keeping priority to the most important variables, iterate through by building models of given sizes, and ranking of the predictors is recalculated in each iteration. Finally, the model performances are compared across different subset sizes to arrive at the optimal number and list of final predictors.
In this study, a repeated 10-fold cross-validation was used to split the data into 10 subsets and repeat 3 times to quantify the model errors by averaging the repeated errors. This technique finally selects top three important variables for the modelling process and need to eliminate the rest variables. Since machine algorithms have their own way of learning the relationship between the x and y, eliminating the least important variables using feature selection with recursive feature elimination technique is not advisable as this stage masks the variable importance at each algorithm.

Step 5. Model Training and tuning**:** The candidate models were individually trained using the training dataset. The performance of trained models was displayed together using a resampling method. Parameter tuning, which is also known as hyperparameter optimization is the process of selecting the constraints such as, the weight of parameters, number of parameters and the learning rate, which are guided by the user to control model learning process. Since different machine learning algorithms requires different constraints and, Caret default tuning of parameters were used in the modelling process.

Step 6. Compare multiple machine learning algorithms: The trained models are compared using regression evaluation techniques such as, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and coefficient of Determination(R^2).

Step 7. Prediction of models using test data set: The last step of the modeling process was prediction of data the testing datasets. A model which performed best was then selected for predicting discharge at canal outlets, keeping other selection criteria into consideration.

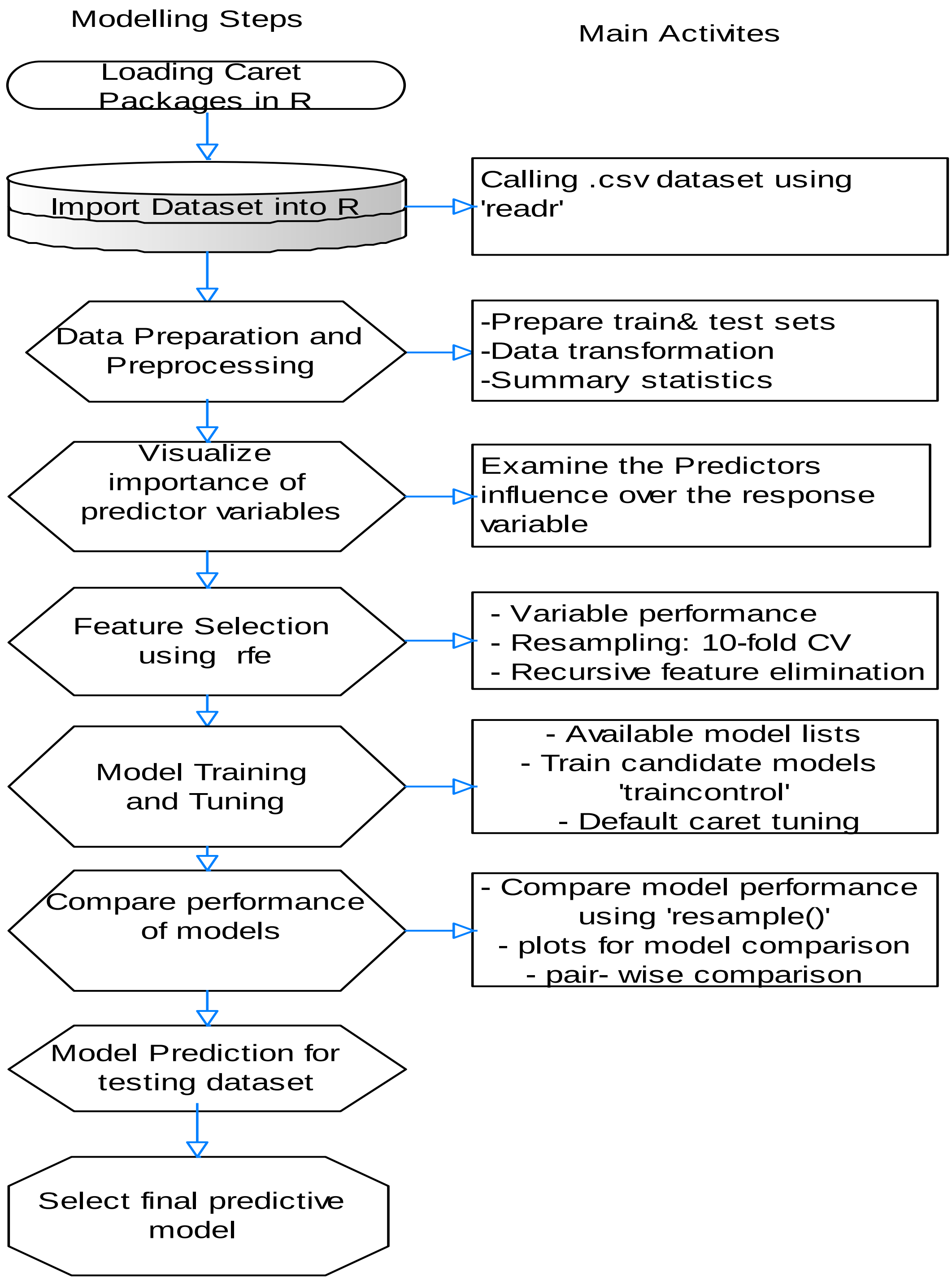

Figure 3-3: Flow chart for model development

b) Developing Multivariate Adaptive Regressive Splines (MARS) Model

MARS is a nonparametric statistical method which develops functional relationships between dependent and independent variables by splitting the training data into separate linear segments called splines with different gradients(slopes). When the piecewise splines are connected smoothly and make basic functions (BFs). These result a model which can handle both linear and nonlinear behavior. The MARS has relatively high ability for mapping input parameters and desired outputs, and developing simple but robust model and rational in term of computational cost. The model generates basic functions by stepwise searching overall possible univariate candidate knots and across interactions among all variables. An adaptive regression algorithm is adopted for automatically selecting the knot locations. This algorithm involves a forward phase and a backward phase. The forward phase places candidate knots at random positions within the range of each predictor variable to define a pair of basic functions (BFs). At each step, the model adapts the knot and its corresponding pair of BFs to give the maximum reduction in sum-of-squares residual error. This process of adding BFs continues until the maximum number is reached, which usually results in a very complicated model. The backward phase involves deleting the redundant BFs that made the least contributions.

For a response variable Y and matrix of predictor variables $X = (x_1, x_2, x_{3\ldots}, x_p)$, the general form of the function derived from MARS model is written as an adaptive function as.

$$Y = f\,(x_1, x_2, x_{3\ldots}, x_p) + \varepsilon = f(X) + \varepsilon \qquad \text{Eq.3.14}$$

Where, ε is the fitting error, f (X) is the built MARS model comprising of basic functions (BFs) which are splines piecewise linear functions, which is used in this study with the form,

Max (0, x-t) with a knot defined at the value t. Max means the maximum, which is the positive part inside it, otherwise it is assigned a zero value. That is, max (0, x-t) = x-t if $x \geq t$ otherwise, 0.

The MARS model f (X), which is a linear combination of BFs and their interactions is expressed as,

$$f(\mathrm{X}) = \beta o + \sum_{m=0}^{M} \beta_{\mathrm{m}}\ \mathrm{BF}_{\mathrm{m}\,(}\mathrm{X}) \qquad \text{Eq.3.15}$$

Where, BF = Basic Function, β = constant coefficient terms estimated using the least square method.

The backward phase improves the model by removing the less significant terms until it finds the best sub-model. Model subsets are compared using the less computationally expensive method of

Generalized Cross-Validation (GCV). The GCV is the mean-squared residual error divided by a penalty that is dependent on model complexity. For the training data with N observations, GCV is calculated as,

$$GCV = \frac{SSE}{n(1-\left(\frac{C(B)}{n}\right)^2} \qquad \text{Eq. 3.16}$$

Where, C(B) = (B+1) +dB, and n= number of records, SSE = sum of square of residuals, C(B) = difficulty criteria.

3.5.4 Evaluation Criteria for applied Machine Learning Models

Evaluation of models refers to describing how well the trained model is performing to predict the targeted problem. In machine learning, the metrics of evaluating regression models are different from the classification models. The most common evaluation metrics in regression models, which are used for the present study are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Coefficient of determination(R^2). Mean Absolute Error (MAE) is the average of the difference between the observed and predicted over the whole dataset, which is described as,

$$MAE = \frac{1}{n} \sum_{I=0}^{n} (y_i - \bar{y}) \qquad \text{Eq.3.17}$$

Where, n is number of observations in the dataset, y_i is the observed data and $\bar{y}$ is the predicted value of y_i. The Coefficient of determination($R^{2)}$ and root mean square error (RMSE) are calculated according to equation 3.6 and equation 3.7 respectively.

The model with the highest value of R^2, smallest values of RMSE and MAE is highly performed and best fit model to the dataset. When the values of R^2 for two models are equivalent, the model with smaller value of the RMSE, which describes the measure of the lack of fit the model to the dataset is selected. In case, when the two metrics for the models resulted differently, the model with the smaller value of RMSE has given priority for final model selection.

4 RESULT AND DISCUSSION

4.1 Evaluating the Accuracy of the DischargeApp

The accuracy of the App discharge measurement was evaluated at low flow canals in comparison to the 90-degree notch weir. The measured discharge using the App varies between 15.65 and 60.18 l/s.

Table 4-1: Descriptive statistics

Variable	Description	Observations	Min	Max	Mean	Std. dev
Qapp (l/s)	App discharge	76	15.65	60.18	34.57	10.33
Qvn (l/s)	Notch discharge	76	15.26	49.89	31.18	7.91

App Accuracy: The accuracy of the app discharge is well described by the percentage of errors. The error indicates the deviation of the app discharge from the notch discharge. From the total discharge observations, 88.2 percent of the app discharge measurements were exceeded the notch discharge. The mean absolute error and mean percent error of the app discharge were ±3.8 l/s and ±11.5 percent respectively. To elaborate this in regular intervals, 21, 40.8,66, 89.5 and 100 percent of measured discharge data showed percent errors smaller or equal to ±5, ±10, ±15, ±20 and ±25 percent respectively. The percentage error was high at relatively high flow conditions.

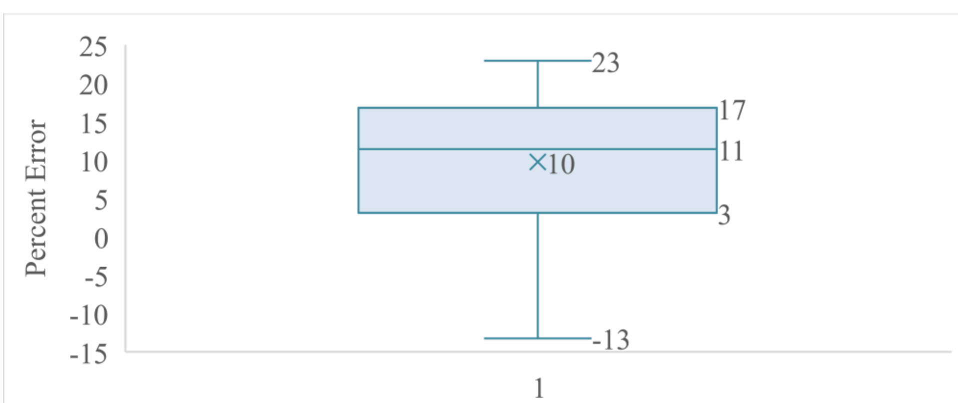

Figure 4-1: Percentage Error of App discharge measurements

Calibration Equation: A regression equation was developed between the two flow measurement techniques. A significance test was made to check the linear relationship between the notch and app discharge. At 95 percent significance level, the absolute value of t-stat is 7.51, which is greater than 1.96. The p-value is much smaller than 0.05 and thus there is a significant linear relationship between the app and the notch discharge dataset. From the values of residual standard error on n-2 degree of freedom, the root mean square errors, RMSE is 1.77 and coefficient of determination (R^2) has different values when considering the intercept (R^2 = 0.95) and removing it (R^2 = 0.91). The aim of removing the intercept value is to give a real meaning for the calibration equation of equation 3.5. When the value of the intercept is non-zero and the value of the app discharge remains zero (no flow), the estimated notch discharge has yet showed non-zero flows (there is a flow). Thus, the developed linear relation between the app discharge and the notch discharge should be without intercept, that is, as no discharge using the app measurement method, also no discharge using the notch method. The result of R^2 thus implies that 91 percent of the discharge measured by the notch is well explained by the app discharge measurement.

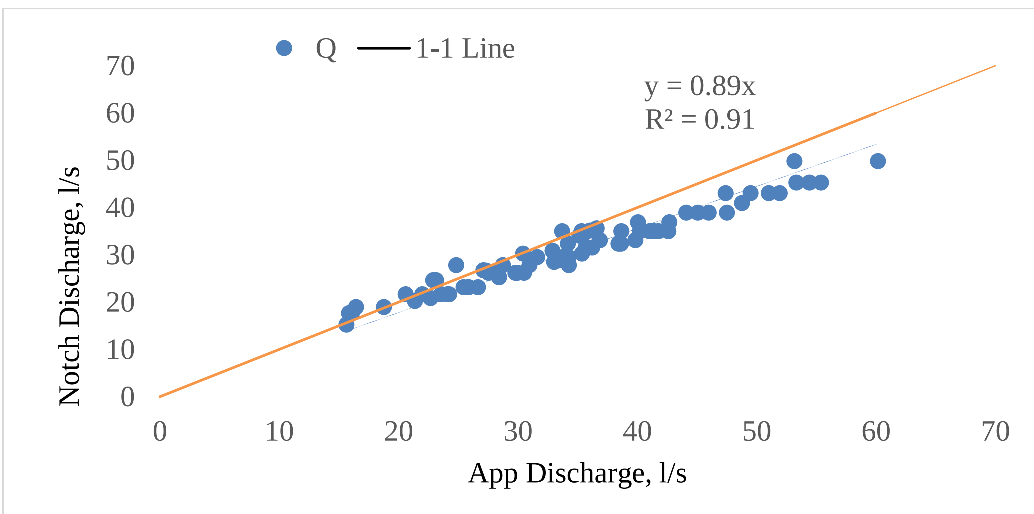

Figure 4-2:Notch discharge vs App discharge measurements

On figure 4.2, the equation y =0.89*x is the developed calibration equation, where, y and x are the notch and app discharge measurements in l/s respectively.

