Developing an efficient irrigation scheduling system using hybrid machine learning algorithm to enhance the sugarcane crop productivity

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Research Article

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Abstract

As a crop with maximum utilization of water, Sugarcane is responsive to water management system throughout lifetime of the crop. Since, due to the fluctuation of climatic variables, the demand of water resources becomes dynamic. This work focuses on the different irrigation system for sugarcane yield using AquaCrop and neural network models. AquaCrop model processes the predetermined data of weather from 1988 – 1989 to 2019 – 2020, soil data, crop data and irrigation system to acquire certain amount of sugarcane yield. The changes occurred in the weather variables consequently affect the crop parameters and irrigation system; thus usage of water is difficult to schedule. So, soil permanent wilting point sensor is deployed in this model to extract the amount of water presents in the soil. The moisture level of soil data is further stored in the cloud called Thingspeak. The soil data are passed on to the cloud via WiFi modem. The future weather data from 2020-2021 to 2049-2050 which are simulated by CCSM4 model and soil sensor data are integrated; then implemented using both conventional neural network and optimized deep learning models in order to classify the irrigation strategies. The firefly optimization helps to optimize the scheduling of the irrigation according to weather and soil data. Hence, water utilized by optimized deep learning model is reduced and predicted more accurately as compared with standard AquaCrop and conventional neural network models. The result of this research is capable of providing an optimized irrigation system with efficient consumption of water saving measures.

Introduction

Water is a fundamental source of agriculture and its outstanding management is a key challenge to maintain the agricultural productivity and enhance the financial growth of the country. When facing the variability of climate, minimizing the labor strength and varying the conditions of soil require novelty in cultivation (Ramachandran et al. 2018). Water stress is commonly caused by agro climatic conditions which are associated with insufficient rainfall, high solar radiation and dry wind making an imbalance between precipitation and evapotranspiration. It predominately occurs if there is a lack of soil moisture to accomplish the crop water necessity at certain period of growth (Razzaghi et al. 2017).

Based upon soil type, planting method, utilizing manures as well as fertilizers, the requirement of water differs. The hot climate related with dried up wind that maximizes the requirement of water to the crop. The warm weather associated with dry wind and drought increase the water requirement of the crop. Hence, irrigation management plays a major responsibility in crop production. Evapotranspiration (ETo) is also an important parameter in setting up the irrigation and water resource management (Farooque et al. 2022).

As discussed by (Vaheddoost et al. 2020), the evaluation of soil permanent wilting point (PWP) can depict the ability of water accessible. PWP provides the amount of water present in the soil that helps in administration of irrigation. It is possible to assess field capacity (FC) and PWP physically and estimate together with possession of soil like sand, clay, silt and organic matter. The manual calculation of FC, PWP and other soil properties in large scale is very expensive and time consuming. Artificial neural

network (ANN), machine learning algorithms and optimization method assist sand, clay, silt and organic matter to evaluate FC and PWP with less cost and convenient. Some research reported that the properties of soil effectively predict FC and PWP either using parametric or non parametric models.

As explained in (Reddy 2012), a soil moisture monitoring system at low cost is interfaced with irrigation system to improve the soil watering. However by fixing sensors that estimate other features of soil, farmers can eligible to select irrigation systems according to the contents level of the soil. Remote controlled irrigation system helps preventing soil stress; hence offering an efficient utilization of water resources. In case of automatic irrigation, soil sensor is predominantly used to extract the dynamic measures of the soil.

IRRIX is a sensor-based software designed for irrigation scheduling. It can automatically irrigate the crop throughout the season as per the routine of uploading sensor data, updating the water availability in the soil and making decision of upcoming irrigation dosage. The irrigation scheduling strategy implemented by IRRIX affords a computerized water balance method which is getting adjusted by soil sensor (Domínguez-Niño et al. 2020). The combination of wireless technologies and irrigation strategies is taken into account for implementation of machine learning techniques. ANN, fuzzy logic, and regression are the methods currently practiced in irrigation management. Machine learning algorithms initially learn the knowledge of the expert to find the pattern of irrigation scheduling and make conclusion in decision making. Decision support systems (DSS) further continue the process to learn and adapt to the environment according with different features (Torres-Sanchez et al. 2020). The report given by (Torres-Sanchez et al. 2020) is that DSS act as a helpful tool for optimal irrigation and implemented in the agricultural field for several years. It improves not only the irrigation management but also increasing the crop growth development.

So far discussed by (Murali et al. 2020), DSS is a flexible and economic model which can be frequently used in agricultural field but it is unfair in implementation of large amount of data. Deep learning algorithms are preferred to execute the big data in effective manner. Due to presence of many hidden layers in deep learning algorithms, vanishing gradient problem may arise during training time. Hence, handling weights and bias of the deep learning model become a complicated job; referred to as degradation issue. To speed up network processing with less error, optimization algorithm supports in optimizing the parameters to obtain appropriate results.

In (Cho and Jun 2011), decision tree and an adaptive particle swarm optimization (APSO) are integrated to reduce the computational burden and provided with optimal results. APSO simply optimizes the threshold values of the selected features; therefore the other features can never be considered if the selected features are selected by decision tree. APSO optimizes the decision tree in order to improve the classification instead of pruning method with less computational cost.

This paper proposes a deep learning algorithm that utilizes enhanced firefly optimization method to classify the irrigation strategies like irrigation1, irrigation2, irrigation3 and irrigation4. In this irrigation management, optimized learning model is developed using weather data extracted by meteorology

station networks to increase the water use efficiency of sugarcane crop. Using past 30 years of weather data, the fixed irrigation recorded by AquaCrop model and optimized irrigation implemented by deep learning model are compared. The future 30 years of weather data are simulated using CCSM4 model and PWP value from soil sensor are used by proposed model for discovering new irrigation pattern to reduce the quantity of water. Depending upon validation of the proposed model water utilized by irrigation is very low as compared with existing AquaCrop fixed irrigation model.

Material And Methods

AquaCrop

AquaCrop model can simulate the yield of sugarcane response to water productivity in four significant steps which is depicted in Fig. 1 (Revathy and Balamurali 2019).

