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Natural Resources Management Framework For Agricultural Irrigation Systems Optimization

Juan Valentin Fernandez
University of Texas at El Paso

NATURAL RESOURCES MANAGEMENT FRAMEWORK FOR AGRICULTURAL IRRIGATION SYSTEMS OPTIMIZATION

JUAN VALENTIN FERNANDEZ

Doctoral Program in Environmental Science and Engineering

APPROVED:

Sergio A. Luna Fong, Ph.D., Chair

Heidi A. Taboada, Ph.D.

Adeeba A. Raheem, Ph.D.

Amit J. Lopes, Ph.D.

Ana C. Cram, Ph.D.

Daniel N. Moriasi, Ph.D.

Stephen L. Crites, Jr., Ph.D.
Dean of the Graduate School

Dedication

To my family and friends.

NATURAL RESOURCES MANAGEMENT FRAMEWORK FOR AGRICULTURAL IRRIGATION SYSTEMS OPTIMIZATION

by

JUAN VALENTIN FERNANDEZ, M.S.

DISSERTATION

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Abstract

Water scarcity has increased substantially in the last decades in many parts of the world, and it is expected to worsen due to the significant increase in global water withdrawals, intensive population growth, and climate change. Water is easily one of the most essential and invaluable global resources due to its many uses, such as drinking, industrial processes, and irrigation. The agriculture sector is one of the most significant water users globally, accounting for nearly 70% of global freshwater withdrawals. Cities and industries compete with the agriculture sector for water sources, producing alarming levels of stress and pollution in the water sources by the increasing numbers of countries and populations. The global population is expected to increase over the following years, reaching 8.6 billion people in 2030 and rising further to 9.8 billion in 2050. To this extent, the agricultural sector will have to increase food production by more than 60 percent. Therefore, increasing water productivity is critical in many countries.

The agriculture sector's main challenges are adapting to climate change and water scarcity impacts on developing low-cost, reliable, and efficient irrigation systems that support water conservation practices, mitigate environmental effects and improve food production. However, their selection and spatial placement for land use represent another challenge at the watershed scale.

In order to achieve the best possible outcome with limited natural resources, this work proposes an irrigation systems optimization framework that integrates The Soil Water Assessment Tool (SWAT) and Multiple Objective Evolutionary Algorithm (MOEA) to identify the optimal spatial placement of land-use and irrigation systems to reduce tradeoffs between conflicting objectives in irrigated agriculture. Hydrologic simulation models are commonly used as water balance and crop estimators. On the other hand, multiple objective optimization has emerged as a

solution to solve many real-life problems. In many situations, evolutionary algorithms can simultaneously optimize conflicting objectives and develop Pareto-optimal sets that decision-makers can use to explore the trade-off between optimal solutions.

Furthermore, the findings of this research will provide decision-makers with the best spatial placement configuration of land-use and irrigation systems that will enable them to plan management practices for each hydrological response unit by considering crop yield, energy consumption, and irrigation system costs. This research will also allow decision-makers to explore different management strategies that can inform them about possible outcomes for different scenarios.

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Chapter 1: Introduction

Water is a fundamental resource and is the most abundant liquid on Earth. Unfortunately, most of it is saline. Water resources are under increasing stress and degradation primarily due to unsustainable consumption, production, and population pressure. Climate change intensifies these factors altering rainfall patterns, hydrological management, and freshwater availability. The imbalance in human demand for water and finite sources will cause and is causing water scarcity and shortages in some parts of the world.

Variations of freshwater volumes over time caused by climate change and intensive use (exploitation) may have drastic impacts on local or regional scales. For instance, shrinking lakes, natural springs that are disappearing worldwide, the decline in river flows, and falling groundwater levels in aquifers systems that experience intensive water withdrawals. Freshwater withdrawals from lakes, streams, aquifers, and reservoirs made by humans have increased during the last century and are still rising in most parts of the world. Fresh water use has increased by a factor of six over the past 100 years (Figure 1). Globally water use is expected to grow approximately 1% per year over the next 30 years. If things continue business as usual, the world will face a 40% global deficit by 2030. Projected water demand is expected to increase by 55% between 2000 and 2050 (United Nations, 2021). It is estimated that about 4 billion people worldwide live in potentially water-scarce areas at least one month per year. The main factors contributing to excessive water use are increasing demand in industry, municipal and domestic use, economic development, shifting consumption patterns, and population growth.

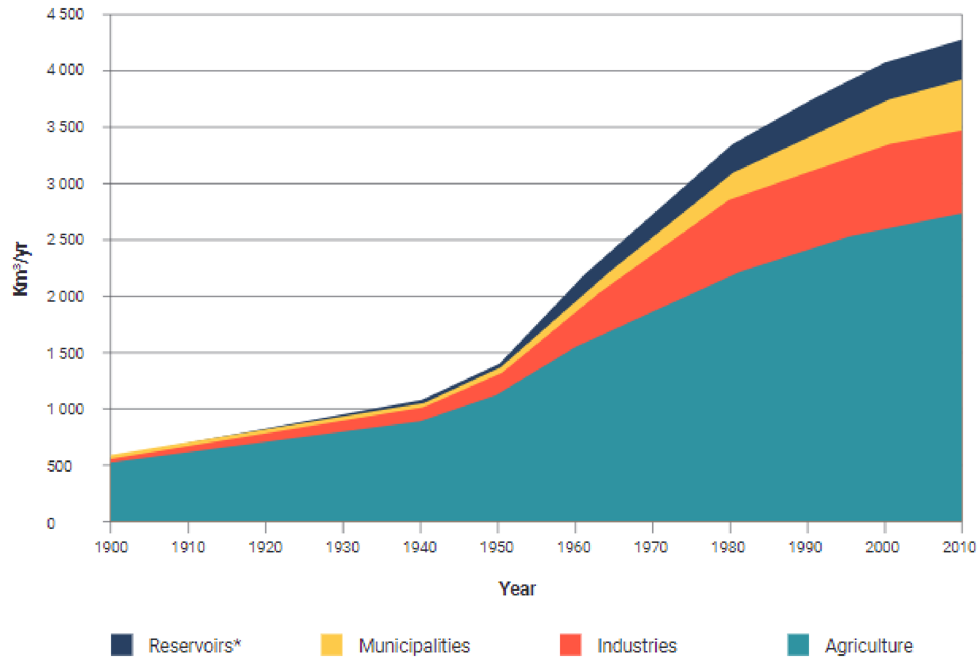


Figure 1: Global water withdrawals 1900-2010 (United Nations, 2021)

Population growth is a crucial driver for water scarcity. The increase in population drives increasing water demand for different human uses. These trends imply challenges for agriculture, the increase in food demand resulting from increased population, and socioeconomic development. Climate change intensifies the challenges by affecting rainfall patterns and the risk of extreme weather events. Climate change is likely to increase the frequency of rainfalls, causing droughts and affecting agriculture's soil moisture, and less surface and groundwater will be available, alongside increased variability in floods will increase socioeconomic losses.

The intense interaction between the multiple drivers that affect water resources will represent a challenge for agriculture. Water, food, and energy are three basic sources essential to maintaining life and socio-economic development. Agriculture is the foundation for food security and is the most significant water resource user influencing energy security. The agriculture sector is one of the largest water users globally. It accounts for nearly 70% of global freshwater withdrawals, according to FAO (2017). Cities and industries compete with agriculture for water sources, producing alarming levels of stress and pollution in the water sources by the increasing numbers of countries and populations. The global population is expected to increase to more than 9 billion people by 2050, and the demand for food is expected to increase by more than 60%. Most of the population increase will occur in urban areas of low-income countries, and food insecurity will be found in these households and areas with depleted natural resources.

Moreover, the global population increase is a significant driver for climate change, which shifts weather patterns that endanger our food production. Climate change can significantly influence the water cycle and increase water treatment costs. The flow of water in surface systems that affect recharge and discharge rates from aquifers can affect the availability and quality of surface and groundwater due to climate variability.

1.1 Problem statement

The main challenges the agriculture sector faces are adapting to the impacts of climate change and water scarcity to develop food production systems that can efficiently feed the growing population in the following years. Water scarcity occurs when the water supply does not meet water demand. According to FAO (2017), by using the appropriate technologies and investments, the possibility exists of having sufficient freshwater resources for agriculture to meet the demand requirements by 2050.

Moreover, inefficient and uncoordinated water use depletes aquifers and reduces river flows, which means that to meet the growing population's food requirements, irrigated food production is expected to increase by more than 50 percent. In addition, low-cost, reliable, and efficient irrigation systems are required to support water conservation practices, mitigate environmental impacts, and improve food production. Water and energy are essential for irrigation and are significant resources that provide economic, social development, and environmental integrity. Consequently, there is a need to identify sustainable irrigation management practices.

In addition, the improvement of agricultural productivity with the depletion of water resources is being addressed globally. Optimizing agriculture productivity depends on the integration and interaction of various factors, the appropriate selection of irrigation systems and strategies considering water availability, climate variability, soil and crop characteristics, and energy, economic, and environmental aspects. Environmental managers worldwide are asked to achieve the best possible outcome with limited sources. Therefore, methods that can tradeoff and balance competing objectives are essential. The most common decision-making approach is based upon accumulated experience to make complex decisions. The decision space is complex, and this situation requires decision-support tools (Horne et al., 2016).

1.2 Watershed management optimization

Computer simulations have become an indispensable tool for solving problems where different activities try to achieve specific objectives or optimize things such as profit, time, yield, and quality. Mathematical optimization is the study of these activities, and there are different mathematical tools and efficient algorithms that can solve complex problems. For instance, managing a watershed for land use can become difficult for decision-makers. Different parameters and management practices can be assessed to provide the best results. Assuming that the goal for the decision maker is to provide maximum crop yield with minimum water usage can represent an infinite number of management practices or configurations that can be explored, and computer simulation models are the best way to accomplish it. For instance, if multiple management practices can be evaluated in multiple fields, the number of combination that exists can be infinite, and evaluating them and obtaining the optimal setting that provides the best results in terms of crop yield and water usage cannot be found without computer simulation

Hydrologic simulation models are used as water balance and crop estimator and have been widely used in agriculture irrigation systems and management practices. This simulation model provides and understanding of what is happening in the watershed by having the ability to evaluate different management practices. Irrigation systems can reduce water usage; however, their selection and spatial placement for land use can be troublesome at the watershed scale. For that reason, multiple objective optimizations have emerged as a solution to solve many real-life problems. In many situations, more than one objective needs to be optimized simultaneously. Different evolutionary algorithms can simultaneously optimize conflicting objectives and develop a Pareto-optimal front that decision-makers can use to explore the trade-off between optimal solutions. In addition, integrating a hydrologic simulation model and optimization method can be a powerful tool to reduce water usage and costs in the agriculture sector while maximizing crop yields.

1.3 Goals and Objectives

The agricultural sector must adapt to the impacts of climate change and water scarcity to improve food production systems to feed the growing population with limited water resources. This research focuses on developing a robust and open-source optimal natural resource management tool that improves management practices for agricultural irrigation systems, land use, and the environment at the watershed scale. To achieve this goal, the following objectives are being considered:

***Objective 1*:** Integrate a Multiple Objective Evolutionary Algorithm (MOEA) to identify the optimal spatial placement of Land-Use and irrigation systems, considering maximizing crop yields while minimizing water usage.

Objective 2: Develop an Irrigation System Assessment framework to quantify energy cost and consumption in agriculture irrigation water from different water sources.

Objective 3: Integrate the Soil Water Assessment Tool (SWAT) hydrological model and the Irrigation System Assessment framework with the MOEA.

Objective 4: Develop a Graphical User Interface (GUI) integrating the irrigation systems framework to enhance the capabilities of SWAT-MEA, which can be used to evaluate any SWAT project, and multiple agricultural irrigation systems and execute the MOEA.

Chapter 2: Literature Review

In recent years, the development of irrigation systems has proven beneficial to mitigate water usage and energy consumption. Systems such as drip and sprinkler irrigation demonstrate that pressurized systems perform better than traditional irrigation systems concerning water usage and crop yield, such as furrow irrigation. In addition, there have been advances in technology that has proven to be beneficial in promoting our understanding of natural resources. Technologies include the development of hydrologic simulation models, optimization tools, and frameworks that can optimize management operations to alleviate the decision-making process. These tools allow us to understand the water cycle and identify what is happening in the watershed by uncertain climate change conditions and different anthropogenic activities, allowing us to develop management operations to mitigate the negative impacts of the different activities. The following sections provide a literature review on different irrigation systems and their applications and some articles related to understanding water, energy, and agriculture interrelationships.

Additionally, a literature review on hydrological simulation models, focusing primarily on the Soil Water Assessment Tool (SWAT), is reviewed to identify research gaps and the state of irrigation systems optimization. Lastly, there have been several assessments where SWAT has been integrated with other models and optimization tools to improve different climate change scenarios, and these areas are described in the following sections. It is important to note that the various studies had several objectives, and this review attempted to categorize them regarding the primary goal.

2.1 Pressurized Irrigation Systems

The oldest form of irrigation is surface irrigation, which allows water to move across the soil surface of agricultural lands by gravity. However, throughout history, the earth's climate has changed, causing uncertainty regarding the future direction of surface and groundwater irrigation. On-farm water pumping uses 23-48% of the energy for crop production (Tarjuero et al., 2015). The energy used by pumping water generates significant greenhouse gas emissions that can accelerate climate change. Climate change uncertainties are responsible for the development of irrigation techniques for successfully growing crops across the world. Irrigation is a controlled application of water to agricultural crops. Recent studies have identified the importance of the different irrigation systems and why it is critical to managing them efficiently to minimize energy consumption and water usage. For instance, irrigation dependent on groundwater is one of the most energy-consuming irrigation methods. Chen et al. (2019) proposed an energy consumption model for groundwater irrigation systems in North China Plain, one of the largest energy consumption areas. The study suggests that replacing irrigation methods like surface irrigation with sprinkler and drip irrigation and cropping system practices can reduce energy consumption for irrigation. Other alternatives to reduce energy consumption have been explored, such as reducing working pressures at the sprinkler nozzles resulting in energy reduction due to low pumping requirements. Zapata et al. (2018) analyzed the irrigation performance of three irrigation treatments with different pressures; a standard brass impact sprinkler with an operating pressure of 300kPa, a standard brass impact sprinkler with an operating pressure of 200 kPa, and a plastic impact pressure of an operating pressure of 200 kPa. The study suggested that there are no differences in the grain yield due to the maize canopy portioning reducing the difference in the irrigation performance indexes among the different pressure treatments. It also suggested that using low-pressure sprinkler irrigation aids energy consumption and maintains water usage and crop yield.

Furthermore, sprinkler irrigation is one of the most common irrigation systems used worldwide due to the ease of adaptation to different soils and topography, and it can irrigate almost all annual crops. In 2010, the percentage of sprinkler irrigation in farms was 23.9% in Portugal, nearly 15% in Spain, 39.4% in Italy, and Greece had 29.4% (Silva, 2017). Albaji et al. (2015) conducted a study in an area of about 15,000 hectares considering different topography characteristics, such as soil properties, slope, depth, salinity, drainage, and calcium carbonate content. The study compared different irrigation systems and suggested that sprinkler and drip irrigation systems improve land productivity due to being more efficient than surface irrigation methods. The comparison revealed that sprinkler irrigation was more effective and efficient in this land area compared to drip irrigation and surface irrigation methods. This is primarily due to the different soil and land characteristics parameters that make certain irrigation systems more suitable than others for specific land characteristics.

In addition, the modernization and optimization of irrigation systems can alleviate water scarcity. The concept of modernization has evolved in recent decades; initially, it was limited to only physical structures and equipment installation, but nowadays, it has been established as a transformation of irrigation management practices to improve resource utilization and the services provided to the farmers. Irrigation management offers a better returned compared to the improvement of irrigation structures. The challenge in irrigation systems may not be the development of new irrigation technology but rather the reduction of technical efficiency differences, yield, and water productivity. This was noticeable in northern Spain, with traditional surface irrigation systems showing approximately 50% efficiency, while a pressurized system with a good design and management can reach approximately 90% efficiency (Playán and Mateos, 2006). Correspondingly, Tarjuero et al. (2015) identified the main technical aspects of irrigation modernization and management that lead to improved water and energy. To improve water and energy use efficiency, the most common approach being used globally is replacing open channel, gravity-based systems with pressurized distribution networks and switching from surface irrigation systems with more efficient pressurized systems, such as sprinkler and drip systems. In addition, the review suggests that applying irrigation on average can increase by six times the primary crop yields generating a gross margin four times the profit of rainfed crops. Peng et al. (2019) developed a water demand prediction model to optimize irrigation networks to determine the optimal network structure to reduce irrigation energy consumption. This study selects three types of drip irrigation networks: comb-shaped, fish bone-shaped, and H-shaped. The results suggested that for flat regions, the H-shaped pipe network was best to improve irrigation efficiency due to the uniformity of the velocity and pressure at the outlet.

Lastly, sprinkler irrigation systems have been integrated with different management practices to mitigate energy consumption and water usage. For instance, Nasseri (2019) presented a study to analyze the combination of sprinkler irrigation and conservation tillage for wheat production. The study compared conventional tillage and surface irrigation with conservation tillage and sprinkler irrigation using energy indices and economic analysis. The study identified 3.2 MJ of energy consumption to produce 1 kg of wheat grain using conservation tillage and sprinkler irrigation compared to 7.2 MJ of energy consumption using conventional tillage and surface irrigation. It suggested that conservation tillage with sprinkler irrigation performed better under all energy indices. Aside from land-use management operations, irrigation scheduling is another management operation that has been used, for instance, Mitchel-McCallister et al. (2020)

evaluated the impact of irrigation timing on the yield and economic profitability, and the study suggests that there is a need for new management strategies to sustain the profitability of the producer.

2.2 Irrigation Optimization Frameworks

In recent years, optimization has proven essential to the decision-making of optimal design, planning, and operation of water resource systems. Different approaches consider irrigation optimization frameworks. These frameworks do not integrate SWAT but provide insights into modeling techniques and considerations in irrigation optimization. Primarily non-linear optimization has proven to be more suitable for solving complex problems that arise in water resource systems management. Elshaikh et al. (2018) reviewed the different concepts, frameworks, and methodologies that have been applied to assess irrigation performance evaluation. The study suggested that the main methods considered to evaluate irrigation performance are fuzzy set theory, direct measurements for indicators, remote sensing, and analytic hierarchy process. Direct measurement for indicators mainly focusses on measuring the performance of direct irrigation water elements. Fuzzy set theory is used to deal with uncertainty in different situations where information is incomplete or imprecise. The analysis hierarchy process is a multi-criteria decision-making technique that decomposes a problem into a hierarchy where each level is composed of specific elements. Remote sensing technique is used to provide satellite data to improve the diagnosis under data scarcity. Other studies consider a hierarchical approach to develop an economic objective optimization model to plan water allocation in deficit agricultural water resources systems (Reca et al., 2001). The model suggests three independent optimization sub-problems with different resolution levels crop, irrigation district, and the whole basin. In the first level, each crop's optimum production function is identified, considering irrigation timing to maximize crop yields. The second level considers land water and irrigation water allocation to generate economic functions in respect to each irrigation area. Lastly, the third level optimizes water allocation taking into account the economic function of each irrigated area. The article suggested that non-linear optimization techniques are suitable for solving water allocation problems compared to linear techniques.

Similarly, Singh (2014) provided a review that reveals a preference for conjunctive simulation and optimization models for solving integrated use management. The simultaneous use of surface water and groundwater for irrigation is referred as conjunctive use, and the purpose is to increase crop yield, supply reliability, and water efficiency. Various programming optimization models have been developed in this area, from linear programming models that cannot handle nonlinear problems to genetic algorithms that have been identified as valuable tools for complex problems, yielding better results than traditional optimization techniques. Jiang et al. (2019) developed an optimization and coordination model with multiple-objectives to optimize irrigation water allocation in multi-stage pumping water irrigation systems. The model was solved based on the decomposition coordination method and considered energy and minimum water requirement as two objectives, and different periods are considered for water allocation and operation. The study suggests that the model could improve the balance of water supply among the different subsystems. Li et al. (2019) provided a stochastic modeling framework to address economic and environmental objectives that is capable of providing policy makers with the ability to determine policy options among water, energy, and land resources.

In that respect, different studies incorporate different parameters to optimize and obtain the best cultivation conditions. Mahmoodi et al. (2020) explored the effects of irrigation interval and water salinity of different parameters (crop yield, evotranspiration, water use efficiency, shoot dry weight, root dry weight, fruit diameter length, plant height, and root length) of eggplant cultivation. Multivariate models were developed to estimate responses, and surface methodology was used to determine the function for optimum desirability, which was then used to determine the optimum region by overlaying the parameter. A simultaneous optimization for all the parameters was performed in order to obtain the best conditions of cultivation using the desirability function. The different interactions of the factors suggested that water interval and water salinity could potentially increase crop yield, minimize water use, and reduce soil salinity in the environment. Likewise, to maximize the irrigation usage of water efficiently, Jiang et al. (2016) proposes a two-level optimization model combining the agro-hydrological model established with eleven subsystems and applying irrigation water usage to optimize under five water supply scenarios.

2.3 Soil Water Assessment Tool for Irrigation and Optimization

The Soil Water Assessment Tool (SWAT) has been used in several studies in order to assess the impact of irrigation and crop yield. There is a need to incorporate a hydrological model and irrigation systems that can simulate irrigation management strategies. Hydrologic modeling is developed for estimating, predicting, and managing water distribution as a function of various parameters that describe soil and watershed characteristics. The commonly required inputs include atmospheric data, and the model parameters include topographic relief, geomorphology, and soil and vegetation properties. There have been many attempts to improve water productivity and minimize water utilization. Controlling schemes for irrigation and drainage are widely adopted practices for agricultural water management. Acceptable schemes for irrigation and drainage, aside from providing proper moisture conditions that favor crop growth, need also to minimize water consumption and transfer. Xi and Cui (2011) focus on paddy rice areas, provide a simulation of the hydrological processes, and introduce an irrigation scheme and drainage process that considers three critical water depths.

Changing irrigation systems from surface to pressurize is another alternative; however, there is a need to evaluate these systems with the use of a hydrological model prior to making them operational. Ahmadzadeh et al. (2016) use the SWAT model to evaluate the impacts of shifting from surface irrigation to pressurized systems of the Zarrineh Rud River in Iran. The study suggests that pressurized irrigation reduces water use, compared to surface irrigation, by about 165 MCM/yr. In another study, Ashraf Vaghefi et al. (2017) analyzed the water productivity of irrigated maize and wheat by using the SWAT-MODSIM model. SWAT was used to model irrigation demands of agricultural regions using dynamic irrigation and MODSIM for water allocation, and the study found that high yield is not dependent on higher water consumption. In China, paddy rice is a major food crop that consumes large amounts of water for irrigation. Wu et al. (2019) use SWAT to simulate the hydrological processes of a basin and propose a new method for calculating agricultural irrigation water consumption from different water sources. Similarly, Zou et al. (2018) utilized SWAT at a regional scale to improve the conventional method for estimating the irrigation water demand of regional crops, and Uniyal et al. (2019) estimated water balance at different scales.

Furthermore, integrating the SWAT model and multiple objective algorithms has been used widely for managing a broad range of water-related issues. Panagopoulos et al. (2012) developed a Decision Support Tool in MATLAB to assess the different irrigation scheduling programs and determine their optimal placement in The Ali Efenti catchment. SWAT is utilized to simulate the water balance and crop yield. The model was set up by testing seven alternative irrigation scheduling programs in SWAT to evaluate the impact on the hydrological response unit and crop yields, and the irrigation amounts and crop yield reduction were stored in a database. Non-dominated Sorted Genetic Algorithm (NSGA-II) was used to optimize total water usage and crop yield objectives. The study suggested that the decision support tool accelerated the optimization process. Campos et al. (2020) also use NSGA II primarily due to its faster convergence. Thomas et al. (2021) develop a genetic algorithm optimization framework for the Bargi reservoir system incorporating the SWAT model to identify the impact of climate change in future climate scenarios. The objective function is to minimize failures in meeting domestic, irrigation, and hydropower demands. The optimization framework uses a Nondominated Sorting Genetic Algorithm II (NSGA II) to obtain a set of optimal operation policies and suggests that the simulation-optimization approach with integrated reservoir operations is suited to address low and high flows related to drought and rainfalls.

Lastly, Panagopoulos et al. (2014) developed a decision support tool with the capability to optimally locate irrigation best management practices. The basin's hydrology was simulated using the SWAT model to represent the effect of four different irrigation water management practices deficit irrigation, conveyance improvement, precision agriculture, and wastewater reuse. The model uses an economic function that uses the unit costs of the best management practices and stores the output data in a database that incorporates gross irrigation water amounts, costs for all hydrological response units, and the best management practice implemented on them. The model then implements a genetic algorithm to identify the optimal combinations of irrigation best management practices regarding the total water abstraction and the cost of implementation according to the SWAT model simulation. Udias et al. (2018) explore management strategies by developing an optimization framework to identify cost-effective irrigation strategies. The framework considers crop water requirements, the impact of irrigation changes on crop yield, and the economic model. SWAT is linked with the economic model through R software.