Figure 4.2 also describes that the dot points decline far below the 1-1 line as it the app discharge goes higher. This implies that the app measurement overestimates the notch discharge at high flow conditions, and fits good at low flow measurements.

The result of the present study contradicts with the latest laboratory experimental study result done by Maxence et al (2019). The study of Maxence et al (2019) was made in the controlled hydraulic laboratory flume, which has a canal section representing lined irrigation canals with flow rates of 20-120 l/s. The result reflected that that the app discharge had errors at low flow conditions whereas, in the present study it was evaluated at unlined irrigation canals with flow rate between 15-65 l/s, and the degree of error is smaller at low flow conditions.

Since the DischargeApp device overestimates discharge relatively at high flow conditions in a purposive manner, this study investigated the trend of this error. It was found that the ratio of average vertical velocity and mean of the streamwise surface velocity remains the same in all measurements with a value of 0.8, which is in reference to the ISO standard method. This value is the correction coefficients of the floating (surface) velocities, which do not rely on water depth of the canal for this case.

The U.S. Department of the Interior Bureau of Reclamation, USBR (2001) had developed a relationship between water depth and float velocity coefficient factor as shown on figure 4.3. When this method is applied in this study, the accuracy of the app discharge measurement was improved.

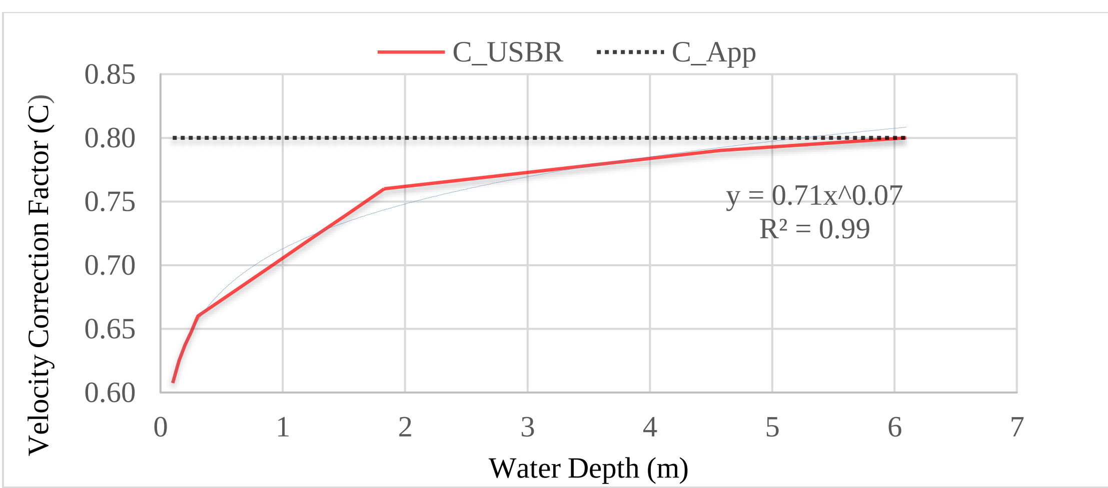

Figure 4-3: Power Curve of Surface Velocity Coefficients

C_USBR = float velocity coefficient factor used by USBR (2001), C_App = surface velocity coefficient factor(C_App =0.8), y = surface velocity correction coefficient (C) and x = water depth of a channel (m).

The new app discharge (Qapp') is estimated by dividing the previous app discharge by its constant surface velocity factor and then multiplying by the surface velocity coefficient factor estimated by the USBR (2001) power curve equation shown on figure 4.3.

The mean discharge deviation of the improved app measurements from the notch discharge ranges within ±2.1 l/s. Despite of exaggerated errors only at three observations, 84.2 and 92.1 percent of the observed discharge remain within the error values of ±10 and ±15 percent respectively. The mean error value is ±7.1 percent (Figure 4.4)

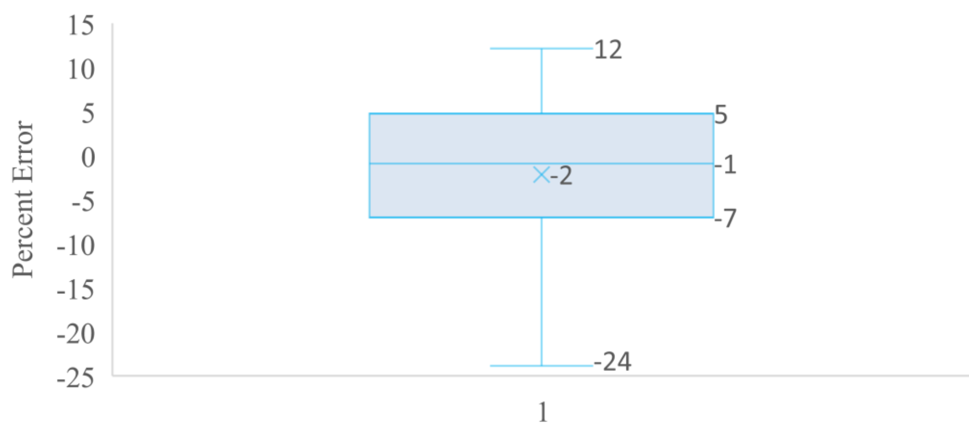

Figure 4-4: Improved Percent Error of App discharge measurements

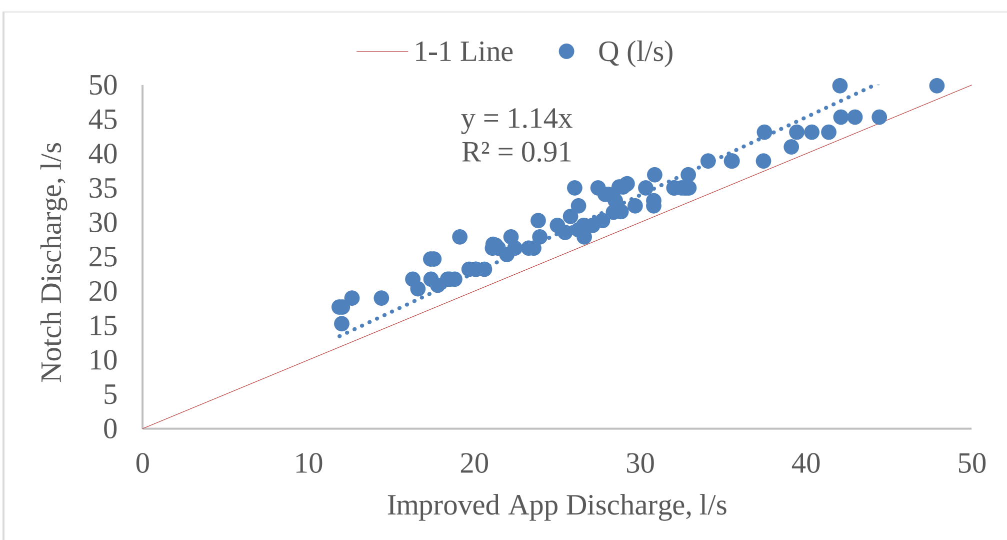

Figure 4-5:Notch discharge Vs improved App discharge measurements

Qvn and Qapp' are the notch and the improved app discharge measurements in l/s respectively.

As shown on figure 4.5, all the recalculated app measurements against the notch discharge measurements lie above the 1-1 line tangentially. This implies the new app measurements (Qapp') slightly underestimate the notch discharges in a consistent manner. Generally, by changing the method of estimating mean vertical flow velocity from ISO standard constant value method to the USBR (2001) water depth based velocity correction coefficient, the accuracy of the app discharge is improved through increasing the percentage of observed discharge data from 66 to 92.1 percent lying within the error range of ±15 percent and the mean discharge deviation reduced from ±3.8 l/s to ±2.1 l/s.

During flow measurements using the DischargeApp, the width of a canal section and the disctance between the markers placed at the canal banks were inserted to the app device. Yet, the offshore disctance, which is the distance between the canal edges and the markers remain user defined. This led to manual calculations and be source of errors to process the discharge estimations by the app.

With the aforementioned above limitations, this study found that DischargeApp is both accurate and adaptable for varied flow operation conditions with no maintenance and installation costs.

4.2 Water Delivery Performance of Quaternary Canal Outlets

There was significant variation of water supply duty (l/s/ha) delivered through quaternary canal outlets. The seasonal average of water supply over the whole irrigation season varied from 1.28 l/s/ha (Chi0206) at tail outlet of Chihona to 2.60 l/s/ha (Adi1004) at the middle outlet of Adibera block. This mean that the most favored irrigation outlet was supplying more than two times of the least favored tail outlet. The dashed horizontal line on figure 4.6 represents the design water supply at quaternary canal outlet structures. Fifty percent of the outlet structures was delivering water below the intended flow of 1.88 l/s/ha. Five outlets out of six head canal outlets, were supplying water more than the intended one whereas, four outlets out of six middle and tail canal outlets each, were delivering irrigation water supply less than the intended irrigation water.

The arrangement of blocks as shown on figure 4.6, from left to right is at their spatial position in reference to the dam of the irrigation scheme. The head (Chihona and Kudmi), middle (Adibera and Tagel) and tail (Andinet and Teleta) reaches of the irrigation scheme were accordingly represented.

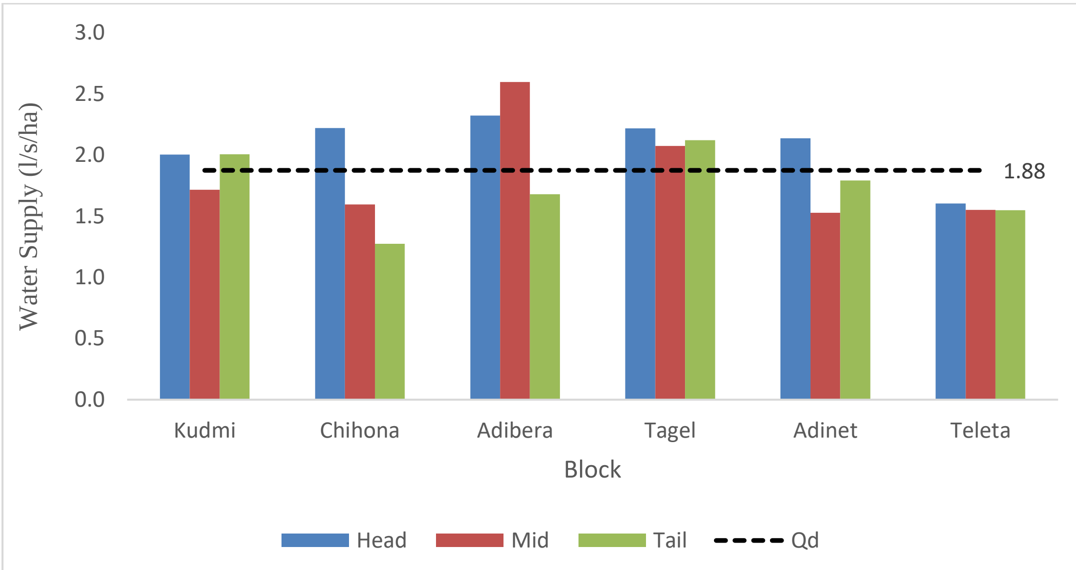

Figure 4-6: Water Supply Variation at quaternary canal outlets

At block level, the average value of water supply delivery decreases from head to tail quaternary canal outlets along a tertiary canal with values at head (2.08 l/s/ha), middle (1.84 l/s/ha) and tail (1.74 l/s/ha). Three indicators were used to evaluate the water delivery performance of the quaternary canal outlets; namely, Adequacy (Pa), Reliability (Pr) and Equity (Pe) performance Indicators.

a) Adequacy Performance Indicator (Pa)

The adequacy performance indicator (Pa) of water supply canal outlets was calculated as the spatial average of delivery performance ratio (DPR). Delivery performance ratio of QC outlets varies between 0.68 and 1.39. The value of DPR close to unity implies an ideal outlet water delivery performance. The lowest value (at Chihona) implies that there was water supply insufficiency at the outlet and the highest value (at Adibera) indicates there was surplus water supplied at this outlet.

The box plots on figure 4.7 reflects that water delivery performance of outlets along a tertiary canal is relatively uniform at Tagel and Teleta block whereas, it is significantly varied at Chihona and Adibera blocks.

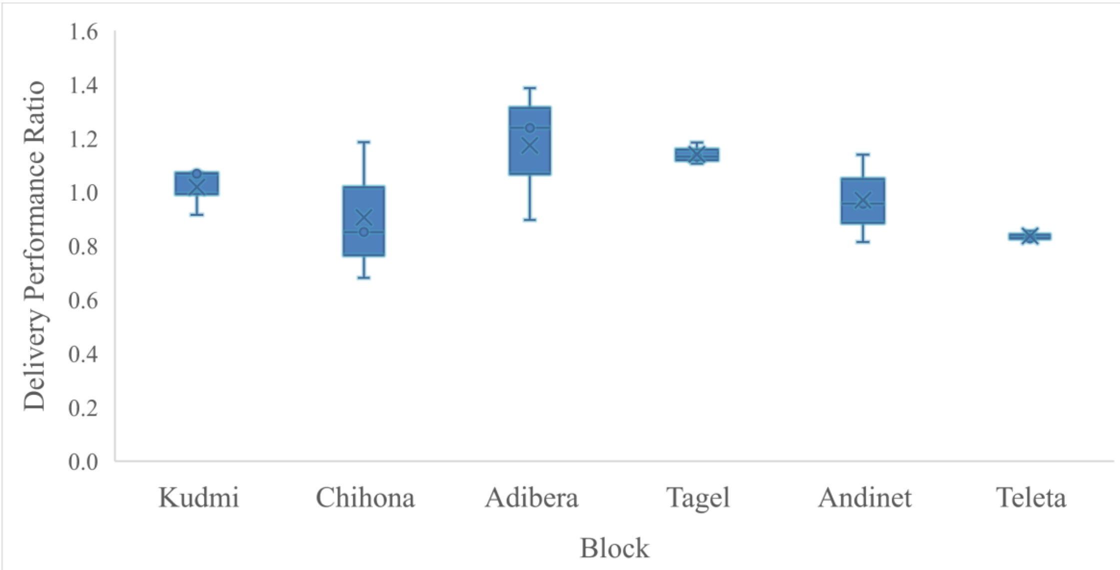

Figure 4-7: Spatial DPR at quaternary canal outlets

At block level, the average DPR value varies between 0.84 (at Teleta) and 1.17 (at Adibera). Murray-Rust et al (2000) suggested that irrigation canals should get at least 70%, but not surpluses more than 10% of the intended discharge. Thus, to have a satisfactory water supply, the DPR values has to be between 0.7 and 1.1. The outlets with the DPR value greater than 1.1 were supplying excess water whereas, those outlets resulting a DPR values less than 0.7 were getting insufficient (only 70% of the intended discharge) discharge, and are fallen under poor adequacy performance outlets. Figure 4.8 shows that all blocks, except Adibera and Tagel scored satisfactory results in terms of water supply adequacy. Adibera and Tagel blocks were supplying 17% and 14% of excess water respectively.

