UNIVERSITY FOR DEVELOPMENT STUDIES

MODELLING THE EFFECTS OF IRRIGATION DEPTHS AND DRAINAGE SYSTEMS ON RICE PERFORMANCE IN THE GUINEA SAVANNAH AGRO-ECOLOGICAL ZONE OF GHANA

BY

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DECLARATION

DECLARATION BY STUDENT

I hereby declare that this thesis is the result of my own original work and that no part of it has been presented for another degree in this University or elsewhere. The work of others, which served as sources of information for this study, has been duly acknowledged in the form of references.

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DECLARATION BY SUPERVISORS

I hereby declare that the preparation and presentation of the thesis was supervised in accordance with the guidelines on supervision of thesis laid down by the University for Development Studies, Ghana.

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ABSTRACT

The study modelled the effects of irrigation depths and drainage systems on the performance of rice in the Guinea Savannah agro-ecological zone of Ghana. The study specifically evaluated the effect of different irrigation application depths and drainage systems on growth and yield of rice, assessed the effects of irrigation application depths and drainage systems on changes in soil electrical conductivity, soil temperature and nitrogen balance in irrigated ecology, estimated Crop Water Stress Index (CWSI) for rice culture in an irrigated ecology and modelled the effects of irrigation application depths and drainage systems on LAI and yield of rice. The irrigation application depths were continuous flooding at 5 cm, 10 cm and 15 cm and alternate wetting and drying (AWD) at – 5 cm, - 10 cm and – 15 cm while the drainage systems were no drainage as control, surface drainage and sub-surface drainage systems. Micro plots with concrete blocks were constructed measuring 1 m × 1 m × 1 m and laid in a Randomized Complete Block Design in a 6 × 3 factorial treatment arrangement replicated three (3) times in 2023 and 2024 growing seasons. Soil electrical conductivity (EC) was used to determine the salinity index of the soil. Monitoring of temperature within the root zone of the crop was done throughout the crop growth cycle depicting each of the six stages in the paddy rice. To compute the baselines, the air temperature, leaf canopy temperature and the vapour pressure deficit (VPD) were used. Results indicated that sub-surface drainage with 5 cm irrigation depth produced the tallest plants (80 – 94 cm), high LAI (2.39 – 3.89), high leaf chlorophyll content (16.24 – 19.93 CCI) and a high yield (6.77 – 9.55 t/ha). No drainage under AWD 15 recorded the shortest plant (65 – 79 cm), lower LAI (0.85 – 2.16), lower Leaf Chlorophyll Content (LCC) (5.37 – 9.50) and lower yield (0.41 – 1.27 t/ha) in both seasons. The salinity level of the soil was high (347.8 µS/cm) in treatments with no drainage and low (186 µS/cm) in sub-surface drainage. Soil temperature results indicated that surface drainage under AWD 15 recorded the highest (37 – 43 ^{o}C) while the lowest (20 – 26 ^{0}C) was recorded in treatments with no drainage under continuous flooding. AWD with sub-surface drainage resulted in higher nitrogen content (0.064 – 0.095 %) while the lowest was recorded in continuous flooding with no drainage (0.038 %) and continuous flooding with surface drainage (0.031 %). Results indicated that CWSI was lower (0.075) in CF 5-10 in 2023 and 0.143 in 2024 due to temperature differences while the highest CWSI (0.831 and 0.857) were recorded in AWD – 15. In 2023, CWSI gave a regression model of $y = - 0.1191x + 0.7587$ and a coefficient of determination (R^2) value of 0.987 while in 2024, a regression model of $y = - 0.0969x + 0.8673$ where (x) represents the irrigation application depths. Observed simulation showed more accurate results for CF 5 with no drainage (d-stat = 0.92 and R^2 = 0.93). The regression analysis of the yield produced a regression equation $y = - 0.242x + 6182.2$ with a coefficient of determination (R^2) value of 0.654. During the evaluation, R^2 for no-drainage condition ranged from 0.81 – 0.97, RMSE ranged from 0.11 – 1.72 and D-index ranged from 0.31 – 0.98. The continuous flooding at irrigation water depth of 5 cm (CF 5) gave the highest Willmot's d-index of agreement of 0.98 while the lowest d-index was recorded on treatment AWD -15. In conclusion, sub-surface drainage system under 5 cm irrigation depth proved to be more efficient in terms improving the growth and yield parameters of rice while at the same time conserving water. The values derived for CWSI in this study can be used to understand the stress dynamics of rice in various stages of growth under different irrigation depths and drainage systems. The performance of rice can be increased greatly by adopting irrigation application depth of 5 cm with drainage management being put in place. CWSI estimation offers a practical tool for drought mitigation and irrigation scheduling in both irrigated and rainfed rice systems.

DEDICATION

This work is warm-heartedly dedicated to my beloved wife, Mrs. Fatima Sesay.

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LIST OF ACRONYMS AND ABBREVIATIONS

AMP	Agricultural Water Management
ANN	Artificial Neural Network
AWC	Available Water Content
AWD	Alternate Wetting and Drying
AWM	Agricultural Water Management
CF	Continuous Flooding
CWSI	Crop Water Stress Index
DSS	Decision Support System
EWP	Economic Water Productivity
EWT	Equivalent Water Content
FAO	Food and Agricultural Organization
FWL	Field Water Level
GIDA	Ghana Irrigation Development Authority
IWUE	Irrigation Water use Efficiency
LAI	Leaf Area Index
LCC	Leaf Chlorophyll Content
MoFA	Ministry of Food and Agriculture
MPC	Model Predictive Control
MWSB	Maximum-Water Stress Baseline
NUE	Nitrogen Use Efficiency
NWSD	Non-Water Stress Baseline
RHC	Receding Horizon Control

RLD	Root Length Density
SDV	Stem-Diameter Variation
TTT	Temperature-Time-Threshold
VPD	Vapour Pressure Deficit
VPG	Vapour Pressure Gradient
WACWISA	West African Centre for Water, Irrigation and Sustainable Agriculture
WAT	Weeks After Transplanting
WTD	Water Table Depth
WTM	Water Table Management
WUE	Water Use Efficiency

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CHAPTER ONE

INTRODUCTION

1.1 Background

Drainage in agricultural land is needed so as to remove excess water in or on the soil. Water is in excess when the amount present adversely affects crop production, by preventing carbon dioxide formed by plant roots and other organisms from being exchanged with oxygen from the atmosphere. This reduces the rate of root development and uptake capacity for water and nutrients of most plants. Drainage is equally important for sustainable crop production otherwise salinity control will not be possible. A study by Lampayan *et al.(* 2015) indicated that, paddy fields, which occupy about 30 % of the world's irrigated cropland have good potential for increased water, nutrient, and crop productivity. However, there are some challenges; more than 75 % of the world's paddy fields are continuously flooded during rice growing season (Wiangsamut *et al.*, 2013), mainly to limit variations in soil moisture and temperature and to depress soil-borne diseases and weed growth (Miniotti *et al.*, 2016).

However, such anaerobic conditions can increase emissions of methane (CH_4) - one of the most important greenhouse gases influencing global warming. In addition, water productivity and crop yield are generally low under continuously flooded irrigation. Furthermore, waterlogging and ponding problems in paddy fields during rainy seasons, when lower temperatures limit rice cultivation, prevent cropping in some parts of the world, which further decreases the productivity of these fields. These conditions have made paddy cultivation economically unsustainable for many farmers who rely on paddy fields for their income (Kumar *et al.*, 2014).

Sub-surface drainage is effective for not only controlling groundwater table depth but also alleviating soil salinization especially in arid and semi-arid agricultural areas. While substantial research efforts have been spent to determine the parameters (e.g., drain depth, drain spacing, and pipe diameter) of sub-surface drainage pipe layout for water drainage in other parts of the world, less attention has been paid to the conduct of similar researches in West Africa to determine the parameters for salt discharge, which is important in arid and semi-arid regions. In arid and semi-arid regions, soil salinization is a serious threat to crop yield and ecological environments (Li *et al.*, 2020). To control soil salinization and preserve agricultural lands, it has become popular to use sub-surface drainage pipes for lowering groundwater levels and discharging soil salt (Qian *et al.*, 2021).

There are a number of open questions for designing drainage pipe layout for salt drainage, because sub-surface drainage pipes were originally used in humid or coastal areas to remove excess precipitation, surface ponding water, or prevent seawater intrusion, and to improve root zone soil conditions (Ritzema and Stuyt, 2015; Jafari-talukolaee *et al.*, 2016). For the conventional soil drainage, various experiments have been conducted to investigate impacts of drainage pipe layout parameters on amounts of water discharge, decreases of groundwater table depth, and drainage duration of surface ponding water (Jafari-talukolaee *et al.*, 2016). Many theoretical studies have also been conducted to guide the layout of sub-surface drainage pipes in these regions when considering to remove the excess water (Yousfi *et al.*, 2014; Liang *et al.*, 2015; Tao *et al.*, 2019). However, these experimental and theoretical results obtained in humid areas for water drainage may not be suitable for salt drainage in arid and semi-arid agricultural areas.

Current field research on drainage-related nutrient reduction strategies is presently limited to a narrow range of time periods, climates, and soil types. Agricultural simulation modelling tools have been used essentially to advance research and scientific understanding of the effects of drainage systems by extending beyond the limits of field research. Early drainage simulation studies found comparable results to field-based monitoring, including NO_3-N loss reduction and increased denitrification with drainage systems. In West Africa, where this study is presently carried out, very little research has been conducted in this regard.

Rice is an aquatic crop, typically farmed in submerged or variable-depth ponds. Changes in water depth brought on by uneven levelling, particularly in large size paddy fields, can have an impact on the development and yield of rice (Talpur *et al.*, 2013). Rice is also the largest consumer of water among all crops. The water productivity of rice is lower than those of other crops (Mboyerwa *et al.*, 2021). Because of the continual flooding environment in the traditional rice production method, rice uses a lot of water and has a low water and nitrogen use efficiency (WUE and NUE, respectively) compared to other cereal crops (Liang *et al.*, 2021).

Around three (3) billion people already eat rice as their primary meal, and demand is anticipated to increase as the global population rises by 0.6 – 0.9 % worldwide until 2050 (Carriger and Vallée, 2015). Rice demand is increasing most rapidly in West and Central Africa each year. By lowering the total amount of water that must be used for each unit of production, especially by managing irrigation application depths and effective control of drainage systems, there is good potential to boost water productivity.

In Ghana, rice is an important strategic crop in the economy which is cultivated as both food and cash crop. Rice consumption continues to increase due to population growth, urbanization and change in consumer habits. According to statistics from Ministry of Food and Agriculture (MoFA), between 2008 and 2020, paddy rice production was in the range of 302,000 MT and 987,000 MT (181,000 to 622,000 MT of milled rice) with large annual fluctuations (Ofori *et al.*, 2023). The total rice consumption in 2020 amounted to about 1,450,000 MT which is equivalent to per capita consumption of about 45.0 kg per annum (Ofori *et al.*, 2023).

Irrigation depth is an important parameter for the prediction of rice growth. Without accounting for water depth, a simulated growth model for instance tends to overestimate the mass output of dry rice shoots (Caton *et al.,* 1999). Impaired tillering has been identified as the morphological reason of yield decreases in rice crops grown in partial submergence. Instead of categorizing a plot of land as irrigated or not, irrigation as an input into the production process must be measured in terms of the timing and amount of water required by crops (Talpur *et al.*, 2013).

Water productivity can be increased by combining proper management practices with water-saving strategies. Water productivity of rice refers to the amount of grain produced per unit of water used. It is an important indicator of the efficiency of irrigation and water management in rice production. High water productivity means that the crop is using water efficiently and that yields are high, while low water productivity indicates water wastage and low yields (Dawe and Dawe, 2016). Water productivity of rice can be improved through a variety of management practices, such as using drought-tolerant varieties, improving irrigation scheduling and water management, and effectively managing the drainage systems (Choudhury *et al.*, 2007).

1.2 Problem Statement and Justification

The demand for food in the world has been projected to be doubled by 2050 (Foley, 2011; UN, 2017) and would significantly increase the consumption of freshwater. This will be a very serious sustainability challenge directly related to the United Nation's Sustainable Development Goals of zero hunger, life below water and life on land (UN, 2017). Brauman *et al.* (2013) stated that the optimal use of water for irrigation purpose will support both food and water security by increasing water productivity which will help in closing the yield gaps. In irrigation practices, proper management of water is important to control salinization and waterlogging. Under-irrigation minimizes the net downward movement of water that helps leach salts from the surface of the soil and the plants' root zone area while over-irrigation causes a rise in the groundwater table where salts in the shallow groundwater precipitate and accumulate.

Due to inefficient management in many agricultural fields and especially for rice fields, water is frequently being wasted and result in low water productivity (Yao *et al.*, 2012). Adaptive agricultural practices which ensure higher water productivity are of immense importance when trying to increase the area of cultivation and conservation of water for production purposes. The global challenge of producing more food with limited or reduced water input in the near future has been noted by several authors (Bouman *et al.*, 2007; Khose *et al.*, 2022; Chawla *et al.*, 2023). Effective drainage management for soil water control plays a major role in the development of the plant and increase in productivity.

The practice of irrigation enables households to generate more income, increase their resilience and in some cases transform their livelihoods. Irrigation, when managed properly and efficiently contributes to agricultural growth and reduce poverty by permitting intensification and diversification hence increased outputs and income, increasing agricultural wage employment and reducing local food prices. In Africa, most of the agricultural production is done by smallholders, who rely on seasonal rainfall that is unpredictable and sporadic. The onset of climate change, insufficient rainfall and occasionally uncontrolled floods results in frequent crop failures which are having a serious effect on the livelihood of the population (Tabari, 2020). As a result, the population is extremely poor and food insecurity threatens each year. Farmers are faced with a lot of challenges; amongst them is that of waterlogging and salinization which can be controlled by installing sub-surface drainage system. The lack of proper drainage systems has led to the fields being waterlogged and saline; hence, low productivity (Nnaji *et al.*, 2022).

Waterlogging and salinization in the root zone of plants are the two most prevalent phenomena that inevitably coexist in semi-arid and arid regions due to poor drainage systems. FAO (2011) indicated that globally, approximately 250,000 and 500,000 hectares of valuable agricultural land is lost annually due to poor drainage systems which ultimately has the tendency of reducing crop production potential. This is a problem that is particularly very prevalent in irrigated rice paddy fields. In West Africa, while waterlogging intensity and salinization of soils are on the increase, sub-surface drainage systems are lacking to effectively control these two phenomena that inevitably co-exist. Artificial drainage is a necessity especially when practicing flood irrigation in rice fields. Several computer models have been designed for better water management systems for high production capacities of agricultural soils, but there is need to check their effectiveness at different locations using different drainage systems.

Many studies have been carried out on drainage management measures to reduce or control the adverse effects of waterlogging on crops. Controlled drainage which is a multi-objective agricultural water management technique has been used by Liu *et al. (*2020) to reduce over-drainage and relieve source pollution caused by field drainage. This has proved to have environmental benefits on drain discharge quantity and quality (Yu *et al.*, 2021). Wesstrom *et al.* (2001) conducted a field water table management experiment and indicated that total drain outflow from controlling the sub-surface drainage decreased compared to conventional drainage and the total amount of nitrate in drain outflow correspond to the reduced outflow rates. Field experiments conducted by Luo *et al.* (2008) also demonstrated that by reducing the depth of the field ditches from 1 m to 0.4 m, the drain outflow was reduced by 50 – 60 %, while the salt concentration was still below the rice tolerance level, thus caused a water table rise of 1.8 cm, reduction of drainage by 50 %, and the ground water drainage reduced by 46 %. Controlled drainage in the field experiments and micro test pit experiments both reduced drain outflow, nitrogen leaching, and altered the soil water balance. Field experiments and micro test pit experiments with drainage boundary conditions have inevitably showed different drain outflows with different soil moisture statuses. In addition, transformations between nitrate nitrogen and ammonium nitrogen in the field and test pits have been seen to be distinctive.

However, the effect of drainage on growth and performance of rice in the West Africa region have had less attention and therefore require extensive research. Hence, the primary objective of this study was to model the effect of drainage systems and irrigation depths on the performance of rice in the Guinea Savannah Agro-Ecological zone of Ghana.

1.3 Objectives of the Study

1.3.1 Main Objective

The main objective of the study was to model the effects of drainage systems and irrigation depths on rice performance in the Guinea Savannah Agro-Ecological zone of Ghana.

1.3.2 Specific Objectives

The specific objectives of the study were to:

1. Evaluate the effects of different irrigation depths and drainage systems on the growth, yield, and water use efficiency of irrigated lowland rice.
2. Analyze the influence of irrigation and drainage systems on soil salinity, temperature, and nitrogen dynamics.
3. Estimate the Crop Water Stress Index (CWSI) under different irrigation-drainage scenarios.

4. Use the DSSAT model to simulate and predict the impact of irrigation and drainage on LAI and rice yield.

1.4 Hypotheses of the Study

To guide the study, the specific objectives were used to formulate the following hypotheses.

1.4.1 Null Hypothesis (Ho)

a. Irrigation depths and drainage systems have no significant effect on the growth, yield, or water use efficiency of irrigated rice.

b. Irrigation depths and drainage systems do not influence soil salinity, temperature, or nitrogen balance.

c. There is no interactive effect of irrigation and drainage on the Crop Water Stress Index (CWSI).

d. The DSSAT model cannot accurately predict the impact of irrigation and drainage on LAI and yield

1.4.2 Alternate Hypothesis (H1)

a. Irrigation depths and drainage systems significantly affect the growth, yield, and water use efficiency of irrigated rice.

b. Irrigation depths and drainage systems influence soil salinity, temperature, and nitrogen balance.

c. The interaction between irrigation and drainage affects the Crop Water Stress Index (CWSI).

d. The DSSAT model can accurately predict the effects of irrigation and drainage on LAI and yield.

1.5 Limitations of the Study

i. Alternate wetting and drying at 15 cm irrigation application depth was used as the minimum baseline in the computation of the CWSI.

ii. Scarcity of water in the research area especially during the dry season posed a serious challenge. However, the researcher resulted in buying both dam and tap water depending on the availability.

1.6 Structure of the Thesis

This thesis has five (5) chapters. Chapter One presents a general introduction, problem statement and justification, main and specific objectives of the study and hypothesis relating to the study.

The literature review on exploring the relevant theories and published research work is covered in Chapter Two with specific focus on overview on drainage of agricultural lands, need and benefit of drainage on crop production, factors related to drainage, drainage policies in some parts of the world, overview of rice production requirements, irrigation depths and drainage on crop growth and yield, irrigation depths and drainage on changes in soil electrical conductivity, soil temperature and nitrogen balance in paddy fields, crop water stress index for rice production and models used in agriculture with respect to irrigation and drainage studies on crop production.

Chapter Three presents the area of study, and materials and methods applied in collecting, preparing and analyzing data.

Chapter Four presents the results and discussion. Finally, the general conclusions and policy implications of the study as well as the recommendations for future research are presented in Chapter Five.

CHAPTER TWO

LITERATURE REVIEW

2.0 Agricultural Drainage and Its Implication for Crop Production

2.1 Meaning and Types of Agricultural Drainage

Agricultural land drainage is a collection of technical techniques and hydraulic structures that enable the removal of excess water and/or salt from the soil volume occupied by crop roots. This creates an environment that is sufficiently oxygenated for roots to develop normally and maintains the proper ratios of air and water to meet crop physiological needs. The end goal is to enable soil sustainability for conditions of improved crop productivity (Gurovich and Oyarce, 2015). Land drainage, which also involves removing soluble salts from the soil, is the process of removing excess surface and sub-surface water from the land in order to improve crop development.

In situations when there is insufficient drainage due to an abundance of water retained in the soil pore space, the amount of oxygen vapour pressure that is available for root crop biological activity and soil microflora and microfauna activity is severely restricted. Due to a decrease in the permeability of root exodermis cell membranes to water and nutrient absorption and an increase in ABA (abscisic acid) concentration, this situation causes a variety of physiological abnormalities in plants, including stomata closure induction processes in leaves (Wang *et al.*, 2020).

Land drainage is the process of removing excess water out of affected areas and disposing of it by ditch construction, open channels, or vertical drains. Land drainage makes it possible to increase farming productivity and re-purpose unproductive areas like marshes and flooded areas (Valipour *et al.*, 2020).

The development of irrigated farming is essential to feeding the world's growing population, which is expected to surpass 9.9 billion people in the next 30 years (UN, 2017). However, in irrigated areas, this progress may result in salinization and waterlogging due to inadequate drainage if sufficient drainage measures are not taken (Zhang *et al.*, 2020). Artificial techniques are frequently employed to remove surplus water from the root zone of plants when the soil holds too much moisture. If the farmer's soil or water supply contains substances that are detrimental to the crop, artificial drainage may also be required. Then, more water is applied to the root zone to extract these elements. The salinity of the soil and irrigation water, the crop's tolerance to salt, the uniformity of the field slope, and other variables all affect how much water is needed for adequate leaching. But extra salts and water seep deep underground if a soil drains easily and the groundwater table is not saturated. Groundwater aquifer contamination may worsen as a result of this percolation.

The two (2) primary drainage systems that can be applied in an agricultural area are surface and sub-surface drainage. According to King *et al.* (2014), a field's drainage needs are determined by various factors, including the type of crop being grown, terrain, soil properties, and appropriate outputs. The process of building open channels and drains to remove excess water from the uppermost portion of the soil is known as surface drainage. According to Nangia *et al.* (2013), surface drainage is the most traditional and straightforward technique available to farmers. According to Schultz *et al.* (2007), surface drainage is the process of using canals and/or land shape to remove surplus water from the surface layer of the land.

Agricultural drainage accomplishes two goals. The first is for the removal of excess surface and sub-surface water. The second is to remove excess soluble salts with the (excess) water from the drained soil profile. There are two drainage system possibilities; a surface drainage system is the first wherein excess water is removed from the land's surface using a surface drain and a sub-surface drainage system is the second. Soil water table control is achieved through the use of a sub-surface drainage system. They can be pipe drains, which are underground pipes, or open drains, which are open ditches with an exposed water table.

According to Xian *et al.* (2017), sub-surface drainage lowers the groundwater table and creates favourable conditions within the rootzone, whereas surface drainage removes excess water from the soil's outer layer before it enters the rootzone. For this reason, much of the world uses sub-surface drainage to get rid of extra water in plant roots (Kennedy *et al.*, 2012).

2.2 Agricultural Drainage and Its Impact on Global Food Production

2.2.1 Poor Drainage and Its Implication on Crop Production

Global food production is significantly impacted by agricultural drainage, which also protects soil resources and irrigation investments. Large-scale drainage projects were constructed globally in the second half of the 20th century on roughly 150 million hectares of land plagued by salinity and flooding issues (Darzi-Naftchali and Shahnazari, 2014). By stepping up and broadening the scope of competitive and financially viable agriculture, these projects significantly improved global food production. In order to address inadequate agricultural drainage circumstances, substantial governmental and private expenditures have been made in soil profile artificial intervention in conjunction with the appended hydraulic infrastructure required to remove the drained water (Darzi-Naftchali and Shahnazari, 2014). As a result, it is crucial that drainage systems be appropriately planned, installed, operated, and maintained. Drainage network planning and design impact how well water and salinity are removed from agricultural soil profiles. The majority of drainage systems in developing nations are far from sufficient or suitable (Rahman *et al.*, 2014).

In many arid regions, inadequate drainage and the resulting salinization pose serious risks to the long-term viability of irrigated agriculture. The three major objectives of agricultural drainage are to reduce soil submergence, manage salinity, and open up new area for agricultural use. As a result, a well-designed drainage system not only enhances already-existing farmland but also brings new areas under cultivation. For effective and sustainable crop production in irrigated areas—both in tropical and rain-fed zones, where crops get all of their hydric requirements from precipitation—the removal of waterlogging conditions from soils by agricultural drainage is essential. While soil drainage occurs naturally in certain places, soil intervention is required in other locations to provide the pre-requisites for an effective artificial drainage system (Ritzema *et al.* 2008).

Waterlogging results from both natural floods and over-irrigation, drawing water from the deeper soil layers to the surface and keeps it in the plant's root zone for an extended amount of time. When soil becomes inundated, this may ultimately disrupt several beneficial characteristics of the stratum. Waterlogging and salinization cause the loss of over 25,000 hectares of irrigated land worldwide (Singh, 2015). This causes air to be forced out of the soil, changing its normal processes and accumulating toxic compounds that hinder plant growth by reducing the amount of oxygen available at the root. Because the plant root needs an adequate supply of oxygen to meet the water and nutritional requirements of the shoot, the soil oxygen concentration should be around 10 % where the ambient molecular oxygen concentration is 21 % (da Ponte *et al.*, 2019).

When there is waterlogging, the rhizosphere and the tip of the root are able to meet their oxygen needs by producing an aerenchyma by removing some cortex cells. These cells help eliminate excess gasses from the root and soil. Elevated soil moisture levels hinder the soil's capacity to distribute oxygen, resulting in hypoxic or anoxic environments that hinder the activities of nitrifying organisms' activities. This leads to a reduction in the amount of nitrogen available in the soil, which will negatively affect the yield of crops that require nitrogen. It follows that a drop in the rate of nitrification is anticipated in the event of waterlogging.

Additionally, when molecular oxygen levels decrease, the physico-chemical properties of the soil undergo a number of changes. By lowering redox potential and excess electron shifts, such as the conversion of Fe^{3+} and Mn^{4+} to Fe^{2+} and Mn^{2+}, respectively, many of these also change the electrochemical composition of soil (Singh and Setter, 2017). Consequently, the solubility of iron and manganese rises to hazardous levels, which may damage plant roots. In addition to the elemental toxicities to the sensitive root tips, a larger concentration of secondary metabolites, such as phenolic and volatile fatty acids, may become detrimental in the low-pH rhizosphere (Coutinho *et al.,* 2018). The soil's pH can be further lowered by the accumulation of volatile organic acids and a greater concentration of CO_2.

Secondary salinization is predicted to increase due to the expansion of irrigated regions, increased water demand brought on by rising global temperatures, and inadequate irrigation and poor drainage techniques. Plants' ability to tolerate salt may be exceeded by an excessive buildup of soluble salts in the root zone, which would negatively impact the rate of plant growth (Ayub, 2020). A soil that has an ECe ≥ 2 dS m^{-1} (at 25 °C) is commonly regarded as saline; however, the salt tolerance of sensitive crops and plants can vary based on the kind of plant, climate, and soil-water balance characteristics.

Salinity stress either directly lowers the plant's uptake of water from the crop root zone, causing osmotic stress on the plant, or deteriorates the transpiring leaves of the plant, a phenomenon known as specific ion effects (Parihar *et al.,* 2015). Plant nutrient imbalances are also imposed by salt in the soil. The yields of sensitive plants can be adversely affected by soil salt levels between 2 and 4 dS m^{-1}, and most crops exhibit a marked decline in growth when soil salinity exceeds 8 dS m^{-1}.

Loss of vegetation consequently makes the soil less stable and more vulnerable to erosion by wind or water. Excessive soil salinity not only harms flora but also reduces the biological functioning of soil micro-organisms to the point where it interferes with respiration, the soil nitrogen cycle, and the uptake of organic matter (Singh, 2016).

2.2.2 Benefits of Drainage on Crop Production

In many soils, the sustained agronomic production depends on the drainage of surplus water. Drainage can increase agricultural yields, lessen production unpredictability from year to year, and create field conditions that are manageable for field operations during planting or harvest. Crop productivity can be affected by drainage system design and management, which can have an effect on the environment (Young *et al.*, 2021). Improved soil aeration is made possible by drainage, which eliminates surplus soil water in the root zone. Extended exposure to saturated weather combined with inadequate soil aeration can cause stress to the crop and lower yield. Drainage can lessen compaction and increase field trafficability, enabling more dependable field access. Compaction is less likely to occur in dryer soils than in moist soils. Crops can develop deeper root systems in fields thanks to drainage, which frees up compacted or obstructed layers and increases crop access to nutrients and soil moisture.

Drainage strategies are one method that has historically been suggested to regulate the amount and quality of outflow and ensure yields. Irrigated agriculture cannot succeed without drainage because it prevents ponding, waterlogging, and/or salinity. There are two forms of drainage: artificial and natural. The majority of places have some natural drainage, which allows extra water to go from farmer's fields to wetlands, lakes, and rivers. However, an artificial or man-made drainage system is needed in situations where natural drainage is insufficient to remove the excess water or salts introduced by irrigation.

Drainage reduces saline levels above the drain, promotes organic matter decomposition, supports root growth, and preserves the land's productivity. A thorough understanding of the intricate relationship between crop, soil, and water quality is necessary for effective drainage design. Proficiency in drain material (drainage conveyance conduit) and drain placement technique (including envelop material selection and design in relation to soil bedding) are also critical (Ali, 2011).

Global food production is significantly impacted by agricultural drainage, which also protects soil resources and irrigation investments. Large-scale drainage projects were constructed globally in the second half of the 20th century on roughly 150 million hectares of land that were prone to salinity and flooding (Gurovich and Oyarce, 2015). This has increased and diversified competitive and financially sustainable agricultural activity, which has greatly improved global food production. Artificial soil profile intervention — coupled with the annexation of hydraulic structures required to remove the drained water — represents a substantial governmental and commercial investment directed toward resolving agricultural drainage deficiencies. Thus, it is imperative that drainage systems be appropriately planned, put in place, run, and maintained (Gurovich and Oyarce, 2015).

Salinity and waterlogging have negative effects on farm economics because they can lead to land abandonment, which makes the land unproductive and causes large production depressions. Saline and waterlogged conditions can significantly limit crop choice, intensification, and diversification. They can also negatively impact agricultural output, making soils difficult to work with. When there is potential for operational control to maintain the water table at a greater level, drainage enhances the soil's ability to function as a storage space (Ritzema, 2015).

According to Singh (2018), maintaining soil moisture, enhancing crop productivity, and facilitating adequate rootzone aeration on poorly drained soils all depend on an efficient artificial drainage system. One way to prevent flooding and save lives and property is through drainage. Strong drainage networks act as a buffer against heavy rainfall in certain areas. In humid tropical regions, irrigation has changed the hydrology of the soils, and natural events like monsoon flooding and waterlogging have made the issue worse.

According to Muma *et al.* (2016), installing a drainage system in any agricultural area has a number of effects, some of which are direct and some of which are indirect. The removal of water from agricultural fields and a reduction in the amount of water retained in or on the soil are the immediate effects. But the main goals of drainage are usually not the direct impacts. Improved aeration of the rootzone for increased crop yield is one of the indirect consequences (Nousiainen *et al.*, 2015). Other indirect advantages include better fertilizer use, decreased weed growth, decreased denitrification, and less restriction on crop selection. Long-term sustainability of irrigated land is achieved through the leaching of salts through drainage, which stops additional salinization of the rootzone (Jafari-talukolaee *et al.*, 2016).

According to Alakukku *et al.* (2010), drainage also increases the amount of land that is accessible, facilitates workable soil, enhances soil structure, increases land carrying capacity, and increases the activity of microfauna by keeping the soil drier, all of which support efficient crop growth. In addition, Fraser and Fleming (2001) claimed that peak flow volumes decreased in streams connected to artificially drained land and that the total runoff spread out more over time, perhaps resulting in a decrease in surface runoff, based on their analysis of the environmental benefits of tile drainage.

Four (4) advantages of tile drainage are categorized by Fraser and Fleming (2001). First, improved drainage may cause changes in landuse; second, it may result in intensive landuse, which raises crop yields and quality and improves crop rotations; and third, it may lower production costs. Finally, the use of tile drainage would enhance resource allocation on the farm by cutting down on the amount of time needed to cover the field, potentially leading to the employment of smaller, more energy-efficient tractors. Reducing the quantity of wet regions or waterlogged/flooded fields inside an agricultural land allows for more versatility in crop arrangement within crop fields and may potentially alter the nature of farming activities (Fraser and Fleming, 2001).

2.3 Factors to be Considered in Designing Agricultural Drainage Systems

Several factors need to be considered when deciding whether or not to install a drainage system. For this review, these factors are grouped into technical, economic and environmental considerations.

2.3.1 Technical considerations

To correctly build and operate a drainage system, one needs to have detailed knowledge about specific soil qualities, such as soil type and texture, the presence of any soil layers that impede water movement, and the pace at which water moves in the soil. For instance, clay soils tend to carry water considerably more slowly than sand; hence, a surface system and closer spacing of tile drains may be required in order to properly drain water from a clay soil. As a result, installation will cost extra. Both surface ditches and tile drains can be positioned wider apart in sandy soils because they are more permeable (Easton and Buck, 2015).

Soil depth is another crucial factor to take into account. In order to establish a tile drainage system for instance, there must be sufficient soil depth (0.9 to 1.5 m is usually advised). Surface systems can be employed in shallow soils, and tile drains need to be laid closer to the soil surface or more closely spaced apart in order to effectively lower the water table. Because it cuts off the deeper flow channels that water can take to reach the drain, the shallow restricting layer lowers the volume of water that a drain can intercept. Once more, this raises the cost of installation. Additionally, sub-surface drains ought to be sufficiently deep to serve as protection against frost, equipment loading, and tillage activities (Shokri-Kuehni *et al.*, 2020).

The drainage coefficient, or a drainage system's design capacity, is another crucial factor to take into account while designing a system. The intended rate of water removal to facilitate crop development and growth is also known as the drainage coefficient, and it is dependent on the type of crop and the soil. The amount of water (measured as the depth in millimeters) that must be drained from a soil in a 24-hour period is known as the drainage coefficient. The diameter or spacing in a field will be impacted by the drainage coefficient in the system design (Ritzema, 1994).

Prior to beginning any design work, the placement of the drainage system outlet should be decided upon. Drains can empty by gravity into naturally occurring streams or other sources of water, man-made open ditches, or bigger subterranean drainage mains. If these outlets have enough depth and capacity to move water throughout the drainage system, then any of them can be used. In situations when a gravity outlet is unavailable, pumping may be an option but it is to be noted that adding and maintaining a pump system to a drainage system significantly increases its cost (Ritzema, 2014).

Ensuring consistent drainage throughout a field is the ultimate objective of a drainage system, which lowers yield variability. Therefore, any system design must take the field topography – that is, the slope, slope length, and slope arrangement into account. In a field, drainage and water circulation are influenced by topography. Compared to flatter fields, steeper field slopes allow excess water to travel laterally downslope in the soil and drain more quickly. Compared to flatter fields, steeply sloping fields typically require fewer drainage systems (i.e., more drains per unit area). Where hill slopes converge, localized damp spots might develop. Because these regions need more drainage than other field areas, designing a drainage system in these places presents special challenges. Potential problem places can be located with the aid of a topographic study (Ritzema, 2014). Topography can affect soil depth and physical properties including permeability, texture, and water-holding capacity in more mountainous terrain, all of which have an impact on drainage system design. Topography affects the outlet's potential location as well. Pumping will be necessary if an outlet is not hydraulically down gradient of the system it drains. Lastly, the most practicable system depends on the geography (Price, 2011).

2.3.2 Economic Analysis

The crops being farmed, the intensity of the drainage, the need for funding, and the possible yield increases from drainage are some of the variables that determine the drainage system's economic advantage. Because sub-surface tile systems require specialized equipment for installation (such as a tile plough or trencher, tile cart, specialized survey equipment, etc.) can be very expensive but at the same time can be more cost-effective than surface ditch systems because they do not require the removal of production land. The least expensive approach, land shaping, does not remove land from production; nevertheless, it only addresses surface ponding and does not address the consequences of saturated, poorly drained soil or a perched water table (Waller and Yitayew, 2016).

The economic payback period of any drainage system can be altered by cropping choices, which is why drainage is more beneficial for higher-yielding or higher-value crops than for loweryielding or lower-value crops. Cropping plans also affect variables like drainage spacing and depth. Crops that cannot withstand prolonged wet circumstances may need more intense drainage than those that can withstand wet conditions. It could be necessary to construct drains deeper for deep-rooted crops than for shallow-rooted ones. The system design must take into account the timing of planting, harvesting, or field management operations as they are crucial for a given crop in order to guarantee a sufficient yield (Ezugwu and Eze, 2019).

2.3.3 Environmental Considerations

Although there are obvious advantages to drainage for agricultural productivity, drainage has a number of detrimental effects on the environment. There is a chance that tile-drained fields will export too many nutrients since conventional drainage management prioritizes water export rather than wise control of local water tables, which typically leads to excessive drainage. Routine ditch management techniques, such as vegetation control and scraping, can also weaken ditch walls and reduce the internal cycling of nutrients in ditch plants, which can lead to erosion and problems with water quality (Sikström and Hökkä, 2016).

Utilizing effective nutrient and pesticide management to minimize losses from the plant root zone, employing winter cover crops to trap nutrients and lessen erosion, and switching out row crops with perennials in the cropping system are some drainage best management practices to minimize off-site losses of undesired contaminants into receiving waters. When constructing new or upgraded field drainage systems, farmers should think about utilizing crop management techniques and landscape elements that lower water discharge rates, nitrogen emissions, and sedimentation (Nahvi *et al.*, 2017).

2.4 Overview of Rice Production Requirement

2.4.1 Growth Stages of Rice

Rice is one of the most significant staple crops providing food for about half of the world's population. It is extensively grown all over the world. Throughout the past 10,000 years, domesticated rice has been a major component of human culture and diet (Wei and Huang, 2019). More than 120 countries throughout the world now have extensive rice farming. The world's annual rice harvest area was 163 million hectares, with India, China, Indonesia, Bangladesh, and Thailand accounting for 67 % of the total (Wei and Huang, 2019). Throughout the last 50 years, the planting area for rice expanded by about 42 % and has continued to progressively rise (Samal *et al.*, 2022).

A 120-day variety when planted in a tropical location spends around 60 days in the vegetative stage, 30 days in the reproductive stage, and 30 days in the ripening stage. Many scientists divide it into stages, although the majority of them use four of them: nursery, vegetative, mid-season, and late season (Talpur *et al*., 2013).

The nursery stage is the time between seeding and transplanting; the duration spans from 20 to 25 days. Rice seeding rates of 30 - 35 kg/ha are adequate. The optimum soil for a nursery is clayey loam or loamy soil. The field should have a proper water drainage system. Nitrogen and phosphate fertilizer at low rates can be applied to the nursery (Salam *et al*., 2001). The time between transplanting and panicle initiation is described as the vegetative stage and the duration ranges from 45 to 90 days. The vegetative stage of rice refers to the initial growth phase of the rice plant after germination, during which the plant primarily focuses on developing its roots, leaves, and stems. This stage begins after the rice seedling emerges from the soil and lasts until the plant enters the reproductive phase and develops panicles. During the vegetative stage, the rice plant produces several leaves and tillers (additional stems) and grows in height (Constantino *et al*., 2018).

The mid-season stage spans between panicle initiation and flowering, which comprises stem elongation, panicle initiation, and flowering with a duration of around 30 days. During this stage, the rice plant continues to grow taller, producing more leaves and tillers, and its root system becomes more extensive. This growth stage is also characterized by the development of the panicle primordium, which marks the beginning of the reproductive stage (Hossain *et al.*, 2017).

The late stage is time between flowering and complete maturity; it lasts roughly 30 days. During this stage, the rice grains develop and fill with starch and other nutrients, and the rice plant begins to senescence, or age, as it approaches maturity. In the late stage, the rice plant requires adequate moisture, nutrients, and sunlight to complete the grain-filling process and ensure optimal grain quality and yield. Proper management practices, such as timely harvesting and threshing, can also help ensure optimal grain quality and minimize yield losses (Yoshida, 2012).

2.4.2 Rice Environment

Rice is cultivated under varying degrees of flooding that is why it grows in a variety of conditions and is productive in many conditions where other crops would fail (Andriesse and Fresco, 1991). The majority of rice environment classifications are based on hydrological parameters. Lowland irrigated rice is farmed in bunded fields with guaranteed irrigation for one or more crops each year. Farmers typically aim to keep 5 - 10 cm of water on the fields. Fields are primarily puddled and plants are transplanted in both irrigated and rainfed lowlands (Kariyasa and Dewi, 2011).

At the field level rice receives up to 2 - 3 times more water per hectare than other irrigated crops. In the rainy season, supplementary irrigation is mostly used to grow irrigated rice, while in the dry season, irrigation is the only method of production (Tuong *et al*., 2016). Lowland rice is traditionally nursed in a seedbed before being transplanted into a main field that is kept under continuous (irrigated) or intermittent (rainfed) ponded water conditions (Tabbal *et al.*, 2002).

Land preparation consists of soaking, ploughing, and puddling. Moreover, puddling as done for weed control lessen soil permeability and percolation losses, and to make field levelling and transplanting easier. Lowland rice has a different water balance than other grains like wheat because of its flooded nature. The total amount of water needed by transplanted rice depends on the size of the discharges, how long it takes to prepare the land, and crop growth. Large reductions in water input can be possible at the field level by minimizing the time for land preparation, seepage and percolation flows (Mukherjee, 2019). In most parts of the world, rice is grown conventionally in continuously flooded lowland irrigation systems (Fawibe *et al.*, 2020).

2.4.3 Nutrient Requirement

An essential component of the soil and plant management system is nutrient management. Understanding the nutrients needed for crops at every growth stage and the soil's capacity to supply them are essential for successful crop production. According to Shrestha *et al.* (2020), rice requires sixteen different nutrients, of which N, P, and K are the basic macro nutrients, Mg, Ca, and S are the secondary macro nutrients, and Zn, Fe, Mn, Cu, B, Mo, and Cl are the micro nutrients. Other than water, fertilizer is the production input that can do the most for a crop, however, results might vary substantially. One crucial component for rice is nitrogen. The rice variety, the season, the soil, and the farmer's cultural practices are some of the variables that affect how well rice consumes nitrogen fertilizers (Ye *et al.*, 2013).

According to Shrestha *et al.* (2020), nitrogen is a crucial element needed for rice yield, uniformity, organ construction, physiological qualities, component synthesis, and their diffusion. Nitrogen (N) is most frequently required for grain formation, booting stages, and panicle initiation during the early to mid-tillage period. Phosphorus (P) helps produce rice and supports physiological metabolism by being involved in the creation of cell membranes and a number of metabolic activities. Phosphorus is essential for maintaining the root development mechanism, disease resistance, and drought tolerance by promoting the early flowering and maturity stage. Potassium (K) functions as an activator of several enzymes and is an intracellular osmotic and membrane protein transfer activator.

Consequently, K plays a crucial role in rice glucose transport and is also necessary for plant metabolism and stress tolerance (Ragel *et al.*, 2019). According to Kong *et al.* (2013), there is a substantial correlation between the application of potassium and the lignification of sclerenchyma cells, vascular bundles, and great resistance to lodging. Applying Silicon (Si) can prevent rice diseases in a manner similar to those of fungicide treatments. Likewise, the application of Manganese (Mn) mitigates some rice diseases. Many diseases are less severe when Boron (B) is applied, and using Chlorine (Cl) can increase the resistance of host plants to disease (Kong *et al.*, 2013).

Emergence, tillering, panicle initiation, booting, heading, and maturation are the crucial stages for rice. Since the crop is more vulnerable during these stages, it should be protected from nutritional stress. One of the primary reasons for crop productivity stagnation is the absence of certain micro and secondary nutrients (Shrestha *et al.*, 2020).

2.4.4 Climatic Requirement

Majority of rice globally is grown in tropical climates, where temperature is a key factor in growth. Since rice is a tropical and sub-tropical plant, it needs temperatures between 20 and 40 degrees Celsius. Low temperatures in temperate zones and high temperatures in lower elevations in the tropics have a negative impact on the crop. This crucial temperature varies depending on the variety, duration of critical temperature, diurnal changes, and changes in the plant's physiology (Nievola *et al.*, 2017).

The amount of solar energy that the rice canopy intercepts influences both grain yield and biomass. A rice crop's needs for solar radiation vary according on the phytophase. A study examining the link between yield and solar radiation at various phenophases revealed a weak relationship at 200 cal cm^{-2} day^{-1} during the vegetative phase and a strong association between 100 and 450 cal cm^{-2} day^{-1} during the reproductive stage and 150 and 400 cal cm^{-2} day^{-1} during the ripening phase (Ding *et al.*, 2019).

The most critical weather factor in rainfed rice ecologies (upland, lowland, and flood-prone) is the amount and distribution of rainfall. It affects irrigated ecosystems indirectly by affecting the availability of water in irrigation sources (tanks, canals, wells, etc.) and by influencing temperature, sun radiation, and wind speed changes that affect crop evapotranspiration. The importance of daily rainfall surpasses that of monthly or annual rainfall. Sridevi and Chellamuthu (2019) noted that it is better to have 100 mm of rain per month spread out evenly during the growing season rather than 200 mm of rain per month that fell in two or three days. For rainfed rice to have a good yield, 200 – 300 mm of water per month is thought to be the bare minimum.

Temperature affects relative humidity, and invariably there is more moisture in the atmosphere in the morning than in the afternoon. A high relative humidity environment is created when rice is grown in standing water. For healthy growth, rice needs a rather high level of humidity. A relative humidity of 80 – 85 % is best for the growth of shoots. Rice growing at 22, 28, or 34 ºC, increasing humidity causes the photosynthetic rate to rise and vice versa (Sridevi and Chellamuthu, 2019).

2.4.5 Soil Requirement

Rice grows best in soils that are rich in clay and organic matter and have a good capacity to retain water. Clay soils or clay loams are ideal for growing rice. Such soils support crops and retain water over extended periods of time. Since rice is a semi-aquatic crop, submerged circumstances are ideal for its growth. Almost any kind of soil can be used to grow rice, though yield varies. Rice grows well in soils having a pH range between 5.5 and 6.5 (Dou *et al.*, 2016).

2.5 Irrigation Depths and Drainage on Crop Growth and Yield

2.5.1 Irrigation

Irrigation is the application of water in a controlled and timely manner to crops for increased or sustained production. Irrigation consists of the water that is applied by an irrigation system during the growing season and also includes application of water at critical stages in crop production such as water field preparation, pre-irrigation, weed control, harvesting, and for leaching salts from the root zone (Malakar *et al.*, 2019).

Water is gradually becoming a scarce resource in the world and irrigated agriculture remains one of the largest and most inefficient users of this resource and has been rated as the highest consumptive use of freshwater (Ingrao *et al.*, 2023). There is high risk of an increase in population and that more people will go without adequate food supplies especially in underprivileged and water scarce communities. The production of food in agriculture needs to be increased by an estimated 60 % by 2050 if food security is to be ensured and irrigation will be employed greatly in order to meet this demand. In the race to enhance agricultural productivity, irrigation will become even more dependent on sub-standard sources of water and increased competition for water resources with other sectors (e.g., tourism or industry) in the attempt to enhance crop productivity (Mehta *et al.*, 2024).

Factors such as consequences of global climate change, alterations in the use of land, agricultural and urban expansion, and over exploitation due to economic development have subjected water resources to severe degradation (Nhemachena *et al.*, 2020; Kalfas *et al.*, 2024). The demand for services supplied by water resources is expected to increase in parallel with the over exploitation and degradation of these resources. Agricultural ecosystems are the principal suppliers of food, but they are also the main users of water resources on a global level. These ecosystems use between 60 % and 90 % of the available water, depending on the climate and economic development of the region (Pedro-monzonís *et al.*, 2015; Velasco-muñoz *et al.*, 2019). Hedley *et al.* (2014) stated that the area dedicated to irrigated crops in the world was 275 million hectares, with an upward growth trend of 1.3 % per year. This accounted for just 23 % of farmed land.

Water scarcity is further worsened by the high-water demand of irrigated rice. Tuong and Bouman (2003) predicted that by 2025, approximately 18 million ha of paddy rice will experience water shortage. Water scarcity in agriculture has remain a global problem that threatens paddy rice productivity. Investing in water control tools such as irrigation is a key factor for agricultural development as it leads to improvement in productivity (Domenech and Ringler, 2013). Domènech (2015) stated that irrigation is an essential component of the modern package of inputs (improved seed, fertilizer, and improved tillage, among others) required to produce crop yields to meet the growing food demand. Irrigation interventions beyond productivity improvement, can also improve nutritional outcomes through availability of food supplies and improved diet, both in quantity and quality and also contribute to poverty reduction (Domenech and Ringler, 2013).

It is therefore necessary to have an idea of the current state of knowledge and explore the effects of irrigation depths and controlled drainage on the performance of crops. This understanding will help ensure adequate crop production to meet increased demand as well as to maintain proper food and soil quality.

2.5.2 Types of Irrigation

Irrigation is a land management strategy that frequently involves permanent and irreversible land modifications, in addition to enhancing agricultural productivity and food security (Valipour *et al.*, 2020). In modern agriculture, there are several irrigation techniques that have been developed to meet specific crop/regional needs. Originally, the irrigation techniques are grouped into three main systems, namely surface, drip and sprinkler (Brouwer *et al.*, 1985). More recent sources that attempt to generalize irrigation techniques across the world tend to group them into four main delivery methods (Bjorneberg, 2013; Irmak, 2020).

1. Surface: the water is delivered to the field through hydrants and it is either spread over the whole area (furrow/basin irrigation) or from its borders (border irrigation) (Bjorneberg, 2013).

2. Sprinkler: the water is delivered as raindrops that precipitate over the agricultural area. There are several variations of this method, and which can depend on the height (over/under the foliage) and diameter of the application, and rate (Phocaides, 2000; Bjorneberg, 2013).

3. Micro: the so-called "localized" irrigation, where the water is delivered directly around a limited soil surface around the plants. Further, the water is applied at a low rate and pressure. However, this method is mainly employed in permanently installed systems, e.g., trees, vineyards (Bjorneberg, 2013).

4. Sub-irrigation: in this method, the water is applied to change the water table height (Bjorneberg, 2013), and it has a high potential for areas with a high degree of drainage requirements (Irmak,

2020). This method is generally used in the horticultural industry in greenhouses and nursery plant productions (Irmak, 2020). However, it is not used in arid or semi-arid areas, as irrigation water is needed for the crop germination (Bjorneberg, 2013).

In the border strip approach, the farm is separated into several strips, each strip being 3 – 20 meters broad and 100 – 400 meters long. There are low borders dividing these segments. Although the strips slope along their length in accordance with natural slope, they are level between borders. However, this strategy necessitates expensive initial land preparation. These strips receive water from the supply canal, which is then slowly directed towards the downstream end, soaking and irrigating the soil in the process. Water moves from the upstream to the downstream end when the supply is cut off (Sable *et al.*, 2019).

In the check/basin method of surface irrigation, the technique works by applying irrigation water to a level or nearly level area that is completely surrounded by dikes. The area is split into several almost flat plots that are encircled by levees. In rotation, water is admitted to these plots from the farmer's watercourse. This technique works well with a broad variety of soil types, from extremely permeable to heavy soils. The farmer has excellent control over how much water is distributed throughout his field. It is possible to reduce the amount of water lost by surface runoff and deep infiltration, allowing for sufficient irrigation of the entire farm (Sable *et al.*, 2019).