2.4 Soil Water Assessment Tool for Nonpoint sources (NPS) Pollution and Optimization

In the past decades, the understanding of nitrogen (N) and phosphorous (P) distribution within the agricultural system and the impacts it produces has grown significantly. Nutrients such as nitrogen, phosphate, and potash are absorbed by crops and are essential to their production. When applied in excess, the nutrients can get lost to the environment, leaching into groundwater and runoff into surface water, which may result in water quality degradation. Huang et al. (2017) determine pollution prevention guidelines using the SWAT model to estimate phosphorous effects and identify the effects on long-term land and soil variations. Water pollution due to a collection of land use activities is referred to as diffuse pollution. Anthropogenic activities may have a direct or indirect impact on diffuse pollution, causing a significant threat to water resources. Agricultural diffuse sources, such as excessive use of fertilizer and pesticides, are leached and transported from agricultural activities (Rocha et al., 2015). Climate change variability causing high rainfalls, droughts, and the excessive use of natural resources have made ecosystems vulnerable to soil erosion. Soil nutrient loss and sediment can occur through soil erosion. It is important to understand the processes and sources of diffuse pollution in order to reduce soil and water degradation. Bossa et al. (2012) use the SWAT model to simulate the dynamics of sediments, nitrates, and organic nutrient runoff to investigate the impacts of crop and fertilizer patterns on crop yield. SWAT is employed to simulate nutrient loadings under different scenarios.

In addition, other studies have mentioned the importance of identifying optimal management practices to mitigate nonpoint source pollution. Dai et al. (2018) developed the

SWAT-based fuzzy credibility chance-constrained programming (SFCCP) method to determine optimal best management practices configurations for nonpoint source pollution (NPS) control. Chen et al. (2016) introduce a Markov algorithm in order to ease the optimal design of best management practices related to water quality mitigation from nonpoint source pollution. The Markov algorithm serves as an intermediary for SWAT to quantify water quality. The proposed framework is tested to minimize nitrogen (N) and phosphorous (P) with an NSGA-II algorithm to optimize the best management scenarios. Panagopoulos et al. (2012) develop a decision support tool by combining a non-point source (NPS) pollution estimator, SWAT model, and a genetic algorithm that serves to optimize the best management practices. SWAT was used to estimate nitrates nitrogen and total phosphorous losses from the different HRUs. The outputs were used to create a database, which was then introduced into MATLAB R2007 GA tool box, NSGA-II, to identify the optimal configuration of management practices.

2.5 Soil Water Assessment Tool Performance and Improvements and Optimization

SWAT has proven effective in quantifying the impacts of different management practices, land use scenarios, and various climate change scenarios. Government agencies and policy makers also adopt it, and in the past 30 years, it has undergone many improvements. For instance, SWAT+ is a reconstructed version of SWAT, and its contribution is noticeable in the improved spatial objects, along with having available new functionalities for aquifers. Models are constantly improved, and that is the case for SWAT+, Wu et al. (2020) coupled the Integrated Parameter Estimation and Uncertainty Analysis Tool (IPEAT) to develop calibration guidelines for SWAT+. The reservoir function of SWAT+ coupled with the calibration tool provides a sensitivity analysis of the reservoir parameters to identify the interactions between the reservoir parameters and the hydrologic process.

There is an increase in groundwater demand in regions with semi-arid climatic conditions, and this is causing regions that experience droughts to over-exploit the groundwater resource. There is a need for tools that can assess watershed resources in order to limit the negative climate change impacts. Perrin et al. (2012) integrated surface water and groundwater resources of a semi-arid watershed. In this study, calibration is based on surface reservoir storage and recharge derived from groundwater balance, suggesting that a properly calibrated model can provide spatial variability in the water fluxes. In many parts of the world, groundwater quantity and quality have suffered severe degradation, and water levels have decreased. Abbaspour et al. (2015) use SWAT to simulate the hydrological model of Europe. The model employs SUFI-2 for calibration and produces a protocol for calibrating large-scale models. There have been many advances in collecting datasets from the Earth's surface and from satellite observations that enhance our understanding of the water cycle. This information allows us to improve our assessments of water circulation and can be used to assess different scenarios, but it does not guarantee robust models. Therefore, scientists encourage using model assessments by integrating different metrics into the models. However, in order to represent the hydrological system properly, calibration should consider equifinality, model inadequacy, and constraint inadequacy (Triana et al., 2019). Hernandez-Suares et al. (2021) developed the Unified Non-dominated Sorting Genetic Algorithm III (U-NSGA-III) by incorporating routines constraining the performance of Ecological Relevant Hydrological Indices (ERHIs) and an evolutionary algorithm. The study was implemented in an agriculture-dominated watershed and developed calibration strategies to produce a balance representation of ecologically relevant hydrological indices and suggests that performance-based calibration is preferred.

In the event of assimilating remotely sensed surface soil moisture data, a major concern is using surface observations to update profile soil moisture. In order to improve streamflow simulations, Patil and Ramsankanran (2017) integrated Soil Moisture Salinity (SMOS) level 3 (L3) retrievals into SWAT hydrological model to improve the soil layer in the SWAT model, thus obtaining better streamflow forecasts. Dumedah and Coulibaly (2013) introduce SWAT and NSGA-II to develop a framework for addressing data assimilation to estimate stream flow and soil moisture. Herman et al. (2015) couple the SWAT model, Stream Health Predictor (ANFIS), Hydrologic Index Tool (HIT), and a genetic algorithm to examine stream health and costs. Similarly, Tan and Yang (2020) provide streamflow simulation in SWAT. The simulation takes into account the distance between rainfall and streamflow stations and explores the effect of missing rainfall data in different periods. Hunink et al. (2012) introduce a new methodology, Green water and Blue water assessment (GBAT), making use of SWAT and different databases in order to quantify the effects on management practices from upstream and downstream areas. To do this, the model analyzes the impacts of streamflow concerning green and blue water.

SWAT integration with different models has improved different parameters of the hydrological model. For instance, Senent-Aparicio et al. (2021) proposed the integration of the SWAT model and QGIS Water Ecosystem Tool (QWET). QWET simulates the vertical distribution of temperature and evaporation by incorporating SWAT simulated flows, and it can be an effective tool for estimating different components of the water balance. Qi et al. (2021), building on previous concept models, introduces the SWAT-HB model by coupling terrestrial and aquatic thermal processes in order to estimate stream water temperatures. The temperature of different terrestrial components, such as surface runoff, lateral flow, and base flow, are considered to assess the thermal processes that influence it, as well as the heat balance of water. The new model was then compared to other models and suggested that in regards to seasonal comparison, the improvement in estimating terrestrial water temperatures provided significant results in spring and winter. Liu et al. (2020) propose the long–term BMP optimization method (LBMP-OM) by integrating the SWAT model with an economic model and MOSFLA to optimize best management practice configuration. This method consists of two parts, the first one being the best management practices optimization for maintenance and replacement strategies and the second optimizing the best management practices configuration.

2.6 Soil Water Assessment Tool with Climate Change impacts

Climate change is a key hydrological problem. In research, assessing different climate change scenarios has become a standard practice for analyzing its effect on hydrological systems. Understanding climate change and the impacts it has on agriculture can help develop management measures for future events. To address possible climate change impacts, Global Climate Models (GCMs) are sources that can be used for futuristic and current parameters. Global Climate models (GCMs) and General Circulation Models (GCMs) are sometimes used interchangeably and provide future climate projections. In different articles, GCMs are integrated into SWAT and are used to simulate the future response of the climate system concerning anthropogenic activities. Climate models present the advantage of performing multiple simulations to provide possible future climate variables. Pandey et al. (2021) presented an integrated modeling approaching using SWAT and GCMs to investigate the hydrological sensitivity of the basin in different climate scenarios. To narrow uncertainty in the simulation, MIROC5, CNRM-CM5, MPI-ESM-LR, GFDL-ESM2G, and IPSL-CM5A-MR are used to estimate the water balance components. General Circulation Models (GCMs) datasets have been applied in hydrological models for long-term hydro-climatic assessments. It becomes challenging to determine the best GCM source for data input due to their unique assumptions, structure, and parameters. Yuan et al. (2020) provide a new approach for selecting the optimal climate model by evaluating SWAT simulations driven by selected GCMs. These methods can be beneficial for studies that rely on using GCM outputs.

Climate change can affect water quality and quantity and can lead to flooding. In this study, Giri and Abropta (2020) investigate the climate change impact potential by utilizing surface runoff, sediment yield, and phosphorous to assess the vulnerability of climate change. On the other hand, Veettil 2020 simulated the streamflow pattern in the SWAT model and included statistical models in order to quantify the influence of climate change and different variables associated with hydrological drought. The Standardize runoff index was used to quantify the hydrological drought. The study suggests that catchment variables are more significant in triggering hydrological drought.

The classification of freshwater resources, blue, green, and gray, can be important in addressing water security. The Blue water footprint evaluates the volume of surface and groundwater consumed from blue water sources corresponding to a production process. Green water footprint relates to using green water sources; for instance, evapotranspiration is usually significant in agriculture and forestry processes. Veetill and Mishra (2016) applied a framework to evaluate the spatial variability of Green and Blue water to quantify water security. The study included climate and anthropogenic factors and suggests that it can aid decision-makers in understanding the status of water availability. The water footprint is an indicator of freshwater use, and this index can be used to quantify water consumption in the entire production supply chain.

Luna et al. (2018) established a method for measuring crop production water footprints using SWAT, where the green water footprint is the volume of precipitation consumed during the crop growth period, and the blue water footprint is the volume from surface or groundwater consumed during that period. The study suggests these models can aid the agricultural water management sector in managing and allocating water resources. Blue water accounts for roughly one-third of the total freshwater availability, and green water for tw0-thirds of the total freshwater. Du and Merwade (2018) use SWAT to simulate hydrological fluxes and asses blue water and green water dynamics in the Ohio River Basin. The study suggests that increased precipitation and reforestation are dominant indicators of climate change and land use. Liang et al. (2020) presented a study using SWAT to simulate blue water and green water scarcity under different climate and land use change scenarios. The study suggests that blue and green water indexes are important in identifying hotspots in water stress areas. The study identifies that blue water scarcity is mainly affected by precipitation and population, while green water scarcity is caused by agriculture and urban land.

2.7 The Water-Food-Energy Nexus

Nexus thinking is a way of thinking that considers and understands water, food, and energy interrelationships. Agriculture is the foundation for food security and influences energy security due to the high usage of water resources. Consequently, integrated management is essential in the water-food-energy nexus for sustainable agriculture. Considering that food production can generate economic benefits as a result of coordinated management of water, energy, and land resources, but in order to benefit economically, the production process requires water, pesticides, and land fertilizers that generate greenhouse gas emissions and non-point source pollution impacting the environment (Li et al., 2019). Namany et al. (2019) provide a review from 2010 to 2019 on the energy-water-food nexus about dynamic decision-making, focusing on mathematical optimization, agent-based modeling, and game theory. The review identified 53 articles, and only 40 were used, and suggested that multiple objective optimizations have great potential to identify solutions for problems with conflicting objectives due to the ability to generate useful results based on the optimization perspective but lack feasibility from the stakeholder point of view. The relationship between water, food, and energy can be seen in irrigated agricultural systems. Food production depends on water availability, and food production consumes water and energy. The relationship between water and energy exists in the use of energy for water pumping in most areas that require the use of irrigation systems. Therefore, Kahil et al. (2019) suggested that a cross-sectoral multi-scale nexus approach can help to identify solutions to water scarcity problems and prevent trade-offs between sectors.

There are different studies that analyze the interdependency of water and energy. For instance, Hamiche et al. (2016) provided a review to understand the interdependency between water and electricity and suggested that a comprehensive understanding of the water-energy nexus is essential to understand the dimensions of the nexus. Water scarcity is of major concern for developed and developing countries. Espinosa-Tason et al. (2020) explored the water-energy nexus in Spain's irrigated agriculture by estimating the water consumed and abstracted as well as the energy required to supply water for agriculture. The study identified an increase in annual water abstraction by 1.02% and an annual increase in energy consumption by 3.4%. The study suggested that the ratio of water to energy is primarily due to the incorporation of pressurized systems to fight water scarcity. Drip irrigation is one of the most common methods to irrigate tomatoes, and Yahyoui et al. (2017) present an autonomous off-grid system for irrigation to correctly handle energy and water requirements.

Chapter 3: Soil Water Assessment Tool

The Soil Water Assessment Tool (SWAT) was developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) and is a continuation of roughly 30 years of modeling experience. SWAT is a robust interdisciplinary watershed-modeling tool acknowledged internationally and can be evident in the little over 2000-peered review publications found when using the acronym "SWAT" in July 2015 (Francesconi et al. 2016). The model has undergone continuous review and expansion since its development, making it useful for different U.S. federal and state agencies, such as the USDA within the Conservation Effects Assessment Project (CEAP). Additionally, it was accepted as a software package for the U.S. Environmental Protection Agency (USEPA) Better Assessment Science Integrating Point and Nonpoint Sources (BASINS) (Gassman et al. 2007).

SWAT is a physically based river basin scale continuous-time model that operates on a daily time step and is used to predict the impact of management on water, agricultural chemical yields, and waste materials in watersheds. The model can execute continuous simulations over extended periods of time and is computationally efficient. In order to develop a simulation, there are different data inputs required, such as weather and hydrology data, soil temperature and properties, plant growth factors, and land management (Gassman et al. 2007).

In SWAT, a watershed is divided into multiple sub-watersheds, which are then divided into unique soil/land use characteristics called hydrological response units (HRUs). Sub-basins are the first level of subdivision and occupy the geographic position, and partitioning the watershed into subbasins, this will allow the user to reference spatially different areas of the watershed to one another (Neitsch et al., 2011). Sub-basins will contain at least one HRU, the main channel or reach a secondary channel, and a pond or wetland may be defined, respectively. In the sub-basin, the land area may be divided into hydrological response units (HRUs), which are segments of a sub-basin that contain homogeneous unique attributes such as land use, management practices, and soil properties. HRUs are the total area in the sub-basin with unique attributes; it is not equivalent to a field and may be dispersed throughout the sub-basin. It is not practical to simulate individual fields; for that reason, the HRU areas are allocated together by similar soil and land use areas to form one single response unit to simplify SWAT simulations. The water balance of each HRU is represented by four storage volumes: snow, soil profile, shallow aquifer, and deep aquifer. Flow generation, sediment yield, and pollutant loadings are summed across all HRUs in a sub-watershed, and the resulting loads are then routed through channels, ponds, and reservoirs to the watershed.

Water balance is the driving force in everything that happens in the watershed, regardless of the type of problem simulated in SWAT. Hydrology simulation of the watershed can be divided into land phase division and water or routing phase. The land phase of the hydrologic cycle is responsible for managing the amount of water, nutrients, sediments, and pesticide loadings to each subbasin's main channel (Figure 2). The second phase, the water or routing phase, handles the movement of water, nutrients, sediment, and pesticides through the watershed's channel network to the outlet (Neitsch et al., 2011).

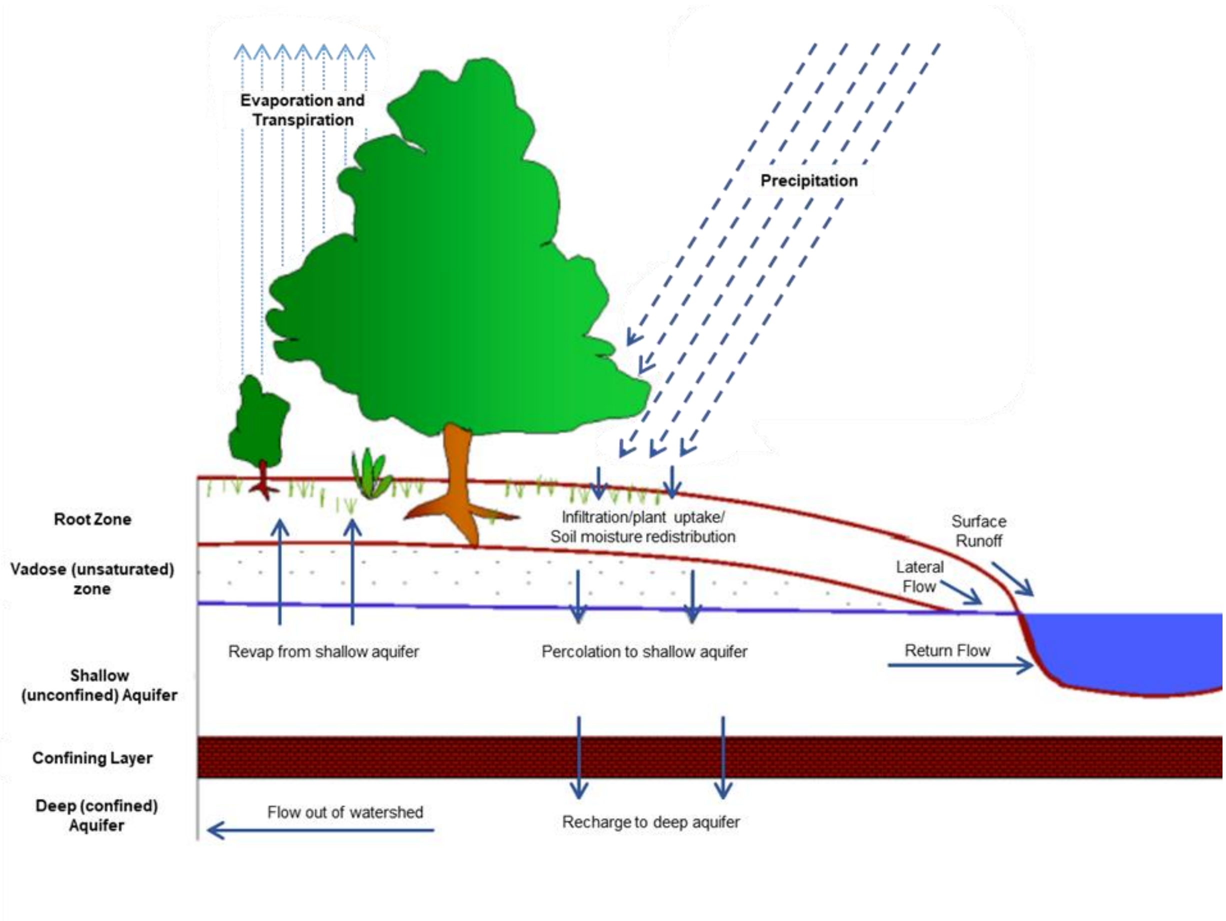


Figure 2: Schematic representation of the hydrologic cycle (Neitsch et al., 2011).

3.1 Land Phase of the Hydrologic Cycle

The watershed is subdivided, and this enables the model to reflect evapotranspiration differences for the various crops and soils available in the model. Total runoff for the watershed is routed and predicted separately for each HRU. This causes an increase in accuracy and enables a better description of the water balance. The hydrologic cycle simulated in swat for water balance is calculated as follows:

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw} \right)$$

where SW_t is the final soil water content, and the initial soil water content is defined by SW_0. The amount of precipitation on day i is defined by R_{day}. The amount of surface runoff on day i by Q_{surf}. The amount of transpiration on day i defined by E_a. The amount of water entering the vadose zone from the soil profile on day i defined by w_{seep} and Q_{gw} is the return flow amounts on day i, respectively.

3.2 Irrigation

SWAT allows the user to select two irrigation options: a manual scheduling application or an automatic irrigation application. The user also has the option to select irrigation water from five types of water sources: reach, reservoir, shallow aquifer, deep aquifer, or a source not specified outside the watershed. The model needs to know the location of the water source; for instance, in a shallow or deep aquifer, the location is specified by the reach number or subbasin number where the source is located. If the water source is a reservoir, the reservoir number needs to be used to specify the location. If the water source for irrigation is a reach, the user will need to input other parameters in order to prevent the reach flow from reaching zero as a result of irrigation water removal. Ultimately, SWAT will determine the amount of water available in the source for any given irrigation event (Neitsch et al., 2011).

3.2.1 Manual Irrigation

The irrigation amount (mm) is defined as the amount of water applied that reaches the soil, and the user has the option to specify the schedule by date or heat units in the manual application. The efficiency factor (min 0 max 100) accounts for losses starting from the source to the soil, and this includes conveyance and evaporative losses. In the manual application, a surface runoff ratio (min 0 max 1) of a fraction of water applied leaves the field as runoff, and the remaining water infiltrates into the soil. (Neitsch et al., 2011). Table 1 identifies the variables found in the manual irrigation operation line:

Table 1: Input variables for manual operation irrigation (Neitsch et al., 2011)

Variables Name	Definition	Input File
Variables in irrigation operation line:		
MONTH/DAY or HUSC	Timing of irrigation operation	.mgt
MGT_OP	Operation code. MGT_OP=2 irrigation operation	.mgt
IRR_AMT	Depth of irrigation water applied on GRU (mm)	.mgt
IRR_EFM	Irrigation efficiency for manual operation (0-1)	.mgt
IRR_SQ	Irrigation surface runoff ratio for manual operation (0-1)	.mgt

3.2.2 Auto-Irrigation

The auto application of irrigation can be triggered in two ways: water stress threshold or soil water deficit threshold. The water stress threshold is a fraction of potential plant growth. The water stress factor ranges from 0.0 to 1.0, where 0.0 indicates that there is no growth of the plant and 1.0 indicate there is no reduction of plant growth due to the water stress. It is usually set between 0.90 and 0.95 Arnold et al. (2013). Water stress is simulated by comparing actual and potential plant transpiration:

$$wstrs = 1 - \frac{E_{t,act}}{E_t} = 1 - \frac{w_{actualup}}{E_t}$$

where $wstrs$ is the water stress for a given day, $E_{t,act}$ is the actual amount of transpiration, E_t is the maximum plant transpiration on a given day, and the plant water uptake is defined by $w_{actualup}$ (mm $H_2 0$). Potential plant growth is modeled by the simulation of the leaf area, light interception, and conversion of intercepted light into biomass under the assumption that a plant specifies the efficiency use of radiation. If plant stress falls below the water stress threshold, the model automatically applies the user-defined maximum water application. Similarly, soil water deficit triggers irrigation application when the soil water in the profile falls below field capacity by more than the soil water deficit threshold (Neitsch et al., 2011). Table 2 represents the variables found in the auto-irrigation operation line:

Table 2: Input variables for Auto Irrigation Operation (Neitsch et al., 2011)

Variables Name	Definition	Input File
Variables in auto-irrigation operation line:		
MONTH/DAY or HUSC	Initialization of auto-irrigation	.mgt
MGT_OP	Operation code. MGT_OP=10for auto- irrigation	.mgt
WSTRS_ID	Auto-irrigation trigger (WSTRS_ID = 0 for plant water stress trigger; WSTRS_ID = 1 for soil water deficit trigger	.mgt
AUTO_WSTR	Water stress that triggers irrigation	.mgt
IRR-EFF	Irrigation efficiency for manual operation (0-1)	.mgt
IRR_SQ	Irrigation surface runoff ratio for manual operation (0-1)	.mgt

3.2.3 Water stress identifier

Automatic irrigation can be triggered by plant water demand or by soil water demand (Neitsch et al., 2011). If the water stress is based on soil water deficit, the water threshold is the soil water deficit below field capacity (mm H_2O). When the water content of the soil profile falls below the water content at field capacity and water stress threshold, the model automatically applies water to HRU, and if there is enough water from the irrigation source, water will be added to the soil until reaching field capacity.

3.2.3.1 Water Uptake

Water uptake is a function of the amount of water required by the plant for transpiration, E_t, and the amount of water available in the soil, SW (Neitsch et al., 2011). In order to calculate the water uptake, the potential water uptake from the soil surface to any depth is estimated:

$$w_{up,z} = \frac{E_t}{[1 - \exp(-\beta_w)]} \cdot \left[1 - \exp\left(-\beta_w \cdot \frac{z}{z_{root}}\right)\right]$$

Where $w_{up,z}$ is the potential water uptake from the soil surface to z, specified depth and β_w is the water usage distribution parameter, and z_{root} is the depth of root development in the soil (mm). The actual water amount uptake is then calculated once the potential water uptake is modified for soil conditions. Actual water uptake is calculated as follows:

$$w_{actualup,ly} = min\left[w_{up,ly}^{n}\left(SW_{ly} - WP_{ly}\right)\right]$$

Where $w_{actualup,ly}$ is the actual water uptake for layer ly, the amount of water in the soil layer on a given day is denoted by SW_{ly}, and water content layer ly at wilting point by WP_{ly}. The total daily water uptake is then calculated as follows:

$$w_{actualup} = \sum_{ly=1}^{n} w_{actualup,ly}$$

The total plant water uptake is also the actual amount of transpiration that occurs on a day:

$$E_{t,act} = w_{actualup}$$

Where $E_{t,act}$ is the actual amount of transpiration (mm H_2O) and $w_{actualup}$ is the plant water uptake total for the day (mm H_2O).

3.2.3.2 Soil water Content

The soil water content SW_t can be defined by the following equation (Neitsch et al., 2011):

$$SW_t = SW_0 + \sum_{i=1}^{t} \left(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw} \right)$$

Where the initial soil water content is defined by SW_0, amount of precipitation on day i is defined by R_{day}, amount of surface runoff on day i by Q_{surf}, amount of transpiration on day i defined by E_a, percolation and bypass flow amounts exiting the soil profile bottom on day i defined by w_{seep} and Q_{gw} t is the return flow amounts on day i.

3.3 Water Sources

The water applied to the HRUs is retrieved from five water sources: reach, reservoir, shallow aquifer, deep aquifer, or a source not specified outside the watershed. The model also contains the option for no irrigation, and the source outside the watershed is assumed to divert from an unlimited source (Arnold et al., 2013); additionally, the model requires the location of the water source.

3.3.1 Reach water balance

The reach water storage and the end of the time step are calculated as follows (Neitsch et al., 2011):

$$V_{stored,2} = V_{stored,1} + V_{in} - V_{out} - tloss - E_{ch} + div + V_{bnk}$$

Where $V_{stored,2}$ represents the volume of water in the reach at the end of the time step (m^3 H_2O). The volume at the beginning of the time step is represented by $V_{stored,1}$, (m^3 H_2O). V_{in} is the volume of water flowing into the reach during the time step (m^3 H_2O). V_{out} represents the volume of water flowing out of the reach during the time step (m^3 H_2O). The volume of water lost from the reach due to transmission through the bed (m^3 H_2O) is defined by $tloss$. E_{ch} defines the reach evaporation for the day (m^3 H_2O). div is the volume of water added or removed from the reach through diversions (m^3 H_2O), and V_{bnk} defines the water added volume to the reach by bank storage return flow.