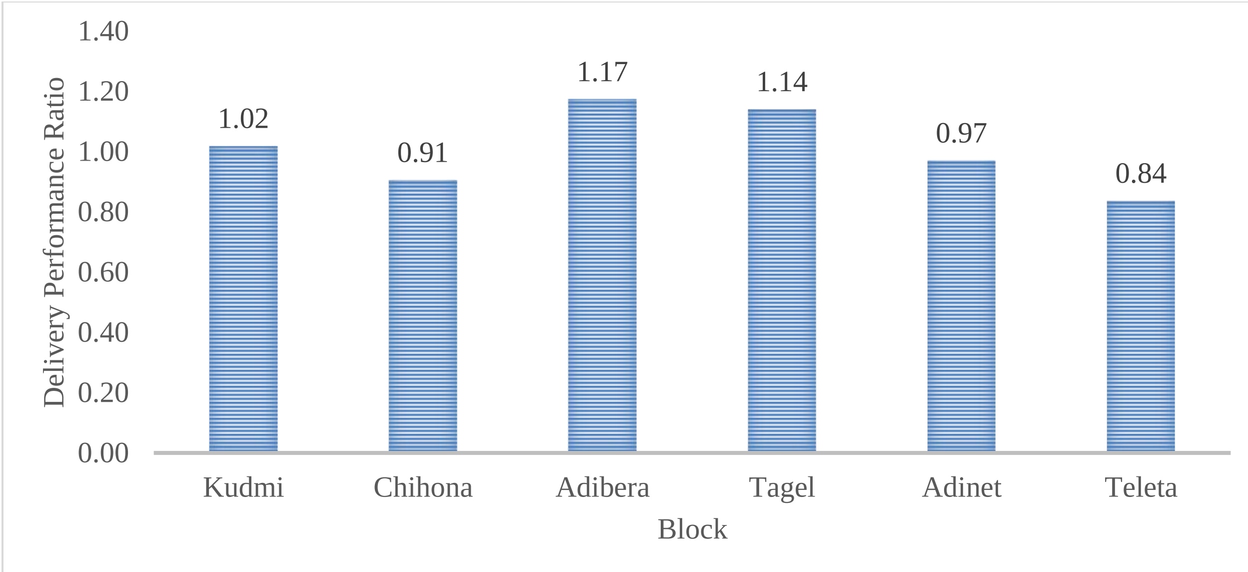

Figure 4-8: DPR of canal outlets at block level

b) Equity Performance Indicator (Pe)

The Equity performance indicator is used to measure the degree of flow variability at canal outlets. The spatial coefficient of variation (CV) is the coefficient of variation of the average DPR over the irrigation months, which is considered as equity performance indicator. In accordance to Molden and Gates (1990), the values of CV less than 0.1, between 0.1- 0.25 and greater than 0.25 are considered as good, fair and poor equity performances respectively. The value of CV close to zero implies that the irrigation canal outlet is supplying the intended discharge well. Molden and Gates (1990) also suggested that a water supply in irrigation systems with values of coefficient of variation up to 0.25 is allowable. The results at figure 4.9 reflects that fourteen out of eighteen quaternary canal outlets were supplying irrigation water within the allowable flow variation over the irrigation months. All canal outlets at Teleta block, which is the most tail reach block in Koga irrigation scheme scored high flow variations over the irrigation months. During field observations, it was seen that water users in Teleta block were claiming for the shortage and irregularity of water flows to their fields. When they complained much, operators released to compromise the condition, but they did not last long to operate the same flow throughout the irrigation season in accordance to the demand, which would be the possible reason for high flow variability in this block.

The highest coefficient of variation (CV=0.43) is yet at the middle outlet of Andinet block. The possible reason for the highest flow variation at this outlet is that the monthly water supply was decreased in the month of April, due to crop harvesting at many farm fields in the block.

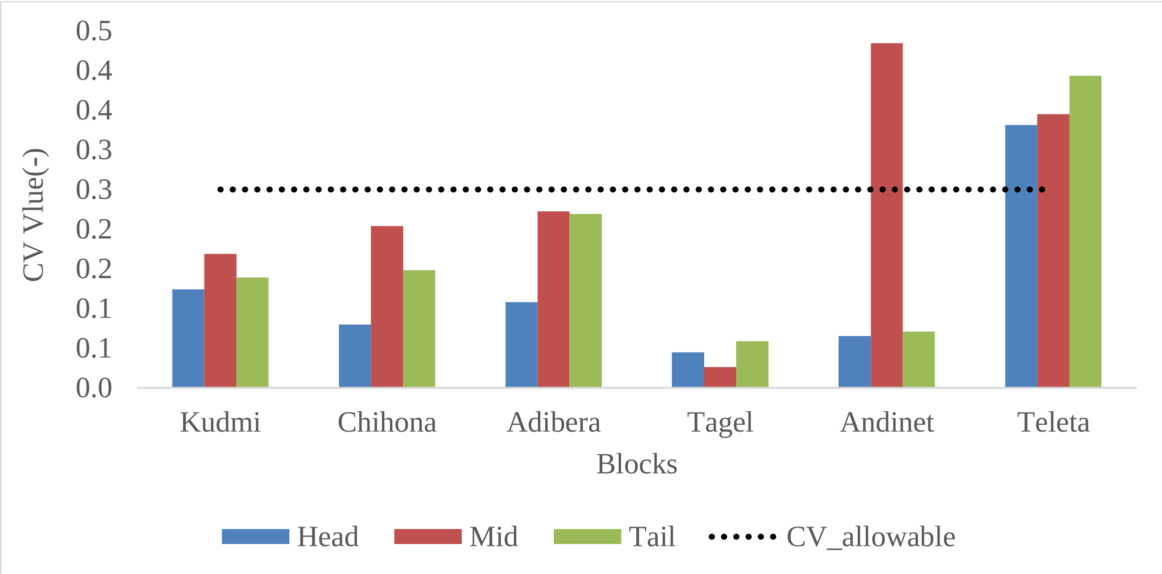

Figure 4-9: Spatial flow variability at quaternary canal outlets

c) Reliability performance indicator (Pr)

The reliability performance indicator measures the temporal variability of water supply through canal outlets. It was calculated using the coefficient of variation of the average delivery performance ratio over block outlets. At a block level, the maximum flow variations for the irrigation months of January and February were observed at Chihona (CV=0.48) and Adibera (CV=0.29) block respectively whereas, for the March and April the maximum variation was at Andinet block with CV values of 0.33 and 0.31 respectively. The temporal coefficient of variation in all months at Teleta, Tagel and Kudmi blocks remain within the allowable flow variation range (CV=0.2). Though the canal outlets at Kudmi, Tagel and Teleta blocks had a reliable water supply throughout the irrigation season, it does not mean that they were supplying adequate water at the whole Irrigation period (Figure 4.10).

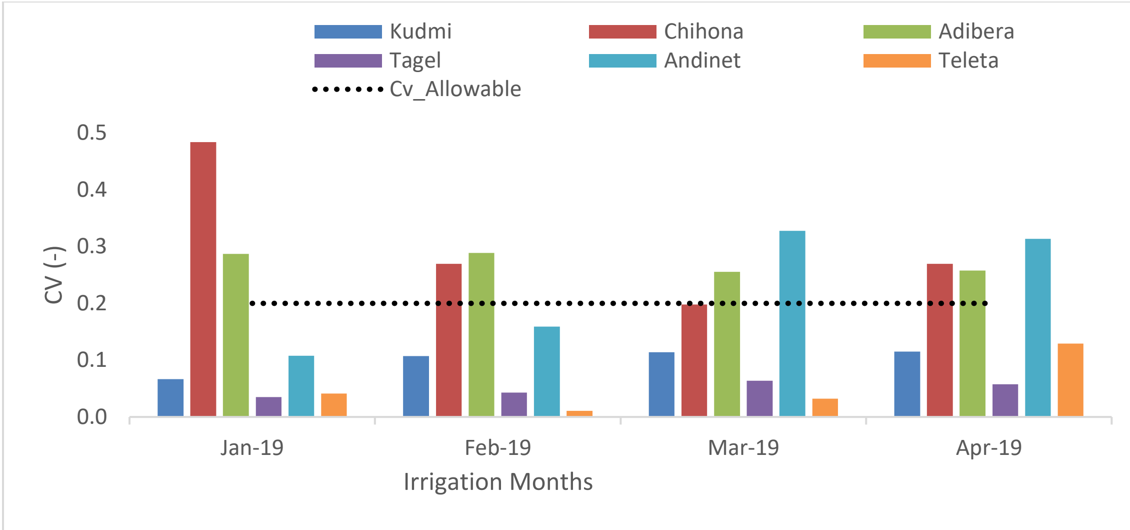

Figure 4-10: Temporal flow variability at Blocks

The three water delivery performance indicators at block level are summarized as shown on table 4.2. The green, yellow and red grid cells are used to indicate good, fair and poor delivery performance status of the blocks respectively. Accordingly, Adibera block failed to score good results in all three performance indicators (adequacy, equity and reliability performance indicators). Despite of the surplus water supplied through the outlets, both spatial and temporal flow variability was good at Tagel block (Table 4.2).

Table 4-2: Measured water delivery performance indicators at Block level

Indicator	Good	Fair	Poor	Kudmi	Chihona	Adibera	Tagel	Andinet	Teleta
Pa	[0.9-1.1]	[0.7-0.9)	>1.1& <0.7	1.02	0.91	1.17	1.14	0.97	0.84
Pe	<0.1	[0.1-0.25]	>0.25	0.14	0.14	0.18	0.04	0.19	0.36
Pr	<0.1	[0.1-0.2]	>0.2	0.1	0.31	0.27	0.05	0.23	0.05

Pa = Adequacy delivery Performance Indicator, Pe = Equity delivery Performance Indicator and Pr = reliability delivery performance indicator.

4.3 Comparison of Models for predicting discharge at Canal Outlets

4.3.1 Variable Importance of Models

A randomized splitting of the data was made several times, into (70,30), (80,20) and (60,40) percent for training and testing sets respectively. Since all trained models performed relatively high at 70 and 30 percent data partitioning proportion, it was used for further modeling process.

Five predictor variables, namely; water level per unit width(h), command area ratio(a), distance of outlets from TC head(l), Manning roughness coefficient of TC canals(n) and rank of operated QC outlet along a TC(r) were used to predict a response variable Q (outlet discharge). To examine how the predictors, influence the output discharge(Q), importance of variables was computed in R programming with caret for each model. The importance level of predictor variables was different for each model.

The caret package in the R programming does not support variable importance (VarImp) for support Vector Machine with radial basis function (SVM) and K-nearest neighbor models. Variable importance for the rest five models is shown on Figure 4.11.

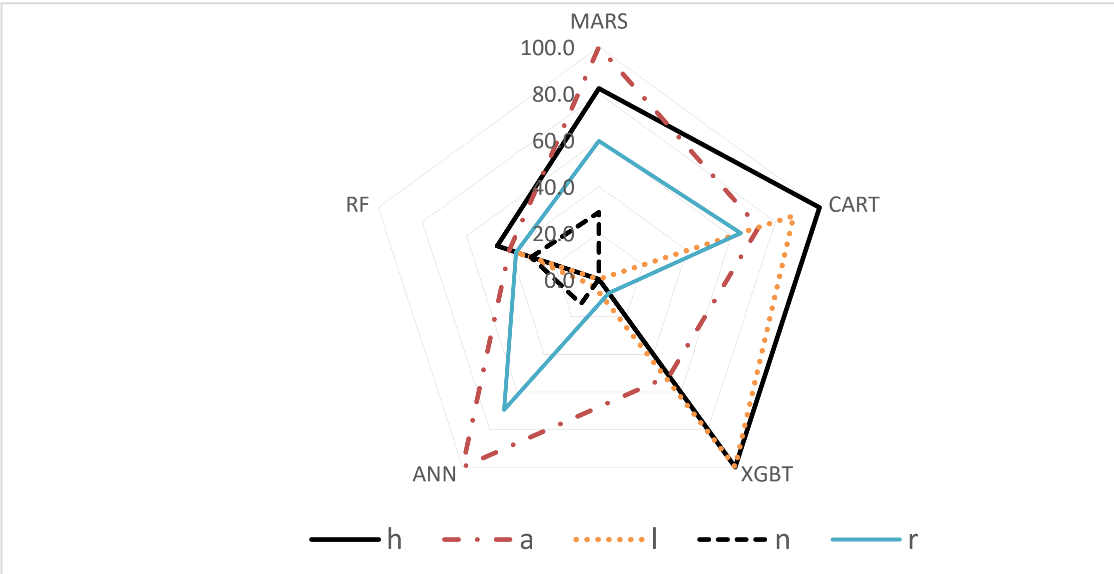

Figure 4-11: Variable Importance for trained models

In figure 4.11, MARS is Multivariate Adaptive Regressive Spline, RF is Random Forest, XGBT is Extreme Gradient Boosting Tree, CART is Classification and Regression Tree and ANN is Artificial Neural Networks.