The growth of sugarcane and water productivity (WP) is mainly determined by crop canopy. The development of canopy cover (CC) differs with respect to various seasons which are calculated by process of disrupting radiations activated by photosynthesis (Steduto et al. 2009). But AquaCrop model estimates the CC based on level of crop leaf and its expansion that are derived from maximum temperature and unmaintained WP. Hence, CC is expressed as

$$CC = \frac{\mathrm{Greencanopycoveringuppermostlayerofsoil}}{\mathrm{Totaluppermostlayerofsoilsurface}} \quad (1)$$

Since WP plays a vital part in AquaCrop to maximize the crop yield, it is referred as a supporting model for irrigation policy. The WP is defined as the quantity of biomass which could be acquired with certain amount of water that is expressed in kg (biomass) per m^3 of water transpired which is given as below

$$WP = \frac{\mathrm{biomassproducedexpressedasKg\,(\,biomass\,)}}{\mathrm{watertranspiredexpressedasm^3\,(\,Tr\,)}} \quad (2)$$

AquaCrop model requires sufficient climatic data, crop data, soil data and field management data in order to fix the irrigation strategy under various seasons for obtaining good CC and balanced WP (Bahmani and Eghbalian 2018).

Deep Learning Model

Deep learning is a set of machine learning algorithms that implements multiple hidden layers to increasingly classify the irrigation strategy from the corresponding weather data and soil data. Before training the data, data normalization process is required to feed into network (Alajrami and Abu-Naser 2020). Data normalization is a preprocessing method where the data should be scaled in the range of 0 to 1. Therefore, the input data are being normalized using Z- score normalization approach to scale the data to zero and a standard deviation of one. The mathematical formula to derive Z- score normalization is as follows:

$$Norm^{'} = \frac{Norm - \bar{A}}{\sigma_A}$$

3

where $\bar{A}$ and σ_A denote the mean value and standard deviation of the attribute Norm.

The normalized data are passed into deep learning network to classify irrigation methods in order to predict the future water administration. ANNs are composed of elements stated as neurons which are multiplied by its weight, and execute it through non-linear activation function (Santos et al. 2019). By implementing a number of hidden layers of neurons, each of the layer that receives information of the input data, and pass the output to the next layers, formally deep learning network hold of input, multiple hidden and output layers correspondingly. The sum of the weighted edges is calculated using gradient descent method and activation function is transmitted to the next layer (Tian et al. 2020).

The difference between simple neural network and deep learning network are schematically represented in Fig. 2. Once the weather and soil data are fed into network, deep learning can automatically optimize the parameters. So, the classification error is minimized during training of network.

Firefly Optimization

The firefly optimization (FFO) algorithm is an optimization algorithm that works on firefly behaviors and it's blinking features. FFO is also called as metaheuristic optimization, since it is capable of finding the optimal results for complicated problems (Johari et al. 2013). FFO follows a set of rules as follows:

1. As fireflies fit into unisex group, the firefly creatures can be attracted by other fireflies.

2. As for any two fireflies, the lightning attractions are being proportional to brightness, the low brightened creature attracts high brightened firefly. When the usual distance extends among fireflies, it's brightness also obviously decreases.
3. The fireflies travel randomly with the purpose of finding the other fireflies rather than the particular firefly.

The Attractiveness and Movements of the Firefly

The attractiveness F of firefly i is fascinated by firefly j with its brightness based upon its distance $r$as defined in the following equation,

$$F(r) = \frac{F_{ij}}{r^2}$$

4

If there are n number of fireflies, x_i is then equal to the solution of firefly i. By means of objective function $f\left(x_i\right)$, the brightness of the firefly i gets attracted to each other. Finally the brightness B of the firefly is picked out to expose the current position of its objective function which is given in (5)

$$B = f\left(x_i\right)$$

5

The lowest brighter firefly is always attracted and migrated towards to the brighter one and each firefly hold a definite attractiveness value β. The attractiveness value β is fairly calculated depend upon the distance between the fireflies. The function belongs to firefly attractiveness is defined as follows.

$$\beta(r) = \beta_0 e^{-\gamma r^2}$$

6

where β_0 denotes the attractiveness of the firefly at value r = 0 and γ refers to the coefficient of media light absorption (Yang et al. 2013) and (Mandal et al. 2015).

Optimized Deep Learning Model – A Proposed Approach

Combining deep learning model with FFO i.e., DL-FFO directs a well-developed model to improve the water management by classifying the irrigation strategies in sugarcane production. Seeing as deep learning neural network implements a lot of hidden layers that is processed by means of activation functions, the degradation issue may occur at the time of training the network (Murali et al. 2020).

FFO helps in practice to compensate the degradation issue because it is merged with the deep learning model internally; thus increasing the network functionality. Since DL-FFO model obtained efficient prediction1, FFO is implemented with deep learning for optimizing weights. The main optimization problem is finding the best fit of the network by learning the optimal values of weight (Mandal et al. 2015). Optimizing the weight of the model results that deep learning network obviously improves the accuracy efficiency and reduces the error value. The implementation of the proposed model is narrated in Fig. 3.

Results Of Discussion

The proposed deep learning model uses R tool for the implementation of algorithms. As compared with traditional mining algorithms, R tool is flexible and efficient to execute the programs precisely. The future weather data are generated by Community Climate System Model (CCSM); it is a climate model which simulates the past, present and future earth climatic state (Gent et al. 2011). It is composed of 4 geophysical common models like atmosphere, sea ice, land surface and ocean that send the information by coordinating the models between them. In this research the future climatic data for the next 30 years (2020–2021 to 2049–2050) is simulated and graphically represented in Fig. 4. The entire dataset holds

soil data along with future climatic temperature and rainfall dataset which is then split out into training set and test set. The training dataset helps to train the DL-FFO model by employing metaheuristicOpt and neuralnet packages whereas the testing dataset obtains the accuracy and error rate of the model.

With the intention of simulating the yield of sugarcane, AquaCrop produces the achievable yield in response to water management system. Sugarcane utilized normally 60–70 tons of water along with requirements of 75 cm of rainfall. During planting of crops, the soil should have adequate moisture. When the accessible water reaches about 50%, the crop must be irrigated until the tillering stage and stem elongation phase. Thus AquaCrop go after static irrigation before simulating the model. Table I distinguishes actual and simulated yield by AquaCrop response to water utilized by fixed irrigation (in tons) for the year 1988–1989 to 2019–2020. It describes the actual sugarcane yield and yield simulated by AquaCrop model together with fixed irrigation management system. In this irrigation system, there may be a chance to occur like water logging which means that there is too much of water present at the root zone of the plant that minimize the oxygen level supply to roots. Therefore the roots can’t arise properly and also destroy the standing crops. As water starts to evaporate, excess irrigation will definitely increases the salt level at the surface of the soil. Lack of sufficient irrigation make roots to dry during summer time, thus leads to plant wilting so as to make less canopy cover development of the leaves.