3.3.2 Reservoir water balance

The reservoir water storage at the end of the day is calculated as follows (Neitsch et al., 2011):

$$V = V_{stored} + V_{flowin} - V_{flowout} + V_{pcp} - V_{evap} + V_{seep}$$

Where V is the water volume in the impoundment at the end of the day (m^3 H_2O), V_{stored} water volume stored at the beginning of the day in the water body (m^3 H_2O), V_{flowin} is the water volume that enters the body of water during the day (m^3 H_2O), $V_{flowout}$ is the water volume that flows out of the body of water during the day (m^3 H_2O), V_{pcp} is the precipitation volume that falls on the water body during the day (m^3 H_2O), V_{evap} is the water volume removed from the body water due to evaporation during the day (m^3 H_2O), and V_{seep} is the water volume lost by seepage from the body of water (m^3 H_2O).

3.3.3 Shallow Aquifer

The shallow aquifer's water balance is calculated as follows (Neitsch et al., 2011):

$$aq_{sh,i} = aq_{sh,i-1} + w_{rchrg,sh} - Q_{gw} - w_{revap} - w_{pump,sh}$$

Where $aq_{sh,i}$ is the amount of water stored in the shallow aquifer on day i (mm H_2O), the amount of water stored in the shallow aquifer on day $i-1$ (mm H_2O) is denoted by $aq_{sh,i-1}$, the recharge amount entering the shallow aquifer on day i (mm H_2O) is denoted by $w_{rchrg,sh}$, the ground water flow/base flow entering the main channel on i (mm H_2O) is denoted by Q_{gw}, the water amount moving into the soil zone due to water deficiencies on day i (mm H_2O) is denoted by w_{revap}, and $w_{pump,sh}$ defines the amount of water removed from the aquifer by pumping on day i (mm H_2O).

3.3.4 Deep Aquifer

The deep aquifer's water balance is calculated as follows (Neitsch et al., 2011):

$$aq_{dp,i} = aq_{dp,i-1} + w_{deep} - w_{pump,dp}$$

Where the amount of water stored in the deep aquifer on day i (mm H_2O) is denoted by $aq_{dp,i}$, the water amount stored in the deep aquifer on day $i-1$ (mm H_2O) is denoted by $aq_{dp,i-1}$, the percolating water amount from the shallow aquifer into the deep aquifer on day i (mm H_2O) is denoted by w_{deep}, and $w_{pump,dp}$ is the water amount removed from the deep aquifer by pumping on day i (mm H_2O)

Chapter 4: Optimization Methods

Optimization can be found everywhere, in transportation networks, engineering design, business planning, and even in our daily lives when we have multiple tasks to complete in a certain amount of time. In these activities, the goal is to achieve certain objectives by optimizing something; it can be profit, distance, time, and quality. Optimization can be defined as a procedure for finding feasible solutions to a problem until no better solution can be found. The problems can be maximization or minimization problems, and the solutions are labeled good or bad in terms of their objective. When the optimization of a problem involves only one objective function, finding the optimal solution is called single-objective optimization. In single-objective optimization, many local optimal solutions may exist in the search space, and single-objective optimization aims to find the global optimum solution. An acceptable solution is one with the best objective function value (Deb, 2001). In general, a single-objective optimization problem is mathematically written as follows:

$$\text{Minimize/Maximize } f(x)$$

Subject to

$$g_j(x) \leq 0, \qquad j = 1,2,\ldots,J$$

$$h_k(x) = 0, \qquad k = 1,2,\ldots,K$$

$$x_h^l \leq x_h \leq x_h^u, \quad h = 1,2,\ldots,H$$

Where, $f(x)$ is the objective function to be minimized or maximized, $g_j(x)$ is the *j*th inequality constraint, J is the total number of inequality constraint functions, $h_k(x)$ is the *k*th equality constraint, K is the total number of equality constraints; x is the design variables vector, H is the total number of design variables, and $x_h^l$and x_h^u are the lower and upper bounds of the hth design variables x_h, respectively.

Most real-world problems involve more than one conflicting objective that needs to be optimized simultaneously. When the optimization of a problem involves more than one objective function, each objective has its own optimal solution, and finding the set of one or more optimal solutions is called multiple objective optimization. In multiple objective optimization, a single solution cannot be entitled as an optimal solution; instead, it identifies the set of trade-off optimal solutions. The different solutions can provide trade-offs among different objectives that require a compromise between the objectives preventing one from selecting a solution that is optimal for only one objective. Therefore, in multiple objective optimization, by taking into account all the objectives, an attempt to identify the set of trade-off optimal solutions is imperative. Having obtained the set of all possible solutions, the dilemma is now what solution one must choose. The user can use higher-level qualitative considerations to make a choice, but it can result in a biased search. However, in the absence of any information, all Pareto optimal solutions are equally important. To identify an ideal approach, the importance now lies in identifying as many possible Pareto-optimal solutions to a problem. Therefore, this suggests that there are two goals in multiple objective optimization (Deb, 2001):

1. To find the set of solutions as close as possible to the Pareto-optimal front.
2. To find a set of solutions as diverse as possible.

The first goal is essential in any optimization assignment. It is important for the solutions to converge as close as possible to the true optimal solutions to guarantee their near-optimality properties. The second goal is specific to multiple objective optimization. In addition to being converged close to the Pareto-optimal front, the solutions need to be sparsely spaced in the Pareto-optimal region. The diversity in this set of solutions provides a confident good set of trade-off solutions among the objectives. Figure 3 provides a representation of the procedure in multiple objective optimization.

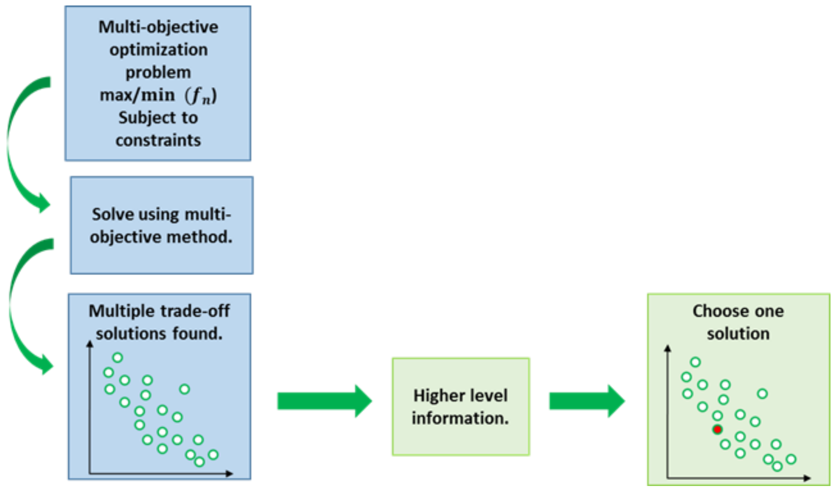


Figure 3: Schematic of a Multiple Objective Optimization Procedure

In multiple objective optimization, there are two goals that are to some extent orthogonal to each other, and since both goals are important, an efficient algorithm must comply with both goals. Accomplishing one goal does not mean that the other goal will be met because of these dual tasks; multiple objective optimizations are more troublesome than single objective optimization. In general, a multiple objective optimization problem can be mathematically written as follows:

$$\text{Minimize/Maximize } f_i(x) \qquad \text{for } i = 1,2,\dots,n$$

Subject to

$$g_j(x) \leq 0, \qquad j = 1,2,\dots,J$$

$$h_k(x) = 0, \qquad k = 1,2,\dots,K$$

$$x_h^l \leq x_h \leq x_h^u, \quad h = 1,2,\dots,H$$

Where n is the total number of objective functions to be minimized or maximized, and the parameter x is the design variables vector that has H design variables. The resulting set of solutions to a multiple objective optimization problem is called the non-dominated set. The non-dominated set can be achieved by making a pair-wise comparison and identifying those solutions that dominate other solutions and those solutions that are non-dominated with respect to each other. The non-dominated set of the entire feasible region is called the Pareto-optimal set (Figure 4). Without loss of generality, let us consider a minimization and maximization problem with vectors a and b. In a minimization problem f_i(a) dominates f_i(b) when, $f_i(\mathrm{a}) \leq f_i(b)$ for all i and $f_i(\mathrm{a}) < f_i(b)$ for at least one i. In a maximization problem f_i(a) dominates f_i(b) when, $f_i(\mathrm{a}) \geq f_i(b)$ for all i and $f_i(\mathrm{a}) > f_i(b)$ for at least one i.

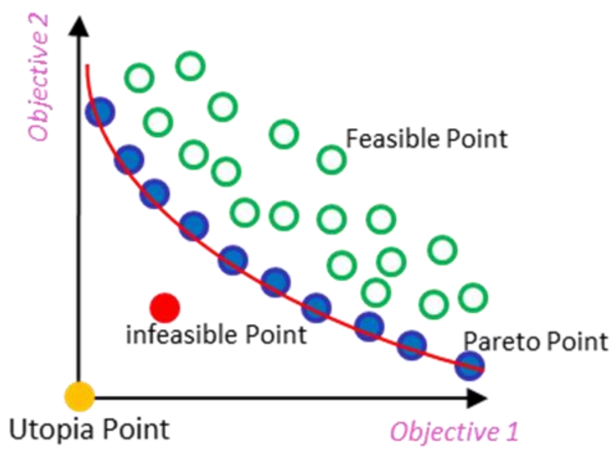


Figure 4: Pareto Optimal Set Visualization

4.1 Single Objective Optimization Methods

There are different ways to deal with multiple objective problems. The following methodologies are used as an extension or generalization of linear programming to handle multiple conflicting objectives. The methods combine the objective functions into an overall aggregated single objective function that identifies one single optimal solution.

4.1.1 Weighted Sum or Scalarization Technique

The weighted sum method is one of the most common approaches that deal with multiple objective optimization. The method converts multiple objective problems into a single objective problem by the weighted sum $F(x)$ of all objectives. In more detail, the weighted sum method can be expressed as follow (Augusto et al., 2012):

$$\text{Minimize:} \qquad F(x) = \sum_{i=1}^{k} w_i {f_i}^s(X)$$

Subject to:

$$X \in S$$

$$w_i \geq 0, \; F(x) = \sum_{i=1}^{k} w_i = 1$$

Where k represents the total number of objectives i, and the decision-maker preferences are expressed by the weights w_i.

The main advantages of this method are based on the simplicity of treating multiple objective problems like a single objective problem by the aggregation of the objectives and the incorporation of the decision-maker priorities through the weights. The main disadvantage of the method is choosing the best weighting coefficients. There is an area of research dedicated to generating and deciding the best possible weights since it can be a cumbersome task.

4.1.2 Goal Programming

Charnes and Cooper (1977) develop a preference-based approach that requires input from the decision maker to set goals for all the objectives. This method was developed for linear models and was one of the earliest techniques designed to approach multiple objective optimization problems. The targets or goals the decision maker incorporates into the model are added as additional constraints. The objective function then minimizes the absolute deviations from the goals or targets the decision maker chose for the objectives. Afterward, the model separates the values into two parts, positive and negative. Positive parts represent achievement, meaning the goal has been reached, and negative parts represent underachievement. The basic structure for Goal programming can be formulated as follows:

$$\text{Minimize:} \quad \sum_{i=1}^{k} w_i(d_i^+ + d_i^-)$$

Subject to:

$$f_i(X) + d_i^+ + d_i^- = b_i, \quad i = 1,2,\dots,k$$

$$d_i^+ \geq 0,\ d_i^- \geq 0 \quad i = 1,2,\dots,k$$

$$d_i^+ d_i^- = 0 \quad i = 1,2,\dots,k$$

$$w_i \geq 0$$

$$X \in S$$

Where b_i represents the goals for all the objectives f_i. Negative values or underachievement denoted by deviation d_i^- and positive values (achievement) denoted by deviation d_i^+. The decision-maker then assigns w_i to define achievement goal levels.

The main advantage of goal programming is the ability to handle large-scale problems, and it can produce a large number of alternatives. The main disadvantage of this method is the ability to weight coefficients and that the Pareto optimal solutions are not guaranteed to be obtained.

4.1.3 Multi Attribute Utility Theory

Utility refers to the satisfaction provided to the decision-maker by the objective function or attribute. In this case, the method expresses decisions between alternatives where the consequences are distinguished by multiple attributes. Concerning multiple attribute utility, the total utility of the solution is a scalar on the scale between 0 and 1, where 0 represents the worst preference or no utility and 1 represents the best. The utility function can be expressed as follows:

$$U(X) = \sum_{i=1}^{k} U_i(X_i) , \quad i = 1,2, \dots , k$$

Where utility expresses the satisfaction of each attribute, the result is a rank evaluation order of the possible alternatives of the decision maker's preference. The overall utility function, after the decision-maker assigns the weights to the attributes, can be expressed as follows (Regier and Peacock, 2017).

$$U(X) = \sum_{i=1}^{k} w_i U_i(X_{i)} , \quad i = 1,2, \dots , k$$

Where w_i is the scaling constant such that $\sum_{i=2}^{k} w_i = 1$. Multi-attribute utility theory's major advantages are that it allows the user to incorporate its preferences, considers uncertainty, and uses deterministic and stochastic decision environments. On the other hand, this method is extremely data-intensive, as it requires data at every step of the procedure; this suggests that the decision-maker can be subjective when incorporating its preferences, which also serves as a major disadvantage.

4.1.4 Ɛ- Constraint

The epsilon-constrained method overcomes some of the convexity problems of the weighed sum techniques. This technique is based upon selecting a primary objective and bounding other objectives with a separate $\varepsilon - constraint$ (Coello et al., 2007). In this method, the decision maker selects one objective out of *n* objectives that need to be minimized; the reminder objectives are then constrained to a target range; if maximization, the objectives are equal or less than a target value; if minimization, the objectives are equal or larger that a target value. For instance, problems are subdivided into two problems, $P_1(\varepsilon_2)$ and $P_2(\varepsilon_1)$ when evaluating bi-objective problems, this can be represented in a general structure as follow:

$$\min f_1(\vec{x})$$

$$subject\ to\ \ \vec{x} \in X\ \ , f_2(\vec{x})\ \leq \epsilon_2$$

and

$$\min f_2(\vec{x})$$

$$subject\ to\ \ \vec{x} \in X\ \ , f_1(\vec{x})\ \leq \epsilon_1$$

In contrast with other aggregating methods, the epsilon-constrained method can identify non-inferior solutions on a convex boundary; however, using hard constraints is inadequate for representing real design objectives. The above mentioned methods are suitable when there is no conflict among the objectives and a single optimal solution exists; however, if there are multiple objectives in conflict, more than one solution exists, and multiple objective optimization is best suited to represent the tradeoffs among the objectives. Therefore, methods that identify the Pareto-optimal are best suited when conflict exists among the objectives.

4.2 Multiple Objective Evolutionary Algorithm Methods

Generally, there are two types of stochastic algorithms: heuristic and metaheuristic. Heuristic algorithms attempt to find acceptable solutions to problems by trial and error. Metaheuristic tend to perform better than heuristics and has two major components: intensification and diversification, or exploitation by exploration. The purpose of these components is to generate a diverse set of solutions to explore the search space and to focus on the search in the local region by exploiting the information that a current good solution is found in this local region. The combination of the two components usually ensures that global optimality is achieved.

Figuratively speaking, let us assume that identifying the optimal solution to a problem is the same as a treasure hunt. For the most part, the most likely scenario is that we will start randomly searching from place to place, trying to identify any clues that would lead us to the treasure. Certainly, we can do this search alone or ask a group of people to help us look for the treasure and share information about the places they have searched and any clues they found (population-based search algorithms). This random search is one of the main characteristics of modern search algorithms. If the search area is very large and there is a time limit, we may not be able to find any clues or the treasure, but if there is no time limit and we can cover the whole search area, it is possible to find the treasure or in terms of optimization the global optimal solution. Generally speaking, optimization algorithms can be classified into two categories: deterministic algorithms and stochastic algorithms. Deterministic algorithms follow a repeatable procedure that will always produce the same result regardless of which day of the week the simulation runs. On the other hand, stochastic algorithms always have some randomness, and the results will always be different each time the simulation is run. Though it is important to note that the final results may not be very far apart from each other, due to the randomness incorporated, the paths taken to achieve that final solution are not exactly repeatable.

In addition, there have been developments in evolutionary algorithms since the 1960s, and in recent decades, they have become very popular for solving combinatorial optimization problems. The term evolutionary algorithm (EA) stands for a class of stochastic optimization methods that simulate the process of natural evolution. The following sections will discuss evolutionary algorithms and the different structures of various MOEAs.

4.2.1 Generic Multiple Objective Evolutionary Algorithm

Evolutionary algorithms are generally characterized by maintaining a set of candidate solutions that undergo a selection process that is usually manipulated by recombination and mutation generic operators. The solution is called individuals, and the set of solutions is called the population. The basic structure of an evolutionary algorithm can be represented as follow (Zitzler, 1999):

Input: *N (population size)*
T (maximum number of generations
P_C *(Crossover probability)*
p_m *(mutation rate)*
Output: *A (nondominated set)*
Step 1: Initialization: *Set* $\boldsymbol{P_0} = \emptyset$ *and t= 0. For i=1,…,N do*
a) *Choose* $\boldsymbol{i} \in \boldsymbol{I}$ *according to some probability distribution*
b) *Set* $\boldsymbol{P_0} = \boldsymbol{P_0} + \{\boldsymbol{i}\}$.
Step 2: Fitness assignment: *For each individual* $\boldsymbol{i} \in \boldsymbol{P_t}$ *determine the encoded decision vector* $\boldsymbol{x} = \boldsymbol{m(i)}$ *as well as the objective vector* $\boldsymbol{y} = \boldsymbol{f(x)}$ *and calculate the scalar fitness value* $F(\boldsymbol{i})$.
Step 3: Selection: *Set* $\boldsymbol{P'} = \emptyset$. *For i = 1,..., N do*
a) *Select one individual* $\boldsymbol{i} \in \boldsymbol{P_t}$ *according to a given scheme and based on its fitness value* $F(\boldsymbol{i})$.
b) *Set* $\boldsymbol{P'} = \boldsymbol{P'} + \{\boldsymbol{i}\}$.
The temporary population $\boldsymbol{P'}$ *is called the mating pool.*
Step 4: Recombination: *Set* $\boldsymbol{P''} = \emptyset$. *For i = 1,...,* $\frac{N}{2}$ *do*
a) *Choose two individuals* $\boldsymbol{i}, \boldsymbol{j} \in \boldsymbol{P'}$ *and remove them from* $\boldsymbol{P'}$.
b) *Recombine* $\boldsymbol{i}$ *and* $\boldsymbol{j}$. *The resulting children are* $\boldsymbol{k}, \boldsymbol{l} \in \boldsymbol{I}$.
c) *Add* $\boldsymbol{k}, \boldsymbol{l}$ *to* $\boldsymbol{P''}$ *with probability* p_c. *Otherwise, add* $\boldsymbol{i}, \boldsymbol{j}$ *to* $\boldsymbol{P''}$.
Step 5: Mutation: *Set* $\boldsymbol{P'''} = \emptyset$. *For each individual* $\boldsymbol{i} \in \boldsymbol{P''}$ *do*
a) *Mutate* $\boldsymbol{i}$ *with mutation rate* p_m. *The resulting individual is* $\boldsymbol{j} \in \boldsymbol{I}$.
b) *b) Set* $\boldsymbol{P'''} = \boldsymbol{P'''} + \{\boldsymbol{j}\}$.
Step 6: Termination: *Set* $\boldsymbol{P_{t+1}} = \boldsymbol{P'''}$ *and* $t = t + 1$. *If* $t \geq T$ *or another stopping criterion is satisfied, then set* $\boldsymbol{A} = p(\boldsymbol{m}(\boldsymbol{P_t}))$ *else, go to Step 2.*

An extensive number of diverse evolutionary algorithm methods exist and generally differ mainly in the fitness evaluation phase. These methods can be categorized as Pareto-based non-elitist approaches (MOGA, NPGA, NSGA,…) and Pareto-based elitist approaches. There are many method variations, but a few will be discussed in the following sections.

4.2.2 Multiple Objective Genetic Algorithm (MOGA)

Fonseca and Fleming (1993) introduced multiple Objective Genetic Algorithms as a variation of Goldberg's technique called MOGA. This method uses Pareto ranking, and fitness sharing is performed by niching. It is a non-elitist method where the rank of the individual corresponds to the number of times it is dominated by other chromosomes. The basic structure for MOGA can be represented by the following pseudo code (Coello et al., 2007):

procedure MOGA($\mathcal{N}'$, g, $\mathrm{f_j}(\mathrm{x}_k)$) $\rhd$ $\mathcal{N}'$ members evolved g generations to solve $\mathrm{f_k}(\mathrm{x})$
    Initialize population $\mathbb{P}'$
    Evaluate Objectives Values
    Assign Rank Based on Pareto dominance
    Compute Niche Count
    Assign Linear Scaled Fitness
    Shared Fitness
    for i =1 to g **do**
        Selection via Stochastic Universal Sampling
        Single Point Crossover
        Mutation
        Evaluate Objective Values
        Assign Rank Based on Pareto Dominance
        Compute Niche Count
        Assign Linear Scaled Fitness
        Shared Fitness
    end for
end procedure

This method's advantage is that it is a simple extension of a single objective genetic algorithm, while some disadvantages are that convergence is usually slow, and in regards to the fitness sharing, there can be problems related to the niche size parameter.

4.2.3 Niched-Pareto Genetic Algorithm (NPGA)

Horn et al. (1994) proposed the Niched-Pareto Genetic Algorithm based on Pareto dominance ranking and fitness sharing. The algorithm does not limit the comparison to two individuals; rather, a number of individuals in the population, usually ten, is used to determine the dominance count. In this case, when there is a tie, meaning that the individuals are either dominated or non-dominated, and the fitness sharing decides the result. The basic structure for NPGA can be represented by the following pseudo code (Coello et al., 2007):

Procedure NPGA $(\mathcal{N}, g, f_k(x))$ $\rhd$ $\mathcal{N}'$ members evolved g generations to solve $f_k(x)$
 Initialize Population P
 Evaluate Objective Value
 for $i = 1$ to g **do**
  Specialized Binary Tournament Selection
  Begin
   if Only Candidate 1 dominated **then**
    Select Candidate 2
   else if Only Candidate 2 dominated **then**
    Select Candidate 1
   else if Both are Dominated or Nondominated **then**
    Perform specialized fitness sharing
    Return Candidate with lower niche count
   end if
  End
  Single Point Crossover
  Mutation
  Evaluate Objective Values
 end for
end procedure

This approach applies Pareto selection to a segment of the population at each run rather than the entire population. Therefore, this suggests that its main strengths are that it is very fast and produces good non-dominated fronts, but its main weakness is that it requires a good choice of the size of the tournament selection to perform well. In the area of groundwater and pollution emissions, NPGA can be implemented. For instance, Erickson et al. (2002) apply an optimization algorithm to a ground water quality management challenge dealing with pump-and-treat (PAT) remediation. The framework uses the Niched-Pareto Genetic Algorithm, and the main objectives are to minimize remedial design cost and contaminant mass remaining. Mayer and Endres (2007) develop a framework to identify the optimal groundwater contaminant source removal design and remediation plume strategies. The optimization problem is solved using NPGA. Grandinetti et al. (2007) implemented an NPGA multiple objective optimization approach to reduce pollutant emissions in the manufacturing industry and costs, specifically industrial wood painting.

4.2.4 Nondominated Sorting Genetic Algorithm (NSGA)

Srinivas and Deb (1994) introduced NSGA as a variation to Goldberg's approach. This method is yet another modification to the ranking procedure; ranking is based on non-domination sorting and fitness sharing by niching. In this method, all the non-dominated individuals are classified into one category where the fitness value is proportional to the size of the population. The main advantage is that it converges fast, while a drawback is that there are problems related to the niche size parameter. The basic structure of NSGA can be represented by the following pseudo code (Coello et al., 2007):

```
procedure NSGA-I(𝒩′, g, f_j(x_k)) ▷ 𝒩′ members evolved g generations to solve f_k(x)
    Initialize population ℙ′
    Evaluate Objectives Values
    Assign Rank Based on Pareto dominance in Each Wave
    Compute Niche Count
    Assign Shared Fitness
    for i =1 to g do
        Selection via Stochastic Universal Sampling
        Single Point Crossover
        Mutation
        Evaluate Objective Values
        Assign Rank Based on Pareto dominance in each Waver
        Compute Niche Count
        Assign Shared Fitness
    end for
end procedure
```

4.2.5 Nondominated Sorting Genetic Algorithm II(NSGA-II)

Deb et al. (2002) proposed the NSGA-II method to eliminate weaknesses of the NSGA method. The main weaknesses associated with NSGA are the high computational complexity of non-dominated sorting, lack of elitism, and the need for specifying the sharing parameter of NSGA. NSGA-II method creates a population of competing individuals and ranks and sorts the individuals. Evolutionary operations are applied to create a new set of offspring. A new selection process is introduced, crowding distance (representing the neighboring density of a solution), to maintain a diverse front by keeping the population diverse; it helps the algorithm explore the fitness landscape. The basic structure of NSGA-II can be represented by the following pseudo code (Coello et al., 2007):

procedure NSGA-II($\mathcal{N}'$, g, $\mathrm{f_k}(\mathrm{x}_k)$) $\rhd$ $\mathcal{N}'$ members evolved g generations to solve $\mathrm{f_k}(\mathrm{x})$
Initialize population $\mathbb{P}'$
Generate random population – size $\mathcal{N}'$
Evaluate Objectives Values
Assign Rank (level) based on Pareto-*sort*
Generate Child Population
Binary Tournament Selection
Recombination and Mutation
for i =1 to g **do**
for each Parent and Child in Population **do**
Assing Rank (level) based on Pareto – *sort*
Generate sets of nondominated vectors along $\mathrm{PF_{known}}$
Loop (inside) by adding solutions to next generation starting form the first front
until $\mathcal{N}'$ individuals found determine Crowding distance between points on each front
end for
Select points (elitist) on the lower front (with lower rank) and are outside a crowding distance
Create next generation;
Binary Tournament selection;
Recombination and Mutation;
end for
end procedure

This method is currently used in most MOEA comparisons and has been used as the foundation for many algorithm designs. It can be suggested that the main strengths of NSGA-II are a fast non-dominated sorting approach, fast, crowded distance estimation, and simple crowded comparison operator. There are different authors who integrate NSGA-II with different models and based on the literature provided in this work (refer to chapter 2), in terms of Hydrology, it can be suggested that NSGA-II is the preferred method to be used with SWAT for design development, more specifically the optimizer found in MATLAB Toolbox.