The output variable (Q) is highly influenced by water level per unit width(h) for the RF, CART, and XGBT models whereas this predictor variable was given least priority of variable importance by ANN model. The area ratio(a) was given the first variable importance level for MARS and ANN models. Cumulative distance of a canal outlet(l) is less important at MARS model. The recursive feature elimination (rfe) with 10-fold cross validation resampling technique selects h, l and r as top three variables over the subset size. The recursive feature selection agrees with the variable importance selection of XGBT model. Selection of variables with the rfe technique and eliminating the bottom least selected variables is not advisable as different models have different variable importance levels.

4.3.2 Performance Evaluation of predictive Models

a) Training stage of models

Among the trained models with the transformed data, the highest model performance was Random Forest, RF (RMSE=0.073 and R^2=0.87) followed by Support Vector Machine with radial basis, SVM (RMSE = 0.074 and R^2 =0.86) and Multivariate Adaptive Regression Splines, MARS (RMSE=0.075 and R^2=0.86). Figure 4.12 from top to down shows the increasing order of model performance in the training dataset. The performance of all the trained models, except CART have no significant differences. The two relatively low performance models were Classification and Regression Tree, CART (RMSE=0.160 and R^2 = 0.37) followed by the K-Nearest Neighbor model, KNN (RMSE=0.078 and R^2 = 0.84). Since Mean Absolute Error (MAE) computes the average magnitude of error between predicted and actual values with no distinction between error direction, the first two regression performance metrices (RMSE and R^2) are merely enough to compare the models. However, when two models have same values of RMSE and R^2, a model with smaller value of MAE can be selected.

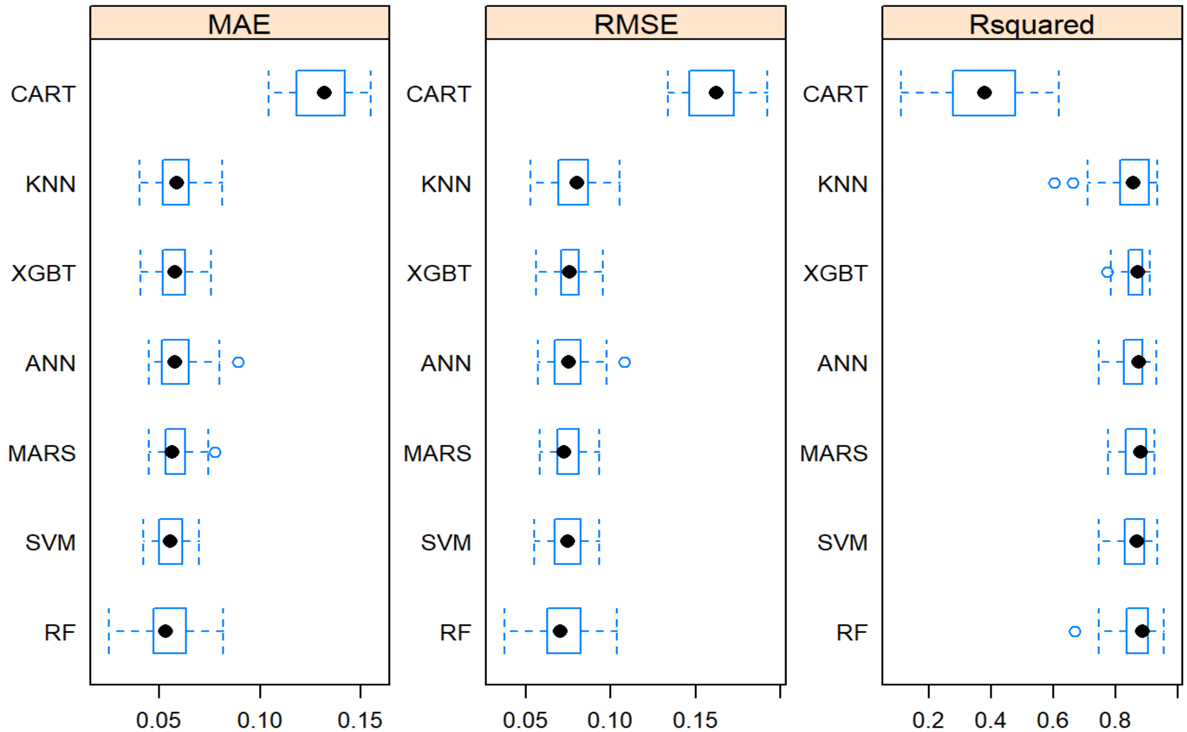

Figure 4-12: Comparative performance of Machine Learning models at training stage

b) **Prediction of models with test data**

From the randomized split dataset, which was partitioned three times with different proportions, 134(30%) pairs of data were used to check the prediction performance of the models. The transformed test set data was used for prediction, and finally the predicted outputs of the models were rescaled (denormalized) to the original data structure. Table 4.3 shows the performance of machine learning models at the test stage.

Table 4-3: Performance of Models with Test dataset

	MARS	ANN	XGBT	CART	SVM	KNN	RF
R^2	0.85	0.84	0.83	0.41	0.84	0.84	0.86
RMSE	3.48	3.54	3.88	5.59	3.42	3.64	2.98

The optimal model at the test stage was still Random Forest, (RMSE = 2.98 and R^2 = 0.86), followed by Multivariate Adaptive Regressive Splines (RMSE = 3.48 and R^2 = 0.85) and Support Vector Machine (RMSE = 3.48 and R^2 = 0.84).

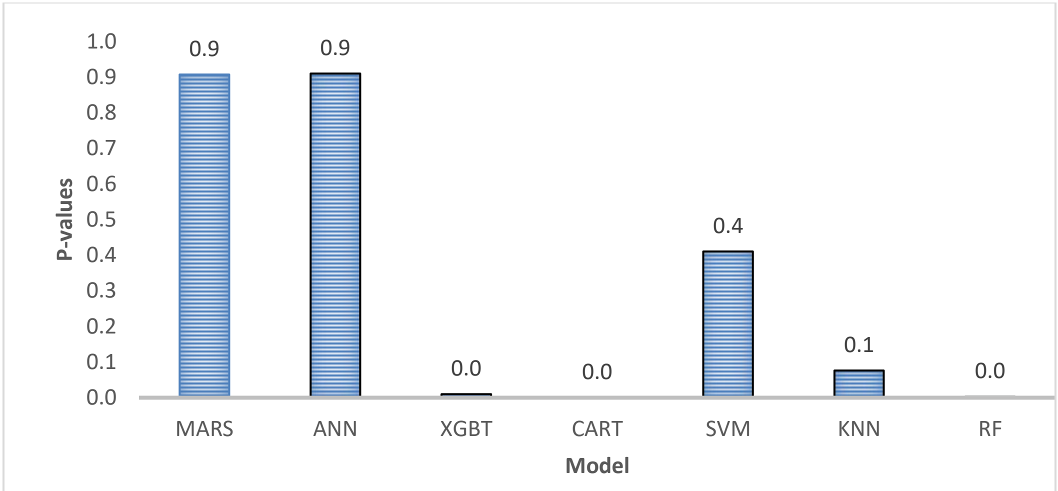

Figure 4-13: Summary of the normality tests for discharge residuals

The p-values on figure 4.13 shows the normality test values for the predicted discharge data using the applied models. The p-value is used to indicate whether the residuals of the original test data set and the predicted discharge follows normal distribution trend or not. The residual discharge of models such as, Random Forest (P = 0.003), Classification and Regression Tree (P = 0.001) and Extreme Gradient Boosting Tree (P = 0.01) have p-values less than 5% (0.05) significance level. This can be interpreted as the residuals of the listed models do not follow the normal distribution path. Compared to RF and SVM models, the equation of the MARS model is relatively interpretable, and the prediction performance is nearly similar with the outperformed RF model. Therefore, MARS was selected as the final model to predict canal outlet discharge using its equation.

4.4 Prediction of Discharge using Multivariate Adaptive Regressive Splines Model

In this study, the target response is discharge(Q) and the input variables are a, h, r, l and n; where a is the area ratio, h is the water level per unit width at the tertiary canal head concrete weir, r is the ranking order of operated outlets along the tertiary canal, l is the cumulative distance of the outlet from the TC head off-take and n is the Manning roughness coefficient of the TC to represent the canal type , whether lined or unlined.

Taking the performance of the models at the training and testing stages into consideration, and also using other model selection criteria, MARS is the final model to predict discharge of the quaternary canal outlets using the available predictor variables. Figure 4.14 shows the order of variable importance for MARS model.

The overall variable importance of the MARS model selects area ratio(a), water level per unit width(h) and rank of operated canal outlets(r) as the first three important variables.

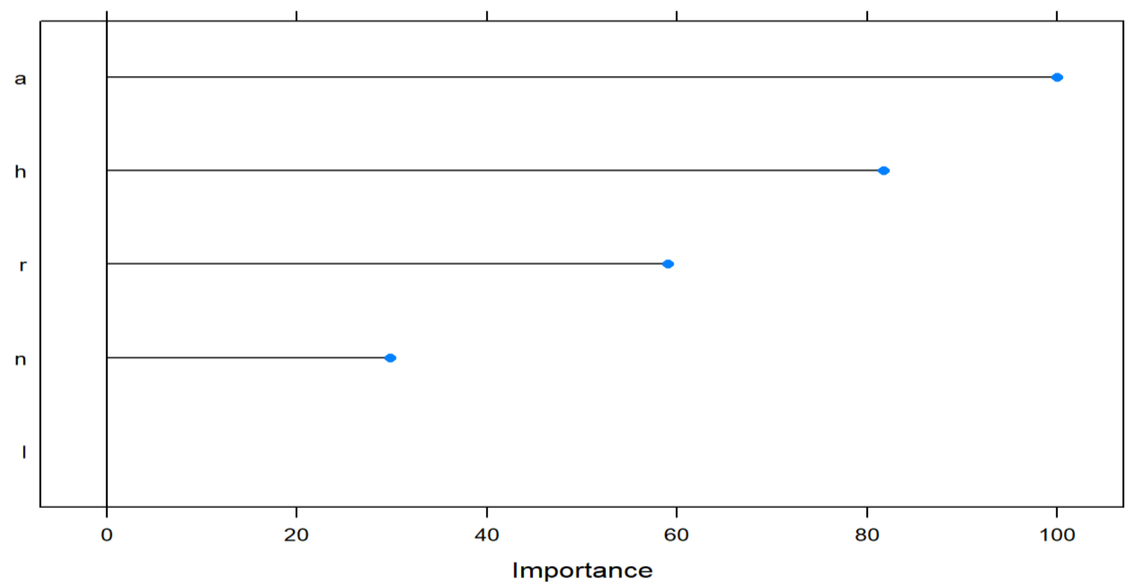

Figure 4-14: Variable Importance with MARS model

Prediction of MARS model: Prediction of discharge with MARS model was made using the test data. The result of the predicted value as shown on figure 4.15 fits well with the test data discharge value. It was first predicted with the transformed data and then rescaled to the original data structure, and more than 85% of the observed discharge was well explained by the predicted discharge.

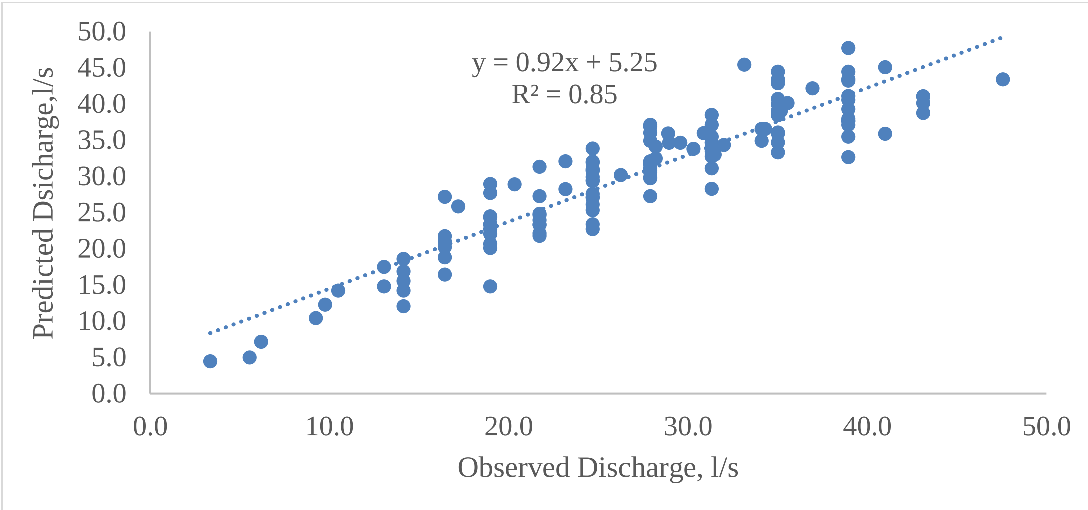

Figure 4-15: Prediction of MARS model using the test data

MARS Model Equations: Basic function equations and their coefficients were calculated by MARS model with caret in the R software. Figure 4.16 shows the number of basic function equations generated using the MARS model. The blue line on the figure shows that as the number of basic functions increase the level of errors decreases.

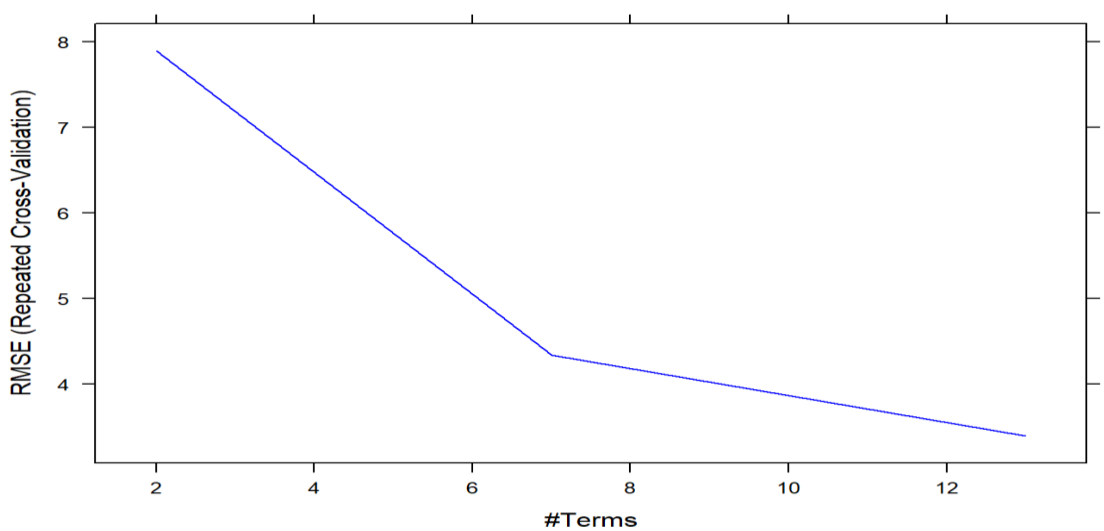

Figure 4-16: Variability of errors with number of basic functions

A 10-fold cross validation with 3 reparations were made to select the parameters and the resampling results across the tuning parameters were selected using the small values of root mean square error (RMSE).

