A REVIEW ON ADVANCED APPLICATIONS OF THE AQUACROP MODEL FOR OPTIMIZED FIELD MANAGEMENT AND CLIMATE CHANGE IMPACT ASSESSMENT

ABSTRACT

For several years, crop models have been applied to describe and to estimate the magnitudes of weather and climate impacts on crop growth and production. This paper describes the AquaCrop model, constructed by the FAO, for the purpose of modelling and evaluation of crop production practices and climate change mitigation measures. AquaCrop is particularly useful for regions characterized with dry lands whereby soil water status plays a major role in yield potential, that is AquaCrop therefore embodies simple, accurate and stable performance. It has been then validated for global climate and management practices for simulation of crop phenology, biomass and yield, water balance and water use efficiency, and evapotranspiration. It has proved efficient in the application in crops like Maize, wheat, barley, tea, sorghum and pulse crops including groundnut and soya beans. Stress coefficients for water, fertilizing and temperature are used by AquaCrop for evaluating their impact on crop canopy growth and dry matter production, stomatal closure, flowering, pollination and harvest index. Three levels of calibration, those of canopy cover expansion, dry matter accruement and the relative amount of moisture in the root zone is also available to simulate growth conditions. Reliability of the developed model is assessed by different statistical measures such as Root Mean Square Error (RMSE), Nash-Sutcliffe efficiency, coefficient of determination (R^2) and ratio (d). It plays the role of the decision support system in the context of climate change effects, water use efficiency, sowing dates, plant density and fertilizer practices under different climate conditions.

INTRODUCTION

AquaCrop is one of the developed models by FAO to provide an improved simulation instrument to meet the increasing demands for efficient crop water management due to climate change factors. Through its predilection to capture crop growth responses to various levels of irrigation and water use efficiency while taking into account intricate factors such as climate, soils and temperature, AquaCrop is a key model for evaluating climate change agriculture interactions (Greaves et al., 2016). To a certain extent AquaCrop is uncomplicated in the inputs it requires from the users – the main crop characteristics and environmental data – avoiding, therefore, other complexities that many other crop models require in order to provide similar outputs (Nzimande et al., 2021). Introducing water productivity is also possible with the help of this theory, which is vital for the analysis of water-scarce areas, mainly because of the increase in average global temperatures and uneven distribution of precipitation (Mabhaudhi et al., 2021). In addition, AquaCrop provides the basis for developing contextualized practices to improve the implementation of innovations at the farm level, including determining suitable planting dates, adjusting irrigation frequencies and designing drought resistant cultivars. As such, the model offers valuable information as to water use efficiency as well as crop yield potential under different climate conditions and, therefore, acts as a great decision-making tool for decision makers in the short-run agricultural operations as well as in the formulation of climate change adaptation policies in the long-run (Peter et al., 2020). This model is especially advantageous for developing nations, where resources are scarce, and the environment is extremely sensitive to climate-related shocks (Signé et al., 2022). Further, the ability of the model to forecast climate changes as they would be abreast the food production also meets a global objective of improving food security especially in vulnerable agro ecological regions (Barasa et al., 2021). Thus, as a contribution to the discussions on sustainable agricultural production, AquaCrop presents a theoretically grounded, quantitative simulation model of crop management capabilities that is still realistic in terms of application and potentially usable in the contexts of global climate change. based on the achievement of data integration and the calibration of AquaCrop models, this tool will still be a useful reference for building sustainable agricultural systems globally (Salman et al., 2021).

Primary reason is that agriculture is a many-sided and rather sensitive branch in terms of weather and climate impacts. Climate change has become an increasingly Wicked problem for the agriculture business since it affects crop yields, resources, and food security for the developing countries with low adaptive ability (Tisch et al., 2020). Climate, crop handling and other related factors are interrelated and are responsible for crop rate and yield. Nevertheless, aggregating them to incorporate the effects of these processes into the assessment of crop plants poses a challenge (Bedeke et al., 2023). Crop models have the ability to receive growth and productivity as feedbacks of different factors such as soil nutrients, salinity, drainage, moisture, soil temperature, tillage practices, types of irrigation (furrow, drip, sprinkler), mulching, dates of sowing, rates of seed, rainfall and management practices of weeds, insect pests and disease (Turner & Kodali, 2020).

Site factors include temperature, wind, rainfall and drought, which depict the level of comfort that populations in specific-regions can experience in regard to planning and management needs (Brogden & Volz,, 2023). Research reveals bioclimatic comfort areas and, accordingly, drought assessments reflect climatic limits. Socioeconomic and political risks relevant to the analyzed droughts are identified. Some of the recent studies that have used the remote sensing have indicated that it will be useful in monitoring drought stress, current and the potentials to future land use changes will be constrained by rising sea levels (Msimanga, 2023). Weather based crop models have come into focus to postulate solutions for increasing crop yields based on regional and or diurnal weather fluctuations. The application of modeling in agriculture (Morari et al., 2021) is driven by several factors:

- Improved comprehension of operations in the soil water atmosphere continuum otherwise known as (SWA).