Table I. Actual Vs Simulated Yield by AquaCrop Model with Fixed Irrigation from 1988–1989 to 2019–2020

Year	Actual Sugarcane Yield Data (t/ha)	Simulated Sugarcane Yield by AquaCrop Model (t/ha)	Water Utilized by AquaCrop Fixed Irrigation (In tons)
1988–1989	119.5	118.4	8170
1989–1990	130.3	128.5	8818
1990–1991	127.1	126.3	9626
1991–1992	122.8	121.0	9368
1992–1993	119.9	116.9	8194
1993–1994	134.5	133.1	9070
1994–1995	127.2	125.8	8632
1995–1996	121	118.0	8260
1996–1997	127	124.0	8620
1997–1998	100.4	98.3	9024
1998–1999	124.49	121.0	8469.4
1999–2000	136.7	132.9	9202
2000–2001	132.9	131.5	8974
2001–2002	96.5	91.8	8790
2002–2003	89.6	86.0	8376
2003–2004	104.9	100.0	9294
2004–2005	131.32	130.8	8879.2
2005–2006	139.91	137.4	9394.6

Year	Actual Sugarcane Yield Data (t/ha)	Simulated Sugarcane Yield by AquaCrop Model (t/ha)	Water Utilized by AquaCrop Fixed Irrigation (In tons)
2006–2007	113.56	111.7	8813.6
2007–2008	116.03	115.0	9961.8
2008–2009	134.25	132.1	9055
2009–2010	107.22	104.8	9433.2
2010–2011	98.84	96.8	9930.4
2011–2012	113.88	99.4	9832.8
2012–2013	118.29	115.7	8097.4
2013–2014	103.33	100.6	9199.8
2014–2015	126.64	121.4	8598.4
2015–2016	86.26	84.7	8175.6
2016–2017	141.74	139.8	9504.4
2017–2018	119.1	117.7	9746
2018–2019	116.9	114.3	8170
2019–2020	122.6	119.7	8818

Dynamic irrigation system helps to reduce the inconvenience throughout the life time of sugarcane. It balances the irrigation procedure according to the moisture level of the soil. Depending upon the soil data, the irrigation gets adjusted in order to increase the water productivity of the crops. This system involves deep learning integrated with sophisticated optimization which is trained by means of future climatic data and soil moisture data. DL-FFO obtains outstanding irrigation system while comparing with conventional neural network model. The utilization amount of water (in tons) through dynamic irrigation for the year 2020–2021 to 2049–2050 is showed in Table II. This table elaborates the future simulated

sugarcane yield by AquaCrop, the quantity of water to be irrigated through conventional NN and DL-FFO algorithm.

Table II. Utilization of Water via Dynamic Irrigation through Traditional and Deep Learning Algorithm

Year	Simulated Sugarcane Yield by AquaCrop model (t/ha)	Water Utilized by traditional irrigation (Using Conventional NN) (In tons)	Water Utilized by optimized irrigation (Using DL-FFO) (In tons)
2020–2021	117.7	7650.5	5650.5
2021–2022	120.5	7832.5	6314.5
2022–2023	133.3	8664.5	6397.9
2023–2024	138.2	8983	6292
2024–2025	116.9	7598.5	6066.1
2025–2026	114.1	7650.5	5872.9
2026–2027	125.8	7416.5	6177
2027–2028	119.0	8177	5973
2028–2029	124.0	7735	6432
2029–2030	108.3	8060	5472.7
2030–2031	121.0	7039.5	6107
2031–2032	126.9	7865	6375.4
2032–2033	128.5	8248.5	6738
2033–2034	111.8	8352.5	5826
2034–2035	130.2	7267	6812
2035–2036	118.0	8463	6788
2036–2037	126.8	7670	6242

Year	Simulated Sugarcane Yield by AquaCrop model (t/ha)	Water Utilized by traditional irrigation (Using Conventional NN) (In tons)	Water Utilized by optimized irrigation (Using DL-FFO) (In tons)
2037–2038	129.4	8242	6058
2038–2039	133.7	8411	6423.1
2039–2040	131.0	8690.5	6122
2040–2041	132.1	8515	6190.2
2041–2042	128.8	8586.5	6114.4
2042–2043	116.8	8372	6358.4
2043–2044	99.4	7592	5560.4
2044–2045	125.7	6461	5673.3
2045–2046	100.6	8170.5	6237.2
2046–2047	121.4	6539	6012.4
2047–2048	114.7	7891	6455.5
2048–2049	139.8	7455.5	6388
2049–2050	120.7	9087	6966.2

While judging with conventional neural network, proposed model works efficiently in producing a fitted irrigation system according to climatic fluctuations. As DL-FFO model exists many hidden layers in between input and output layer, the model increases the competence of the algorithm. While training the proposed model, the intermediate neurons are linked with neighbor neurons of the nearest layer by means of weights. The weights are updated iteratively till the algorithm reaches the best possible prediction with less error rate. The training time of the network is probably increased and error rates are minimized through expanding the number of hidden layers of the optimized deep learning model which is showing in Table 3.

Table III. Execution of Proposed Model with Different Set of Hidden Layers

Neurons present in the hidden layer	Standard Error Rate	Network Training Time (in sec)	Steps
2-2-2	37.113539	14.57	2838
3-2-3	37.113237	15.12	3976
3-3-3	21.279408	19.60	7464
4-1-2	0.156811	30.86	10765
4-2-2	0.149075	37.21	12523
4-2-3	0.111943	40.78	14070
4-3-3	0.023723	45.65	14418
4-4-3	0.006638	51.08	15751
4-4-4	0.004999	59.45	16009

The output of the proposed model is depicted in Fig. 5. This model classifies the irrigation management system into irrigation1, irrigation2, irrigation3, and irrigation4. The method irrigation1 utilizes 67–70 tons of water, irrigation2 utilizes 63–67 tons of water, irrigation3 utilizes 60–63 tons of water and irrigation utilizes less than 60 tons of water. The proposed model prefers irrigation2 first and then irrigation1 as appropriate irrigation systems throughout the development of sugarcane. Irrigation3 and irrigation4 are occasionally implemented.