A three times repeated cross validation of five variables were used to generate fifteen terms. The final values used for the MARS model were 13 out of 15 terms and 5 out of 5 predictor variables. From 13 selected terms, one is the intercept and the other 12 are the basic functions. The values of Generalized Cross-Validation (GCV=11.9), Generalized Rsq (GRSq=0.86), RSq = 0.88 and the intercept ($\beta o = 26.5$) were estimated using the package called earth in the R environment. After estimating $\beta o = 26.5$, equation 3.15 can be simplified into;

$$f(X) = 26.5 + \sum_{m=0}^{12} \beta_m \ BF_m(X) \qquad \text{Eq.4.1}$$

Table 4-4: Basic Functions of MARS model

Basic function	Equation	Coefficient (β)
BF $_1$(x)	Max (0, 0.62-h)	-60.2
BF_2(x)	Max (0, -BF_1(x))	50.2
BF_3(x)	Max (0, 0.12-a)	-291.0
BF_4(x)	Max (0, a-0.13)	-255.7
BF_5(x)	Max (0, a-0.17)	1497.4
BF_6(x)	Max (0, a-0.18)	-1702.4
BF_7(x)	Max (0, 404.35-l)	0.0
BF_8(x)	Max (0, - BF_7(x))	0.0
BF_9(x)	Max (0, l-713))	0.0
BF_{10}(x)	Max (0, n-0.02)	758.2
BF_{11}(x)	Max (0, r-4)	-13.2
BF_{12}(x)	Max (0, r-6)	22.2

Since the coefficients of basic functions BF_7(x), BF_8(x) and BF_9 (x) are zero, the $\beta_m BF_m(X)$ terms are removed from equation 4.1 and only 9 basic functions are left from the total of 12 functions. Equation 4.2 describes the developed MARS model equation used to predict canal outlet discharge.

$$f(X) = 26.5 - 60.2{*}BF_1 + 50.2{*}\ BF_2 - 291.0{*}\ BF_3 - 255.7{*}\ BF_4 + 1497.4{*}\ BF_5 - 1702.4{*}BF_6 + 758.2{*}\ BF_{10} - 13.2{*}\ BF_{11} + 22.2{*}\ BF_{12} \qquad \text{Eq.4.2}$$

Where, BF_1, BF_2, BF_3……, BF_{12} are basic functions, $f(X)$ represents the predicted canal outlet discharge Q (l/s) and X values are the variables.

The first two basic functions (BF_1 and BF_2) are terms of variable h, and the next four consecutive functions (BF_3-BF_6) are equations generated from variable a whereas, BF_{10} consists variable n, and BF_{11} and F_{12} are generated from variable r.

Different sub-equations can be developed from equation 4.2 by eliminating some variables as follows:

$f(h, a)$ = 26.5-60.2*BF_1 +50.2* BF_2-291.0* BF_3 -255.7* BF_4 +1497.4* BF_5-1702.4*BF_6 Eq.4.2(a)

$f(h, n, r)$ = 26.5-60.2*BF_1 +50.2* BF_2 +758.2* BF_{10} -13.2* BF_{11} +22.2* BF_{12} Eq.4.2(b)

$f(h, a, r)$ = 26.5-60.2*BF_1 +50.2* BF_2 -291.0* BF_3 -255.7* BF_4 +1497.4* BF_5 -1702.4*BF_6 -13.2* BF_{11} +22.2* BF_{12} Eq.4.2(c)

When the terms which contain variables a and h are selected, equation 4.2 is reduced to equation 4.2(a). When eliminating only variable a, the equation is expressed as equation 4.2(b). Equation 4.2(c) is developed when the top three variable importance by the MARS model are selected. The prediction performance of the developed equations is well described on table 4.5.

Table 4-5: Discharge Prediction Equations of MARS

Input Variable	Equation	R^2	RMSE
a, h	Eq.4.2(a)	0.38	5.40
h, n, r	Eq.4.2(b)	0.60	6.34
a, h, r	Eq.4.2(c)	0.71	5.66
a, h, r, n	Eq.4.2	0.80	4.27

From the four equations on table 4.5, equation 4.2 with variables h, a, n and r has best prediction performance.

The results reflect that the degree of explanatory variables to describe the predicted discharge output increases as the number of variables increase whereas, the residual error sum is not necessarily decreasing as the number of variables increase.

Equation 4.2 is the final model equation of MARS used to predict canal outlets discharge, which seems a little bit long equation. However, it has relatively high performance to predict discharge and it is also relatively easy to interpret as compared to other neuron and tree-based regression models.

The only varying parameter to estimate discharge at a quaternary canal outlet, located at certain distance from the tertiary off-take is the water level per unit width (h) of the tertiary canal off-take weir whereas, the remaining parameters are slightly constant for a quaternary canal outlet. Once the constant parameters are measured, the outlet discharge at any location along a tertiary canal, can be simply predicted at the desired time by using the MARS model equation. Thus, outlet discharge estimation is possible only by measuring the varying water level released at the tertiary canal off-take.

Estimating irrigation discharge at several quaternary canal outlets of the scheme using other ordinary methods such as, orifice flow measurements are a tedious work and consumes much time. Therefore, developing a model equation which allows to predict canal discharge is an alternative approach to improve irrigation scheme governance and efficiency, which was the main goal of this study.

5 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

Accurate measurement of irrigation water is the central subject to improve water delivery performance of irrigation schemes. The accuracy of the DischargeApp was evaluated at quaternary canals of Koga Irrigation Scheme. In comparison to 90-degree notch weir, 89.5 percent of the discharge data measured by the app lies within the error range of ±20 percent. The app discharge overestimates discharge at high flows compared with low flows at field channel flow conditions in a purposive manner.

When velocity correction factor of the app is changed from a constant value (C=0.8) to a water depth-based factor method, the accuracy of the app discharge is improved through increasing the percentage of observed discharge data from 66 to 92.1 percent lying within the error range of ±15 percent and the mean discharge deviation reduced from ±3.8 l/s to ±2.1 l/s. The improved app discharge also underestimates the notch weir measurement slightly at all flow conditions. With its rare limitations, DischargeApp is a novel, accurate and cost-effective device for channel flow measurement, where other flow measurement techniques are not suitable.

Water delivery performance of quaternary canal outlets were assessed in Koga irrigation scheme during the irrigation season of 2019, and significant water supply variations were found at spatial and temporal scales. The most favored irrigation canal outlet was delivering two times of the least favored outlet, and about 61% of the outlets were delivering water supply below the intended flow.

At block average, the three performance indicators namely, adequacy (Pa), equity (Pe) and reliability (Pr) delivery performance indicators scored values varied between 0.84-1.17, 0.04-0.36 and 0.05-0.31 respectively. Out of the six blocks, four, five and three blocks scored satisfactory results in terms of water supply adequacy, equity and reliability performances respectively.

An empirical relation was developed between discharge at quaternary canals with available information using predictive machine learning algorithms. Multivariate Adaptive Regressive Splines (MARS) was selected based on prediction performance and model equation interpretability criteria to predict discharge at quaternary canal outlets.

The performance of the developed MARS model was, R^2 = 0.86 and RMSE = 3.6 at the model training stage and R^2 = 0.85 and RMSE = 3.48 at the test stage for the rescaled data structure. Since the distance parameter is eliminated due to its zero regression coefficients, the developed MARS equation uses four variables to predict discharge.

5.2 Recommendations

The developed MARS model allows irrigation operators to predict water supply at quaternary canal outlets. The model equation can be applied at Koga and other data scarce irrigation schemes, which have similar canal flow networks, taking the field conditions and data availably into consideration.

The discharge application device entitled DischargeApp can be applied to measure flow rates at irrigation canals without interrupting the existing flow operation condition. With few constraints, the app is accurate to measure channel flow rates, where other optional methods are absent, with no requirements of investment cost for maintenance and installation.

The DischargeApp developers' team is recommended to address the following limitations of the app, which were investigated in this study to make it a more comprehensive flow measurement tool:

The app discharge was recalculated using a velocity correction coefficient, which relies on canal water depth, in reference to the US Department of interior Bureau of Reclamation (2001) recommendations, and the accuracy was exceedingly improved in the new method. Besides this, manual calculation of the offshore distance, is the sources of failure for discharge computations using the app. Once the distance between the place marks and the canal width are defined, the distances between the canal edges and the place marks have not be user defined.

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7 APPENDIX

7.1 Appendix A: Data for Evaluation of the DischargeApp

Appendix A-1: Statistical Summary of Discharge

Type III Sum of Squares analysis (Qvn(l/s)):

Source	DF	Sum of squares	Mean squares	F	Pr > F
Qapp(l/s)	1	4463.84	4463.84	1427.11	< **0.0001**

Model parameters (Qvn(l/s)):

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	5.354	0.713	7.508	**<0.0001**	3.933	6.775
Qapp(l/s)	0.747	0.020	37.777	**<0.0001**	0.708	0.787

Appendix A-2: Correction coefficients for float velocities (USDIBR,2001)

Average depth in reach(ft)	Coefficient
1.0	0.66
2.0	0.68
3.0	0.70
4.0	0.72
5.0	0.74
6.0	0.76
9.0	0.77
12.0	0.78
15.0	0.79
>20.0	0.80

7.2 Appendix B: Data for Water Delivery Performance Assessment

Appendix B-1: Location and Layout of Experimental sites

Block Name	Block Location from the Dam	TC Name	QC Outlet Labeled	Outlet reach along TC	Outlet Location		Cumulative distance of outlet from TC offtake (m)	QC Irrigated Area(ha)
					Longitude	Latitude		
Kudmi	Head	TC-06	Kud0601	Head	11.363	37.113	174.00	14.71
			Kud0603	Mid	11.366	37.111	533.00	12.31
			Kud0605	Tail	11.367	37.110	713.00	12.42
Chihona	Head	TC-02	Chi0202	Head	11.403	37.122	28.30	16.42
			Chi0205	Mid	11.400	37.117	659.00	15.13
			Chi0206	Tail	11.399	37.115	843.60	13.53
Adibera	Mid	TC-10	Adi0602	Head	11.427	37.083	25.40	16.07
			Adi0604	Mid	11.429	37.081	404.00	12.06
			Adi0606	Tail	11.431	37.078	820.00	13.11
Tagel	Mid	TC-02	Tag0201	Head	11.421	37.125	18.00	16.29
			Tag0203	Mid	11.423	37.124	225.95	16.38
			Tag0205	Tail	11.425	37.124	475.50	14.46
Andinet	Tail	TC-01	And0110	Head	11.482	37.120	1136.00	15.15
			And0112	Mid	11.486	37.119	1568.50	6.73
			And0114	Tail	11.488	37.118	1734.86	15.45
Teleta	Tail	TC-06	Tel0601	Head	11.503	37.109	20.00	16.35
			Tel0605	Mid	11.509	37.112	791.73	16.31
			Tel0607	Tail	11.512	37.114	1169.39	16.55

TC= Tertiary Cana, QC=Quaternary Canal, Mid=Middle, Block =Secondary Canal

In Labeled QC outlet Kud0601, Kud = Block,06 =TC number, 01=QC number

Appendix B-2: Measured Irrigation water supply in Quaternary canal outlets

Block Name	Outlet	Qa(l/s/ha)			
		Jan-19	Feb-19	Mar-19	Apr-19
Kudmi	Kud0601	2.353	1.865	2.000	1.794
	Kud0603	2.061	1.522	1.847	1.436
	Kud0605	2.179	1.820	2.307	1.726
Chihona	Chi0202	2.375	2.360	2.010	2.139
	Chi0205	1.180	1.593	1.974	1.637
	Chi0206	1.026	1.458	1.380	1.239
Adibera	Adi1002	2.626	2.429	2.119	2.113
	Adi1004	2.066	2.161	2.913	3.253
	Adi1006	1.451	1.335	1.783	2.155
Tagel	Tag0201	2.219	2.155	2.359	2.143
	Tag0203	2.073	2.031	2.149	2.039
	Tag0205	2.121	1.984	2.093	2.286
Andinet	And0110	2.315	2.117	2.136	1.976
	And0112	2.451	1.568	1.067	1.023
	And0114	1.980	1.707	1.766	1.721
Teleta	Tel0601	2.044	1.991	1.473	0.906
	Tel0605	1.893	1.957	1.571	0.790
	Tel0607	2.026	1.954	1.516	0.700

Qa = Measured monthly average water supply or duty (l/s/ha)