In rice production, surface irrigation techniques are the most widely utilized in the globe, despite their low efficiency and uniformity, which can be attributed to poor water management and designs (Kaur *et al.*, 2020). Inefficient irrigation is a defining characteristic of surface irrigation techniques, such as furrow, border, and basin irrigation. This results in water waste, salinization, and contamination of surface and groundwater resources (Levidow *et al.*, 2014; Mitiku *et al.*, 2024).

Flood irrigation necessitates a lot of labour due to the high-water levels in paddy fields, and farmers typically utilize manual equipment to control the input and output flow. Nonetheless, Liu *et al.* (2024) indicated that flood irrigation may be sustained with the use of good water management techniques.

Many approaches in water saving have been tested to increase the rice production including direct seeded rice (DSR) (Farooq *et al.*, 2011), alternate wetting and drying (AWD) (Rejesus *et al.*, 2011; Lampayan *et al.,* 2015), aerobic rice (Singh, 2013; Ishfaq *et al.,* 2020), system of rice intensification (Toungos, 2019), saturated soil culture (Tuong and Bouman, 2003), intermittent dry spells (Feng *et al.*, 2007) and a lot more.

As an alternative to the flooding of rice fields in traditional cultivation, the practice of alternate wetting and drying (AWD) involves allowing the surface water of rice fields to disappear before the field is irrigated again. The essence of AWD is maintaining intermittently aerobic soil conditions. This reduces the amount of water that is required for rice production and constrains the biotic process of methanogenesis in the soil, thereby reducing the amount of methane gas that is emitted into the atmosphere.

Adoption of water-saving techniques in rice not only increase the paddy yield but also increase carbon sequestration, helps in resource (water, labour, energy, and time) saving, and reduce the emission of greenhouse gases (GHGs) (Yang *et al.,* 2017). The potential benefits of AWD system include: requires 23 – 33 % less water (Chu *et al.,* 2015; Carrijo *et al.,* 2017), reduces the anthropogenic GHGs emission by 45 – 90 % (Linquist *et al.*, 2015), improves water use efficiency (WUE) (Yao *et al.*, 2012; Djaman *et al.*, 2018) and maintains or even increase the grain yield (Chu *et al.*, 2015). The intermittent irrigation with AWD in rice has been effective in decreasing insect pest (92 %) and disease (100 %) infestation (Bouman *et al.,* 2007; Chapagain and Yamaji, 2010).

2.5.3 Irrigation Scheduling

Irrigation, essential for food production and landscape maintenance, affects soil water dynamics, water quality, and soil chemistry. For optimum irrigation scheduling, sound knowledge of the soil water status, crop water requirements, crop water stress status and potential yield reduction under water-stressed conditions is required (Moursi *et al.,* 2019). Irrigation scheduling is the practice of using some method to decide when to start an irrigation system and how much water to apply. It provides answers on when and how much water to apply. Irrigation scheduling is the technique to timely and accurately give water to a crop. It is a planning and decision-making activity that the farmer or operator of an irrigated farm is involved in before and during most of the growing season. Critical crop growth stage approach, soil moisture depletion approach and atmospheric evaporativity approach are various methods of scheduling irrigation.

Irrigation scheduling has been studied extensively in the past to determine the appropriate time and quantity of water for irrigation (Hassan-Esfahani *et al.,* 2015; Thorp *et al.,* 2017). Irrigation scheduling has been described as the primary tool to improve water use efficiency, increase crop yields, increase the availability of water resources, and provoke a positive effect on the quality of soil and groundwater. Irrigation requirement of crops varies with soil type, and agroclimatic conditions. No matter what method is used, they all start with knowing when and how much rain has been received on the field and then using some mechanism to decide on when to irrigate. For effective management and to improve the productivity of irrigation water, both temporal and spatial distribution of irrigation supply are important.

The timely irrigation supply with desirable quantity is dealt with by irrigation scheduling. The application of water below the evapotranspiration (ET) requirement is termed as Deficit Irrigation (DI). Irrigation supply under DI is reduced relative to the amount needed to meet maximum ET.

Total irrigation application is not proportional to irrigation requirements of the crop. Deficit irrigation aims at stabilizing yields and at obtaining maximum water productivity rather than maximum yields (Geerts and Raes, 2009). Reducing depth of irrigation, refilling a part of the soil water capacity of the root zone, or reducing the irrigation frequency helps to manage DI. The adoption of this technique implies appropriate knowledge of crop water use and responses to water deficits, including the identification of critical crop growth periods and of the economic impacts of yield reduction strategies (Oweis and Hachum, 2006).

The water balance method can be used for real-time irrigation scheduling and can be linked to the climatic forecast to assess the agricultural drought. In an effort to improve plant growth and to achieve high yield and/or quality, irrigation scheduling (IS) seeks to provide plants with appropriate quantities of water at appropriate times. Given that some of these methods focus on soil moisture status or plant responses to soil moisture, the determination of target soil moisture levels, along with estimates (either calculated or measured) of current soil moisture status are key to both scheduling irrigation, and the precise replenishment of soil moisture to target levels. Accordingly, factors in the soil-crop-atmosphere system affecting soil moisture must be considered in the scheduling process (Gu *et al.*, 2020).

Scharwies and Dinneny (2019) stated that, the importance of water in plants arises from its role in supporting photosynthesis, regulating temperature via evaporative cooling, maintaining structure through cell turgor pressure (i.e., in maintaining leaf orientation), and transporting nutrients into and throughout the plant, thereby supporting its growth. While irrigation guarantees crop growth in regions where rainfall is insufficient to support crop growth and yield, it must be scheduled properly, lest crops suffer water stress at a critical growth stage, or excess water applied that leads to ponding, waterlogging, runoff and/or deep seepage, thereby leaching applied nutrients and polluting water bodies. Though in regions where soil salinity is of a concern, excessive water is required to be applied to leach the salts down in the soil profile. Vellidis *et al.* (2016) stated that the quantity of water applied and the timing of its application are both of significant importance in irrigation scheduling whether in landscape or agricultural applications.

A good irrigation schedule, achieved through well informed irrigation scheduling criteria, can provide significant irrigation water savings, whether it can be for landscape applications or agricultural crop yield and quality. Grabow *et al.* (2013) highlighted four types of irrigation scheduling approaches among those that have been proposed and developed and be distinguished according to what scheduling rests upon. These include, evapotranspiration (ET) and soil water balance (ET-WB), soil moisture status, plant water status, and simulation model output.

2.5.3.1 Evapotranspiration (ET) and Soil Water Balance (ET-WB)

Grabow *et al.* (2013) stated that the ET-WB method is a widely used irrigation scheduling method whereby the main consumptive element, crop evapotranspiration (ETc), is first estimated according to methods outlined in the Food and Agriculture Organization (FAO) Irrigation and Drainage Paper 56 (Allen *et al.*, 1998), and the daily soil water deficit then calculated on the basis of the soil water balance equation. Irrigation events are scheduled when the total water depletion exceeds the readily available water (RAW) as presented in Equation 2.1.

$$RAW = MAD \times \left(\theta_{fc} - \theta_{pwp}\right) \times RZD \quad \text{Eqn 2.1}$$

Where:

RZD – Root zone depth or that of a soil layer within the root zone,

MAD – Management allowed depletion (i.e., a fraction of the total available water that is allowed to be depleted),

θ_{fc} – Volumetric soil moisture at field capacity, and

θ_{pwp} – Volumetric soil moisture at the permanent wilting point.

Davis and Dukes (2010) stated that, the ET-based method depends strongly on the accuracy of the estimated ET_o, building a better crop coefficient (Kc) curve over the growing season using a single or dual crop coefficient or site-specific calibration approach, evaluating soil properties to determine the soil's water holding capacity, and measuring site specific rainfall. Improving the accuracy of estimating all these parameters is the main challenge of ET-WB based approach, and therefore to minimize the accumulative error of soil water deficit estimation. Another challenge of this approach that was stated by DeOreo *et al.* (2016) is the spatial and temporal variability for a large-scale ET estimate.

Some computer applications, including software and decision support systems (DSSs), have been developed to implement ET-WB based irrigation scheduling and to liberate farmers from laborious calculations and the need to understand the science of the method. Among these are the Smart Irrigation apps (Vellidis *et al.*, 2016). These applications are related strictly to irrigation scheduling, namely irrigation timing and quantity determination, without considering economic and government regulatory factors (Yang *et al.*, 2017). Smart Irrigation apps are interactive ET-based irrigation scheduling tools that operate on smartphone platforms. Several apps have been developed for different plants, such as citrus, turf, strawberry, cotton, avocado and vegetables, and is still under development for other crops, like blueberry and soybean. There is however a gap on the irrigation scheduling applications that are specific to Africa.

2.5.3.2 Soil-Moisture-Based Irrigation Scheduling

The soil-moisture-based irrigation scheduling methods compare monitored soil moisture (inferred from sensor measurements) to soil-moisture-based thresholds to trigger the timing of irrigation. Migliaccio *et al.* (2010) stated that, monitored soil moisture is commonly measured by time domain transmission sensors or reflectometry probes, neutron probes, capacitance sensors, granular matrix sensors, etc. Related to soil moisture, soil water tension or soil matric potential (ψm) measured by tensiometers, is another parameter used to quantify soil water available for plant use. In an effort to benefit crop growth, yield, and quality, soil-moisture-based irrigation scheduling methods focus mainly on determining when irrigation should be applied to maintain root zone soil moisture within an appropriate range (Viani, 2016).

Various methods have been proposed to determine irrigation timing based on a lower limit or threshold of soil moisture (θ_{th}) (Zotarelli *et al.*, 2011; Haley and Dukes, 2012), e.g., $\theta_{th} \leq 0.12$ m^3 m^{-3}; or when soil tension (ψ_m), reaches a set threshold (Migliaccio *et al.*, 2010), e.g., $|\psi_m| > 25$ kPa. The threshold value varies according to soil properties and crops, and is determined either through field experiments, where crop responses to different levels of water stress under various irrigation treatments are investigated (Huang *et al.*, 2017), or drawn from existing studies (Haley and Dukes, 2012). Therefore, these thresholds are optimized for specific locations and crop species due to their responses to crop growth, yield, and quality, etc. Thompson *et al.* (2007) proposed an alternative to determine threshold values of ψ_m, using an indicator of plant water stress, the leaf water potential (ψ_{leaf}). A linear regression was established between ψ_m and ψ_{leaf} for conditions ranging from well-watered to non-watered, and the point where the relationship broke from a linear relationship was chosen as the ψ_m threshold. Thompson *et al.* (2007) also proposed an in-situ approach for determining the lower limit in ψ_m-based irrigation management, by monitoring reductions in soil moisture as a reflection of crop water uptake.

Wang *et al.* (2017) indicated that, without considering leaching requirements for soil salinity control, recharging the soil up to a value lower than θ_{fc} is recommended to avoid percolation and to increase the water use efficiency (WUE). When applying irrigation up to the soil's θ_{fc}, soil properties need to be appropriately estimated. Among the irrigation amount determination methods, applying a fixed amount of irrigation is effective in alleviating water stress, at the risk of, however, leading to either deep percolation or insufficient irrigation, resulting in water and nutrient loss or impaired crop growth.

The soil-moisture-based method has the advantage of allowing variable rate of irrigation scheduling due to its capacity to measure spatial and temporal soil moisture variability in the field. Accordingly, the spatial differences in irrigation quantity required for different blocks of the field can be considered. As an alternative to using a sensor array Hedley *et al.* (2013) investigated the use of an electromagnetic mapping technique to map the soil water status and soil properties including available water content (AWC) and θ_{fc}, which were used to determine the triggering threshold (θ_{th} or AWC_{th}). In contrast to the low spatial resolution of soil moisture measurements using traditional sensors, electromagnetic mapping techniques have the potential to achieve a high spatial resolution in both soil moisture and soil properties, and therefore serve to map θ_{th} to a higher resolution and schedule a more accurate variable rate irrigation. Evett *et al.* (2011) stated that, the major weakness of a soil-moisture-based irrigation scheduling approach resides in the inaccuracy of soil moisture measurements using sensors. Practically, soil-moisture sensors are used to track soil water trends but should be coupled with other irrigation scheduling approaches.

2.5.3.3 Plant-Based Irrigation Scheduling

Instead of using the soil moisture threshold to schedule irrigation in soil-moisture-based irrigation scheduling methods, plant-based irrigation scheduling methods use plant-water-status-related indices. Plant-based irrigation scheduling methods are based on the relationship between crop water stress and soil water deficit. Accordingly, they can be used to define the optimum soil moisture level for crop growth. As the sensitivity to water deficit varies among different plant species, plant tissues, and crop phenological stages, a wide range of plant-based stress measurements have been proposed as being relevant to irrigation scheduling.

Padilla-Díaz *et al.* (2016) identified two major categories of plant-based measurements for irrigation scheduling;

1. plant-water-status-based i.e., direct measurements of leaf/xylem/ stem water potential and indirect measurements of leaf thickness, stem and fruit diameter variation, and turgor pressure; and
2. those based on plant physiology i.e., measurements of sap flow, xylem cavitation, stomatal conductance, and thermal sensing.

An efficient plant-based irrigation programme depends on whether whatever measurement is made is sensitive enough to properly assess the water deficit for the specific plant/crop (Bellvert *et al.*, 2016). For example, plants with strong endogenous control systems maintain a stable leaf water status over a wide range of evaporative demand or soil water supplies; therefore, one cannot use plant water status as the index for irrigation scheduling. Since leaf/ xylem/stem water potential are not well adapted for automation of irrigation scheduling due to difficulties in real-time measurement, stem diameter variation (SDV), sap flow and canopy temperature sensing are more often applied in automatic irrigation systems. Reviewing several SDV-derived irrigation scheduling approaches, including maximum daily stem shrinkage/growth rate.

Fernández and Cuevas (2010) pointed out that the effectiveness of an SDV-derived index must be evaluated, because many factors other than water status may affect the index, e.g., growth patterns, crop load, plant age, and field management practices. Besides, SDV measurements tend to be affected by noises from raindrops and small animals. Expert supervision is routinely required, which compounds the limited applicability of SDV-derived indices for automating irrigation.

Given the recent development of thermal sensing using infrared thermometers and other thermography techniques, canopy temperature (T°C) has recently been applied as a key factor for irrigation scheduling. Commonly used canopy-temperature-based methods include the temperature-time-threshold (TTT), crop water stress index (CWSI), and temperature stress day (TSD). Wanjura *et al.* (2006) indicated that, the temperature-time-threshold method triggers irrigation only when T°C exceeds a crop specific temperature threshold ($T°_{th}$) for a pre-determined time period (time threshold, t_{th}) within one (1) day.

The TTT method has been evaluated on a number of occasions (O'Shaughnessy *et al.*, 2011; DeJonge *et al.*, 2015; Osroosh *et al.*, 2016), and was reported to show promise for auto-irrigation scheduling, given appropriate $T°_{th}$ and t_{th} values determined in previous studies. However, it can be inaccurate because canopy temperature can be affected by the ambient temperature, e.g., T°C can be high on a hot day even if the crop is well watered. Moreover, DeJonge *et al.* (2015) indicated that, the TTT method only consider canopy temperature threshold and the time when the threshold was exceeded, but no attention was paid to the extent to which $T°_{th}$ is exceeded. Moreover, the irrigation amount determined by peak daily ET can be inaccurate and may cause deep seepage.

The crop water stress index (CWSI) method was proposed by Idso *et al.* (1981) as a method which schedules irrigation on the basis of the crop's water stress based on the T°C and atmospheric vapour pressure deficit (VPD). The CWSI is calculated as per Equation 2.2:

$$CWSI = \frac{(T^o_c - T^o_a) - D_2}{D_1 - D_2} \quad \text{Eqn 2.2}$$

Where:

$T°_a$ – Air temperature,

T°C – Canopy temperature,

D_1 – Max (T°C − $T°_a$) (water stressed crop; maximum stress baseline) and

D_2 – Min ($T°C - T°_a$) (well-watered crop; no-water-stress baseline).

Baselines D_1 and D_2, which are usually a linear function of vapour pressure deficit (VPD), are used to represent the effect of VPD. The CWSI is close to zero when the crop is well watered and closer to 1.0 as the water stress gets more severe.

This method is normally used to determine irrigation timing through an evaluation of the CWSI under different irrigation treatments, and the baseline temperature is normally acquired through experiments with fully stressed and non-stressed treatments (Emekli *et al.*, 2007; Gontia and Tiwari, 2008). The CWSI threshold can be set by users and can serve to trigger irrigation using thermal-sensed T°C. The accuracy of baselines is the key to this method, especially for D_2 (Idso *et al.*, 1981).

As leaf temperature fluctuates rapidly with changes in radiation, wind speed, and air temperature, the baseline temperature in CWSI is affected by the environmental variations as well. In areas under more humid environment (lower VPD) and lower levels of radiation, the sensitivity of baselines in CWSI calculations is reduced and thereby the reliability of CWSI method decreases. To cope with the low sensitivity of baselines, Jones (1999) suggested to measure maximum and minimum T°C using infrared thermometers from a dry (non-transpiring, by covering the leaf with petroleum jelly) and wet real leaf surface, respectively. O'Shaughnessy *et al.* (2011) proposed a CWSI time threshold (CWSI-TT) method in order to overcome the limitation that the CWSI has to be measured near solar noon or soon after, and under cloud free conditions. Similar to the TTT method, the CWSI-TT method triggers irrigation when the observed CWSI value exceeds the CWSI threshold for longer than the time threshold.

2.5.3.4 Model Based Irrigation Scheduling

In this review, limitations are done on those model-based irrigation scheduling methods that are intended for determining irrigation timing and amount for a specific field, rather than the determination of the distribution of water resources for several fields and/or crops. Among these model-based irrigation scheduling methods, the utilization of process-based models and regression models are summarized. Irrigation can be scheduled using simulated results from a process-based model. For regression models, irrigation can be scheduled using optimized algorithms built on the soil water balance equation.

i. Process-Based Models

Irrigation scheduling can be done on the basis of crop/plant responses to soil moisture, and is therefore subject to the influence of the atmosphere, the growth stages of the crop, and the soil type, etc. as highlighted by the scheduling methods above. To obtain a more precise and dependable irrigation schedule, models founded on a theoretical study of the crop's growth process and considering the effects of the soil-crop-atmosphere system in a holistic manner have been tested (Chen *et al.,* 2019). Among these models are the Soil and Water Assessment Tool (SWAT), CROPWAT, AquaCrop, and RZWQM2 models. These models, after appropriate calibration, can accurately simulate crop responses to variable atmospheric and soil conditions and management scenarios, e.g., the Root Zone Water Quality Model (RZWQM2) model (Ma *et al.*, 2012). As these models contribute to investigating crop responses to different irrigation management regimes, they can as well serve the purpose of scheduling irrigation. However, process-based models are commonly used for irrigation planning but not real-time decision-making. To fill this gap, Gu *et al.* (2017) developed a software known as IrrSch, to determine irrigation timing and amount based on RZWQM2 which simulated plant water stress and soil water regime. This software, along with irrigation control hardware, has been adopted in an on-going field experiment to test its feasibility in real-time irrigation scheduling for cotton (Chen *et al.*, 2019).

Irrigation events modelled in SWAT can be scheduled either by the user – by providing inputs for application dates, amounts, and application efficiencies or by an automatic irrigation module (Neitsch *et al.*, 2011), whereby irrigations are triggered by either a water stress threshold or a soil water deficit threshold fixed by the user. The quantity of water applied is calculated to replenish the root zone soil to field capacity (though a lesser amount is suggested to avoid excessive percolation if rainfall occurs in the following days) or a fraction thereof for deficit irrigation. The SWAT model calculates water stress by comparing actual and potential plant transpiration.

Transpiration is either simulated by the Penman-Monteith method or derived as a linear function of potential evapotranspiration (ET_{pot}) and Leaf Area Index (LAI) (Neitsch *et al.*, 2011; Sun and Ren, 2014). Both Sun and Ren (2014) and Maier and Dietrich (2016) found that, when used for irrigation scheduling, the SWAT model consistently overestimated the amount of irrigation required. Therefore, the model's accuracy in automatic irrigation control needs to be improved.

The CROPWAT model is user-friendly and has been successfully used to calculate the impact of climate change on crop water use (Surendran *et al.*, 2015). The programme is used for simulating crop yield response to water and is a decision support system developed by the Land and Water Development Division of the FAO. Its main functions are to calculate reference evapotranspiration, crop water and irrigation requirements in order to develop irrigation schedules under various management conditions and scheme water supply and to evaluate rainfed production, drought effects and efficiency of irrigation practices.

CROPWAT uses what is essentially the ET-WB method, combined with the ability to predict yield reduction due to water stress (Doorenbos and Kassam, 1979). To schedule irrigation, CROPWAT requires climatic data (temperature, relative humidity, wind speed, sunshine hours, rainfall), crop data (planting date, Kc curve, rooting depth at different growth stages, the allowable soil moisture depletion level, and the yield response factor K_y), along with soil data (total available soil water content, initial soil water depletion). Irrigation under CROPWAT can be triggered by a soil moisture threshold at fixed intervals, by a predetermined depleted amount of water, or by a reduction in ET. The water depth applied is the amount to bring soil moisture back to field capacity or to a fixed level below or above field capacity; otherwise, the replenishment point is at the user's discretion. In the latest version of CROPWAT (version 8.0), all the calculations are based on the two FAO publications of the Irrigation and Drainage Series, namely, No. 56 (Allen *et al.*, 1998) and No. 33 (Doorenbos and Kassam, 1979).

The FAO's simplified crop model, AquaCrop (Raes *et al.*, 2009), developed to simulate attainable crop biomass and harvestable yield in response to available water, can schedule irrigation events by manually specifying the time and depth of each application, or by the model automatically developing a schedule. In the latter case, irrigation is scheduled either at a fixed time interval and depth, or by a fixed percentage of allowable water depletion of the root zone. The AquaCrop model was developed with a view to balance simplicity, robustness, and accuracy and is a more suitable model for farmers to use than the more complex models available (Foster *et al.*, 2017).

The AquaCrop model simulates water-driven plant growth and yield. It is suitable for evaluating the effect of irrigation schedules on crop yield. The model calculates the soil water balance, considering rainfall, irrigation, capillary rise, runoff, evaporation, transpiration, and deep percolation. To simulate plant growth and yield requires climate, soil, crop, and field management characteristics to be specified in the model. Using the AquaCrop model and drawing on a long series of historical climate data, Geerts and Raes (2009) optimized irrigation frequency during sensitive crop growth stages based on indicative crop development traits at the onset of each stage. A simplified readable irrigation chart was subsequently generated for farmers. However, this simplified irrigation chart only suggests the irrigation frequency during the critical crop growth stage, without information on the amount of irrigation or adjustment due to atmospheric conditions of given years. Linker and Sylaios (2016) presented an efficient model-based procedure for generating near-optimal irrigation schedules for real-time applications utilizing the AquaCrop model.

Developed by USDA-ARS, RZWQM2 is a one-dimensional model with emphasis on management effects on hydrologic cycle, water quality, and crop production (Ma *et al.*, 2012). Equipped with the Decision Support System for Agrotechnology Transfer (DSSAT) model (Hoogenboom *et al.*, 2023) and the Simultaneous Heat and Water (SHAW) model (Flerchinger and Saxton, 1989), RZWQM2 simulates crop growth on a daily basis under different field management practices and specific soil-plant-atmosphere systems. The RZWQM2 model provides several irrigation scheduling methods: by fixed interval, triggered by a root zone depletion (MAD), or triggered by a threshold of the ratio of actual ET to potential ET.

By obtaining field observed climate data and online forecasting data using a software they developed, Gu *et al.* (2017) applied the RZWQM2 model to simulate the predicted crop water stress, and to judge whether irrigation was required on a daily basis. The irrigation depth was calculated to return the current soil water content to field capacity. In this way, irrigation can be scheduled in a real-time sense as long as the real-time atmospheric data are available. The RZWQM2 model also integrates fixed intervals, specified dates, or an option dependent on soil water depletion in the root zone in its irrigation module.

Other models reportedly used for irrigation scheduling purposes include DAISY, a one-dimensional mechanistic soil-plant-atmosphere system model (Seidel *et al.*, 2016) and SIMETAW (Simulation of Evapotranspiration of Applied Water), a model capable of assessing climate change impacts on future irrigation demand, thereby facilitating user development of adaptation strategies (Mancosu *et al.*, 2016). Seidel *et al.* (2016) used a partially calibrated DAISY model to schedule irrigation; when the soil ψ_m reached a fixed threshold, an irrigation of fixed depth was triggered. A web-based user interface was developed to run the modified van Genuchten model (to convert the soil water tension data to volumetric water content) and to derive irrigation scheduling recommendations (Vellidis *et al.*, 2016).

The effectiveness of process-based model-derived irrigation scheduling depends on the precision of the model itself and the quality of calibration. For example, Xu *et al.* (2019) found that the AquaCrop tended to underestimate soil moisture with a root-mean-square error of 0.15 $cm^3\ cm^{-3}$ after calibration, which may affect the irrigation scheduling. Therefore, before applying process-based models in irrigation scheduling, they must be calibrated; thus, historic field measurements are needed.

Linker and Kisekka (2017) indicated that, the use of process-based models in irrigation scheduling have mostly been the focus of research efforts to evaluate historical water management, to predict future water demands in a certain area, and to optimize the soil water depletion levels for a crop etc. Research on real time irrigation scheduling based on model outputs still demands an ongoing process. Thorp *et al.* (2017) used the CSM-CROPGRO-Cotton model to assist in-season irrigation scheduling by estimating evapotranspiration. Gu *et al.* (2017) developed an irrigation scheduling software based on RZWQM2. Water-stress-based methods, such as those employed in the SWAT model (Neitsch *et al.*, 2011; Sun and Ren, 2014) and the RZWQM2 model (Gu *et al.*, 2017) are generally more reasonable and practical once they are assured of an accurate prediction in plant water stress after calibration and validation. However, without links to precise weather forecasts, these models, when involved in real-time irrigation scheduling, may derive an erroneous timing and quantity of irrigation for a field, especially when a large rainfall event occurs soon after irrigation.

ii. Regression Models

Unlike using process-based models for irrigation scheduling, some researchers have recently proposed methods using regression models. Lopes *et al.* (2016) in minimizing the total volume of irrigation during the entire growing season transformed the irrigation planning problem into an optimal control problem. The optimal control problem was subjected to a soil water balance function, minimum soil moisture constraint, and maximum irrigation amount for a single event.

However, this algorithm required model-derived whole-year weather data, which were unpredictable and may lead to the failure of the proposed method. To overcome this problem, Lopes *et al.* (2016) further improved the irrigation planning by applying model predictive control (MPC) techniques, where the optimal control problem was frequently recomputed at each interval by taking into account measured system variables. The MPC method was first applied by Park *et al.* (2009) and was known as receding horizon control (RHC) method. This was applied to the problem of irrigation management, by incorporating sensor measurements (feedback), predictive models, and optimization algorithms to maintain soil moisture levels.

An MPC algorithm was also tested by Saleem *et al.* (2013) for real-time irrigation scheduling based on soil water balance and a given soil moisture range; however, the system dynamic function was based on a simple water balance equation and crop evapotranspiration and precipitation were assumed to be directly available. To solve this problem, Delgoda *et al.* (2016) combined an MPC algorithm with the AquaCrop model, where the system dynamic function was given by a linear first-order time-series model based on system identification from AquaCrop. The AquaCrop model also provided feedback on the root zone soil moisture deficit during the MPC's optimization process. A major advantage of using MPC/RHC algorithms in irrigation scheduling is its ability to be programmed into a controller and thereby be used in real-time applications. Park *et al.* (2009) executed the RHC algorithm in a real-time manner on a field computer through collecting real-time soil moisture, temperature, and meteorological data, while Saleem *et al.* (2013) developed an MPC controller for the purpose of real-time irrigation scheduling.

Using only weather data to simulate changes in soil moisture, Tsang and Jim (2016) employed artificial intelligence (AI) algorithms, featuring an artificial neural network (ANN) and fuzzy logic to develop an optimal irrigation strategy. The ANN was trained to predict soil moisture based on four daily weather variables, while the fuzzy-neural network served to determine irrigation timing and depth. Navarro-Hellín *et al.* (2016) proposed a machine learning programme to serve as a reasoning engine to manage agricultural irrigation, thereby replacing the expert agronomist.

The machine learning programme employed PLSR and ANFIS (machine learning technologies) to calculate appropriate irrigation decisions considering the weather, crop, and soil characteristics, along with field measurements from soil sensors. Linker *et al.* (2016) used both the crop model AquaCrop and a non-linear constrained optimization to investigate the highest yield achievable for any given water quantity through optimizing the water-depletion level and replenishment level implemented at five different growth stages. With a well-calibrated RZWQM2 model to assess the derived solutions, Nguyen *et al.*, (2017) applied an ant colony algorithm to search for an optimal irrigation schedule to maximize the net return of a single crop.

However, for real-time irrigation scheduling, regression methods using either optimization or artificial intelligence algorithms must be validated since they are commonly trained using the historical weather data, which may not actually possess the same trend as the current weather data. The effect of the uncertainty of predicted weather data should also be evaluated. The performance of regression models should be compared to that of other methods, e.g., soil moisture-based, plant-based, or process-based models, so that the effectiveness could be evaluated. Development of those software and controllers that integrated with regression models/algorithms is challenging but is driven by the commercial value of real-time irrigation scheduling. Fortunately, with the development of AI hardware, e.g., Raspberry Pi that is able to run complex mathematical algorithms, those regression irrigation scheduling methods can be implemented in real time with low cost.

2.5.4 Water Table Management

Water is essential to life and, together with temperature, a key determinant of global patterns of plant distribution and productivity (Chakraborty, 2021). Although variation in precipitation is associated with large-scale variation in forest structure and dynamics, soil water availability to plants is the result of the fine-scale interplay of precipitation and terrain properties at landscape scales. The major landscape factors affecting the redistribution of water entering the system as rainfall are topography and soil texture (Fan, 2015). Topography affects the water flow to groundwater, and groundwater movement to lower gravitational positions (lower relative elevation in the landscape) creates gradients of increasing water availability from uplands towards valleys (Fan, 2015). The retention of water depends on soil texture, decreasing with soil particle size, so that it is greater in clay than in sand (Wang, *et al.*, 2017). The dynamics of drainage water and retention in the soil supply the groundwater, influencing seasonal and inter-annual fluctuations in the water table (O'Geen, 2013), and also affect soil-water conditions in the rooting zone.

Water Table Management (WTM) can be described as the process of regulating soil moisture content for optimum crop growth. Water table management systems such as tile/conventional drainage, controlled drainage and controlled drainage with sub-surface irrigation can be viewed as successive improvement in ensuring the efficient use of water combined with beneficial management practices that will increase crop productivity, maximize the use of agricultural lands and enhance sustainability of irrigation schemes and farmlands. Skaggs *et al.*, (2012), Morrison *et al.* (2014) and Askar *et al.*, 2020) have mentioned the benefits of water table management including but not limited to increasing water storage capacity in the soil profile, improving soil physical properties, bringing about a significant reduction of nitrate concentrations in tile drainage outflows, and increasing crop yield. It improves the off-farm water quality, enhances water use efficiency, reducing water losses to unusable sinks, reducing water degradation and reallocates water to higher priority uses (Chawla *et al.*, 2023). Irrigated agriculture without adequate management can be detrimental to environmental quality and jeopardize sustainability efforts because of inefficient use of inputs (water, fertilizer and labour) leading to nitrogen leaching into water bodies, soil salinity hazards and ineffective irrigation schemes (Khan and Hanjra, 2008).

Lagod (2019) stated that in integrated water resource management, the conjunctive use of surface water and groundwater is a standard policy to meet the water needs and cope with the environmental impacts of man's activities. Several authors have also underlined that the wrong human activities in the earth's biosphere–hydrosphere–geosphere have created a global water imbalance and crisis which threatens the life of the many individuals and numerous natural ecosystems (Xu *et al.*, 2019; Malhi *et al.*, 2020; Salehi, 2022). Improving the efficiency of the water management and agronomic practices will go a long way in alleviating the problems and consequences of water scarcity, thereby increasing farmers' socio-economic and sustainable livelihoods (Lyra *et al.,* 2022; Chawla *et al.,* 2023).

Lyra *et al.* (2022) highlighted the effects of agronomic and water resources management scenarios on groundwater balance, seawater intrusion, and nitrate pollution and the comparison of the developed scenarios relative to the current crop production and water management regime. In their findings, they indicated that the measurement of groundwater levels is important to avoid depletion of groundwater resources as earlier stated. Groundwater level measurement assists in determining the hydrological stress acting in an aquifer and provides data for efficient management. For long-term forecast and management, groundwater level measurements should be capable of supplying data to develop a groundwater model (Aderemi *et al.*, 2022).

Water table depth (WTD) can be used as a proxy for the accessibility of groundwater to plants, mediated by root depth, which is highly constrained by WTD, and soil density (Constantino *et al.*, 2018). During normal dry seasons, the water table level drops and the soil surface becomes drier, but the intensity of this effect depends not simply on climate but also on the soil retention properties and subsidy of groundwater flowing from higher topographic positions. Water table depth is expected to play a key role in plant growth and mortality. Excess water in shallow water table conditions during the wet season leads to anoxic stress, which can result in reduced plant growth. Water excess inhibits oxygen flow to the roots and limits plant growth, because alternative anaerobic routes of energy production are much less efficient than aerobic respiration (Parolin, 2012). Thus, optimal conditions for growth might be restricted to a short window of time, limiting the potential for biomass accumulation. Additionally, to avoid anoxic conditions, tree roots are typically superficial in shallow water table environments (Costa *et al.*, 2023).

Growing rice in waterlogged soil or continuously flooded paddies, for instance, is ideal for microbes to produce large quantities of greenhouse gas. Farming practices should thus be improved in order to decrease methane emissions while reducing the amount of water consumed during the growing season. Alternate Wetting and Drying (AWD) is a practice that allows the water table to drop below soil surface before re-flooding. When AWD is applied, fields are drained up to a depth of 15 cm of topsoil (Ishfaq *et al.*, 2020). The following irrigation dosage only occurs once water drops below the 15 cm level, as monitored via a perforated tube inserted into the soil. AWD is a method to manage irrigation so that water is not wasted but it aids the root growth, facilitates higher nutrient uptake, and increases land and water productivity. Water, whether on the surface or underground, is the most essential and significant natural resource for sustaining life on earth and for the sustainable growth of socio-economic sectors such as irrigation and industrialization (Chu *et al.*, 2018).

In areas with shallow groundwater, controlled drainage allows the water table level to be set at the desired height by retaining an appropriate amount of drainage water in collecting ditches. During the coldest and rainiest period, when rainfall exceeds evapotranspiration rate, controlled drainage can be used to avoid complete water outflow and reduce nutrient losses to surface waters. However, at the same time, particular attention must be paid to prevent waterlogging. During the driest period (dry season), water table management is crucial to retain as much water as possible in order to avoid drought stress. In general, to optimize water use, proper timing and accuracy are required in regulating water table level (Ale, 2014).

Different drainage management strategies and devices are now available to increase water retention and regulate water table level, so that controlled drainage is also effectively applied at watershed scale with positive results (Tolomio and Borin, 2018). At the same time, though, great fluctuation in water table level during different seasons, low organic matter content in these soils, and the different climatic conditions may constitute peculiar traits that influence the effects of water table management (Tolomio and Borin, 2018).

2.5.5 Water Use Efficiency

It has been established that irrigation uses the most agricultural water and accounts for the majority of water losses in the sector. Improving the effectiveness of water use in irrigation systems has become extremely important, though, as water is becoming increasingly scarce as a result of competition from other sectors. This has been highlighted by Sharma *et al.* (2015) who indicated that improving water use efficiency is a critical response to growing water scarcity and the need to leave enough water in rivers and lakes to sustain ecosystems and meet the demands of industry. According to Evans *et al.* (2012), this calls for a paradigm shift away from crop yield maximization per unit of land area to crop yield maximization per unit of water consumed. The objective of irrigation management today is to boost crop yields while using fewer water resources. Water use efficiency is a term that has been used in a variety of contexts to describe the careful use of scarce water resources in agriculture to increase yields.

According to Biswas *et al.* (2021), the term "water use efficiency" actually refers to the measurement of the increase in crop yield that is attained per unit of water added during irrigation as compared to the average crop yield attained without irrigation. According to the perspective of irrigation scientists and engineers, Sharma *et al.* (2015) presented a different definition of water use efficiency as the proportion of irrigation water transpired by crops during their growth period to the water diverted from rivers or other natural sources during the same period. According to Sharma *et al.* (2015), this definition emphasizes how efficiently water is delivered to crops and shows how much water is lost at the plot, farm, command, or system level.

Some researchers Paramasivan and Selvarani (2017) and Biswas *et al.* (2021) have used the term "water productivity" to avoid the apparent ambiguity that comes with the use of the term "water use efficiency". These words have frequently been used interchangeably. Since both terms have similar definitions and are expressed in the same units (kg/m^3), the use of the term "water productivity" may be appropriate. In order to manage water resources and sustainably increase crop production, there is an increased effort being made worldwide to increase crop water productivity. It has been determined that reducing evaporation, deep percolation, and run-off will increase the water use index or water productivity. To improve water use efficiency in irrigation, it is crucial to choose the right irrigation method, the crop to be watered, the type of soil, as well as the timing and amount of irrigation (Levidow *et al.*, 2014). It has been discovered that there are significant differences in the water use efficiency of crops under various irrigation techniques, water application rates, and frequency.

The need to assess the economic water productivity of crops has become increasingly important in recent years due to water scarcity and the growing competition for the resource among different economic sectors. Economic water productivity (EWP) compares the net economic value of crops to the amount of water used in producing the crop (Abdul-Ganiyu *et al.*, 2015). A more sustainable method of on-farm water management, according to Chawla *et al.* (2023), is to maximize yield per unit of water used. When deciding whether it is prudent and economically wise to grow specific crops and increase their production, knowledge of the economic water productivity of crops is very helpful. The most productive crop can be chosen using data on economic water productivity. The fact that the concept of EWP is sensitive to market prices and may vary at different places and sometimes presents a challenge (Abdul-Ganiyu *et al.*, 2015).

Irrigation water use efficiency (IWUE) is defined as the yield (grains) obtained per seasonal irrigation water applied (Nair *et al.*, 2013). Water applied can be from irrigation or precipitation or both. However, emphasis is on irrigation water use efficiency.

$$\text{IWUE (kg mm}^{-1}\text{)} = \frac{\text{Yield (kg)}}{\text{SIW (mm)}} \quad \text{.. Eqn 2.3}$$

Where:

FY – Total yield of crop, and

SIW – Seasonal irrigation water applied.

The water losses in rice production are caused by evaporation, transpiration, percolation, seepage and over bund flow. Transpiration is the only productive water loss, whereas seepage, percolation, over bund flow, and evaporation are all non-productive water flows and can be considered as loss flows at field level (Bouman *et al.*, 2007).

As was already mentioned, both the need for more rice production and the scarcity of water are steadily getting worse. Less water will be available for agriculture in the future, creating an urgent need for agricultural practices that conserve water. There are various methods for producing rice using less water. Breeding, changing cropping practices, such as switching from transplanting to direct seeding, or simply improving irrigation channels, land levelling, puddling, tillage, and proper bunds, can all result in genotype-specific improvements toward drought resistance. In water-saving production systems, less standing water leads to a lower water head, which reduces seepage and percolation. Additionally, there is no evaporation from the water surface when there is no water layer (Borrell *et al.*, 1997). As a result, it may be possible to reduce production costs while increasing water productivity. Possible drawbacks in these systems include reduced biomass, decreased yield, increased weeds, soil cracking, the requirement for adopted varieties, as well as a potential increase in workload.

Water productivity is a key consideration when evaluating water-saving systems. According to Bouman *et al*. (2007), this shows how much marketable grain is produced for every volume of water used for transpiration, evapotranspiration, irrigation, or rainfall. According to Tuong *et al.* (2005), water productivity increases as yield increases or as water use decreases or as water is conserved.

2.6 Effects of Different Irrigation Application Depths on Rice Growth and Yield

Three distinct phenological phases are sequentially present during the growth of rice. This pattern of phenological change in rice suggests a connection between the health of the plant's vegetative phase and the reproductive and ripening phases of its leaves. Numerous issues can arise in production systems that use less water, and as water usage is reduced further, negative effects on rice may also become more pronounced (Singh *et al.,* 2021). Risks include decreased biomass synthesis, altered phenological development, decreased yield, and an increase in spikelet sterility, among others. It may result in increased weed growth and soil cracking in the field. A lower leaf area index, less photosynthesis, and an earlier onset of senescence all leading to a reduction in yield as stated by several authors (Choudhury *et al.*, 2007; Rejesus *et al.*, 2011).

According to Elsadek *et al.* (2023) continuous flood irrigation led to higher losses of irrigation water and that prior to anthesis, reduced water supply can affect development by delaying tillering, panicle initiation, and anthesis; however, after anthesis, it can speed up development by causing rapid leaf senescence. Large rice yield gaps in Sub-Saharan Africa have been attributed to a variety of factors, including inadequate use and access to inputs (such as water, nutrients, pesticides, and diseases), a lack of farm mechanization, and a lack of knowledge among smallholder farmers regarding best agronomic management techniques (Devkota *et al.*, 2021).

The productivity and resilience of rice production in Sub-Saharan Africa and other smallholder farming regions worldwide are significantly hampered by limited access to fertilizers (including nitrogen) and irrigation water (Wang *et al.*, 2016). As a result, there is an increasing need to keep an eye on rice yields in order to close productivity gaps, such as those brought on by water stress and fertility restrictions. Farm managers make decisions about application schedules based on crop phenological phases (Arouna *et al.*, 2021). Fageria *et al.* (2011) stated that to aid in yield prediction by informing farmers when management interventions are required, rice crops must be effectively monitored for growth dynamics at various phenological phases with different irrigation depths.

When using the alternate wetting and drying technique (AWD), Pascual and Wang (2017) evaluated various water depths to achieve high water productivity in irrigated lowland rice. As a result of plant water stress during active tillering and panicle initiation growth stages, the results obtained demonstrated that adequate yield and water savings could be achieved. The challenge for water efficiency in rice production is to reduce water use while maintaining or increasing grain yields to satisfy the demands of a population that is constantly expanding (Mallareddy *et al.*, 2023). It has been discovered from research that irrigation can be reduced without compromising grain yield (Zhang *et al.*, 2012). However, it has not been possible to achieve attractive increases in output that would give farmers the incentive to reduce their irrigation rates with the conventional irrigated flooded rice production systems promoted by rice scientists at various research organizations (Pascual and Wang, 2017). Farmers should be given the tools they need to increase rice production while also enhancing the quality of their soil and environment and using less of their scarce freshwater resources.

Rice grown in various water depths had a noticeable impact on grain weight and spike characteristics. As opposed to shallower water depth, deeper water depth has negative effects on the weight of the grains and the spike characteristics. The total yield, on the other hand, exhibits an adverse effect in those deeper and shallower water depths corresponding to 10 cm (Talpur *et al.*, 2013).

In addition, rice can be grown in ponds with intermittent or continuous submersion depending on the farmer's preference and the availability of water. In order to avoid practical problems, intermittent or variable ponding should be used instead of continuous ponding. In essence, further research is required to determine the effects of various ponding water depths under various water regimes, including continuous, intermittent, and variable ponding, as well as under various fertigation levels, on rice crop production and water use. The strong greenhouse gas methane has been found to emit less when the soil is kept in flooded anaerobic conditions for a shorter period of time. Instead, the switch to aerobic conditions increases microbial activity, soil organic matter (SOM) decomposition, and CO_2 emissions (Hossain *et al.*, 2021). SOM is crucial for the sustainability of agriculture and the health of the soil. Soil fertility and the sustainability of rice farming may be significantly impacted by the shift to more aerobic conditions.

It has also been discovered that the use of water-saving irrigation affects soil nutrient availability as well as fertilizer losses through surface runoff and seepage (Yang *et al.*, 2017). Consequently, the use of water-saving irrigation has many effects. The aerated conditions encourage nutrient release and inhibit nitrogen immobilization, assisting in SOM mineralization and favouring high yields. Additionally, Yang *et al.* (2017) draws the conclusion from recent studies that, within certain bounds, AWD can increase yield by reducing redundant vegetative growth, raising hormonal levels, enhancing root growth and canopy structure, and improving carbon remobilization from vegetative tissues to grains.

2.7 Effects of Drainage on Rice Growth and Yield Performance

In agricultural farmlands, water can exceed the requirements of crops especially when the irrigation system practiced is flooding or when there is high intensity of rainfall or when there is an upward flux from an aquifer, lateral seepage or runoff from adjacent fields. Singh *et al.* (2021) noted that agricultural land accumulates water on its surface, raising groundwater tables, if it is unable to naturally remove extra water (e.g., through runoff or deep percolation to aquifers). The rise in groundwater tables is proportional to the amount of extra water. Groundwater tables that rise to the upper soil layers where crop roots are found cause water to begin replacing oxygen in the soil profile, which reduces or completely inhibits the roots' ability to breathe. This concept has been described by Singh (2019) as waterlogging. Soil salinization and waterlogging have been considered as twin menace of poor drainage conditions which has become a threat to agriculture in many countries. Hossain (2019) stated that 1,125 million hectares of land have been affected by salinity of which 76 million hectares of land are affected by human-induced salinization.

It is generally acknowledged that drainage is a crucial agricultural management practice (AMP) for lowering CH_4 emissions which is a greenhouse gas (GHG) in paddy systems. Due to its capacity to decrease water-filled pore space, increase redox potential, and foster soil aeration, drainage has been thoroughly demonstrated to be an effective CH_4 abatement approach in paddy systems (Haque *et al.,* 2016). However, there is still a great deal of uncertainty regarding how drainage affects yield in paddy systems with various soil and agricultural management conditions.

Most frequently, artificial drainage systems are required to promptly remove the extra water in agricultural fields. Yet, in some instances, due to over-irrigation and canal seepage, agricultural output inside the command areas of irrigation systems is hampered despite the expansion of irrigation facilities. In many cases the size and severity of the disease are increasing (Lund *et al.*, 2023). The twin issues of too much water during the rainy season and not enough water during the dry season are typically present in rice fields that are prone to flooding, whether they are rain-fed or irrigated. The production places with such scenarios could be considerably boosted if their drainage difficulties are to be rectified (Xu *et al.*, 2022).

The early-season drainage could result in rice yield reduction because rice is more sensitive to water stress at the initial stage of growth, but later drainage before the crop reached to the maximum tillering could increase the rice yield due to the reduction in ineffective tillers (Islam *et al.,* 2018). The impact of drainage periods on soil N_2O emissions often depended on the timing of fertilization (Islam *et al.,* 2018), and early-season drainage may increase N_2O emissions since the majority of fertilizer was applied before planting. The key of decision-making for drainage period is to maximize rice yield while mitigating GHG emission. Extending the drainage duration contributes to greater probability of suppressing the CH_4 emission peaks, thus facilitating the reduction of CH_4 emissions (Itoh *et al.,* 2011). Nevertheless, longer drainage duration may contrarily contribute to increased global warming potential (GWP) of the total GHG emissions (CH_4+N_2O) in some regions due to it stimulation in N_2O emissions (Itoh *et al.,* 2011; Li *et al.*, 2015).

In paddy systems, drainage is often used in conjunction with other agricultural AMPs, such as nitrogen fertilizer and residue management. It is understandable to apply large amounts of nitrogen fertilizer to achieve a high yield (Sainju *et al.*, 2020), but nitrogen fertilizer is the most critical element affecting N_2O emissions, even more important than water regimes (Wang, 2018). Although the effect of drainage on rice yield remains controversial, the results of this meta-analysis, based on a global scale, supported the view that drainage had no substantial influence on rice yield (drainage increased rice yield by 0.3 %), which was confirmed by another meta-analysis (Liu *et al.*, 2019).

Inundation due to periodic excess of water from rainfall or river overflow is common because natural drainage is constrained by limited head at outflow or by low internal percolation. Flooding in these areas may damage the crop by prolonged submergence, plant uprooting or lodging. Traditional flooding irrigation not only aggravates agricultural water stress and limits the potential for high rice yield, but it also increases the length of internodes, reduces the mechanical strength of stems and raises the risk of lodging due to continuous flooding (Hao *et al.*, 2022).

Rice plants exhibit a greater tolerance to high soil water level or flooding than most other crops. While soil rootzone aeration is a requirement for good upland crop production, rice plants also thrive in shallow ponded water since they are able to transport oxygen from the shoot to the root system efficiently (Panda and Barik, 2021). However, the frequent interpretation of this unique characteristic that drainage is not important for rice culture is wrong. Many irrigation systems, developed without proper recognition of the role of drainage in rice cultivation, are suffering the ill consequences of inadequate drainage. Wetland rice culture requires water control for which adequate drainage provisions are essential to remove excess water from rainfall or the irrigation source (Angelakis *et al.*, 2020).

2.8 Drainage Systems and Different Irrigation Application Depths on Changes in Soil Temperature, Soil Electrical Conductivity and Nitrogen Balance in Paddy Fields.

2.8.1 Effects of Drainage Systems and Different Irrigation Application Depths on soil Temperature

Numerous biological and chemical processes in the soil are regulated by temperature. For example, quicker soil warm-up is one of the most often mentioned advantages of sub-surface drainage on poorly drained soils. Any soil must attain a certain temperature in order for plant processes like germination to occur. Excess fluid evaporation removes specific heat from the soil, causing poorly drained soil to warm more slowly than well-drained soil (García-García *et al.,* 2023).

The measurement of the warmth of the soil is known as the soil temperature. One of the most significant variables influencing plant growth is soil temperature. According to Frey *et al.* (2013), the ideal range of soil temperature for plant growth is between 20 and 30°C. Under sub-optimal (20 °C) and supra-optimal (35 °C) temperatures, the rate of plant growth substantially decreases. Furthermore, temperature affects every soil action. As such, the edaphic environment is significantly influenced by the thermal regime of the soil. The temperature regime of the soil affects the release of nutrients for root absorption. According to Adak *et al.* (2015), it is a physical parameter that is crucial to maintaining crop productivity and sustainability.

The focus on soil temperature has switched in order to achieve productivity through irrigation, mostly due to the positive trend in world temperature. The primary cause of climate change, which has been shown to have an impact on numerous industries and sectors of the economy, is temperature. According to Adak *et al.* (2015), soil temperature is crucial for maintaining crop productivity, sustainability, and control over biological and biochemical processes. These processes inevitably impact the formation of soil organic matter, the effectiveness of fertilizers, seed germination, plant development, a plant's capacity to withstand the dry season, nutrient uptake and decomposition, and the incidence of disease and insects.