4.2.6 Strength Pareto Evolutionary Algorithm (SPEA)

Zitzler and Thiele (1998) proposed the Strength Pareto Evolutionary algorithm (SPEA) using a mixture of established techniques and new techniques to find Pareto-optimal solutions in parallel. The algorithm combines Pareto-optimal storage, dominance, and clustering techniques into a single algorithm. The fitness of an individual is based on the external Pareto set only. The solutions stored in the external Pareto participate in the selection. A new Pareto based niching method is introduced; this method preserves diversity in the population and does not require a distance parameter. The basic structure can be represented by the following pseudo code (Coello et al., 2007)

procedure SPEA($\mathcal{N}'$, g, $f_k(x)$)
    Initialize Population $\mathbb{P}'$
    Create empty external set $\mathbb{E}'(|\ \mathbb{E}'\ | < |\ \mathbb{P}'\ |)$
    for i =1 to g **do**
        $\mathbb{E}' = \mathbb{E}' \cup \mathcal{ND}(\mathbb{P}')$ ▷ Copy members evaluating to be nondominated of P to E
        $\mathbb{E}' = \mathcal{ND}(E)$ ▷ Keep only member evaluating to nondominated vectors in E
        Prune $\mathbb{E}'$ (using clustering) if max capacity of $\mathbb{E}'$ is exceeded
        $\forall_{i \in \mathbb{P}'}$ Evaluate $(\mathbb{P}'_i)$ ▷ Evaluate fitness for all members of $\mathbb{E}'$ and $\mathbb{P}'$
        $\forall_{i \in \mathbb{E}'}$ Evaluate $(\mathbb{E}'_i)$
        $\mathcal{MP} \longleftarrow \mathcal{T}(\mathbb{P}' \cup \mathbb{E}')$ ▷ Use binary tournament selection with
            ▷ replacement to select individuals from $\mathbb{P}' + \mathbb{E}'$
            ▷ (multiset union) until the mating pool is full
        Apply crossover and mutation on $\mathcal{MP}$
    end for
end procedure

The method is different from other MOES in that instead of solving the diversity problem by fitness sharing, and it relies on Pareto-dominance to maintain multiple stable niches. In literature, Wang et al. (2009) describe the pump scheduling optimization problem, which was solved using different MOEAS. The study suggested that even though there is a difference in parameters that affect each algorithm, the overall performance in SPEA is better and is a more suited alternative for the pump-scheduling problem.

4.2.7 Strength Pareto Evolutionary Algorithm 2 (SPEA2)

There is also a revised version of SPEA called SPEA2 introduced by Zitzler et al. (2002). This method is developed to avoid a tie in the fitness metric. The main differences are the method introduces a finite grained fitness metric, and this takes into account the number of individuals that dominate each individual for each individual; the method uses the nearest neighbor technique to guide the search more efficiently and includes a method that preserves boundary solutions. The basic structure can be represented as follow (Coello et al., 2007):

1: **procedure** SPEA2 ($\mathcal{N}'$, g, $f_k(x)$)
2: Initialize Population $\mathbb{P}'$
3: Create empty external set $\mathbb{E}'$
4: **for** i =1 to g **do**
5: Compute fitness of each individual in $\mathbb{P}'$ and $\mathbb{E}'$
6: Copy all individual evaluating to nondominated vectors $\mathbb{P}'$ and $\mathbb{E}'$ to $\mathbb{E}'$
7: Use the truncation operator to remove elements from E when the capacity of the file has been extended
8: If the capacity of $\mathbb{E}'$ has not been exceeded then use dominated individuals in $\mathbb{P}'$ to fill $\mathbb{E}'$
9: Perform binary tournament selection with replacement to fill the mating pool
10: Apply crossover and mutation to the mating pool
11: **end for**
12: **end procedure**

There are different authors that integrate SPEA2 into their models. For instance, Zhang et al. (2012) improved the calibration of SWAT; they introduced a multi-core aware multi-objective optimization tool using SPEA2 and SWAT. Muleta and Nicklow (2002) introduce a decision support system integrating SWAT and SPEA2 to control the environmental impacts of non-point source pollution that result from erosion.

Chapter 5: Methodology

This research focuses on developing an irrigation system assessment framework that optimizes energy consumption and energy cost per acre. This model integrates SWAT hydrologic model and the irrigation assessment framework with the multiple objective evolutionary algorithm to identify the optimal spatial placement of Land-Use and irrigation systems. A Graphical User interface (GUI) is developed to allow the user to identify and evaluate multiple management practices. The integration of these models will identify the tradeoff, balance competing objectives, and improve the decision-making process. Furthermore, this framework will further extend previous works developed by Cram et al. (2022) and Moriasi et al. (2022) by assessing agriculture irrigation water systems introduced in each management practice and evaluating energy cost per acre and energy consumption per acre. The model will simulate different management practices to predict the water balance and crop yield and to identify the different events occurring in the watershed. Additionally, the management practices scenarios are further evaluated with a multiple objective evolutionary algorithm (Taboada et al., 2008) to identify the optimal management practices spatial configuration within the watershed for the conflicting objectives.

5.1 Optimization Framework

The proposed optimization framework in figure 5 displays the flow diagram for integrating SWAT, irrigation systems, and the MOEA. The framework allows the user the flexibility to simulate many different management practices from different SWAT simulations and integrates irrigation systems into the current management practice that are then optimized. The optimization framework requires an initial SWAT simulation, and there are different parameters that the simulation needs. For instance, the user can incorporate a digital elevation model, soil characteristics, land use, different agricultural management data (in this section, auto-irrigation is set up for the model), watershed data, climate data, and other additional data needed by the user can also be incorporated to the SWAT model. Once there is an initial SWAT simulation, the proposed tool uses that information and allows the user to explore several management practices; this step repeats several times depending on the number of management practices that will be evaluated. Afterward, the framework integrates different irrigation systems into the model, expanding the initial management practice, and after this step, the database is populated with the different management practices and irrigation systems. The last step is to evaluate the management practices created using a multiple objective evolutionary algorithm. The next sections will provide a detail explanation of the optimization framework.

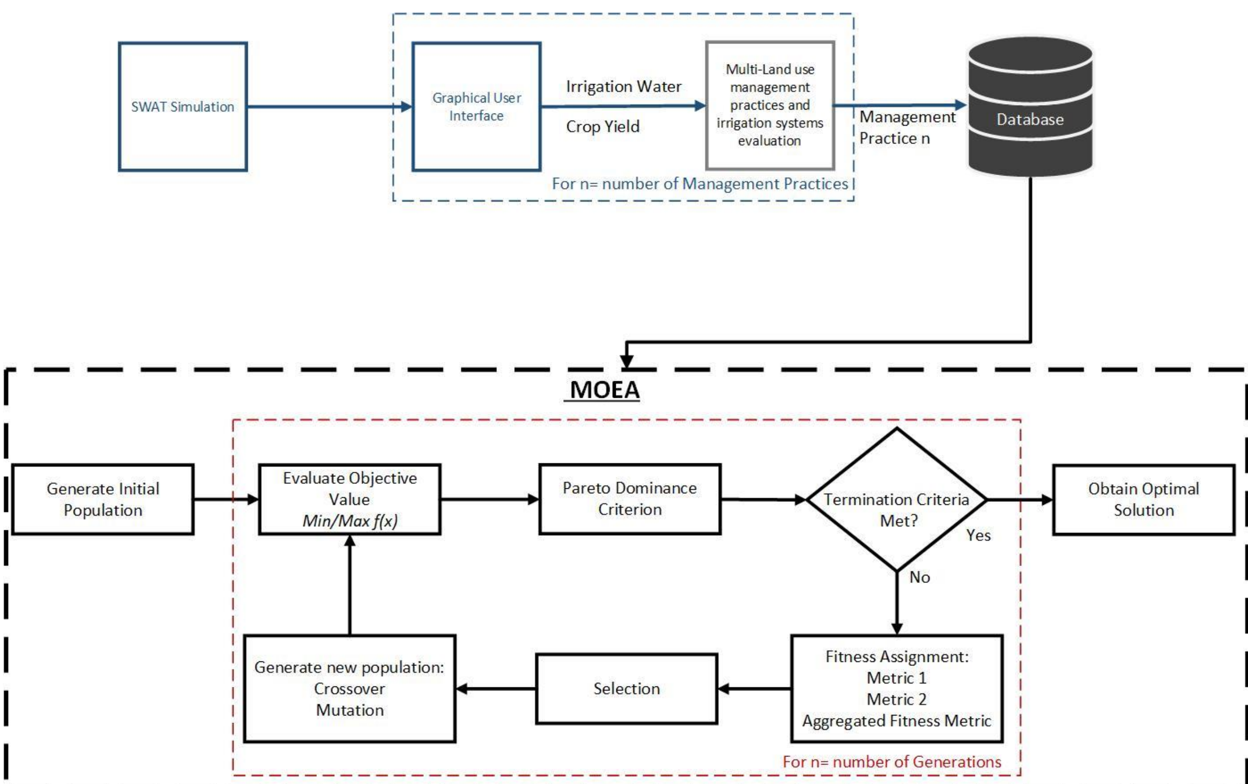


Figure 5: Optimization Framework

5.2 SWAT-MEA

The initial stages of SWAT-MEA were introduced by Cram (2019), allowing users to evaluate different management practices. The initial SWAT simulation required for SWAT-MEA produces management files that provide different characteristics for each HRU, for instance, land use, management operations, and the parameters. SWAT-MEA overwrites the management files for each management practice and re-executes SWAT to assess each management practice. Once the management practices are evaluated, an optimization algorithm identifies the optimal placement and land use for the HRUs. The tool does not account for irrigation systems in the management practices scenarios.

5.3 Management Practices

The model initializes with creating a simulation in SWAT. The SWAT model, depending on the user's knowledge and preferences, needs different information and layers such as a digital elevation model, soil layer, land use layer, climate data, watershed data, or any other that will further predict the watershed's water balance and crop yields. The output files that result from the simulation are integrated into the developed tool to assess different management practices. The structure of SWAT-MEA was maintained for the new tool, but the source code was updated to account for different irrigation systems. The steps are as follows:

- The user will add the directory name of the folder that has the management files because the tool needs to be able to read the management files from the initial SWAT simulation. The results will appear in this folder as well.
- The user then adds the SWAT parameters: the number of HRUS in the simulation and the executable version (.exe) of the simulation.
- The next step is to select the HRUs that will be included in the optimization.

- The next step is selecting the parameters the user wishes to maximize and minimize.
- The next step is to create the operation schedule with the different operations for the management practice Figure 6. The available operations are: plant/begin growing season, irrigation, fertilizer application, pesticide application, harvest and kill, tillage, harvest only, kill/end of growing season, grazing, Auto-irrigation, auto-fertilization, street sweeping, release/impound, continuous fertilization, continuous pesticide, burn, skip to beginning of the year.

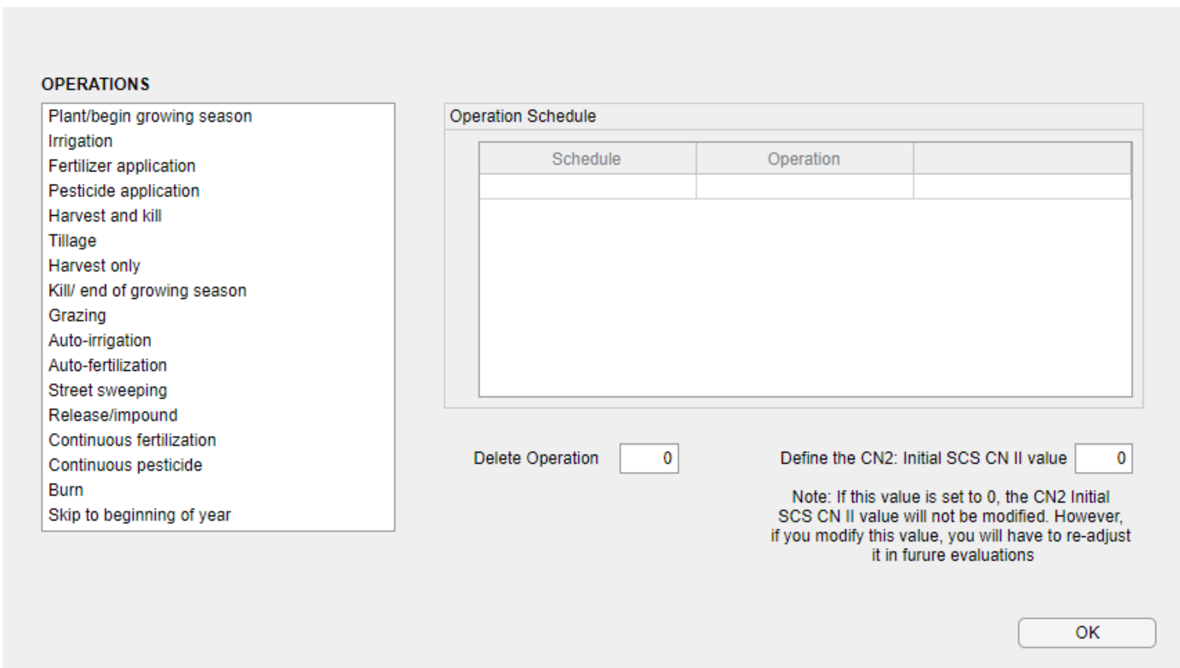


Figure 6: Operation Schedule Graphical User Interface

  - When the user selects the Auto-irrigation operation in Figure 7, the irrigation is applied to an HRU from one of five types of water sources. The parameters that the user defines are as follows:
    - Water Stress Identifier

                - Plant water demand
                - Soil water content
            - Auto Irrigation Sources
                - No irrigation
                - Divert water from reach
                - Divert water from reservoir
                - Divert water from shallow aquifer
                - Divert water from deep aquifer
                - Divert water from unlimited source outside watershed
            - Amount of irrigation water applied each time auto irrigation is triggered (mm):   Min 0 Max 100
            - Water stress threshold that triggers irrigation: Min 0.0 Max 1.0
            - Irrigation efficiency (fraction): Min 0.0 Max 1.0
            - Surface runoff ratio: Min 0.0 Max 1.0
            - Irrigation source location: Min 1 Max is the number of subbasins
    - Once the user applies the auto-irrigation parameters, the user now has the option to include irrigation systems in the management practice. If the user adds an irrigation system, the next step is selecting the "Add Irrigation System" button.

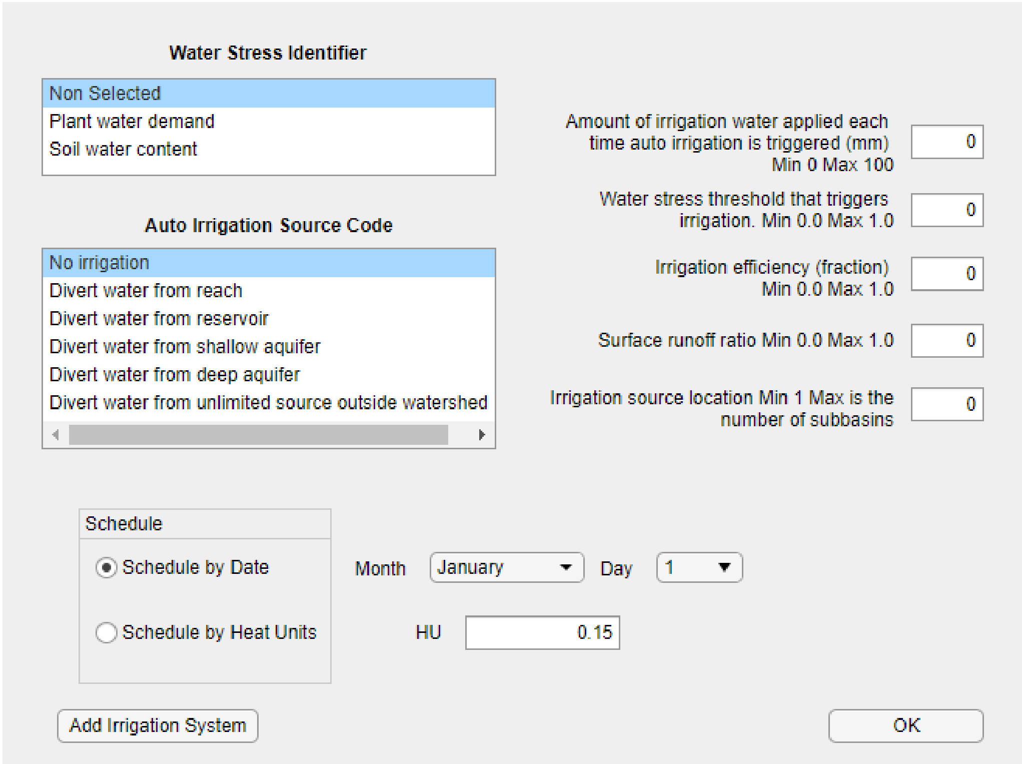


Figure 7: Auto-Irrigation Parameters Graphical User Interface

- In this step (Figure 8), the user will be able to add information related to the irrigation system that is used for evaluation in that management practice; the mathematical approach for this part is described in the next section. The parameters for the irrigation system being evaluated are as follow:
  - Irrigation Working Pressure
  - Pressure Loss due to Friction
  - Pump Efficiency
  - Motor Efficiency
  - Drive Efficiency
  - Useful Life

- Depth to Groundwater per year for the time step, this parameter will automatically show the number of years in the simulation and will require information for the depth to groundwater per year, staring on the first year of the simulation until the last year of the simulation
- Cost of kWh per year for the time step, this parameter will automatically show the number of years in the simulation and will require information related to the cost of kWh per year, starting on the first year of the simulation until the last year of the simulation

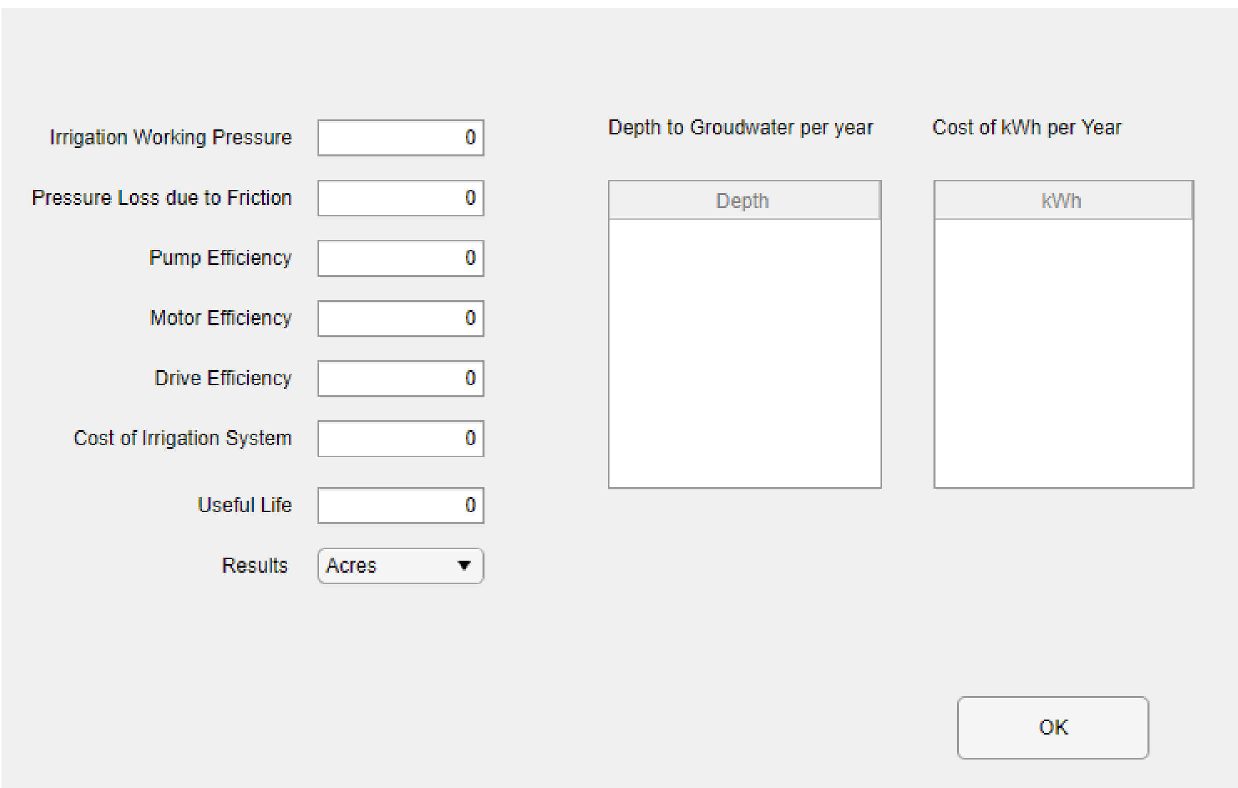


Figure 8: Irrigation System Parameters Graphical User Interface

- Once the operation schedule for the management practice is complete and the auto-irrigation system parameters are complete, the user will then select the ”ok” button in the operation schedule window.
- The simulation requires at least two management practices due to being a multiple objective optimization algorithm. Therefore, a new window will appear, asking the user to add more management practices or not.
- After selecting the option to add more management practices, the operation schedule window will appear again. This process repeats for several management practices defined by the user, starting from the operation schedule window to the window that asks the user to add more management practices or not. The flow chart diagram of this process is in Figure 9, the auto irrigation process is part of the operation schedule, but when selected, it will open a new window where the irrigation system can be added, and the rank values were added when considering rank objective, which is a recent modification to the initial SWAT-MEA.