- Interactive activities of the experts in different branches of knowledge.
- Optimization of solving stiffer form of equations due to development of new computational codes.
- Major improvements of the hardware and the supporting-software systems.
- Large databases built over many years of experimental and survey work mainly in the developed world.
- The need to include as many processes of the SWA as possible to provide the broadest possible picture of this turbulent system.

As more and more aspects of human life become computerized, the chances of crop simulation-models to be of help when it comes to dealing with a number of issues technology or otherwise concerning agricultural sustainability, food security, optimum utilization of resources, and protection of the environment will increase (Annie et al., 2023). Nonetheless, the work on simulating the future consequences on intricate matters of food security still goes on especially about local effects in the agro-ecological zones at the national level. For this reason, the countries and the international communities will greatly benefit from the development of elaborate national and international knowledge and data bases of the impacts that concerns the four constituent parts of food security (Paracchini et al., 2020).

AquaCrop is specifically noteworthy when compared to the broad class of crop models, which have to strike a delicate balance of being accurate, simple, tough, and effortless. The model is for computation based end-users like the extension specialists, water managers, personnel involved in irrigation organizations and economists who need simplistic models for planning and regression analysis (Morelli et al., 2023). Similar success has been talked in various crops like forages, vegetables, grains, fruits and root/tuber crops and almost all classes of soils, climates and management practices in different parts of the world. In any case, details of different stress coefficients (Ks), specific parameters, as well as management practices remain scarce information. Hence, this paper presents a synthesis of crop growth simulation using AquaCrop model as a modelling tool for climate change decision support, crop productivity, and food security (Tolomio & Casa, 2020). It also presents a clear synthesis of data on different crop parameters, crop factors, calibration, and validation processes so as to make it easier for the user.

Objectives

The main objective of this paper is to assess the application of the AquaCrop-model under different soil, climate, and management practices, with the following specific objectives:

- To learn about the ideas and approaches of the AquaCrop-model.

- AquaCrop-modeled field productions can be used to assess AquaCrop-model applications when deployed as an on-farm decision support tool under different levels of soil, climate, and management regimes.
- To narrow down on appropriate measures for change in climate that can enhance the productivity of crops and food security.

Crop Growth Simulation Models: Definitions and Concepts

Crop simulation models help improve appreciation of architectural and physiological structure of crop growth and development, processes and data extrapolation and prediction. Crop model on the other hand is aSimulation of plant growth while model is an abstraction of identifiable system using a set of equations which would depict its behavior (Wu, 2023). Models mimic or mimic the behavior of a crop, or parts of it such as the leaves, roots, stem, yield, and other factors that are related to development of a crop, and the soil moisture content on a daily basis, climate or weather conditions, and the practices to be followed on the crop (Lesk et al., 2022).

Crop simulation models reflect the current scientific information available from the field of crop physiology, plant breeding, agronomy, agro-meteorology, soil physics, soil chemistry, fertility, pathology, entomology, and economics (Sharangi et al., 2023). These models are useful for the assessment of changes in genetic quality, for the approximation of historical genetic changes from experimental information and for the suggestion of congeneric types of plants in larger surroundings, to promote agro-advisory systems for weather and diseases (Trewavas et al., 2023). Environmental factors acting on crop, soil factors and dynamics, crop genotype and phenotypes, and management practices have a profound impact on yield. Climatic factors such as seasonal and daily climatic requirements are influential in cropping strategies and disease incidences, crop yield, and crop value (Vadez et al., 2024; Gojon et al., 2023). Therefore crop simulation models have the potential to provide crop growth responses to weather conditions, soil type, crop management and genetic composition. They explain the joint action of weather, properties of the soil, and crop factors that affect performance and crop simulation models that serve as an important adjunct in field research for designing new crop management systems (Cooper et al., 2021).

Types of Crop Models

Crop models may be classified according to their aim, crop focus, and structure. Typically, there are two categories of crop models: descriptive and explanatory, but in practice, the contours of the classification are not always clear because the majority of process-oriented models contain elements of empirical equations. Regression models as well as other purely empirical models are significantly different.

Simulation Models: They are intended to simulate system behavior during short time steps (daily time steps) while accounting for daily weather and soil status. They permit the identification of management choices and analysis of a variety of management strategies. Simulation models generically use one or more differential equations to determine rate and state variables throughout the planting to harvest continuum (Ackermann & Eden, 2020).

Optimizing Models: These models are used for finding the decision-making inputs needed for managing in operation of the practical system models, solving these models with optimization algorithms (Ridha et al., 2021).

Static Models: Time is not a factor in developing static models, yet crop products are stock and build up over time.

Dynamic Models: These models produces quantitative forecasts of some phenomenon like yield or rainfall and for which there is no concept of probability distribution, variance or random parameters. Thus, the dynamic models may be insufficient for certain applications, especially for the purpose of rains forecast (Ramsey, 2020).

Descriptive Models: The descriptive models give an almost direct representation of the behavior of a system. They employ the obtained experimental data to develop one or more mathematical formulas that would describe the operating behavior of the system involved.

Empirical Models: Empirical models are mathematical models, where the real world is represented with few variables of the said system. They are applied in crop forecasting but are usually not realistic and versatile; they are based on data derived from observations and look like regression equations which have few variables.