Throughout the crop growth season, Adak *et al.* (2015) observed that inadequate soil temperature causes spatio-temporal fluctuations, retards crop maturity, and delays crop germination. Because soil temperature is essential in preserving the global balance of carbon and nitrogen, it also influences the pace at which soil organic matter decomposes. Chemical and biological activities such as oxidation and re-oxidation reactions, microbial decomposition of organic waste, and ecosystem respiration are all impacted by temperature. The cycle of nutrients in terrestrial ecosystems, both above and below the surface, is significantly influenced by temperature (Hartley *et al.*, 2021).

Sufficient knowledge of surface temperature and soil moisture estimation will be required in order to comprehend the interactions between the atmosphere and land surface more fully. According to Kaufmann *et al.* (2003), a rise in surface temperature will inevitably cause the soil's moisture content to drop, raising the temperature of the soil. Due to its ability to control the amount of precipitation that enters runoff, infiltration, depressions, surface storage, and other processes, soil moisture is an important component of the water and energy cycle. Researchers will be able to estimate and predict evapotranspiration if the relationship between soil moisture and surface temperature is thoroughly investigated (Awada *et al.*, 2024).

During the crop growing season, inadequate soil temperature causes spatio-temporal variations and delayed maturation. Soil temperature is directly impacted by two phenomena: climatic change and global warming (Sun *et al.*, 2019). According to Schnecker *et al.* (2023), soil respiration and biomass production are accelerated by the rise in microbial activity caused by global warming. Soil temperature will rise, nevertheless, in response to rising surface air and land temperatures.

The relationship between evapotranspiration and soil temperature is such that an increase in evapotranspiration causes a corresponding rise in soil temperature, and vice versa. Environmental elements including temperature, relative humidity, soil water, light, wind, etc. all significantly increase evapotranspiration (Driesen *et al.,* 2020).

According to Onwuka and Mang (2018), heat, the amount of water delivered to the soil, and vegetation all have a considerable impact on soil temperature. The biophysical characteristics of the soil are influenced by the quantity of heat that is delivered to the soil surface and the quantity of heat that is lost from the soil surface across the soil profile. It is established that soil continues to be the primary absorber of ambient heat; as a result, soil absorbs heat during the day and releases it into the atmosphere at night. An increase in soil temperature will boost microbial activity and soil nitrogen mineralization, which will improve crop productivity (Joshi *et al.*, 2017). Moderate soil temperature also affects the activities of some enzymes in the soil. Conversely, low soil temperature will promote organic breakdown by increasing microbial activity and decreasing nitrogen mineralization. In addition, soil temperature affects aggregate stability, soil moisture content, and soil aeration (Joshi *et al.*, 2017).

The breakdown of organic matter, soil micro-organisms, soil macro-organisms, and bioactivity are a few of the biological characteristics of soil. Different soil temperature ranges have varied effects on soil bioactivity, such as increasing soil respiration. The activity of soil-dwelling enzymes that breakdown polymeric organic matter is enhanced at soil temperatures between 10 and 28 degrees Celsius, leading to an increase in soil respiration. Additionally, at such soil temperature ranges, microbial respiration, microbial intake of soluble substrates, and soil nitrogen mineralization rates will all increase (Daunoras *et al.,* 2024). In the meantime, microbial activity and the transport of soluble substrates will be slowed down and soil pH will drop below freezing.

Lower soil temperature is a result of increased precipitation or high irrigation application depths. Rainfall will raise the moisture content of the soil, which will inevitably cause the temperature of the soil to drop (Sehler *et al.*, 2019). The relationship between precipitation and surface air temperature affects soil temperature in a way that increase in surface air temperature will also raise soil temperature. This will also increase transpiration and evaporation rates, which will inevitably lower soil moisture content (Liang *et al.*, 2024).

An ecosystem, biome, and plant growth that are all in good health depend on the soil temperature being properly managed under regulated irrigation and drainage systems. The pace at which water viscosity, surface tension, and relative hydraulic conductivity in the soil are regulated for plant growth is also determined by the temperature of the soil. Because soil temperature is essential to preserving the global balance of carbon and nitrogen, it has an impact on how quickly organic matter in the soil decomposes (Sehler *et al.*, 2019). Numerous techniques, such as irrigation, drainage, mulching, tillage, cover crops, or shading, can be used to control soil temperature (Demo and Asefa Bogale, 2024).

2.8.2 Effects of Drainage Systems and Irrigation Application Depths on Soil Electrical Conductivity

Aside improving agricultural output, irrigation unavoidably modifies the characteristics of the soil. A steady improvement in soil fertility under irrigation conditions is generally predicted when irrigation water is of a good quality, does not induce soil salinity, sodicity, or pollution, and does not result in soil erosion (Singh, 2021). Based on the requirements of agricultural crops as well as the quantity and quality of available water resources, irrigation schedules and application depths are decided. According to Nikolskii *et al.* (2019), the adverse effects of irrigation on soil are typically linked to soil erosion caused by water, the use of water with low quality (high salinity or bad chemical composition, as well as treated or untreated wastewater), and salinity or sodicity of the soil.

In areas where appropriate agricultural management in response to particular environmental conditions has allowed the development of a fragile balance between salt build-up and removal rates in the soil profile, soil salinization poses a latent threat to soil quality and agricultural sustainability. This equilibrium may be upset, with detrimental effects on crop productivity and soil functionality, by potentially shifting climatic conditions, transient variations in irrigation water availability and quality, the depth of the saline water table, or adjustments to the soil and water management (Prajapati *et al.*, 2023).

Chang *et al.* (2019) found that irrigation significantly affected the salinity of the soil. Since paddy rice is farmed in an environment that floods frequently, the majority of conventional water management techniques try to keep the field at a standing depth of water all season long. When irrigation is continuously flooded, water productivity is often low and there is a likelihood of salt build-up depending on the salt concentration of the irrigation water. Finding strategies to preserve rice production while conserving irrigation water is also necessary since the productivity of irrigated agro-ecosystems is threatened by dwindling water availability for agriculture.

Drainage of agricultural land is a typical practice to boost output, protect long-term irrigation investments, and preserve land resources. Drainage is particularly essential in semi-arid and arid areas because it has the leaching capacity to regulate the accumulation of salt in the soil profile and crop root zone. Reducing the intensity of drainage and conserving irrigation water can be achieved in drained paddy fields by regulating the depth of drainage and permitting drainage only during certain times (Skaggs *et al.*, 2012).

There have been reports that paddy yields are impacted by the quality of irrigation water. The physico-chemical characteristics of the irrigation water are typically linked to the consequences. High salinity levels, which impact the availability of nutrients, high Na^+ levels, which interfere with soil infiltration for irrigation water, and the toxicity of some elements when present in excess in irrigation water are issues associated with irrigation water quality. Irrigation water containing dissolved salts and trace elements is typically the consequence of either natural weathering of the earth's crust or human activity, such as the incorrect disposal of sludge and wastewater that has not been properly treated or excessive fertilizer use. Consequently, for increased paddy rice yields, better irrigation water quality management techniques might be required (Mpanda *et al.,* 2021).

Although soil electrical conductivity (EC) has been utilized as an indirect predictor of salinity levels and the amount of nutrients available for plant absorption, it has no direct effect on plant growth (USDA-NRCS, 2014). EC has been used as a surrogate measure of salt concentration, organic matter, cation-exchange capacity, soil texture, soil thickness, nutrients (such as nitrate), water-holding capacity, and drainage conditions. EC is used to divide up management units, distinguish between different types of soil, and forecast crop yields and soil fertility in site-specific management and high-intensity soil surveys (USDA-NRCS, 2014).

Effective irrigation techniques can lower EC by washing soluble salts from the soil and below the rooting depth. Excessive irrigation and waterlogging should be avoided because a rising water table might introduce soluble salts into the root zone. Each crop's leaching requirement needs to be determined in order to prevent the negative impacts of high EC (salinity). Leaching requirement, or the amount of extra water needed to maintain a desired salinity level, is the proportion of water needed to drain excessive salt below the root zone (Letey *et al.,* 2011).

High EC is a result of soluble salts' propensity to build and stay close to the soil surface in desert, low-rainfall, and places that get saline irrigation water. In comparison to the adjacent higher lying, more drained areas, low spots, depressions, or other places where water collects typically have higher EC values. When water seeps into soils, it can react with weathering materials such as bedrock, releasing salts and causing saline seeps on side slopes. Cropping, irrigation, land usage, and the use of compost, manure, and fertilizer all have an impact on soil EC (USDA-NRCS, 2014). It is necessary to ascertain the salt content of the irrigation water while managing for salinity on irrigated land. When irrigation water is applied in quantities that are too little for the salts to leach out or when the salt content of the water is considerable, salts build up in the root zone and raise the EC. Excess salts can be leached below the rootzone and the desired EC level for the crop grown can be maintained by irrigating with more water than is required. Applying too much irrigation water should be done carefully since it can saturate the soil and cause salts to build up (USDA-NRCS, 2014).

2.8.3 Effects of Drainage Systems and Irrigation Application Depths on Nitrogen Concentration

A crucial component in the cultivation of rice is nitrogen. In lowland rice production systems that are rainfed and irrigated, paddy soils undergo an extended period of submergence. Nitrate (NO_3) is formed and lost simultaneously in adjacent aerobic and anaerobic soil zones, which is a unique characteristic of submerged soils. As anaerobic conditions take over, the deposited NO_3 in aerobic soils during the dry season is lost by leaching and nitrification-denitrification. According to Tuyishime *et al.* (2020), nitrogen (N) losses in drainage water are undesirable since they indicate the loss of important nutrients and consequently an economic loss. Furthermore, because of their effect on surface water eutrophication, N losses in drainage water give rise to environmental problems. Making decisions to increase N use efficiency and prevent N pollution in paddy fields requires an understanding of the scope and mechanisms of N losses in these areas (Darzi-naftchali and Shahnazari, 2014). In addition to lowering N losses via leaching, field water management can foster an environment that is favourable for crop growth (Skaggs *et al.*, 2012).

In many nations with intensive farming systems, agricultural non-point source pollution is a significant environmental problem (Xiong *et al.*, 2015). Many lakes and streams have been linked to water body eutrophication due to nitrogen (N) and phosphorus (P) loading from unmanaged agricultural non-point sources, including runoff and leaching from paddy fields (Gao *et al.*, 2016). Because nitrogen is lost quickly through surface runoff, denitrification, leaching, and ammonia volatilization, irrigated rice uses relatively little nitrogen. Furthermore, illogical drainage increases the amount of N lost from the paddy fields to nearby waters by reducing the water's residence period and accelerating P and N losses (Wang, 2018).

According to Liao *et al.* (2024), the high-efficiency water and fertilizer management mode, which applies 140 – 215 mm of irrigation and 210 – 270 kg/ha of N fertilizer, can greatly increase yield in comparison to other methods. The distribution and transport of water and nitrogen in the soil are influenced by the application of N fertilizer and the groundwater table. The impacts of crop development, irrigation, and soil water transport will result in a strong water potential gradient and high nitrogen concentration in the upper soil layer following N application. Water and nitrogen seep in, causing nitrogen leaching as well as a reduction in crop uptake and usage of both nutrients (Wang, 2018).

Water saving technology adoption may change the dynamics of N and P and reduce nutrient losses (Tan *et al.*, 2013). According to Suwanmaneepong *et al.* (2023), AWD reduced nitrogen losses when compared to traditional irrigation with the same N management. Darzi-Naftchali and

Ritzema (2018) came to the conclusion that well-managed drainage systems can lower N losses in drainage water and increase paddy rice yields during a field study conducted in Iran.

According to Leghari *et al.* (2016), nitrogen is essential for raising crop production since it boosts crop yield per unit of applied water. The root dispersion of wheat has been found to be impacted by nitrogen and irrigation regimes. This has a significant impact on soil water consumption and soil NO_3-N concentration (Wang *et al.*, 2016; Chang *et al.*, 2019). When wheat is growing vegetatively, for example, minor nitrogen shortfall and water constraints generally lead to increased vertical root penetration, which lowers root length density (RLD) in the upper soil layer and raises RLD in deeper layers (Wang *et al.*, 2016; Chang *et al.*, 2019) hence, roots in the deep soil layers (> 0.8 m) are essential for nutrient and moisture absorption (Chang *et al.*, 2019). According to Leghari *et al.* (2016), a sufficient supply of nitrogen significantly increases the rice plant's vigour, encourages vegetative growth, and speeds up the growth of its leaves and stem. Additionally, it improves the quality and quantity of protein in grains and promotes the absorption and use of other nutrients.

The majority of rice produced worldwide is grown in lowland, irrigated, or rainfed conditions on flooded soils. Because rice can oxidize its rhizosphere by absorbing atmospheric oxygen that diffuses from the leaves through intercellular pathways, it can flourish in these conditions. However, compared to upland settings, flooding causes a number of physical, chemical, and biological alterations in the soil that have an impact on how the applied urea behaves. Physically, when an initially dry soil is flooded, the structural aggregates of the soil matrix become saturated, and many of the aggregates disintegrate due to pressure created by trapped air in the soil (Fathi, 2022).

From a biological perspective, the respiration mechanisms of aerobic soil bacteria require the consumption of oxygen. Since the rate of oxygen diffusion via water is slower than it is in the absence of water, oxygen in the soil is rapidly reduced after floods. In these circumstances, anaerobic microbes proliferate by oxidizing soil constituents as electron acceptors and using decomposable organic matter as a source of energy. These substances undergo reduction in the order that thermodynamics determines; nitrates, hydroxides, sulfates, CO_2, manganese oxides, ferric oxides, and occasionally phosphates (Koudjega *et al.,* 2019).

Due to continuous field flooding during rice growth, flooded rice soils are chemically characterized by a lack of oxygen in the system, which causes soil layers to differentiate into an oxidized surface layer zone and an underlying reduced zone. Slow differentiation happens in deep floodwater layers. However, differentiation happens rapidly when the floodwater layer is shallow and has a high concentration of dissolved oxygen. The way nitrogenous fertilizers behave on rice soils is significantly impacted by these physico-chemical and biological alterations (Koudjega *et al.*, 2019).

When urea is added to paddy soil, it hydrolyzes and produces ammonium (NH_4^+), a very unstable ion, within the soil system. The NH_4^+ that is formed can either volatilize into ammonia (NH_3) form or be absorbed by plant roots; be temporarily adsorbed by organic and mineral particles in the soil, be fixed by soil micro-organisms or oxidize into nitrate (NO_3^+), which can then be absorbed by rice roots or lost from the root zone with leaching water. In reduced conditions, this nitrate can also serve as a precursor for denitrification, which in turn causes the emission of nitrogen gas, nitrous oxide, and an oxide (He *et al.*, 2021).

2.9 Crop Water Stress Index (CWSI)

2.9.1 Water and Rice Production

Rice is staple food that is consumed in most parts of the world, which makes it essential in the fight against food insecurity, particularly in nations with fragile economies (Wasaya *et al.*, 2022). Over half of the world's population depends on rice for food security, and by 2030, it is predicted that worldwide rice production would rise from 58 to 567 million tons (Mohidem *et al.*, 2022). Furthermore, increased productivity, crop intensity, and diversification are expected to boost global rice production to more than 1,035 million tonnes by 2050 (Sathoria and Roy, 2022). Since rice is an aquatic or semi-aquatic crop, it has high requirements for the utilization of freshwater. Rice consumption makes up more than 80 % of Asia's irrigated freshwater resources. As a result, increasing grain output while conserving water is a significant problem for rice cultivation. Similar trends can be seen in Africa and other regions of the world (Bin Rahman and Zhang, 2023).

Food security is seriously threatened by the worsening water crises in nations that farm rice (Udimal *et al.*, 2017). In many poor nations, rice is a key crop for ensuring food security. A drop in rice output can have an impact on food security (Surendran *et al.*, 2021). The production of rice is impacted by water scarcity, which can also raise costs and make it unaffordable for the underprivileged. Reduced agricultural production and soil degradation can result from the depletion of water resources used for rice farming. In addition to increasing salinization and waterlogging, excessive use of water resources can lower agricultural output (Surendran *et al.*, 2021).

The depletion of water resources and the reduced performance observed under rice irrigation schemes are mostly caused by continuous flooding and basin irrigation, which is commonly used worldwide for rice cultivation at a water depth of 5 to 10 cm (Luo *et al.*, 2022). Due to a lack of knowledge about irrigation water needs, the amount of irrigation water demand (IWD) remains high even with the promotion of water-saving irrigation technology such alternate wetting and drying (Luo *et al.*, 2022). For instance, Hossain *et al.* (2021) found that in Bangladesh, the rice irrigation water needs varied between 358 mm to 445 mm; Luo *et al.* (2022) recorded that irrigation water for rice in China varied from 135 mm to 288 mm; Bouraima *et al.* (2015) stated that the irrigation water needed for rice crops in Northern Benin were estimated to be 383 during the rainy season and 1148 mm during the dry season. Similarly, de Vries *et al.* (2010) reported that irrigation water requirements for rice crops in Sahelian regions ranged from 480 mm to 1490 mm. However, according to Abdul-Ganiyu *et al.* (2015), 10ETC and 15ETC were measured at 627.3 mm and 940.95 mm respectively.

In contrast, crop water requirements (CWR), or the amount of water consumed by the crop representing crop evapotranspiration (ETc), is different from crop irrigation water demand, which is typically low or non-existent during the rainy season in highly rainy areas (Kilemo, 2022; Luo *et al.*, 2022). Rice irrigation water demand (IWD) is defined as the amount of water needed to meet the water losses of a disease-free crop growing under unrestricted soil conditions and achieving full production (He *et al.*, 2022).

Crop water requirements are influenced primarily by crop factors (e.g., growth stage, cultivars, crop physiology, etc.) and reference evapotranspiration (ETo), irrigation water demand, on the other hand, is influenced by agronomic practices (such as land preparation, irrigation scheme patterns, etc.), soil types (such as texture, slope, hydraulic, etc.), season (such as rainfall), and farmers knowledge and skills. Therefore, by addressing the variables that affect it and using irrigation water-saving management techniques, as well as enhancing producers' capacity to implement best management practices, irrigation water demand can be decreased (Djaman *et al.*, 2018).

The availability of water for irrigation is expected to change due to changes in temperature and precipitation patterns, which could lead to both water shortages and flooding. It is anticipated that as global temperatures rise, the hydrological cycle will become more intense, leading to longer dry spells in certain regions and more intense rainfall events in others (Mallareddy *et al.*, 2023). Elevated temperatures are anticipated to increase evaporation rates and soil water loss, perhaps resulting in decreased soil moisture content and an increased frequency of droughts. This could result in severe crop water stress that could impair crop productivity since rice need enough moisture in the soil to grow and produce high yields.

2.9.2 Crop Water Stress Index (CWSI)

The Crop Water Stress Index (CWSI) is used as an index to describe the extent of crop water deficiency based on canopy surface temperature, ambient air temperature, and soil water dynamics (Khan *et al.*, 2022). The CWSI, which is based on data from plant canopy temperature and air vapour pressure deficit, quantifies the relative transpiration rate that a plant is producing at the moment of measurement. The CWSI can be found by measuring the air temperature, the leaf temperature, and air humidity (relative humidity, wet bulb temperature etc.).

Berni *et al.* (2009) reported that the CWSI is an easy and fast way to determine water stress. In light of this, numerous studies have been conducted to evaluate the CWSI for the application of varying irrigation regimes in various crops in different locations (Ünlü *et al.*, 2011; Aladenola and Madramootoo, 2012; Sezen *et al.*, 2014; Alghory and Yazar, 2018).

The CWSI relationship was proposed by Idso *et al.* (1981) as:

$$CWSI=\frac{[(T_c-T_a)_m-(T_c-T_a)_{li}]}{[(T_c-T_a)_{ls}-(T_c-T_a)_{li}]} \qquad \text{Eqn 2.4}$$

Where:

Tc – Canopy temperature and

Ta – Air temperature.

The "*m*" subscript denotes the difference between the two measured temperatures, *li* (inferior limit) denotes the non-water stress baseline (NWSB) expressed as the difference between the two temperatures when evapotranspiration is not restricted by water availability, and *ls* (superior limit) denotes the hypothetical non-transpiring upper baseline expressed as the difference between the two temperatures when evapotranspiration is zero. The CWSI is estimated by determining the relative distance between the lower baseline representing non-stress conditions (well-irrigated condition) and the upper baseline representing no-transpiration (totally stressed condition). The CWSI varies between 0 (no water stress condition) and 1 (severe water stress condition).

The CWSI in Equation 2.4 can be reduced and rewritten as;

$$CWSI=\frac{(dT-dT_i)}{(dT_s-dT_i)} \qquad \text{Eqn 2.5}$$

Where:

dT – Difference of measured air and crop temperatures,

dTs – Upper limit of the air temperatures minus the canopy temperature (crop without transpiration) and

dTi – Lower limit of temperatures in the air minus the canopy temperature (fully-irrigated crop).

The air vapour pressure deficit (VPD) is used to normalize the difference between a plant's canopy temperature (Tc) and air temperature (Ta) in respect to evaporative demand, which forms the basis of the CWSI algorithm. For the normalization related to the VPD, the Tc–Ta relationship under the two boundary conditions is taken into account. A plant will transpire at its potential rate in two conditions: the lower limit, which is well-watered; and the upper limit, which has a transpiration rate of zero. The NWSB, or lower bound, illustrates the linear relationship between the Tc–Ta and VPD. An essential component in the CWSI computation is the canopy temperature under various boundary conditions (Khan *et al.*, 2022).

According to Irmak *et al.* (2000), in Mediterranean, semi-arid cropping circumstances, the CWSI is a useful tool for tracking and measuring the water stress of maize when combined with the canopy temperature measured with an infrared thermometer. Using the canopy energy balance, da Silva and Ramana (2005) investigated the diurnal and seasonal variations of the CWSI of cotton crops. Several diurnal cycles were obtained, along with key parameters like the canopy temperature, air temperature, net radiation, wind speed, and psychometric measurements, at regular intervals of 10:00 and 14:00 hours. Additionally, in order to compute the CWSI, the link between the canopy-air temperature difference and the vapour pressure deficit of beans grown under drip irrigation under a completely irrigated treatment was established, comparing conditions with no stress to those with increased water stress (Alghory and Yazar, 2018). Gonzalez-dugo *et al.* (2014) used infrared thermometers to measure short-term fluctuations in canopy temperature across three seasons (2009–2011) in Spain in order to estimate the values of the CWSI for various fruits.

The canopy temperature has been shown to be a good predictor of plant moisture content. Based on the previously mentioned studies, crop yields, ambient air temperatures (Tc–Ta), and soil moisture availability in the root zone are significantly correlated. Additionally, some researchers have discovered that the CWSI is a reliable predictor of crop yields and irrigation schedule (Khan *et al.*, 2022).

Crop water status is a crucial water stress indicator utilized in irrigation management (Cohen *et al.*, 2016; Han *et al.*, 2018). Consequently, accurate plant water stress assessment is critical to effective irrigation scheduling. Despite the fact that soil-based techniques are more frequently employed, plant-based techniques are gaining popularity as a direct substitute for actual plant water status (Jones and Vaughan, 2012). Therefore, it is necessary to ascertain the plant water stress threshold values at which irrigation can be initiated.

In an experiment conducted by Ramos-fernandez *et al.* (2024), CWSI results showed fluctuations between 0 and 1 for rice. Water stress was evident during the tillering period as the CWSI values stayed high (0.2 and 1). Conversely, CWSI values were lower during the reproductive period. However, CWSI readings increased to 0.8 throughout the maturity period, especially at the time of a pasty and waxy grain, indicating a water deficit.

2.9.3 Methods of Estimating CWSI

i. Remote Sensing Methods to Detect Crop Water Stress

Without making direct physical touch, remote sensing gathers data from ambient elements, soil, and crops (Panda *et al.,* 2023). Its rapid detection of changes in crop growth that conventional methods often overlook has enhanced and optimized agricultural productivity. Sun *et al.* (2021) stated that remote sensing system provides specific information crucial to the research of irrigation scheduling, quantity, and duration, and allows for a highly accurate estimation of crop temperature. Zhou *et al.* (2021) posited that one of the factors that defines a crop's relationship with its environment is crop water stress, which must be evaluated in order to schedule irrigation. As a ubiquitous indication for assessing stress on the leaf and canopy scales, the CWSI has gained recognition in the field of agriculture. This approach provided a more comprehensive analysis of water stress at the plot and regional levels, encompassing evapotranspiration. Increasing water savings and enhancing agricultural sustainability need the implementation of efficient irrigation scheduling strategies (Osroosh *et al.,* 2016).

A crop's physiological status, biochemical status, and irrigation use efficiency can all be obtained by measuring the crop's relative water content (RWC) (Yi *et al.*, 2014). These parameters, such as leaf water potential and moisture availability, can be efficiently monitored for prompt and effective action, thanks to remote sensing systems (Zhang *et al.*, 2021). Using spectral remote-sensing devices, which analyze spectral data to produce easily accessible information, RWC can be ascertained with great accuracy. For instance, Yin *et al.* (2021) effectively obtained timely and reliable RWC data using remote-sensing spectral devices. Researchers can determine the amount of stress that a leaf is experiencing or may experience in the future by assessing the equivalent water thickness (EWT) of a leaf. This assessment yields the available water quantity per unit leaf area. Based on measurements of the leaves, this remote sensing method may accurately evaluate crop water stress, which is essential for making some decisions.

Crop EWT is influenced by the amount of solar radiation received as well. EWT and crop leaf moisture are connected. A large volume of water is absorbed and transpired when there is strong solar radiation since there is a greater need for water. Crop water demand and moisture availability can be estimated using EWT measured by distant sensors. The EWT assessment values (low and high) are continuously monitored by the remote sensing sensors. While a rapid increase and positive values indicate mild crop water stress, extreme occurrences of EWT assessment result in crop death (Rodriguez-dominguez *et al.*, 2022).

Knowing the leaf water content is crucial for calculating crop water stress at the RWC level. Through the use of remote sensing technology, the association with leaf water content is found. An imbalance results in low water potential and stress on the leaf water content. When the amount of water absorbed by the root system and the amount of water evaporated from the leaves are not equal, an imbalance occurs. Water stress on leaves varies according to plant condition. There is an indirect relationship between temperature and transpiration rate. The water availability of the leaves under higher transpiration conditions results in reduced crop water stress, whereas poor transpiration causes high crop water stress. Remote sensing systems measure temperature, transpiration rate, cooling, and heating impacts; the data is then analyzed for the purpose of assessing agricultural water stress (Ahmad *et al.*, 2021).

Passive signals are used by satellite systems like soil moisture active passive (SMAP) and soil moisture and ocean salinity (SMOS) to measure soil moisture. These systems' L-band frequency measurement allows for the best possible temporal and spatial precision (25–40 km) for mapping the worldwide near-surface (0–5 cm) soil moisture. Using data assimilation techniques and processing models, they can also examine the near-surface soil moisture content up to the crop root zone (upper 1 m). These systems' functions include doing analysis and keeping an eye on the soil moisture at different locations and sparse monitoring chains (Sabater *et al.*, 2007).

Using an infrared ray gun as a remote sensing technique, Lopez-Lopez *et al.* (2011) verified agricultural water stress by analyzing crop evapotranspiration (ETc) for soil matrix potential. The findings revealed that crops under less water stress might record values between 1.21 and 1.31 VPD, with an R^2 of 0.68. Using a thermal remote-sensing system, Romero-Trigueros *et al.* (2019) examined the crop water stress index and discovered values ranging from 0 to 0.68 and from 0.02 to 0.71 in different years.

In order to have a better curve or model fit for determining water stress and/or ET, vegetation indices frequently need adjustment variables or further calibration. According to DeJonge *et al.* (2015), crop coefficients for irrigation scheduling based on vegetation index can assist minimize the amount of water used in agriculture by adjusting irrigation rates to a crop's actual water requirements as it grows rather than to a modelled crop growing in ideal conditions.

ii. Canopy Temperature Method

For several crops, the CWSI, which is based on canopy temperature, has been widely used as a tool to schedule irrigation and show the water status of plants (Aladenola and Madramootoo, 2012; Bellvert *et al.*, 2016; Cohen *et al.*, 2016). CWSI theory is based on the principle that transpiration lowers leaf surface temperature, and that when soil moisture in the root zone is lost, stomatal conductance and transpiration also drop and leaf temperature rises. The idea of using CWSI to improve irrigation scheduling gained traction when Idso *et al.* (1981) developed an empirical method of quantifying crop water stress and observed a linear relationship between canopy temperatures measured using infrared thermometry and air temperature and vapour pressure deficit. Two baselines are used in the empirical CWSI. When a crop is well-watered and transpiring at its maximum rate, the lower baseline shows canopy temperature (Tc) minus air temperature (Ta), and the upper baseline shows (Tc–Ta) when the crop is not transpiring.

O'Shaughnessy *et al.* (2011) and Gonzalez-dugo *et al.* (2014) have investigated the application of CWSI in crop scheduling and water stress monitoring. In order to successfully automate grain sorghum irrigations, O'Shaughnessy *et al.* (2011) integrated a Time-Temperature Threshold (TTT) into a theoretical index (CWSI-TTT). Nonetheless, the study noted an issue with under irrigation during the growth season, which was brought on by cloud cover and the impact of shifting crop characteristics on measurements from infrared thermometers.

Using a theoretical CWSI, Osroosh *et al.* (2016) created an adaptive irrigation scheduling system. This approach uses a dynamic threshold that is calculated by tracking the CWSI trend, in contrast to the classic CWSI algorithm where the threshold is a constant value.

2.10 Modelling Water Regimes on Soil Water Balance and Crop Water Productivity Indices

2.10.1 Overview of Agricultural Models for Soil Water Balance and Crop Water Productivity

The many components that make up agriculture interact with one another and their environment to define how the agricultural system as a whole works (Jones *et al.*, 2016). Changes taking place inside the system boundaries may not have an effect on the environment itself, but these interdependent pieces are exposed to an external environment that may influence how they behave. Systems are extremely significant in research and engineering across all industries, including agriculture, despite the fact that they are sometimes defined as abstractions of the real world for specific reasons. An agricultural system, sometimes referred to as an agro-ecosystem, is a collection of components that cooperate to cultivate land and rear animals in order to harvest food, fiber, and energy from the planet's natural resources. Additionally, these systems might have negative environmental implications (Jones *et al.*, 2016).

Even with large resource requirements, field and farm experiments might not yield sufficient data in terms of both time and space to determine suitable and efficient management techniques. Therefore, in the development of sustainable management techniques across a range of agro-ecological and socio-economic settings, agricultural system models are becoming more and more relevant. Models can help agricultural managers, research scientists, and policymakers find management options for optimizing sustainability goals over area and time, provided the required soil, management, climatic, and socio-economic data are available. They can help identify potential problem areas where more in-depth fieldwork might be carried out (Antle *et al.*, 2015).

Decision Support Systems (DSSs) are computer software programmes that employ models and other data to generate recommendations for specific sites in the areas of pest control, farm financial planning, animal enterprise management, and general crop and land management (Jones *et al.*, 2016).

According to Antle *et al.* (2015), the bulk of DSS software packages have been utilized by farm consultants and other professionals who work with farmers and policymakers, even though certain DSS software may be used directly by farmers. Models of agricultural production systems were first developed in the 1960s, according to Jones *et al.* (2016). Among the first to model agricultural systems was a physicist from Wageningen University by the name of C. T. de Wit. In the middle of the 1960s, he proposed that agricultural systems could be modelled using ideas from biology and physics.

Crop growth modelling makes use of the knowledge of multiple disciplines, such as soil science, physiology, agronomy, plant breeding, and meteorological science, in a process-oriented approach. Given the present trends of cross-disciplinary collaboration in the business and public sectors, the stage is set for agricultural development, which is essential for the advancement of decision support system design. Currently available computerized systems combine technical knowledge of crop growth with economic and meteorological variables as decision support systems.

Agricultural models use eco-physiological processes to simulate plant physiology and development as a function of crop management and weather conditions, which are used as model inputs (Reynolds *et al.*, 2018). The identification and comprehension of the problem are the first two (2) steps to consider when developing a model. According to Jones *et al.* (2016), crop modelling is an emerging area of agricultural systems that needs basic data for development as well as multidisciplinary research data. The biggest barrier to model application is knowledge of model structures, complicated agricultural systems, and model operations and functioning.

According to Vadas *et al.* (2013) models can mimic and assess aspects of agricultural management and interactions that are not directly quantifiable. They can be used to predict the interactions between crops, water, soil, and environment when quantitative data are not available (Radcliffe *et al.*, 2015). Given the constraints of time and resources, models can offer research with a higher order of magnitude than field surveys. According to Vadas *et al.* (2013), modelling research also forces researchers to assess and codify their comprehension of processes, which aids in identifying knowledge and data shortages. ADAPT, AGNPS, APSIM, ANIMO, APLE, APEX, AQUACROP, CHEMFLO, CROPWAT, DRAINMOD, DSSAT, EnDrin, EPIC, FHANTM, GAMES, GLEAMS, HYDRUS-1D/2D/3D, ICECREAM, LEACHM, MACRO, PLEASE, RZWQM2, SurPhos, SWAT, WaSim, and others are among the agricultural models.

2.10.2 Basic Review of Some Agricultural Models

i. DrainMod Model

a. Model Description

DRAINMOD is a one-dimensional field-scale process-based model that was initially created by Skaggs (1980) to simulate the water table and sub-surface drainage outlets. According to Skaggs *et al.* (2012), DRAINMOD has been tested in a range of climate and soil conditions, simulating the hydrology of soils with shallow water tables that were either intentionally or insufficiently drained. The hydrologic component of the model also contains formulas and techniques for illuminating different hydrologic processes. DRAINMOD simulates the hydrology of an artificially drained field using two (2) simple water balance equations: one for the soil surface and the other for a portion of the soil profile with a unit area that is located in the middle of two (2) parallel drains and extends from the soil surface down to the top of a restrictive soil layer.

It uses two fundamental equations as presented in Equations 2.6 and 2.7.

$P = F+\Delta S+RO$ ……………………………………………………………………………Eqn 2.6

$\Delta V_a=D+ET+VLS-F$ ……………………………………………………………………… Eqn 2.7

Where:

P – Precipitation (cm),

F – Matrix infiltration (cm),

ΔS – Change in surface storage (cm),

RO – Surface runoff (cm),

ΔV_a – Change in water-free pore space (cm),

D – Sub-surface drainage (cm),

ET – Evapotranspiration (cm), and

VLS – Vertical and lateral seepage (cm).

In the model, water can pond on the soil surface and fill the surface depressional storage when the precipitation rate is higher than the soil infiltration rate or the soil profile is saturated. Surface depressional storage must be filled up before there is surface runoff. The difference between precipitation and the total amount of infiltration and change in water retained on the soil surface is known as runoff, and it is calculated using the surface water balance equation.

The equation developed by Green and Ampt (1911) as stated by Van den Putte *et al.* (2013) is used to determine infiltration as presented in Equation 2.8.

$f=K+KM_dS_f/F$ ……………………………………………………………………… Eqn 2.8

Where:

f – Infiltration rate, (cm h^{-1}),

F – Cumulative infiltration (cm),

K – Vertical hydraulic conductivity of the transmission zone (cm h^{-1}),

M_d – Difference between final and initial volumetric water contents ($cm^3\ cm^{-3}$), and

S_f – Effective suction at the wetting front (cm).

For a specific soil with a given initial condition, Equation 2.8 may be written to derive Equation 2.9 as follows:

$f = A/F+B$ ………………………………………………………………………...…… Eqn 2.9

Where:

A ($cm^2\ h^{-1}$) and B ($cm\ h^{-1}$) are parameters that depend on soil properties and plant factors, such as extent of cover, depth of root zone, and soil water content when rainfall begins.

The DRAINMOD model continuously evaluates a drainage system's performance over time. The basis of the model is the water balance for a section of soil profile located between the drains from the impermeable layer to the soil surface. The model is used to evaluate the effects of water management system on crop output under drought stress, excess water stress, salt stress, and planting delay in simulated crop rotation. While accounting for the quality of the irrigation water, this model predicts the depth of the water table, the amount and salinity of the drainage water, the change in soil salinity, and crop yields (Pourgholam-Amiji *et al.*, 2021).

Water-free pore space changes as a result of evapotranspiration (ET), seepage losses, and sub-surface drainage. This is calculated using the water balance equation for the soil profile. When water is allowed to freely migrate to the drain region and the ponding depth is larger than the roughness of the soil surface (Kirkham's depth), the drainage flow is calculated using the steady-state Hooghoudt equation as provided by Bouwer and van Schilfgaarde (1963). Unlike experiments, simulation models can be effectively used to examine water management systems using complex scenarios and a range of boundary conditions when they are calibrated correctly

(Nozari *et al.,* 2021). Many researchers have simulated agricultural production management of irrigation and drainage systems using DRAINMOD.

Wang *et al.* (2006) computed drainage discharge in southwest Ohio using DRAINMOD and found that the model's predictions were reasonably accurate. In a different study, Wahba and Christen (2006) modelled the daily water table, drainage, and salt output in Southeast Australian irrigated areas using DRAINMOD-S. In semi-arid regions of Australia, the authors suggested using DRAINMOD-S to create various drainage plans and management techniques. For the El-Tina plain in Sina, Egypt's northwest, Foda *et al.* (2020) used DRAINMOD-S to assess the long-term effects of applying controlled drainage (CD) as a water-saving technique on agricultural productivity and soil salinity.

b. Model Requirement and Output

Soil, weather, crop, and drainage system-related input factors are required by DRAINMOD. The soil inputs data consist of the following: the lateral saturated hydraulic conductivity for each soil layer, the soil-water characteristic curve for each layer, the volume of water drained and upward flow as functions of water table depth (WTD), and the infiltration parameters for the Green and Ampt Equation. Hourly precipitation data, highest and lowest daily temperatures, and, if available, daily potential evapotranspiration (PET) values are the weather inputs. If hourly precipitation data are not available, daily records can be used and uniformly spread over four or six hours every day, centered at either 6:00 a.m. or 6:00 p.m. (Skaggs *et al.,* 2012).

One of the primary inputs that DRAINMOD uses to forecast patterns of water distribution in a given study region is potential evapotranspiration. A variety of methods have been developed to generate estimates for ETo values since the process of land potential evapotranspiration is invisible and, for the most part, costly and complicated to assess. If data are provided, PET can be computed using the Thornthwaite (1948) approach or read as an input file by the model. Calculating evapotranspiration (ET) supply involves utilizing the user-defined WTD relationship and upward flux.

A dry zone that can extend as far down as the rooting depth is created when water is extracted from the upper layers insufficiently to meet the ET demand. DRAINMOD calculates lateral and vertical seepage using methods based on Darcy's Law. The information pertaining to field working conditions, root depth during the growing season, growing days, ideal planting date, and crop stress parameters are all included in the crop data. The depth to the impermeable layer, effective drain radius, initial water table depth, storage parameters, drain depth and spacing are examples of drain system parameters. In addition, whether the model is configured to replicate sub-irrigation or controlled drainage, parameters specifying the settings for the drain outlet are needed.

The user specifies lateral and/or vertical seepage parameters, if appropriate. Infiltration, sub-surface drainage, surface runoff, ET, vertical and lateral seepage, water table depth, and drained pore volume in the soil profile are all included in the hydrologic predictions made by DRAINMOD. Daily, monthly, and year output reports are possible (Skaggs *et al.*, 2012). The user can choose to view summary outputs on a daily, monthly, yearly, or ranked basis. Hydrologic variables, such as infiltration, sub-surface drainage, surface runoff, evapotranspiration, vertical and lateral seepage, water table depth, and drained or water-free pore space in the soil profile, are predicted. Predicted outcomes could include variables showing the hydrologic state of wetland areas, depth of irrigation water applied, and anticipated crop yields (Skaggs *et al.*, 2012).

c. Strength of DrainMod

The strength of the DRAINMOD include:

i. For a variety of soil types, climate scenarios, and agricultural techniques, DRAINMOD can simulate the dynamics of soil carbon and nitrogen on drained fields (Ale *et al.*, 2012).

ii. According to Singh *et al.* (2012), the model mimics the intake of plants as well as their mineralization, immobilization, nitrification, denitrification, ammonia (NH_3) volatilization, atmospheric deposition, and N losses through surface runoff and sub-surface drainage.

iii. It mimics the application of mineral N fertilizers, animal manure, and tillage, as well as the management of plant residues.

iv. The fact that DRAINMOD is a process-based model with independently measurable or determined inputs is one of its main advantages. The physical basis of the inputs allows selection of values within a tolerable range in the calibration process, even in cases when site parameters and soil properties cannot be measured (Skaggs *et al.*, 2013)

v. According to Ale *et al.* (2009), the model performs a good job of representing the hydrology, drainage performance, and drainage management strategies on lands with a shallow water table.

vi. The model can accurately simulate the effects of different managed drainage depths on drain discharge rates.

vii. It can accurately simulate how the salinity of irrigation water affects the accumulation of salt in the root zone.

d. Limitations of DrainMod

The limitations of the DRAINMOD include:

i. There can be more inputs needed to describe many hydrologic processes.

ii. The shallow water table lands for which the model was designed were those with inadequate or artificial drainage systems. These poorly drained soils are frequently found in landscapes where a significant portion of the watershed has deep water tables and naturally well drainage (Skaggs *et al.,* 2013).

iii. The procedures for data preparation are discouragingly many and complex for amateurs.

ii. APSIM Model

a. Model Description

The Agricultural Production Systems Simulator (APSIM) model is used by hundreds of researchers worldwide because of its dependable mechanistic approach to simulating biophysical processes inside farming systems (Holzworth *et al.*, 2014). The APSIM modelling framework consists of a set of biophysical modules that simulate biological and physical processes in farming systems. To control how the simulation is run, the user can specify the management rules that should be applied to the scenario being simulated using a set of management modules. The model includes several modules to assist with data input and output to and from the simulation, in addition to a simulation engine that performs the simulation and controls all communications sent between the various modules (Holzworth *et al.*, 2014).

The environment of APSIM is a helpful resource for researching whole-farm systems, like crop and pasture rotations and sequences, as well as for addressing tactical and strategic planning. Users can learn more about how climate, soil types, and management affect crop and pasture productivity with APSIM. It is a useful tool for researching agronomic adaptations, such as modifications to cultivar types, planting dates, irrigation/fertilizer schedules, etc.

Models developed for different research initiatives are combined into the APSIM modelling framework. For mutual gain, this enables the transfer of research from one discipline or topic to another. Furthermore, it facilitates model or sub-model comparisons on a single platform through the use of the "plug-in-pull-out" technique. The user can configure a model by choosing a set of sub-models from a variety of crop, soil, and utility modules. The user can specify any logical combination of modules by just "plugging in" the ones that are required and "pulling out" the ones that are no longer needed.

Subsequently, the APSIM framework was extended to include the ORYZA2000 rice model created by Bouman and Van Laar (2006), enabling the computer to simulate rice. The "dryland-specific" soil modules were replaced with the integrated APSIM soil modules (Gaydon *et al.,* 2017) that depict realistic soil water, carbon, and nitrogen dynamics in rice-based cropping systems. The APSIM soil water balance modules took the place of the soil water routines found in the original ORYZA2000 model. Scientists throughout the world that grow rice are using this new modelling framework called APSIM-Oryza frequently (Brown *et al.,* 2011; Heinemann *et al.,* 2012; Qiu *et al.,* 2019).

b. Model Requirement and Output

An APSIM simulation's configuration entails determining which modules to use and which data sets each module requires. APSIM modules often require initialization and temporal data as the simulation progresses. Examples of simulation-specific parameter data are cultivar, site, and management characteristics. Conversely, generic data indicates the module for every simulation. Typical site parameters include soil qualities for soil modules, temperature data for meteorological modules, properties of the soil surface, and characterization of surface residue. Management, which provides a set of rules, calculations, and messages to modules used in the simulation, is specified in an easy-to-understand language (Holzworth *et al.*, 2014).

Soil qualities, daily climatic data, cultivar characteristics, and agronomic management are examples of input data. Soil water balance components like irrigation/rainfall, transpiration, evaporation, runoff, and drainage are needed as input to model water balance. Changes in agricultural and pasture yields, yield components, and losses from soil erosion are examples of output data for several climate change scenarios (Gaydon *et al.*, 2012).

c. Strength of the APSIM Model

The strength of the APSIM Model as documented include:

i. APSIM can simulate more than 20 crops and forests such as alfalfa, barley, chickpea, cotton, cowpea, eucalyptus, lupin, maize, peanuts, pigeon pea, rice, sugarcane, sunflower, tomato, wheat etc (Chisanga *et al.*, 2020).

ii. By integrating with geographic information systems (GIS), APSIM outputs can be utilized for geographical research (Peng *et al.*, 2020).

iii. A simulation can be carefully configured by users, giving them the option to choose the right level of detail.

iv. In simulating soil water balance in individual soil layers and system water-balance components, APSIM has shown acceptable performance (Gaydon *et al.*, 2017).

d. Limitations of the APSIM Model

The limitations of the APSIM Model include:

i. The distribution of APSIM is overseen by a license mechanism designed to preserve the product's integrity. Licenses are granted solely upon verification that the necessary training and support for the specified study can be provided (Keating *et al.*, 2003).

ii. It has a strict version control and distribution system.

iii. DSSAT Model

a. Model Description

The Decision Support System for the Transfer of Agrotechnology (DSSAT) is a micro-computer software package that was developed by an international team of scientists. It analyzes the risks, productivity, and resource utilization associated with different crop production systems. It is a group of computer programmes created to simulate agricultural crop growth. The modular design of DSSAT, which provides a range of alternatives to characterize processes like evapotranspiration and soil organic matter building, facilitates testing different representations of processes essential to crop growth (Alexandrov and Hoogenboom, 2000).

The International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) initiative was supported by the United States Agency for International Development (USAID) in 1992 to address food security in underdeveloped countries. A systems analysis of agricultural productivity served as the foundation for IBSNAT. This project's objective was to use an investigative methodology to test the hypothesis that modelling systems are essential for enhancing agriculture. A multinational team of scientists working with IBSNAT produced computer software with a suite of models called the Decision Support System for Agrotechnology Transfer (DSSAT) to evaluate yield, resource utilization, and hazards associated with different crop production systems (Tsuji *et al.*, 1998).

A user interface, computer programmes, files, and data formats are all parts of the crop model integration to DSSAT. The models simulate plant growth, development, and yield as a function of plant genetics, weather, soil conditions, and crop management practices (Abayechaw, 2021). Among the many crops that are simulated are cereals (maize, wheat, rice, sorghum), legumes (peanut, soybean, beans), grazing grass, roots, and tubers (cassava, potatoes). The cereal simulation modules are derived from the modelling work of CERES (Crop-Environment-Resource Synthesis), carried out in the 1980s. Singh *et al.* (1993), Ritchie *et al.* (1985), and Jones *et al.* (1986) were the developers of the CERES-rice, CERES wheat, and CERES-maize modules, respectively. The CROPGRO was the source of the legume module, which included PNUTGRO, SOYGRO, BEANGRO among others (Boote *et al.*, 1998).

The DSSAT model has been improved over time with version 2.1 being the first. Later versions included 3.0, 3.5, 4.0, 4.5, and 4.6, 4.7.5, and the most recent version, 4.8.2 which was released in 2023 (Hoogenboom *et al.*, 2023). Crop growth models integrate the effects of weather, pests, management, genetics, and soils on daily growth, making them useful tools for understanding geographic variations in yield. The Decision Support for Agrotechnology Transfer (DSSAT) models are the most widely used crop growth models. They were developed to support changes in soil water, carbon, and nitrogen as well as the growth, development, and yield of crops grown on a consistent plot of land (Hoogenboom *et al.*, 2019).

Since the quality of simulation results is greatly influenced by data inputs, DSSAT offers tools to assist modelers in organizing meteorological, soil, and crop management input data. Particularly difficult inputs are the genotype-specific parameters (GSPs), which quantify cultivar differences. Calibration to field trial measurements is the most popular approach for estimating GSPs, and DSSAT provides tools for both managing calibration data and computing the required GSPs (Hoogenboom *et al.*, 2019).

The components of the Cropping System Model (CSM) are modular in nature, with interfaces that allow for module additions or replacements and components arranged according to scientific fields. At the moment, CSM integrates all crop models as modules using a single weather module and a single soil module. The new cropping system model includes models of over 40 crops, which were derived from the original SOYGRO, PNUTGRO, CERES-Maize, and CERES-Wheat crop growth models (Hoogenboom *et al.*, 2020).

b. Model Inputs and Requirement

A number of utility programmes, a series of weather generation programmes, crop simulation models, a data base management system for soil, weather, genetic coefficients, and management inputs, and a strategy evaluation programme to assess options such as variety selection, planting date, plant population density, row spacing, soil type, irrigation, fertilizer application, initial conditions on yields, water stress in the vegetative or reproductive stages of development, and net returns are all included in the DSSAT model package (Hoogenboom *et al.*, 2019).

The DSSAT crop model requires the following inputs: weather, soil surface characteristics, soil profile, and crop management variables. For crop model calibration and assessment, the aforementioned crop model inputs are required in addition to one or more observations, such as yield, yield components, and the primary phenological dates for grain cereals and legumes, such as the first flowering date and maturity date.

The basic input data required by the DSSAT, with specific reference to the CERES-Rice model, include the daily weather data (maximum and minimum temperature, precipitation, solar radiation), soil data (including initial soil water content, nitrate, and ammonium as well as soil layer thickness), crop management data, and the cultivar-specific parameters (CSPs) or genetic coefficients that describe physiological processes and developmental differences among crop hybrids or varieties. Leaf area index (LAI) measurements provide information about plant growth throughout time and are commonly used as inputs for crop simulation models (Hoogenboom *et al.*, 2019).