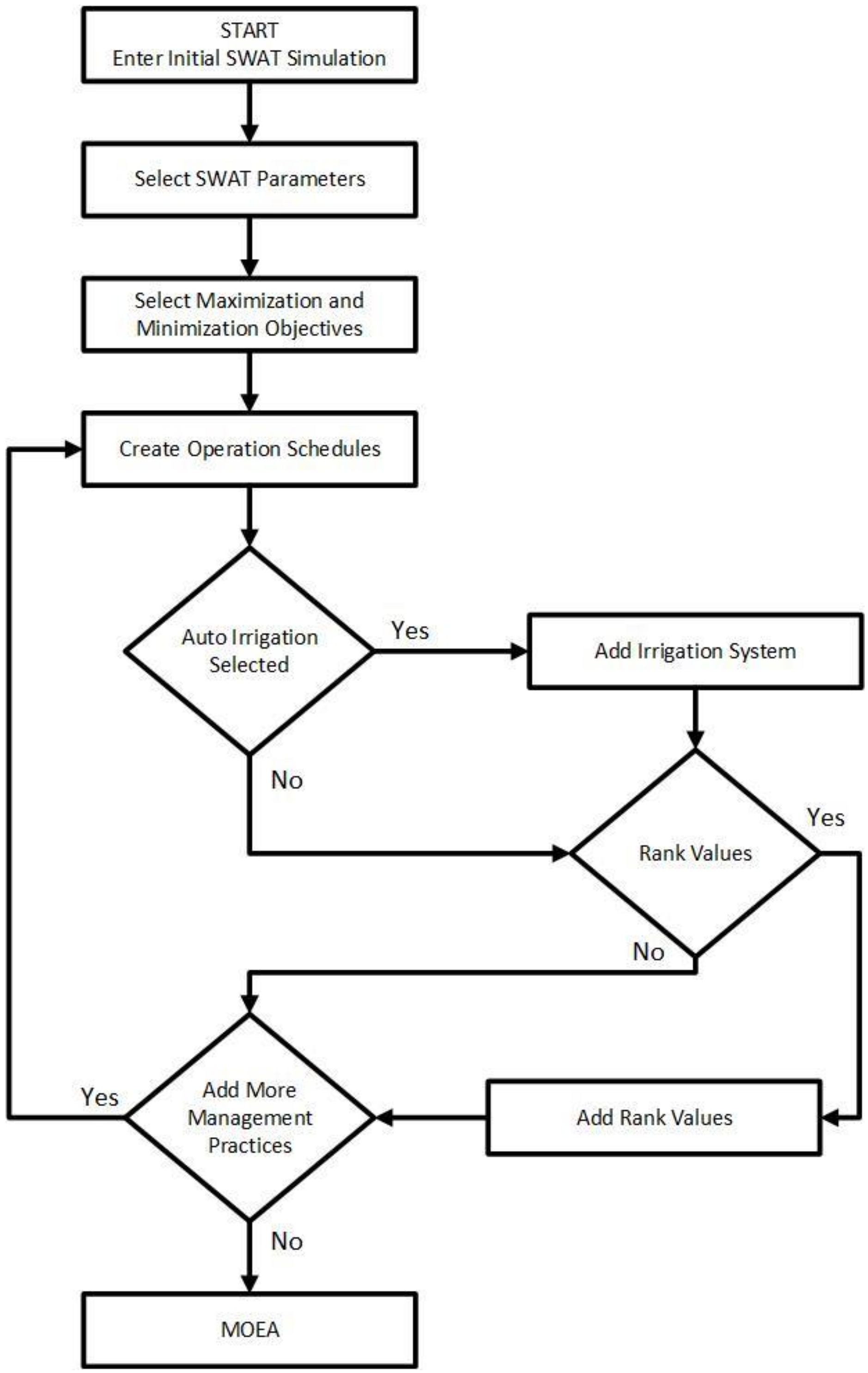


Figure 9: Optimization Framework Flow Chart

5.3.1 Output Files

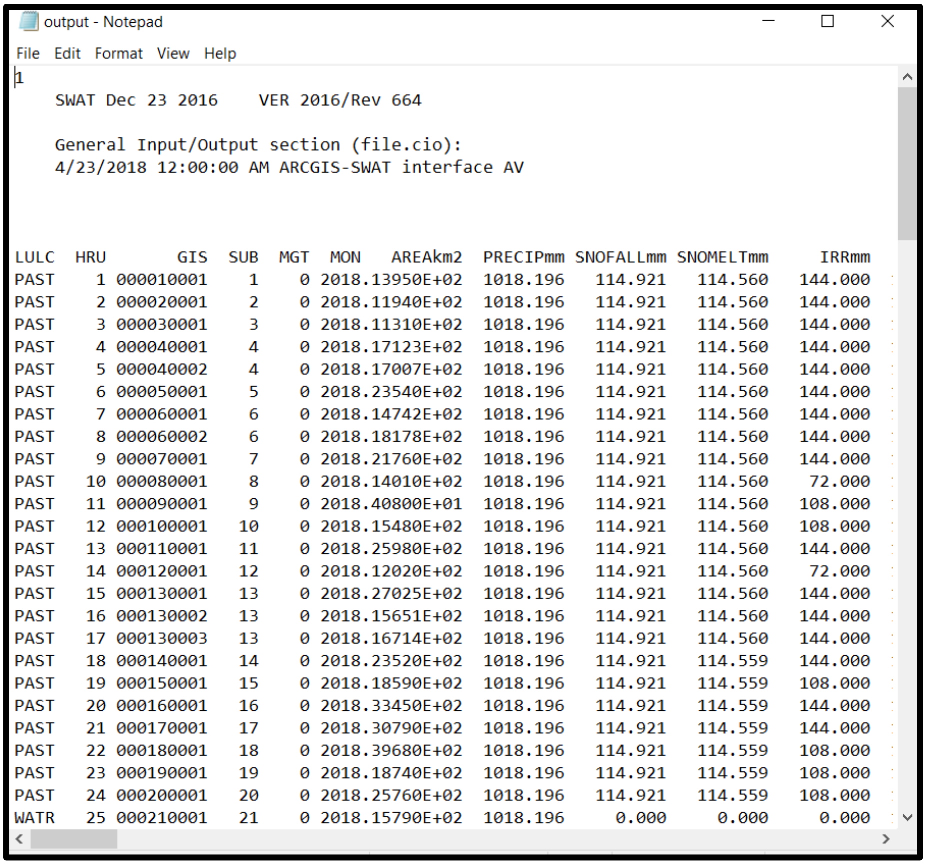
The initial SWAT simulation produces different files related to the simulation, which can be found in the TxtInOut. The files are needed to execute the management practices in the optimization tool, and it contains information related to land use, management operations, and different parameters for the simulation. The tool overwrites the management files for each management practice, and once evaluated, the simulation produces two files that contain the information used for the objectives of this study.

- Output.std: This file (Figure 10) is used to extract the amount of crop yield (kg/ha) for every HRU for the number of years that the simulation. It is also used to extract the area (km^2) of each HRU in the simulation, and the area is a variable used to evaluate energy consumption and cost.

```
output - Notepad
File  Edit  Format  View  Help
    SWAT Dec 23 2016     VER 2016/Rev 664

    General Input/Output section (file.cio):
    4/23/2018 12:00:00 AM ARCGIS-SWAT interface AV

                                        Average Plant Values (kg/ha)

  HRU        1 SUB    1 PAST  Yld =     82.9 BIOM =    7272.5
  HRU        2 SUB    2 PAST  Yld =     82.6 BIOM =    7279.5
  HRU        3 SUB    3 PAST  Yld =     82.3 BIOM =    7282.5
  HRU        4 SUB    4 PAST  Yld =     82.7 BIOM =    7276.3
  HRU        5 SUB    4 PAST  Yld =     82.7 BIOM =    7276.3
  HRU        6 SUB    5 PAST  Yld =     82.7 BIOM =    7277.9
  HRU        7 SUB    6 PAST  Yld =     82.6 BIOM =    7278.2
  HRU        8 SUB    6 PAST  Yld =     83.1 BIOM =    7266.7
  HRU        9 SUB    7 PAST  Yld =     83.0 BIOM =    7272.3
  HRU       10 SUB    8 PAST  Yld =     95.1 BIOM =    5647.1
  HRU       11 SUB    9 PAST  Yld =     79.5 BIOM =    4644.0
  HRU       12 SUB   10 PAST  Yld =     79.5 BIOM =    4643.6
  HRU       13 SUB   11 PAST  Yld =     82.7 BIOM =    7277.6
  HRU       14 SUB   12 PAST  Yld =     94.8 BIOM =    5645.3
  HRU       15 SUB   13 PAST  Yld =     82.5 BIOM =    7280.3
  HRU       16 SUB   13 PAST  Yld =     83.1 BIOM =    7264.5
  HRU       17 SUB   13 PAST  Yld =     82.5 BIOM =    7280.2
  HRU       18 SUB   14 PAST  Yld =     82.9 BIOM =    7273.9
  HRU       19 SUB   15 PAST  Yld =     79.5 BIOM =    4641.0
  HRU       20 SUB   16 PAST  Yld =     82.6 BIOM =    7281.4
  HRU       21 SUB   17 PAST  Yld =     82.7 BIOM =    7280.1
  HRU       22 SUB   18 PAST  Yld =     79.6 BIOM =    4642.3
  HRU       23 SUB   19 PAST  Yld =     79.6 BIOM =    4639.1
  HRU       24 SUB   20 PAST  Yld =     79.6 BIOM =    4641.4
  HRU       25 SUB   21 WATR  Yld =      0.0 BIOM =       0.0
```

Figure 10: output.std file example

- Output.hru: The irrigation applied changes every time step for each HRU; the depth to groundwater and cost of kWh varies annually; therefore, to evaluate energy consumption and energy cost, the tool will extract the irrigation values that will be used from the output.hru file (Figure 11) every time the management scenario is executed.



```
output - Notepad
File  Edit  Format  View  Help
1
    SWAT Dec 23 2016    VER 2016/Rev 664

    General Input/Output section (file.cio):
    4/23/2018 12:00:00 AM ARCGIS-SWAT interface AV


LULC  HRU       GIS  SUB  MGT  MON   AREAkm2  PRECIPmm SNOFALLmm SNOMELTmm     IRRmm
PAST     1 000010001    1    0 2018.13950E+02  1018.196   114.921   114.560   144.000
PAST     2 000020001    2    0 2018.11940E+02  1018.196   114.921   114.560   144.000
PAST     3 000030001    3    0 2018.11310E+02  1018.196   114.921   114.560   144.000
PAST     4 000040001    4    0 2018.17123E+02  1018.196   114.921   114.560   144.000
PAST     5 000040002    4    0 2018.17007E+02  1018.196   114.921   114.560   144.000
PAST     6 000050001    5    0 2018.23540E+02  1018.196   114.921   114.560   144.000
PAST     7 000060001    6    0 2018.14742E+02  1018.196   114.921   114.560   144.000
PAST     8 000060002    6    0 2018.18178E+02  1018.196   114.921   114.560   144.000
PAST     9 000070001    7    0 2018.21760E+02  1018.196   114.921   114.560   144.000
PAST    10 000080001    8    0 2018.14010E+02  1018.196   114.921   114.560    72.000
PAST    11 000090001    9    0 2018.40800E+01  1018.196   114.921   114.560   108.000
PAST    12 000100001   10    0 2018.15480E+02  1018.196   114.921   114.560   108.000
PAST    13 000110001   11    0 2018.25980E+02  1018.196   114.921   114.560   144.000
PAST    14 000120001   12    0 2018.12020E+02  1018.196   114.921   114.560    72.000
PAST    15 000130001   13    0 2018.27025E+02  1018.196   114.921   114.560   144.000
PAST    16 000130002   13    0 2018.15651E+02  1018.196   114.921   114.560   144.000
PAST    17 000130003   13    0 2018.16714E+02  1018.196   114.921   114.560   144.000
PAST    18 000140001   14    0 2018.23520E+02  1018.196   114.921   114.559   144.000
PAST    19 000150001   15    0 2018.18590E+02  1018.196   114.921   114.559   108.000
PAST    20 000160001   16    0 2018.33450E+02  1018.196   114.921   114.559   144.000
PAST    21 000170001   17    0 2018.30790E+02  1018.196   114.921   114.559   144.000
PAST    22 000180001   18    0 2018.39680E+02  1018.196   114.921   114.559   108.000
PAST    23 000190001   19    0 2018.18740E+02  1018.196   114.921   114.559   108.000
PAST    24 000200001   20    0 2018.25760E+02  1018.196   114.921   114.559   108.000
WATR    25 000210001   21    0 2018.15790E+02  1018.196     0.000     0.000     0.000
```

Figure 11: output.hru file example

5.4 Multiple Land Use management practices and irrigation systems evaluation

The information simulated in the previous section will be used to evaluate energy consumption and energy cost. In this step, the management practices can increase by incorporating different irrigation systems to evaluate each management practice. To execute this process, each management practice output.hru and output.std file will be used to extract the irrigation applied, Irr in *feet*, for each HRU for the time period and the HRU area, HRU_{area} in *acres*, that will be used to estimate the $Volume\ (acre \cdot feet)$ and the energy required and costs during the time period. The average annual energy cost function is expressed in equation (1) as follows:

$$Energy_{cost} = \left(\frac{AE_{cost}}{HRU_{area}}\right) \tag{1}$$

Where $Energy_{cost}$ represents the average annual energy cost per acre (*kWh/acre*), AE_{cost} represents the annual energy cost per year (*$*), and the area (*acres*) for each HRU is represented by HRU_{area}. Different sources for generating electricity can cause a significant difference in the cost of energy required for the different irrigation systems. The annual energy cost function is expressed in equation (2) as follows:

$$AE_{cost} = AE_{required} \cdot K_{cost} \tag{2}$$

Where annual energy cost is a function of the energy required (*kWh*) per year represented by $AE_{required}$, and K_{cost} represents the cost per kilowatt-hour (*$/kWh*). The annual energy required per year is expressed in equation (3) as follows:

$$AE_{required} = Energy_{pumped} \cdot Volume \tag{3}$$

Where the annual energy required/used per year (kWh/year) is represented by $AE_{required}$ and depends directly on the volume pumped, the irrigation system, and the efficiency of the pump, motor, and drive source. Energy consumption is represented by $Energy_{pumped}$ and the

$Volume = Irr \cdot HRU_{area}$. The estimation of energy consumption is related to the total pressure head used by each system and is expressed in equation (4) as follows:

$$Energy_{pumped} = \left(\frac{TH(1.023)}{\mu_{pump} \cdot \mu_{motor} \cdot \mu_{drive}}\right) \tag{4}$$

Where the energy pumped in kWh per acre·ft is represented by $Energy_{pumped}$, and is a function of total pressure head (*feet*), TH, the pump efficiency factor is represented μ_{pump}, the motor efficiency factor μ_{motor}, and the drive efficiency factor μ_{drive}. The total pressure head required to pump and apply water is expressed in equation (5) as follows:

$$TH = Lift + OP + f_{losses} \tag{5}$$

Where the total pressure head is the sum of the $Lift$ that represents the depth to groundwater (*feet*), the operating pressure (feet) represented by OP for the different irrigation systems; drip irrigation ranges from 10 PSI -20 PSI, and sprinkler ranges from 25 PSI to 40 PSI. The friction losses related to the irrigation system is expressed by f_{Losses} are in which 20% of pressure losses are typically added to the head of the systems to guarantee uniformity (Daccache et al., 2014).

Furthermore, depending on the irrigation system, there is an initial estimated capital cost per acre over its useful life. Equation (6) provides the total cost of the irrigation system as follows:

$$Total_{cost} = Energy_{cost} + I_{system} \tag{6}$$

Where the total cost is represented by $Total_{cost}$ and is a function of the average energy cost per acre for each year and the capital cost per acre ($/acre) of the irrigation system is represented by I_{system}. This evaluation will be accomplished for each management practice and will serve to create the database with management practices that consider different irrigation systems.

5.5 Database

The previous sections explained the process of evaluating different management practices. The optimization tool was used to create different management scenarios; it needed an initial SWAT simulation, input from the user, and integrated different irrigation systems into the management practices. Every time the tool executes a management practice, the output results in a uniform matrix with the objectives to be maximized and minimized, which serves to populate the database. Internally the database is populated as follows (Figure 12):

- The matrix/table is uniform, and it is saved in a matrix variable where the size (*a* x *b* x *c*) represents the following:
  - *a.* Contains three rows where the first row provides the management practice being evaluated and the following rows the objectives used for the optimization
  - *b.* Provides the number of columns related to the number of HRUs in the simulation
  - *c.* Provides the number of tables for each management practice that is being evaluated

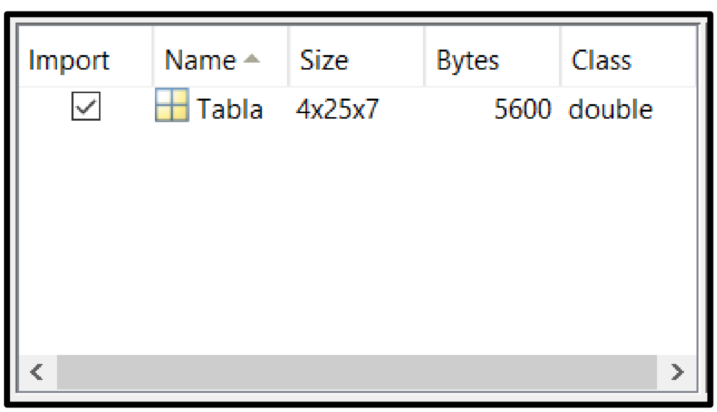
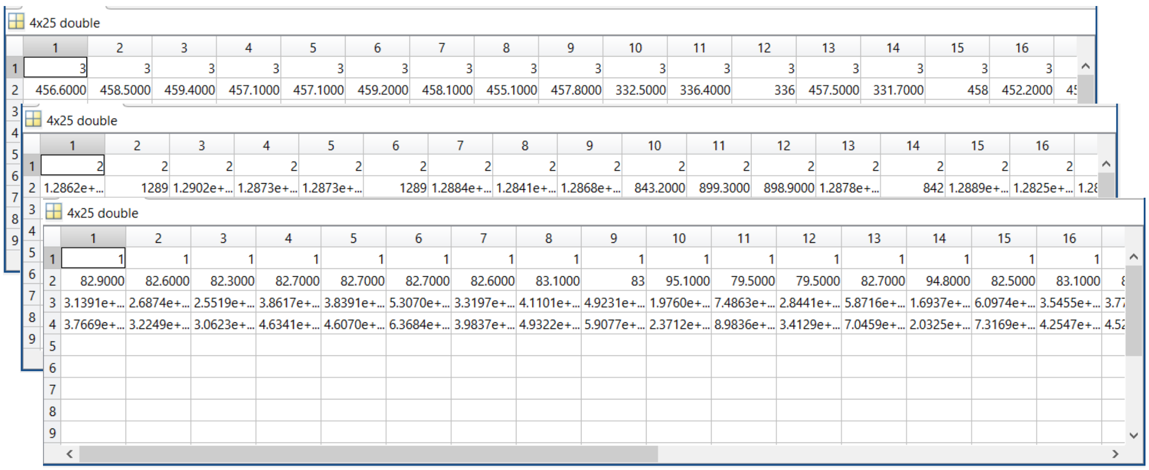


Figure 12: Management Practices in Database

- The management practice table (Figure 13) that populates the database is encoded as the chromosome that will be used in the multiple objective evolutionary algorithm, the chromosome and steps for the optimization algorithm will be explained in the following section.



4x25 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
2	456.6000	458.5000	459.4000	457.1000	457.1000	459.2000	458.1000	455.1000	457.8000	332.5000	336.4000	336	457.5000	331.7000	458	452.2000

4x25 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
2	1.2862e+...	1289	1.2902e+...	1.2873e+...	1.2873e+...	1289	1.2884e+...	1.2841e+...	1.2868e+...	843.2000	899.3000	898.9000	1.2878e+...	842	1.2889e+...	1.2825e+...

4x25 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	82.9000	82.6000	82.3000	82.7000	82.7000	82.7000	82.6000	83.1000	83	95.1000	79.5000	79.5000	82.7000	94.8000	82.5000	83.1000
3	3.1391e+...	2.6874e+...	2.5519e+...	3.8617e+...	3.8391e+...	5.3070e+...	3.3197e+...	4.1101e+...	4.9231e+...	1.9760e+...	7.4863e+...	2.8441e+...	5.8716e+...	1.6937e+...	6.0974e+...	3.5455e+...
4	3.7669e+...	3.2249e+...	3.0623e+...	4.6341e+...	4.6070e+...	6.3684e+...	3.9837e+...	4.9322e+...	5.9077e+...	2.3712e+...	8.9836e+...	3.4129e+...	7.0459e+...	2.0325e+...	7.3169e+...	4.2547e+...

Figure 13: Management Practices and the Objectives

- The tables show a matrix of 4x25 where the first row is used to identify what management practice is being evaluated. The next rows identify the different objectives that are maximized or minimized. The number of columns is used to identify the HRU for the simulation; in the figure above, there are 25 HRUs. These tables populate the database, it can have many different management practices, but the evolutionary algorithm requires at least two for the optimization.

5.6 Multiple Objective Evolutionary Algorithm (MOEA)

Finding the solution to a problem where several objectives need to be simultaneously optimized may be a difficult task to achieve. There is conflict among the objectives in multiple objective problems, and the search space is highly complex. The MOEA has two main goals in terms of the Pareto-front, to achieve proximity and diversity. Proximity means finding solutions that are close as possible to the Pareto-optimal front, and diversity refers to finding solutions spread over the Pareto-optimal front that differ in their objective values as much as possible. The following sections provide an explanation of the procedure used in identifying Pareto-optimal solutions.

5.6.1 Chromosome Encoding

In the previous sections, the evaluated objectives were introduced into the database as a 4x25 table representing the chromosome for the problem. The encoding of the chromosome is the first step when solving the problem, and the chromosome structure depends entirely on the problem. The chromosome, in some way, should contain information about the solution it represents. Some important vocabulary:

- Gene: A single encoding cell that represents a characteristic of the solution. In this scenario, each gene contains information related to the HRU and the objectives being evaluated
- Chromosome: A string of “genes” that represents a solution. In this scenario, the chromosome represents the management practice.
- Population: The number of “chromosomes” available to test: In this scenario, the population represents the multiple management practices to evaluate.

There are different encoding methods to represent the chromosome:

- Binary encoding: This is the most common method for encoding. The chromosome is represented by a binary string of 1s and 0s, and each gene of the chromosome represents a characteristic of the problem.
- Permutation encoding: This method of encoding is mostly used in problems that require a certain order. The chromosome uses integer values that represent a position in a sequence.
- Value encoding: This method of encoding is usually used in complicated problems where binary encoding cannot be used to fully represent the problem. The chromosome uses a string of values: integer, real number, or even a character. It is useful for some problems, but specific crossover or mutation techniques will occasionally need to be developed for these chromosomes.

In this study, value encoding is used to represent the chromosome. For instance, for a scenario that has management practices where one objective is to maximize and two objectives minimize, the management practice represents the chromosome and the genes of the HRUs. In Figure 14, there are 25 HRUs in the simulation; the first row corresponds to the management practice evaluated with its respective objective values for the HRU, where the second row corresponds to the objective being maximized, the third row corresponds to the objective being minimize, and the fourth row to the objective being minimize. The chromosome can increase or decrease the number of objectives depending on what the user wishes to evaluate in the optimization tool, but at least two objectives are needed.

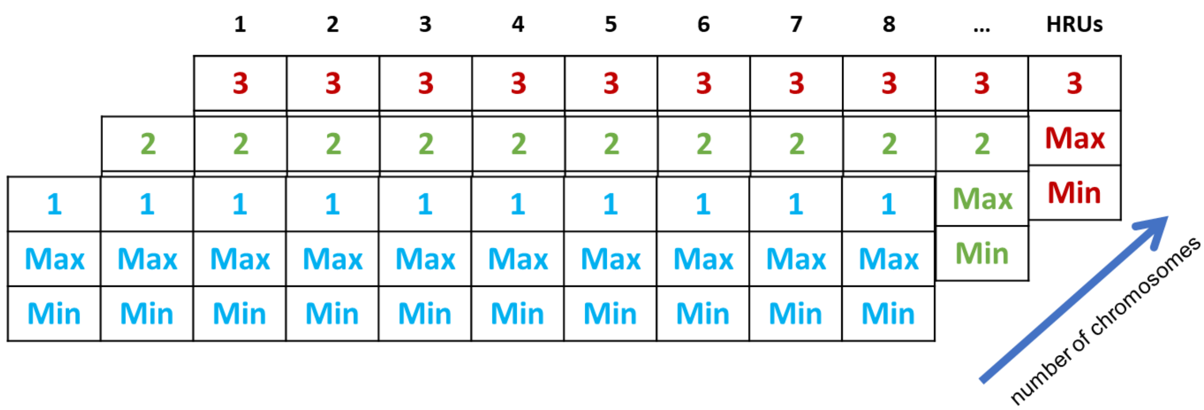


Figure 14: Chromosome encoding

This evolutionary algorithm is computer-based and mimics mechanisms of evolution as key elements in their design and implementation. Therefore, the chromosomes will combine to generate new chromosomes (possible solutions, new individuals, children).

5.6.2 Initialization

After defining the chromosome encoding, the first step of the algorithm is to generate a pseudo-random predefine number of individuals as an initial set of solutions to explore. The user defines the parameter for the initial random population of n chromosomes. This initial population initiates the exploration of the search space, and depending on the size of this population, the time it takes the algorithm to generate the Pareto-optimal set will be influenced. In order to do this step, the chromosomes created for the management practices will mix until generating the initial random population defined by the user. Figure 15 represents this process as follows:

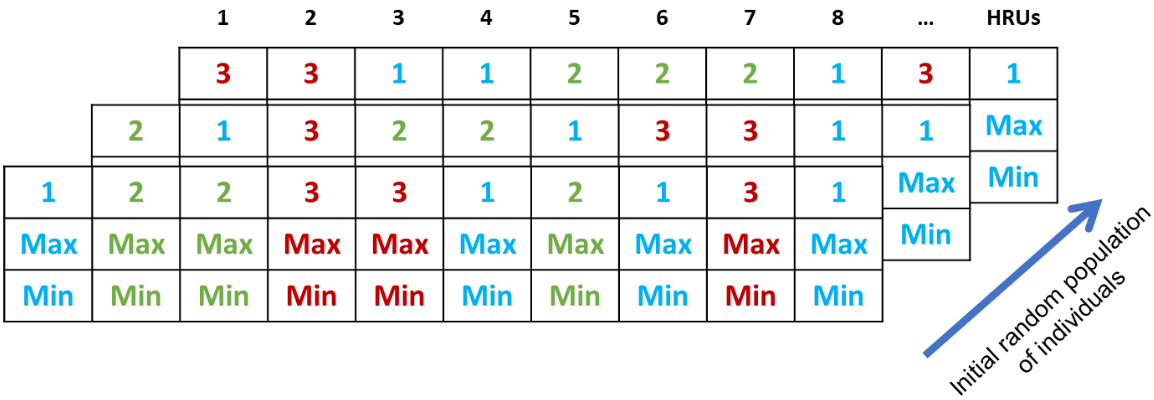


Figure 15: Initial population

5.6.3 Dominance Count

The algorithm seeks to achieve the simultaneous optimization of all the objectives. Thus the individuals in the population are evaluated by the number of objective functions and then assessed by the Pareto dominance criterion. The concept of Pareto dominance serves to identify the number of solutions dominated by each individual. To this extent, the dominance count operation eliminates solutions that are dominated in all the objectives regarding other solutions, the solutions that are non-dominated in at least one objective will be used in the next generation to generate new individuals. The purpose of this step is to achieve proximity to the Pareto-optimal front.

5.6.4 Fitness Evaluation

It can be suggested that the multiple objective evolutionary algorithm seeks to achieve two goals: Proximity represents the closeness to the Pareto front and to maintain population diversity. Distance-based metric and dominance-count metric evaluate these goals as follow:

- Fitness metric 1: Distance-based $f_1(i)$, to maintain diversity, higher fitness is given to individuals that are farther away from other solutions in the Pareto front. The following steps are used:
    1. Normalization of the objectives is used to avoid unit discrepancies as follows:

    $$\frac{f_{i(x)} - f_i^{min}}{f_i^{max} - f_i^{min}}$$

    Where, $f_{i(x)}$ represents the value in the non-dominated set, f_i^{min} represents the smallest value in the non-dominated, and f_i^{max} represents the largest value in the non-dominated set

    2. Evaluate using Euclidean distance between each solution to the rest of the solutions. Non-dominated solutions whit the highest distance are given higher fitness values to achieve diversity.
- Fitness metric 2: Dominance count-based, $f_2(i)$ is used to approximate the true Pareto front by selecting more dominating individuals.
- Aggregated Fitness Metric: Aggregates the two fitness metrics and assigns equal weights to each fitness metric in an attempt to achieve proximity and diversity.