Explanatory Models: They give a quantitative account of the phenomena and processes that determine the systems properties and behavior. The growth of quantifiable parameters such as photosynthesis rate and expansion of scaled up as well as qualitative parameters such as crop biomass and yield can be determined using an Exploratory crop growth models. Some of these models are often used in irrigation management base on water balance (Morales et al., 2020).

Crop Model Applications

Crop growth models are used in many areas of applications, such as yield forecasting, agriculture, farm management, climatology and agro-meteorology. Through these models, it becomes possible to identify potential growth and set biological constraints on agricultural production where crop yields can be forecast and crop performances in large regions extrapolated and interpolated based on the results of other scientific disciplines (Morales & Villalobos, 2023). The applications of crop simulation models can be categorized as follows:

- The environment palms for characterization
- Optimizing Crop Management

- Pest and disease are other challenges of crop production that requires proper management.
- Impact of Climate Change
- Yield Forecasting
- Optimal Sowing Dates

Research Understanding: Such model construction helps to consolidate ideas gained from separate disciplines' studying; it is possible to reveal principal actors in the system and the gaps of knowledge when constructing models (Franco et al., 2021).

Integration of Knowledge across Disciplines: Crop models are viewed as some integration layers on one or another level connecting different branches of science, hence facilitating interdisciplinary cooperation (Silva & Giller, 2020)

Improvement of Experiment Documentation and Data Organization: Crop models help in exposing experimental data in a systematic manner and organizing this data in a systematic manner (Jones et al., 2017).

Site-Specific Experimentation: Models can be blown up to individual contexts, which allows one to evaluate crop development, yield, climate, and farming practices with a local adjustment (Wang et al., 2022).

Yield Analysis: Examination by models with strong physiological support makes it possible to generalize the results obtained to other settings, thereby improving the understanding of yield fluctuations.

Climate Change Projections: Since crop production depends on weather conditions, changes in the weather system all over the world will have a major effect on crop production efficiency and yields. Therefore, climate analysis for the current and future is important for the formation of the adaptation measures (Habib et al., 2022).

Scoping Best Management Practices: Crop Models are useful to determine the eco friendly managing practices that will improve yield of crops. It refers for instance, to choices such as the right time to sow or plant in areas receiving irregular rain such as arid and semi-arid areas. Moreover, models can predict the most appropriate rate of application of fertilizers, types of irrigation, types of soil management, for example tilling and mulching, and even drainage/infiltration (Bodner et al., 2021).

Yield Forecasting: Pre-harvest estimations of crop yields over large regions are very important to researchers and farmers in terms of setting up work and resource plans.

Extrapolation to Alternative Cropping Cycles: Physiological based models enable extrapolation to other experimental years and sites, thus allowing the estimation of temporal and spatial changes (Hanson & Walker, 2020).

Limitations of Crop Models

The ability of crop models to predict crop development, yield, soils, and climate is therefore hampered by inadequate knowledge of endogenous processes and compute capabilities (Reynolds et al., 2021). In some cases, the results given by the model depend even on the input parameters used for model estimation. Data sampling errors affect the observed data negatively, and accuracy in climatic data affects performance of the models. While historical weather data play an important role in model development, long-term data are scarce; sometimes there are not enough records, or only few variables are available (rainfall, minimum and maximum temperature etc.) (Van et al., 2021). Therefore, performances of the crop models depend with the user experience, accuracy of the experimental measurements and sampling methods. As the saying goes, garbage in, garbage out – meaning that to get a good model, one has to feed it with good field data.

AquaCrop Model: Concepts and Description

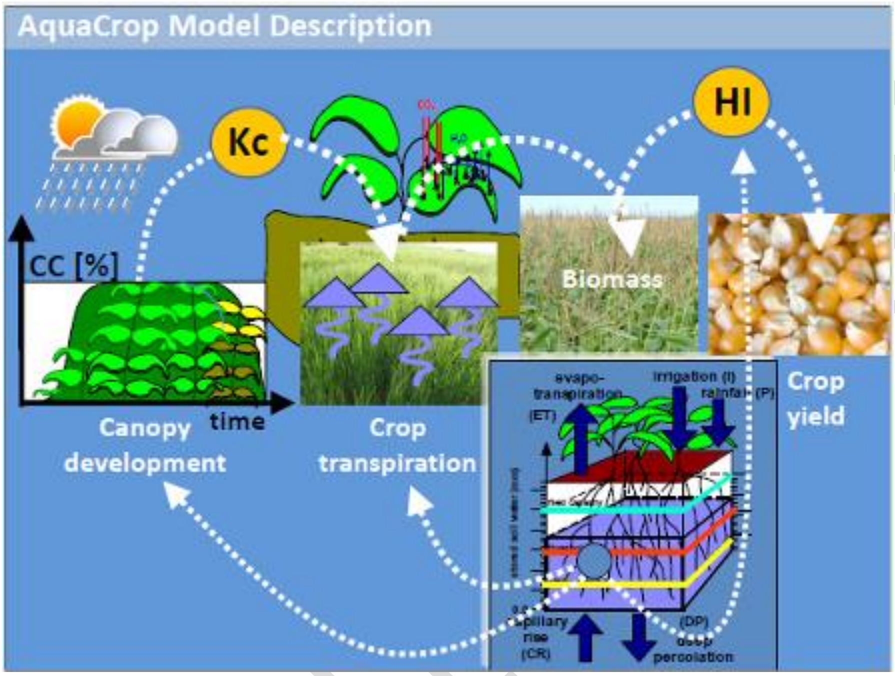
In light of this, the AquaCrop model meets criteria of simplicity, robustness and captures higher accuracy thus can be essential for many practitioners, mainly irrigation and water management practitioners, extension worker, government agencies, NGO and researchers. The model in this model is used for on-farm practice, irrigation scheduling and planning for climate change, and other researches on soil water balance. It has been developed for a purpose of studying the effect of water and management of soil on the germination of a large number of herbaceous crops and their productivity(Sanatawy et al., 2021; Shaheb et al., 2021). Being easy to use and delivering accurate results, AquaCrop has been applied to simulate crop growth and yield for maize (Nie et al., 2021; Araya et al., 2016) tea barley, wheat, rice, sunflower, cotton, potato, hot pepper, cabbage, sugarcane and faba bean, under different management, soil and climatic factors.