The experiment file (File X), which defines crop management for a specific experiment (set of model runs or treatments), and the weather data (FileW), in-season growth data (File T), summary averages (File A), cultivar files (File C) and reference soil data (File S), are the components of the CERES-Rice model simulation. This file separation is necessary because, although the experimental file is specific to a single experiment, soil definitions and meteorological data can be utilized in multiple simulations and crops. For every simulation run, the model generates a number of output files (Hoogenboom *et al.,* 2020).

c. Strength of the DSSAT Model

The strengths of the DSSAT Model as documented include:

i. To simulate the multi-year effects of crop management practices, DSSAT integrates crop, soil, and meteorological data sets with crop models and application programs (Hoogenboom *et al.*, 2020).

ii. Based on weather, genetics, soil water, soil carbon, soil nitrogen, and management in one or more seasons and crop rotations at any place where the least number of inputs is available, DSSAT is capable of modelling monocrop production systems (Hoogenboom *et al.*, 2019).

iii. It offers a platform that makes it simple to include modules for additional biotic and abiotic elements, like plant diseases and soil phosphorus (Hoogenboom *et al.*, 2020).

iv. To support model evolution, documentation, and enhancement, it offers a platform that makes it simple to compare various modules for particular components (Hoogenboom *et al.*, 2023).

d. Limitations of DSSAT Model

The limitations of the DSSAT Models have been documented as follows:

i. The crop models that are contained in DSSAT are its primary limitation. The system only includes models for roughly 42 crops, and the models do not account for all environmental and management parameters (Abayechaw, 2021).

ii. As at now, the DSSAT model has no component to forecast how pests, tillage, intercropping, surplus soil and other variables will affect crop production.

iii. One weakness of the DSSAT ecosystem and many other crop modelling systems is the limited capability for handling the impact of biotic stresses caused by insect pests, diseases, and weeds (Abayechaw, 2021).

CHAPTER THREE

MATERIALS AND METHODS

3.1 Description of Study Area

The research was on-station conducted at the WACWISA experimental field, at the Nyankpala Campus of the University for Development Studies, Tamale situated in the Northern Region of Ghana. The field lies within coordinates of N $9^0 24^{'}$37.31976", W $0^0$58'53.73984" (Figure 3.1) and altitude of 158 m above sea level. According to Abdul-Ganiyu *et al.* (2018) the typical raining season of the zone starts from May and ends in October giving way to onset of the dry season. The remaining prolonged months (November – April) defines the dry season within which irrigation is fully practiced in the agro-ecology. Temperature is consistently high, averaging an annual range of 29 to 39 ^oC and an estimated reference evapotranspiration (ETo) above 1,600 mm/y (Abdul-Ganiyu *et al.,* 2012; Abdul-Ganiyu *et al.,* 2018). The vegetation of the experimental site is typically of Guinea Savannah and characterised by grassland with interspersed trees. Common tree species found in the area are of economic value. They include *Azadiracta indica* (Neem), *Parkia biglobosa* (Dawadawa) and *Vitellaria paradoxa* (Shea). The soils of the zone are generally well drained sandy loam with flat topography. The climate of the area is warm and semi-arid with unimodal annual rainfall of 800 – 1300 mm (Nakamura *et al.,* 2015; Abdul-Ganiyu *et al*., 2018).

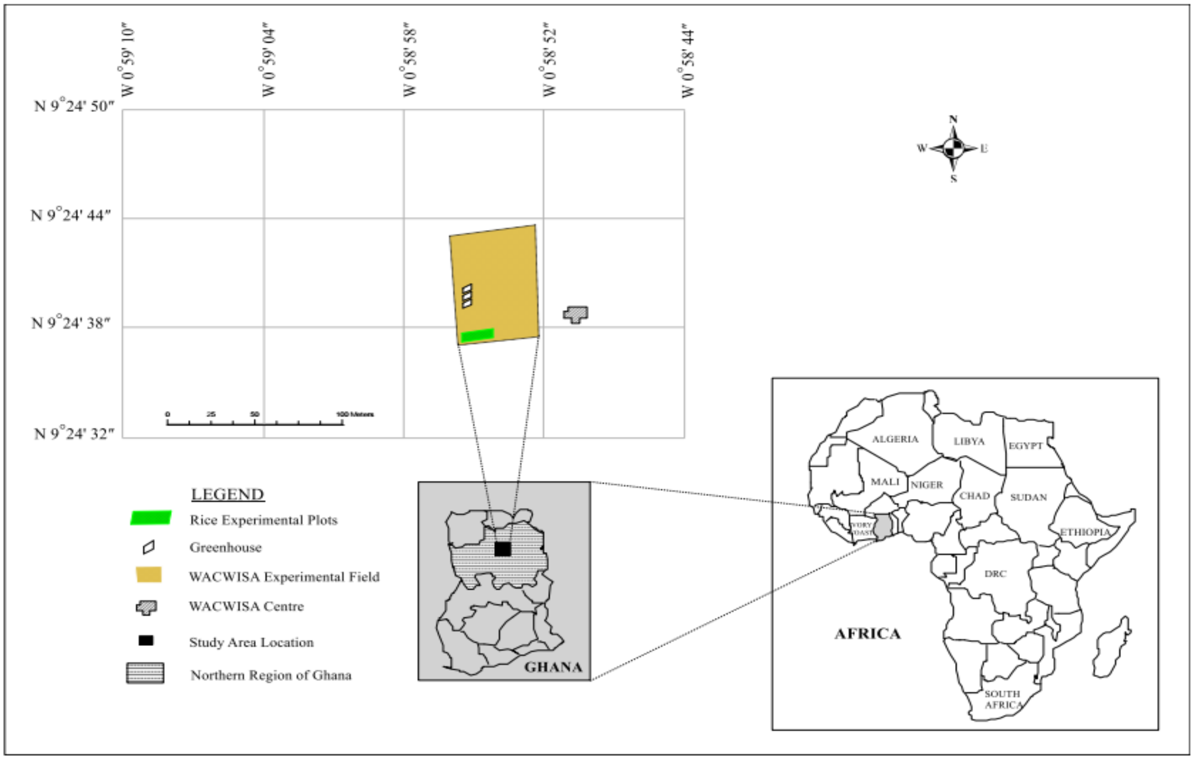


Figure 3.1: Map Showing Experimental Field Location

3.2 Materials for Field Data Collection

The materials used for the study are presented in Table 3.1

Table 3.1: Field Data Collection Materials

	Field Data Collection Materials	Function/Uses
	Cement, Chippings and river sand	For the construction of micro-plots
	Core samplers	Collection of undisturbed portions of the soil as samples
	Piezometers	Determination of levels of water
	GPS	Taking geographical coordinates
	Graduated Cylinder	Measuring drainage discharge
	pH meter	Measurement of soil acidity
	Rain gauge	Measuring amount of rainfall during cropping season
	PVC pipes	For the installation of irrigation and drainage systems
	Decagon 5TM sensors	Monitoring volumetric water content
	Auger	Sampling of soils
	Leaf Ceptometer	Measurement of leaf area index
	Chlorophyll meter	Measurement of relative chlorophyll content
13	PhotosynQ	Measurement of multiple photosynthetic parameters

3.3 Data Sources and Methods

3.3.1 Desk Review

A desk study which involved reviewing relevant literature including journals, articles, thesis and reports on irrigation application depths and drainage systems worldwide as well as work done in Ghana was carried out. An in-depth review was also done on the use of models in agriculture with a view of understanding the dynamics of several models for accurate prediction of agriculture-related scenarios.

3.3.2 Field Data Sources

A range of activities were conducted in the experimental field in order to facilitate the collection of data. These included setting up the experimental design, construction of microplots, setting up and managing of the experiment and collection of data through measurements and observations.

3.3.3 Construction of Microplots

Microplots were constructed to offer a convenient environment that mimics lowland ecology (Plate 3.1a and b). Cement blocks were moulded using cement, sand and water.

Dimension of the blocks = 400 mm × 195 mm × 125 mm.

Dimension of each plot include:

Height = 1 m

Top and bottom are square of side = 1 m × 1 m

Thickness of wall = 15 cm

Freeboard representing the leftover height after microplot was filled with soil = 20 cm

Sub-surface drainage system was installed at a depth of 40 cm. In irrigated lands, drain pipes are equipped with envelopes to safeguard the sub-surface drainage system against the three (3) main hazards of poor drain-line performance: high flow resistance in the vicinity of the drain, siltation, and root growth inside the pipe. In this experiment, gravel was used as an envelope material and 60 mm plastic drain pipes (PVC) were installed with a 0.1 % slope (Plate 3.2a). For the surface drainage system, the pipes were installed at 20 cm from the top of the microplot. Irrigation pipes were installed using 25 mm PVC pipes as sub-mains and laterals (Plate 3.2b), while 48 mm PVC pipes were used as main line which was connected to a reservoir. The water was pumped from the reservoir by means of submersible pump using solar powered panels as energy source. This system was able to deliver a flow of 25 litres per minute to all the plots.

Plate 3.1a: Construction of Microplots **b. Microplots**

Plate 3.2a: Installation of Sub-Surface Drainage System b. Installation of Irrigation System

3.3.4 Plot Preparation

Profiling of soil was done to a depth of 30 cm from lowland ecology and the soil was transported and filled in all the plots according to the soil layers. Water was flooded to allow the soil to settle properly and then filled again to the required depth. The plots were irrigated and puddled two weeks before transplanting to destroy existing weeds and reduce the seed bank. The plots were levelled manually using hand-hoes.

3.3.5 Experimental Design

The experiment was a split plot laid in a Randomized Complete Block Design (RCBD) in a 6 × 3 factorial treatments arrangements replicated three (3) times. Drainage systems were the main plots and were at 3 levels (No drainage; surface drainage and sub-surface drainage) while irrigation depths were the sub-plots and were arranged at six (6) levels. Irrigation treatments included:

CF 5: Continuous flooding at 5 cm.

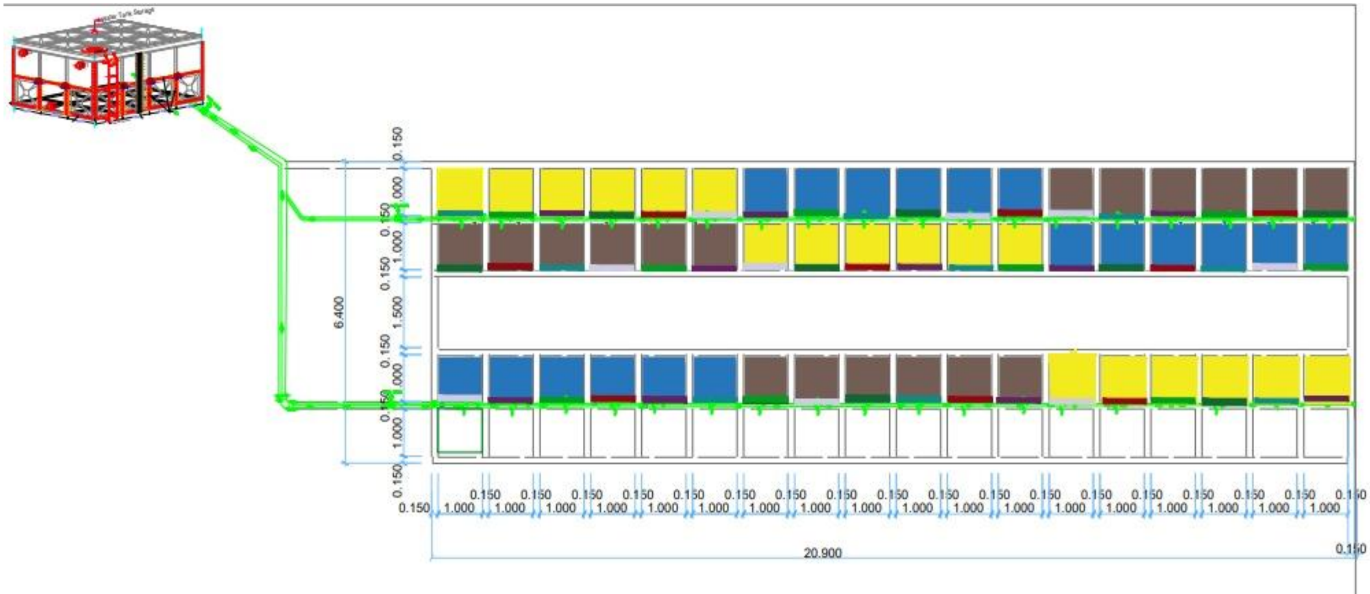
CF 5 – 10: Continuous flooding at 5 cm from transplanting to complete heading and then 10 cm to harvest.

CF 5 – 10 – 15: Continuous flooding at 5 cm from transplanting to booting; 10 cm from booting to complete heading and then 15 cm to harvest.

AWD – 5: Alternate wetting and drying at depletion of 5 cm water level below soil surface.

AWD – 10: Alternate wetting and drying at depletion of 10 cm water level below soil surface.

AWD – 15: Alternate wetting and drying at depletion of 15 cm water level below soil surface.



LEGEND FOR FIELD LAYOUT		
MAIN PLOTS (DRAINAGE)		Surface Drainage
		Sub-surface Drainage
		No Drainage

Figure 3.2 Layout of Main Plots

Rep: 1

1 b	2 e	3 f	4 a	5 c	6 d	7	8 d	9 f	10 a	11 b	12 e	13 c	14	15 d	16 c	17 b	18 f	19 e	20 a

Rep: 2

1 a	2 c	3 b	4 d	5 e	6 f	7	8 c	9 a	10 e	11 f	12 b	13 d	14	15 f	16 a	17 c	18 e	19 d	20 b

Rep: 3

1 c	2 d	3 a	4 f	5 b	6 e	7	8 a	9 f	10 b	11 d	12 c	13 e	14	15 d	16 b	17 e	18 a	19 c	20 f

Figure 3.3 Layout of Irrigation Depths

a) CF 5: Continuous flooding at 5 cm;

b) CF 5 – 10: Continuous flooding at 5 cm from transplanting to complete heading and then 10 cm to harvest;

c) CF – 5 – 10 – 15: Continuous flooding at 5 cm from transplanting to booting; 10 cm from booting to complete heading and then 15 cm to harvest;

d) AWD – 5: Alternate wetting and drying at depletion of 5 cm water level below soil surface;

e) AWD – 10: Alternate wetting and drying at depletion of 10 cm water level below soil surface; f) AWD – 15: Alternate wetting and drying at depletion of 15 cm water level below soil surface.

3.3.6 Nursery Establishment

AGRA Seeds with a crop cycle of 130 days were sought from the Savannah Agricultural Research Institute (SARI) of the Council for Scientific and Industrial Research (CSIR) at Nyankpala having the following parameters:

Germination percentage = 92 %

Purity = 90 %

Test weight = 25 g

Using a spacing of 20 cm × 20 cm

Plant population per hectare was established using Equation 3.1.

$$\text{Plant Population} = \frac{\text{Area (ha)}}{\text{Spacing}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eqn 3.1}$$

Seed rate was determined using Equation 3.2.

$$\text{Seed rate} = \frac{\text{Plant population(per ha)} \times \text{No.seeds per hill} \times \text{Test weight (g)}}{\text{Germination (\%)} \times \text{Purity (\%)} \times 1000 \times 1000} \quad \ldots\ldots\ldots\ldots \text{Eqn 3.2}$$

Using a seed rate of 30 kg/ha, AGRA rice seeds were nursed in order to establish the experiment. The choice of the variety was because it is widely cultivated by farmers within the study area due its appreciated characteristics and cycle length. Nursery consisted of 1 m x 2 m bed size and a height of 0.10 m. As fertilization requirement, organic compost was incorporated into the topsoil before seeds were sown in drills and covered with a thin layer of soil. The nursery beds were watered immediately after seeding. Rice straw was placed over the bed to protect the seeds and create the conducive environment needed for germination. The straw was removed after four days following complete seed emergence.

3.3.7 Transplanting

Each plot was labelled in order to avoid confusion in administering the treatments. The nursery was watered before uprooting seedlings. Two seedlings were transplanted per hill. The transplanted seedlings were 23 days old due to delay in getting the microplots ready. Seedlings were uprooted and planted at a spacing of 20 cm x 20 cm inter and intra-row respectively with the guide of a graduated planting line which has been marked 20 cm apart. Gaps were filled one (1) week after transplanting (WAT) to maintain the recommended number of plants per plot.

3.3.8 Irrigation Scheduling

Rice is typically grown in bunded field that are continuously flooded to ensure sufficient water and control of weeds. The plots in the experiment were irrigated by means of surface irrigation system using pipes as described in 3.2 a and b. Applied volume of water to reach the desired depths was obtained using the following equation:

$IR = A \times \mathbf{h}\ (m^3)$ …………………………………………………………………………… Eqn 3.3

Where:

IR – Amount of irrigation water (m^3) for a desired depth above the soil surface,

A – Surface area of the plot (m^2), and

h – Desired water depth above the soil surface (m).

Table 3.2:Irrigation Frequency Based on Application Depth

Treatment	Application (m^3)	Period	Frequency (days)
CF 5	0.05	Throughout growing season	1
CF 5 - 10	0.05	From transplanting to complete heading	1
	0.10	From complete heading to harvesting	1
CF 5-10-15	0.05	From transplanting to booting	1
	0.10	From booting to complete heading	1
	0.15	From complete heading to harvesting	2
AWD -5	0.05	Throughout growing season	1
AWD -10	0.05	Throughout growing season	2
AWD -15	0.05	Throughout growing season	3

3.3.9 Effects of Drainage Systems and Different Irrigation Depths on Crop Growth and Yield of Irrigated Lowland Rice.

On station experiment was conducted in 2023 and 2024 growing seasons as described in the experimental design. Before crop cultivation, composite soil samples were collected from the lowland ecology at a depth of 30 cm to determine soil physical and chemical properties. AGRA rice cultivar was used in the experiment and was nursed 3 weeks before transplanting. The choice of this variety was because it was widely cultivated by farmers within the study area due to its appreciated characteristics and cycle length. All agricultural operations such as land preparation, transplanting, fertilizing, chemical application, weeding and harvesting were carried out in accordance with conventional methods used within the ecological zone.

During the first seven days after transplanting (DAT), water depth was maintained at 2 cm for all the treatments to promote the recovery and establishment of rice seedlings as noted by Gao *et al.* (2018). Then, after seven days, the various treatments were established according to the design. Perforated PVC pipes (60 mm diameter) were installed vertically at a depth of 100 cm in the plots having alternate wetting and drying (AWD) to observe field water level (FWL) that would inform level of water deficit. This was observed daily and when the minimum level of FWL reached as per design of the plot, the system was irrigated to the maximum water level during the irrigated experimental period. During the rainy season, the same was done and when daily rainfall could not meet the crop water requirement as per the design, supplementary irrigation was carried out and total quantity of water applied to the crop of the various treatments measured and documented. A weather station was installed at the middle of the experimental site to monitor rainfall and other weather parameters. Drainage was done at four stages of the plant growth:

- Drained water 2 days prior to nitrogen application
- Drained water 5 days following tillering
- Drained water 5 days following flowering
- Drained water 10 days to ripening

Exceptions to the above were during the rainy season when the depth of the water layer exceeded the maximum depth of irrigation application rates/rain storage, the water was drained to the upper limit of the irrigation application rates/rain storage in time. Drainage water was collected in graduated buckets which served as drainage tanks.

A compound fertilizer (N: P_2O_5: K_2O, 15:15:15) was basally applied at a rate of 300 kg/ha. Urea (nitrogen content: 46.4 %) was used at the tillering and panicle initiation at rates of 100 kg/ha and of 50 kg/ha respectively and the same amount of fertilizer was applied to each treatment. During the dry season, Crownpyrifos insecticide was used to treat stem borers as insect pests. Weeding was done manually during the entire experiment.

Fields were critically inspected during the vegetative stages, reproductive stages and maturity stage to identify varietal off-types and removed them to safeguard varietal purity. Some of the identification of the off-types included plant height, leaf shape and colour, growth cycle, grain shape and colour, presence of awn sheath colour. Harvesting was done manually using sickle and on plot basis, threshed on a tarpaulin, then sundried, packaged and stored for weighing.

Data was collected on agro-hydrological conditions, growth components, grain and yield components and water productivity of rice under the various treatments.

3.4 Data Collection Procedure

3.4.1 Soil Chemical and Physical Properties

The grid method was used to map the field where the soil was collected to fill the microplots and sampling points were identified for soil extraction within horizons 0 – 30 cm with the aid of soil auger. Three (3) composite soil samples (downstream, midstream and upstream) were taken and labelled accordingly with the aid of a masking tape and permanent marker. Composite samples were processed in the laboratory for the determination of chemical properties such as Nitrogen (N), Phosphorus (P), Potassium (K), Calcium (Ca), Magnesium (Mg), pH, Electrical Conductivity (EC) and Organic Matter (OM) content. Additional soil samples were taken within horizons 0 – 15 cm and 15 – 30 cm using the core rings for laboratory determination of texture and bulk density. With the known relative proportions of the soil constituents and organic matter content, the pedotransfer function of the SPAW Hydrology Model was used to confirm the soil's wilting point, field capacity, soil saturation and soil available water. The soil saturated hydraulic conductivity was also determined using the pedotransfer function of the SPAW Hydrology Model.

The determination of particle size distribution was done using the hydrometer method and soil reaction (pH) was determined in 1:2.5 soil-water suspension (Kargas *et al.*, 2020). Cation exchange capacity (CEC) was determined by saturating the samples with sodium acetate; electrical conductivity (EC) in 1:2.5 soil-water saturation and organic matter using Walkley-Black method. Field capacity and wilting point water content were determined using pressure plate and pressure membrane apparatus. Total nitrogen was determined using Kjheldal method (Sáez-Plaza *et al.*, 2013).

3.4.2 Irrigation Water Quality Assessment

The irrigation water quality parameters such as pH, salinity, Total Dissolved Solids (TDS), electrical conductivity, turbidity, total soluble salts (TSS), total nitrite (NO_2 – N), total nitrate (NO_3 – N) and total ammonium (NH_4 – N). These parameters were tested at the West African Centre for Water, Irrigation and Sustainable Agriculture (WACWISA) water quality laboratory.

3.4.3 Estimation of Seasonal Irrigation Water Requirement (SIW)

A "bucket" test was conducted to measure the average volume of water flowing through the inlet per unit time during irrigation. During the test, a bucket of known volume (L) was placed at the opening of the inlet pipe and flow of water into the bucket timed (seconds) and stopped when full. The test was repeated for several times and the average time and volume of water captured calculated from the series of measurements. Thereafter, the volume (l) was divided by time (s) to give discharge (l/s). The individual volumes representing the number of irrigation events in the season was summed to arrive at the seasonal irrigation water requirement for each plot.

3.4.3 Estimation of Irrigation Water Use - Efficiency (IWUE)

IWUE is defined as the ratio of total crop yield to the seasonal irrigation water applied to the crop (Howell, 2002). The application of water to meet the daily crop demand can be from irrigation or precipitation or both. However, this report emphasized on water provided by irrigation; thus, irrigation water –use efficiency (kg/m^3).

$$(IWUE)\ (kg\ m^{-3}) = \frac{FY\ (kg)}{SIW\ (m^3)} \quad \ldots\ldots\ldots\ldots \text{Eqn 3.4}$$

Where:

IWUE – Irrigation Water Use - Efficiency,

FY – Total grain yield of rice, and

SIW – Seasonal irrigation water applied.

3.5 Agronomic Data Collection Procedure

3.5.1 Tiller Count

The number of tillers was counted weekly from 4 WAT to the 11 WAT. This was to get accurate and precise data of time-course changes of the number of tillers and to help understand the time of maximum tiller number stage. This was done by randomly selecting ten (10) plants per plot. The means of these plant tillers were counted and recorded.

3.5.2 Plant Height

Five plants in a plot were randomly selected and tagged and their heights measured at maturity, just before harvest. Plant height was taken by measuring the length from the ground level to the tip of the tallest panicle. The mean plant height was then calculated for each treatment.

3.5.3 Relative Leaf Chlorophyll Content (RLCC)

The non-destructive method of measuring the chlorophyll content of leaves was done throughout the growing season. Leaf chlorophyll content was measured using the CCM-200 plus Chlorophyll Meter, OPTI-SCIENCES, INC. The device is widely used on a variety of both C_3 and C_4 plants and is fast, reliable and user-friendly. Measurements were taken between the active plant hours of 12 hrs – 14 hrs local time. A total of ten (10) leaves were considered per plant for measurements and from 10 randomly selected plants in each experimental unit and their means recorded for the chlorophyll readings (CCI) for the experimental unit.

3.5.4 Leaf Area Index (LAI)

Leaf area index (LAI) was measured using AccuPAR Ceptometer LP-80, Decagon Devices, Inc. between the active plant hours of 12 hrs – 15 hrs local time. A total of three points were considered per plot for measurements in each experimental unit. The device has been widely used in the determination of LAI in most crops (Finzel *et al.,* 2012; Francone *et al*., 2014). The Ceptometer is user-friendly and runs directly on battery with an external Photosynthetic Active Radiation (PAR) sensor. Other main components of the Ceptometer are a probe with 80 imbedded sensors and an integrated microprocessor-driven data logger to access readings. For accuracy of LAI measurements, readings were taken with high PAR values above 800 $\mu molm^{-2}s^{-1}$. The device measures the intercepted light in plant canopies to calculate LAI in m^2/m^2.

3.5.5 Canopy Cover

Canopy cover is a measurement of the percentage of the ground that is covered by green plants leaves, stems as well as flowers. Regular determination of canopy cover during the growing season is important for tracking crop growth and managing irrigation, fertility and pests. The Canopeo app developed by Oklahoma State University was used to monitor canopy cover throughout the research period. This is a simple, handy and rapid approach powerful tool that can assist with monitoring of canopy cover. It is a free app for iOS and Android mobile devices and can be downloaded from canopeoapp.com, the Apple App Store or Google Play Store. Canopeo analyses pixels based on a ratio of red – to – green and blue – to – green pixels as well as an excess green pixel. The result is an image where colour pixels are converted into black and white with white pixels corresponding to green canopy and black pixels representing non-green background (Patrignani and Ochsner, 2015). Photos were taken at four different sides within a plot and the mean recording taken. This was to ensure that measurements were representative of the plots.

3.5.6 Number of Panicles

During the 9th WAT, number of panicles was counted manually. Three (3) samples were selected from each plot and the mean of those samples recorded.

3.5.7 Panicle Length

Panicle length was measured with the help of a meter rule. Five (5) panicles were selected from each plot and their length being measured. The mean values were recorded for analysis.

3.5.8 Grain per Panicle

Ten panicles were selected at random from each plot. The grains were then counted per panicle, totalled, averaged and values recorded.

3.5.9 Yield

Harvesting was done when the grain moisture was around 20 %. Because the grain moisture at harvest was more than 16 %. They were dried to reduce the moisture content until 14 % moisture content was obtained. Grains were measured per plot using a digital balance and the grain moisture was measured immediately using a grain moisture meter. The net plot yield of the rice was weighed using an electronic scale. The weights in kg/plot were noted and adjusted to kg/ha at 14 % moisture content by using the following formulae:

G_w at 14 % moisture content = $G_w\ (g) \times \frac{[100 - \text{Grain moisture content (\%)}]}{86}$ ……………………… Eqn 3.5

Grain yield (kg/ha) at 14 % moisture content = $\frac{G_y}{1000} \times \frac{10000}{A}$ ……………………………. Eqn 3.6

Where:

G_w – Grain weight (g)

G_y – Grain yield (g), and

A – Net harvest area (m^2)

3.5.10 Thousand Grain Weight

Thousand grains of ten harvested panicles from the grain yield of net plots of each treatment were counted and totalled. The samples were then weighed using an automatic electronic balance and the weights recorded.

3.6 Agronomic Data Analysis

The data gathered on physiological traits of rice and irrigation water- use efficiency were pooled together and subjected to analysis of variance (ANOVA) for split plot design using GenStat Statistical Package Version 12. Mean separation for significant effects was performed using least significant difference test at 5 % confidence level. Means of traits that emanated from the interaction of treatments were plotted and presented as bar graphs using MS-Excel.

3.7 Effects of Irrigation Depths and Controlled Drainage on Changes in Soil Electrical Conductivity, Temperature and Nitrogen Balance in Irrigated and Rainfed Rice Fields

Soil electrical conductivity (EC) was used to determine the salinity index of the soil. Soil samples were taken from each plot for analysis at the WACWISA soil laboratory. Soil electrical conductivity meter was used to measure the (EC), after which the EC meter was then inserted into a solute solution of 1:2.5 (soil: water ratio) to measure the electrical resistance (Kargas *et al.*, 2020). This parameter was analysed before cultivation and after harvesting.

Monitoring of temperature within the rootzone was done using TDR 150 moisture/temperature/ EC sensor. Five points were considered around the root system of the plants at the middle of each plot. The mean of these points was used to represent the soil temperature for each plot. This was done throughout the crop growth cycle depicting each of the six stages in the paddy rice stages after transplanting i.e., re-greening, tillering, jointing-booting, heading-flowering, milking and ripening. Temperature changes in the soil was compared across treatments for tillering, jointing-booting, heading-flowering and milking stages using GenStat version 12 statistical package.

Nitrogen content in the soil for all cropping periods was determined using soil samples collected at depths of 0 – 30 cm using an auger. One composite sample per plot, deriving a total of fifty-four (54) samples for the entire experiment were taken during the 6, 8 and 10 weeks after transplanting. These samples were analysed for Total Nitrogen at the West African Centre for Water, Irrigation and Sustainable Agriculture (WACWISA) laborratory using Kjheldal method (Sáez-Plaza *et al.*, 2013).

3.8 Estimation of Crop Water Stress Index (CWSI) for Rice Culture in an Irrigated Ecology

With the measurement of air humidity (relative humidity, wet bulb temperature, etc.), the air temperature and the leaf temperature, it was possible to determine the CWSI.

The Crop Water Stress Index (CWSI) is a measure of the relative transpiration rate occurring from a plant at the time of measurement, using data from plant canopy temperature and vapour pressure deficit of the air. The CWSI relationship proposed by Idso *et al.* (1981) was followed as:

$$CWSI=\frac{[(T_c-T_a)_m-(T_c-T_a)_{li}]}{[(T_c-T_a)_{ls}-(T_c-T_a)_{li}]} \quad \text{Eqn 3.7}$$

Where:

Tc – Canopy temperature and *Ta* is the air temperature.

m subscript – Difference between the two measured temperatures,

li (inferior limit) – non-water stress baseline expressed as the difference between the two temperatures when evapotranspiration is not restricted by water availability, and

ls (superior limit) – Hypothetical non-transpiring upper baseline expressed as the difference between the two temperatures when evapotranspiration is zero.

The CWSI is estimated by determining the relative distance between the lower baseline representing non-stress conditions (well-irrigated condition) and the upper baseline representing no-transpiration (totally stressed condition). The CWSI varies between 0 (no water stress condition) and 1 (severe water stress condition).

The CWSI equation 3.7 can be reduced and rewritten as;

$$CWSI=\frac{(dT-dT_i)}{(dT_s-dT_i)} \quad \text{Eqn 3.8}$$

Where:

dT – Difference of measured air and crop temperatures, dTs – Upper limit of the air temperatures minus the canopy temperature (crop without transpiration) and

dTi – Lower limit of temperatures in the air minus the canopy temperature (fully-irrigated crop).

The CWSI was computed using the difference between measured canopy and air temperatures (dT_m) and the lower (dT_{LL}) and upper (dT_{UL}) limits of canopy – air temperature difference.

The canopy temperature of plants, relative humidity and the ambient temperature as at the time of measurement were taken using multispec photosync. Temperature measurements were taken between 12hrs – 13:30hrs local time. Care was taken to avoid the tendency of measuring ground surface temperature. A total of ten measurements per plot were considered from randomly selected plants in each experimental unit. Temperature readings (˚C) per plant represented an average of the ten leaves.

Based on Idso *et al.* (1981) method, dT_{LL} and dT_{UL} were calculated as linear function of atmospheric vapour pressure deficit (VPD) and vapour pressure gradient (VPG) respectively.

$$dT_{LL} = m \times VPD + b \quad \text{Eqn 3.9}$$

$$dT_{UL} = m \times VPG + b \quad \text{Eqn 3.10}$$

$$VPD = e_s \times (T_a) - e_a \quad \text{Eqn 3.11}$$

$$e_s = 0.6108 \times EXP\left(\frac{17.27 \times T_a}{T_a + 237.3}\right) \quad \text{Eqn 3.12}$$

$$e_a = e_s(T_a) \times \left(\frac{RH}{100}\right) \quad \text{Eqn 3.13}$$

Where:

m and b – Slope and intercept of the linear equation, respectively,

dT_{LL} – VPD relationship – Non-water stressed baseline,

dT_{UL} – VPG relationship – Non-transpiring baseline, VPG – Difference between the air saturated water vapour pressure at temperature T_a and the air-saturated vapour pressure at temperature $T_a + b$,

E_a – Actual vapour pressure (kPa),

T_a – Air temperature (^{0}C), and

RH – Relative humidity

3.9 Modelling the effect of drainage systems and irrigation depths on LAI, grain yield and crop water productivity indices of rice.

3.9.1 The DSSAT Model

With the Leaf Area Index (LAI) and yield data available, the Decision Support System for Agrotechnology Transfer (DSSAT) Model was calibrated and used to model how drainage systems and irrigation application depths might affect rice performance. The model uses a variety of data sources to run, including field data, weather, crop, soil, management, and other variables that must be calibrated before simulation can begin.

3.9.2 Input Data Required by DSSAT Model

The DSSAT model requires a minimum data set for model operation. It uses data on the site where the model is to be operated, daily weather data, soil properties, and management practices in the experimental field. Important crop management factors include planting date, planting depth, row spacing and direction, plant population, fertilization, irrigation, inoculation, residue applications, tillage, and harvest date.

3.9.3 Weather Data Input

For the DSSAT Model to perform recommended simulations on crops, daily meteorological data is needed. However, before DSSAT can perform simulations, the model needs a minimum set of data. The experimental site's daily minimum and maximum temperatures, rainfall, and solar radiation are among the meteorological parameters needed as inputs. A weather station located on the field provided daily weather monitoring of the experimental site in order to supply the necessary climatic data for the model calibration. WeatherMan software was used to enter the resulting weather data into DSSAT.

3.9.4 Soil Characteristics Data

The data on soil properties were obtained by the morphological characterisation within 0 – 60 cm soil depths of the experimental site. Soil data included chemical, physical and hydraulic properties within the soil layers used as input file to the DSSAT Model. Properties of the soil are presented in Table 3.3. Other relevant soil data set were adjusted as proposed by Gijsman *et al.* (2007) and included Soil albedo (0.13), evaporation limit (6), fertility factor (1), drainage rate (0.6) and runoff curve number (61).

Table 3.3: Soil Properties of the Experimental Site Used in the Calibration of the DSSAT Model

Soil depth (cm)	PWP (cm^3/cm^3)	FC (cm^3/cm^3)	SAT (cm^3/cm^3)	TAW (cm^3/cm^3)	Initial (cm^3/cm^3)	Bulk Density (g/cm^3)	pH	O.C (%)	Total N (%)
0 – 10	0.039	0.136	0.464	0.094	0.136	1.42	5.43	0.985	0.049
10 – 20	0.039	0.136	0.464	0.094	0.136	1.42	5.43	0.985	0.049
20 – 30	0.098	0.177	0.441	0.094	0.177	1.48	5.95	0.856	0.047
30 – 40	0.098	0.177	0.441	0.086	0.177	1.48	5.95	0.856	0.047
40 – 50	0.132	0.216	0.432	0.086	0.216	1.52	6.54	0.641	0.039
50 – 60	0.132	0.216	0.432	0.082	0.216	1.52	6.54	0.641	0.039

FC = Field Capacity, PWP= Permanent Wilting Point, SAT = Water Content at Saturation, TAW = Total Available Water, OC = Organic Carbon, N = Nitrogen

3.9.5 Crop Management Data

Crop file was created for AGRA rice cultivar defining the inputs used during production. The management inputs considered were fertilizer (type, rate and time of application), daily irrigation amounts, planting date and method. Other input parameters under the crop file included plant density and related field conditions. Aside the above parameters, the treatment structure i.e. drainage systems and irrigation regimes were defined and created for each factor. The factors were then interacted and linked together keeping the other input variables constant. Model simulation was set to begin on the transplanting date for the 2023 growing season i.e. 4th April, 2023 until final harvest for the combined treatment. This was also done for the 2024 growing season whose transplanting date was 14th January, 2024. The test statistics was evaluated to ascertain the level of correlation to inform acceptance of model calibration.

3.9.6 CERES-RICE Description

Ceres-Rice model was selected as a tool for simulating growth and yield of rice under different environment and management strategies. The Ceres-Rice model simulates rice crop growth and development from either planting or transplanting to physiological maturity and is based on the physiological processes that describe the response of rice to local soil and weather conditions. Potential growth is mainly dependent upon photosynthetically active radiation (PAR), light interception and the light conversion efficiency, while actual growth is a constraint of crop management, soil and weather interactions.

The input data required to run the DSSAT models include daily weather data, i.e. maximum and minimum temperature, rainfall, and solar radiation; soil data, genetic coefficients and crop management information, such as date of planting, age of seedlings, row and plant spacing, rates and dates and amount of fertilizer and irrigation applied. Input data files of Ceres-Rice model are as per IBSNAT standard input/output formats and file structure described in DSSAT v 4.5 (Hoogenboom *et al.,* 2023).

3.9.7 Calibration of the Cultivar file for Genetic Coefficient of Rice

The calibration of the Ceres-Rice model was based on data from measured data of grain yield in 2023-2024 field experiment. The genetic coefficients of the AGRA rice variety that affect the occurrence of phonological stages in the Ceres-Rice models were derived using the GLUE Estimator of DSSAT v 4.6. This program estimates the coefficients for a genotype by iteratively running the crop model with an approximate value of the coefficients concerned. The genetic coefficient of the AGRA cultivar was generated from the default Basmati 385 rice cultivar already imbedded in the CERES-RICE Model of DSSAT. Table 3.4 presents calibrated results on genetic coefficient of rice from the cultivar file. The calibration was done using Basmati 385 cultivar with inputted soil and weather data of the experimental field as well as specified field cultural practices. Thereafter, the model was used to run simulations on drainage systems and different irrigation application depths to ascertain the predictive performance of the model in comparison to measured data on selected parameters that included LAI and Grain Yield of rice. Predicted model outcomes on growth phenology and desired traits of the simulated parameters were checked for accuracy using the evaluation statistics of root mean square error (RMSE), Willmott's d-index of agreement (D) and coefficient of determination (R^2).

Table 3.4: Genetic Coefficient for AGRA

Genetic parameters	Description	Coefficient for Basmati	Coefficient for AGRA
P1	Time period (expressed as growing degree days (GDD) in °C above a base temperature of 9 °C from seedling emergence during which the rice plant is not responsive to changes in photoperiod	498.30	615.30
P20	Critical photoperiod or the longest day length (in h) at which the development occurs at a maximum rate	12.90	11.70
P2R	Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in °C) for each hour increase in photoperiod above P20	130.1	26.40
P5	Time period in GDD °C) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9 °C	420.0	443.90
G1	Potential spikelet number coefficient as estimated from the number of spikelets per g of main culm dry weight (less lead blades and sheaths plus spikes) at anthesis	74.76	62.72
G2	Single grain weight (g) under ideal growing conditions, i.e., non-limiting light, water, and nutrients and absence of pests and diseases	0.022	0.024
G3	Tillering coefficient (scaler value) relative to IR64 cultivar under ideal conditions	0.53	0.71
THOT	Temperature (°C) above which spikelet sterility is affected by high temperature.	30.9	31.4
PHINT	Time interval in degree-days for each leaf-tip to appear under non-stressed conditions. Range 55-90 ºC – d. Default 83 ºC – d. Calibration: Recommend to not change unless field data on leaf numbers are available.	83.0	83.0

3.9.8 Statistical Analysis of Agronomic and Soil Data

Data was tested for conformity to the analysis of variance (ANOVA) assumptions. The data was then subjected to analysis of variance (ANOVA) for spilt plot design. Treatment means were separated using Duncan Multiple Range Test (DMRT) at 5 % confidence level where statistical difference was found by using GenStat 12 edition statistical package. Pearson correlation and simple regression analysis were performed on the measured parameters to ascertain their level of associations and relationships where necessary. Microsoft excel version 2016 was further used to graphically represent the relationship and model equations.

3.9.9 Model Performance

The performance of the CERES-RICE model of DSSAT was evaluated using multiple statistical indicators of goodness-of-fit such as the root mean square error (RMSE), Pearson's coefficient of determination (R^2) and index of agreement (d) (Willmott, 1981; Willmott and Matsuura, 2005; Willmott *et al.,* 2012).

a. Pearson's Coefficient of Determination (R^2)

The R^2 describes the degree of colinearity between predicted and observed data. It describes the proportion of the variance in observed data explained by the model. Its value ranges from 0 to 1, with higher values indicating less error variance; typically, values greater than 0.5 are considered acceptable (Santhi *et al.*, 2001; Van Liew *et al.*, 2003). It can also be expressed as the squared ratio between the covariance and the multiplied standard deviations of the observed and predicted values. Therefore, it estimates the combined dispersion against the single dispersion of the observed and predicted series. Its value is calculated using Equation 3.14.

$$\mathbf{R^2} = \left[\frac{\sum_{i=1}^{n}(O_i-\bar{O})\,(P_i-\acute{P})}{\sqrt{\sum_{i=1}^{n}(O_i-\bar{O})^2}\,\sqrt{(P_i-\acute{P})^2}}\right]^2 \text{..} \textbf{Eqn 3.14}$$

Where:

Oi - The ith observation for the parameter being evaluated,

Pi - The ith predicted value for the parameter being evaluated,

Ṕ - The mean of the predicted value,

$\bar{O}$ - The mean of the observed value, and

n - The total number of observations.

b. Index of Agreement (d)

The d index was developed by Willmot (1981) to overcome the poor sensitivity of NSE and R^2 in determining differences between observed and predicted means and variances. It represents the ratio of the mean square error and the potential error (Willmot, 1984) and is defined as the potential error in the denominator representing the largest value that the squared difference of each pair can attain. The range of *d* is like that of R^2 where *d* lies between 0 (no correlation) and 1 (perfect fit). Willmot (1981) defined potential error as the sum of the squared absolute values of the distances from the predicted values to the mean observed value and distances from the observed values to the mean observed value. The *d-index* can detect additive and proportional differences in the observed and simulated means and variances; however, it is overly sensitive to extreme values due to the squared differences (Legates and McCabe, 1999).

$$d = 1 - \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{\sum_{i=1}^{n} (|P_i - \bar{O}|) + |O_i - \bar{O}|^2} \quad \text{.......... Eqn 3.15}$$

c. Root Mean Square Error (RMSE)

RMSE is commonly used error index in statistics. Lower values of RMSE is mostly used as an indicator for perfect model performance, however, few publications have quantified considerations of a low RMSE based on observed standard deviation (Chu and Shirmohammadi, 2004; Singh *et al.*, 2004). RMSE is calculated as presented in Equation 3.17:

$$RMSE = \left[\frac{1}{n} \sum (P_i - O_i)^2\right]^{0.5} \quad \text{.......... Eqn 3.16}$$

Where:

n - The number of observations,

Pi - The predicted value for the i^{th} measurement, and

Oi - The observed value for the i^{th} measurement.

It varies from the optimal value of 0, depicting perfect model simulation to a large positive value.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Soil Physico-Chemical Properties of Experimental Field

The soil physical and chemical properties of the experimental field is presented in Table 4.1. The soils within 0 – 60 cm were classified as sandy loam based on composition of sand, silt and clay. It was noted that, the percentage of clay increased with an increase in soil depth. Soil texture affects the rate at which water moves through the soil and the pattern of water movement. In sandy soils for instance, water will move straight down whereas it will show some lateral movement in soils with clay content. Senjobi and Ogunkunle (2011) noted that, soil texture influences water retention capabilities of soils at different locations. Soils with high clay content tend to have high water holding capacity and that, the soil texture and crop rooting depth affect total amount of water stored in the soil within the plants rooting zone. These findings agreed with that of Buri *et al.* (2012) who reported that, the topsoil textures of savannah agro-ecological zones are either loam, silt loam or sandy loam.

The bulk density was recorded as 1.42, 1.48 and 1.52 g cm^{-3} for 0 – 20, 21 – 40 and 41 – 60 cm soil depths respectively (Table 4.1). It was noted that the bulk density increased with soil depth. This agreed with Al-Shammary *et al.* (2018) who reported that, bulk density typically increases with depth because of changes in soil texture, gravel content and structure.

Soil water thresholds were determined at field capacity (FC) and permanent wilting point (PWP) (Table 4.1). With the exception of the top layer (0 - 20 cm), the rest of the layers have values that fall within the desired range of sandy soils (15 – 25 %) as reported by Datta *et al.* (2017). This suggest that the top layer has very low water holding capacity.

Permanent wilting point is the threshold at which it becomes difficult for plants to extract water at a rate fast enough to keep up with their water demand and is therefore referred to as the lower limit of total available water. In irrigation management, water content at field capacity of the soil is considered to be ideal and is therefore often referred to as the upper threshold (Datta *et al.*, 2017).

Table 4.1: Soil Physical and Chemical Characteristics of the Experimental Field Before Transplanting

Soil Characteristics	**Depths (cm)**		
	0 – 20	**21 – 40**	**41 – 60**
Sand (%)	69.8	73.2	70.28
Silt (%)	27.6	14.0	10.96
Clay (%)	2.6	12.7	18.76
Soil Texture	Sandy Loam	Sandy Loam	Sandy Loam
Bulk Density (g cm^{-3})	1.42	1.48	1.52
Water Content at Saturation (% v/v)	46.4	44.1	43.2
Water Content at Field Capacity (% v/v)	13.6	17.7	21.6
Water Content at Permanent Wilting Point (% v/v)	3.96	9.8	13.2
Saturated Hydraulic Conductivity (cm hr^{-1})	9.9	4.3	2.34
Acidity or Alkalinity (pH)	5.43	5.95	6.54
Cation Exchange Capacity (meq 100 g^{-1})	3.470	4.860	3.240
Organic Carbon (%)	0.985	0.856	0.641
Total N (%)	0.049	0.047	0.039

The saturated hydraulic conductivity (KSAT) of the experimental soils is presented in Table 4.1. The unsaturated soil's matric suction or water content are the main determinants of the hydraulic conductivity parameter. It is a crucial soil hydraulic feature that controls water movement, which influences water flow (Fatehnia *et al.*, 2014). Applying water at a rate higher than the soil can absorb can also result in runoff, which erodes the soil and may even cause fertilizer loss, and ponding. That is why hydraulic conductivity is an important parameter in drainage studies (Fatehnia *et al.*, 2014).

As presented in Table 4.1, the pH of the soil in the experimental field ranged from 5.43 to 6.54 and increase with an increase in soil depth. According to Whiting *et al.* (2014), most crops can grow and develop at an acceptable pH of between 6.0 and 7.5. Mostly, a pH of 4.6 or lower is too acidic for plants, a pH of 5.5 tends to reduce microbial activities, and a pH of more than 8.3 is too alkaline. Ilagan *et al.* (2014) stated that rice grows best on soils with a pH between 5.5 and 7.0. This suggest that only the topsoil has lower pH below the recommended rate for rice cultivation.

Cation exchange capacity (CEC) represents the total amount of exchangeable cations that a soil can hold. The CEC as presented in Table 4.1 is within the range for rice cultivation (2.12 – 11.39 Cmol+/kg) as stated by Aondoakaa and Agbkwuru (2012). CEC is used as a measure of fertility, nutrient retention capacity, and the capacity to protect groundwater from cation contamination Messiga *et al.* (2013). Cation Exchange Capacity (CEC) is also influenced by soil type with respect to the clay type and amount and organic matter content in the soil. As stated by Brady and Weil (2002), the soils in the experimental field are sandy loam, and are within the range of CEC for sandy loam soils.

Table 4.1 also presents a decrease in the mean organic carbon of soil in deeper layers but it was very low in all the soil depths. This however, agreed with the findings of Aondoakaa and Agbakwuru (2012) that, the organic carbon levels in soil depths are significantly different from each other and is significantly low compared to the standard organic carbon requirement for rice cultivation of 1.20 – 21.0 %. Organic carbon being the main component of soil organic matter (SOM) and indicators for soil health, plays a significant role in the production of food, mitigation and adaptation to climate change, and the achievement of the Sustainable Development Goals (Clara *et al.*, 2017). The amount of SOC stored in a given soil is dependent on the equilibrium between the amount of carbon entering the soil and the amount of carbon leaving the soil as carbon-based respiration gases resulting from microbial mineralisation and, to a lesser extent, leaching from the soil as dissolved organic carbon (Clara *et al.*, 2017). Increasing the quantity and quality of soil organic carbon improves soil structure stability, water retention capacity, porosity and soil fertility (Zheng *et al.*, 2021). A conversion factor of 1.724 to estimate the soil organic matter from soil organic carbon determination have been suggested (Pribyl, 2010). Using this factor, results of the study showed a decrease in trend in the mean SOM at deeper layers. The soils in the experimental field are very low in SOM as compared to the values recorded by Aondoakaa and Agbakwuru (2012). This is similar to the findings of Buri *et al.* (2012) who indicated that, within the savannah agro-ecology of Ghana, organic matter levels are comparatively lower with general mean levels. Soils containing organic matter have a better structure that improves water infiltration, and reduces the soil's susceptibility to compaction, erosion, desertification and landslides.

Results of total nitrogen content of the soil in the experimental field are presented in Table 4.1. The findings of this study on total nitrogen conforms with those of Buri *et al.* (2012) who indicated that, the savannah zones have much lower levels of total nitrogen with much lower variability compared to other ecological zones. Kunda *et al*. (1996) indicated that, nitrogen is required in substantial amount as a macro-nutrient for quality as well as high yield production of rice. According to Skaggs *et al.* (2012), improvement in water management strategies in paddy fields that are well drained is possible for the proper management of nitrogen through the implementation of adequate drainage management practices to ensure a decreasing drainage intensity and efficient nitrogen utilization.

4.2 Assessment of Irrigation Water Quality

Two sources of water were used for the study and therefore the quality of water used during the irrigation was assessed and the results presented in Table 4.2.

Table 4.2: Irrigation Water Quality Indicators

Parameters	**Tap**	**Dam**
pH	8.35	7.68
Temperature (^{0}C)	29.4	29.3
Electrical Conductivity (µs/cm)	148.1	185.5
Total Dissolved Solids (mg/L)	74.1	92.8
Resistivity (kΩ.cm)	6.75	5.39
Turbidity (NTU)	3	50
NO_2 - N (mg/L)	<0.03	0.04
NO_3 - N (mg/L)	<0.08	0.86
NO_4 - N (mg/L)	0.11	0.70

Table 4.2 presents the physico-chemical parameters characterising the quality of water used for irrigation of rice in this study. Two different types of water (tap and dam) were used in this study depending on the availability at different times within the seasons.

The pH was recorded at 8.35 for tap water and 7.68 for the dam water. These values fall well within the FAO standard permissible limits of 6.50 – 8.40 for water used for irrigation purposes. pH of irrigation water can also affect the availability of nutrients and soil structure, reduce plant growth and yield through the unavailability of nutrients and alteration of microbial activity which is crucial in decomposition and nutrient cycling (Dewangan *et al.,* 2023). TDS of the tap water was recorded as 74.1 mg/L while that of the dam water was 92.8 mg/L. High levels of dissolved solids can affect the osmotic potential of crops resulting in an interruption of smooth water uptake by plants. The TDS recorded in this study is considered to be acceptable and falls within the threshold for rice cultivation (< 2000) but above the 30 mg/L maximum recommended limit of the Food and Agriculture Organization (FAO) and the 50 mg/L of the WHO for irrigation water for vegetable production (Adjovu *et al.,* 2023).