Using conventional NN algorithm, the number of irrigations occurred for the next 30 years are represented in the Fig. 6. It clearly shows that the occurrences of irrigation1 are very high in number and irrigation2 is a little lower than the irrigation1 occurrences. The occurrences of irrigation3 and irrigation4 are probably less than 3 in count for each year. Therefore most of the time the conventional model requires 67–70 tons of water (method irrigation1) whereas DL-FFO model frequently utilizes 63–67 tons of water (method irrigation2) for every upcoming year. In Fig. 7, DL-FFO model frequently prefers irrigation2 method and then decide on irrigation1in rare cases. Hence it is possible to save practically about 50,000 tons of water.

This research compared AquaCrop, conventional NN, DL-FFO as shown in Fig. 8 to attain better irrigation management system for the next 30 years. Almost 4000 tons of water productivity gets improved in proposed model because when being compared with fixed and traditional irrigation model, sugarcane necessitates maximum 8,000 to 10,000 tons of water productivity. Thus proposed model utilized possibly 6000 tons of water for better crop development during 2020–2021 to 2049–2050.

This research obtained comparative results by simulating AquaCrop model and neural network models including conventional neural network and DL-FFO. The key results of this work integrated a smart

irrigation management system by simulating future weather conditions and designing the irrigation patterns according to soil parameters which minimized the utilization of water in general. The utilization of water is approximately estimated by simulating the three different kinds of model for the next 30 years are depicted in Fig. 9. Among these three models, DL-FFO model roughly minimizes 1, 25,000 tons of water utilized by sugarcane field.

Table IV explains the results of three different models i.e., correctly classified data, incorrectly classified data and accuracy rate. Both conventional neural network and DL -FFO efficiently classifies the irrigation strategies. But DL-FFO achieves high accuracy prediction which significantly increases the training speed and minimizing the error. Hence it enhances the time efficiency and memory scalability. It has been clearly found that the performance of DL-FFO model produced 98.63 of accuracy as compared with conventional neural network model.

Table IV. Testing of the Proposed Deep Learning Model

Learning Algorithms	Correctly Classified Data				Incorrectly Classified Data	Accuracy Rate
	Irrigation1	Irrigation2	Irrigation3	Irrigation4		
Conventional Neural Network	1800	955	210	155	176	94.66
DL-FFO	**713**	**2218**	**225**	**95**	**45**	**98.63**

Conclusions

Planning of water resources in agricultural field is a tricky task because of fluctuating climatic factors. To sustain better water management, an optimized irrigation model is proposed especially for irrigation purpose to reduce the utilization of water explicitly and discover the irrigation experiences for the canopy development of sugarcane crops. The proposed model i.e., DL-FFO finely classified the irrigation strategies with 98.63% of accuracy which is trained with future temperature and rainfall together with soil data. Hence, the optimized irrigation system obviously minimizes the consumption of water and also enhances the growth of canopy cover. It is concluded that DL-FFO can yield an optimistic yield of sugarcane with minimal amount of water since compared with AquaCrop and conventional neural network model. The proposed model proved to be more helpful when implemented under irrigation management conditions which could analyze the impact of climate change on sugarcane production; thus helping in development of adaption methods to reduce the vulnerability of sugarcane production in upcoming years.