Key Parameters in AquaCrop

The AquaCrop model focuses on five primary parameters that respond to governing factors: planting and flowering date, soil depth, over head cover and above ground biomass, and yield (Nzimande, 2021). The model starts with predicting the changes in crop canopy with time from emergence to reach beyond the potential crop height using realistic factors like; the initial canopy cover per seedling (CCo), plant density, growth canopy coefficient (CGC), and maximum canopy cover(CCx) (Colbach et al., 2021). In this regard, AquaCrop 'singles out green canopy cover rather than the leaf area index(Li et al., 2024).

The model also includes the root system of the plant in the form of the effective rooting depth as well as that of the water extraction. The effective rooting depth is therefore described as the extent of depth within which the majority of root water uptake is derived from(Liu et al., 2021). Still, there can be differences owing to crop species, and this model input has been adjusted with respect to soil profile, and extraction patterns as suggested in Figure 1.

Fig 1 : AquaCrop Model



The graphical representation points to the fact that various dynamic physiological processes are determined by climatic as well as soil factors. Biomass production is assumed to be a function of evapotranspiration while crop yield is obtainable from biomass through the harvest index. In AquaCrop, canopy development is described using the phenological state of green CC or degree of canopy cover. Growth of canopy area starting at emergence and up to full canopy closure is exponential during the first half of plant development and exponential decay in the second half. This process is quantified using the following equations:

$CC=CC_0 * e^{CGC*}$

$CC = CC_x – (CCx-CC_0) e* CGC$

These equations offer an ideal approach toward enabling simulation of crop growth characteristics in a context of AquaCrop (Berhane et al., 2018).

Where, in the AquaCrop model CC stands for the canopy cover at time t and CCo is the initial canopy cover or the canopy cover at t=0. The canopy growth coefficient is depicted by the acronym CGC and is represented by fractions of a day or degree day. CCx defines the canopy cover, while and ttt indicates the time duration in days or degree days.

The AquaCrop model effectively keeps the relationship between crop water consumption and crop yield direct. This approach developed from the FAO Irrigation and Drainage paper No. 33 by dissecting non-productive soil evaporation (EEE) from productive crop transpiration (Tr). The model allows the direct platform estimate of biomass from actual crop transpirational loss with the use of water productivity factor. The core equation that governs the AquaCrop growth engine is:

B = WP∗∑(3/TriEToi)B = WP∗∑((3i)/(TrETo)) (3)

Here, BBB is the total biomass yield in terms of the biomass amount per unit area (kg/m^2), TriTr_iTri denotes the daily crop evapotranspiration, EToiETo_iEToi stands for the reference evapotranspiration and WP∗WP^WP∗ is crop water use efficiency.

From the modeled plot of plant growth N x B x E x C, for most crops only a fraction of the total generated biomass is used in the harvested organs giving yield (Y). The ratio of yield to biomass is known as the harvest index (HI), expressed mathematically as:

Y = HI · B Y = HI B (4)Y = HI·B(4)

Two components are believed to be essentially independent of each other, at least regarding the underlying processes that delivers biomass production (BP) and harvest index (HI). Hence, the breakdown of yield into biomass as well as harvest index allows assessment of the impacts of specific environmental conditions or stress effects on BP and HI. Figure 2 shows the overall calculation scheme of the AquaCrop model and the way how the model was developed progressively ((Berhane et al., 2018).