The level of turbidity for tap water used was 3 NTU while that of dam water was 50 NTU. When irrigating with turbid water, the suspended particles can also physically damage the surface of the plant, causing scarring or abrasions or can clog the stomata of the leaves, which are tiny pores that allow for the exchange of gases. When stomata are blocked, the plant may not be able to photosynthesise properly, leading to reduced growth and productivity (Harrison *et al.,* 2020). This, however, will not have much effects on rice considering the method of irrigation. The results are similar to those of Akpan-Idiok *et al.* (2012) who in a similar study in Nigeria on irrigation water quality assessment recorded similar values of 5.0 – 49.3 NTU.

The Electrical Conductivity (EC) was recorded at 148.1 and 185.5 (μs/cm). EC is a measure of the dissolved soluble salts in water. The EC of water recorded from both tap and dam water were lower than the maximum limit of 1000 μS/cm set by the FAO and as such, may not be a threat to the growth of the rice (Kadyampakeni *et al.*, 2017). The results for turbidity, EC and pH reported in this study are far below threshold value for rice production and will not cause salinity, permeability and toxicity problems except under extremely poor drainage and/or water management practices (Alrakabi and Ramadan, 2017).

The recorded levels of nitrite (NO_2^-N) and nitrate (NO_3^-N) were < 0.03 and 0.04 respectively (Table 4.2). These were within the FAO maximum recommended standard of 50 mg/L on water quality for irrigation (Balejčíková *et al.*, 2020). Nitrate is a key nutrient for plant growth, but excessive amounts of nitrate in irrigation water can lead to nitrogen pollution and eutrophication in water bodies. When plants are irrigated with water containing high levels of nitrate, they may exhibit reduced growth, as well as increased susceptibility to pests and diseases (Ashie *et al.*, 2024). The Water Framework Directive (WFD) of the European Union sets maximum allowable limits of 50 mg/L for nitrate and 0.1 mg/L for nitrite in irrigation water. Nitrite is toxic to plants and can inhibit plant growth and development. When plants are exposed to high levels of nitrite in irrigation water, they may exhibit stunted growth, yellowing of leaves, and reduced yields. Additionally, high levels of nitrite in irrigation water can lead to soil degradation and reduced soil fertility, which can further impact plant growth and yield (Ciji and Akhtar, 2019)

4.3 Effects of Drainage Systems and Different Irrigation Application Depths on Crop Growth Yield, and Water Use Efficiency of Irrigated Lowland Rice.

4.3.1 Effects of Drainage Systems and Different Irrigation Application Depths on Plant Height

The results of plant height of rice as influenced by drainage systems and different irrigation application depths are presented in Table 4.3.

Table 4.3: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Plant Heigh

Seasonal Year	WAT	Plant Height (cm)																
		Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD@ -5	AWD @ -10	AWD@ -15	CF - 5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	$D\times I_d$	P-Value	CV %
2023	5WAT	54	63	69	62	2.3^{***}	<.001	54	55	52	69	70	71	3.3^{***}	<.001	5.7^{*}	0.019	5.5
	7WAT	61	70	74	69	1.9^{***}	<.001	62	61	59	75	75	78	2.6^{***}	<.001	4.5^{**}	0.004	4.0
	10WAT	72	75	85	77	2.5^{***}	<.001	70	69	67	87	84	86	3.5^{***}	<.001	6.1^{***}	<.001	4.7
	13WAT	79	82	94	85	3.9^{***}	<.001	73	75	74	101	93	95	5.5^{***}	<.001	9.5^{***}	<.001	6.7
2024	5WAT	39	47	57	48	1.0^{***}	<.001	51	35	31	55	56	60	1.5^{***}	<.001	2.6^{***}	<.001	3.2
	7WAT	48	54	67	56	1.0^{***}	<.001	55	46	39	64	66	67	1.5^{***}	<.001	2.6^{***}	<.001	2.7
	10WAT	56	64	76	65	1.2^{***}	<.001	62	53	50	76	72	79	1.7^{***}	<.001	2.9^{***}	<.001	2.6
	13WAT	65	72	80	72	3.1^{***}	<.001	70	61	58	82	80	83	4.4^{***}	<.001	7.6^{ns}	0.274^{ns}	6.3

*Where: $D \times I_d$ = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95 % confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$*

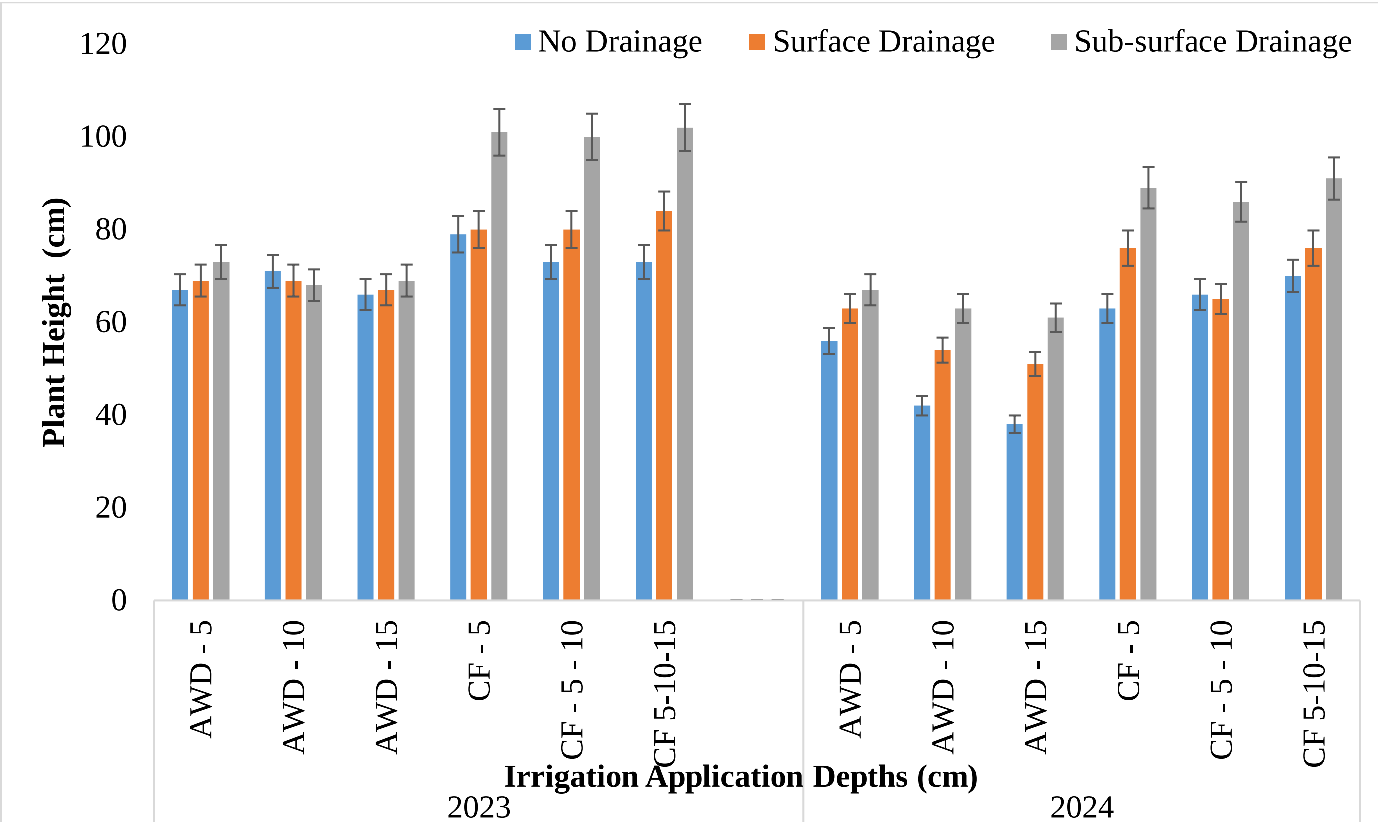


Figure 4. 1: Effect of Drainage and Irrigation Application Depths on Plant Height at 10WAT of Rice

Results in Table 4.3 revealed significant differences ($p<0.05$) in the interaction effect of treatments (D × I) on plant height in all the weeks measured in the two growing seasons (2023 and 2024). Drainage systems showed significant differences with sub-surface drainage system recording a mean height of 94 cm while the lowest value was recorded on plots with no drainage (79 cm) at 13 WAT. From Figure 4.1, sub-surface drainage system in combination with continuous flooding with 5 - 10 - 15 cm (CF 5-10-15) depth of water produced the highest mean plant height of 102 cm, followed by CF 5-10 with 101 cm and CF 5 with 100 cm at 10 WAT. Results indicated no significant differences between CF 5, CF 5-10 and CF 5-10-15 and as such increasing the amount of irrigation did not contribute to increase in water productivity and water use efficiency. Similar results were obtained during the second season with CF 5 - 10 - 15 cm depth of water producing the highest mean plant height of 91 cm, followed by CF 5-10 with 76 cm and CF 5 with 70 cm.

Plant height is an essential morphological indicator to measure crop growth. An appropriate plant height is conducive to the rational distribution of the canopy, improving the use of light energy, and improving crop production and yield (Burgess *et al.*, 2017). The results in Table 4.3 however, showed that throughout the growth period of rice, the trend in the change of plant height for each treatment was consistent; the growth rate increased rapidly from transplanting till the maturity stage. In the first season, the interaction of drainage and irrigation application depths on plant height of each treatment was significantly different ($p \leq 0.05$). As the plants developed, the difference among the treatments became even more significant. However, during the second season, a similar trend was observed but there was no significant difference during the 13WAT in the second season (p = 0.275).

The plant height, stem diameter, and canopy showed an increasing trend with the increase in the amount of irrigation. Irrigation promotes the branching and canopy width, leaf growth and development, and photosynthetic capability of plants (Yan *et al.*, 2019).

The findings of this study are in line with those of Balusamy *et al.* (2019) who stated that, the provision of sub-surface drainage system in agricultural fields increased the plant height of maize crop, due to removal of a large amount of soluble salts, waterlogging free condition and increased nutrient availability in drained field which favoured plant growth and development. Similarly, Sousa *et al.* (2011) reported that, there was an 80 % increase in plant height in drainage system installed field, whereas it was only 50 % in the undrained field. The results which indicated tallest rice plants in sub-surface drainage system is in line with the findings of Darzi-naftchali and

Shahnazari (2014) who also found a significant increase in rice plant height in subsurface drainage treatments.

4.3.2 Effects of Drainage Systems and Different Irrigation Application Depths on Leaf Area Index (LAI)

Table 4.4 and Figure 4.2 highlight the results on leaf area index of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons.

Table 4.4: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Leaf Area Index

Seasonal Year	WAT	LAI (m^2 m^{-2})																
		Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD@ -5	AWD @ -10	AWD@ -15	CF - 5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	3WAT	1.28	1.55	2.77	1.87	0.346^{***}	<.001	1.81	1.73	1.14	2.39	2.10	2.03	0.489^{***}	<.001	0.848^{**}	0.034	27.3
	7WAT	2.11	2.31	2.85	2.42	0.223^{***}	<.001	2.54	2.29	1.87	2.77	2.58	2.49	0.316^{***}	<.001	0.547^{ns}	0.101	13.6
	10WAT	2.33	2.56	3.07	2.66	0.017^{***}	<.001	2.84	2.50	2.25	3.01	2.85	2.48	0.024^{***}	<.001	0.041^{***}	<.001	0.9
	13WAT	2.69	3.00	3.39	3.03	0.266^{***}	<.001	3.03	2.82	2.43	3.49	3.16	3.23	0.377^{***}	<.001	0.652^{ns}	0.208	13.0
2024	5WAT	0.68	0.80	1.70	1.06	0.093^{***}	<.001	0.94	0.67	0.53	1.47	1.22	1.51	0.132^{***}	<.001	0.228^{***}	<.001	13.0
	7WAT	1.01	1.03	1.72	1.25	0.230^{***}	<.001	1.24	0.90	0.70	1.55	1.49	1.63	0.325^{***}	<.001	0.562^{ns}	0.334	27.1
	10WAT	1.20	1.46	2.03	1.56	0.056^{***}	<.001	1.66	1.31	0.94	1.77	1.80	1.87	0.079^{***}	<.001	0.137^{***}	<.001	5.3
	13WAT	1.68	1.96	2.54	2.06	0.111^{***}	<.001	2.11	1.88	1.29	2.40	2.28	2.40	0.157^{***}	<.001	0.271^{*}	0.016	7.9

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of variation, P. value = Probability value, LSD = Least significance difference of means at 95% confidence level, WAT = Weeks after Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

The results revealed significant ($p<0.05$) interaction effect of treatments on LAI in both growing seasons (Table 4.4). In 2023 growing season, the interaction of drainage and irrigation application depths was significant at 3WAT and 10WAT ($p<0.05$) while during the 2024 growing season, the interaction of the treatments were significant ($p<0.05$) at 3WAT, 10WAT and 13WAT (Table 4.4). Sub-surface drainage in combination with CF 5 recorded the highest leaf area index of 3.89 m^2m^{-2} followed by sub-surface drainage with CF 5-10 with an LAI of 3.62 $m^2m^{-2.}$ The lowest was recorded on treatments with no drainage in combination with AWD-15.

During 2023 growing season, irrigation application depth and sub-surface drainage of CF 5-10-15 and AWD -15 were not significantly different (Table 4.5). During 2024 growing season, AWD-5 (2.24), CF 5 (2.3), CF 5-10 (2.39) and CF 5-10-15 (2.3) m^2m^{-2} were not significantly different from each other (Table 4.5). However, at 10 WAT, results revealed significant differences on individual factors of irrigation application depths and drainage systems in all the weeks recorded (Table 4.4).

Table 4.5: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Leaf Area Index at 10WAT

Year	Treatments	No Drainage	Surface Drainage	Sub-surface Drainage
2023	AWD – 5	2.71^{g}	2.84^{h}	2.96^{i}
	AWD - 10	2.24^{b}	2.55^{e}	2.71^{g}
	AWD - 15	2.16^{a}	2.27^{b}	2.33^{c}
	CF - 5	2.48^{d}	2.66^{f}	3.89^{k}
	CF - 5 - 10	2.22^{b}	2.72^{g}	3.62^{j}
	CF 5-10-15	2.16^{a}	2.34^{c}	2.93^{i}
	$LSD_{(0.05)}$	0.041		
	P-Value	<.001		
2024	AWD - 5	1.09^{b}	1.64^{fg}	2.24^{i}
	AWD - 10	1.07^{b}	1.14^{b}	1.73^{gh}
	AWD - 15	0.78^{a}	0.85^{a}	1.2^{bc}
	CF - 5	1.41^{de}	1.62^{fg}	2.3^{i}
	CF - 5 - 10	1.31^{cd}	1.7^{gh}	2.39^{i}
	CF 5-10-15	1.51^{ef}	1.81^{h}	2.3^{i}
	$LSD_{(0.05)}$	0.137		
	P-Value	<.001		

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different

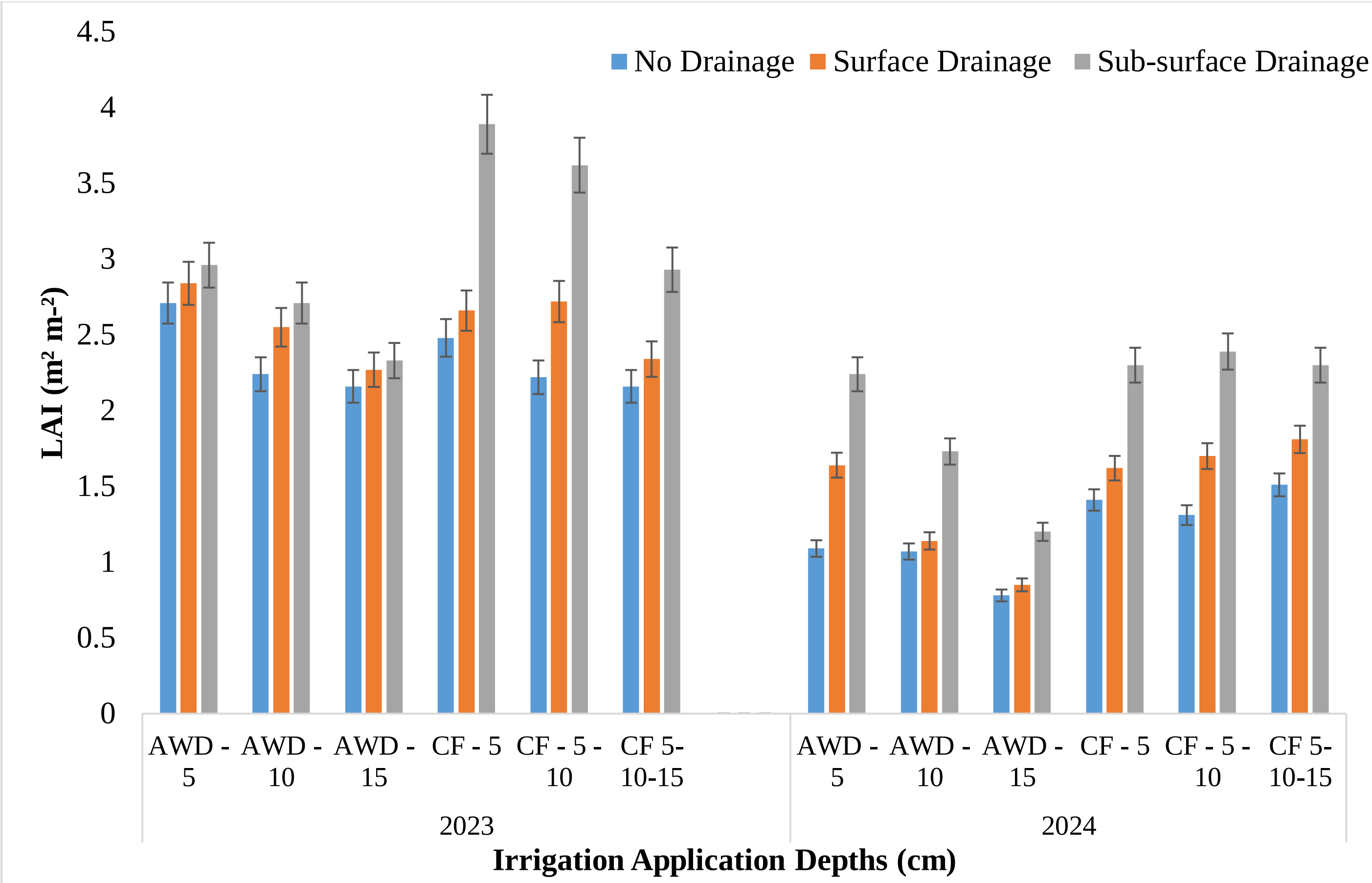


Figure 4. 2: Effect of Drainage and Irrigation Application Depths on Leaf Area Index at 10WAT of Rice

Leaves are plant organs considered as the regulators of plants to climate factors due to their stomate functions. It was observed in this study that, the LAI increases during the plant growth stages in both seasons. This agrees with the findings of Ishfaq *et al.* (2020) who during their research, the rice leaf area index at maturity (150 DAT) was maximum on treatments with high irrigation application depths. The water treatment was a factor that influenced the significant differences observed in these values. Leaf Area Index (LAI) is an important indicator of rice yields and the availability of this information during key phenological phases can support more informed farming decisions. LAI is defined as half of the all-sided green leaf area per unit ground area and is a key biophysical parameter that reflects the physiological processes of plants, and thus is an important proxy for crop development (Rogers *et al.*, 2021). The leaf area index (LAI) of rice is crucial in the quantitative description of the canopy structure and photosynthetic processes (He *et al.*, 2019).

4.3.3 Effects of Drainage Systems and Different Irrigation Application Depths on Leaf Chlorophyll Content

Table 4.6 and Figure 4.3 highlight the results on leaf chlorophyll content of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons.

Table 4.6: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Leaf Chlorophyll Content

Seasonal Year	WAT	Leaf Chlorophyll Content (CCI)																
		Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	3WAT	10.06	11.43	12.44	11.31	1.197^{***}	<.001	11.11	10.03	8.31	14.06	12.30	12.04	1.693^{***}	<.001	2.933^{*ns}	0.327	15.6
	7WAT	11.86	15.84	15.07	14.26	0.192^{***}	<.001	12.33	12.12	12.18	15.49	15.11	17.31	0.272^{***}	<.001	0.471^{***}	<.001	2.0
	10WAT	13.06	16.73	18.14	15.97	1.595^{***}	<.001	15.78	14.21	11.57	18.57	17.49	18.21	2.255^{***}	<.001	3.907^{ns}	<.122	14.7
	13WAT	14.24	16.91	19.40	16.85	1.541^{***}	<.001	16.62	14.62	12.61	20.47	17.67	19.11	2.179^{***}	<.001	3.775^{*}	0.013	13.5
2024	5WAT	6.86	8.01	9.34	8.07	0.957^{***}	<.001	7.40	6.55	5.17	10.69	9.04	9.57	1.354^{***}	<.001	2.345^{ns}	0.260	17.5
	7WAT	8.59	10.47	12.62	10.56	0.368^{***}	<.001	9.24	8.04	6.60	12.95	12.66	13.87	0.520^{***}	<.001	0.900^{***}	<.001	5.1
	10WAT	9.86	11.78	14.05	11.90	0.248^{***}	<.001	9.89	9.29	7.94	14.56	14.34	15.37	0.351^{***}	<.001	0.608^{***}	<.001	3.1
	13WAT	11.29	14.04	16.62	13.98	0.889^{***}	<.001	11.92	11.74	8.55	16.65	16.95	18.08	1.257^{***}	<.001	2.177^{***}	<.001	9.4

*Where: CCI = Chlorophyll Content Index, D x I_d = Combination of Drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95 % confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

The results revealed significant ($p<0.05$) interaction effect of treatments on Leaf Chlorophyll Content (LCC) at 7WAT and 13WAT in the 2023 growing season and at the 7WAT, 10WAT and 13WAT in the 2024 growing seasons (Table 4.6). Sub-surface drainage in combination with CF 5 recorded the highest leaf chlorophyll content of 20.47 CCI followed by sub-surface drainage with CF 5-10-15 with an LCC of 19.11 CCI. The lowest was recorded on treatments with no drainage in combination with AWD -15 with an LCC of 12.61 CCI.

In 2023 growing season, sub-surface drainage in combination with CF 5-10-15 got the highest interaction effect on LCC at 7WAT with 19.93 CCI while surface drainage in combination with AWD -15 recorded the lowest LCC of 9.50 (Table 4.7). During 2024 growing season the highest interaction of mean LCC was recorded on treatment with sub-surface drainage in combination with CF 5-10-15 with LCC of 16.24 CCI while the lowest was on no drainage in combination with CF 5-10 with LCC of 9.53 CCI (Table 4.7).

Table 4.7: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Leaf Area Index at 7WAT

Year	Treatments	No Drainage	Surface Drainage	Sub-surface Drainage
2023	AWD – 5	10.83^{d}	15.23^{h}	10.93^{de}
	AWD - 10	11.37^{e}	17.87^{k}	10.13^{bc}
	AWD - 15	9.50^{a}	16.70^{j}	10.33^{c}
	CF - 5	14.23^{g}	12.60^{f}	19.63^{l}
	CF - 5 - 10	9.80^{ab}	16.07^{i}	19.47^{l}
	CF 5-10-15	15.40^{h}	16.60^{j}	19.93^{l}
2024	AWD - 5	7.37^{bcd}	9.47^{f}	10.89^{gh}
	AWD - 10	7.11^{bc}	8.14^{de}	8.87^{ef}
	AWD - 15	5.37^{a}	6.52^{b}	7.91^{cd}
	CF - 5	10.55^{g}	12.55^{j}	15.74^{l}
	CF - 5 - 10	9.53^{f}	12.36^{ij}	16.08^{l}
	CF-5-10-15	11.60^{hi}	13.79^{k}	16.24^{l}

LSD; Least Significance Difference of means at 95 % confidence level, P. value=Probability value. Values with the same letter are not significantly different

However, there was no significant differences in treatments with CF-5, CF-5-10 and CF-5-10-15 during the growing seasons. The graphical representation is presented in Figure 4.3.

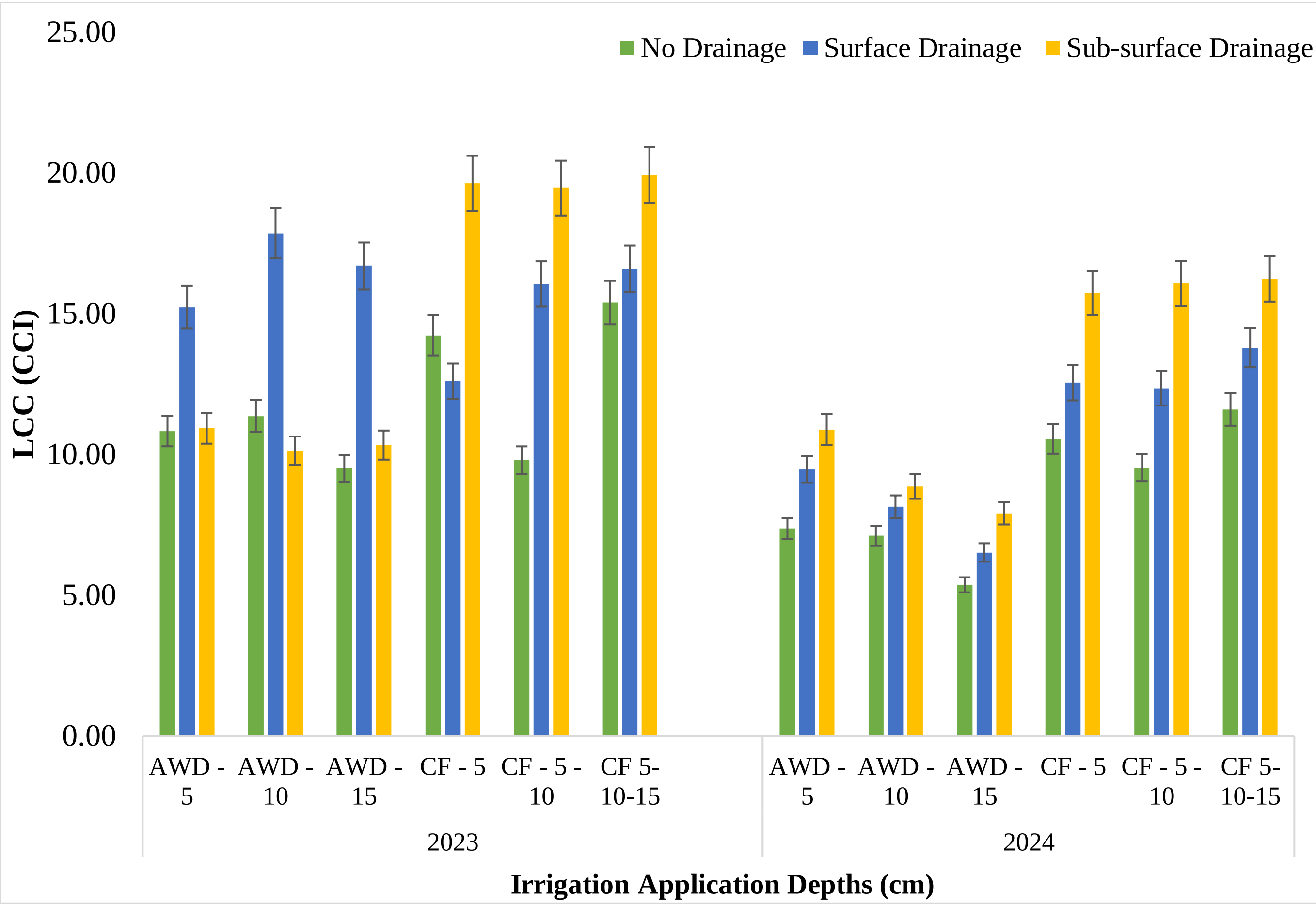


Figure 4.3: Effect of Drainage and Irrigation Application Depths on Leaf Chlorophyll Content at 7 WAT of Rice

Similar results have been presented by Yang *et al.* (2024) who have linked it to the improved root condition in sub-surface drainage system which can increase the soil redox potential inducing a prolonged synthesis and transport of cytokinins in roots and also extended photosynthetic activity. Chlorophyll content in leaves was significantly different among the different drainage systems and irrigation application depths in the 7WAT and 13WAT in the 2023 growing season. The difference in LCC has been documented by Mishra and Salokhe (2010), who confirmed that higher levels of chlorophyll are maintained in the leaves of plants less flooded compared to those that are always flooded. Thakur *et al.* (2014) noted that, less flooded rice plants have a higher utilization capacity of light and a greater photosynthetic rate than those plants that are always flooded. This ensures a sufficient supply of assimilates to the root which will result in the growth and development of the plants.

These bigger roots and greater root activity under treatments that are less flooded increases root oxidation activity and root-sourced cytokinins (Henry *et al.*, 2012), which are believed to play a major role in promoting cell division and thereby delaying leaf senescence (Pascual and Wang, 2017). Reduction in chlorophyll content has also been attributed to the stomata closure due to abscisic acid (ABA) transport from older to younger leaves (Yu *et al.*, 2019). Waterlogging decreases the leaf chlorophyll content due to the inhibition of enzymatic activities related to photosynthesis. This decrease in chlorophyll directly or indirectly affects the photosynthetic capacity of plants. This decrease in transpiration and photosynthesis is attributed to stomata closure which restricts CO_2 movement (Chu *et al.*, 2018).

4.3.4 Effects of Drainage Systems and Different Irrigation Application Depths on Tiller Count

The results on tiller count of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.8 and Figure 4.4.

Table 4.8: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Tiller Count

Seasonal Year	WAT	Tiller Count																
		Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	$D \times I_d$	P-Value	CV %
2023	3WAT	8	8	8	8	1.3^{ns}	0.683	7	7	7	10	8	9	1.8^{*}	0.010	3.2^{*}	0.131	24.1
	4WAT	16	18	20	18	2.2^{**}	0.003	15	13	12	24	21	22	3.1^{***}	<.001	5.4^{**}	0.060	18.6
	5WAT	16	18	21	18	1.9^{***}	<.001	15	14	13	25	21	20	2.6^{***}	<.001	4.5^{**}	0.008	15.3
	6WAT	18	20	23	21	1.8^{***}	<.001	17	16	15	27	25	24	2.5^{***}	<.001	4.3^{***}	<.001	12.6
2024	3WAT	4	5	6	5	0.957^{***}	<.001	4	4	3	6	6	7	0.7^{***}	<.001	1.2^{***}	0.001	14.4
	4WAT	8	8	11	9	0.368^{***}	<.001	7	7	7	11	11	11	0.8^{***}	<.001	1.3^{***}	<.001	8.9
	5WAT	10	10	13	11	0.248^{***}	<.001	11	8	9	13	13	13	1.3^{***}	<.001	2.2^{***}	<.001	11.8
	6WAT	14	14	18	15	0.889^{***}	<.001	14	11	12	17	17	19	2.1^{***}	<.001	3.7^{**}	0.005	14.7

*Where: $D \times I_d$ = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

Results indicated significant differences on drainage systems except at 3 WAT when drainage was not significant (p=0.683). Irrigation application depths were significant through all the weeks. In 2023 growing season, the highest mean tiller count (23) was recorded on sub-surface drainage system while the lowest (18) was recorded on treatment with no drainage at 6 WAT. On the irrigation application depths, the highest (27) mean tiller count was recorded on plots with CF-5 while the lowest (15) was recorded on plots with AWD -15. On the other hand, in 2024 growing season, the highest (19) tiller count was recorded in CF-5-10-15.

In 2023 growing season, sub-surface drainage in combination with CF 5 recorded the highest mean (34.3) interaction effect of tiller count at 6WAT while surface drainage in combination with AWD -15 recorded the lowest mean tiller (13.3) (Table 4.9). During 2024 growing season, the highest interaction of mean tiller count (25.3) was recorded on treatment with sub-surface drainage in combination with CF-5-10-15 while the lowest (10.3) was on surface drainage in combination with AWD -15 (Table 4.9).

Table 4.9: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Tiller Count at 6WAT

Year	Treatments	No Drainage	Surface Drainage	Sub-surface Drainage
2023	AWD – 5	17.5^{abcd}	16.0^{abc}	17.9^{abcd}
	AWD - 10	16.2^{abc}	15.3^{abc}	17.1^{abcd}
	AWD - 15	15.5^{abc}	13.3^{a}	14.8^{ab}
	CF - 5	20.0^{cde}	25.3^{fg}	34.3^{h}
	CF - 5 - 10	19.2^{bcd}	26.0^{fg}	29.3^{g}
	CF 5-10-15	21.5^{def}	26.0^{fg}	24.0^{ef}
2024	AWD - 5	12.3^{ab}	13.3^{ab}	17.7^{cde}
	AWD - 10	11.0^{a}	10.7^{a}	11.0^{a}
	AWD - 15	13.0^{ab}	10.3^{a}	12.7^{ab}
	CF - 5	16.0^{bc}	14.0^{abc}	20.3^{e}
	CF - 5 - 10	13.7^{abc}	17.7^{cde}	20.3^{e}
	CF-5-10-15	15.3^{bc}	16.3^{bcd}	25.3^{f}

LSD; Least Significance Difference of means at 95 % confidence level, P. value=Probability value. Values with the same letter are not significantly different

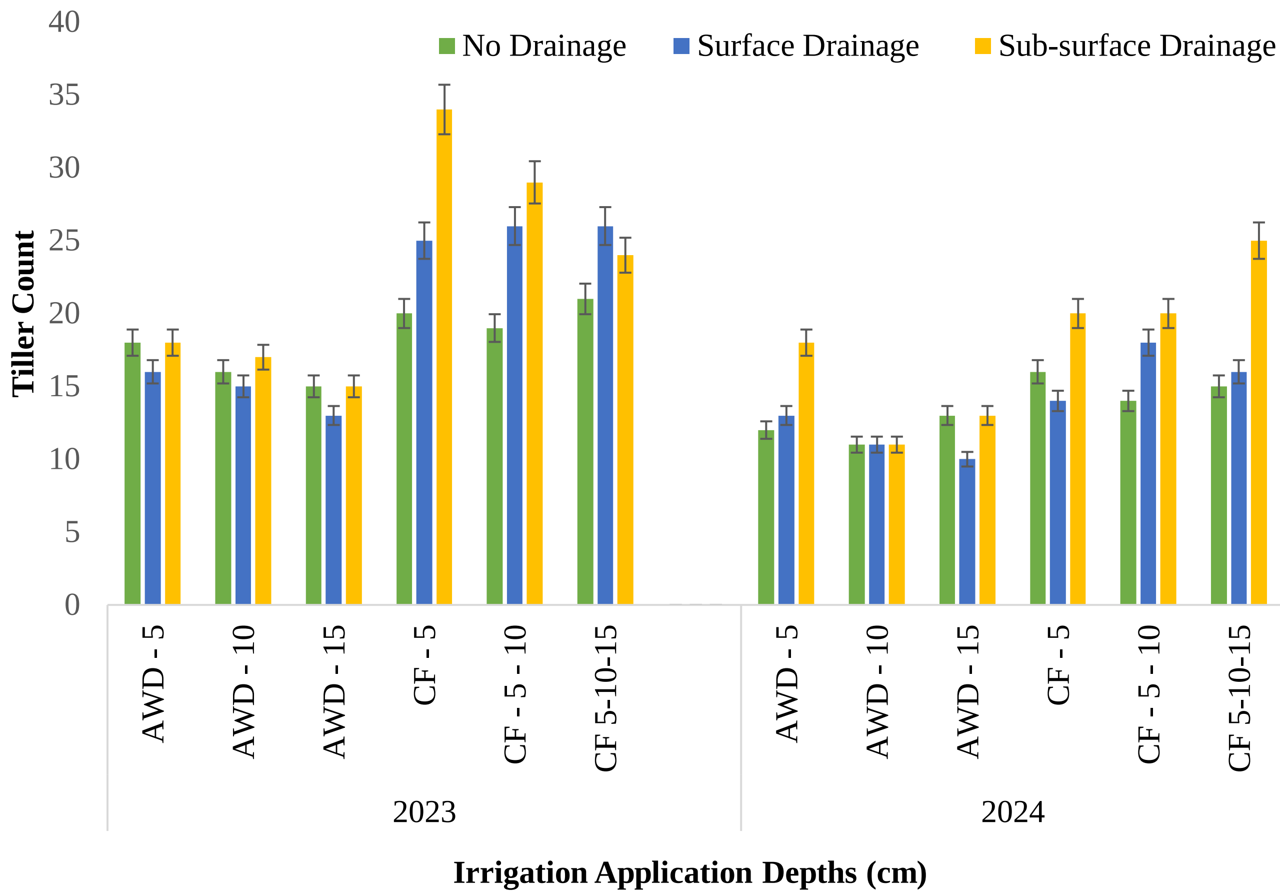


Figure 4. 4: Effect of Drainage and Irrigation Application Depths on Tiller Count at 7WAT of Rice

Tillering is a crucial agronomic characteristic of rice since it affects the structure and yield of the plants. According to Wang *et al.* (2018) and Luo *et al.* (2021) tillers grow at an angle centered on the main stem after developing from the leaf axillary bud on the mother stem. The quantity and angle of tillers have an impact on production; large-angled tillers decrease harvest efficiency, planting density, and yield, while small-angled tillers raise the risk of disease (Dias de Oliveira *et al.*, 2015; Hu *et al.*, 2020).

During this study, high number of tiller count was observed on sub-surface drainage system. The findings corroborate with those of Darzi-Naftchali and Shahnazari (2014) who also found a significant increase in rice tiller numbers in sub-surface drainage treatments.

Singh (2013) stated that a higher number of tillers recorded in surface and sub-surface drainage systems compared to plots with no drainage may be attributed to practices such as water management undertaken to maintain paddy soils mostly under aerobic conditions and active soil aeration. During the periods of drainage, enough oxygen is supplied to the root system to accelerate soil organic matter mineralization and inhibit soil N immobilization, all of which contribute to increasing the soil fertility and produce more essential plant-available nutrients to favour rice growth (Tan *et al.*, 2013). Thakur *et al.* (2014) also explained that tillering is directly linked to continuous root development (through adventitious roots), which remains active under reduced irrigation application depths, while the roots under CF degenerate significantly.

Using the alternating wetting and drying technique (AWD), Pascual and Wang (2017) and Kima *et al.* (2015) assessed various water depths to achieve high water productivity in irrigated lowland rice. The acquired results indicated that it was possible to achieve sufficient yield and water savings, but at the cost of plant water stress during the periods of vigorous tillering and panicle initiation development. To satisfy the demands of an ever-increasing population, the challenge for sustainable rice production is to increase water use efficiency while lowering the quantity of water needed to maintain or increase grain yields (Liao *et al.*, 2024).

Maintaining an irrigation application depth of 5 cm throughout the growing seasons yielded a significant increase in the number of tillers. This is supported by the findings of Mishra and Salokhe (2010) and Kima *et al.* (2014), who detailed that rice does not need to be continuously submerged with depths greater than 5 cm to produce high yields if adequate water of 5 cm depth is maintained at critical growth stages. This promotes the tillering ability to improve plant/culm height and strengthen tillers.

During the 2024 growing season, tiller count was decreased considerable as compared to that of 2023 growing season (Figure 4.4). This could be attributed to the higher temperatures observed during the growing period. High temperature can reduce rice panicle quantity and tillering. For instance, Soda *et al.* (2018) found that rice plants stressed by high temperatures have their number of tillers, and yield per plant dropped by 35 % and 28 %, respectively.

4.3.5 Effects of Drainage Systems and Different Irrigation Application Depths on Canopy Cover

The results of rice canopy cover as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.10 and Figure 4.5

Table 4.10: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Canopy Cover

Seasonal Year	WAT	Canopy Cover (%)																
		Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	4WAT	49.52	57.14	59.57	55.41	3.606***	<.001	51.34	42.09	32.57	67.58	69.18	69.7	5.100***	<.001	8.833^{ns}	0.727	9.6
	7WAT	60.95	62.73	65.56	63.08	0.539***	<.001	57.11	49.84	44.79	72.99	76.89	76.84	0.762***	<.001	1.319***	<.001	1.3
	10WAT	70.08	75.59	78.07	74.58	3.141***	<.001	69.24	67.08	64.19	82.10	81.98	82.89	4.441***	<.001	7.693^{ns}	0.997	6.2
	13WAT	75.20	79.81	82.27	79.09	0.482***	<.001	75.07	73.03	68.21	79.57	88.22	90.47	0.682***	<.001	1.180***	<.001	0.9
2024	4WAT	34.78	43.71	54.50	44.33	0.671***	<.001	43.79	32.77	22.74	54.52	54.37	57.8	0.949***	<.001	1.643***	<.001	2.2
	7WAT	47.87	54.03	62.59	54.83	2.237***	<.001	52.14	42.77	35.78	64.93	66.91	66.47	3.164***	<.001	3.164^{ns}	0.165	6
	10WAT	58.97	64.53	70.55	64.68	0.832***	<.001	59.03	55.47	45.56	74.41	75.5	78.12	1.177***	<.001	2.038***	<.001	1.9
	13WAT	69.20	78.62	81.32	76.38	2.590***	<.001	74.29	68.72	65.93	81.83	83.46	84.04	3.663***	<.001	6.345^{ns}	0.966	5

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

From Table 4.10, sub-surface drainage system recorded the highest canopy cover at 13WAT of 82.27 % and 81.32 % while no drainage recorded 75.2 % and 69.2 % respectively for 2023 and 2024 growing seasons. In terms of irrigation application depth, CF 5-10-15 recorded 90.47 % and 84.04 % while AWD -15 recorded 68.21 % and 65.93 % respectively for 2023 and 2024 growing seasons. Drainage and irrigation application depths were significant ($p<0.05$) in all the weeks observed. The results of irrigation application depths at 7 WAT is presented in Figure 4.5. However, the interaction of drainage and irrigation application depths during the 2023 growing seasons were significant ($p<.001$) at 7 WAT and 13 WAT (Table 4.10) while during the 2024 growing season, the interaction effect was significant during 4 WAT and 13 WAT.

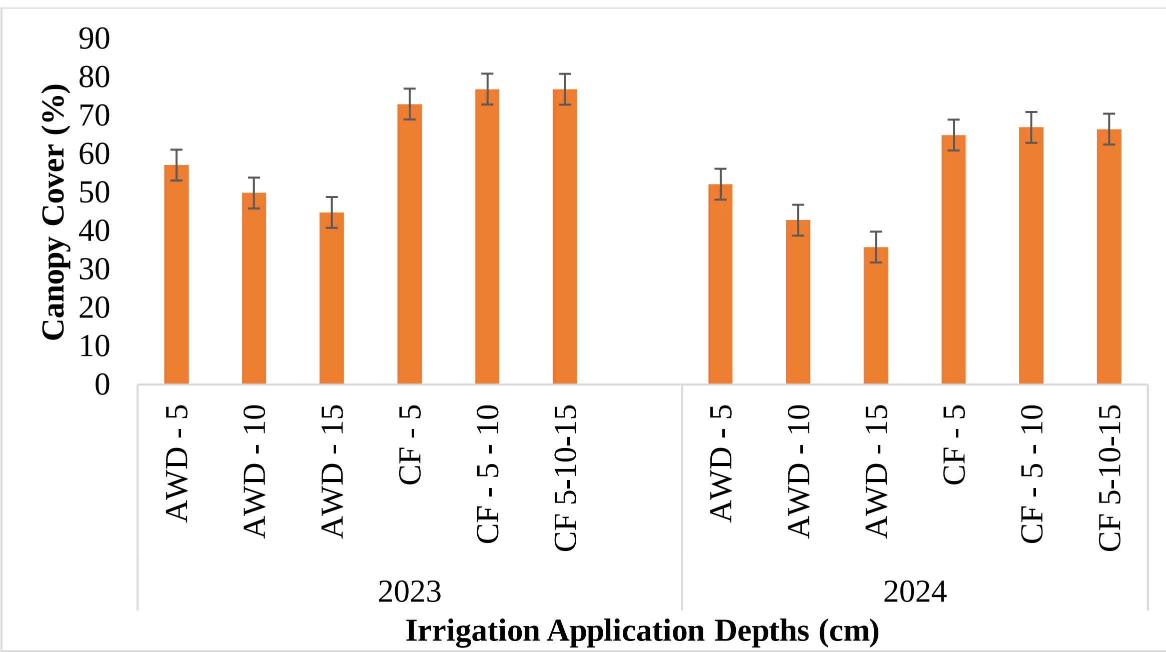


Figure 4.5: Effect of Irrigation Application Depths on Canopy Cover at 7WAT of Rice

The mean value of maximum canopy cover at 13 WAT was 79.09 % and ranged between 68.21 % and 90.47 % for the 2023 growing season, while that of the 2024 was 76.38 % and ranged between 65.93 % and 84.04 %. The study agrees with those of Abdul-Ganiyu *et al.* (2015) who recorded similar values in both on-station and on-farm experiments. Canopy values were higher in CF plots than AWD plots. This could be attributed to the fact that, when rice crop is grown under flooded conditions, it will develop bigger leaves, and hence have extended Canopy Cover (CC), while those under water stress conditions will produce smaller leaves resulting in smaller CC.

Studies conducted by Yang *et al.* (2017) concluded that, AWD within certain limits can increase yield by reducing redundant vegetative growth, elevating hormonal levels, improving canopy structure and root growth, and enhancing carbon remobilization from vegetative tissues to grains. Abdul-Ganiyu *et al.* (2015) noted that the reduction in leaf area (by reduced leaf expansion, rolling, and senescence) results in reduced light interception, which reduces total crop photosynthesis and hence total biomass production. They also noted that leaf and canopy expansion reduced soon after the soil dried below saturation in most cultivars; even in upland cultivars, expansion begins to be inhibited when only a small fraction of the total available water (TAW) has been depleted. Rice growth and yield formation are impacted when the soil water content falls below saturation. This is mostly due to decreased leaf surface area, photosynthetic rate, and sink size, which in turn reduces the amount of biomass produced overall.

Canopy cover (CC) is a good predictor variable for plant growth parameters such as leaf area index and above ground biomass. Sufficient water supply under irrigated lowland rice systems often leads to excessive vegetative growth and canopy structure (Yang and Zhang, 2010)

4.3.6 Effects of Drainage Systems and Different Irrigation Application Depths on Number of Panicles

The results of number of panicles of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.11 and Figure 4.6.

Table 4.11: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Number of Panicles in Rice

Seasonal Year	Number of Panicles																
	Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
	No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	$D \times I_d$	P-Value	CV %
2023	10	12	15	12	1.3***	<.001	8	6	5	18	19	18	1.8***	<.001	3.2 **	0.001	15.4
2024	7	9	12	9	0.6***	<.001	6	6	4	13	12	14	0.9***	<.001	1.5***	<.001	9.8

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

The number of panicles m^{-2} significantly varied with irrigation application depths and drainage levels (Table 4.11).

From Table 4.11, the sub-surface drainage system recorded the highest number of panicles of 15 and 12 while no drainage recorded 10 and 7 panicles respectively for the 2023 and 2024 growing seasons. In terms of irrigation application depth, CF 5-10 recorded 19 and CF 5-10-15 recorded 14 panicles respectively for the 2023 and 2024 growing seasons while the lowest number of panicles were recorded on AWD -15 treatments with 5 and 4 panicles respectively for 2023 and 2024 growing seasons. Drainage and irrigation application depths were significant ($p<.001$). The result of significant differences in irrigation application depths is presented in Figure 4.5. However, the interaction of drainage and irrigation application depths during the two growing seasons was significant ($p<.001$) (Table 4.12). It is worth noting that sub-surface drainage in combination with AWD -5 was not significantly different from treatments with no drainage in combination with continuous flooding at 5, 10, and 15 cm in the 2024 growing season (Table 4.12). However, treatments with sub-surface drainage system in combination with continuous flooding recorded the highest number of panicles.

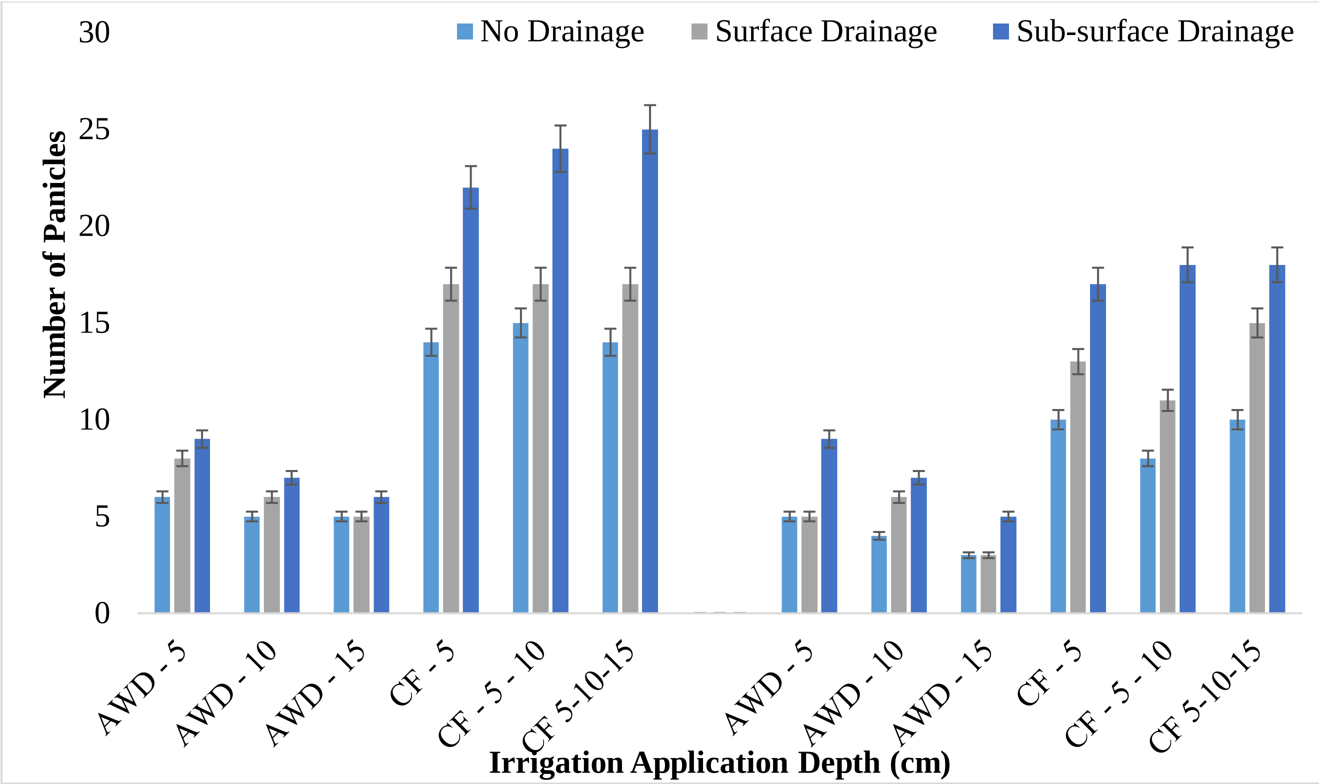


Figure 4.6: Effect of Drainage and Irrigation Application Depths on Number of Panicles of Rice

Table 4.12: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Number of Panicles

Year	Treatments	No Drainage	Surface Drainage	Sub-surface Drainage
2023	AWD – 5	6[ab]	8[ab]	9[b]
	AWD - 10	5[a]	6[ab]	7[ab]
	AWD - 15	5[a]	5[a]	6[ab]
	CF - 5	14[c]	17[c]	22[d]
	CF - 5 - 10	15[c]	17[c]	24[d]
	CF- 5-10-15	14[c]	17[c]	25[d]
2024	AWD - 5	5[c]	5[c]	9[fg]
	AWD - 10	4[abc]	6[cd]	7[de]
	AWD - 15	3[a]	3[a]	5[bc]
	CF - 5	10[gh]	13[i]	17[k]
	CF - 5 - 10	8[ef]	11[h]	18[k]
	CF-5-10-15	10[gh]	15[j]	18[k]

LSD; Least Significance Difference of means at 95 % confidence level, P. value=Probability value. Values with the same letter are not significantly different.