Declarations

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Figures

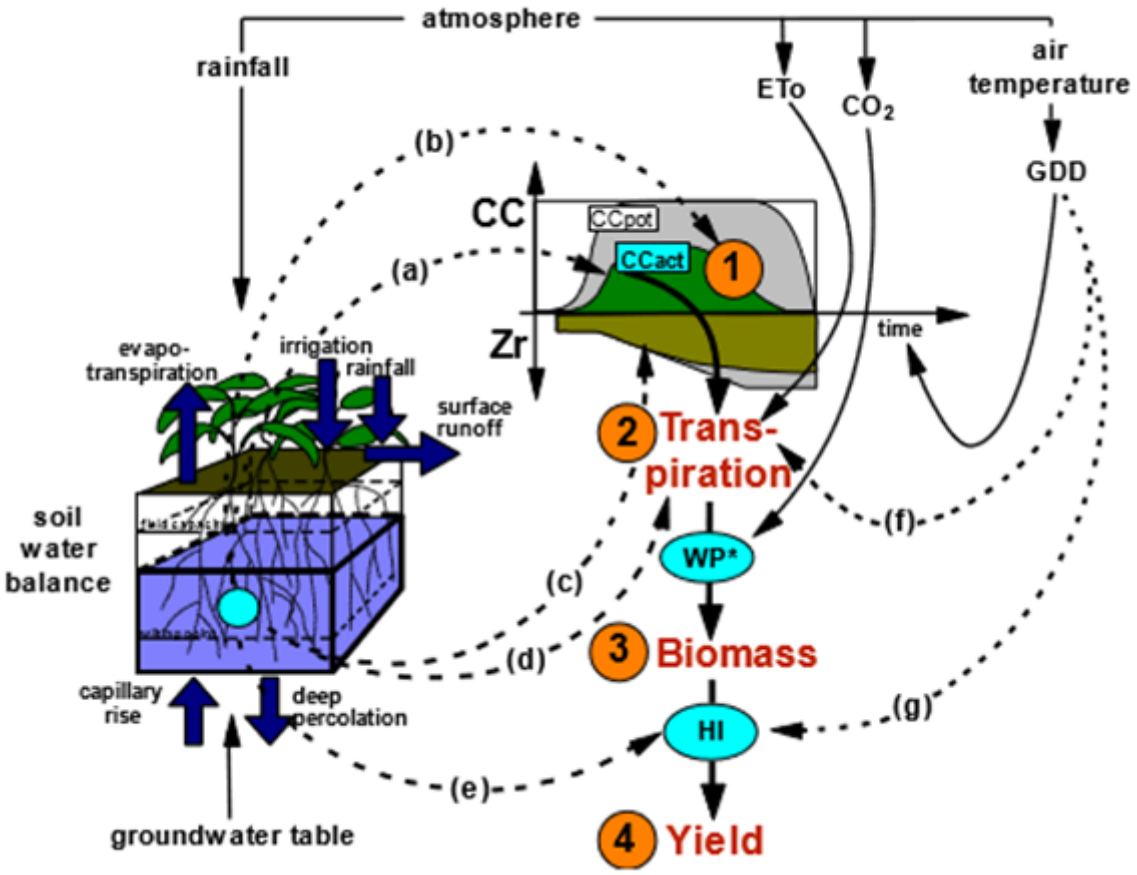

Figure 1

Simulation Process of AquaCrop

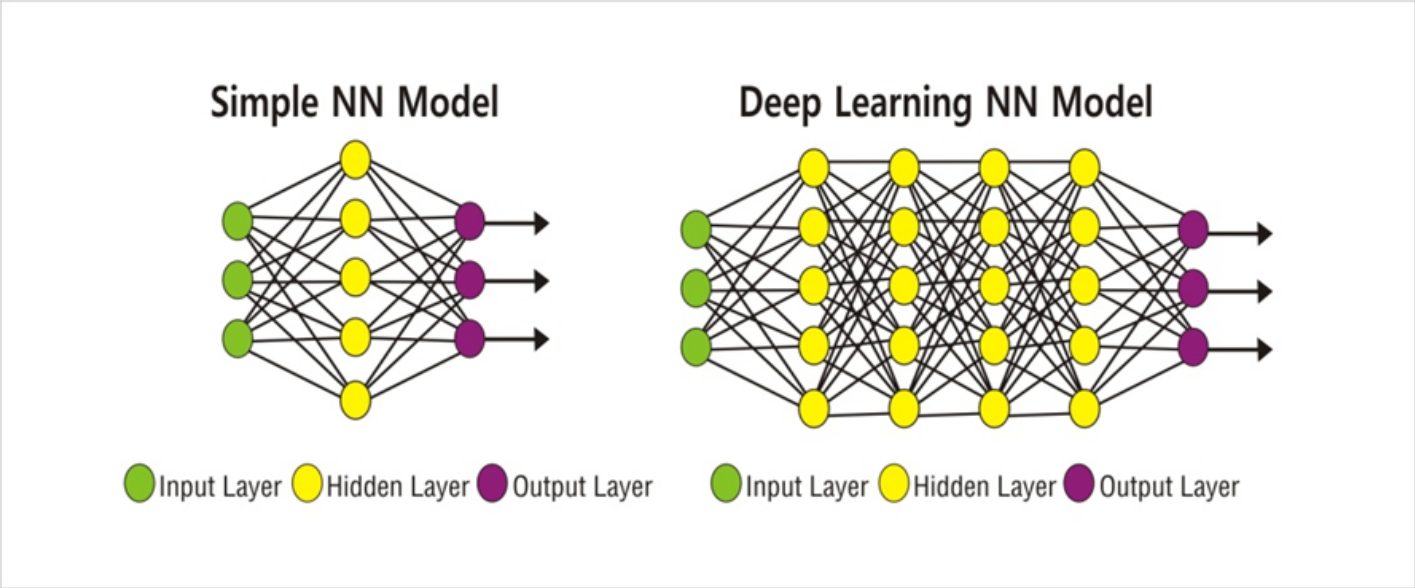

Figure 2

Simple NN vs Deep Learning NN Model