5.6.5 Selection

The selection operator intends to improve the average quality of the population by giving higher-quality solutions a higher probability of survival. Elitism is used to ensure that a subset of the best-fitted individuals survives in each iteration into the next generation. The aggregated fitness metric determines the fitness of an individual. Tournament selection is used by randomly selecting two individuals, and the most fitted of the two goes into the next generation. This process continues until the defined elitism percentage is reached. The most fitted individuals that go into the next generation will be used to produce new individuals.

5.6.6 Crossover

The primary purpose of the crossover operator is to provide genetic material from the previous generation to the subsequent generation. After the selection of the fittest individuals that go into the next generation is accomplished, the selected individual will undergo this process to generate a new population of individuals. Random single-point crossover is used to generate the new individuals that were not selected by elitism in the previous step. The first segment of genes of parent one joins the second segment of genes of parent two, and the first segment of parent two joins the second segment of parent one. Figure 16 serves as a representation of how crossover works for the respective management practice.

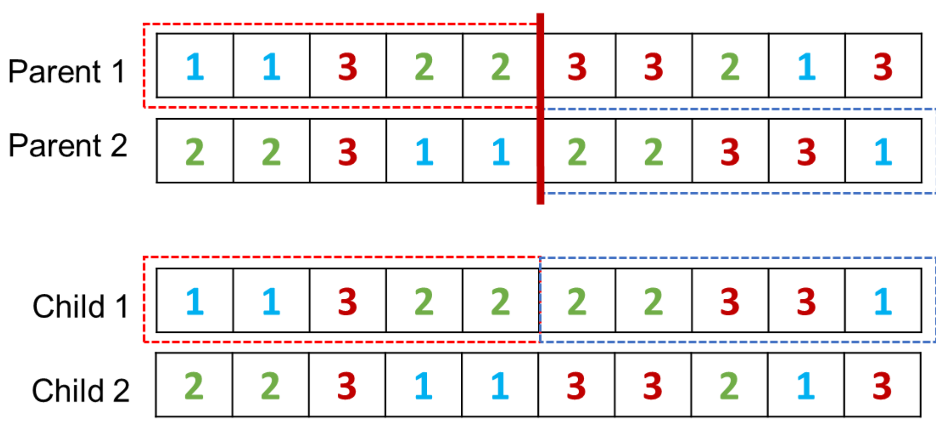


Figure 16: Crossover visualization

5.6.7 Mutation

The main purpose of the mutation operator is to introduce a certain amount of randomness to the search. This operator is used in the new offspring produced in the previous step; the purpose of this step is to keep the population evolving and avoid falling into local optimum. Single point mutation is used on a small percentage of the new offspring. Figure 17 represents the mutation process where a gene in the chromosome of the individual created undergoes the mutation process by interchanging genes with another individual.

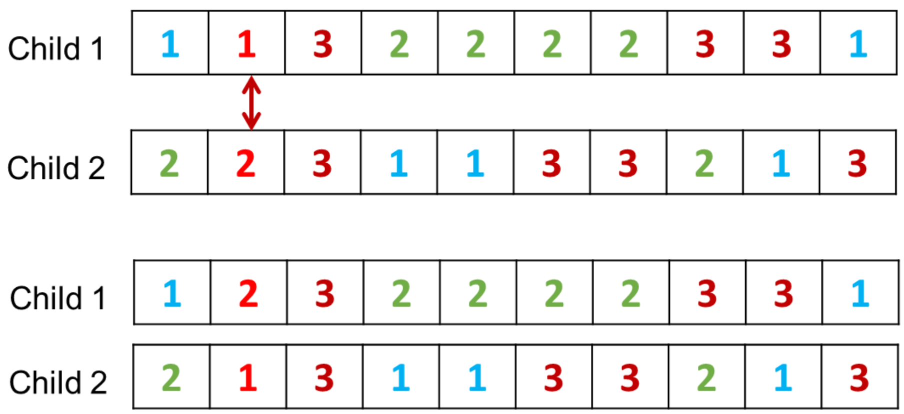


Figure 17: Mutation example

5.6.8 Termination

The process of generating new solutions is performed until the stopping criteria are met. The algorithm stops until it reaches a predetermined number of generations; the user defines the number of generations for the stopping criteria. There are other ways to determine the stopping criteria; for instance, a threshold can be used to detect when the algorithm has reached a steady state, meaning that it is no longer evolving.

5.7 SWAT and MATLAB interactions

The previous sections provided a detail description of how the optimization tool works. It explained the different files that are needed from the initial SWAT simulation and how the simulation is set up in the graphical user interface. Figure 18 provides a summary diagram of the interactions between SWAT and MATLAB, which are the tools used for the irrigation optimization tool. In general, there are different sources (few mentioned in the diagram) with information related to soil layer, landuse, digital elevation model and weather data that the user can use to create the initial SWAT simulation that is needed. Depending on the quality of the information different climate change scenarios can be simulated in SWAT to explore conditions that can affect the water cycle in order to design watershed management scenarios that can mitigate these impacts. In SWAT the user has to make different management decisions related to the sources of the information and the different agricultural parameters.

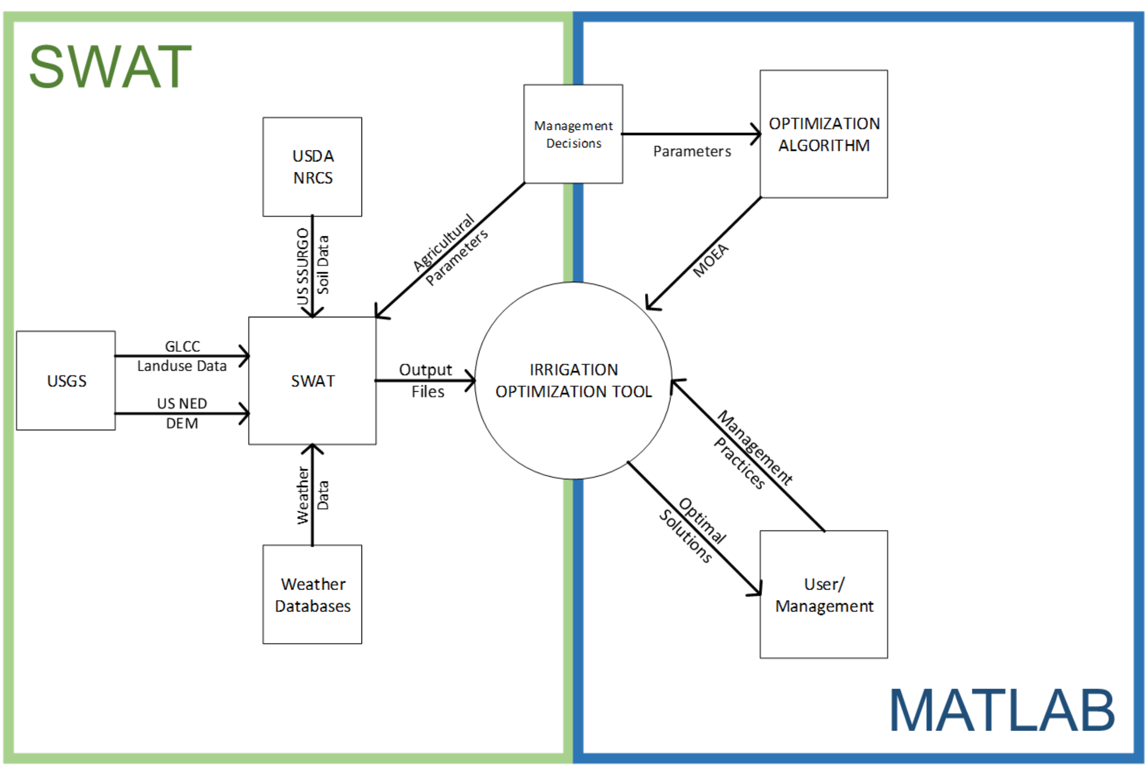


Figure 18: Irrigation Optimization Tool interactions

Furthermore, MATLAB is used to code the graphical user interface to create the management practices from the output files provided by the SWAT simulation. The tool includes the addition of different irrigation systems to extend the management practices scenarios and a multiple objective evolutionary algorithm is coded to provide the optimal placement for the management practices. In the optimization tool, there are management decision that need to be made such as the parameters for the optimization algorithm, depending on the parameters chosen the Pareto-optimal set and the time to generate it will be affected due to the complexity of the search space. Lastly, once all the factors are integrated in the irrigation optimization tool the user can start developing different management scenarios to identify the best possible outcome for the scenario.

Chapter 6: Case Studies

This chapter presents different case studies applying the developed irrigation systems optimization framework. The case studies were located in a watershed located in central Oklahoma. The optimization framework runs in a desktop computer with Intel® Xeon® CPU E3-1231 V3 @ 3.40GHz processor and 16 GB of RAM. The optimization framework demonstrates the flexibility to simulate different management practices, using an initial SWAT simulation and optimizing different objectives with the integrated MOES. Additionally, it provides the optimal configuration of the recommended management practice that could be used in the watershed's hydrological response unit.

6.1 Irrigation Systems Overview

Irrigation can be defined as the agricultural process of applying controlled water amounts to land to assist in crop production. Irrigation improves agricultural crop growth and landscape maintenance and produces new vegetation growth in dry areas and during dry periods where rainfall is less than average. This suggests that the main goal of irrigation systems is to provide the crops with suitable amounts of water at the proper time. Proper irrigation will alter the entire growth process, from seedling preparation to crop yield and quality. Irrigation systems involve the equipment that is required to provide water to the crops, and there are many factors that need to be taken into account when considering an irrigation system. Farmers need to be mindful of water availability, the application efficiency of the system, the depth or lift from which the water is pumped, the pressure needed to operate the system, energy sources, energy costs, and system costs. Application efficiency is the percentage of water used by a crop and varies among systems due to differences in design, maintenance, management, and environmental factors such as soil types and climatic conditions. The 2018 Irrigation and water management census of agriculture found an increase of one percent of farms since 2013 in the United States used irrigation at some point during the year, and U.S. total water applied (acre-feet) decreased by 5.8% from 2013, respectively. There are various methods of irrigation, and they vary in how water is supplied:

- Surface irrigation is the oldest and most common method for crop irrigation (USDA, NRCS 2012), and there are different configurations that can be classified as basin irrigation, border irrigation, furrow irrigation, and wild flooding. These systems can be useful when water is sufficient but has a considerable water loss.
- Sprinkler irrigation applies water in the form of a spray formed from the flow of water under pressure over small nozzles or openings (USDA, NRCS 2016). These systems are suitable for most crops and adaptable to nearly all soils due to their wide range of discharge capacities. The pressure is usually obtained by pumping, and they can be divided into two categories, periodic-move, and fixed systems. In periodic movement systems, the sprinklers move in either a circular or a straight path. In fixed systems, the sprinklers remain in a fixed position. There are various types of irrigation systems, such as center pivots, side-rolls, and traveling sprinklers, to name a few. These types of systems are beneficial for controlling water application rates, amounts, and timings that reduce water loss.
- Microirrigation systems apply water in frequent application of small quantities of water on or below the soil surface as drops or miniature sprays over emitters along a water delivery line. Most emitters operate at low pressures ranging from 3 to 20 psi (USDA, NRCS 2013). The types of systems include drip irrigation, subsurface drip irrigation, bubbler, jet mist, and spray systems, to name a few. These systems are designed to apply water directly to

the soil and allow more efficient infiltration. Several factors affect the selection of the irrigation type, such as system cost, soil type, climatic conditions, water quality, and pumping costs. They are initially expensive to purchase, but their potential for increased yield allows the user to recover in a short amount of time.

6.1.1 Operating pressure and Costs

Operating pressure affects pumping costs, where higher-pressure systems make irrigation more expensive compared to low-pressure systems. Depending on the system use and the advances in technology, there are different operating pressures in pounds of pressure per inch of water (psi) that can be designed. In Amosson et al. (2011), five different irrigation systems were studied with different operating pressures. Furrow systems usually have an operating pressure of 10psi, low elevation spray application (LESA) of 15psi, Low Energy Precision Application (LEPA) of 15psi, Mid-elevation spray application (MESA) of 25psi and Subsurface drip irrigation SDI) of 15psi. Additionally, the Economic Research Service provides data on the shares for higher-efficiency low-pressure sprinkler irrigation for systems less than 30psi.

Furthermore, the gross investment for each quarter section system varies depending on the irrigation system. In the same study, the investment costs for the systems were identified as $208.56/acre for furrow systems, $1,200/acre for subsurface drip irrigation systems, and $556/acre for quarter-mile center pivot irrigation systems (Amosson et al., 2011). In Stubbs (2016), capital and operational costs can influence agricultural producers' adoption of irrigation technologies not necessarily for water conservation but for potential economic gains. Additionally, it identified major irrigation technologies used in the United Sated in 2013, where 122,000 farms use pressure systems and 85,000 farms use gravity systems. The estimated costs for select irrigation technologies found in this report are as follow: Low-Flow Micro Sprinklers $2,800/acre, Sub-

Surface Drip can range from $1,200/acre to $1,800/acre, Surface Drip $860/acre, Linear Move Tower $850/acre, Center Pivot can range from $340/acre to $620/acre, and Furrow $210/acre.

6.2 Watershed Description

The study area used in this simulation is the Fort Cobb Reservoir Watershed, located in central Oklahoma (Figure 19). The model requires Geographic Information System data layers, elevation model, soil layer, and land use data in order to create the model using the ArcSWAT interface. The simulation based on the data layers used delineated the watershed into 71 sub-basins, 901 hydrological response units (HRUs), and covers an area of about 804.07 km^2 for more details about the model inputs. Please refer to Moriasi et al. (2022) for model calibration and validation.

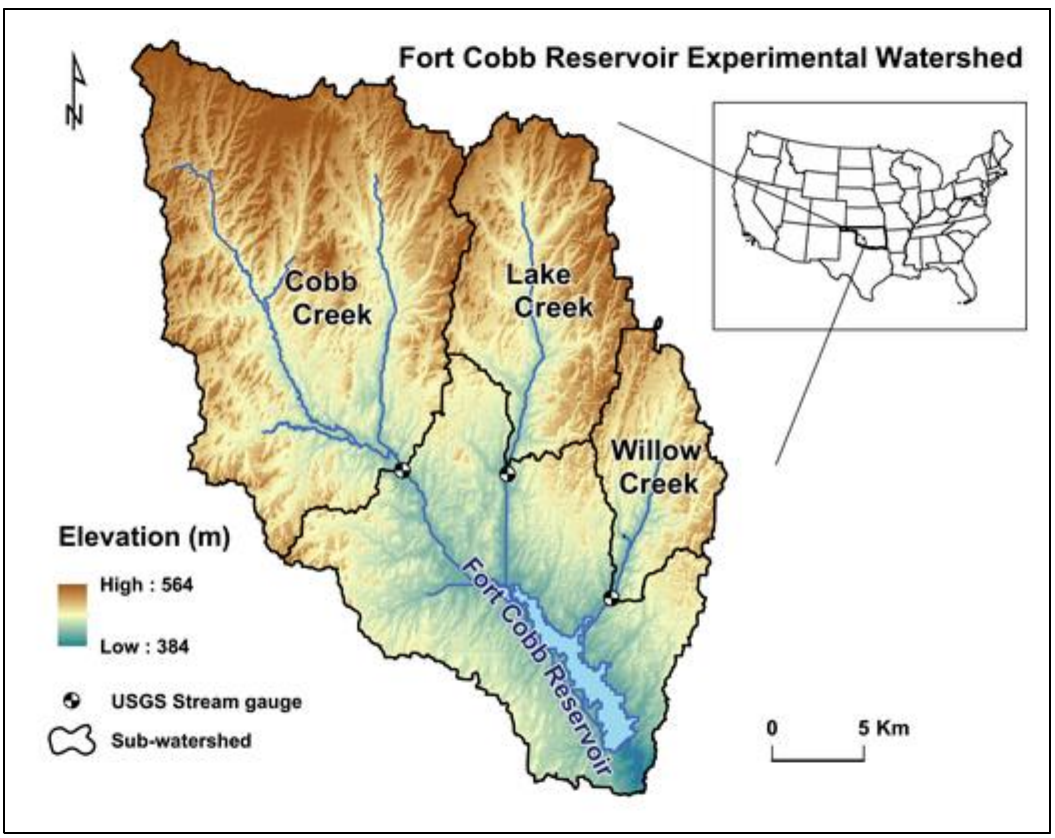


Figure 19: Fort Cobb Reservoir Experimental Watershed (FCREW) (Moriasi et al., 2022)

6.2.1 Groundwater Level Monitoring Well Data

The Fort Cobb Reservoir Experimental Watershed has several groundwater level wells that are monitored by The Oklahoma Water Resources Board (OWRB), and the annual average data is available for public use. Micronet and Mesonet stations provide the data for the study. Micronet stations are a network of automated weather stations designed to improve atmospheric monitoring. Mesonet stations are a network of environmental monitoring stations that measure the environment at the size and duration of mesoscale weather events. Figure 20 provides information on the wells' location and the data sources.

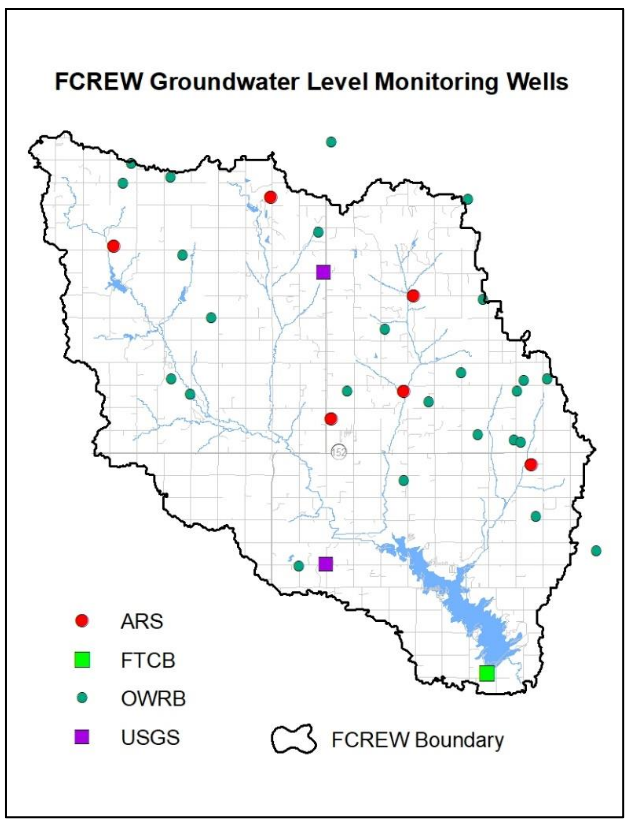


Figure 20: Groundwater Level Monitoring Wells

The ORWB provides hourly groundwater depth data from six different wells located at the Agricultural Research Service (ARS) Micronet stations. The Mesonet stations for this study are located on the FortCobb Reservoir dam and provide well depth data from the FortCobb (FTCB). Additionally, daily groundwater depth data for wells located near Eakly, OK, and Alfalfa, OK, can be found in the U.S. Geological Service (USGS). The period for the simulation is from January 1994 to December 2016, and Table 3 provides the annual average groundwater level data with the minimum and maximum groundwater depth levels, respectively.

Table 3: Forth Cobb reservoir Watershed Depth to Groundwater data

Year	**Average GW Level Data (m)**		
	Min	Average	Max
1994	10.4	17.7	29.5
1995	10.1	18.0	29.4
1996	9.9	17.7	29.2
1997	10.3	17.6	28.9
1998	6.1	22.0	44.0
1999	6.5	22.3	43.5
2000	7.5	22.0	43.0
2001	6.3	22.2	42.7
2002	7.2	22.1	42.2
2003	6.4	21.9	41.9
2004	11.3	23.4	41.7
2005	11.2	23.1	41.5
2006	10.8	22.1	41.4
2007	11.3	22.2	41.3
2008	9.4	21.4	41.2
2009	8.0	21.0	40.6
2010	13.3	19.4	29.2
2011	13.8	20.2	29.6
2012	15.5	21.1	30.1
2013	16.9	21.6	30.5
2014	18.5	21.8	28.0
2015	19.0	21.2	26.3
2016	18.1	20.6	25.6

6.2.2 Electricity Average Prices

The U.S. Energy Information Administration (EIA) is responsible for collecting, analyzing, and publicizing energy information and promoting understanding of energy, and understanding its interaction with the economy and environment. Table 4 provides information on the cost of a kilowatt-hour in Oklahoma from 1994 to 2016. The kilowatt-hour cost is provided for the residential, commercial, and industrial sectors, respectively.

Table 4: Oklahoma cost of a kilowatt-hour

Year	**Average Price (Cents/kilowatt-hour)**		
	Residential	Commercial	Industrial
1994	7.03	6.09	4.07
1995	6.82	5.78	3.75
1996	6.71	5.80	3.78
1997	6.63	5.73	3.63
1998	6.57	5.66	3.65
1999	6.60	5.58	3.60
2000	7.03	6.14	4.09
2001	7.27	6.35	4.29
2002	6.73	5.75	3.81
2003	7.47	6.38	4.59
2004	7.72	6.55	4.76
2005	7.95	7.00	5.11
2006	8.55	7.34	5.46
2007	8.58	7.33	5.41
2008	9.09	7.88	5.90
2009	8.49	6.76	4.82
2010	9.14	7.45	5.35
2011	9.47	7.60	5.46
2012	9.51	7.32	5.09
2013	9.67	7.77	5.49
2014	10.03	8.09	5.85
2015	10.14	7.68	5.35
2016	10.20	7.66	5.02

6.3 Management Practices

The management files used in the study produce information that is unique to the land use and management operation for each HRU. The optimization framework proposed will overwrite the initial files to re-execute SWAT for each management practice, and then the irrigation systems evaluation will be integrated to assess energy consumption and energy costs. In Moriasi et al. (2022), there are five crop management files, with the operation schedule for each. Considering that the Auto-irrigation operation is used to apply irrigation to the HRU for the simulation period and to evaluate the different irrigation systems, in this study, the operation schedules that require only Auto-irrigation will be used to evaluate the optimal placement of the management practice. The operation schedule for soybean, peanuts, and grain sorghum crop management systems is used in the following tables (Table 5-10), where Auto-irrigation operation drip and sprinkler irrigation are used.

Table 5: Soybeans with Drip Irrigation System Operation Schedule

Month	Day	SWAT Operation Name	Description
June	1	Tillage operation	Zerotill
June	5	Tillage operation	Zerotill
June	10	Pesticide application	Metolachlor
June	10	Pesticide application	Pendimethalin
June	15	Plant or begin growing season	Soybeans
June	15	Fertilizer application	00-15-00
June	20	Auto-irrigation initialization	Drip Irrigation
July	1	Tillage operation	Zerotill
July	10	Pesticide application	Glyphosate
November	1	Harvest-and-kill operation	
November	15	Tillage operation	Zerotill
		Skip-a-year operation	

Table 6: Soybeans with Sprinkler Irrigation System Operation Schedule

Month	Day	SWAT Operation Name	Description
June	1	Tillage operation	Zerotill
June	5	Tillage operation	Zerotill
June	10	Pesticide application	Metolachlor
June	10	Pesticide application	Pendimethalin
June	15	Plant or begin growing season	Soybeans
June	15	Fertilizer application	00-15-00
June	20	Auto-irrigation initialization	Sprinkler
July	1	Tillage operation	Zerotill
July	10	Pesticide application	Glyphosate
November	1	Harvest-and-kill operation	
November	15	Tillage operation	Zerotill
		Skip-a-year operation	

Table 7: Peanuts with Drip Irrigation System Operation Schedule

Month	Day	SWAT Operation Name	Description
April	16	Fertilizer application	18-46-00
April	17	Tillage operation	Zerotill
April	18	Tillage operation	Zerotill
April	19	Tillage operation	Zerotill
April	19	Plant or begin growing season	Peanuts
April	20	Auto-irrigation initialization	Drip Irrigation
October	15	Harvest-and-kill operation	
October	18	Tillage operation	Zerotill
		Skip-a-year operation	

Table 8: Peanuts with Sprinkler Irrigation System Operation Schedule

Month	Day	SWAT Operation Name	Description
April	16	Fertilizer application	18-46-00
April	17	Tillage operation	Zerotill
April	18	Tillage operation	Zerotill
April	19	Tillage operation	Zerotill
April	19	Plant or begin growing season	Peanuts
April	20	Auto-irrigation initialization	Sprinkler Irrigation
October	15	Harvest-and-kill operation	
October	18	Tillage operation	Zerotill
		Skip-a-year operation	

Table 9: Grain Sorghum with Drip Irrigation System Operation Schedule

Month	**Day**	**SWAT Operation Name**	**Description**
May	27	Fertilizer application	46-00-00
May	28	Pesticide application	Alachlor
May	28	Tillage operation	Zerotill
May	28	Tillage operation	Zerotill
June	1	Plant or begin growing season	Grain Sorghum
June	20	Auto-irrigation initialization	Drip Irrigation
October	15	Harvest-and-kill operation	
October	18	Tillage operation	Zerotill
October	20	Tillage operation	Zerotill
		Skip-a-year operation	

Table 10: Grain Sorghum with Sprinkler Irrigation System Operation Schedule

Month	Day	SWAT Operation Name	Description
May	27	Fertilizer application	46-00-00
May	28	Pesticide application	Alachlor
May	28	Tillage operation	Zerotill
May	28	Tillage operation	Zerotill
June	1	Plant or begin growing season	Grain Sorghum
June	20	Auto-irrigation initialization	Sprinkler Irrigation
October	15	Harvest-and-kill operation	
October	18	Tillage operation	Zerotill
October	20	Tillage operation	Zerotill
		Skip-a-year operation	

6.4 Case Study 1: Optimization of Yield and Irrigation Energy Cost

This study evaluates yield (kg/ha) and irrigation energy cost ($/ha) in six different management scenarios. Thus the objective functions are to Maximize Yield and Minimize Energy Cost. This section will use the management operation schedules provided in the previous section. Table 11 provides the values for the parameters used in the management practices.