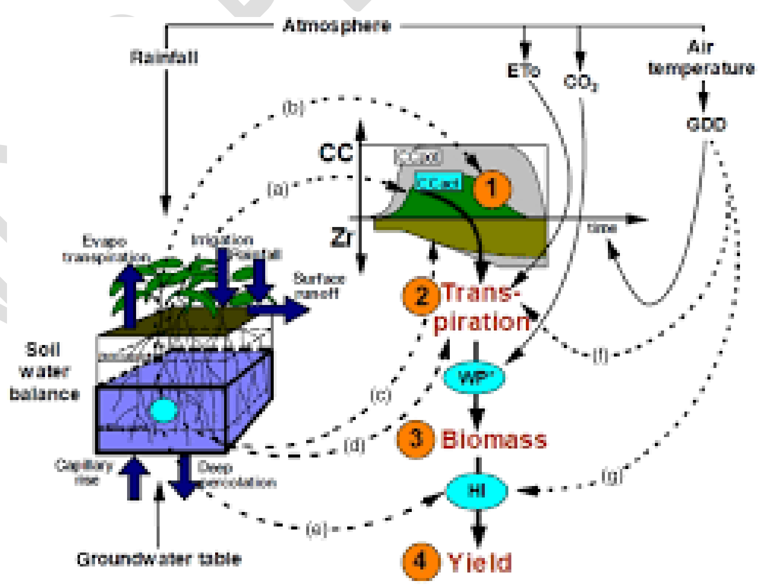


Fig 2: AquaCrop Calculation Scheme with Indicated Processes (a-e) Impacted by Water Stress

Yield Response Factor

The parameter for the yield response to water deficit conditions is the yield reduction factor (Ky). Consequently the impact of water stress relative yield decrease and relative evapotranspiration deficit are different across species and it becomes desirable to estimate this relationship. This is expressed by the empirically determined yield response factor (Ky). Yield response factor represents the relationship between crop production process and water usage, and may encompass a biological, physical, or chemical nature. The estimates of the yield response factor are grouped into the following empirical equation(Beaudoin et al., 2023). Crop yield response at different growth stages can be calculated as follows:

$$1-YmYa=Ky(1-ETmETa)$$

This equation helps in comprehending the yields effects in the situation, where water is abundant, or scarce.

a. Yx and Ya denote here the theoretical and actual yields of crops while ETx and ETa refer to the actual and theoretical evapotranspiration. Ky is called the yield response factor that defines yield losses due to decreased evapotranspiration. It reflects this relationship in their water production function. According to (Yang et al., 2020) the Ky values are crop-specific and fluctuate throughout the growing season, depending on the growth stages:

- **Ky>1Ky > 1Ky>1:** It is a water-sensitive crop, mainly because small reductions in the amount of water on the crop, because of stress, trigger proportionately greater yield impacts.
- **Ky<1Ky < 1Ky<1:** It also has higher water use efficiency than the control, partially recovering from the stress and experiencing less than proportional yields decline for decreased water use.
- **Ky=1Ky = 1Ky=1:** Water conservation means yield reduction and therefore, correlation exists between the two.

Table 1: Seasonal Ky Values from FAO Irrigation and Drainage:

Crop	Ky (Yield Response Factor)
Alfalfa	1.1
Banana	1.2 - 1.35
Maize	1.25
Onion	1.1
Potato	1.1

Soybean	0.85
Sunflower	0.95
Tomato	1.05
Sugarcane	1.2

Yield response of crops to water is generally species specific. Yield response factors (Ky) vary from crop to crop as shown in the table below, Table 1. Water stress vulnerability in plants varies in the family and species as well at the developmental stages within a species. For instance, flowering and yield formation stages are the most affected by stress as opposed to stress experienced during ripening. In contrast, vegetative stage is less sensitive to water stress if only the plant can recover from water deficit (Aru et al., 2022). The Ky values for crops at various growth stages are listed below in a tabular form in TABLE 2.

Table 2: Soil Water Stress Coefficients and Their Effect on Crop Growth

Soil Water Stress Coefficient	Direct Effect	Target Model Parameter
Ksaer: Soil water stress coefficient for water logging (aeration stress)	Reduces crop transpiration	Trx
Ksexp,w: Soil water stress coefficient for canopy expansion	Reduces canopy expansion and (depending on timing and strength of the stress) might have a positive effect on the harvest index	CGC and HI
Kspol,w: Soil water stress coefficient for pollination	Affects flowering and (depending on duration and strength of the stress) might have a negative effect on the harvest index	Hlo
Kssen: Soil water stress coefficient for canopy senescence	Reduces green canopy cover and hence affects crop transpiration	CC
Kssto: Soil water stress coefficient for stomatal closure	Reduces crop transpiration and the root zone expansion, and (depending on timing and strength of the stress) might have a negative effect on the harvest index	Trx and HI

Implications of the yield response factor

This yield response to water deficit is the most important aspect for production planning. Hence, where both crops are grown in the same locality and the intention is to optimize production per volume of water, provision of water supply should be given to maize. On the other hand when the overall production within the given region is the ultimate goal where the constraint is not land based on the amount of water, the available water should be utilized fully in meeting the water requirements of Maize over an area of limited size (Kheir et al., 2021). The results for overall production of sorghum, irrigation can be expanded to physical area that water can reach, even if the water demand is not fulfilled in full extent, but certain limits of water scarcity must not be overstepped.

Calculation Procedures

The calculation procedures to determine actual yield (Ya) based on Equation 1 involve four steps:

Estimate Maximum Yield (Yx): Estimate the highest possible yield from an adapted crop variety by its genetic potential and climatic conditions neglecting the prospects of agronomic factors, such as water and nutrient supply, pests, and diseases (Cortés & López, 2021) .

Calculate Maximum Evapotranspiration (ETx): Maximize potential evapotranspiration using standard approaches, in order to guarantee crop's need for water uptake is met (Pereira et al., 2021).