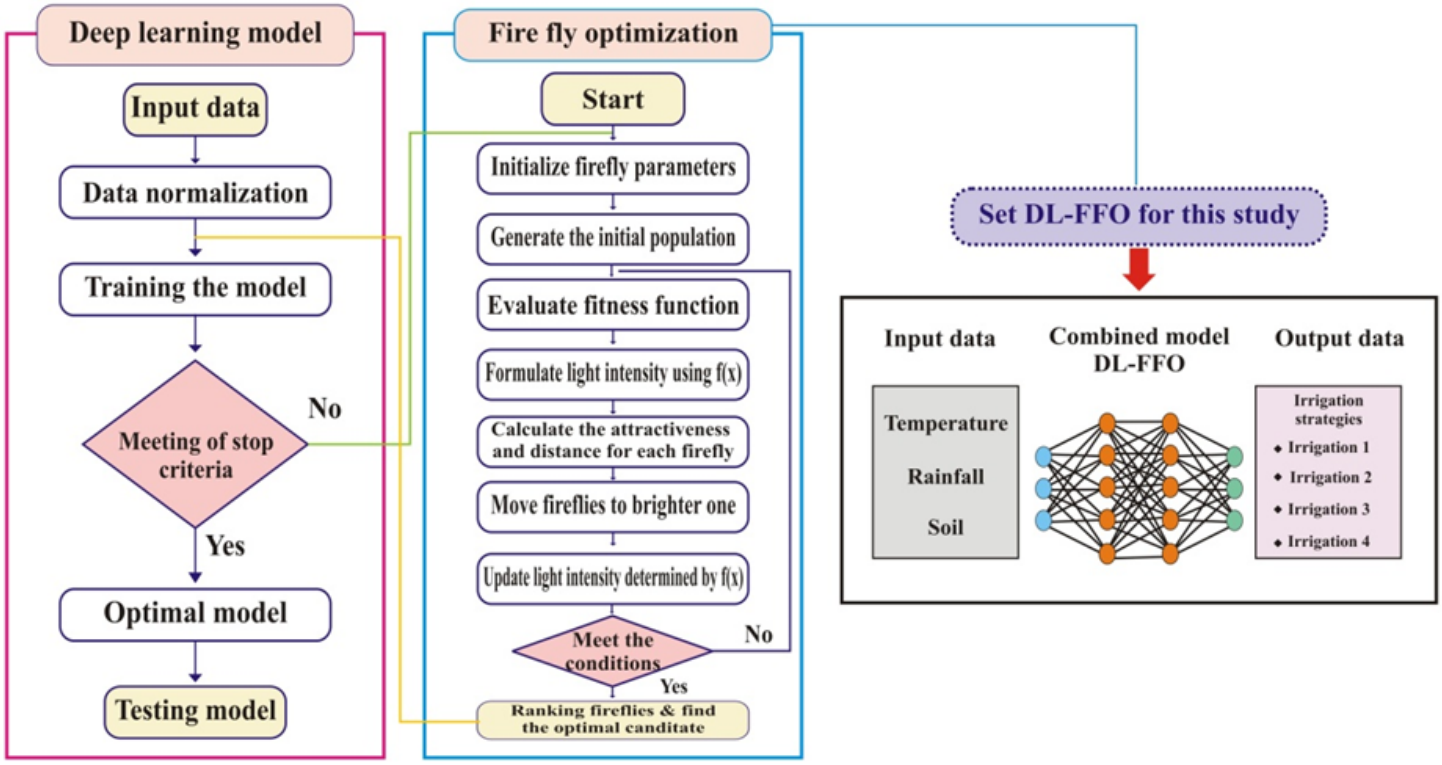

Figure 3

Schematic Representation Work Flow of Proposed Model

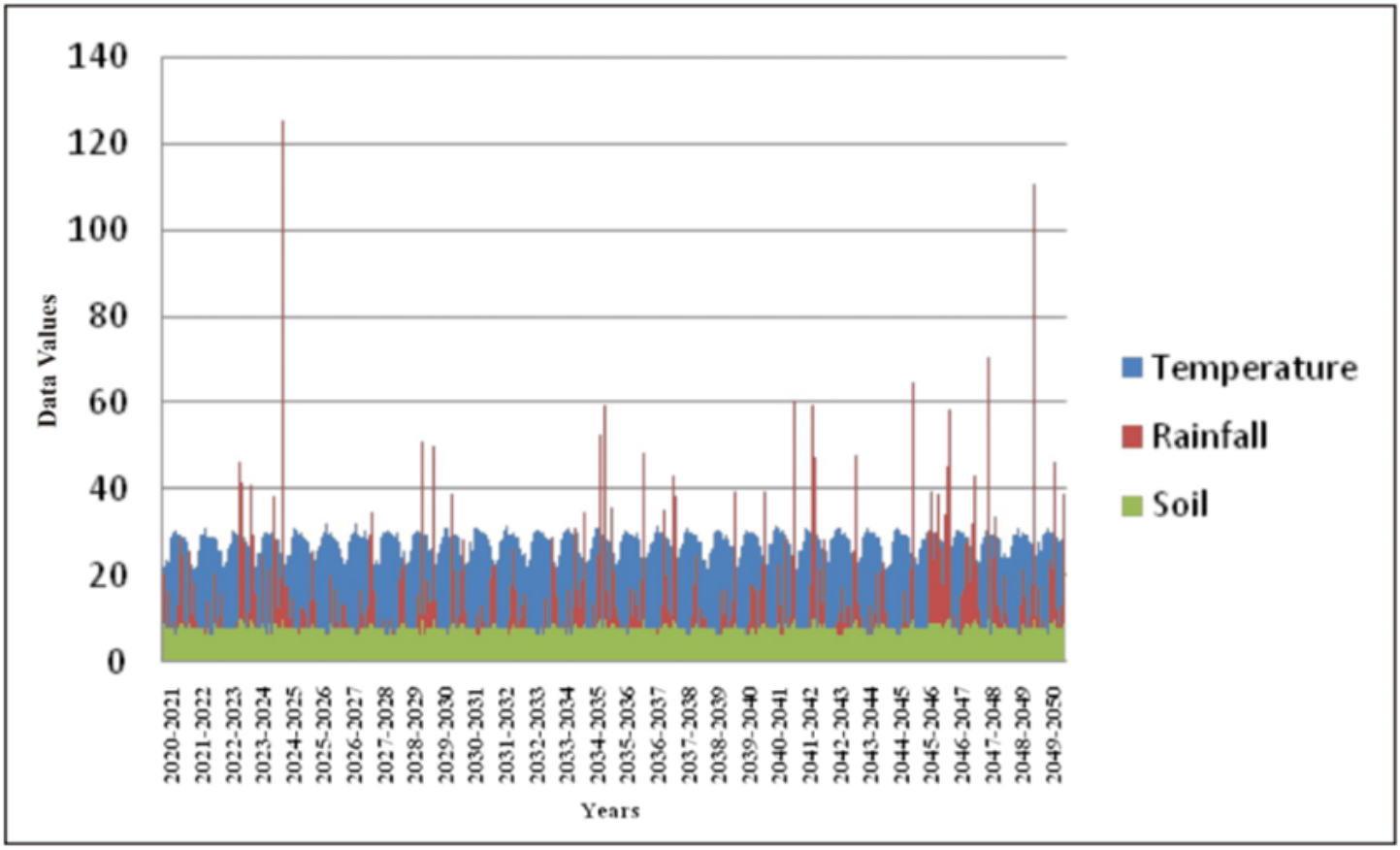

Figure 4

Future Climate Data from 2020-2021 to 2049-2050

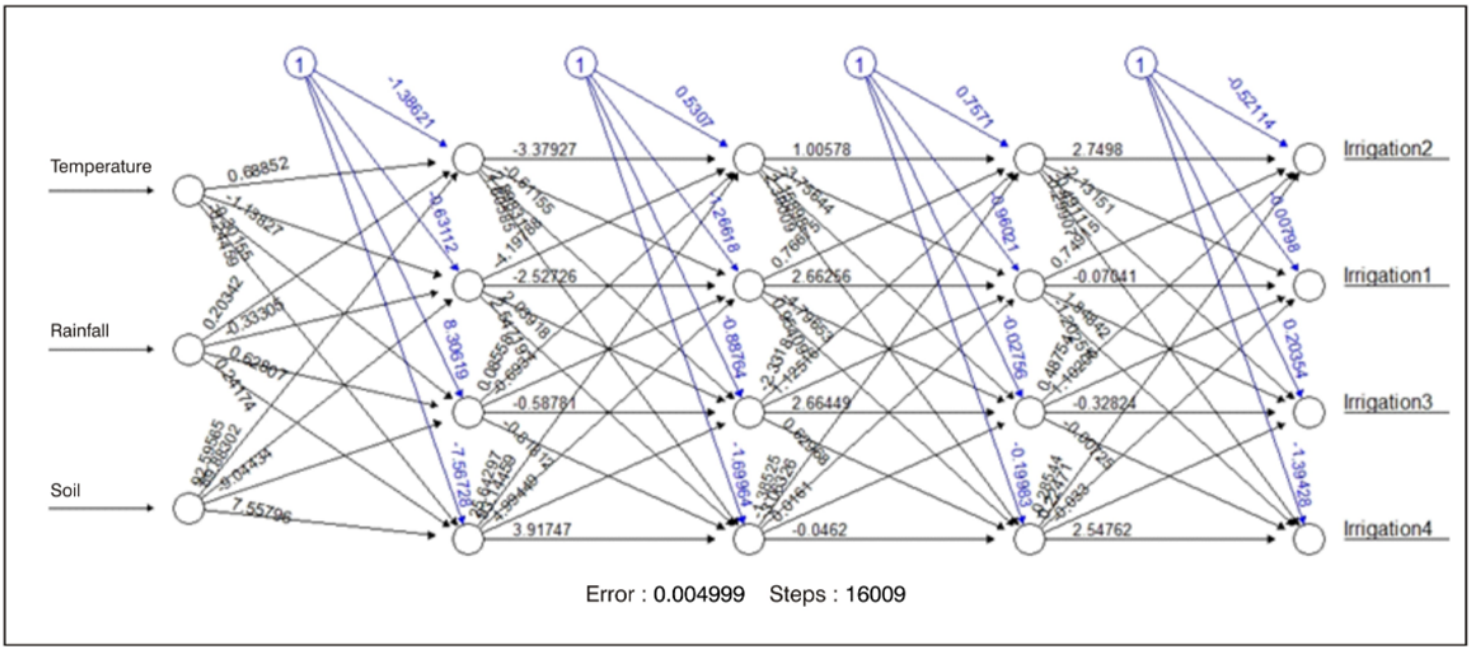