Continuous flooding condition facilitates adequate moisture supply and more nutrient uptake resulting in efficient dry matter partitioning and subsequent increase in panicle length. These results were in line with Orasen *et al.* (2019). In an experiment conducted by Orasen *et al.* (2019), irrigation maintained at a considerable irrigation application depth of 5 cm up to the panicle initiation stage followed by submergence condition registered a higher number of panicles m^{-2}.

4.3.7 Effects of Drainage Systems and Different Irrigation Application Depths on Panicle Length

The results of panicle length of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.13 and Figure 4.7.

Table 4.13: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Panicle Length in Rice

Seasonal Year	**Panicle Length (cm)**																
	Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
	No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	16.17	19.56	20.89	18.87	1.96***	<.001	15.22	14.33	11.78	24.56	22.78	24.56	2.78***	<.001	4.81 **	0.028	15.4
2024	11.89	13.11	19.94	14.98	0.89***	<.001	15	11.78	9	17.56	18.44	18.11	1.27***	<.001	2.20***	<.001	8.9

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$*

Table 4.13 highlight study results on treatment effect on panicle length of rice as influenced by drainage system and different irrigation application depths. However, the interaction effect on panicle length was significant throughout the two growing seasons.

In 2023 growing season, the longest panicle was observed in irrigation application depths of CF 5 and CF -5-10-15 with panicle length of 24.56 cm while the lowest was observed in AWD -15 with panicle length of 11.78 cm. During the 2024 growing season, the longest panicle was observed in CF 5-10 irrigation application depth with panicle length of 18.44 cm while the shortest panicle (9.0) was observed in AWD -15.

The interaction effect of drainage and irrigation application depths (D x I_d) was significant ($p<0.001$) in the two growing seasons (Table 4.14). Sub-surface drainage in combination with CF-5 produced the longest panicle of 28.7 cm, followed by CF 5-10 in combination with sub-surface drainage with panicle length of 27.7 cm during the 2023 growing season. Meanwhile, AWD -15 in combination with no drainage produced the shortest panicle of 12.7 cm and 7.7 cm for 2023 and 2024 growing seasons respectively (Table 4.13). During the 2024 growing season, CF 5-10 in combination with sub-surface drainage produced the longest panicle of 28.3 cm, followed by CF 5 in combination with sub-surface drainage with panicle length of 25.3 cm (Figure 4.7).

Table 4.14: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Panicle Length

Year	Treatments	No Drainage	Surface Drainage	Sub-surface Drainage
2023	AWD – 5	14.7abc	14.0abc	17.0bc
	AWD - 10	13.7abc	15.7abc	13.7abc
	AWD - 15	11.0a	11.7ab	12.7abc
	CF - 5	18.0cd	27.0ef	28.7f
	CF - 5 - 10	17.0bc	23.7ef	27.7ef
	CF 5-10-15	22.7de	25.3ef	25.7ef
2024	AWD - 5	9.0a	16.0c	20.0d
	AWD - 10	8.7a	9.7ab	17.0c
	AWD - 15	11.7b	7.7a	7.7a
	CF - 5	11.3b	16.0c	25.3e
	CF - 5 - 10	15.0c	12.0b	28.3f
	CF- 5-10-15	15.7c	17.3c	21.3d

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different.

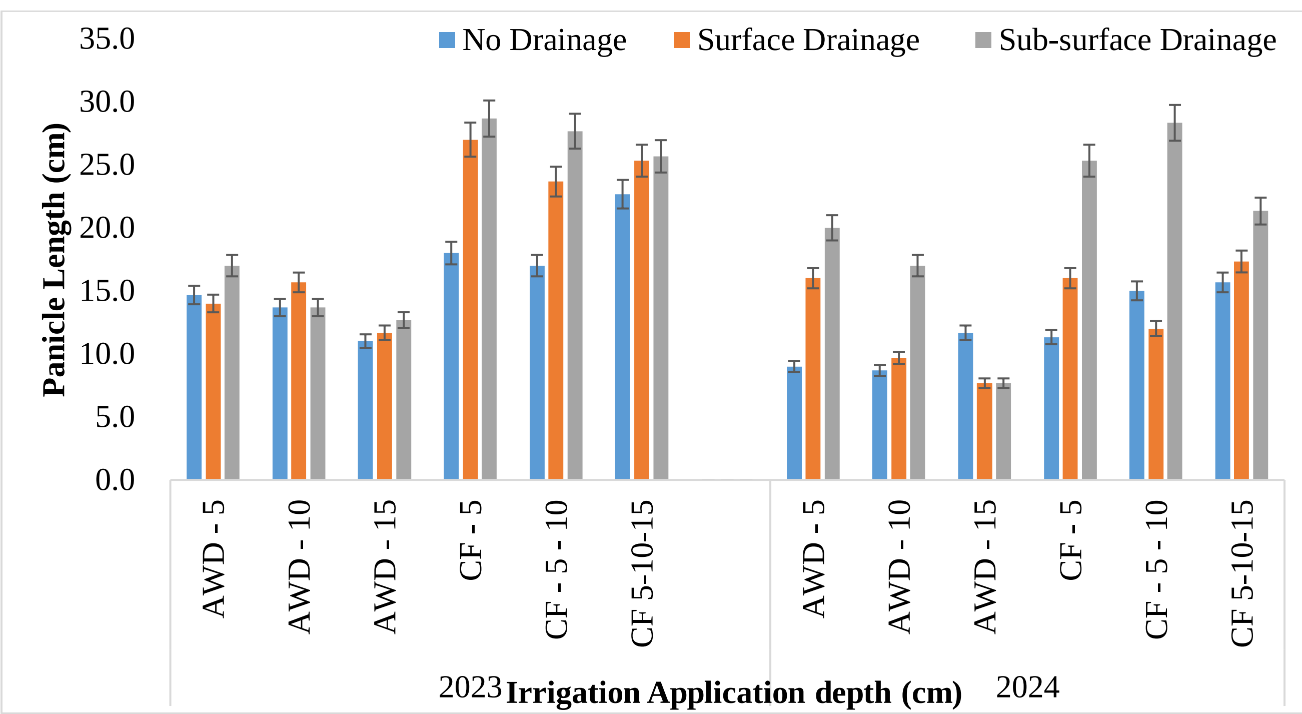


Figure 4.7: Effect of Drainage and Irrigation Application Depths on Panicle Length of Rice

The stress of a water deficit resulted in a shorter panicle. These results are consistent with those of Abdelaty *et al.* (2022), who found that drought stress resulted in numerous structural and functional disturbances in floral organs, causing problems with fertilization or premature seed abortion, a reduction in the amount of time of grains fill out, early senescence, a decrease in photosynthesis, and an increase in the remobilization of soluble sugar from grains to other vegetative parts. These findings were noted when water stress occurred during the reproductive stage.

Several authors have pointed out that some of the factors that contribute to a decrease in grain production under water stress include a decrease in panicle length, number of panicles per plant, number of spikelets per panicle, number of filled grains per panicle, spikelet fertility, and 1000-grain weight (Fahad *et al.*, 2017; Saddiq *et al.*, 2021; Long *et al.*, 2023).

The results show increased panicle length in non-stressed plots. This is in agreement with the findings of Hashem *et al.* (2016), who noted that when water is available, biological and physiological processes are enhanced. This leads to an increase in the production and translocation of the dry matter content from source to sink, which results in more panicles, greater grain filling, and greater grain weight. This could explain the observed increases in panicle length under non-stress conditions.

4.3.8 Effects of Drainage Systems and Different Irrigation Application Depths on Filled Grains per Panicle

The results of the number of filled grains per panicle of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.15 and Figure 4

Table 4.15: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Filled Grains per Panicle in Rice

Seasonal Year	Filled Grains per Panicle																
	Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
	No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	$D \times I_d$	P-Value	CV %
2023	105.8	124.5	151.1	127.1	16.0***	<.001	80	70.8	58.4	190.5	175.4	187.8	22.7***	<.001	39.23**	0.008	18.6
2024	74.56	91.28	122.5	96.11	2.77***	<.001	55.56	44.67	37.78	144.6	138.2	155.9	3.92***	<.001	6.79***	<.001	4.3

*Where: $D \times I_d$ = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

Table 4.15 highlights study results on treatment effect on number of filled grains per panicle of rice as influenced by drainage system and different irrigation application depths. In 2023 growing season, the mean value of filled grains was highest in irrigation application depths of CF 5 (190.5), followed by CF 5-10-15 (187.8) while the lowest was observed in AWD -15 with 58.4 filled grains per panicle. During the 2024 growing season, the highest mean value of filled grains was observed in CF 5-10-15 irrigation application depth with 155.89 filled grains per panicle while the lowest (37.78) was observed in AWD -15 (Figure 4.8).

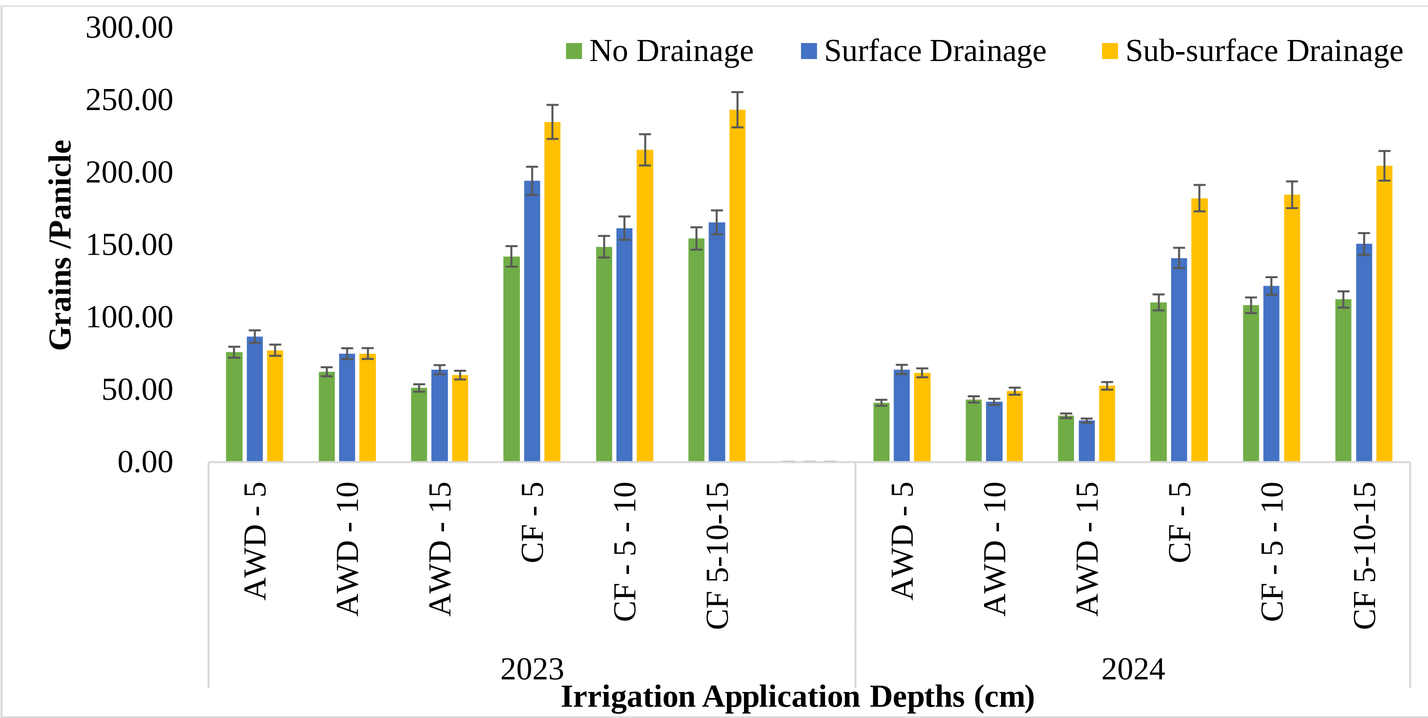


Figure 4.8: Effect of Drainage and Irrigation Application Depths on Filled Grains per Panicle of Rice

The interaction effect of drainage and irrigation application depths (D x I_d) was significant p=0.008) and (p<.001) for 2023 and 2024 growing seasons respectively (Table 4.16). Sub-surface drainage in combination with CF 5-10-15 produced the highest mean value of filled grains per panicle of 243.4, followed by CF-5 in combination with sub-surface drainage with a mean value of 235.0. Meanwhile, AWD -15 in combination with no drainage produced the lowest mean value of filled grains per panicle of 51.2 and 32.0 for 2023 and 2024 growing seasons respectively (Table 4.16). During the 2024 growing season, CF 5-10-15 in combination with sub-surface drainage produced the highest mean value of 204.65, followed by CF 5-10 in combination with sub-surface drainage with a mean value of 184.67 (Table 4.16).

Table 4.16: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Filled Grains per Panicle

		Filled Grains per Panicle		
Year	**Treatments**	**No Drainage**	**Surface Drainage**	**Sub-surface Drainage**
2023	AWD – 5	75.90[a]	86.70[a]	77.30[a]
	AWD - 10	62.40[a]	74.90[a]	75.00[a]
	AWD - 15	51.20[a]	63.80[a]	60.10[a]
	CF - 5	142.10[b]	194.30[cd]	235.00[de]
	CF - 5 - 10	148.80[b]	161.60[bc]	215.70[de]
	CF-5-10-15	154.50[bc]	165.60[bc]	243.40[e]
2024	AWD - 5	41.00[b]	64.00[e]	61.67[e]
	AWD - 10	43.33[bc]	41.67[b]	49.00[cd]
	AWD - 15	32.00[a]	28.67[a]	52.67[d]
	CF - 5	110.33[f]	141.00[h]	182.33[i]
	CF - 5 - 10	108.33[f]	121.67[g]	184.67[j]
	CF -5-10-15	112.33[f]	150.67[i]	204.67[k]

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different

Reduced number of spikelets results in decreased number of grains per panicle which leads to yield reduction (Bouman *et al.*, 2007). In a two-year study (2009–2010), Rahman *et al.* (2015) observed a higher spikelet number m^{-2} in flooded treatment than in stressed treatment in 2009 but the opposite trend was observed in 2010. Higher panicle number m^{-2} was observed in the sub-surface drained area. This trait is the most important factor in increasing the grain yield of rice and 89 % of yield change is due to the effect of the number of panicles and grains filled per panicle (Li *et* *al.*, 2021). Li *et al.* (2014) reported that optimum rice yield could not be attained without optimum panicle density of uniform maturity.

Zhang *et al.* (2021) reported that when stomata closed, the crops initiated their mechanisms to resist water stress, which included a significant increase in abscisic acid, soluble protein, and soluble sugar content within the cells. This action of adjusting to cope with the stress would result to a significant decrease in growth and yield parameters.

Kato and Katsura (2010) reported that grains per panicle of some cultivars declined sharply with sub-optimal water conditions with greater reduction in the number of panicle and spikelet numbers. This might be due to insufficient moisture in more stressed plants resulting in reduced N uptake and decreased dry matter production.

4.3.9 Effects of Drainage Systems and Different Irrigation Application Depths on 1000 Grain Weight

The results of the number of 1000-grain weight of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.17 and Figure 4.9.

Table 4.17: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on 1000 Grains Weight of Rice

Seasonal Year	1000 Grain Weight (g)																
	Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
	No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	25.38	27.2	27.22	26.6	0.84^{***}	<.001	24.66	23.4	22.24	29.42	28.72	31.17	0.84^{***}	<.001	2.048^{ns}	0.081	4.6
2024	17.71	17.53	21.24	18.83	0.60^{***}	<.001	17.1	16.64	14.54	21.65	21.94	21.09	0.85^{***}	<.001	1.47^{***}	<.001	4.7

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

There was an interaction effect of drainage systems and irrigation application depths on the 1000-grain weight (Table 4.17). The highest 1000-grain weight (31.17 g) was recorded in sub-surface drainage under CF 5-10-15 in 2023 while in 2024, the highest (21.94 g) was recorded in sub-surface drainage under CF 5-10. Similarly, the lowest 1000-grain weights of 22.24 g and 14.54 g were recorded in no drainage under AWD -15 irrigation in the 2023 and 2024 growing seasons respectively (Table 4.19). The interaction effect of drainage and irrigation application depths (D x I_d) was not significant p=0.081) in the 2023 growing season but significant during the 2024 growing season (p<.001) (Figure 4.9).

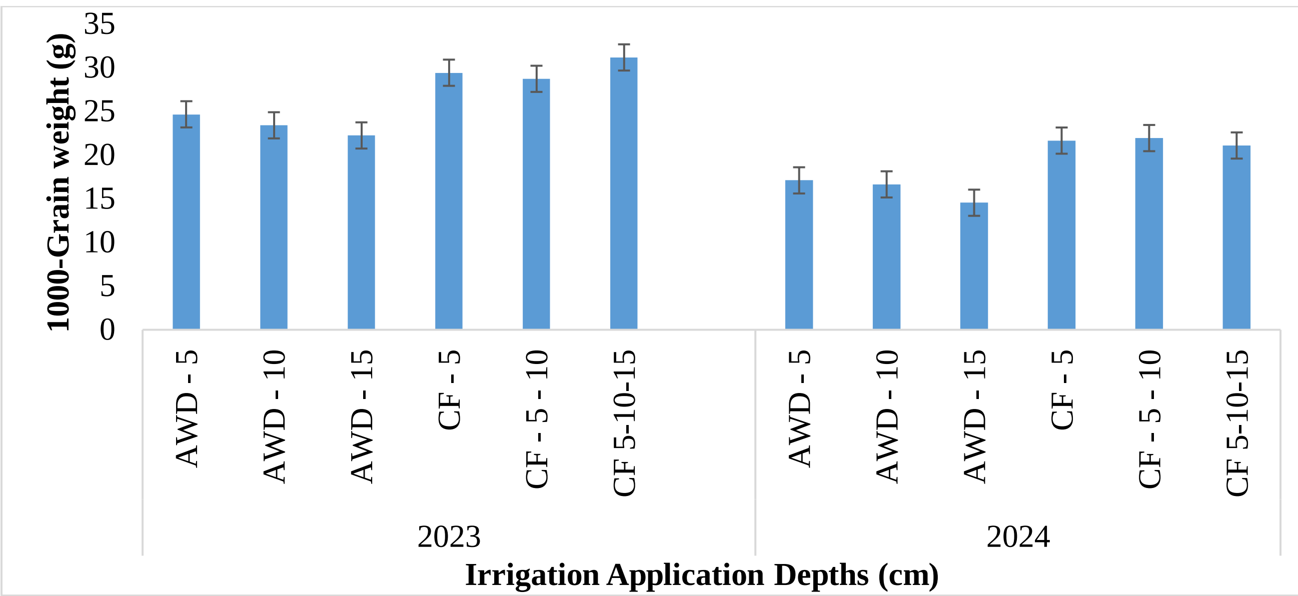


Figure 4.9: Effect of Drainage and Irrigation Application Depths on 1000-Grains Weight

The treatments did not produce similar 1000-grain weight in the two seasons and is in contrast with Anning *et al.* (2018) who asserted that 1000-grain weight is not significantly affected by water stress. Yoshida (2012) reported that 1000-grain weight is a genetic trait and therefore the environment has an insignificant effect on it. Moreover, Momo *et al.* (2013) reported that withdrawing water after complete heading has no effect on 1000-grain weight.

Variation of 1000-grain weight among different drainage treatments showed no specific trend. Variations in grain weight are generally small since seed size is rigidly controlled by the size of the hull. According to Yoshida (2012), under most conditions, the 1000-grain weight of field crops is a very stable varietal character. Surekha *et al.* (2006) reported that, the 1000-grain weight was not affected significantly by crop management practices. Rahman *et al.* (2013) observed negligible differences in 1000-grain weight between the mid-season drainage and flooded treatments.

4.3.10 Effects of Drainage Systems and Different Irrigation Application Depths on Rice Yield

The results on the yield of rice as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.18 and Figure 4.10

Table 4.18: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Rice Yield

Seasonal Year	Yield (t/ha)																
	Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
	No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	2.65	4.72	5.89	4.42	0.65***	<.001	2.12	1.84	0.81	7.31	6.62	7.84	0.92***	<.001	1.59 ***	<.001	21.8
2024	2.67	3.52	4.59	3.6	0.35***	<.001	3.48	2.19	1.57	4.39	4.83	5.12	0.49***	<.001	0.85 ***	<.001	14.2

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, *** = significantly different at $P \leq 0.001$.*

Table 4.18 highlights result on rice yield as influenced by the treatments during the two growing seasons. Both the main effect and the interaction effect of drainage and irrigation application depths (D x I_d) were significant (p<.001) for the two growing seasons. As such, the interaction effect will be discussed. Sub-surface drainage in combination with CF-5 produced the highest rice yield of 9.55 t/ha, followed by CF-5-10-15 in combination with sub-surface drainage with a yield of 9.52 t/ha in the 2023 growing season while AWD -15 in combination with no drainage produced the lowest yield of 0.41 t/ha (Table 4.19). During the 2024 growing season, CF-5-10-15 in combination with sub-surface drainage produced the highest yield of 6.77 t/ha, followed by CF-5-10 in combination with sub-surface drainage with a yield of 6.60 t/ha (Table 4.19).

Table 4.19: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on the Yield of Rice

		Yield (t/ha)		
Year	**Treatments**	**No Drainage**	**Surface Drainage**	**Sub-surface Drainage**
2023	AWD – 5	1.14^{ab}	1.98^{abc}	3.23^{cde}
	AWD - 10	1.42^{ab}	1.61^{abc}	2.48^{bcd}
	AWD - 15	0.41^{a}	0.96^{ab}	1.06^{ab}
	CF - 5	3.83^{de}	8.55^{g}	9.55^{g}
	CF - 5 - 10	4.22^{e}	6.14^{f}	9.50^{g}
	CF-5-10-15	4.90^{ef}	9.10^{g}	9.52^{g}
	$LSD_{(0.05)}$	1.60		
	P-Value	<.001		
2024	AWD - 5	3.03^{efg}	3.5^{fgh}	3.90^{ghi}
	AWD - 10	1.53^{abc}	2.1^{bcd}	2.93^{def}
	AWD - 15	1.27^{ab}	1.17^{a}	2.27^{cde}
	CF - 5	3.30^{fg}	4.77^{ijk}	5.10^{jk}
	CF - 5 - 10	3.57^{fgh}	4.33^{hij}	6.60^{l}
	CF-5-10-15	3.33^{fg}	5.27^{k}	6.77^{l}
	$LSD_{(0.05)}$	0.85		
	P-Value	<.001		

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different

Figure 4.10 shows a graphical representation of means of the interactive effect of drainage systems and irrigation application depths on the yield of rice.

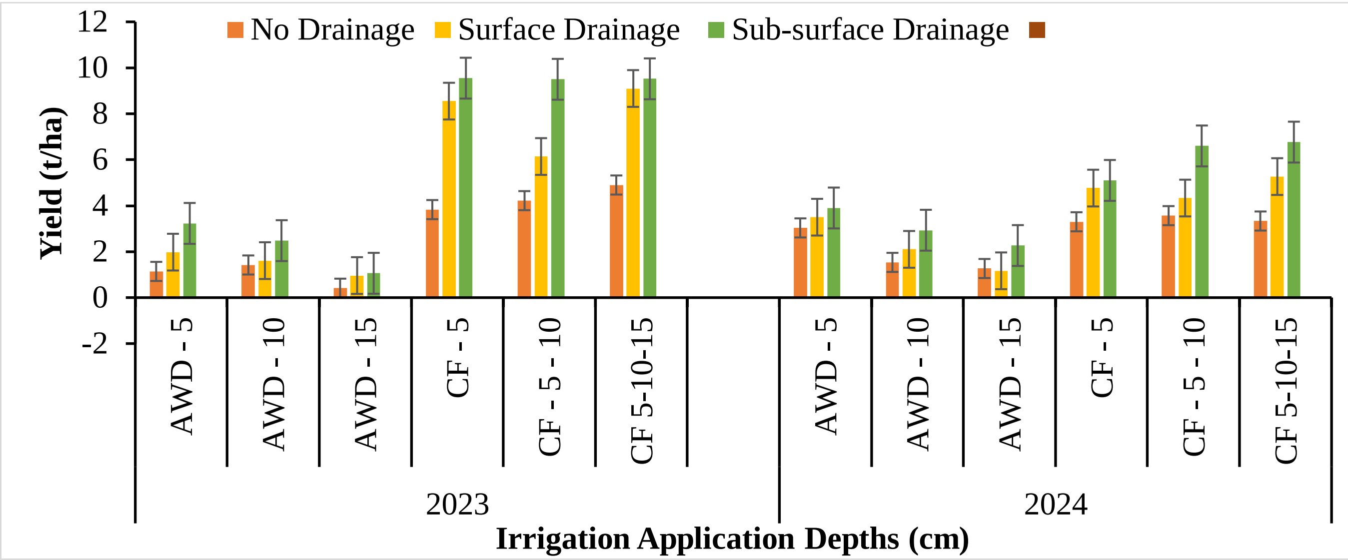


Figure 4.10: Effect of Drainage and Irrigation Application Depths on Rice Yield

In all the two years, sub-surface drainage outperformed the other types of drainage systems. This was explained by Cannarozzi *et al.* (2018) who stated that under abiotic stress conditions, reactive oxygen species (ROS) levels are always elevated compared to pre-stress levels. Excessive production of various ROS such as superoxide radicals, hydroxyl radicals, hydrogen peroxide, and singlet oxygen found in hypoxia-stressed leaf and root tissues can also cause severe damage to plants. All of these lead to restricted root growth, reduced tiller number, premature leaf senescence and production of sterile florets thus affecting the grain yield.

While it takes time for phytotoxic compounds to accumulate, the lack of oxygen is sufficient to alter plant metabolism to a critical point. Waterlogging and flooding cause an oxygen shortage, which lowers the amount of energy available in the roots and inhibits energy-dependent functions like nutrient absorption. One additional possible explanation for the inhibition of growth and yield performance of plants under waterlogging is nitrogen deficiency.

According to Pérez-jiménez *et al.* (2018), reduced photosynthetic rate, reduced stomatal conductance, decreased root hydraulic conductivity, and reduced translocation of photo assimilates are the main causes of the significant reduction in carbohydrate (the energy reserve) production during total submergence or subsequent de-submergence. Plant growth is impacted by waterlogging, which significantly reduces production.

A huge yield gap was observed between the two growing seasons. This could be attributed to the differences in temperatures. In Figure 4.11 and 4.12, it is observed that temperatures during the 2023 growing season were lower than those of 2024 growing season simply because of the differences in the months the study was conducted. This attribution of higher temperatures having a significant effect on growth and yield components of rice have been supported by Theivasigamani *et al.* (2022) who stated that rice varieties have different flowering duration and significantly different flower opening time (FOT), ranging from early morning to midnight. Qiu *et al.* (2019) stated that high temperatures shorten the flowering time, limiting the time for pollination. Grain filling takes place throughout the maturity stage and involves the process of converting sucrose produced by photosynthesis into starch, which is the major carbohydrate in rice and an important determinant of grain quality and yield.

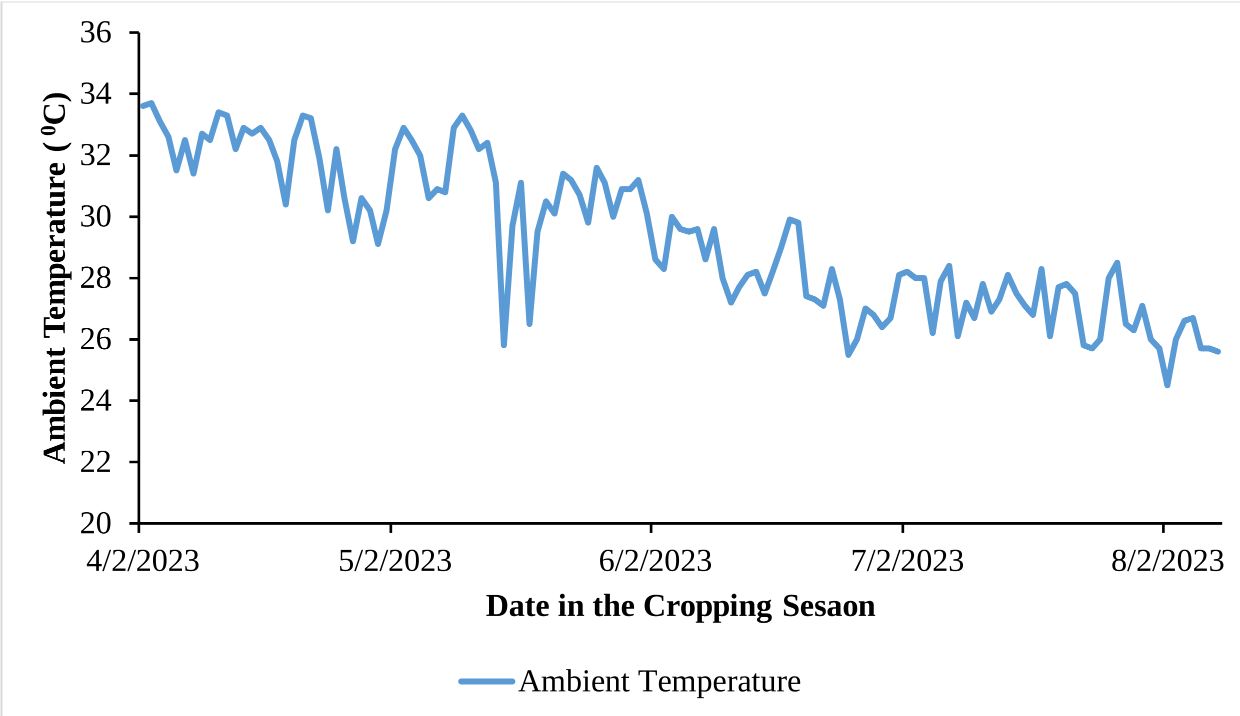


Figure 4.11: Ambient Temperature of the Experiment Field During the 2023 Growing Season

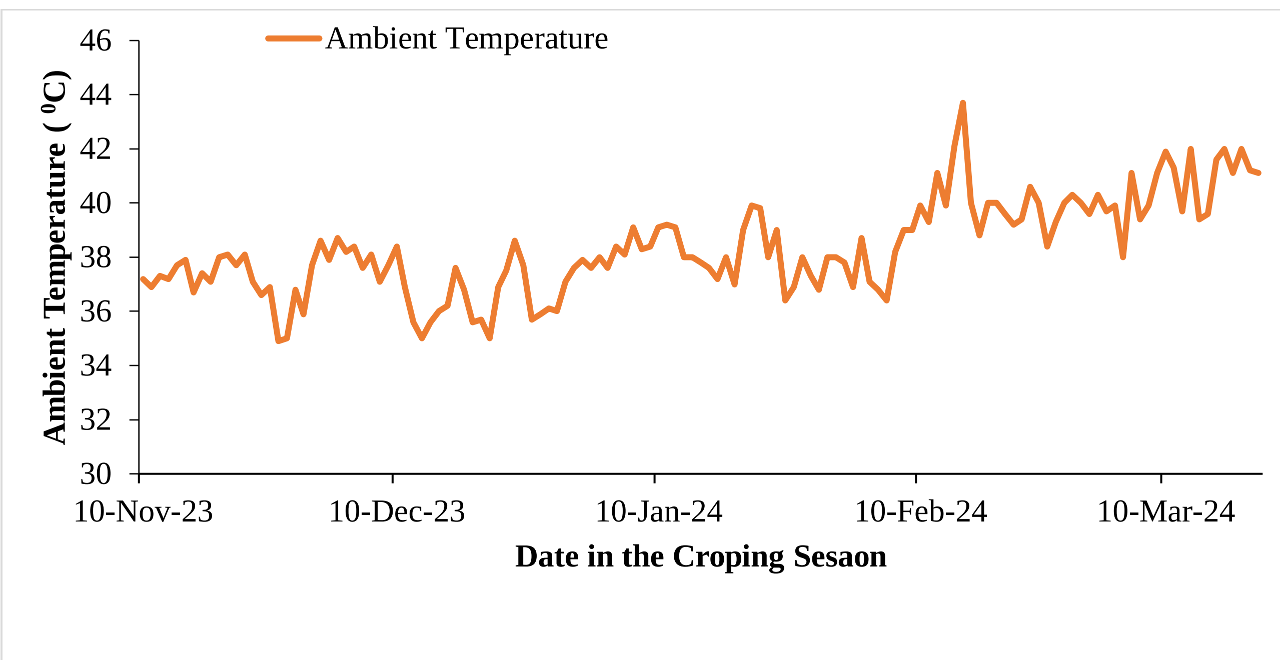


Figure 4.12: Ambient Temperature of the Experiment Field During the 2024 Growing Season

The yield gap in 2023 and 2024 growing season supports the findings of Sreenivasulu *et al.* (2015) who observed that high temperature during grain filling reduced rice yields by 50 %. It can also cause the failure of grain filling in rice and wheat by affecting the accumulation of starch granules, ultimately resulting in yield losses (Chen *et al.*, 2017; Impa *et al.*, 2021). High-temperature stress during grain filling also induces DNA methylation in the promoters of abscisic acid (ABA), catabolic genes and α-amylase genes, which can delay the germination of the resulting seeds (Suriyasak *et al.*, 2020).

Wang *et al.* (2021) highlighted three (3) mechanisms that could affect starch accumulation as a result of high temperature. Firstly, high temperature can shorten the grain filling period, resulting in insufficient grain filling and inadequate starch accumulation, thus reducing in grain yield. Secondly, high temperature can reduce the gene expression and bioactivity of key enzymes involved in the conversion of sucrose to starch in endosperm, reducing the rate of starch synthesis and thus affecting total starch content and starch accumulation patterns, especially the amylose content of endosperm starch. Thirdly, high temperature can inhibit photosynthesis in other vegetative organs such as stems and leaf sheaths, resulting in an insufficient supply of fixed carbon from vegetative organs to spikelets, a slower grain filling rate, and a lower grain weight.

Increased mean air temperature and abnormal high temperature events, such as extreme heatwaves, affect the growth and physiological conditions of crops throughout the growing season. Moreover, high temperature phenomena during the growing season reduce a crop's capacity to gain any possible beneficial effects of increased accumulated degree days under global warming (Oh *et al.*, 2023). In addition, even if the temperature is not high throughout the growing period, extreme events such as heatwaves can cause serious damage to rice production because pollen viability in rice exposed to high temperatures is reduced (Oh *et al.*, 2023). This spikelet sterility will not only reduce yield but will also affect growth and physiological responses during the reproductive growth period.

The saturated irrigation and alternate wetting and drying irrigation can maintain or even increase grain yield if the lowest water potential is controlled reasonably according to various soil properties when compared with flooding irrigation (Ishfaq *et al.*, 2020). In our findings an increase in yield was observed on treatments that are continuous flooded than those with alternate wetting and drying. These findings are similar to those stated by Shao *et al.* (2014) while studying the effects of controlled irrigation and drainage on grain yield of paddy rice. The absence of a layer of flooding water will expose the stems of the rice plant to temperature extremes and will negatively affect the plant growth, which will ultimately affect the grain yield (Ishfaq *et al.*, 2020).

Several previous studies have reported more than 50 % yield reductions, confirming successful water stress screening (Shamsudin *et al.*, 2016; Swamy *et al.*, 2017). A reduction in panicle weight, panicle length, number of panicles per plant, number of spikelets per panicle, number of filled grains per panicle, spikelet fertility, and 1000-grain weight are some of the causes of grain yield reduction under water stress (Li *et al.*, 2021; Wang *et al.*, 2024).

Crop water stress have been noted to result to reduced effective tillers and panicle development during the earlier stage and affected the reproductive physiology by interfering with pollination, fertilization, and grain filling during the later stage. The reason for grain yield reduction with water stress mainly decreased in the number of filled spikelet per panicle (Gao *et al.*, 2019). Comparison of different irrigation regimes in rice production indicated that flooding irrigation achieved the highest grain yield while intermittent irrigation gave lowest grain yield (Arouna *et al.*, 2023).

Some literature reported that the grain yield of rice was reduced by AWD irrigation (Farooq *et al.*, 2011; Kima *et al.*, 2015; Elsadek *et al.*, 2023) or when exposed to unsaturated soil conditions (Bouman *et al.*, 2007). For soils, the finding of grain yield showed 63.9 % increase in well saturated soils compared to alternate wetting and drying because the increase in soil clay content resulted in more fine particles that could hold water and nutrient by swelling after watering Therefore, it could retain more water and nutrients needed by the rice plant, consequently raising the number of panicles as well as the filled spikelet per panicle (Dou *et al.*, 2016).

Sarvestani *et al.* (2008) asserted that water stress at flowering stage significantly reduced grain yield. The study outcome is in line with previous studies of Yang *et al.* (2007) and Chu *et al.* (2018) that, practicing AWD throughout the plant cycle reduces grain yield significantly due to reduced soil moisture. However, Sun and Ren (2014) and Chu *et al.* (2015) observed a higher grain yield in AWD plants than continuous submergence plants. Moreover, Anning *et al.* (2018) and Ofori and Anning (2019) reported a similar grain yield between AWD and continuous submerged treatments. The discrepancies in these findings may be due to the fact that AWD varies in terms of frequency and duration of drying periods and the type of soil used (Bouman *et al.*, 2007).

In terms of drainage system, the findings of the study are in line with those of Darzi-Naftchali and Shahnazari (2014) who noted that grain yield in the sub-surface drainage treatments was significantly higher than that of the no drainage system.

4.3.11 Effects of Drainage Systems and Different Irrigation Application Depths on Irrigation Water Use Efficiency (IWUE)

The results on the irrigation water use efficiency as influenced by drainage and different irrigation application depths and their interactions over the two growing seasons are presented in Table 4.20 and Figure 4.13.

Table 4.20: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Irrigation Water Use Efficiency of Rice

Seasonal Year	Water Use Efficiency (kg m^{-3})																
	Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
	No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	1.67	1.36	2.32	1.78	0.11***	<.001	2.91	2.28	1.66	1.99	1.04	0.83	0.15***	<.001	0.27 ***	<.001	9
2024	1.1	1.5	1.9	1.5	0.21***	<.001	2.8	1.8	1.5	1.5	0.8	0.7	0.30***	<.001	0.52 *	0.049	20.7

*Where: D x I_d = Combination of drainage and irrigation application depth, CV = Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95 % confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

Table 4.20 highlights result of irrigation water use efficiency as influenced by the treatments during the two growing seasons. In the 2023 growing season, both the main and interactive effects were significantly different ($p<.001$) (Table 4.20). It was observed during this season that, AWD -5 recorded the highest water use efficiency (2.91 kg m^{-3}) and was followed by AWD -10 (2.28 kg m^{-3}) while the lowest was observed in CF-5-10-15 with a IWUE of 0.83 kg m^{-3}. During the 2024 growing season, the main effect was significant at $p<.001$ but the interaction effect of drainage and irrigation application depths (D x I_d) were significant at $p=0.049$. AWD -5 was observed to have the highest IWUE of 2.80 kg m^{-3}, followed by AWD -10 with IWUE of 1.80 kg m^{-3}. The lowest was observed in CF-5-10-15 with IWUE of 0.70 kg m^{-3} (Figure 4.12). However, sub-surface drainage system was observed to have the highest IWUE of 2.32 kg m^{-3} and 1.90 kg m^{-3} for 2023 and 2024 respectively (Table 4.20).

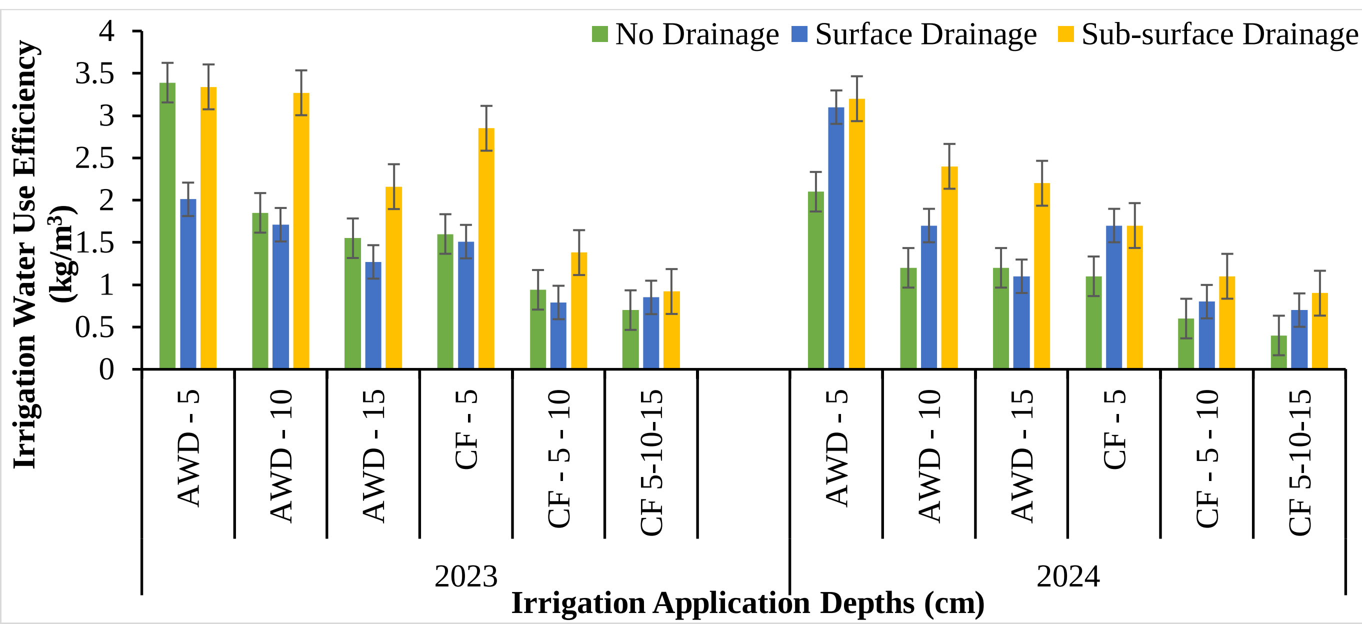


Figure 4.13: Effect of Drainage and Irrigation Application Depths on Irrigation Water Use Efficiency

The findings of this research corroborate with those of Abdul-Ganiyu *et al.* (2015) who noted more efficient water use in producing rice under field capacity, saturation, and 10 % ETC because they gave higher WUE values than continuously flooded treatments. According to Cui *et al.* (2022) flood irrigation is one of the most significant issues restricting irrigation water use efficiency. Koech and Langat (2018) noted that low irrigation water use efficiency is linked to poor timing and uneven distribution of water applications. Kilemo (2022) remarked that water use efficiency can be improved through the implementation of improved agronomic practices, technical, managerial, and institutional advancement.

Li and Wu (2024) stated that, water resource management remains a critical component of achieving one of the 2030 Sustainable Development Goals which is "ending extreme poverty, hunger, and ensuring environmental sustainability". Water scarcity has become a growing social and economic concern for policymakers and other sectors competing for water resources.

Studies by Yang *et al.* (2007) and Chu *et al.* (2018) have revealed that WUE does not only depend on water-saving technology applied but also on the cultivar type. These observations suggest that the response of rice growth to irrigation regimes varies with rice genotypes. The results of this study could not however assert to this statement since only one cultivar was used. There is therefore the need to use more rice cultivars to investigate cultivar differences in response to the interaction of these treatments.

4.4 Effects of Drainage Systems and Different Irrigation Application Depths on Soil Electrical Conductivity, Soil Temperature and Nitrogen Balance in Irrigated Ecology

4.4.1 Effects of Drainage Systems and Different Irrigation Application Depths on Soil Electrical Conductivity in Irrigated Ecology

The results on the soil electrical conductivity as influenced by drainage and different irrigation application depths and their interactions on rice over the two growing seasons are presented in Table 4.21 and Figure 4.14.

Table 4.21: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Soil Electrical Conductivity

Seasonal Year	WAT	Soil Electrical Conductivity (µs/cm)															
		Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	BS	125.1	121.9	123.1	123.4	9.36^{ns}	0.794	124.8	126	119.9	122.1	130.3	117.1	13.24^{ns}	0.411	22.93^{ns}	0.352	11.2
	AH	344.4	249.4	344.4	252.7	17.11^{***}	<.001	232.7	280.4	301.2	241.1	232.3	228.2	24.2^{***}	<.001	41.91^{*}	0.038	10
2024	BS	290.2	204.1	127.7	207.3	6.34^{***}	<.001	176.1	250	230.4	220.6	191.6	175.6	8.97^{***}	<.001	15.5^{***}	<.001	4.5
	AH	347.8	274.8	186	269.5	22.5^{***}	<.001	272.4	271.7	302.2	260.9	244.7	265.3	31.86^{*}	0.027	55.18^{*}	0.043	12.3

*Where: BS = Before Sowing, AH = After Harvesting, D x I_d = Combination of Drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

The soil electrical conductivity (EC) was observed before sowing and after harvesting. From Table 4.21, in the 2023 growing season, the soil electrical conductivity was not significant (p=0.352) in the interactive effects before sowing. However, after harvesting, interactive effect of drainage and irrigation application depths was significant (p=0.038) (Table 4.21). AWD-15 in combination with no drainage recorded the highest soil EC of 389.3 µs/cm while CF-5-10-15 in combination with sub-surface drainage recorded the lowest soil EC of 112.7 µs/cm. During 2024 growing season, CF-5-10-15 in combination with no drainage recorded the highest soil EC of 388.0 µs/cm while CF-5-10-15 in combination with sub-surface drainage recorded the lowest soil EC of 153.3 µs/cm (Figure 4.14). However, the EC levels for the soils in the experiment were lower than the threshold of 4000 - 5000 µs/cm for traditional varieties and 10000 µs/cm for salt tolerant varieties as stated by Islam *et al.* (2020).

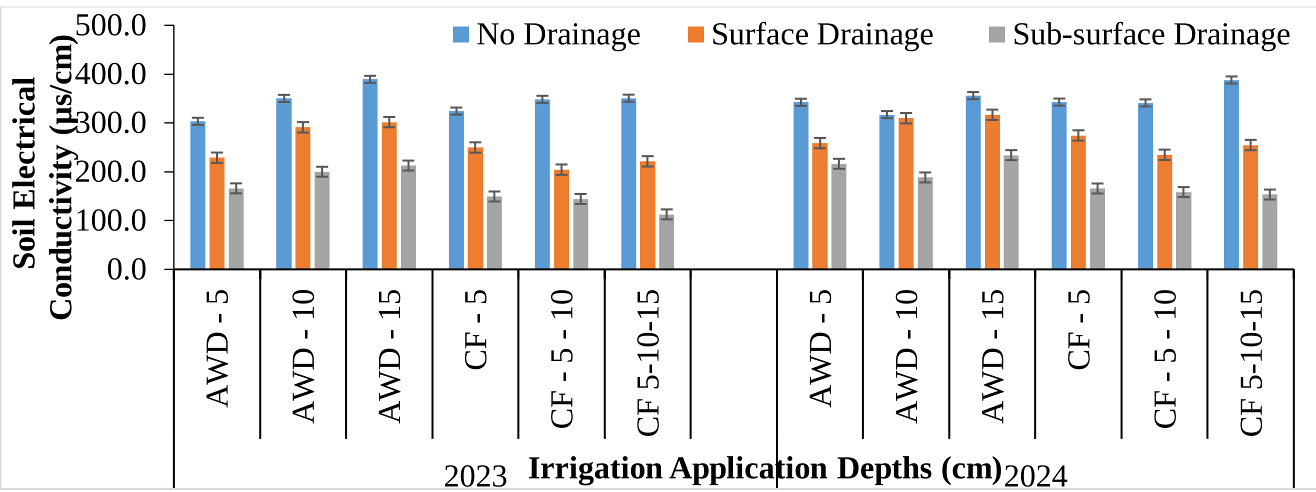


Figure 4.14: Effect of Drainage and Irrigation Application Depths on Soil Electrical Conductivity

In this study sub-surface drainage outperformed surface and no drainage conditions in terms of soil properties. Waterlogging, poor drainage, and elevated EC might result from inadequate water infiltration. Although soil EC has been utilized as an indirect predictor of salt levels and the quantity of nutrients available for plant absorption, it has no direct effect on plant development

(USDA-NRCS, 2014). EC has been used as a surrogate of salt content, organic matter, cation-exchange capacity, soil texture, soil thickness, nutrients (such as nitrate), water-holding capacity, and drainage conditions. High EC can be a sign of salinity (EC > 4 dS/m) issues, which hinder microbial activity and crop growth by preventing the crop from absorbing water even when it is there. Because sodium is harmful to plants, soils with high EC from high sodium concentrations typically have poor drainage and structure. In many instances, lowering the salt content and EC requires a mix of drainage and irrigation (USDA-NRCS, 2014).