Determine Actual Crop Evapotranspiration (ETa): Determine the approximate amount of evapotranspiration under certain circumstances with reference to availability of water to the crop (Tolomio & Casa, 2020).

Evaluate Actual Yield (Ya): Employ the appropriate yield response factor (Ky) on the yield and in total for the entire growing season or for the various growth phases (Saudy et al., 2023).

How to Calculate Maximum Yield (Yx)

Yield level of a crop (Yx) with respect to specific management intensity depends mainly on its genotypic potential and response to environmental conditions. It is defined as the obtained yield of a high-yielding variety adapted to the growing period, time available for the genotype to grow and mature, nutrition, pest and disease stresses do not affect yield (Begna, 2020).

Method of computing the maximum evapotranspiration (ETx)

Maximum evapotranspiration (ETx) indicates where water supply is in excess and the formation of water stress is impossible. ETx refers to the rate of maximum evaporative demand of a healthy crop on a large scale field under good agronomic and water management practices. Therefore, ETx is computed using the reference evapotranspiration (ETo) and the crop coefficient (Jaramillo et al., 2020).

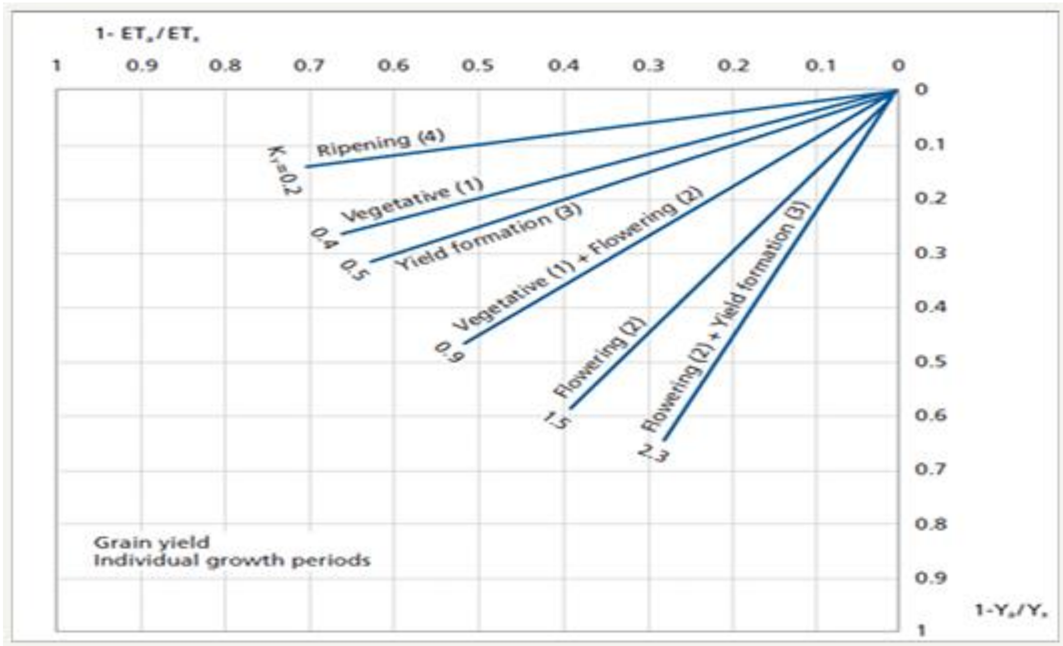


Fig 3: Water Production Functions for Maize Under Deficit Conditions

The higher the Ky value, the more substantially yield drops for the same decrease in ET owing to water deficit during the particular period or growing season (refer to Figure 3).

Aqua Crop Model for Irrigation Water Management and Soil Moisture Balance

Hence the AquaCrop model plays a central role in the management of irrigation water in view of climate change that has a direct bearing on crop yield and food security. Tackling the availability of water from the ancient period the availability of water hinders the crop production in the areas where they are not sufficient to feed the crops (Hussain et al., 2022). Within the AquaCrop framework, water management is approached through several key parameters:

Rain-Fed Agriculture: This scene is without any filtration process of irrigation.

Irrigation: The type of irrigation that was used in a particular experiment is also freely selectable by the users; this may be drip irrigation, sprinkler irrigation, or probably surface irrigation such as furrow or flood irrigation among others. There are limb parameters like water depth and irrigation schedule and the model can automatically produce irrigation schedules in fixed intervals, water depth or percent soil moisture (Hadidi et al., 2022).

Irrigation Strategies: Within AquaCrop, the user has the means for applying such techniques as supplemental and deficit irrigation regimes.

Intensive management of the smallholders' irrigation systems under rain fed scheme is essential in increasing the crop yield as well as in responding to the climate variability. AquaCrop is a water-driven modelling system that can predict yields responses to water with limited essence and little data input for most field and vegetable crops globally. This tool has been applied correctly for water management, in irrigation scheduling, and in deficit irrigation for a variety of crops; wheat, maize and others; tea crop ; barley; and the cotton crop (Snyder et al., 2024)

The AquaCrop model calculates crop intake requirements for water (ETC), crop coverage, biomass and yield, soil leakage and water accumulation in the root zone, and overall performance under conditions of climate change. It can imitate low level water application by means of deficit applications and total applications (Cheng et al., 2021). Use of AquaCrop model for estimating deficit or supplemental irrigation conditions is very important for enhancing crop water productivity and irrigation water use efficiency in the arid and semi arid regions. Research conducted on the use of deficit irrigation bore crop response functions for the conditions which arise with water deficits at various growth phases (Chand et al., 2020).