Appendix B-3: Temporal Flow Variability at QC outlets

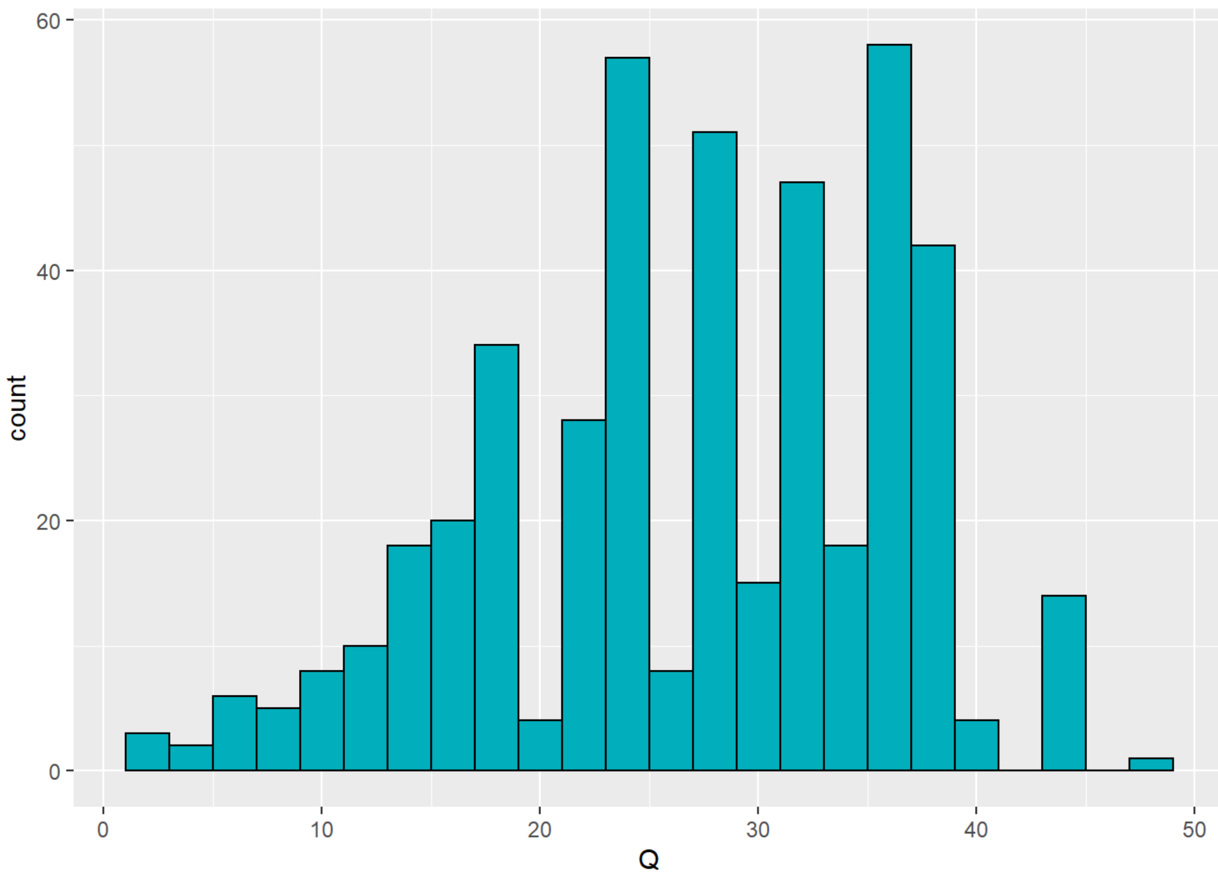
Block Name	Outlet	Water Delivery Performance Ratio (DPR)			
		Jan-19	Feb-19	Mar-19	Apr-19
Kudmi	Kud0601	1.25	0.99	1.07	0.96
	Kud0603	1.10	0.81	0.99	0.77
	Kud0605	1.16	0.97	1.23	0.92
Chihona	Chi0202	1.27	1.26	1.07	1.14
	Chi0205	0.63	0.85	1.05	0.87
	Chi0206	0.55	0.78	0.74	0.66
Adibera	Adi1002	1.40	1.30	1.13	1.13
	Adi1004	1.10	1.15	1.55	1.74
	Adi1006	0.77	0.71	0.95	1.15
Tagel	Tag0201	1.18	1.15	1.26	1.14
	Tag0203	1.11	1.08	1.15	1.09
	Tag0205	1.13	1.06	1.12	1.22
Andinet	And0110	1.23	1.13	1.14	1.05
	And0112	1.31	0.84	0.57	0.55
	And0114	1.06	0.91	0.94	0.92
Teleta	Tel0601	1.09	1.06	0.79	0.48
	Tel0605	1.01	1.04	0.84	0.42
	Tel0607	1.08	1.04	0.81	0.37
CV(DPR)		**0.21**	**0.16**	**0.22**	**0.37**

CV(DPR) = Coefficient of Variation of DPR

7.3 Appendix C: Data Analysis for Predictive model Development

Appendix C-1: Plots of Discharge data for modelling

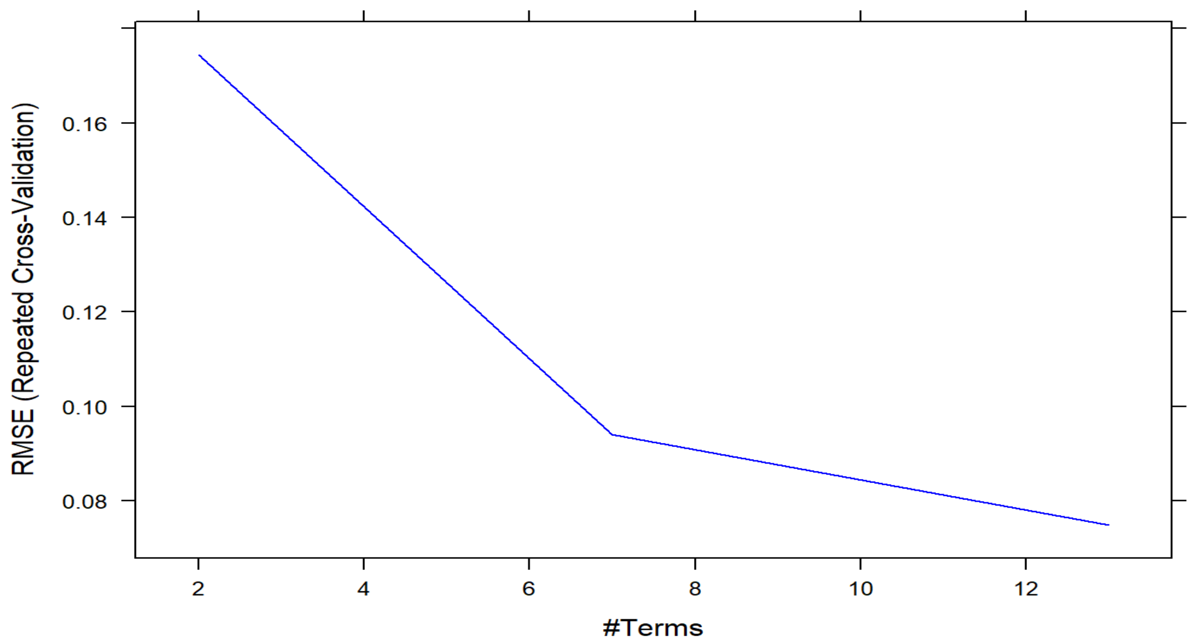
Frequency of Measured Discharge data



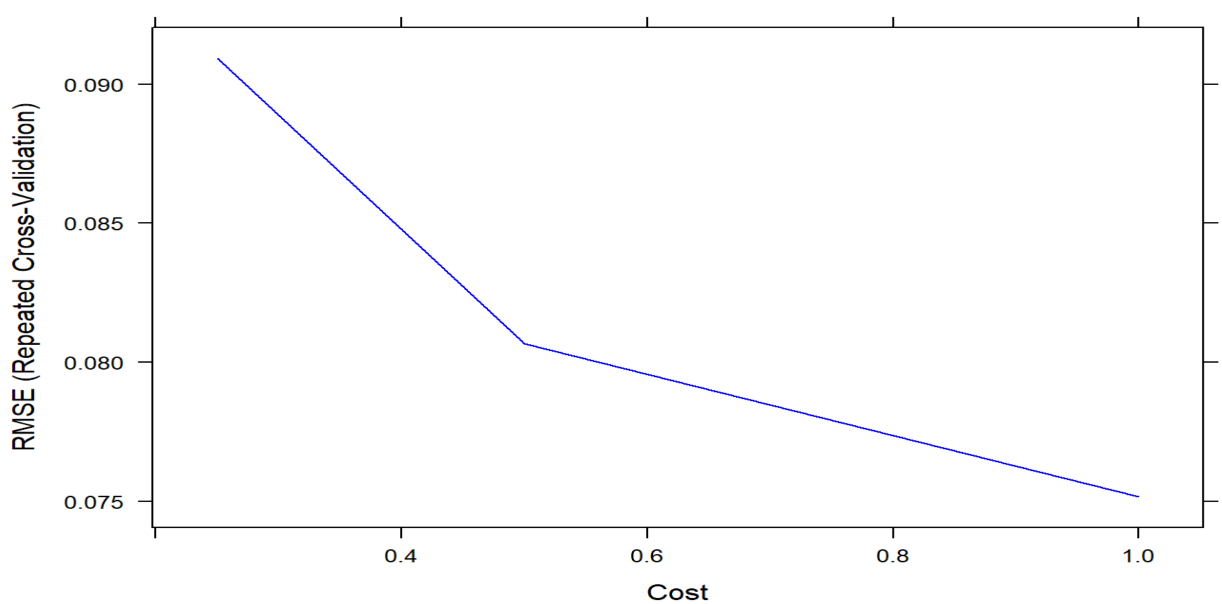
Q = outlet discharge(l/s), which is response variable for model development

Appendix C-2: Plots of fitted Models in terms of RMSE

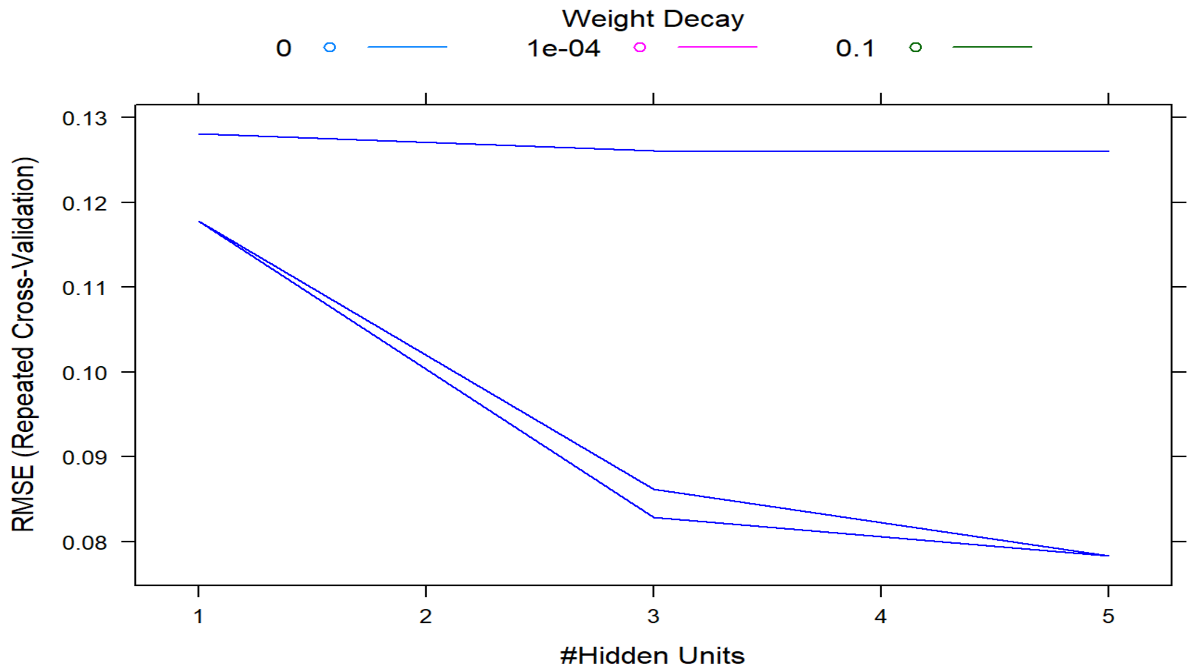
MARS Model:



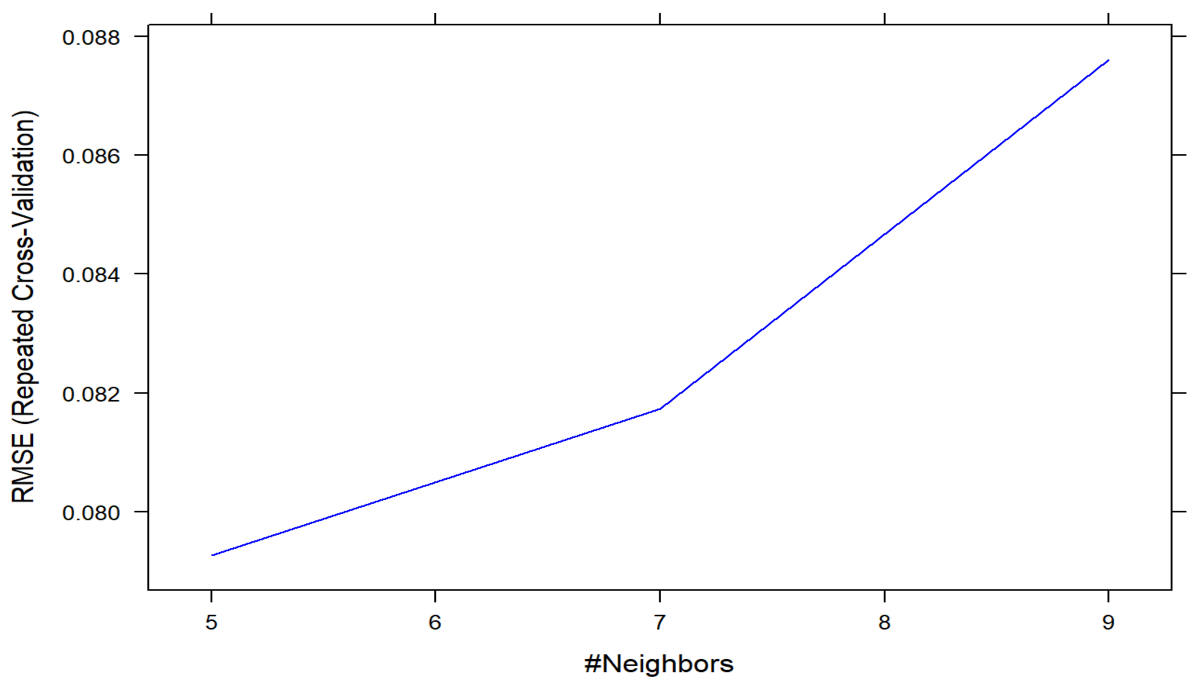
SVM Model:



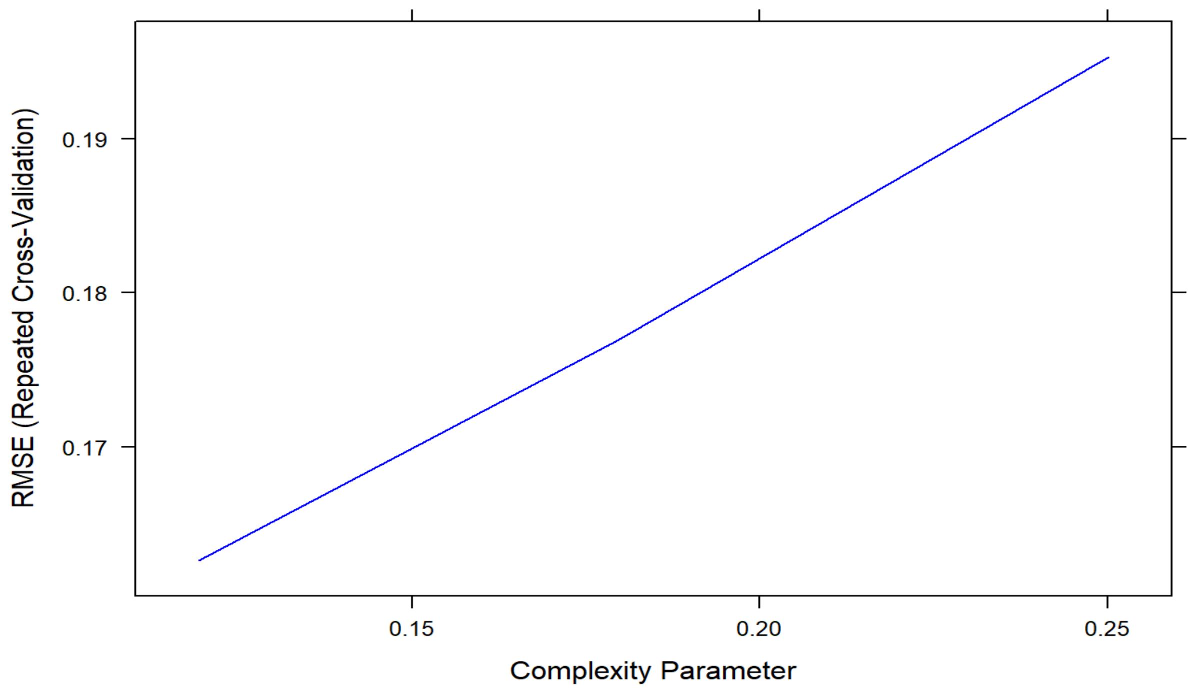
ANN Model:



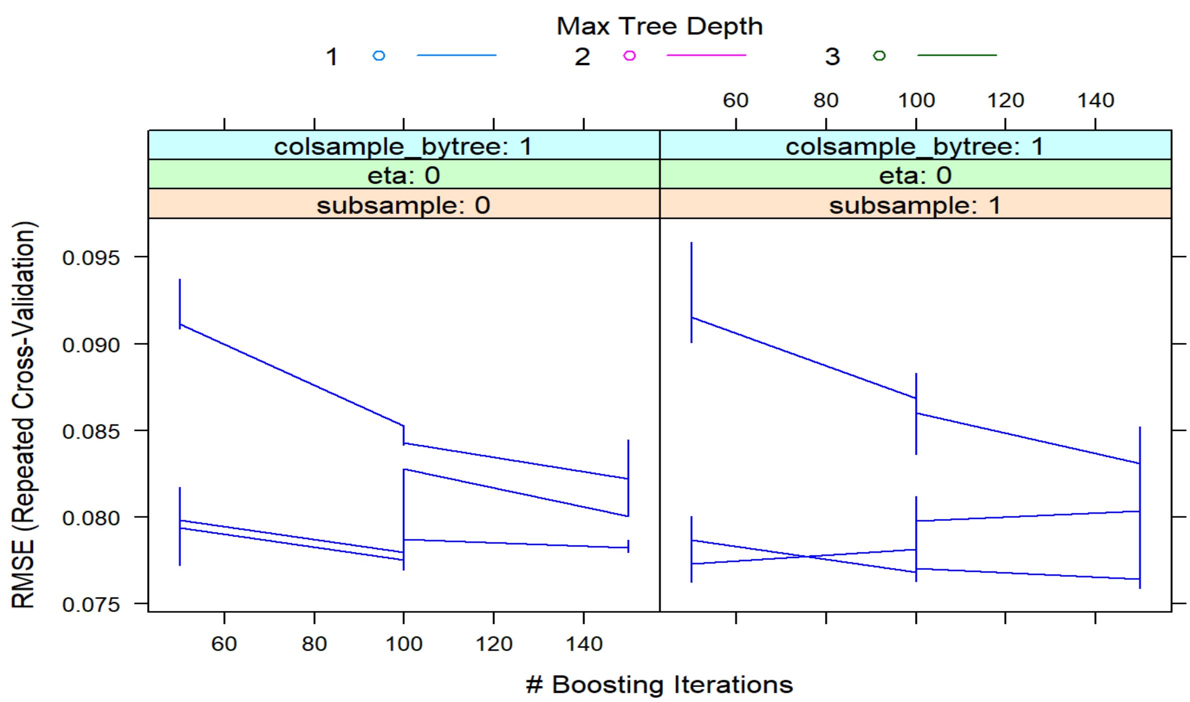
KNN Model:



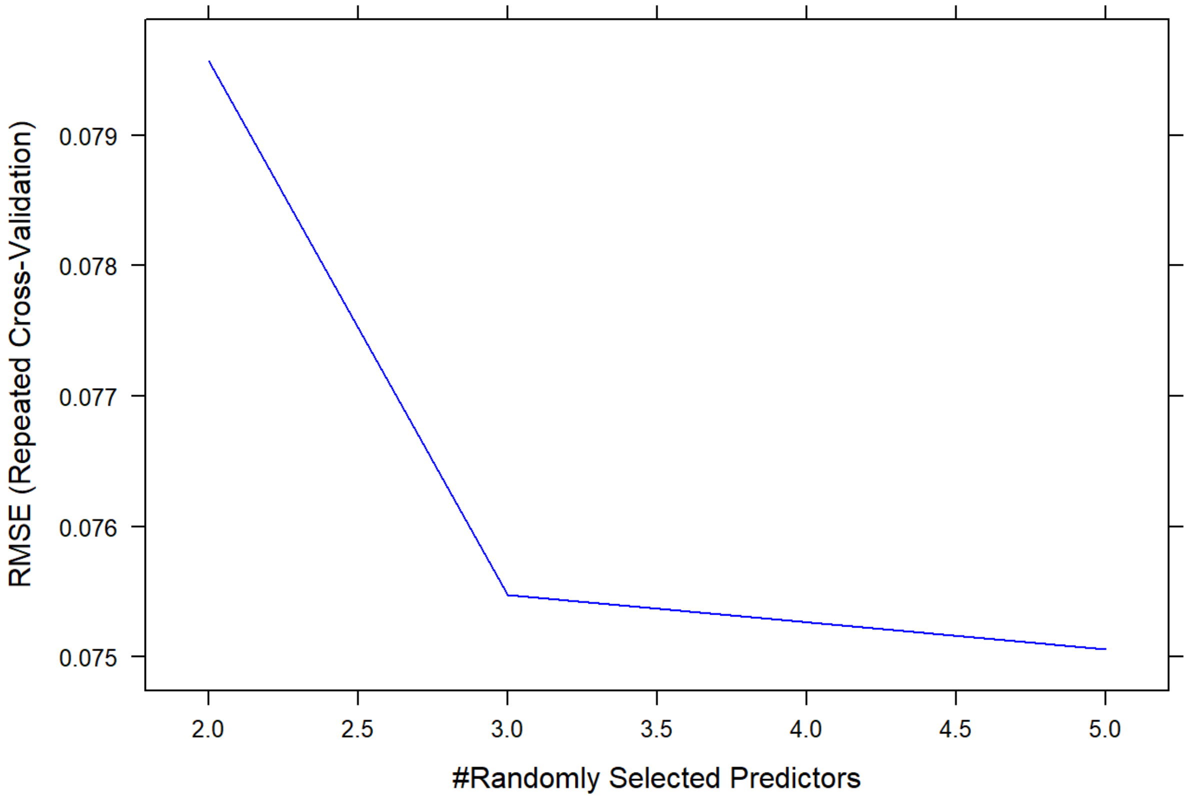
CART Model:



XGBT Model:

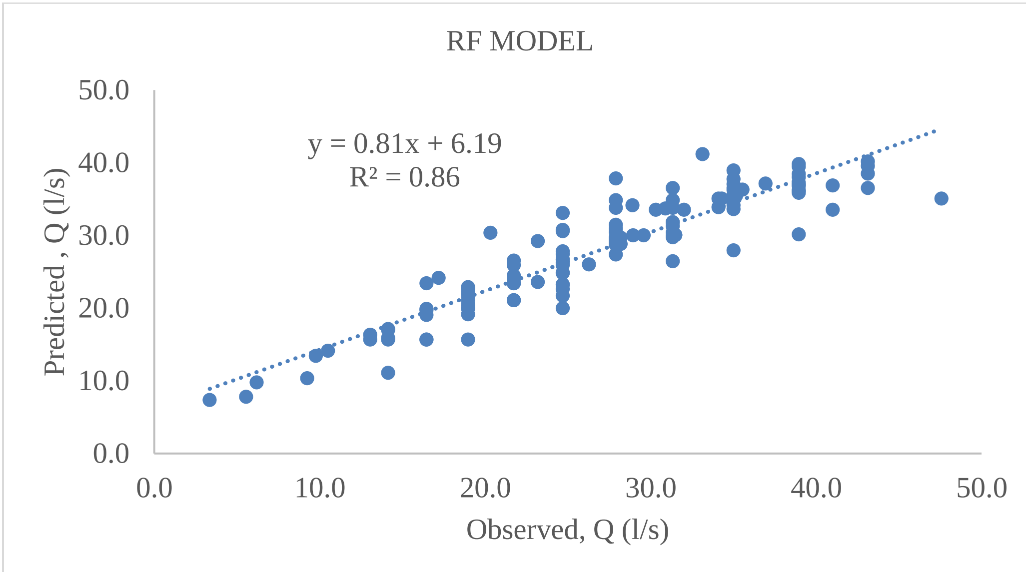


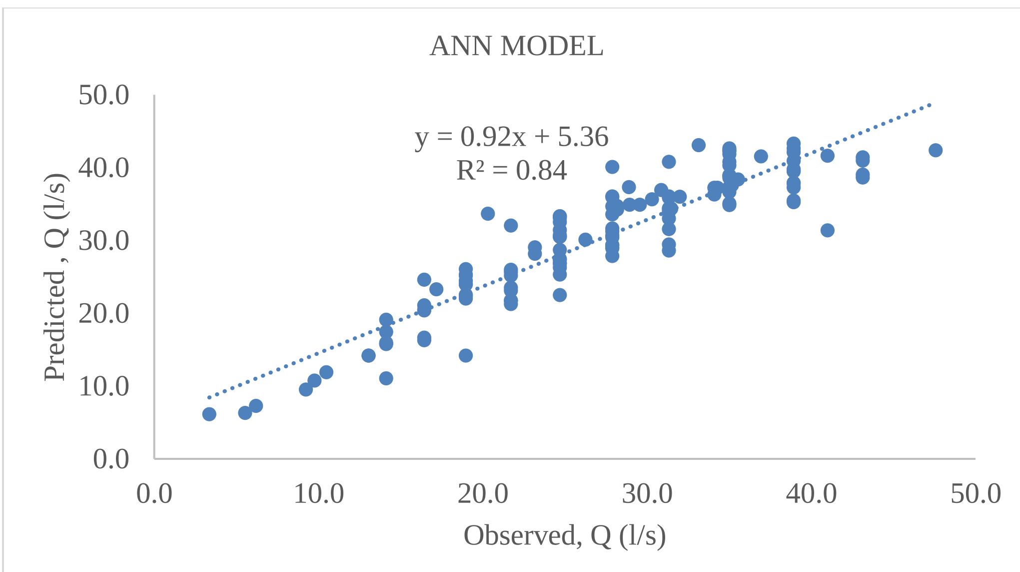
RF Model:

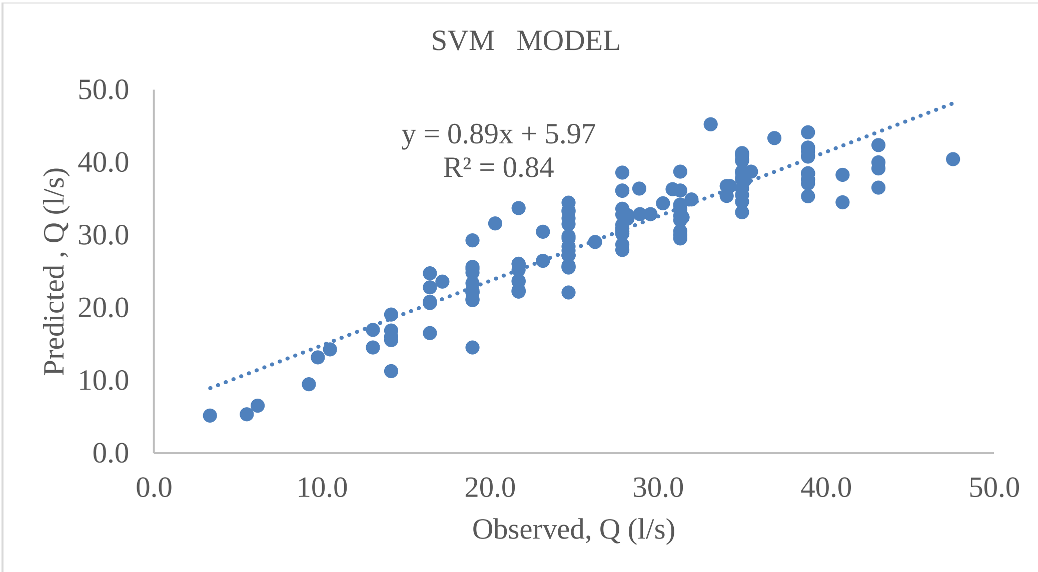


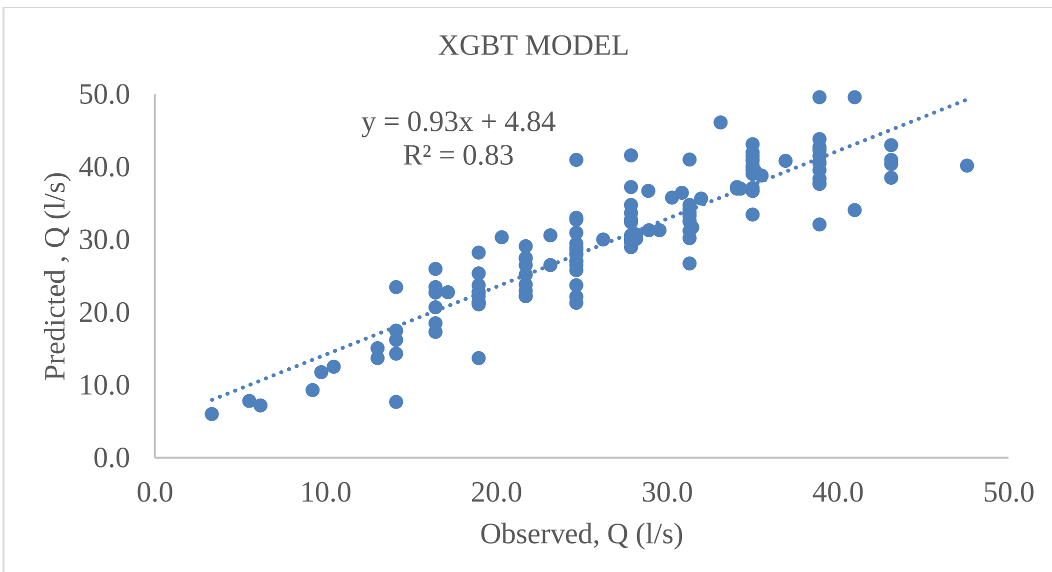
RMSE (Repeated Cross-Validation)
0.079
0.078
0.077
0.076
0.075
2.0
2.5
3.0
3.5
4.0
4.5
5.0
#Randomly Selected Predictors