Sub-surface drainage has been regarded as an effective technique for the development of saline soils and has been utilized as a very successful strategy to address floods and salinity threats (Ritzema, 2014). Experiments on enhancing saline-alkali lands with sub-surface drainage have been conducted by several researchers with promising outcomes (Tao *et al.*, 2019; Li *et al.*, 2021). By releasing surplus soil water and salts and managing the groundwater table, sub-surface drainage lowers the moisture and salinity conditions of the soil, enhancing plant physiological growth index and boosting agricultural yields (Singh, 2021). Salts can be more easily leached from the soil profile's root zone and soil salinization can be avoided with sub-surface drainage (Ritzema, 2014). In heavy paddy soil, Itoh *et al.* (2011) demonstrated a clear change in soil properties as a result of installing a sub-surface drainage system. The flow characteristics of the soil profile may change as the soil gets better.

Changes in the chemical properties like electrical conductivity of soil occur as a result of the elimination of oxygen from the rhizosphere caused by waterlogging or flooding (Valente *et al.*, 2012). These changes are linked to physical reactions between the soil and water and also because of biological processes set in motion as a result of excess water or oxygen deficiency (Valente *et* *al.*, 2012). Sahrawat (2015) remarked that soil pH, redox potential and electrical conductivity are the most important chemical changes that occur in flooded or submerged rice soils.

Chang *et al.* (2019) found that, irrigation significantly affected the salinity of the soil. Since paddy rice is farmed in an environment that floods frequently, the majority of conventional water management techniques try to keep the field at a standing depth of water all season long. When irrigation is continuously flooded, water productivity is often low and there is a likelihood of salt buildup depending on the salt concentration of the irrigation water. Drainage is particularly essential in semi-arid and arid areas because it has the leaching capacity to regulate the accumulation of salt in the soil profile and crop root zone.

4.4.2 Effects of Drainage Systems and Different Irrigation Application Depths on Soil Temperature in Irrigated Ecology

The results on the soil temperature as influenced by drainage and different irrigation application depths and their interactions on rice for the two growing seasons are presented in Table 4.22 and Figure 4.15.

Table 4.22: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Soil Temperature

Seasonal Year	WAT	Soil Temperature (^{0}C)															
		Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	D×I_d	P-Value	CV %
2023	6WAT	28	28.6	24.1	26.9	2.69**	0.003	25.7	31.2	34.8	24.8	22.7	22.1	3.80***	<.001	6.580^{ns}	0.326	14.7
	7WAT	29.6	27	25.3	27.3	3.93^{ns}	0.099	28.9	31.4	25.3	25.5	23.5	23.2	5.56**	0.007	9.63^{ns}	0.529	21.2
	8WAT	23.94	29.57	29.91	27.81	0.73***	<.001	33.09	31.19	32.8	23.21	23.11	23.44	1.03***	<.001	1.78***	<.001	3.9
	9WAT	24.53	28.47	24.82	25.95	1.64***	<.001	29.44	28.86	32.62	22.17	21.61	20.94	2.32***	<.001	4.01^{ns}	0.1	9.3
2024	6WAT	31.02	32.17	27.09	30.09	2.85**	0.002	28.74	34.21	37.81	27.79	26.86	25.14	4.03***	<.001	6.98^{ns}	0.304	14
	7WAT	35.48	35.56	31.06	34.03	2.25***	<.001	36.72	37.12	41.96	30.44	29.36	28.6	3.18***	<.001	5.51*	0.042	9.8
	8WAT	29.75	35.52	34.79	33.36	1.63***	<.001	35.74	37.93	39.51	28.7	29.39	28.86	2.31***	<.001	3.99**	0.005	7.2
	9WAT	28.38	34.96	28.51	30.61	0.87***	<.001	33.63	34.18	36.88	28.28	25.49	25.23	1.23***	<.001	2.12***	<.001	4.2

*Where: D x I_d = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$*

Table 4.22 shows the main and interactive effect of drainage and irrigation application depths on soil temperature. It could be observed that in both seasons, the main effects are significantly different ($p<.001$) in all the weeks except for 7 WAT which was not significant ($p>0.05$). The interactive effect in the 2023 growing season did not show significant differences except for 8 WAT which was observed to be significant at $p<.001$. Meanwhile, during the 2024 growing season, all the weeks observed were significant ($p<.001$) except at 6 WAT which had $p>0.05$ (Table 4.22).

Surface drainage in combination with AWD -15 recorded the highest soil temperature of 37.07 ^{0}C, in the 2023 growing season while CF 5-10-15 in combination with no drainage recorded the lowest soil temperature of 20.13 ^{0}C. During the 2024 growing season, AWD-15 in combination with surface drainage recorded the highest soil temperature of 43.07 ^{0}C, while the lowest temperature of 26.33 ^{0}C was recorded in CF-5-10-15 in combination with no drainage (Table 4.22). These results are graphically illustrated in Figure 4.15.

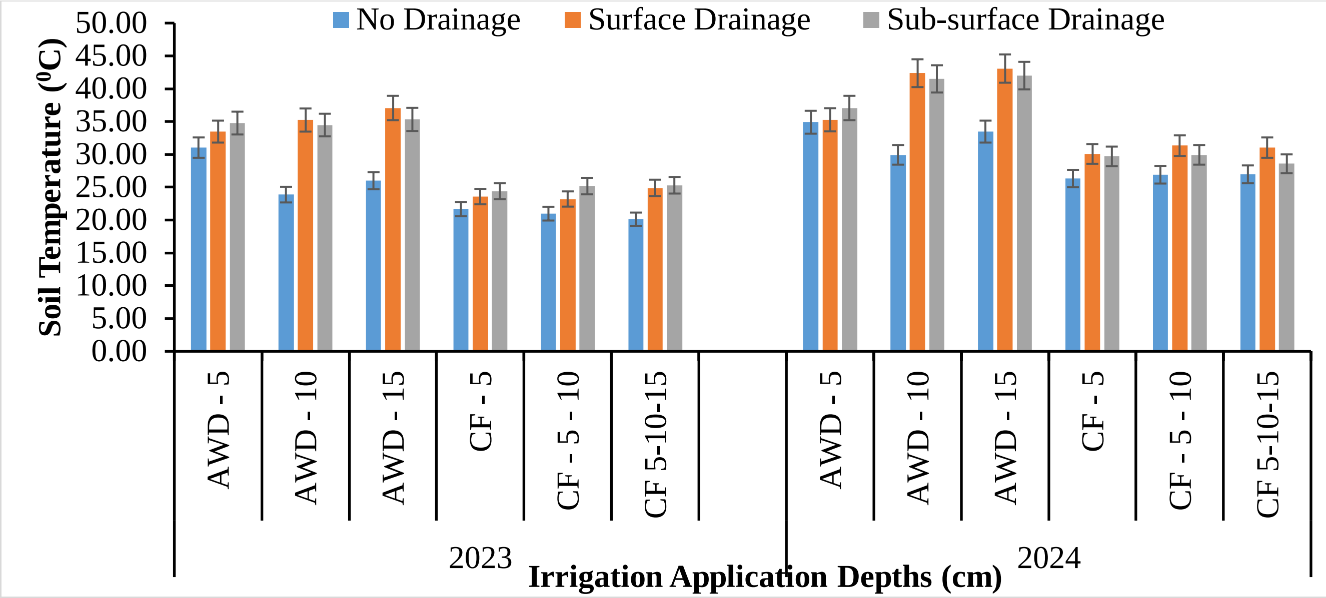


Figure 4.15: Effect of Drainage and Irrigation Application Depths on Soil Temperature at 8 WAT

Table 4.23: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Soil Temperature at 8WAT

		Soil Temperature (⁰C)		
Year	**Treatments**	**No Drainage**	**Surface Drainage**	**Sub-surface Drainage**
2023	AWD – 5	31.03^{f}	33.47^{g}	34.77^{g}
	AWD - 10	23.87^{cd}	35.23^{gh}	34.47^{g}
	AWD - 15	26.00^{e}	37.07^{h}	35.33^{gh}
	CF - 5	21.67^{ab}	23.57^{cd}	24.40^{cde}
	CF - 5 - 10	20.97^{a}	23.20^{bc}	25.17^{cde}
	CF 5-10-15	20.13^{a}	24.90^{cde}	25.30^{de}
2024	AWD - 5	34.90^{de}	35.27^{de}	37.07^{e}
	AWD - 10	29.93^{abc}	42.37^{f}	41.50^{f}
	AWD - 15	33.47^{cde}	43.07^{f}	42.00^{f}
	CF - 5	26.33^{a}	30.07^{abc}	29.70^{abc}
	CF - 5 - 10	26.90^{ab}	31.33^{bcd}	29.93^{abc}
	CF-5-10-15	26.97^{ab}	31.03^{bcd}	28.57^{ab}

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different

Because of the energy balance at the ground surface, the temperature of the soil should closely correspond to the temperature of the air (Staniec and Nowak, 2016). Temperature of the soil is thought to be a major climatic element affecting ecosystem activities, particularly those that occur below the surface. Soil temperature is crucial in supporting decision-making for various activities, including soil respiration, crop production, insect proliferation, germination, pavement design, etc., (Kath and Pembleton, 2019).

Water has a comparatively large heat capacity compared to the low heat capacity of soil particles. This indicates that dry soils may be heated or cooled more quickly than moist ones. Additionally, compared to wetter soils, dry soils typically show greater temperature variations. While the dry heat capacities of sandy and clayey soils are similar, the impact of soil texture on soil water storage means that the texture of the soil has a significant indirect effect on the heat capacity through its influence on the soil moisture state. To put it briefly, soil water is the main factor influencing heat capacity. The soil's capacity to conduct—or transfer—heat is indicated by its thermal conductivity. The thermal conductivity is highly correlated with the heat capacity (Yousefi and Tariku, 2021).

Temperature and water content are two crucial physical aspects of soil that affect plant development. Plant development can be severely inhibited by conditions that are not ideal for temperature and water levels. To promote plant development, field management of soil water and temperature has frequently been done as distinct procedures, using mulching on the soil's surface to regulate temperature and irrigation to manage water. Water has a high heat capacity; hence varying soil water regimes or irrigation techniques will almost certainly result in varying temperatures (El-Beltagi *et al.*, 2022). It is worth noting that during this study, various irrigation application depths influenced soil temperature differently and this might have contributed to the differences in growth and yield components of rice.

Different irrigation techniques can significantly affect the local micro-climate, which includes temperature and humidity and is crucial for plant growth. Soil temperature will always rise in response to a decrease in soil moisture brought on by an increase in surface temperature. The water and energy cycle is significantly influenced by soil moisture (Song *et al.*, 2019).

4.4.3 Effects of Drainage Systems and Different Irrigation Application Depths on Total Nitrogen Balance in Irrigated Ecology

The results on Total Nitrogen as influenced by drainage and different irrigation application depths and their interactions on rice over the two growing seasons are presented in Table 4.24 and Figure 4.16.

Table 4.24: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Total Nitrogen

Seasonal Year	**WAT**	**Total Nitrogen (%)**																
		Treatment Drainage (D)						**Irrigation Application Depth (I_d)**								**Interaction Effect**		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	$D \times I_d$	P-Value	CV %
2023	6WAT	0.053	0.059	0.075	0.063	0.007^{***}	<.001	0.077	0.067	0.054	0.073	0.051	0.055	0.009^{***}	<.001	0.0163^{*}	0.048	15.7
	8WAT	0.105	0.114	0.142	0.12	0.013^{***}	<.001	0.142	0.132	0.105	0.133	0.101	0.109	0.018^{***}	<.001	0.0308^{ns}	0.352	15.4
	10WAT	0.059	0.062	0.07	0.063	0.007^{**}	0.009	0.077	0.069	0.051	0.071	0.055	0.056	0.010^{***}	<.001	0.0178^{ns}	0.575	17
2024	6WAT	0.042	0.043	0.049	0.045	0.004^{***}	<.001	0.048	0.052	0.035	0.052	0.039	0.041	0.005^{***}	<.001	0.009^{***}	<.001	12.1
	8WAT	0.091	0.112	0.126	0.11	0.004^{***}	<.001	0.108	0.137	0.098	0.116	0.096	0.102	0.006^{***}	<.001	0.010^{***}	<.001	5.7
	10WAT	0.057	0.057	0.068	0.061	0.005^{***}	<.001	0.063	0.069	0.056	0.068	0.051	0.056	0.007^{***}	<.001	0.013^{***}	<.001	12.7

*Where: $D \times I_d$ = Combination of drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

Table 4.24 shows the main and interactive effect of drainage and irrigation application depths on soil temperature. The main effects in both seasons were significantly different (p<.001) in all the weeks measured. The interactive effect in the 2023 growing season did not show significant differences except for 6 WAT which was observed to be significant at p<.001. Meanwhile, during the 2024 growing season, all the weeks observed were significant at p<.001 (Table 4.24).

At 6 WAT, sub-surface drainage in combination with AWD -5 recorded the highest soil nitrogen of 0.095 % which has the same value as CF-5 in the 2023 growing season while AWD -15 in combination with no drainage recorded the lowest total nitrogen of 0.038 %. During the 2024 growing season, AWD -10 in combination with sub-surface drainage recorded the highest total nitrogen of 0.064 %, while the lowest (0.064 %) was recorded in CF-5-10-15 in combination with surface drainage (Table 4.24). These results are graphically illustrated in Figure 4.16.

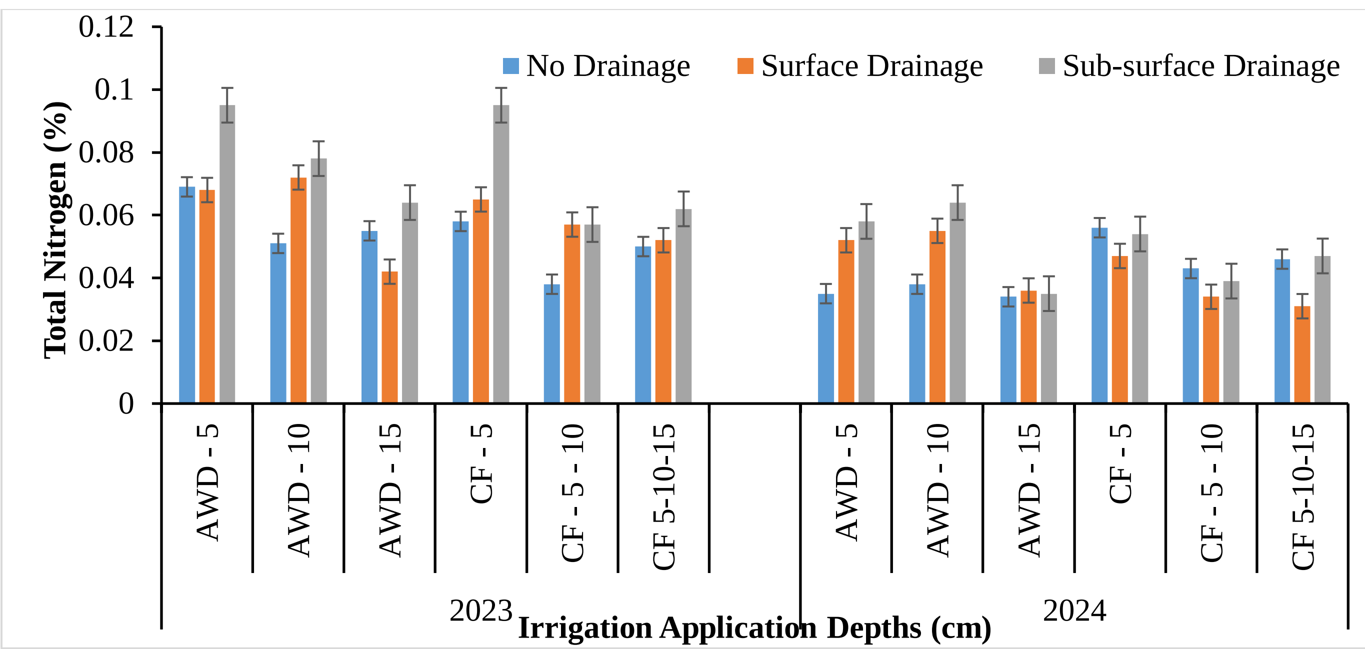


Figure 4.16: Effect of Drainage and Irrigation Application Depths on Total Nitrogen at 6WAT

Table 4.25: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Soil Total Nitrogen at 6WAT

		Soil Temperature (^{0}C)		
Year	**Treatments**	**No Drainage**	**Surface Drainage**	**Sub-surface Drainage**
2023	AWD – 5	0.069[cde]	0.068[cde]	0.095[f]
	AWD - 10	0.051[abc]	0.072[de]	0.078[e]
	AWD - 15	0.055[abcd]	0.042[ab]	0.064[cde]
	CF - 5	0.058[bcd]	0.065[cde]	0.095[f]
	CF - 5 - 10	0.038[a]	0.057[abcd]	0.057[bcd]
	CF-5-10-15	0.050[abc]	0.052[abc]	0.062[cde]
2024	AWD - 5	0.035[ab]	0.052[efg]	0.058[gh]
	AWD - 10	0.038[abcd]	0.055[fgh]	0.064[h]
	AWD - 15	0.034[ab]	0.036[abc]	0.035[ab]
	CF - 5	0.056[fgh]	0.047[def]	0.054[fg]
	CF - 5 - 10	0.043[bcde]	0.034[ab]	0.039[abcd]
	CF-5-10-15	0.046[cdef]	0.031[a]	0.047[def]

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different.

The findings of this study corroborate with Tomer *et al.* (2017) who stated that soils that have poor drainage and are ponded or saturated with water cause denitrification to occur resulting in loss of N as a gas which can result in the emission of potent greenhouse gases, yield reduction, and increased N fertilizer expense. The nitrogen transformations in drained and aerated soils differ significantly from those in submerged soils. These variations have an impact on the microbial activity and dominant soil microorganisms, as well as on N turnover, availability, and losses. Understanding the bio-geochemical conditions present in submerged soils is essential to address the variations in N transformations between drained and submerged soils (Gaydon *et al.*, 2012).

The results of this study are further explained by Parit *et al.* (2020) who stated that, one distinct characteristic of submerged soils that influences nitrogen conversions is the oxygen deficiency in most of the root zone. Because they have evolved gas exchange mechanisms, plants suited for submerged soils allow gases, including oxygen, to enter the root zone through the emergent portions of the plant. Aerenchyma tissue, which is porous inside, transports oxygen to the roots of many of these plants, including rice, where the majority of the oxygen is used up in root respiration. Reduced components are oxidized by some of the oxygen that reaches the roots and seeps into the surrounding soil. As a result, there is a significantly larger anaerobic soil zone around the small aerobic zone (Takahashi *et al.,* 2014).

The types of nitrogen found in submerged soils are mostly comparable to those found in aerated soils; however, the oxidation status of the soil has a significant impact on the relative amounts of the N forms, especially nitrate and ammonium, as well as N transformation. In drained, aerated soils, nitrate is the predominant form of inorganic nitrogen; in submerged soils, $NH4^+$ is the major and stable form of inorganic nitrogen that accumulates. This nitrate might build up since it is not easily denitrified in the aerated soil. Ammonium does not become nitrate in the anaerobic zone of submerged soils. Similar to aerated soils, the primary nitrogen transformation processes in submerged soils include biological N_2 fixation, mineralization, immobilization, nitrification, denitrification, and ammonia (NH_3) volatilization (Beeckman *et al.,* 2018). These processes are altered by soil submergence, and one distinctive characteristic of submerged soils is the simultaneous production and loss of NO_3^-, which takes place in the adjacent aerobic and anaerobic soil zones. Compared to aerated soils, submerged soils provide ideal conditions for N loss by nitrification, denitrification, and NH_3 volatilization (Buresh *et al.,* 2015; Marschner, 2021).

One nutrient that is necessary for plant development is nitrogen. Soil bacteria must transform nitrogen into forms that the roots can absorb in order for plants to use it. But in rare cases, especially when the soil is extremely flooded, nitrogen can be highly mobile in the soil and easily lost. The kind of soil and the length of time the soil is soaked determine how nitrogen is lost during a flood. The most leaching-prone type of nitrogen is nitrate (NO_3). After the application of inorganic fertilizers, especially those containing nitrate, nitrate nitrogen losses by leaching can be substantial (Zhu *et al.*, 2023).

When higher soil temperatures are experienced, losses of N can be severe, increasing soil microbial activity and decomposition of plant residues and soil organic matter which releases nitrate (mineralization). Long-term waterlogging reduces the soil's ability to absorb oxygen and increases the risk of denitrification, which depletes nitrogen (Wang *et al.*, 2021). Although aerobic microbes are in charge of converting nitrogen, they also require oxygen to exist. Therefore, under wet conditions, soil nitrogen is transformed into its gas forms by anaerobic bacteria — microbes that do not require oxygen — which are then expelled from the soil and become unavailable for plant absorption. In flooded rice systems, nitrogen (N) fertilizer is applied to boost grain yield, but the rice crop will not absorb all of the N (Zou *et al.*, 2023). Up to 50 % of the total nitrogen applied can be lost in flooded rice systems. This can happen through a number of processes, including nitrogen oxide (NO_x) emissions from simultaneous nitrification and denitrification, ammonia (NH_3) volatilization, and N leaching (Zou *et al.*, 2023).

However, the findings of this study on total nitrogen conforms with those of Buri *et al.*, (2012) who indicated that, the savannah zones show much lower levels of total nitrogen with much lower variability compared to other ecological zones with Ghana.

4.5 Effects of Drainage Systems and Different Irrigation Application Depths on Crop Water Stress Index of Rice

4.5.1 Maximum Water Stress Baseline (MWSB) and Non-Water Stress Baseline (NWSB)

The baseline regression equations were developed for panicle initiation and complete heading stages of rice during both seasons. In the 2023 growing season, the lower limit (LL) baseline was developed from plots with higher irrigation application depths (CF-5 - 10 - 15) and the regression equation was developed following the Idso's empirical approach and given as T_c-T_a= -1.2213(VPD) + 0.8881 with a coefficient of determination (R^2) of 0.82 (Figure 4.17). The upper limit (UL) baseline was developed from plots with maximum stressed conditions (AWD - 15). The regression equation yielded a relationship given as T_c - T_a= -1.4295(VPD) + 8.008 with a coefficient of determination (R^2) of 0.83 (Figure 4.18).

During the 2024 growing season, the lower limit baseline produced a regression equation of T_c-T_a= - 0.9035(VPD) - 3.1642 and a coefficient of determination (R^2) of 0.80 (Figure 4.17). The upper limit yielded a relationship given as T_c-T_a= - 1.5451(VPD) + 11.635 with a coefficient of determination of 0.89 (Figure 4.18).

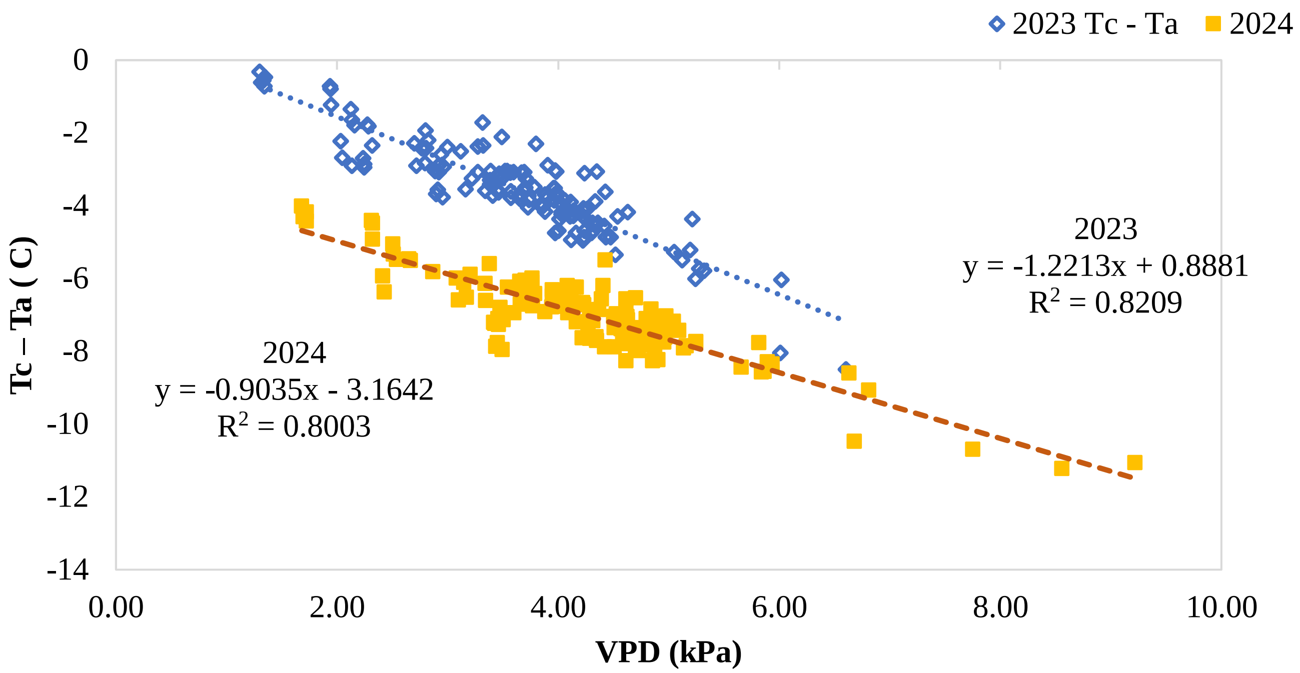


Figure 4.17: Non-Water Stressed Baseline for the Lower Limit (LL) for 2023 and 2024 Growing Seasons

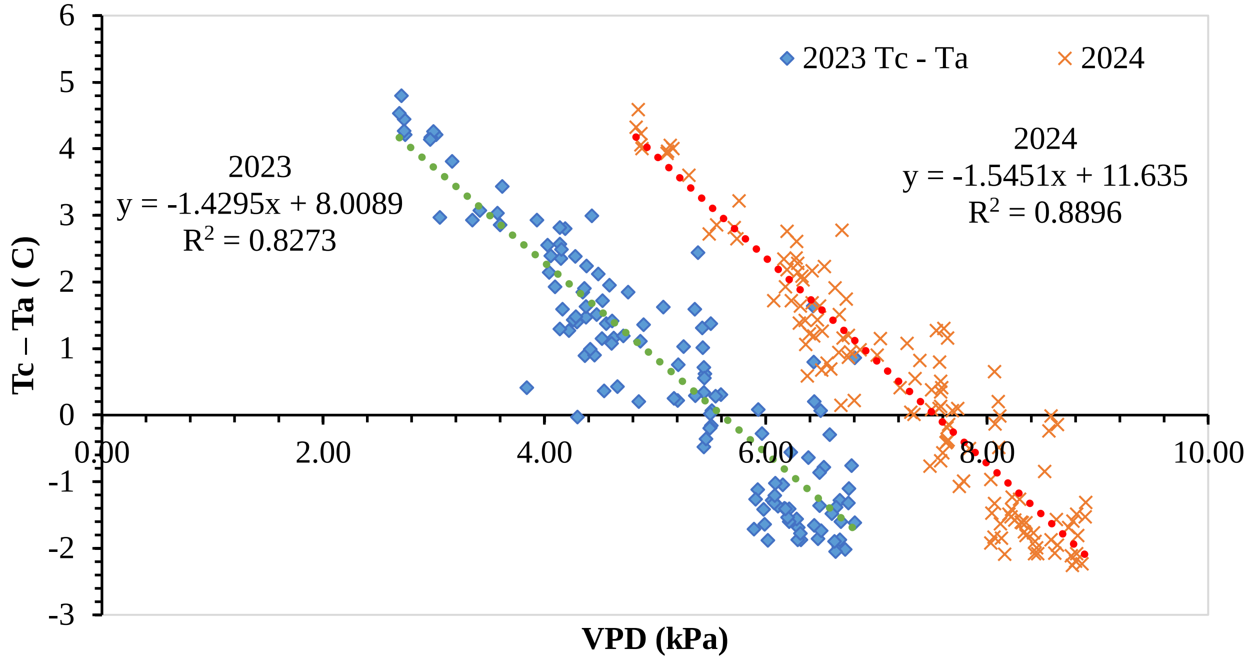


Figure 4.18: Maximum-Water Stressed Baseline for the Upper Limit (UL) for 2023 and 2024 Growing Seasons

Variations in canopy and ambient temperatures were observed during different phenological stages. This revealed significant fluctuations in environmental conditions throughout the crop cycle. This was attributed to the occurrence of rainfall which resulted to a decline in temperatures during certain days preceding monitoring as well as being influenced by the irrigation application depths of certain plots. Conversely, increase in crop temperatures were observed during the panicle initiation stage and this can be connected to the sensitivity of rice plants to water stress during this stage. Panicle initiation in rice was observed to be delayed by water stress due to reduced transpiration process resulting to higher temperatures (Sarma *et al.,* 2023).

According to Moonmoon and Islam (2017), rice is particularly vulnerable to water stress during the reproductive stage, which dramatically lowers grain output by lowering the quantity of entire grains and spikelets per panicle. During the reproductive stage, when rice plants grow male and female gametophytes, anthesis, pollination, and fertilization, they are more susceptible to heat stress than they are during the vegetative stage (Jagadish *et al.*, 2015; Arshad *et al.*, 2017). Heat-stressed plants undergo a reduction in non-structural carbohydrates, smaller glumes, and underdeveloped vascular bundles during the panicle-initiation stage, which eventually results in a loss in grain weight (Wu and Yang, 2019).

4.5.2 Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Crop Water Stress Index of Rice

The results on the crop water stress index as influenced by drainage and different irrigation application depths and their interactions on rice over the two growing seasons are presented in Table 4.26 and Figure 4.19.

Table 4.26: Effects of Drainage Systems and Different Irrigation Application Depths and their Interaction on Crop Water Stress Index

Seasonal Year	WAT	Crop Water Stress Index																
		Treatment Drainage (D)						Irrigation Application Depth (I_d)								Interaction Effect		
		No Drainage	Surface Drainage	Sub-surface	Grand mean	LSD (0.05)	P-Value	AWD @ -5	AWD @ -10	AWD @ -15	CF -5	CF-5-10	CF-5-10-15	LSD (0.05)	P-Value	$D \times I_d$	P-Value	CV %
2023	4WAT	0.41	0.37	0.25	0.34	0.06^{***}	<.001	0.4	0.51	0.69	0.2	0.13	0.12	0.091^{***}	<.001	0.158^{ns}	0.755	27.8
	8WAT	0.33	0.47	0.24	0.35	0.05^{***}	<.001	0.33	0.51	0.67	0.22	0.23	0.14	0.07^{***}	<.001	0.115^{**}	0.006	19.7
	10WAT	0.45	0.35	0.44	0.41	0.06^{**}	0.005	0.46	0.55	0.74	0.35	0.25	0.13	0.08^{***}	<.001	0.144^{*}	0.037	21.1
2024	4WAT	0.54	0.5	0.35	0.46	0.02^{***}	<.001	0.54	0.62	0.74	0.33	0.26	0.28	0.03^{***}	<.001	0.04^{***}	<.001	5.4
	8WAT	0.56	0.55	0.4	0.56	0.02^{***}	<.001	0.56	0.81	0.66	0.37	0.35	0.28	0.03^{***}	<.001	0.05^{***}	<.001	5.7
	10WAT	0.57	0.07	0.44	0.53	0.05^{***}	<.001	0.6	0.66	0.8	0.38	0.4	0.32	0.07^{***}	<.001	0.121^{*}	0.014	13.8

*Where: $D \times I_d$ = Combination of Drainage and irrigation application depth, CV= Coefficient of Variation, P. value = Probability value, LSD = Least Significance Difference of means at 95% confidence level, WAT = Weeks After Transplanting, * = significantly different at $P \leq 0.05$, ** = significantly different at $P \leq 0.01$., *** = significantly different at $P \leq 0.001$.*

Table 4.26 shows the effect of drainage systems and different irrigation application depths on CWSI for rice. The results indicated no interaction (P = 0.755) between drainage systems and irrigation application depths at 6 WAT (that is, panicle initiation phase) but during 2024, interaction effect was significant at p< .001. However, individual treatments for irrigation (p< .001) and drainage (p< .001) were significantly different from each other. During complete heading, there was significant interaction effect of drainage and irrigation application depths (D×I) on CWSI at 8 WAT with p=0.006 and p< .001 for 2023 and 2024 seasons respectively (Table 4.26).

At 8 WAT, surface drainage in combination with AWD -15 recorded the highest CWSI of 0.831 while CF 5-10 in combination with sub-surface drainage recorded the lowest CWSI 0.075 in the 2023 growing season. During the 2024 growing season, AWD -15 in combination with no drainage recorded the highest CWSI of 0.857, while the lowest (0.143) was recorded in CF-5-10-15 in combination with sub-surface drainage (Table 4.27). These results are graphically illustrated in Figure 4.18.

Table 4.27: Duncan's Multiple Range Test on the Interactive Effect of Drainage Systems and Different Irrigation Application Depths on Crop Water Stress Index at 8WAT

		Crop Water Stress Index		
Year	**Treatments**	**No Drainage**	**Surface Drainage**	**Sub-surface Drainage**
2023	AWD – 5	0.293^{cde}	0.450^{fgh}	0.237^{cd}
	AWD - 10	0.478^{gh}	0.727^{j}	0.333^{def}
	AWD - 15	0.610^{i}	0.831^{j}	0.566^{hi}
	CF - 5	0.236^{cd}	0.263^{cd}	0.174^{abc}
	CF - 5 - 10	0.207^{bcd}	0.412^{efg}	0.075^{a}
	CF-5-10-15	0.180^{abc}	0.163^{abc}	0.083^{ab}
	LSD $_{(0.05)}$	0.115		
	P-Value	0.006		
2024	AWD - 5	0.553^{g}	0.630^{h}	0.500^{ef}
	AWD - 10	0.750^{j}	0.690^{i}	0.533^{fg}
	AWD - 15	0.857^{k}	0.817^{k}	0.747^{j}
	CF - 5	0.357^{c}	0.473^{de}	0.287^{b}
	CF - 5 - 10	0.427^{d}	0.440^{d}	0.173^{a}
	CF-5-10-15	0.427^{d}	0.273^{b}	0.143^{a}
	LSD $_{(0.05)}$	0.047		
	P-Value	<.001		

LSD; Least Significance Difference of means at 95% confidence level, P. value=Probability value. Values with the same letter are not significantly different

The irrigation method known as alternate wetting and drying (AWD) has a direct impact on the temperature of the soil, and it was expected that different levels of water stress would elicit a response. As a result, the highest crop temperature (Tc) values were recorded with AWD -15, while the lowest value was observed with continuous flooding (CF-5 - 10 -15). Furthermore, the values of the crop water stress index (CWSI) exhibited variations ranging from 0 to 1. When the rice plants were reaching complete heading stage, CWSI values remained high (0.2 and 1), indicating water stress.

The findings agree with Katimbo *et al.* (2022) who when calculating daily CWSI found out that CWSI varied for all treatments under different water sufficiency levels during the growing season.

Such differences depict the influence of moisture availability on managing water stress in the treatments.

4.5.3 Relationship Between Irrigation Application Depths and Crop Water Stress Index of Rice

Figure 4.18 shows a relationship between irrigation application depths and CWSI. The Irrigation application depths in Figure 4.18 corresponds to the following:1 = AWD-15; 2 = AWD-10; 3 = AWD-5; 4 = CF 5; 5 = CF 5-10 and 6 = CF-5-10-15. Irrigation methods have a direct impact on the temperature of crops and it was expected that different levels of irrigation would elicit a response. As a result in 2023, the highest CWSI (0.74) was recorded on AWD-15 while the lowest value (0.12) was observed in the CF-5-10-15. In 2024, the highest (0.81) CWSI was recorded on AWD -15 while the lowest (0.26) was observed in CF-5-10. CWSI and irrigation application depths produced a strong linear relationship in both seasons. In 2023, it gave a regression model of y = - 0.1191x + 0.7587 and a coefficient of determination (R^2) value of 0.987 while in 2024, a regression model of y = - 0.0969x + 0.8673, where (x) represents the irrigation application depths.

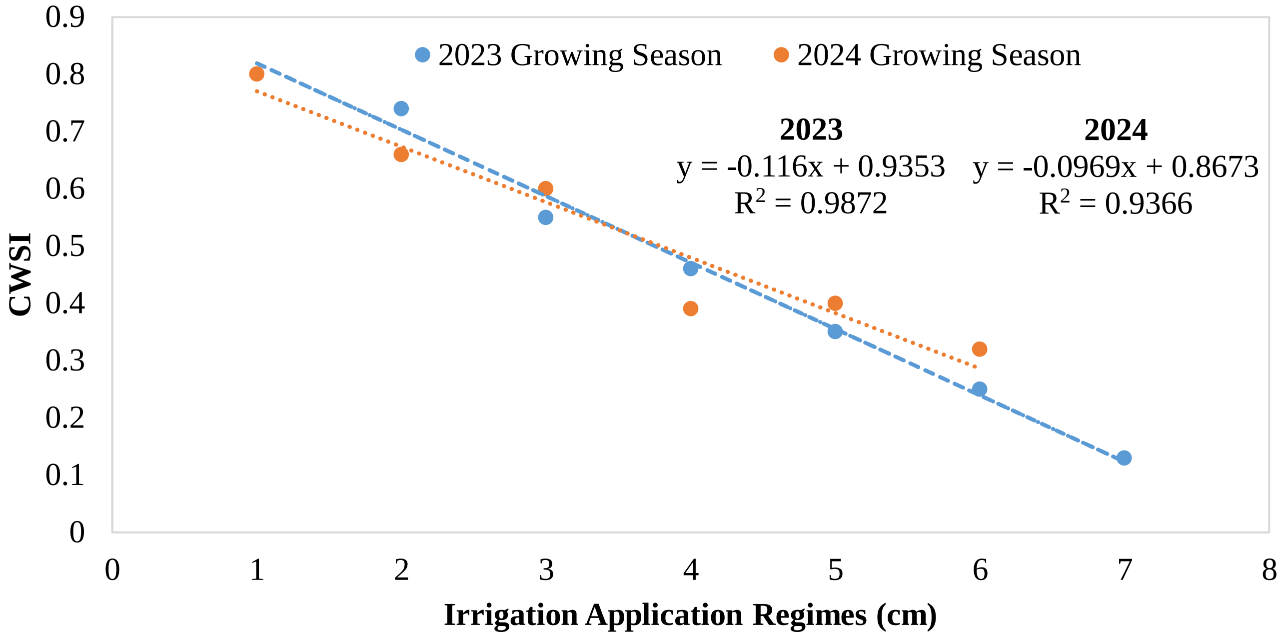


Figure 4.19: Crop Water Stress Index (CWSI) as a Function of Irrigation Application Depths for 2023 and 2024 Growing Seasons

The findings of this study are in line with those of Konate *et al.* (2021) who conducted an experiment using flooding and AWD in a semi-arid environment to compute CWSI values for rice. They used vapour pressure deficit (VPD) versus temperature differentials (T_c - T_a) technique during their computation. Their result showed CWSI values of 0.2 - 0.768 for rice. Similar works were carried out by Visitacion *et al.* (2022) and Godson-Amamoo *et al.* (2022) who recorded similar values of 0.025 - 1 and 0.015 - 0.349 respectively.

4.5.4 Relationship between Crop Water Stress Index (CWSI) and Rice Yield as Affected by Irrigation Application Depths

The relationship between yield (t ha^{-1}) and the seasonal mean CWSI values was linear. This relationship indicated that the CWSI and yield of rice are inversely proportional to each other, meaning that the yield of rice will decrease with an increase in the CWSI. A simple regression model was produced and given as; y= - 12.548x + 12.411 with an R^2 = 0.96 in the 2023 growing season. Meanwhile, in the 2024 growing season, a simple regression model; y= - 7.4943x + 7.6035 with an R^2 = 0.98 was produced (Figure 4.20). In both seasons, the R^2 values showed an indication of a strong correlation between crop water stress and rice yield. When the CWSI was at its lowest point, rice yield reached its maximum level. The yield potential of rice can be predicted using this relationship. An analysis comparing crop yield and irrigation management is important for the efficient use of local resources (Fan and Schütze, 2024).

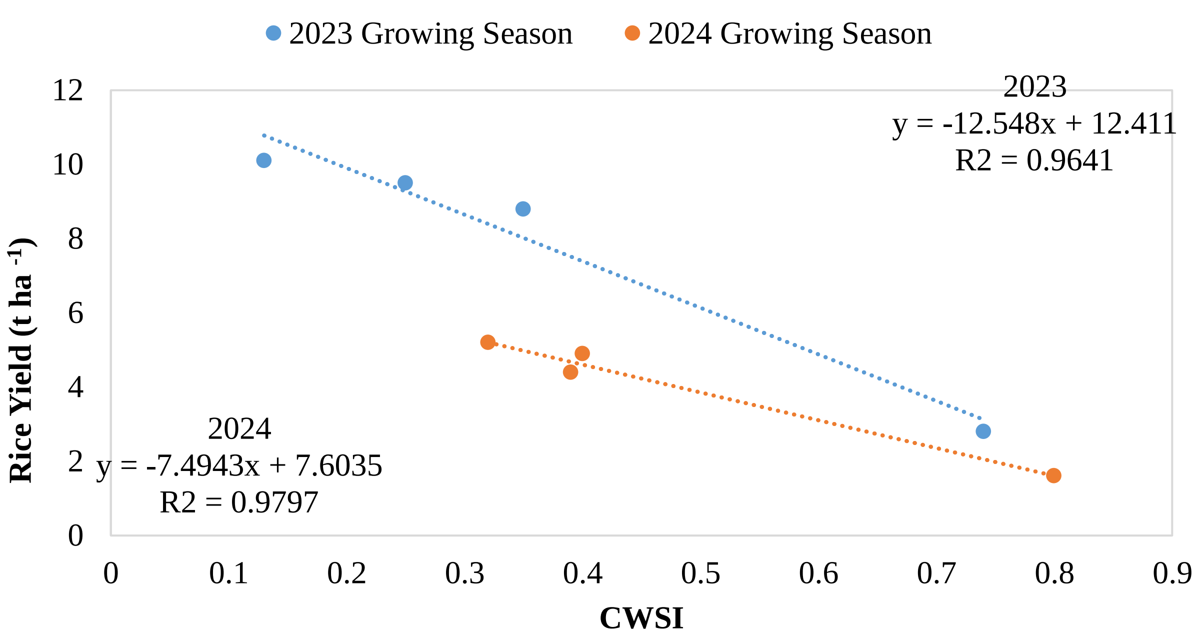


Figure 4.20: Rice Yield as a Function of Crop Water Stress Index (CWSI) for 2023 and 2024 Growing Seasons.

According to Saddiq *et al.* (2021), grain yield is significantly influenced by the timing of water stress. According to their study, the rice yield per hectare decreased by 39.79 % as a result of the water stress that was created during panicle initiation, while reductions of 24.11 and 11.72 % were noted at flowering and grain filling, respectively. Additionally, Thakur *et al.* (2014) observed that drought stress during the reproductive development stage resulted in a 29 –78 % drop in rice grain output. Visitacion *et al.* (2022) stated that even a brief period of dryness during the flowering stage of rice crops can eventually lead to complete sterility of the spikelets and ultimately result in a very large yield drop for crops receiving severe water stress treatment. Several researchers have noted a strong relationship between grain yield and the irrigation application depth (Liao *et al.*, 2008; Mehmood *et al.,* 2023).

4.6 Model Calibration and Validation on the Effect of Irrigation Application Depths on Leaf Area Index of Rice

The CSM-CERES-Rice model was calibrated with experimental data collected during the 2023 rice cropping season to simulate the effect of irrigation water depths on the performance of AGRA Rice variety.

The experimental files created for purposes of calibration and validating the model included the A-File which contains performance data like grain yield, maximum leaf area (LAI), anthesis and maturity dates, etc., T-File contains time course data like periodic LAI, dry matter, leaf weight, stem weight, etc. The genetic coefficient (GC) of rice was parameterized using that of Basmati rice already calibrated and embedded in the DSSAT model. Recalibration of the GC of Basmati rice was done using observed data on the phenological growth parameters such as days to anthesis, days to emergence and days to physiological maturity. The success of the recalibration was aided by the Generalized Likelihood Uncertainty Estimator (GLUE) Utility which uses a pseudo-Baysian method for estimating the values of genetic coefficient. These values were used for model simulation for AGRA rice cultivar using CSM CERES- Rice model. The genetic coefficients for AGRA rice derived from the recalibrated GC of Basmati rice are presented in Table 4.28.

4.6.1 Genetic Coefficients (GC) for AGRA Rice

Table 4.28: Genetic coefficients of AGRA Rice cultivar

Coefficient	Definition	Basmati Rice	AGRA Rice
P1	Time period (expressed as growing degree days [GDD] in ºC - d above a base temperature of 9 ºC) from seedling emergence during which the rice plant is not responsive to changes in photoperiod. This period is also referred to as the basic vegetative phase of the plant.	498.3	615.30
P2R	Extent to which phasic development leading to panicle initiation is delayed (expressed as GDD in ºC-d) for each hour increase in photoperiod above P2O.	130.1	26.40
P5	Time period in GDD ºC-d) from beginning of grain filling (3 to 4 days after flowering) to physiological maturity with a base temperature of 9 ºC.	420.0	443.90
P20	Critical photoperiod or the longest day length (in hours) at which the development occurs at a maximum rate. At values higher than P2O developmental rate is slowed, hence there is delay due to longer day lengths.	12.9	11.70
G1	Potential spikelet number coefficient as estimated from the number of spikelets per gram of main culm dry weight (less leaf blades and sheaths plus spikes) at anthesis.	74.76	62.72
G2	Single grain weight (g) under ideal growing conditions, i.e. non-limiting light, water, nutrients, and absence of pests and diseases.	0.022	0.024
G3	Tillering coefficient (scalar value) relative to IR64 cultivar under ideal conditions.	0.53	0.71
PHINT	Phyllochron Interval (ºC-d). Time interval in degree-days for each leaf-tip to appear under non-stressed conditions.	83.0	83.0
THOT	Temperature (ºC) above which spikelet sterility is affected by high temperature.	30.9	31.40
TCLDP	Temperature (ºC) below which panicle initiation is further delayed (other than P1, P2O and P2R) by low temperature.	15	15
TCLDF	Temperature (ºC) below which spikelet sterility is affected by low temperature.	15	15

4.6.2 Test Statistics on the Calibrated CSM CERES-RICE Model of DSSAT

For testing the capability of CERES-RICE model in simulating the response of rice to different irrigation water depths, a comparison between predicted and measured variables was performed for treatments presenting the optimum growing conditions for rice. The model calibration was done using observed data on maximum leaf area index for the 2023 growing season from optimum irrigation condition (CF 5) under no drainage condition as illustrated in Figures 4.21 and 4.22.

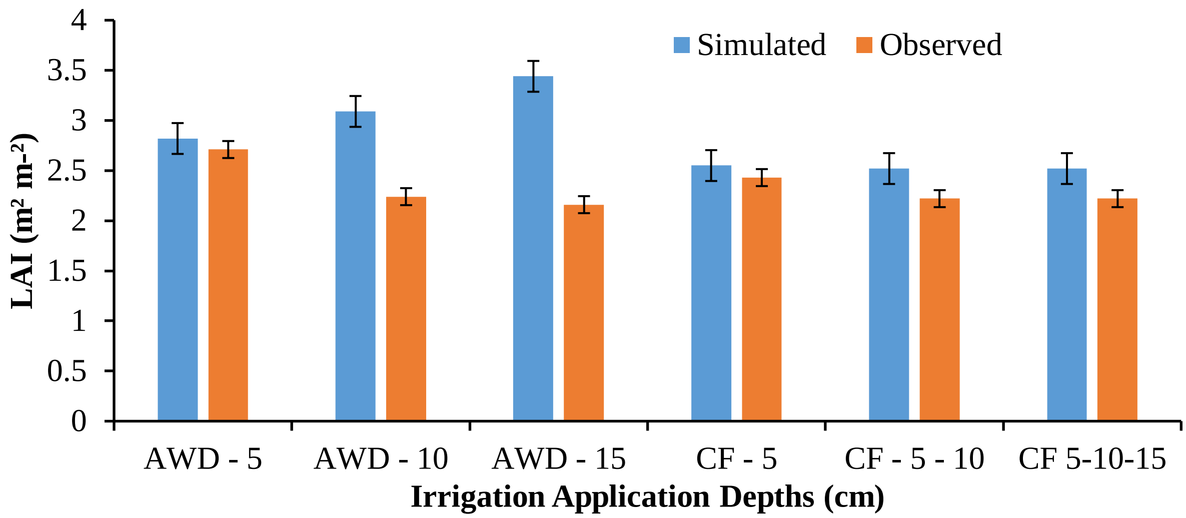


Figure 4.21: Measured and Predicted Maximum Leaf Area Index as influenced by Irrigation Application Depths under No Drainage Condition

The observed simulations showed more accurate results as presented in Table 4.29 and 4.30 for CF-5 with no drainage (d-stat = 0.92 and R^2 =0.93). After calibration of the model, comparison was made between simulated and observed grain yield as presented in Table 4.31. Though there is a drainage component in the DSSAT model under the field details, this was not sensitive during the simulation process as the simulated results for the yield was same for the different drainage systems under different irrigation application depths. Hence, the outputs of the model were based on the different irrigation application depths. Moreover, the model performed better in terms of simulated and observed yield on treatments with AWD -5, AWD -10, CF-5 and CF-5-10 for no drainage and surface drainage while it did not perform well as the depletion level went to 15 cm. Also, the model showed poor performance as the level of irrigation application depths increased to CF 5-10-15. The regression analysis of the yield produced a regression equation y = - 0.242x + 6182.2 with a coefficient of determination (R^2) value of 0.654 (Figure 4.23). In general, the results from the model validation indicated that CERES rice version 4.8 was able to predict growth and development for AGRA rice variety using different irrigation application depths in a good manner and therefore can be used for further evaluation.