Yield reduction due to water stress is estimated in AquaCrop using the stress coefficients (Ks). When soil water depletion in the root zone is less than upper threshold, water stress is assumed to be minimal (Ks = 1) and no effect is observed on crop processes. To however in reduce soil water yet in the root zone deposit declines from the upper stigma, specific processes experience stress from soil water stress. Nevertheless, as soon as the SM decreases below the lower threshold, negative effects increase (set Ks = 0); the processes are inhibited. The four major coefficients adopted to estimate such effects are associated with leaf expansion rate, stomatal conductance, canopy browning, and pollination drops (Yadav et al., 2022).

Application of AquaCrop Model for Simulating Soil Moisture Balance

AquaCrop has a distributed form and may have up to five different layers with different texture in the profile, including all traditional textural classes defined in the USDA triangle (Roquette et al., 2022). The model also performs a daily water balance that records all water inputs and outputs, including infiltration, surface runoff, deep drain, evaporation, and transpiration rates and changes in water body (Mohajerani et al., 2021). This daily soil water balance is important in observing the physical and physiological events on crops.

One thing that differentiates AquaCrop's water balance is the separation of the water lost through evaporation of the soil (Es) from that lost through transpiration of the plant (Tc). When simulating Es, the model includes conditions such as mulching, withered canopy cover, localized irrigation and partial soil wetting and the canopy shade effect (Allen et al., 2020). The soil moisture balance is calculated using the equation:

ETC = Purchases + Investments – Receipts – Donations ± Change in Stocks (7)• ETC = crop water demand• P = precipitation it may rain, snow, hail or sleet• S = Δ m, where m is the matrix of change in the soil moisture that may be either positive or negative. Ariable depths, accommodating up to five layers of different textures along the profile, incorporating all classical textural classes outlined in the USDA triangle (Malone & Searle, 2021). The model conducts a daily water balance, accounting for all incoming and outgoing water fluxes such as infiltration, runoff, deep percolation, evaporation, and transpiration while tracking changes in water content (Liebhard et al., 2022). This daily soil water balance is crucial for monitoring the physical and physiological processes of crops.

A unique aspect of the AquaCrop model's water balance is its distinction between soil evaporation (Es) and crop transpiration (Tc). In simulating Es, the model incorporates factors such as mulching, withered canopy cover, localized irrigation with partial wetting, and shading effects from the canopy (Tuzet et al., 2022). The soil moisture balance is calculated using the equation:

$$\{ETC\} = P + I - R - D + \Delta S$$

Where:

- ETC = crop water requirement
- P = precipitation (typically rainfall)
- I = irrigation
- R = runoff
- D = drainage
- S = change in soil moisture (can be positive or negative)

Water deficits are considered in AquaCrop by using stress coefficients (Ks) to characterise the impacts of water stress on crop physiological processes. At or above the upper threshold of root is zone depletion, Ks is equal to 1 indicating that water stress is nonexistent From the upper threshold, stress affects crop processes as stored soil water reduces below the stated limit. At one end of the defined boundary, the damage associated with Ks is maximal causing a complete halt in growth (París et al., 2021). Table 3 presents a summary of effects of soil water stress in different processes Here, Table 3 Impacts of changes in SWC on different processes. Precision and assessing experiences used in testing the AquaCrop model in various crops and soil types show it can predict the moisture content in the soil and daily water movement (He et al., 2021).

THE USE OF AQUACROP MODEL IN SOIL FERTILITY AND SALINITY PROGRAMMING

Soil Fertility Management

It is, therefore, important to have an understanding of its productivity and fertility before taking up farming as a business. Although AquaCrop does not directly simulate nutrient cycles and balances, it adjusts fertility effects through a set of soil fertility stress coefficients for four key productivity components: canopy growth coefficient (CGC), maximum canopy cover (CCx), canopy decline coefficient (CDC), water productivity (Berhane et al., 2024). Soil fertility stress is a scale that is equally divided into percentage; 0% meaning no stress at all or no limitation in soil fertility and 100% meaning the crop cannot be produced in such soil. Soil fertility coefficients (Ks) are ranged from 1 (no soil fertility stress) through 0 (full soil fertility stress). This is shown in Table 4 where fertility stress has been known to influence canopy and biomass formation.