Table 11: Irrigation Systems for Case Study 1

Parameters	Drip	Sprinkler
Irrigation Working Pressure	20 (PSI)	35 (PSI)
Pressure loss due to Friction	20%	20%
Pump Efficiency	90%	80%
Motor Efficiency	90%	90%
Drive Efficiency	90%	90%
Results	ha	ha

The management practices that will be evaluated in this scenario are in Table 12. In this table, the first column, management code, represents the management schedule operation evaluated in the optimization framework. The second column represents the crop operation schedule defined in section 6.3. The third column represents the irrigation system used for the crop operation schedule. The parameters for each irrigation system used in this scenario can be found in the previous table, where the irrigation working pressure for drip is 20 PSI and for sprinkler 35 (PSI).

Table 12: Management Practices for Case Study 1

Management Code	Crop Operation Schedule	Irrigation System
1	Soybeans	Drip
2	Soybeans	Sprinkler
3	Peanuts	Drip
4	Peanuts	Sprinkler
5	Grain Sorghum	Drip
6	Grain Sorghum	Sprinkler

The watershed has 901 HRUs and a 22-year period. The objectives for this scenario are to maximize crop yield and minimize energy costs. The plant/begin growing season operation generates the growth for the specific plant in all HRUs; soybeans, peanuts, and grain sorghum will be used in these operations. The Pesticide application used for Metolachlor is 2.2 kg/ha, Pendimethalin 0.8 kg/ha, Glyphosate 1.12 kg/ha, and Alachlor 2 kg/ha. The fertilizer application used for 00-15-00 is 140 kg/ha, 18-46-00 124 kg/ha, and 46-00-00 40 kg/ha. The plant stress demand for all the scenarios is 90% of the potential.

The MOEA executes an initial population of 1,000 individuals to begin searching the space and a stopping criterion of 1,000 generations. Elitism is 25% with a crossover of 75%, and since we want a small percentage of randomness in the model, a mutation of 1% is used, respectively. The optimal solution found with the given settings is displayed in Table 13. Based on the HRUs where a crop has grown, an average of 6614.420 kg/ha of crop yield is produced on the watershed, and an average energy cost of $120.171 per ha was found, respectively. Additionally, the optimal solution table provides the configuration of what management practice is recommended to be used. For instance, in the table in HRU 1 to 3, there is no crop production because that HRU is not suitable for production. On the other hand, for HRU 4, management practice four is recommended to be implemented, which represents growing peanuts and using a sprinkler irrigation system, and for HRU 5, management practice five is recommended, which represents growing grain sorghum and using drip irrigation.

Table 13: Optimal Solution for Case Study 1

HRU	Management Practice	Yield (kg/ha)	Energy Cost/ha
1	0	0	0
2	0	0	0
3	0	0	0
4	4	15646.2	164.2650107
5	6	136.7	63.20074837
6	0	0	0
7	0	0	0
8	0	0	0
9	0	0	0
10	0	0	0
11	0	0	0
12	0	0	0
13	0	0	0
14	0	0	0
15	0	0	0
16	2	2007.2	103.2875936
17	2	2000.7	122.6210292
18	5	135.9	43.35553899
19	5	238.8	68.89648074
20	5	618.1	62.71027762
21	6	638.3	111.9666443
.	.	.	.
.	.	.	.
.	.	.	.
901	3	16224.5	141.4620379
	Average	6614.420	120.171

The MOEA identified that the Pareto-Optimal set has 23 non-dominated solutions. In Figure 21, the normalized values are graphed, where objective 1 is the maximization of crop yield and objective 2 is the minimization of energy cost. Ultimately, one solution needs to be chosen from the Pareto-optimal set, and considering that we have maximization and minimization objectives, the ideal point is found at (1,0). Thus the solution closest to this point is defined by the red mark.

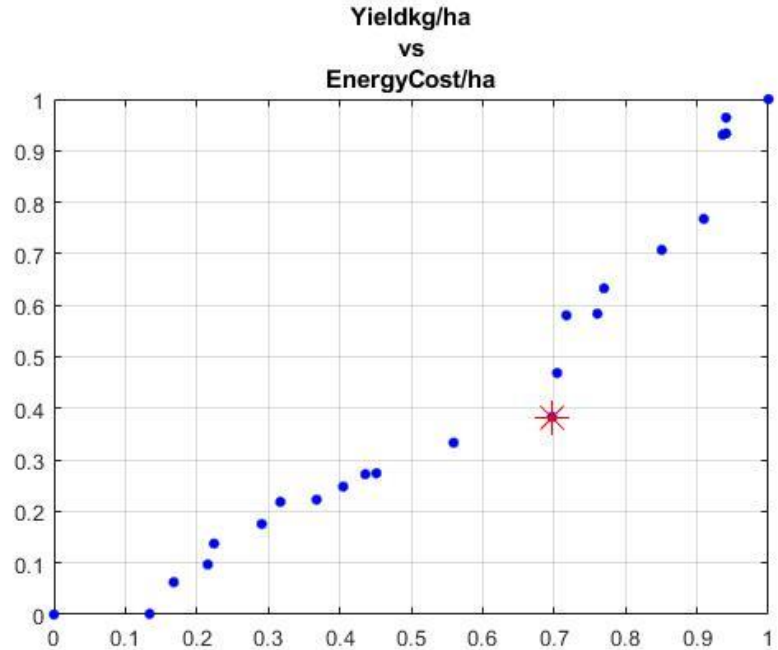


Figure 21: Two-dimensional view Yield vs Energy Cost

Furthermore, the solution closest to the ideal point is suggested for implementation in the watershed for case study 1. The spatial location of the different management practices for the optimal conditions is represented in Figure 22.

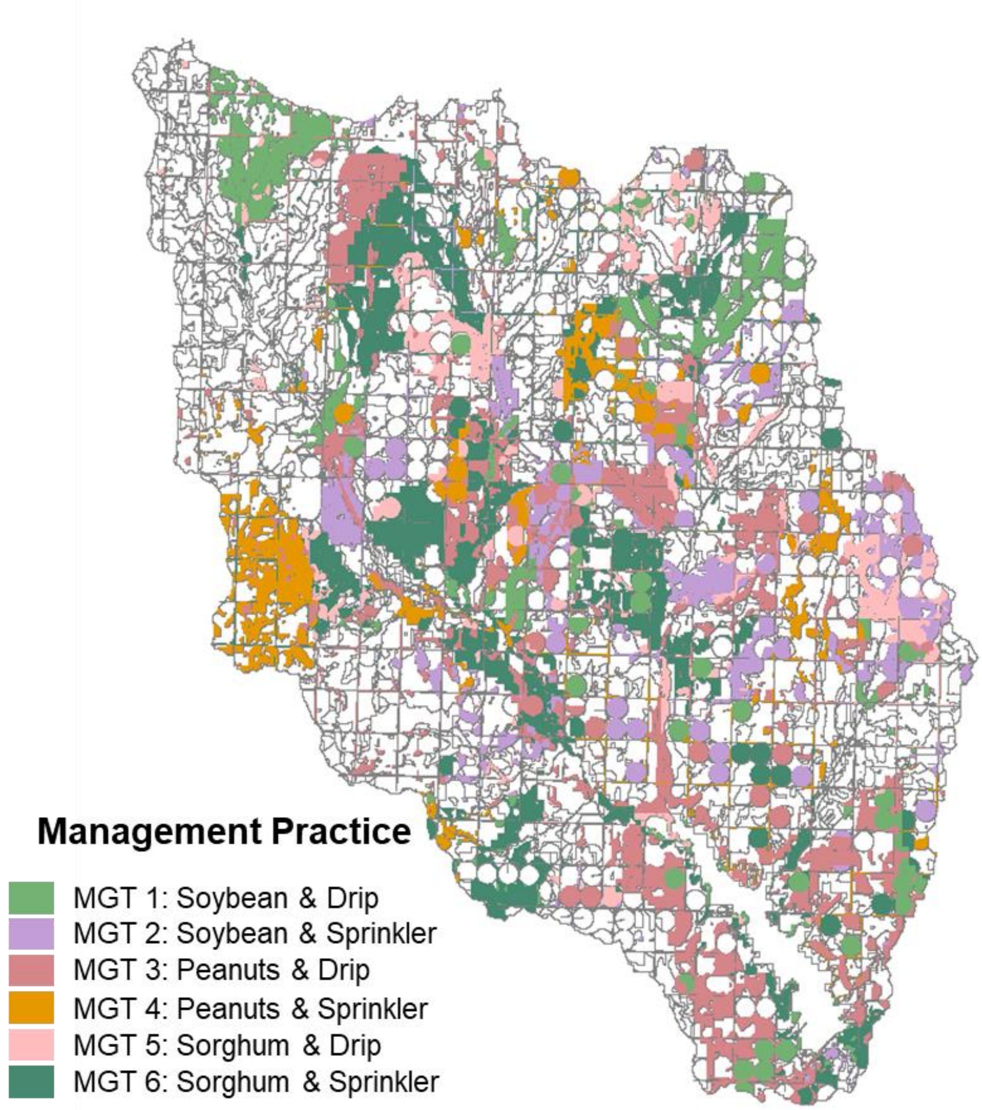


Figure 22: Case Study 1 Optimal Solution Distribution in the Watershed

6.4 Case Study 2: Optimization of Yield, TP, TN, SYLD, and Irrigation Energy Cost

This study aims to evaluate crop yield ranking, Total Nitrogen (TN) kg/ha, Total Phosphorous (TP) kg/ha, Sediment yield (SYLD) metric tons/ha, and irrigation energy costs (\$/acre) in six different management scenarios. Thus, the objective functions are to Maximize Crop Yield Ranking, Minimize TN, Minimize TP, and Minimize Energy Cost. The management operation schedules provided in section 6.2 will be used for this scenario. Table 14 provides the values for the parameters that will be used in the management practices. Figures 23 and 24 provide a visualization of how the parameters are set in the developed graphical user interface. It is important to note that the values in the cost of the irrigation system and useful life are set to zero. This does not mean that the irrigation system cost is zero; it simply means that those costs are not taken into account for this study.

Table 14: Irrigation Systems for Case Study 2

Parameters	**Drip**	**Sprinkler**
Irrigation Working Pressure	20 (PSI)	35 (PSI)
Pressure loss due to Friction	20%	20%
Pump Efficiency	90%	80%
Motor Efficiency	90%	90%
Drive Efficiency	90%	90%
Results	acres	acres

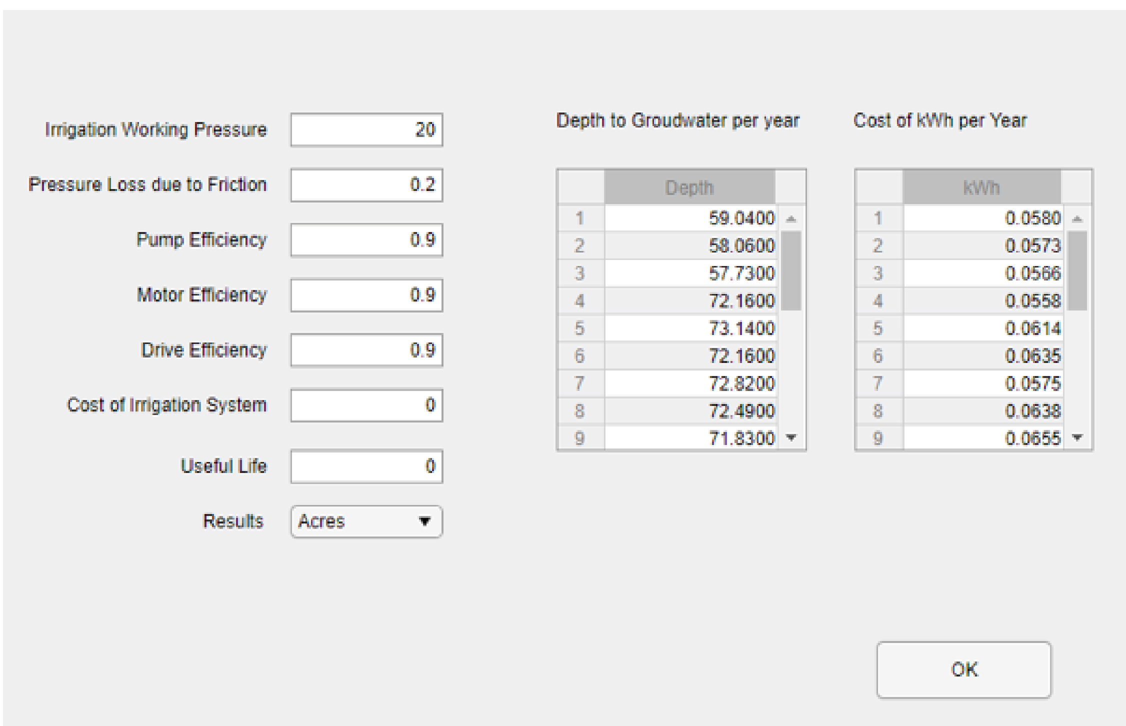


Figure 23: Graphical User Interface for Drip Irrigation System

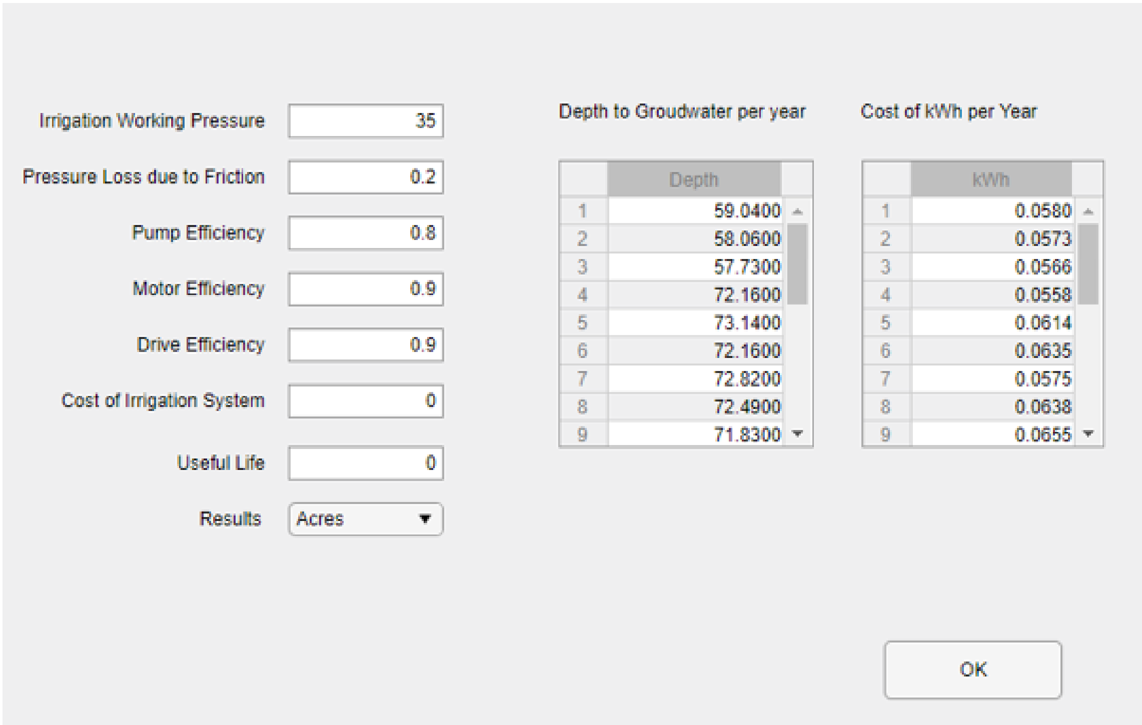


Figure 24: Graphical User Interface for Sprinkler Irrigation System

The management practices that are evaluated in this scenario are in Table 15. As in this previous case study, the first column represents the management schedule operation evaluated in the optimization framework. The second column represents the crop operation schedule, and the third column represents the irrigation system used for the crop operation schedule. The parameters for each irrigation system used in this scenario can be found in the previous figures.

Table 15: Management Practices for Case Study 2

Management Code	**Crop Operation Schedule**	**Irrigation System**
1	Soybeans	Drip
2	Soybeans	Sprinkler
3	Peanuts	Drip
4	Peanuts	Sprinkler
5	Grain Sorghum	Drip
6	Grain Sorghum	Sprinkler

The watershed has 901 HRUs and a 22-year period, and this scenario has five objectives that need to simultaneously optimize. The Pesticide application used for this scenario is the same as in case study 2, for Metochlor 2.2 kg/ha, Pendimethalin 0.8 kg/ha, Glyphosate 1.12 kg/ha, and for Alachlor 2 kg/ha. The fertilizer application stays the same; for 00-15-00 is 140 kg/ha; for 18-46-00, 124 kg/ha; and for 46-00-00, 40 kg/ha. The plant stress demand for all the scenarios is 90% of the potential.

The MOEA executes an initial population of 500 individuals; the stopping criterion is 500 generations. Elitism is 25% with a crossover of 75%, and a mutation of 1% is used, respectively. The optimal solution found with the given settings is displayed in Table 16, and based on the HRUs where a crop was grown, the most often crop yield rank was 3, and the least was rank 4. An average TN of 74.75 kg/ha was found, TP averaged 34.34 kg/ ha, SYLD averaged 21.17 metric tons/ha, and an average energy cost of $52.29 per acre was found. Additionally, the optimal solution table provides the configuration of what management practice is recommended for every HRU.

Table 16: Optimal Solution for Case Study 2

HRU	Management Practice	Yield	Rank	TotalN	TotalP	SYLDt/ha	EnergyCost/acre
1	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0
4	3	15646.20	5	193.99	50.36	9.39	44.32
5	5	136.70	0	4.90	25.35	28.58	17.06
6	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0
16	5	619.50	0	6.81	22.29	17.46	25.38
17	1	2000.70	3	35.94	37.52	36.50	33.11
18	2	2032.30	3	35.07	28.98	22.17	28.59
19	1	2031.80	3	35.41	29.80	18.97	38.14
20	2	2007.20	3	34.87	29.39	15.88	41.80
21	2	1999.70	3	36.03	38.19	37.91	49.34
901	3	16224.5	5	211.955	85.865	21.914	57.24771
			Average	74.75	34.34	21.17	52.29

The MOEA identified 85 non-dominated solutions in the Pareto-Optimal set, and in Figure 25, the normalized values are graphed. Ultimately, one solution needs to be chosen from the Pareto-optimal set, and considering that we have five objectives: maximization, minimization, minimization, minimization, and minimization, the ideal point is found at (1,0, 0, 0, 0). Thus the solution closest to this point is defined by the red mark.

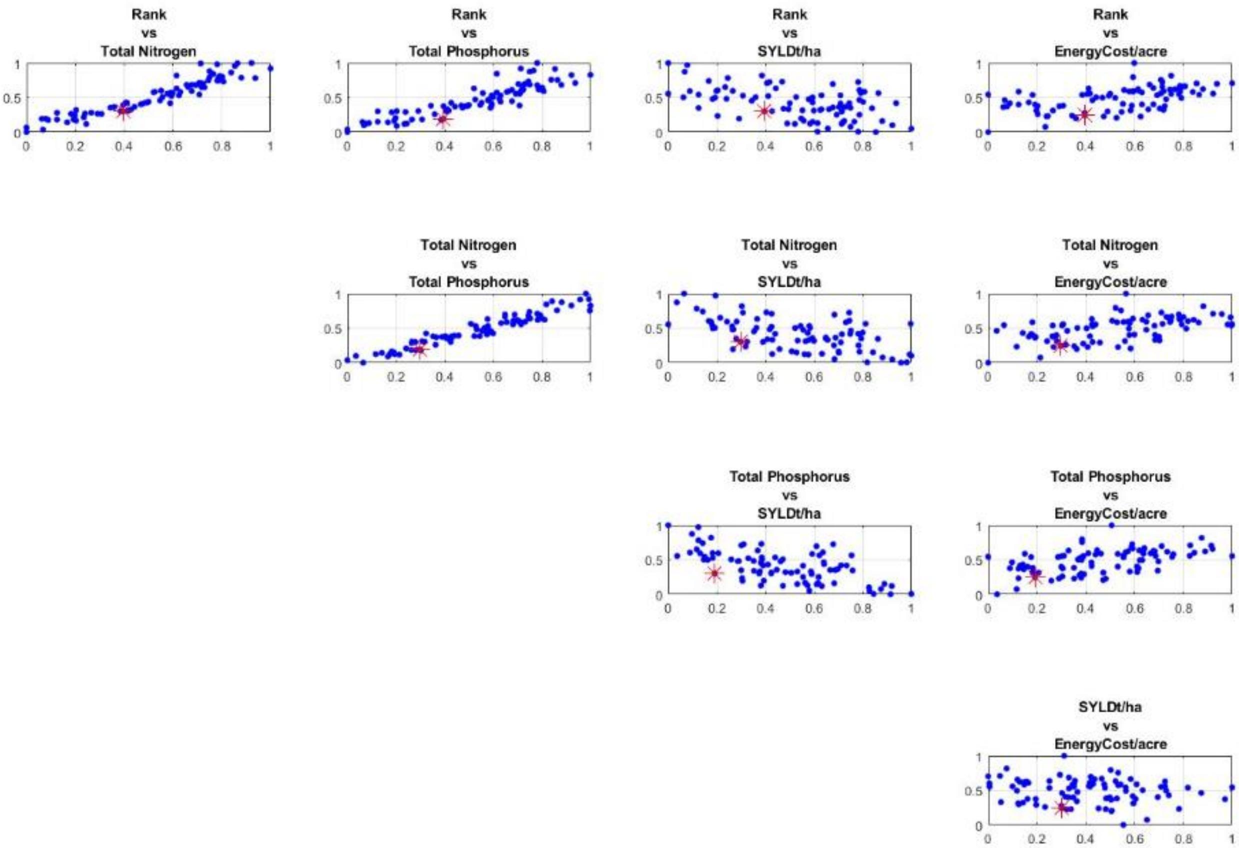


Figure 25: Bi-Dimensional View of Five Objectives

Furthermore, the solution closest to the ideal point is suggested for implementation in the watershed for case study 2. The spatial location of the different management practices for the optimal conditions is represented in Figure 26.

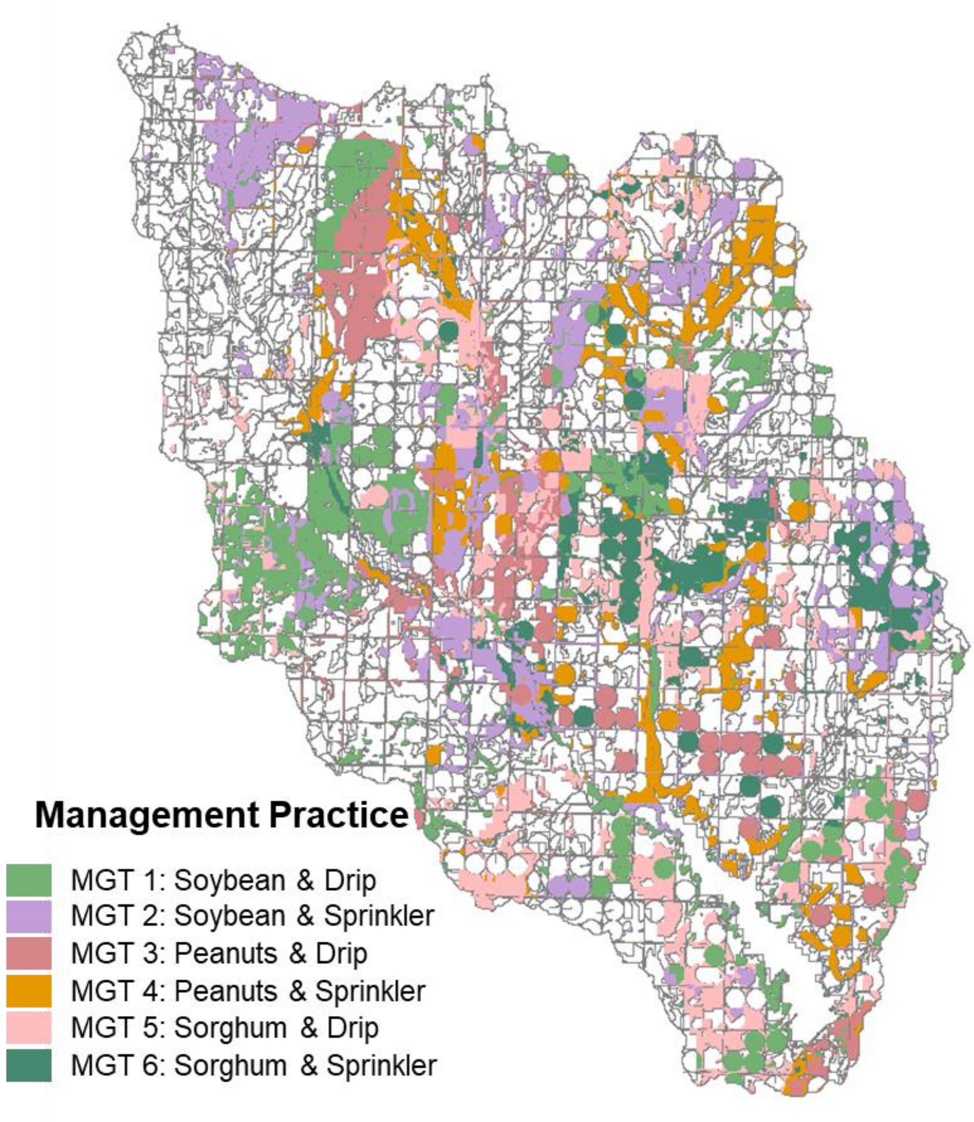


Figure 26: Case Study 2 Optimal Solution Distribution in the Watershed

6.5 Case Study 3: Optimization of Yield, Irrigation Energy Cost, and Total Cost

The aim of this study is to evaluate crop yield (kg/ha), irrigation energy cost ($/acre), and total cost ($/acre) in six different management scenarios. Thus, the objective functions are to Maximize Crop Yield Ranking, Minimize TP, Minimize TP, Minimize Energy Cost and Minimize Total cost. The management operation schedules provided in section 6.13 will be used for this scenario. Table 17 provides the values for the parameters that will be used in the management practices. Figures 27 and 28 provide a visualization of how the parameters are set in the developed graphical user interface. It is important to note that the values in the cost of the irrigation system represent an estimate of the cost of the equipment for the irrigation section, based on what was identified in studies mentioned in previous sections and the useful life for the systems. These values will change depending on the irrigation system configuration the user decides to explore.