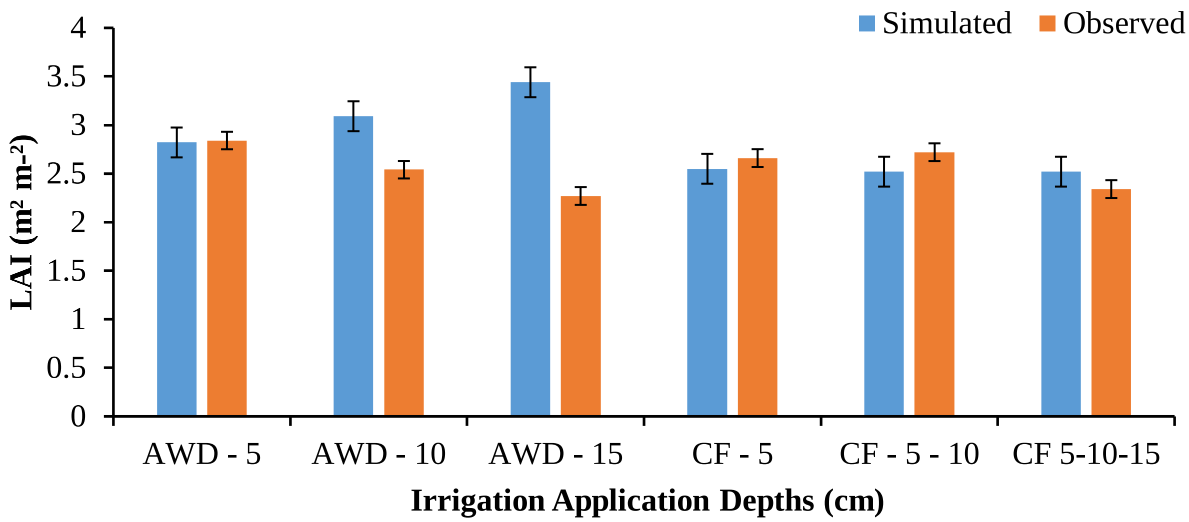


Figure 4.22: Measured and Predicted Maximum Leaf Area Index as influenced by Irrigation Application Depths under Surface Drainage Condition.

Table 4.29: Statistics for Measured and Predicted Maximum Leaf Area Index as Influenced by Irrigation Depths under No Drainage and Surface Drainage Conditions

Treatment	Yield (kg/ha)					
	No Drainage			Surface Drainage		
	R	RMSE	d-Stat	R	RMSE	d-Stat
AWD -5	0.94	0.25	0.96	0.96	0.43	0.89
AWD -10	0.94	0.37	0.91	0.85	0.45	0.84
AWD -15	0.94	0.88	0.72	0.95	0.69	0.78
CF-5	0.92	0.31	0.93	0.73	0.76	0.68
CF-5-10	0.85	0.39	0.87	0.73	0.76	0.77
CF-5-10-15	0.71	0.34	0.90	0.78	0.63	0.80

Table 4.30: Simulation on the Effect of Irrigation Application Depths on Yield of Rice for the 2024 Growing Season

Treatment	Yield (kg/ha)					
	No Drainage		Surface Drainage		Sub-surface Drainage	
	Simulated	Observed	Simulated	Observed	Simulated	Observed
AWD -5	5050	4500	5050	2667	5050	4433
AWD -10	5447	2300	5447	2133	5447	4067
AWD -15	6340	1500	6340	1233	6340	2100
CF-5	4633	4767	4633	4500	4633	8500
CF-5-10	4610	5400	4610	4533	4610	7967
CF-5-10-15	4605	5333	4605	6500	4605	7000

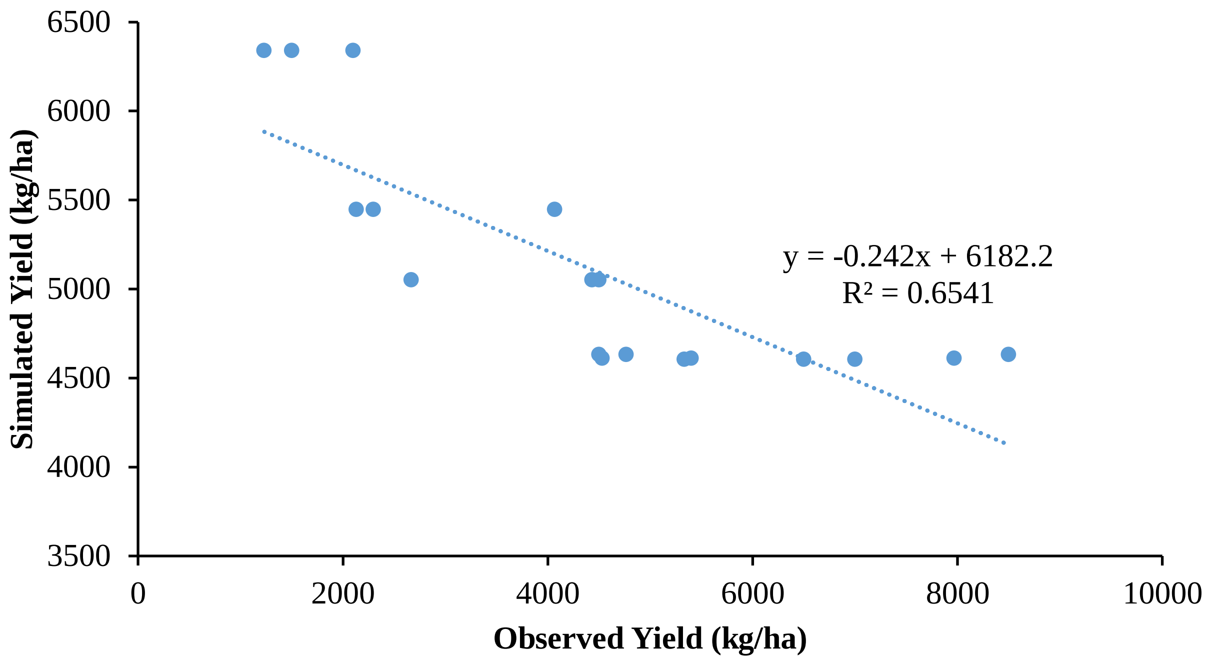


Figure 4.23: Measured and Predicted Yield as influenced by Irrigation Application Depths during the 2023 Growing Season

Lubbock and Lopez (2021) noted that model calibration involves fine-tuning genotype-specific parameters to ensure that simulated results closely match field data observations and the accuracy in simulation of yield, phenology and growth needs the appropriate coefficient. However, Zaki and Radwan (2022) noted that these genetic coefficients may vary due to variation in the developmental rate at different phases of each cultivar.

4.6.3 Model Evaluation Statistics

DSSAT Model can be used to assist both in strategic decision making, such as planning for climate change or to avoid salinization, yield forecasting and planning for national food requirements and in tactical decision making such as irrigation scheduling and fertilizer and pest management. The prediction of CERES-Rice model on leaf area index and rice yield on the different irrigation application depths and drainage systems was generally very good. The evaluation statistics used (coefficient of determination - R^2, Wilmotts D-index of agreement and the root mean squared error - RMSE) suggested that the performance of the model was very good and can be accepted for the prediction of leaf area index as influenced by different irrigation application depths. Notably, R^2 for no-drainage condition ranged from 0.81 – 0.97, RMSE ranged from 0.11 – 1.72 and D-index ranged from 0.31 – 0.98. The continuous flooding at irrigation water depth of 5 cm (CF 5) gave the highest Willmot's d-index of agreement of 0.98 while the lowest d-index was recorded on treatment AWD -15. Under surface drainage condition, the highest d-index was recorded at CF 5-10 while the lowest was recorded in AWD -15 (Table 4.31). This imply that, the model is perfect in simulating the performance of rice under optimum soil water conditions influenced by the high frequency of irrigations associated with the 5 – 10 cm irrigation depths.

Table 4.31: Model Evaluation on the Effect of Irrigation Application Depths on Leaf Area Index of Rice for the 2024 Growing Season

Treatment	Evaluation Statistics				
	Simulated	Observed	R^2	d-stat	RMSE
No Drainage					
AWD -5	2.51	1.77	0.81	0.68	0.66
AWD -10	2.62	1.60	0.96	0.64	0.81
AWD -15	3.53	1.14	0.97	0.31	1.72
CF-5	1.89	1.94	0.92	0.98	0.11
CF-5-10	1.83	1.80	0.96	0.96	0.16
CF-5-10-15	1.83	1.85	0.92	0.97	0.12
Surface Drainage					
AWD -5	2.51	2.03	0.99	0.89	0.43
AWD -10	2.62	1.78	0.93	0.71	0.76
AWD -15	3.53	1.03	0.95	0.28	1.75
CF-5	1.89	2.37	0.85	0.86	0.33
CF-5-10	1.83	2.09	0.97	0.95	0.19
CF-5-10-15	1.83	2.47	0.90	0.78	0.44
Sub-surface Drainage					
AWD -5	2.51	2.53	0.96	0.90	0.34
AWD -10	2.62	2.27	0.85	0.91	0.37
AWD -15	3.53	1.69	0.71	0.43	1.34
CF-5	1.89	2.91	0.72	0.37	1.07
CF-5-10	1.83	2.95	0.78	0.37	1.12
CF-5-10-15	1.83	2.88	0.53	0.31	1.13

Where; RMSE= Root Mean Square Error, D=Willmott's d-index of agreement, R^2=Coefficient of determination.

Table 4.32: Model Evaluation on the Effect of Irrigation Application Depths on Yield of Rice for the 2024 Growing Season

Treatmemt	Yield (kg/ha)					
	No Drainage		Surface Drainage		Sub-surface Drainage	
	Simulated	Observed	Simulated	Observed	Simulated	Observed
AWD -5	5163	3033	5163	3500	5163	3900
AWD -10	5441	1533	5441	2100	5441	2933
AWD -15	6503	1267	6503	1167	6503	2267
CF-5	3506	3300	3506	4767	3506	5100
CF-5-10	3377	3567	3377	4333	3377	6600
CF-5-10-15	3377	3333	3377	5267	3377	6767

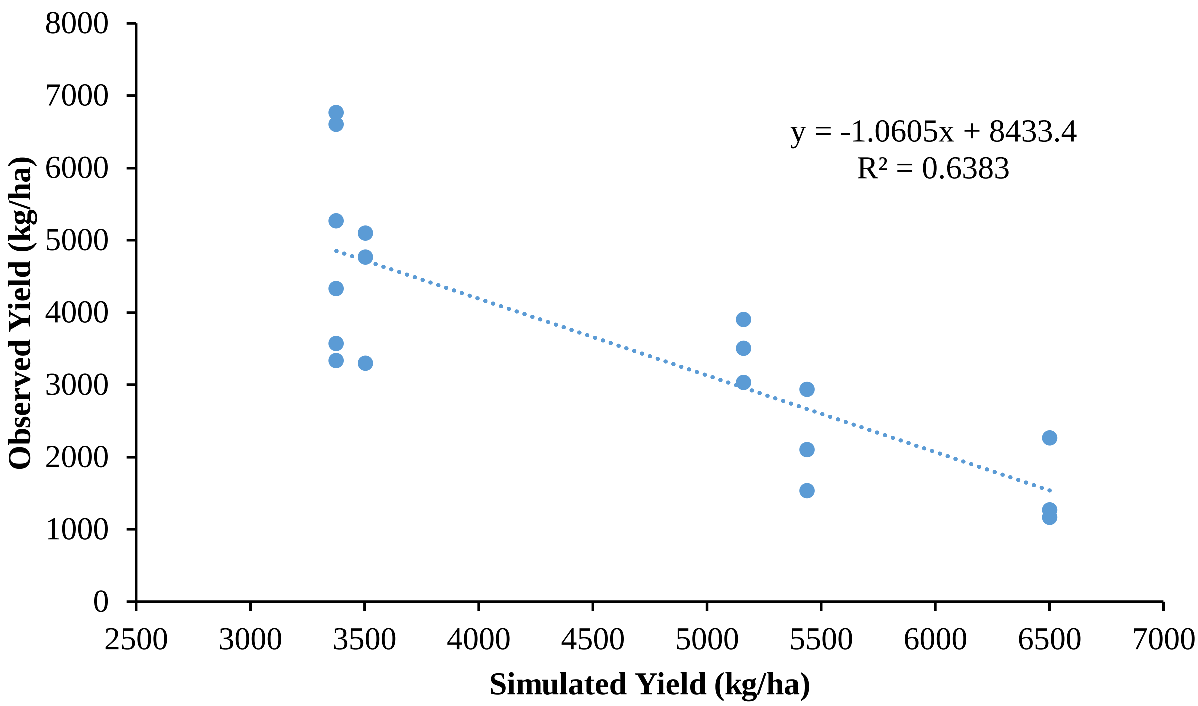


Figure 4.24: Measured and Predicted Yield as influenced by Irrigation Application Depths during the 2023 Growing Season

The evaluation of the model using the yield data gave an R^2 value of 0.64. DSSAT model like any other model may overestimate or underestimate values depending on factors such as treatment combinations, soil, weather and management data. Sar and Mahdi (2017) for instance indicated that over a 6-year simulation process, DSSAT overestimated the grain yield in all the years of simulation except for two years (2009 and 2013), where model underestimated yield in agro-climatic zone of Bihar. In fact, this study provides an insight into the complex issue of evaluation and model performance.

Evaluation results indicated that the model provided useful information for the studied treatments. The model was effectively able to predict the yield of especially the treatments AWD -5, AWD -10, CF-5 and CF-5-10. The results are supported by the findings of Elgadi (2019) as the model was able to able to simulate the yield. Vilayvong *et al.* (2015) also found that CSM–CERES–Rice adequately accounted for predicting yields for some treatments but simulated fairly good for others. This, however, could be used to define suitable management practices for improved rice production.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In this study, a field experiment was conducted during 2023 and 2024 growing seasons to investigate the effect of drainage systems and different irrigation application depths on the performance of rice in the Guinea Savannah ecological zone of Ghana. The following conclusions were made under this study.

5.1.1 Growth, Yield and Irrigation Water Use Efficiency of Rice

Growth and yield parameters such as plant height, leaf area index, leaf chlorophyll content, tiller count, canopy cover, number of panicles, panicle length, filled grains per panicle, 1000-grains weight and yield were affected by the different treatments. Sub-surface drainage produced the tallest plant, highest leaf area index and chlorophyll content, highest mean tiller count, highest canopy cover and number of panicles. In terms of yield, sub-surface drainage with CF-5 and CF-5-10-15 produced the highest yield. With regards to irrigation water use efficiency, AWD -5 produced the highest IWUE under sub-surface drainage system. CF 5-10-15 produced the lowest IWUE. Growth, yield and IWUE responded well to drainage conditions than no drainage conditions. AWD -5 responded very well in terms of water saving but extending to AWD -15 compromised the yield greatly. When increasing the severity of water saving efforts, negative effects of yield emerged and became increasingly pronounced.

5.1.2 Soil Electrical Conductivity, Soil Temperature and Nitrogen Balance in Irrigated Ecology

Results of soil analysis revealed that electrical conductivity was within the threshold for rice cultivation. However, sub-surface drainage was able to control electrical conductivity of the soil than surface and no drainage conditions. Sub-surface drainage can be used as an effective technique for the control of salinity and the improvement of saline soils and should be utilized as a strategy to address salinity threats in schemes with high salinity index.

Soil temperature decreased with an increase in the irrigation application depths. The severely stressed (AWD – 15) in combination with surface drainage gave the highest soil temperature. During this study, various irrigation application depths influenced the soil temperature of the experimental units differently and thus, contributed to the differences in growth and yield performance of rice.

Total nitrogen content of the soil varied among the different treatments. Nitrogen was less in highly stressed (AWD – 15) treatments with no drainage, while it was more in AWD – 5 with sub-surface drainage condition. The findings concluded that sub-surface drainage with AWD – 5 was found to be an effective means of reducing N losses in irrigated rice ecology.

5.1.3 Crop Water Stress Index for rice at Different Stages

According to the findings of the study, CWSI was increased in treatments with AWDs. Results also indicated changes in the CWSI within the growth stages. Variations in canopy and ambient temperatures were observed during different phenological stages. This revealed significant fluctuations in environmental conditions throughout the crop cycle. By making use of CWSI techniques, irrigation engineers, farmers and agriculturists can apply specific irrigation methods and scheduling that are customized to the unique requirement of each crop at different growth stages. This will enable optimization of water consumption and enhancing crop water productivity. The highest crop temperature (Tc) value was recorded with AWD -15, while the lowest value was observed with continuous flooding (CF-5 - 10 -15). Furthermore, the values of the crop water stress index (CWSI) exhibited variations ranging from 0 to 1. When the rice plants were reaching complete heading stage, CWSI values remained high (0.2 to 1), indicating water stress.

The implementation of the AWD irrigation technique resulted in a noteworthy elevation in the rice crop water stress index (CWSI) in contrast to the continuous flooding (CF) method. Therefore, if alternate wetting and drying is to be implemented in any irrigation programme, critical periods during rice growth stages should be taken into consideration so as not to compromise the yield to a large extent. In both seasons, there was an indication of a strong correlation between crop water stress and rice yield. When the CWSI was at its lowest point, rice yield reached its maximum level. The yield potential of rice can be predicted using this relationship. An analysis comparing crop yield and irrigation management is important for the efficient use of local resources.

5.1.4 Modeling Rice Growth and Yield performance Using DSSAT Model

The study calibrated and evaluated CERES-Rice model in DSSAT with different drainage systems and irrigation application depths. The CF-5 under no drainage was considered optimum and hence used in the calibration of the model using data from the 2023 growing season. To avoid variable performance of CERES-Rice model in DSSAT, proper calibration and evaluation in the environment of interest i.e., response of rice to the various treatments was done in order to ascertain its usefulness in applying it to evaluate other management options.

The 2024 growing season was used for the evaluation and it predicted yield and LAI with reasonable accuracy. The model showed less accuracy in predicting very stressed conditions and highly flooded conditions. However, the results of the evaluation showed that the model can be used to determine growth and yield parameters with some level of accuracy. The drainage component, though it was embedded in the DSSAT model did not respond well to the different drainage treatments. More work on the drainage aspect in the model should therefore be given due consideration in order to better the performance of the model.

5.2 Policy Recommendations

Given the significance of the results and their broader implications, it is essential to translate these findings into actionable strategies. The recommendations outlined below aim to inform policy and improve practice.

1. The performance of rice can be increased greatly by adopting irrigation application depth of 5 cm with drainage management being put in place.
2. Alternate wetting and drying at 5 cm can be practiced to ensure water management while at the same time not compromising yield. It can serve as a more sustainable and efficient alternative for water conservation purposes.
3. Drainage systems especially sub-surface have proven to be a very effective tool in water management. Irrigation schemes in West Africa and Ghana in particular should explore the effective implementation of drainage practices to support improved performance of crops, contribute to land management practices and overall improvement of agricultural productivity.

4. Computations of CWSI for rice should be extended to a larger number of rice fields to obtain better characterization of the heterogeneity of the ecological zone.
5. CWSI estimation methodology should be adopted as a useful tool to mitigate drought damage in both irrigated and rainfed conditions.
6. Irrigation planners should consider choosing irrigation application depths and sub-surface drainage system in order to find a compromise between salinity control and irrigation water use efficiency.
7. Drainage component in DSSAT model should be made to be reflected as treatment in the field interface to enhance model performance in terms of drainage simulations.

5.3 Recommendations for Further Research

In light of the findings and the limitations identified in the study, there remains considerable opportunity for further exploration. The following recommendations are therefore proposed to guide future research efforts, deepen understanding of the effect of irrigation and drainage on crop performance, and address areas that warrant additional empirical investigation.

1. Further research should be conducted on different cultivars of rice and fertilizer regimes on the treatments to ascertain their response on the growth and yield of rice.
2. The use of satellite data to validate the observed data on CWSI for rice could be beneficial in adopting CWSI values for management decisions.
3. An economic evaluation on the use of different drainage systems should be conducted to better advise farmers and decision makers on which method to employ.

4. Although the physical and chemical characterization of the soil were not part of the focus of this study, a further study into the soil characteristics should be conducted because these parameters play vital roles in water movement and governance in the soil.
5. The impact of irrigation application depths and controlled drainage on greenhouse gas emission especially methane in rice fields should be investigated.

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APPENDICES

Appendix 1a: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 5WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	56.51	28.26	2.40	
REP.*Units* stratum					
Drainage	2	2096.43	1048.21	89.11	<.001
Irrigation_Depths	5	3524.82	704.96	59.93	<.001
Drainage.Irrigation_Depths	10	302.58	30.26	2.57	0.019
Residual	34	399.96	11.76		
Total	53	6380.30			

Appendix 1b: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 7WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	49.389	24.695	3.30	
REP.*Units* stratum					
Drainage	2	1729.308	864.654	115.57	<.001
Irrigation_Depths	5	3237.970	647.594	86.56	<.001
Drainage.Irrigation_Depths	10	247.812	24.781	3.31	0.004
Residual	34	254.377	7.482		
Total	53	5518.857			

Appendix 1c: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 10WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	655.90	327.95	24.60	
REP.*Units* stratum					
Drainage	2	1854.49	927.25	69.54	<.001
Irrigation_Depths	5	3931.10	786.22	58.97	<.001
Drainage.Irrigation_Depths	10	1528.85	152.89	11.47	<.001
Residual	34	453.34	13.33		

Total	53	8423.69			

Appendix 1d: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 13WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	428.04	214.02	6.52	
REP.*Units* stratum					
Drainage	2	2365.04	1182.52	36.05	<.001
Irrigation_Depths	5	7169.70	1433.94	43.71	<.001
Drainage.Irrigation_Depths					
	10	3118.74	311.87	9.51	<.001
Residual	34	1115.30	32.80		
Total	53	14196.81			

Appendix 1e: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 5WAT in the 2024 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	16.333	8.167	3.40	
REP.*Units* stratum					
Drainage	2	2948.111	1474.056	613.69	<.001
Irrigation_Depths	5	6503.278	1300.656	541.50	<.001
Drainage.Irrigation_Depths					
	10	209.444	20.944	8.72	<.001
Residual	34	81.667	2.402		
Total	53	9758.833			

Appendix 1f: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 7WAT in the 2024 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	5.481	2.741	1.15	
REP.*Units* stratum					
Drainage	2	3325.148	1662.574	696.28	<.001
Irrigation_Depths	5	6115.926	1223.185	512.26	<.001
Drainage.Irrigation_Depths					
	10	352.852	35.285	14.78	<.001
Residual	34	81.185	2.388		
Total	53	9880.593			

Appendix 1g: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 10WAT in the 2024 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	9.037	4.519	1.52	
REP.*Units* stratum					
Drainage	2	3797.370	1898.685	639.40	<.001
Irrigation_Depths	5	6773.648	1354.730	456.21	<.001
Drainage.Irrigation_Depths					
	10	448.185	44.819	15.09	<.001
Residual	34	100.963	2.969		
Total	53	11129.204			

Appendix 1h: Analysis of Variance (ANOVA) for Effect of Treatments on Plant Height at 13WAT in the 2024 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	78.93	39.46	1.90	
REP.*Units* stratum					
Drainage	2	2198.26	1099.13	53.05	<.001
Irrigation_Depths	5	5297.26	1059.45	51.14	<.001
Drainage.Irrigation_Depths					
	10	267.74	26.77	1.29	0.274
Residual	34	704.41	20.72		
Total	53	8546.59			

Appendix 2a: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 3WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.5923	0.2961	1.13	
REP.*Units* stratum					
Drainage	2	22.5252	11.2626	43.16	<.001
Irrigation_Depths	5	8.1405	1.6281	6.24	<.001
Drainage.Irrigation_Depths					
	10	6.0085	0.6009	2.30	0.034
Residual	34	8.8717	0.2609		
Total	53	46.1383			

Appendix 2b: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 7WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.7769	0.3885	3.58	
REP.*Units* stratum					
Drainage	2	5.2175	2.6088	24.02	<.001
Irrigation_Depths	5	4.3252	0.8650	7.97	<.001
Drainage.Irrigation_Depths					
	10	1.9430	0.1943	1.79	0.101
Residual	34	3.6920	0.1086		
Total	53	15.9546			

Appendix 2c: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 10WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.0087444	0.0043722	7.02	
REP.*Units* stratum					
Drainage	2	5.2276333	2.6138167	4194.17	<.001
Irrigation_Depths	5	3.7591111	0.7518222	1206.38	<.001
Drainage.Irrigation_Depths					
	10	2.7636556	0.2763656	443.46	<.001
Residual	34	0.0211889	0.0006232		
Total	53	11.7803333			

Appendix 2d: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 13WAT in the 2023 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	2.3984	1.1992	7.76	
REP.*Units* stratum					
Drainage	2	4.3982	2.1991	14.23	<.001
Irrigation_Depths	5	6.0863	1.2173	7.87	<.001
Drainage.Irrigation_Depths					
	10	2.2148	0.2215	1.43	0.208
Residual	34	5.2558	0.1546		
Total	53	20.3536			

Appendix 2e: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 5WAT in the 2024 Growing season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.06707	0.03354	1.77	
REP.*Units* stratum					
Drainage	2	11.12730	5.56365	294.01	<.001
Irrigation_Depths	5	7.53295	1.50659	79.62	<.001
Drainage.Irrigation_Depths					
	10	1.74176	0.17418	9.20	<.001
Residual	34	0.64340	0.01892		
Total	53	21.11248			

Appendix 2f: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 7WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.5063	0.2531	2.20	
REP.*Units* stratum					
Drainage	2	5.8486	2.9243	25.45	<.001
Irrigation_Depths	5	6.5003	1.3001	11.31	<.001
Drainage.Irrigation_Depths					
	10	1.3619	0.1362	1.19	0.334
Residual	34	3.9068	0.1149		
Total	53	18.1240			

Appendix 2g: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 10WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.031344	0.015672	2.29	
REP.*Units* stratum					
Drainage	2	6.482233	3.241117	472.70	<.001
Irrigation_Depths	5	5.837511	1.167502	170.28	<.001
Drainage.Irrigation_Depths					
	10	0.630389	0.063039	9.19	<.001
Residual	34	0.233122	0.006857		
Total	53	13.214600			

Appendix 2h: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Area Index at 13WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.00185	0.00092	0.03	
REP.*Units* stratum					
Drainage	2	6.84823	3.42411	128.02	<.001
Irrigation_Depths	5	8.24705	1.64941	61.67	<.001
Drainage.Irrigation_Depths					
	10	0.71031	0.07103	2.66	0.016
Residual	34	0.90942	0.02675		
Total	53	16.71685			

Appendix 3a: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 3WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	10.358	5.179	1.66	
REP.*Units* stratum					
Drainage	2	51.538	25.769	8.25	0.001
Irrigation_Depths	5	177.483	35.497	11.36	<.001
Drainage.Irrigation_Depths					
	10	37.404	3.740	1.20	0.327
Residual	34	106.222	3.124		
Total	53	383.005			

Appendix 3b: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 7WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	2.54037	1.27019	15.76	
REP.*Units* stratum					
Drainage	2	161.12704	80.56352	999.83	<.001
Irrigation_Depths	5	187.97426	37.59485	466.57	<.001
Drainage.Irrigation_Depths					
	10	332.05074	33.20507	412.09	<.001
Residual	34	2.73963	0.08058		
Total	53	686.43204			

Appendix 3c: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 10WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	26.491	13.246	2.39	
REP.*Units* stratum					
Drainage	2	247.036	123.518	22.28	<.001
Irrigation_Depths	5	329.330	65.866	11.88	<.001
Drainage.Irrigation_Depths					
	10	94.000	9.400	1.70	0.122
Residual	34	188.455	5.543		
Total	53	885.313			

Appendix 3d: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 13WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	63.848	31.924	6.17	
REP.*Units* stratum					
Drainage	2	239.834	119.917	23.17	<.001
Irrigation_Depths	5	376.586	75.317	14.55	<.001
Drainage.Irrigation_Depths					
	10	143.688	14.369	2.78	0.013
Residual	34	175.959	5.175		
Total	53	999.915			

Appendix 3e: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 5WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	10.648	5.324	2.67	
REP.*Units* stratum					
Drainage	2	55.657	27.828	13.94	<.001
Irrigation_Depths	5	191.307	38.261	19.16	<.001
Drainage.Irrigation_Depths					
	10	26.325	2.633	1.32	0.260
Residual	34	67.886	1.997		
Total	53	351.822			

Appendix 3f: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 7WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.0099	0.0050	0.02	
REP.*Units* stratum					
Drainage	2	146.7470	73.3735	249.30	<.001
Irrigation_Depths	5	403.3833	80.6767	274.12	<.001
Drainage.Irrigation_Depths					
	10	24.7547	2.4755	8.41	<.001
Residual	34	10.0068	0.2943		
Total	53	584.9017			

Appendix 3g: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 10WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.2914	0.1457	1.08	
REP.*Units* stratum					
Drainage	2	158.6169	79.3085	590.19	<.001
Irrigation_Depths	5	465.0647	93.0129	692.18	<.001
Drainage.Irrigation_Depths					
	10	9.8522	0.9852	7.33	<.001
Residual	34	4.5688	0.1344		
Total	53	638.3942			

Appendix 3h: Analysis of Variance (ANOVA) for Effect of Treatments on Leaf Chlorophyll Content at 13WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	1.480	0.740	0.43	
REP.*Units* stratum					
Drainage	2	255.400	127.700	74.20	<.001
Irrigation_Depths	5	643.132	128.626	74.73	<.001
Drainage.Irrigation_Depths					
	10	80.372	8.037	4.67	<.001
Residual	34	58.518	1.721		
Total	53	1038.903			

Appendix 4a: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 3WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	35.174	17.587	4.86	
REP.*Units* stratum					
Drainage	2	2.791	1.396	0.39	0.683
Irrigation_Depths	5	65.573	13.115	3.63	0.010
Drainage.Irrigation_Depths	10	60.058	6.006	1.66	0.131
Residual	34	122.919	3.615		
Total	53	286.515			

Appendix 4b: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 4WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	13.85	6.92	0.65	
REP.*Units* stratum					
Drainage	2	152.31	76.15	7.12	0.003
Irrigation_Depths	5	1224.99	245.00	22.90	<.001
Drainage.Irrigation_Depths	10	217.85	21.79	2.04	0.060
Residual	34	363.77	10.70		
Total	53	1972.76			

Appendix 4c: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 5WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	50.091	25.046	3.34	
REP.*Units* stratum					
Drainage	2	218.636	109.318	14.56	<.001
Irrigation_Depths	5	1063.633	212.727	28.33	<.001
Drainage.Irrigation_Depths	10	226.824	22.682	3.02	0.008
Residual	34	255.302	7.509		
Total	53	1814.486			

Appendix 4d: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 6WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	30.678	15.339	2.30	
REP.*Units* stratum					
Drainage	2	189.494	94.747	14.18	<.001
Irrigation_Depths	5	1189.448	237.890	35.60	<.001
Drainage.Irrigation_Depths	10	331.020	33.102	4.95	<.001
Residual	34	227.229	6.683		
Total	53	1967.868			

Appendix 4e: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 3WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	6.7037	3.3519	6.85	
REP.*Units* stratum					
Drainage	2	40.7037	20.3519	41.61	<.001
Irrigation_Depths	5	117.2037	23.4407	47.93	<.001
Drainage.Irrigation_Depths	10	18.8519	1.8852	3.85	0.001
Residual	34	16.6296	0.4891		
Total	53	200.0926			

Appendix 4f: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 4WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	15.4444	7.7222	11.99	
REP.*Units* stratum					
Drainage	2	92.1111	46.0556	71.54	<.001
Irrigation_Depths	5	226.0000	45.2000	70.21	<.001
Drainage.Irrigation_Depths	10	60.5556	6.0556	9.41	<.001
Residual	34	21.8889	0.6438		
Total	53	416.0000			

Appendix 4g: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 5WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	8.444	4.222	2.47	
REP.*Units* stratum					
Drainage	2	65.444	32.722	19.11	<.001
Irrigation_Depths	5	224.167	44.833	26.18	<.001
Drainage.Irrigation_Depths					
	10	76.556	7.656	4.47	<.001
Residual	34	58.222	1.712		
Total	53	432.833			

Appendix 4h: Analysis of Variance (ANOVA) for Effect of Treatments on Tiller Count at 6WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	82.333	41.167	8.41	
REP.*Units* stratum					
Drainage	2	217.000	108.500	22.18	<.001
Irrigation_Depths	5	452.611	90.522	18.50	<.001
Drainage.Irrigation_Depths					
	10	156.556	15.656	3.20	0.005
Residual	34	166.333	4.892		
Total	53	1074.833			

Appendix 5a: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 4WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	176.40	88.20	3.11	
REP.*Units* stratum					
Drainage	2	988.79	494.40	17.45	<.001
Irrigation_Depths	5	11318.48	2263.70	79.88	<.001
Drainage.Irrigation_Depths					
	10	195.28	19.53	0.69	0.727
Residual	34	963.55	28.34		
Total	53	13642.51			

Appendix 5b: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 7WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	10.2578	5.1289	8.11	
REP.*Units* stratum					
Drainage	2	194.2078	97.1039	153.64	<.001
Irrigation_Depths	5	9213.3333	1842.6667	2915.49	<.001
Drainage.Irrigation_Depths					
	10	327.8456	32.7846	51.87	<.001
Residual	34	21.4889	0.6320		
Total	53	9767.1333			

Appendix 5c: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 10WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	102.23	51.12	2.38	
REP.*Units* stratum					
Drainage	2	602.70	301.35	14.02	<.001
Irrigation_Depths	5	3357.38	671.48	31.24	<.001
Drainage.Irrigation_Depths					
	10	36.25	3.62	0.17	0.997
Residual	34	730.75	21.49		
Total	53	4829.31			

Appendix 5d: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 13WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	8.3244	4.1622	8.22	
REP.*Units* stratum					
Drainage	2	464.0144	232.0072	458.38	<.001
Irrigation_Depths	5	3458.4639	691.6928	1366.59	<.001
Drainage.Irrigation_Depths					
	10	557.1567	55.7157	110.08	<.001
Residual	34	17.2089	0.5061		
Total	53	4505.1683			

Appendix 5e: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 4WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	3.5470	1.7735	1.81	
REP.*Units* stratum					
Drainage	2	3509.1137	1754.5569	1789.67	<.001
Irrigation_Depths	5	8873.9698	1774.7940	1810.31	<.001
Drainage.Irrigation_Depths					
	10	225.5330	22.5533	23.00	<.001
Residual	34	33.3330	0.9804		
Total	53	12645.4965			

Appendix 5f: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 7WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	7.00	3.50	0.32	
REP.*Units* stratum					
Drainage	2	1967.97	983.99	90.23	<.001
Irrigation_Depths	5	8092.49	1618.50	148.42	<.001
Drainage.Irrigation_Depths					
	10	168.85	16.88	1.55	0.165
Residual	34	370.77	10.90		
Total	53	10607.08			

Appendix 5g: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 10WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	5.380	2.690	1.78	
REP.*Units* stratum					
Drainage	2	1208.200	604.100	400.43	<.001
Irrigation_Depths	5	7874.775	1574.955	1043.97	<.001
Drainage.Irrigation_Depths					
	10	219.033	21.903	14.52	<.001
Residual	34	51.293	1.509		
Total	53	9358.681			

Appendix 5h: Analysis of Variance (ANOVA) for Effect of Treatments on Canopy Cover at 13WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	177.11	88.55	6.06	
REP.*Units* stratum					
Drainage	2	1457.65	728.83	49.84	<.001
Irrigation_Depths	5	2796.24	559.25	38.25	<.001
Drainage.Irrigation_Depths					
	10	48.67	4.87	0.33	0.966
Residual	34	497.16	14.62		
Total	53	4976.83			

Appendix 6a: Analysis of Variance (ANOVA) for Effect of Treatments on Number of Panicles in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	6.162	3.081	0.85	
REP.*Units* stratum					
Drainage	2	290.306	145.153	40.07	<.001
Irrigation_Depths	5	1941.525	388.305	107.19	<.001
Drainage.Irrigation_Depths					
	10	145.220	14.522	4.01	0.001
Residual	34	123.170	3.623		
Total	53	2506.384			

Appendix 6b: Analysis of Variance (ANOVA) for Effect of Treatments on Number of Panicles in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	1.0000	0.5000	0.60	
REP.*Units* stratum					
Drainage	2	276.3333	138.1667	165.80	<.001
Irrigation_Depths	5	914.3889	182.8778	219.45	<.001
Drainage.Irrigation_Depths					
	10	92.7778	9.2778	11.13	<.001
Residual	34	28.3333	0.8333		
Total	53	1312.8333			

Appendix 7a: Analysis of Variance (ANOVA) for Effect of Treatments on Panicle Length in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	20.037	10.019	1.19	
REP.*Units* stratum					
Drainage	2	213.370	106.685	12.68	<.001
Irrigation_Depths	5	1476.981	295.396	35.12	<.001
Drainage.Irrigation_Depths	10	201.741	20.174	2.40	0.028
Residual	34	285.963	8.411		
Total	53	2198.093			

Appendix 7b: Analysis of Variance (ANOVA) for Effect of Treatments on Panicle Length in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	13.481	6.741	3.83	
REP.*Units* stratum					
Drainage	2	678.481	339.241	192.71	<.001
Irrigation_Depths	5	670.093	134.019	76.13	<.001
Drainage.Irrigation_Depths	10	473.074	47.307	26.87	<.001
Residual	34	59.852	1.760		
Total	53	1894.981			

Appendix 8a: Analysis of Variance (ANOVA) for Effect of Treatments on Filled Grains per Panicle in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	4088.4	2044.2	3.66	
REP.*Units* stratum					
Drainage	2	18635.2	9317.6	16.67	<.001
Irrigation_Depths	5	181363.3	36272.7	64.89	<.001
Drainage.Irrigation_Depths	10	16785.5	1678.5	3.00	0.008
Residual	34	19006.0	559.0		
Total	53	239878.5			

Appendix 8b: Analysis of Variance (ANOVA) for Effect of Treatments on Filled Grains per Panicle in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	434.78	217.39	12.97	
REP.*Units* stratum					
Drainage	2	21318.78	10659.39	635.95	<.001
Irrigation_Depths	5	138488.89	27697.78	1652.47	<.001
Drainage.Irrigation_Depths					
	10	11463.00	1146.30	68.39	<.001
Residual	34	569.89	16.76		
Total	53	172275.33			

Appendix 9a: Analysis of Variance (ANOVA) for Effect of Treatments on 1000 – Grain Weight in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	39.475	19.738	12.95	
REP.*Units* stratum					
Drainage	2	40.007	20.003	13.13	<.001
Irrigation_Depths	5	597.339	119.468	78.40	<.001
Drainage.Irrigation_Depths					
	10	28.863	2.886	1.89	0.081
Residual	34	51.807	1.524		
Total	53	757.491			

Appendix 9b: Analysis of Variance (ANOVA) for Effect of Treatments on 1000 – Grain Weight in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	10.0262	5.0131	6.36	
REP.*Units* stratum					
Drainage	2	157.9305	78.9652	100.20	<.001
Irrigation_Depths	5	440.3569	88.0714	111.75	<.001
Drainage.Irrigation_Depths					
	10	105.2355	10.5236	13.35	<.001
Residual	34	26.7956	0.7881		
Total	53	740.3447			

Appendix 10a: Analysis of Variance (ANOVA) for Effect of Treatments on Yield in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	17.4739	8.7370	9.42	
REP.*Units* stratum					
Drainage	2	96.6494	48.3247	52.13	<.001
Irrigation_Depths	5	449.1457	89.8291	96.90	<.001
Drainage.Irrigation_Depths					
	10	50.5839	5.0584	5.46	<.001
Residual	34	31.5196	0.9270		
Total	53	645.3725			

Appendix 10b: Analysis of Variance (ANOVA) for Effect of Treatments on Yield in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	2.6804	1.3402	5.17	
REP.*Units* stratum					
Drainage	2	33.4026	16.7013	64.38	<.001
Irrigation_Depths	5	95.4104	19.0821	73.56	<.001
Drainage.Irrigation_Depths					
	10	11.1263	1.1126	4.29	<.001
Residual	34	8.8196	0.2594		
Total	53	151.4393			

Appendix 11a: Analysis of Variance (ANOVA) for Effect of Treatments on Water Use Efficiency in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.25966	0.12983	5.06	
REP.*Units* stratum					
Drainage	2	8.70799	4.35399	169.62	<.001
Irrigation_Depths	5	27.49306	5.49861	214.21	<.001
Drainage.Irrigation_Depths					
	10	4.71917	0.47192	18.38	<.001
Residual	34	0.87277	0.02567		
Total	53	42.05264			

Appendix 11b: Analysis of Variance (ANOVA) for Effect of Treatments on Water Use Efficiency in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	1.14424	0.57212	5.86	
REP.*Units* stratum					
Drainage	2	5.76972	2.88486	29.53	<.001
Irrigation_Depths	5	26.66893	5.33379	54.60	<.001
Drainage.Irrigation_Depths					
	10	2.08214	0.20821	2.13	0.049
Residual	34	3.32158	0.09769		
Total	53	38.98660			

Appendix 12a: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Electrical Conductivity Before Sowing in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	1821.8	910.9	4.77	
REP.*Units* stratum					
Drainage	2	88.9	44.5	0.23	0.794
Irrigation_Depths	5	992.4	198.5	1.04	0.411
Drainage.Irrigation_Depths					
	10	2210.6	221.1	1.16	0.352
Residual	34	6494.9	191.0		
Total	53	11608.6			

Appendix 12b: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Electrical Conductivity After Sowing in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	1867.4	933.7	1.46	
REP.*Units* stratum					
Drainage	2	292600.8	146300.4	229.35	<.001
Irrigation_Depths	5	42063.8	8412.8	13.19	<.001
Drainage.Irrigation_Depths					
	10	14379.4	1437.9	2.25	0.038
Residual	34	21688.6	637.9		
Total	53	372600.0			

Appendix 12c: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Electrical Conductivity Before Sowing in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	408.44	204.22	2.33	
REP.*Units* stratum					
Drainage	2	238099.11	119049.56	1357.88	<.001
Irrigation_Depths	5	42930.44	8586.09	97.93	<.001
Drainage.Irrigation_Depths	10	12015.11	1201.51	13.70	<.001
Residual	34	2980.89	87.67		
Total	53	296434.00			

Appendix 12d: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Electrical Conductivity After Sowing in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	12845.	6423.	5.81	
REP.*Units* stratum					
Drainage	2	236452.	118226.	106.89	<.001
Irrigation_Depths	5	16131.	3226.	2.92	0.027
Drainage.Irrigation_Depths	10	24234.	2423.	2.19	0.043
Residual	34	37605.	1106.		
Total	53	327267.			

Appendix 13a: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 6WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	68.93	34.47	2.19	
REP.*Units* stratum					
Drainage	2	217.73	108.86	6.92	0.003
Irrigation_Depths	5	1141.62	228.32	14.51	<.001
Drainage.Irrigation_Depths	10	188.68	18.87	1.20	0.326
Residual	34	534.89	15.73		
Total	53	2151.86			

Appendix 13b: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 7WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	166.66	83.33	2.47	
REP.*Units* stratum					
Drainage	2	167.01	83.50	2.48	0.099
Irrigation_Depths	5	646.14	129.23	3.84	0.007
Drainage.Irrigation_Depths	10	308.90	30.89	0.92	0.529
Residual	34	1145.12	33.68		
Total	53	2433.82			

Appendix 13c: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 8WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.517	0.259	0.22	
REP.*Units* stratum					
Drainage	2	403.907	201.954	174.68	<.001
Irrigation_Depths	5	1138.239	227.648	196.90	<.001
Drainage.Irrigation_Depths	10	160.224	16.022	13.86	<.001
Residual	34	39.310	1.156		
Total	53	1742.197			

Appendix 13d: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 9WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	74.803	37.401	6.40	
REP.*Units* stratum					
Drainage	2	173.749	86.875	14.88	<.001
Irrigation_Depths	5	1110.299	222.060	38.02	<.001
Drainage.Irrigation_Depths	10	104.575	10.458	1.79	0.100
Residual	34	198.564	5.840		
Total	53	1661.990			

Appendix 13e: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 6WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	79.93	39.97	2.26	
REP.*Units* stratum					
Drainage	2	255.62	127.81	7.22	0.002
Irrigation_Depths	5	1067.62	213.52	12.06	<.001
Drainage.Irrigation_Depths	10	218.80	21.88	1.24	0.304
Residual	34	601.89	17.70		
Total	53	2223.86			

Appendix 13f: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 7WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	36.86	18.43	1.67	
REP.*Units* stratum					
Drainage	2	238.57	119.28	10.80	<.001
Irrigation_Depths	5	1294.34	258.87	23.44	<.001
Drainage.Irrigation_Depths	10	244.00	24.40	2.21	0.042
Residual	34	375.43	11.04		
Total	53	2189.20			

Appendix 13g: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 8WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	109.613	54.807	9.47	
REP.*Units* stratum					
Drainage	2	355.768	177.884	30.74	<.001
Irrigation_Depths	5	1099.911	219.982	38.01	<.001
Drainage.Irrigation_Depths	10	188.948	18.895	3.26	0.005
Residual	34	196.773	5.787		
Total	53	1951.013			

Appendix 13h: Analysis of Variance (ANOVA) for Effect of Treatments on Soil Temperature at 9WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.

REP stratum	2	0.343	0.171	0.10	
REP.*Units* stratum					
Drainage	2	508.869	254.435	155.26	<.001
Irrigation_Depths	5	1095.553	219.111	133.71	<.001
Drainage.Irrigation_Depths					
	10	100.286	10.029	6.12	<.001
Residual	34	55.717	1.639		
Total	53	1760.768			

Appendix 14a: Analysis of Variance (ANOVA) for Effect of Treatments on Total Nitrogen at 6WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.00012859	0.00006430	0.66	
REP.*Units* stratum					
Drainage	2	0.00463737	0.00231869	23.94	<.001
Irrigation_Depths	5	0.00557215	0.00111443	11.51	<.001
Drainage.Irrigation_Depths					
	10	0.00207574	0.00020757	2.14	0.048
Residual	34	0.00329274	0.00009685		
Total	53	0.01570659			

Appendix 14b: Analysis of Variance (ANOVA) for Effect of Treatments on Total Nitrogen at 8WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.0007988	0.0003994	1.16	
REP.*Units* stratum					
Drainage	2	0.0132041	0.0066021	19.15	<.001
Irrigation_Depths	5	0.0136599	0.0027320	7.93	<.001
Drainage.Irrigation_Depths					
	10	0.0039894	0.0003989	1.16	0.352
Residual	34	0.0117206	0.0003447		
Total	53	0.0433728			

Appendix 14c: Analysis of Variance (ANOVA) for Effect of Treatments on Total Nitrogen at 10WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.

REP stratum	2	0.0014731	0.0007366	6.37	
REP.*Units* stratum					
Drainage	2	0.0012677	0.0006339	5.48	0.009
Irrigation_Depths	5	0.0051457	0.0010291	8.90	<.001
Drainage.Irrigation_Depths					
	10	0.0009979	0.0000998	0.86	0.575
Residual	34	0.0039322	0.0001157		
Total	53	0.0128166			

Appendix 14d: Analysis of Variance (ANOVA) for Effect of Treatments on Total Nitrogen at 6WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.00002359	0.00001180	0.41	
REP.*Units* stratum					
Drainage	2	0.00060859	0.00030430	10.48	<.001
Irrigation_Depths	5	0.00242548	0.00048510	16.71	<.001
Drainage.Irrigation_Depths					
	10	0.00196052	0.00019605	6.75	<.001
Residual	34	0.00098707	0.00002903		
Total	53	0.00600526			

Appendix 14e: Analysis of Variance (ANOVA) for Effect of Treatments on Total Nitrogen at 8WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.00007337	0.00003669	0.95	
REP.*Units* stratum					
Drainage	2	0.01090381	0.00545191	141.07	<.001
Irrigation_Depths	5	0.01060681	0.00212136	54.89	<.001
Drainage.Irrigation_Depths					
	10	0.00629419	0.00062942	16.29	<.001
Residual	34	0.00131396	0.00003865		
Total	53	0.02919215			

Appendix 14f: Analysis of Variance (ANOVA) for Effect of Treatments on Total Nitrogen at 10WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.

REP stratum	2	0.00060848	0.00030424	5.18	
REP.*Units* stratum					
Drainage	2	0.00168848	0.00084424	14.37	<.001
Irrigation_Depths	5	0.00239831	0.00047966	8.16	<.001
Drainage.Irrigation_Depths					
	10	0.00546596	0.00054660	9.30	<.001
Residual	34	0.00199819	0.00005877		
Total	53	0.01215943			

Appendix 15a: Analysis of Variance (ANOVA) for Effect of Treatments on Crop Water Stress Index at 4WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.062705	0.031353	3.45	
REP.*Units* stratum					
Drainage	2	0.251155	0.125578	13.80	<.001
Irrigation_Depths	5	2.417151	0.483430	53.13	<.001
Drainage.Irrigation_Depths					
	10	0.059766	0.005977	0.66	0.755
Residual	34	0.309342	0.009098		
Total	53	3.100120			

Appendix 15b: Analysis of Variance (ANOVA) for Effect of Treatments on Crop Water Stress Index at 8WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.014698	0.007349	1.53	
REP.*Units* stratum					
Drainage	2	0.481671	0.240835	50.28	<.001
Irrigation_Depths	5	1.807352	0.361470	75.46	<.001
Drainage.Irrigation_Depths					
	10	0.152214	0.015221	3.18	0.006
Residual	34	0.162862	0.004790		
Total	53	2.618797			

Appendix 15c: Analysis of Variance (ANOVA) for Effect of Treatments on Crop Water Stress Index at 10WAT in the 2023 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.015210	0.007605	1.01	
REP.*Units* stratum					
Drainage	2	0.093089	0.046544	6.17	0.005
Irrigation_Depths	5	2.160199	0.432040	57.25	<.001
Drainage.Irrigation_Depths					
	10	0.171428	0.017143	2.27	0.037
Residual	34	0.256603	0.007547		
Total	53	2.696529			

Appendix 15d: Analysis of Variance (ANOVA) for Effect of Treatments on Crop Water Stress Index at 4WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.0001815	0.0000907	0.15	
REP.*Units* stratum					
Drainage	2	0.3528926	0.1764463	284.52	<.001
Irrigation_Depths	5	1.7804981	0.3560996	574.21	<.001
Drainage.Irrigation_Depths					
	10	0.1345519	0.0134552	21.70	<.001
Residual	34	0.0210852	0.0006202		
Total	53	2.2892093			

Appendix 15e: Analysis of Variance (ANOVA) for Effect of Treatments on Crop Water Stress Index at 8WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.0062704	0.0031352	3.83	
REP.*Units* stratum					
Drainage	2	0.3098815	0.1549407	189.52	<.001
Irrigation_Depths	5	1.8928315	0.3785663	463.06	<.001
Drainage.Irrigation_Depths					
	10	0.1189407	0.0118941	14.55	<.001
Residual	34	0.0277963	0.0008175		
Total	53	2.3557204			

Appendix 15f: Analysis of Variance (ANOVA) for Effect of Treatments on Crop Water Stress Index at 10WAT in the 2024 Growing Season

Source of variation	d.f.	s.s.	m.s.	v.r.	F pr.
REP stratum	2	0.005626	0.002813	0.53	
REP.*Units* stratum					
Drainage	2	0.193448	0.096724	18.25	<.001
Irrigation_Depths	5	1.624320	0.324864	61.30	<.001
Drainage.Irrigation_Depths	10	0.143952	0.014395	2.72	0.014
Residual	34	0.180174	0.005299		
Total	53	2.147520			