Table 4 : Soil Salinity Stress Coefficient

Soil Salinity Stress Coefficient	**Direct Effect**	**Target Model Parameter**
KsCCx	Reduces canopy cover	CCx
Ksexp	Reduces canopy expansion	CGC
Kssto	Reduces crop transpiration	Kssto
fCDecline	Decline of the canopy cover once maximum canopy cover is reached	

Salt Balance and Soil Salinity Management

Soil fertility stress is expressed by the average of the electrical conductivity of saturation soils in the root zone. By using the model in AquaCrop, the model can estimate the rate of salt that is entering a plant and the rate of salt ions that can leave the plant. They either infiltrate from the surface through the agency of water or by water from an underlying water table that supplies saline water to the soil (Minhas et al., 2020). The upper and lower salinity stress coefficients (Ks) are 0 and 1. At the lower limit of 4-ECe, there is crop damage to growth and development hence a Ks lower than one. However, when Ks reaches values close to the upper limit of the scale, for high salinity of the soil, it causes serious constrains into the crop growth and yield and may totally cease at a value of zero (Cameron, 2020). Table 4 presents a synthesis of the impact of water soluble soil salinity stress coefficients on crop growth and development indices.

Cropping models of aquaculture related to climate change adaptation and mitigation processes

Climate change forecasts show that the world will be warmer by 50 years at most. Yet, the effects of increasing temperatures on rainfall temporal and spatial distribution in the SATs of

Africa and Asia are still uncertain. Cross-sectional studies for the current situation have also been carried out as well as projections for the future where northern climate is expected to show variable climates in the 2030/50s that is very unpredictable affecting the crop growth and productivity (Samuelson et al., 2022).

Literature review on climatic change at different locations of the study area shows proving higher Maximum as well as minimum temperature in the future in Ethiopia. Increased level of CO_2 concentration under various conditions will affect crops yield of in mid to the end of the 21st century. It is also expected that temporal and spatial rainfall variability will influence the rate of crop growth as well as its productivity, thus sowing period flexibility and supplement with irrigation as among the major coping strategies (Ainsworth & Long, 2021).

Statistical Indicators Applied for Evaluating the Efficiency of the AquaCrop Model

Observed crop and soil moisture parameters replicated by the AquaCrop model range from basic inputs that have been calibrated. However, the efficiency and accuracy of simulated parameters for example soil moisture content, dry matter, crop canopy cover, transpiration, runoff and drainage has to be tested against statistical indices in order to determine how closely the simulated scenario fits the observed one.

Root Mean Square Error (RMSE): A number of these methods includes; RMSE which defines total or average difference between observation and simulation (Liemohn et al., 2021). It is calculated as follows:

Normalized Root Mean Square Error (N-RMSE): In AquaCrop versions 5 and 6, N-RMSE is used to assess the simulacra and original estimated parameters with the closer to zero, being the better results.

Coefficient of Determination (R^2): This indexing provides the statistics of the overall goodness of the model as fitted. As mentioned in the AquaCrop manual, although the referential analytical function of R^2 would suggest that it exactly compares the measured with predicted values, in the case of modelling studies, R^2 reflects the proportion of the variance in observed values that can be accounted for by a particular model. P-values vary between 0 and 1, where closer to 1, depict better model efficiency.

Coefficient of Efficiency (E): Mentioned by Nash and Sutcliffe in 1970, this index measures the magnitude of the difference between actual and proposed data: It quantifies the overall deviation of simulated values from the mean of observed values:

CONCLUSION AND RECOMMENDATIONS

Crop models have been widely applied to generate potential strategies of raising crop yield potential in different climates and soil types, as well as farming practices. They are used to measure impacts of climate change on crop growth and yield, estimate crop evapotranspiration, irrigation requirement, soil water management, LAI, growth of dry matter and yield. Crop models are used for farm level decision making concerning micro management practices such as irrigation, water conservation in the soil and run off, genetic engineering of crops, and to measure water and nutrient deficiencies at various developmental stages of crops. Crop modeling has other significant types of integrated research engagements inclusive of multidisciplinary activities for extensive research outcomes. Interaction between computer engineers, agronomists economists and breeders, soil scientists and climatologists can improve the credibility and relevance of crop simulation models enabling farmers to access research information and increase production to meet food security in the country. AquaCrop, DSSAT, APSIM, and Wofost models have been successfully used in different studies on field on effects of moisture stress and deficit, on irrigation and nutrient stresses especially nitrogen, sowing date and climate change on crop yield in Ethiopia. The AquaCrop model holds a good compromise between usability, stability, and realism while evaluating various crop parameters and management practices under different climatologic, edaphic, and managerial environments. This model adequately mimics crop cover canopy, biomass accumulation, and relative soil moisture regimes based on stress coefficients like stomatal closure, canopy size increase, pollination, flowering.

Simulation of crop canopy of the AquaCrop model, dry matter, soil moisture balance, grain yield, evapotranspiration, water use efficiency and runoff are compared with the observed or measured data and the performance of the model is judged by using various statistical parameters such as Root Mean Square Error (RMSE), Normalized Root Mean Square Error (N-RMSE), Index of agreement, and Model efficiency. The current crop models such as AquaCrop can quantify the impacts climate change on crops under current climate conditions and future climates. As such, governments, policymakers, and relevant stakeholders in agricultural research should focus on new practical research directions, personnel development (training, seminars, experience exchange), and funding/photo268.JPG and infrastructure support (laboratories, instruments, and equipment).

The growing complexities of agricultural research call for unfolding new qualities in university, research center, NGOs and other stakeholders in the twilight of the 21st century. For enhanced food security and upgrade of the wellbeing of Ethiopian farmers, there is need for enhancement of inter and intra organizational communication.

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