Table 17: Irrigation Systems for Case Study 3

Parameters	**Drip**	**Sprinkler**
Irrigation Working Pressure	15 (PSI)	25 (PSI)
Pressure loss due to Friction	20%	20%
Pump Efficiency	90%	80%
Motor Efficiency	90%	90%
Drive Efficiency	90%	90%
Cost of System	1200	560
Useful Life	25	25
Results	acres	acres

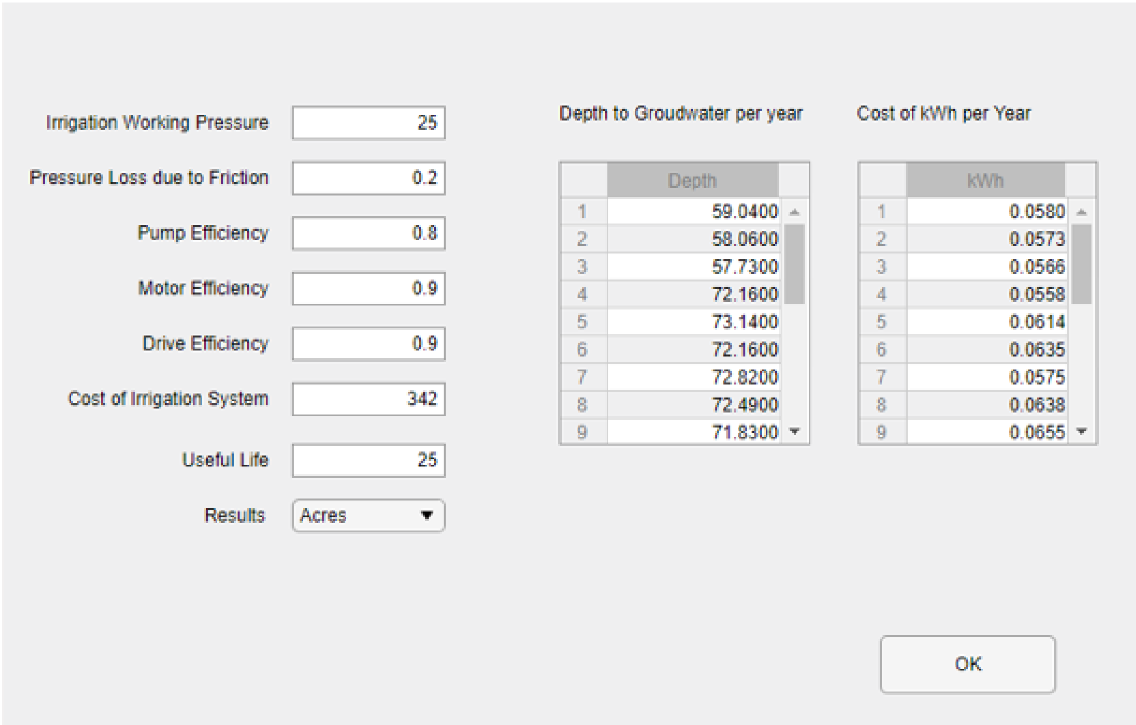


Figure 27: Graphical User Interface for Sprinkler Irrigation System

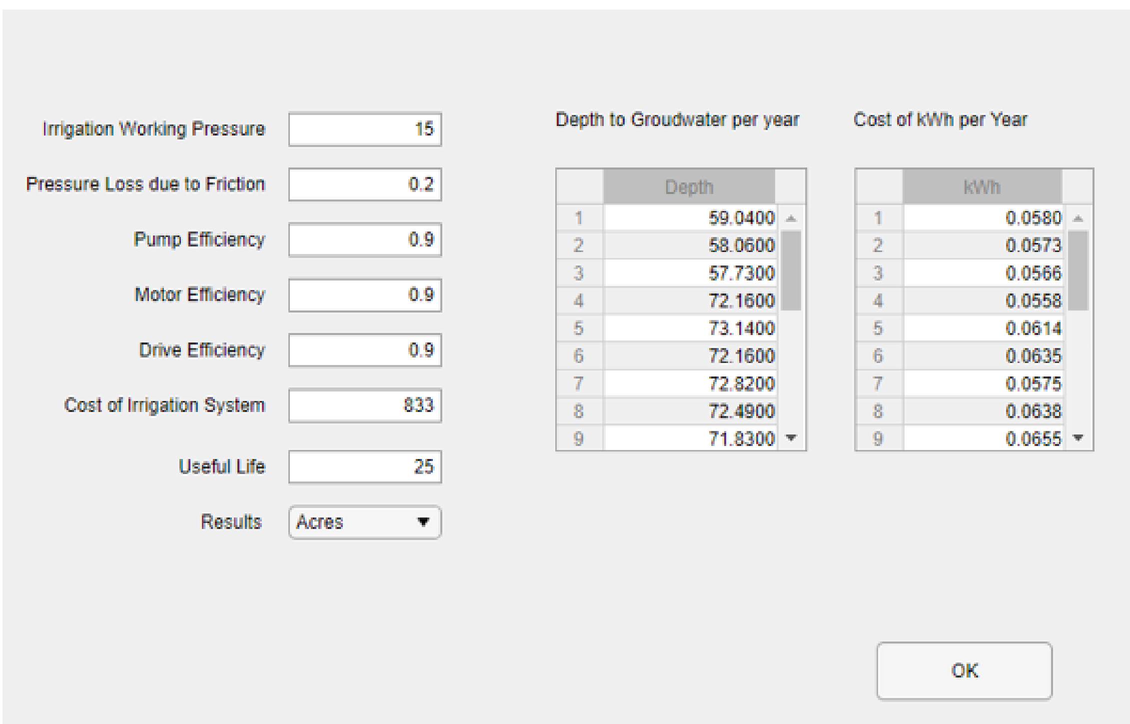


Figure 28: Graphical User Interface for Drip Irrigation System

The management practices that are evaluated in this scenario are in Table 18. As in this previous case study, the first column represents the management schedule operation that was evaluated in the optimization framework. The second column represents the crop operation schedule, and the third column represents the irrigation system being used for the crop operation schedule. The parameters for each irrigation system used in this scenario can be found in the previous figures.

Table 18: Management Practices for Case Study 3

Management Code	Crop Operation Schedule	Irrigation System
1	Soybeans	Drip
2	Soybeans	Sprinkler
3	Peanuts	Drip
4	Peanuts	Sprinkler
5	Grain Sorghum	Drip
6	Grain Sorghum	Sprinkler

The watershed has 901 HRUs and a 22-year period, and this scenario has three objectives that are optimized simultaneously. The Pesticide application used for this scenario is the same as in case study 2, for Metochlor 2.2 kg/ha, Pendimethalin 0.8 kg/ha, Glyphosate 1.12 kg/ha, and for Alachlor 2 kg/ha. The fertilizer application stays the same; for 00-15-00 is 140 kg/ha; for 18-46-00, 124 kg/ha; and for 46-00-00, 40 kg/ha. The plant stress demand for all the scenarios is 90% of the potential.

The MOEA begins searching the space with an initial population of 500 individuals, and the stopping criterion is 500 generations. Elitism is 25%, with a crossover of 75%, and a mutation of 1% is used, respectively. The optimal solution found with the given settings is displayed in Table 19, and based on the HRUs where a crop was grown, the study found an average yield of

6260.47 kg/ha, an average energy cost of $41.91 per acre, and an average total cost of $77.40 per acre was found. Additionally, the optimal solution table provides the configuration of what management practice is recommended to be used in every HRU.

Table 19: Optimal Solution for Case Study 3

HRU	Management Practice	Yield (kg/ha)	Energy Cost/acre	Total cost/acre
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	3	15646.20	39.40	87.40
5	4	15646.20	55.40	77.80
6	0	0	0	0
7	0	0	0	0
8	0	0	0	0
9	0	0	0	0
10	0	0	0	0
11	0	0	0	0
12	0	0	0	0
13	0	0	0	0
14	0	0	0	0
15	0	0	0	0
16	6	619.50	31.71	54.11
17	3	15699.80	49.47	97.47
18	3	15957.70	38.13	86.13
19	5	238.80	24.80	72.80
20	6	618.10	31.71	54.11
21	6	638.30	37.78	60.18
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
901	5	619.10	28.17	76.17
	Average	6260.47	41.91	77.40

The MOEA identified 149 non-dominated solutions in the Pareto-Optimal set, and in Figure 29, the normalized values are graphed. Ultimately, one solution needs to be chosen from the Pareto-optimal set, and considering that we have three: maximization, minimization, and minimization, the ideal point is found at (1,0, 0). Thus the solution closest to this point is defined by the red mark.

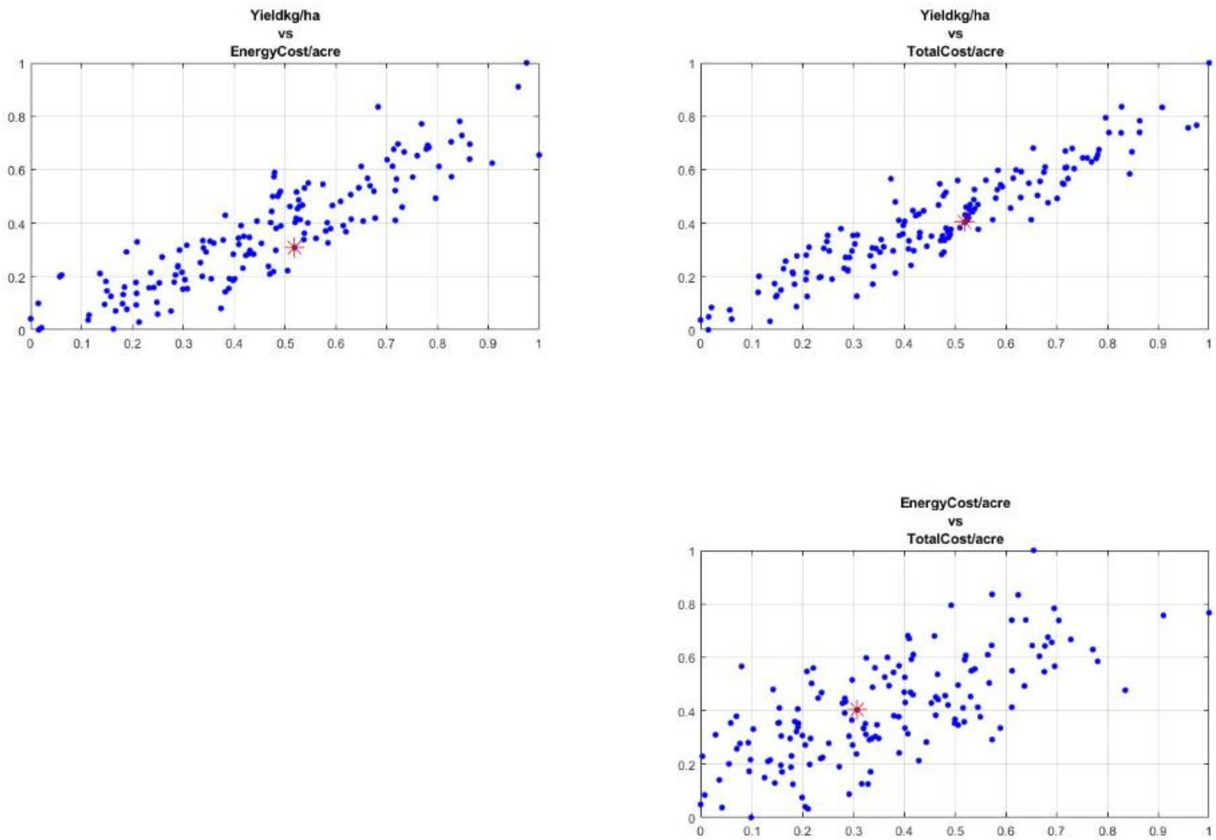


Figure 29: Bi-dimensional view of three objectives

Furthermore, the solution closest to the ideal point is suggested for implementation in the watershed for case study 3. The spatial location of the different management practices for the optimal conditions is represented in Figure 30.

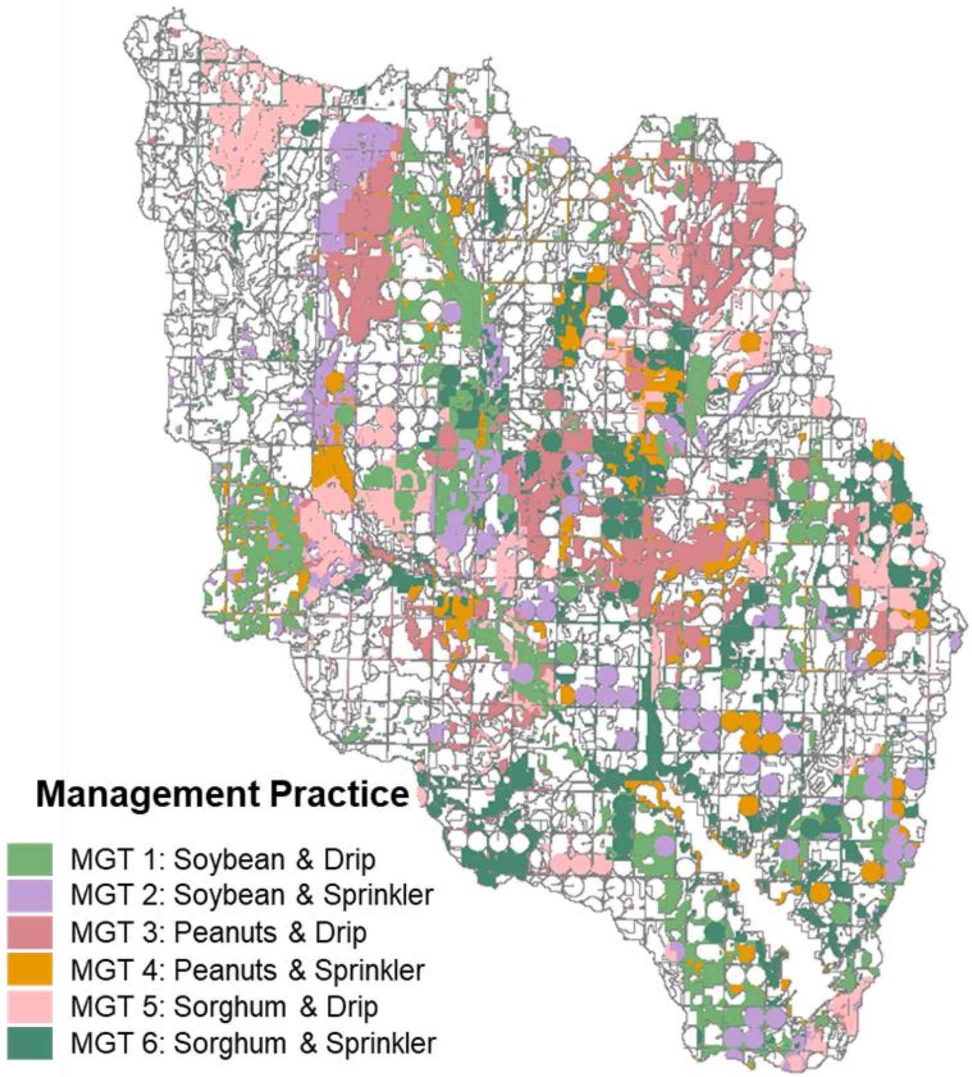


Figure 30: Case Study 3 Optimal Solution Distribution in the Watershed

6.6 Results and Discussion

The case studies provided possible solutions for managing the 901 HRUs in the watershed. The Pareto-optimal set identifies all the possible solutions of the study, represented by the blue color, while the red color represents the suggested solution due to its closeness to the ideal point. The results from the irrigation optimization framework in terms of irrigation energy costs and total costs are aligned with several studies. For instance, in Oklahoma, the Oklahoma Water Resource Board (2011) found that groundwater levels declined, causing an increase in water pumping costs. The study found that in 2008 the average irrigation pumping costs in Oklahoma averaged about $74 per acre. Many irrigated farms rely on pumps for water distribution regardless of the water source. Taghvaeian and Mehata (2020) found that in Oklahoma average cost of irrigation water is about $42 per acre for groundwater and $18 per acre for surface water irrigation.

Additionally, Schaible and Ailery (2012) reported that in 2008 the Western States averaged about $76 per acre for irrigated agriculture when pumping from wells; however, total variable costs can vary depending on the water source. Wichelns (2010) found that the average cost of off-farm source irrigation in the U.S. in 2003 ranged from $12-$213 per hectare to a national average of $104 per hectare. Heimlich (2003) reported that the average costs of irrigation water in 1998 varied depending on the source groundwater ranges from $2-$69 per acre, and off-farm sources for all the states can range from $2-$175 per acre respectively.

Chapter 7: Conclusions and Future Research

7.1 Conclusions

Water scarcity has worsened in the last decades in many parts of the world due to the large increase in water withdrawals, population growth, and climate change. Cities and industries compete with the agricultural sector for water sources, and this is causing alarming levels of pollution by the increasing population. At the same time, food demand is expected to increase, and agricultural production is required to increase to keep up with the demand, with irrigated agriculture playing a major role. The decrease in natural resources and food demand emphasizes the need to increase water productivity.

The main challenge that the agriculture sector faces is adapting to the impacts of climate change and water scarcity to develop food production systems that can efficiently feed the growing population in the following years. To meet production demands, it is important to develop new strategies that optimize agriculture productivity that is dependent on the integration and interaction of various factors, on the appropriate selection of irrigation systems and strategies taking into account water availability, climate variability, soil and crop characteristics, energy, economic, and environmental aspects.

In order to achieve the best possible outcome with limited natural resources, this research proposes an irrigation system assessment framework to identify the optimal spatial placement of land use and irrigation systems to reduce tradeoffs between conflicting objectives in irrigated agriculture. The Soil Water Assessment Tool (SWAT) is a hydrologic simulation model used as a water balance and crop estimator to quantify energy cost and energy consumption in agriculture irrigation water from different water sources. The hydrological model incorporates a multiple objective evolutionary algorithm (MOEA) considering the maximization of crop yield and minimization of energy cost and consumption to develop a Pareto-optimal front that decision-makers can use to explore the trade-off between optimal solutions.

In chapter two, an extensive literature review was included. The review explored different areas related to pressurized irrigation systems and irrigation optimization frameworks to identify how irrigation systems have progressed through time and the implementation and assessments of different areas of study. The review also provided different assessments of the SWAT model, and the articles were divided into different categories, and in most articles, more than one category was addressed. The literature review suggested that when SWAT is coupled with an optimization framework, NSGA-II from MATLAB Toolbox is very popular among researchers. In addition, when assessing irrigation in SWAT, schedule irrigation and deficit irrigation are mostly used, and the review suggested that there is a need to include different irrigation systems for evaluation.

In chapter three, an overview of SWAT is included. This chapter summarizes the land phase of the hydrological cycle to provide an understanding of its functionality. A description of the Auto-irrigation function in SWAT is provided because the irrigation optimization framework developed in this work uses the Auto-irrigation option. The different water sources in SWAT are described, and the water stress identifiers as well, to provide an overview of how SWAT works when adding irrigation.

Chapter four attempts to provide a general description of single and multiple objective optimization and addresses the Pareto-optimal front. A few popular methods for single objective optimization are provided, suggesting that when there is more than one conflicting objective different methods should be used. In addition, a few popular methods for multiple objective evolutionary algorithms are described along with their application in different SWAT assessments. These methods suggested that evolutionary algorithms are suited for multiple objective optimization when there is more than one conflicting objective and that there are many diverse evolutionary algorithm methods that generally differ mainly in the fitness evaluation phase.

In chapter five, the proposed irrigation optimization framework is introduced. An initial SWAT simulation is needed, and this simulation is then used in the graphical user interface. The user then starts creating the operation schedule; when the auto-irrigation option is selected, a new window will appear, allowing the user to add irrigation systems to be used for the evaluation. Since this is a multiple objective optimization framework, the tool requires more than one management practice. This chapter explains how the database is created and gives an overview of the MOEA used, from the chromosome encoding to the different processes of dominance count, selection, crossover, mutation, and termination. The MOEA will provide the optimal configuration of the suggested management practice to be implemented for each HRU.

Chapter six provides different case studies. The first case study had two objectives maximization of yield and minimization of energy cost per acre, and this study was used to identify the relations between crop yield and energy cost per hectare and to compare drip and sprinkler irrigation systems. The second study explores five different objectives: max crop yield ranks, min TN, min TP, min sediment yield, and min energy cost; there are different output results that SWAT provides, and in most studies, pollution is included in the studies. In this case, total nitrogen, total phosphorous, and sediment yield objectives were included to assess the spatial placement of the management practices when more objectives need to be simultaneously optimized. The last study explores three objectives max crop yield, min energy cost, and min total cost. Depending on the irrigation system used, there are differences in energy and system costs. For instance, a drip irrigation system needs a higher initial investment than a sprinkler irrigation system. However, when comparing irrigation energy cost per acre, drip irrigation costs less than sprinkler irrigation.

Therefore, this scenario adds the total cost objective, which is a function of irrigation energy cost and initial investment cost, to provide a further understanding of the selection of irrigation systems.

Furthermore, the most important thing to note is that this model requires an initial SWAT simulation and the knowledge from the decision-maker to design and explore different management scenarios. The quality of the SWAT simulation based on the setup in terms of the layers used, watershed data, and climate data will affect the results of the framework. In addition, based on the results, irrigation and sprinkler irrigation energy costs are aligned with several studies, and this can suggest that the tool can be useful to alleviate the decision-making process to identify the optimal spatial placement of land-use and irrigation systems. Although, it is important to mention that a variety of different irrigation systems work best in different regions with different pressure and efficiencies parameters that can be used for evaluation. One recommendation for the decision maker is to identify the farmers in the area and develop a survey of the different management practices and irrigation systems used to simulate better management practices that be more representative of the area to provide better results.

Lastly, the main contribution of this work is the proposed irrigation optimization framework that further expands recent developments by incorporating irrigation systems into the management practice scenarios. SWAT was used as a water balance, and crop estimator and energy consumption were evaluated based on the outputs. SWAT was then coupled with a multiple objective optimization algorithm, and a graphical user interface was developed to allow the user to create multiple management scenarios and evaluate multiple irrigation systems.

7.2 Future Research

In recent years, there have been many developments regarding SWAT; from the literature, many studies have integrated SWAT with different models to improve the assessment or representation of hydrology in watershed management scenarios. With the development of the irrigation optimization framework and the user-friendly tool developed in this study, there is room to improve it, similar to what the research community has done with SWAT. New watershed simulations are needed to fully grasp the extent of this framework.

The next step is to make this tool an executable, but plenty of work needs to be done related to usability. To some extent, it is user-friendly, but there are ways to improve its usage; for instance, currently, the process of entering management scenarios has to be done every time the user decides to add a new management practice. The management scenario is not saved after completion, and only the output results are saved in a folder. In the event that the user decides to explore the same management practice at another time, the user will need to write or create the management practice again. To improve the ease of having to repeat steps, something that can be done is to save the management practices parameters in an archive and provide an option to add them. This does not affect the tool's functionality; it simply saves time when creating management scenarios.

Currently, energy in kWh is being evaluated in this study. The next step to expand the study is to translate energy into carbon emissions and quantify the environmental impact of the irrigation system used. A life cycle assessment from cradle to gate can be performed to assess the impacts of different materials irrigation systems are built from. For instance, different plastic materials provide higher emissions than others, which can affect the irrigation system selection if the environmental impact objective is considered in the study. This assessment will consider the raw material extraction phase to the production phase to better quantify environmental impacts. There are tools with extensive databases that support life cycle assessments, such as GaBi Software and Simapro. Overall, this study can be further expanded by incorporating an environmental impact objective considering a life cycle assessment of different irrigation systems and the electricity emissions.

Furthermore, there are different SWAT simulations, and the proposed tool may need to be modified to account for the different parameters of the simulation. It will be interesting to work with different SWAT simulation models to understand the capabilities of the tool and expand it, as in Moriasi et al. (2022), where the user wanted to add a new objective, the ranks to prioritize based on the range of crop yields. Lastly, an irrigation system calculator that designs the system based on the user's preferences can be added to the tool in the distant future. Different online calculators are available that assist irrigation system installers in quantifying parts and quantities of the materials needed for the project. Like many other tools, these calculators are not exact but provide the user a better understanding of the costs associated with the design of the irrigation system and save them time.

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Vita

Juan V. Fernandez was born in El Paso, Texas. He received his B.S. in Industrial Engineering in December 2015 and his M.S. in Industrial Engineering from The University of Texas at El Paso. He is the oldest of four siblings and will be the first one in his family to obtain a doctoral degree

During his college career, he was a research assistant and had the opportunity to present his work at multiple conferences and teach engineering courses. He was also part of different internships with the United States Department of Agriculture (USDA) in the Agriculture Research Service (ARS) and with the National Institute of Food and Agriculture (NIFA), respectively. His research interests include optimization, sustainability, watershed management, supply chain management, and manufacturing.