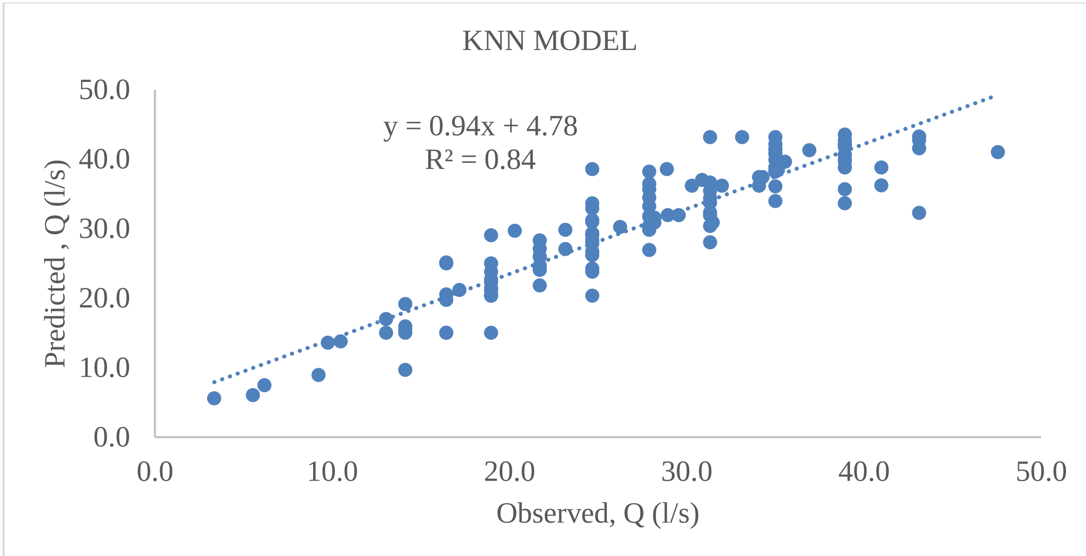
Appendix C-3: Prediction of Discharge using Applied Learning Models

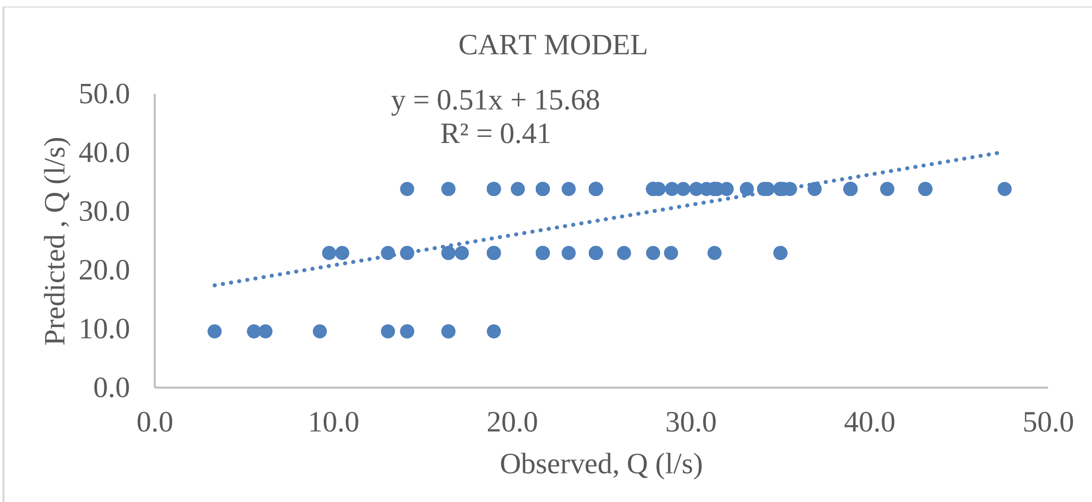





SVM MODEL
y = 0.89x + 5.97
R² = 0.84
Predicted , Q (l/s)
Observed, Q (l/s)
0.0
10.0
20.0
30.0
40.0
50.0


XGBT MODEL
y = 0.93x + 4.84
R² = 0.83
Predicted , Q (l/s)
Observed, Q (l/s)
0.0
10.0
20.0
30.0
40.0
50.0





x = the test discharge data set used for prediction of model and y= the predicted discharge by the model

Appendix C-4: Correlation Matrix of Applied Models

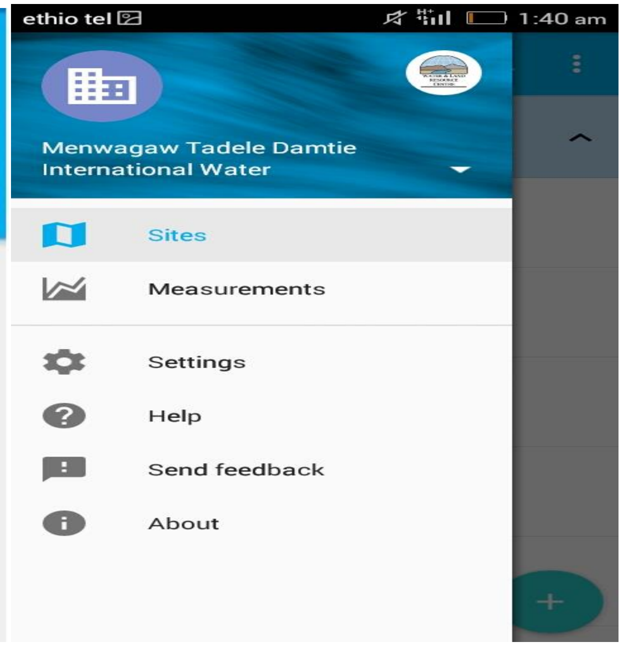
	Qobs	MARS	ANN	XGBT	CART	SVM	KNN	RF
Qobs	**1.00**	0.92	0.92	0.91	0.64	0.92	0.92	0.93
MARS	0.92	**1.00**	0.98	0.97	0.71	0.98	0.96	0.96
ANN	0.92	0.98	**1.00**	0.97	0.70	0.98	0.97	0.97
XGBT	0.91	0.97	0.97	**1.00**	0.68	0.97	0.96	0.97
CART	0.64	0.71	0.70	0.68	**1.00**	0.72	0.69	0.72
SVM	0.92	0.98	0.98	0.97	0.72	**1.00**	0.98	0.97
KNN	0.92	0.96	0.97	0.96	0.69	0.98	**1.00**	0.97
RF	0.93	0.96	0.97	0.97	0.72	0.97	0.97	**1.00**

Qobs = Observed discharge for test data set

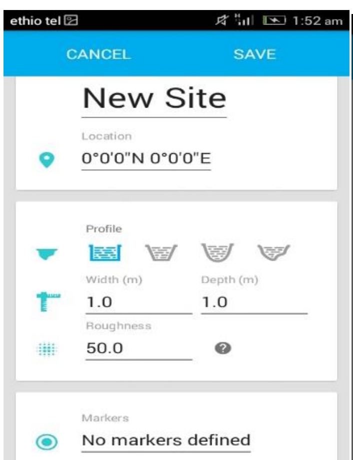
7.4 Appendix D: Photographs and Figures

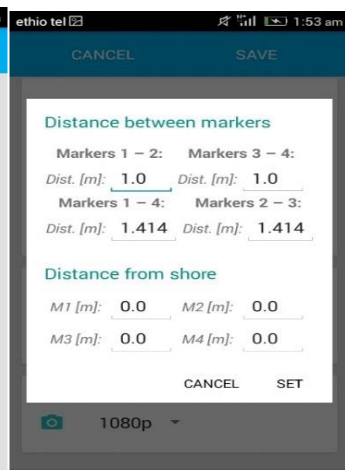
Appendix D-1: DischargeApp Photos and Figures

Creating user's account for the DischargeApp

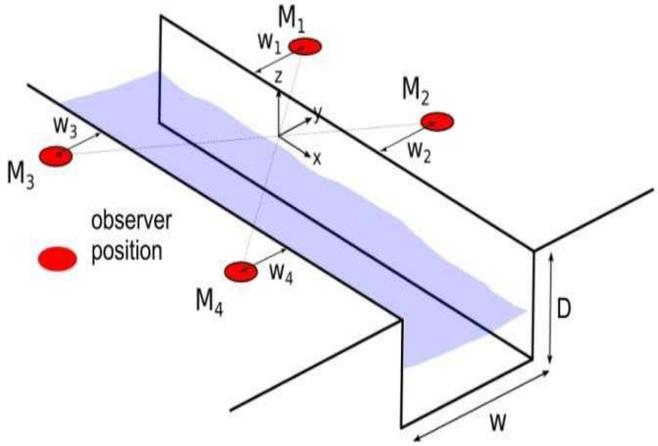


New Site selection and configuration

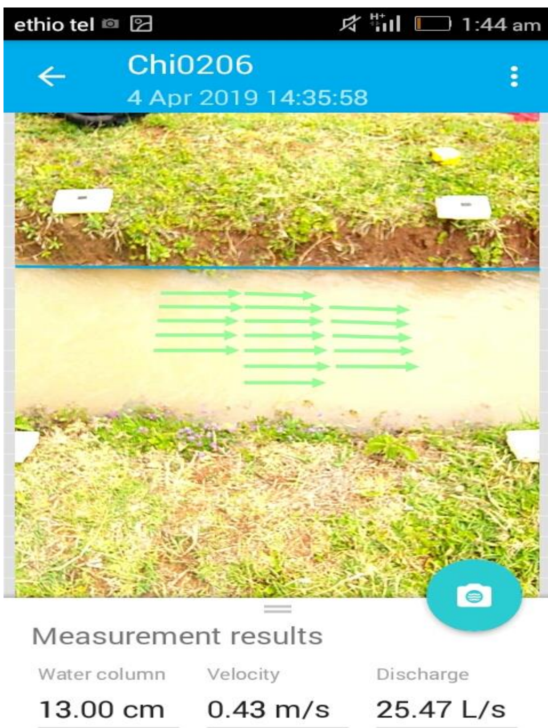


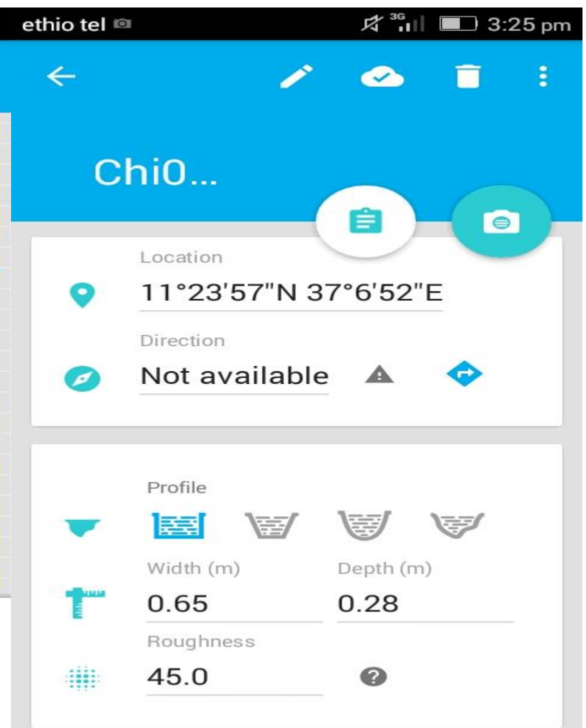


Configuration of observer's position for video recording

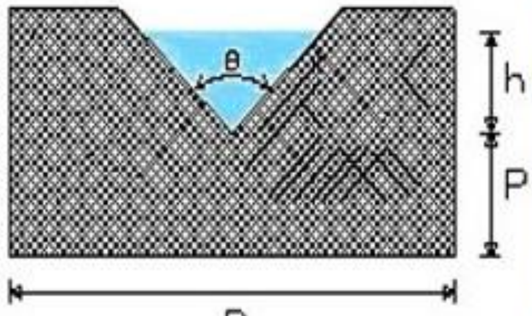


Processing and uploading flow measurement results





Appendix D-2: Photographs of installed v-notch weirs



B=100cm, P=2-5cm, Hmax= 30cm, θ =90

Graded V- Notch weir installed at QC

Appendix D-3: Photographs of Existing Irrigation Structures

Rectangular concrete Weir at TC Off-take

Outlet structures at Quaternary canals