Figure 5

Output of the DL-FFO model

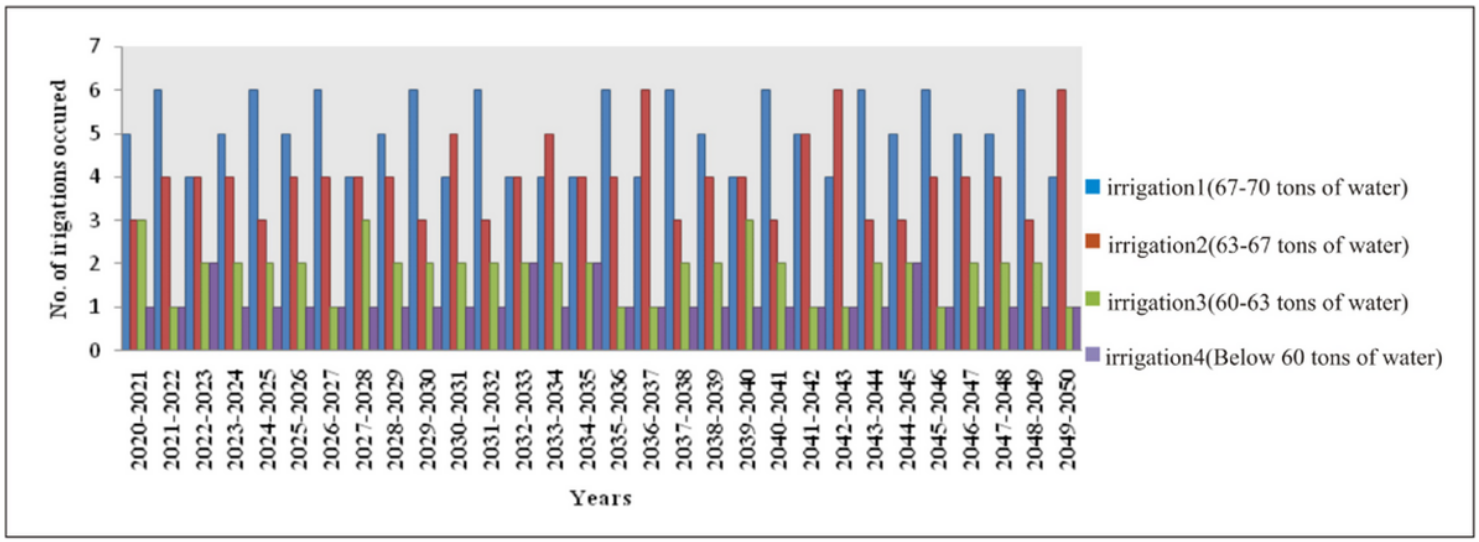

Figure 6

Occurrence of irrigation using conventional algorithm

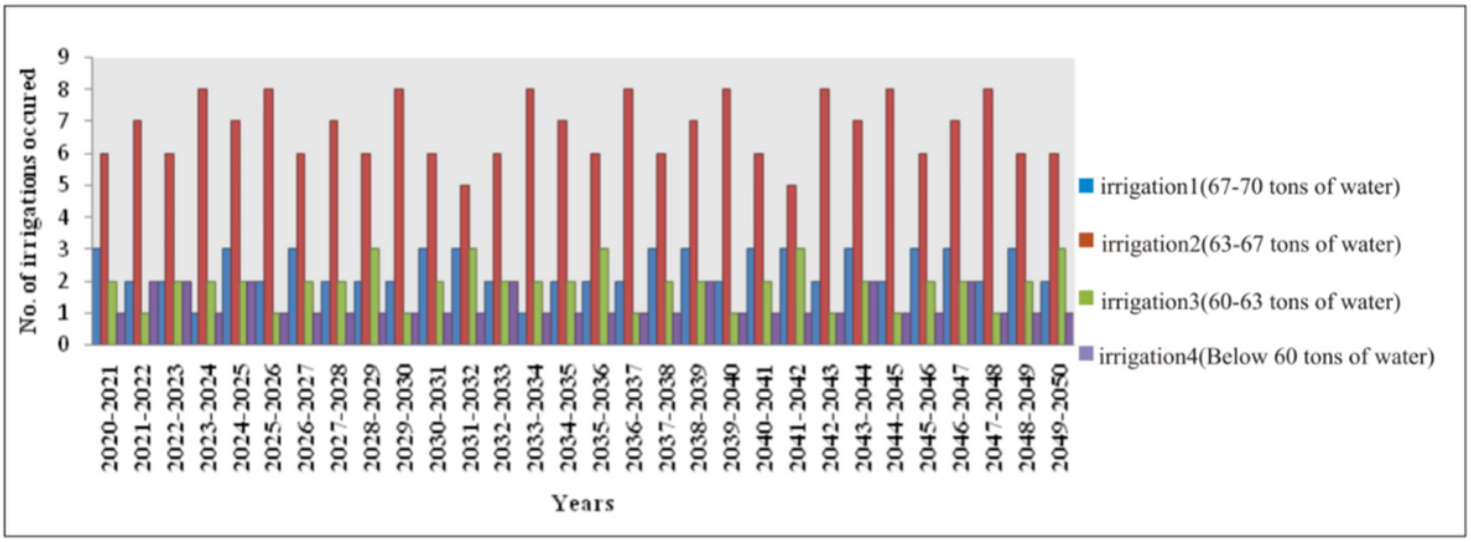

Figure 7

Occurrence of Irrigation using DL-FFO Algorithm

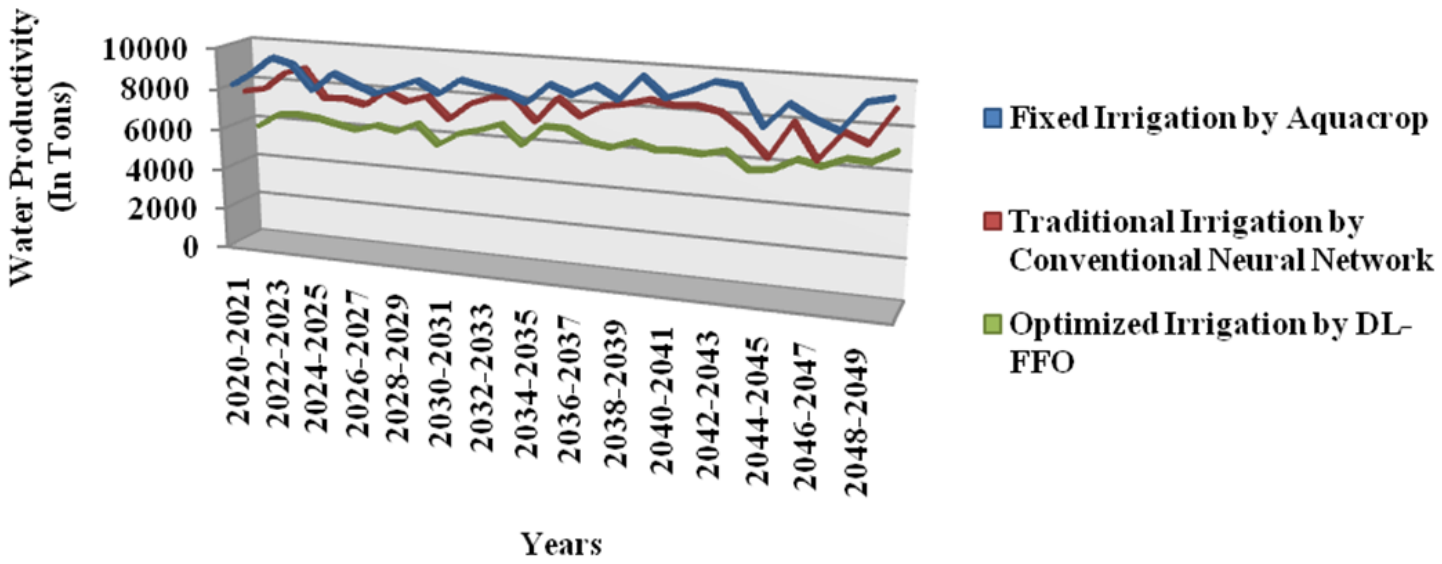

Figure 8

Comparison of Water Productivity for the Next 30 Years

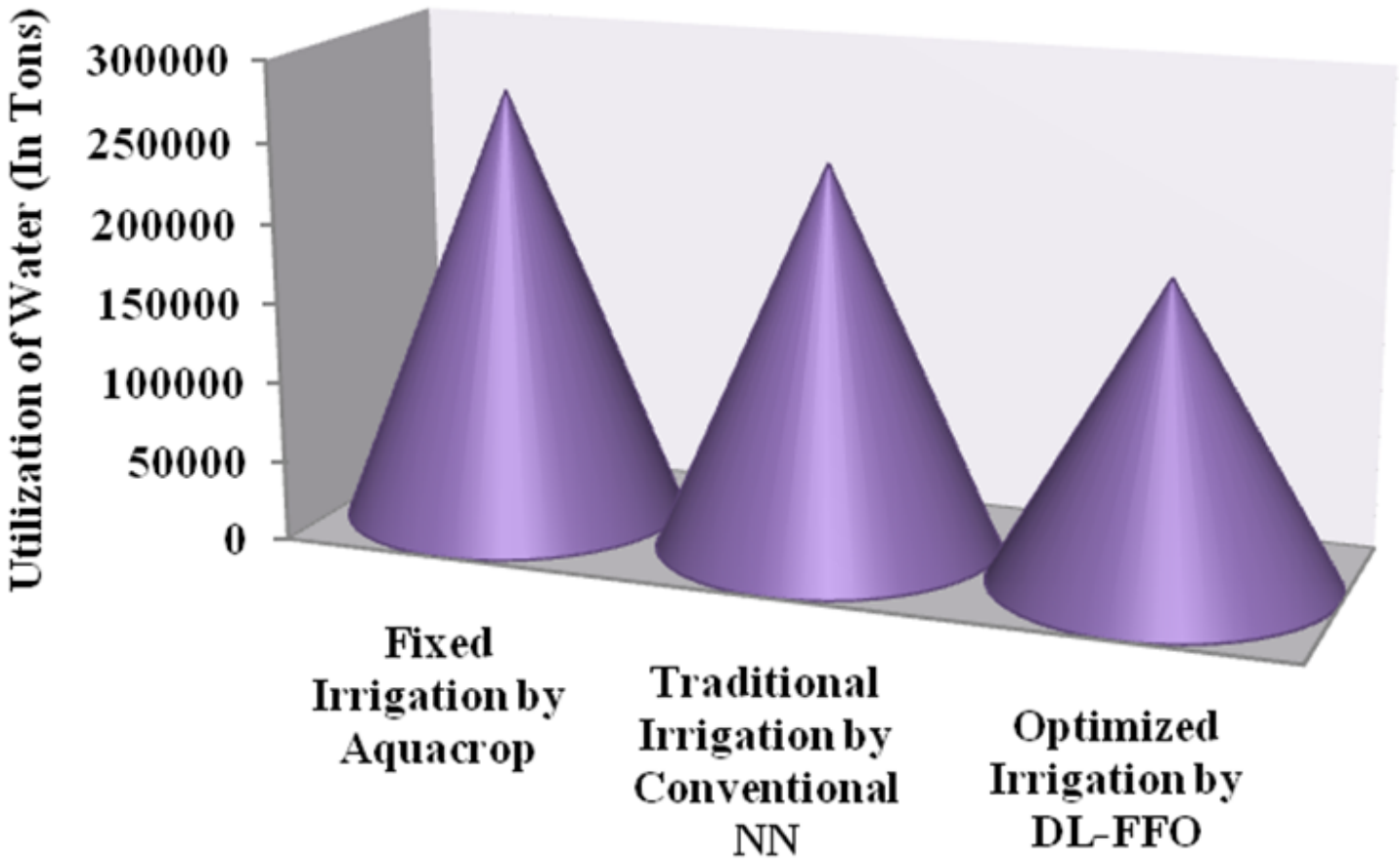

Figure 9

Estimating the Utilization of Water using 3 Different Set of Models