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Research Article

An Artificial Intelligence Approach to Manage Crop Water Requirements in South Africa

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Abstract: Estimation of crop water requirements is of paramount importance towards the management of agricultural water resources, which is a major mitigating strategy against the effects of climate change on food security. South Africa water shortage poses a threat on agricultural efficiency. Since irrigation uses about 60% of the fresh water available, it therefore becomes important to optimise the use of irrigation water in order to maximize crop yield at the farm level in order to avoid wastage. In this study, combined application of an artificial neural network (ANN) and a crop – growth simulation model for the estimation of crop irrigation water requirements and the irrigation scheduling of potatoes at Winterton irrigation scheme, South Africa was investigated. The crop-water demand from planting to harvest date, when to irrigate, the optimum stage in the drying cycle when to apply water and the amount of irrigation water to be applied per time, were estimated in this study. Five feed –forward backward propagation artificial neural network predictive models were developed with varied number of neurons and hidden layers and evaluated. The optimal ANN model, which has 5 inputs, 5 neurons, 1 hidden layer and 1 output was used to predict monthly reference evapotranspiration (ETo) in the Winterton area. The optimal ANN model produced a root-mean-square error (RMSE) of 0.67, Pearson correlation coefficient (r) of 0.97 and coefficient of determination (R^2) of 0.94. The validation of the model between the measured and predicted ET_o shows a r value of 0.9048. The predicted ETo was one of the input variables into a crop growth simulation model, called CROPWAT. The results indicated that the total crop water requirement was 1259.2 mm/decade and net irrigation water requirement was 1276.9 mm/decade, spread over a 5-day irrigation time during the entire 140 days of cropping season for potatoes. A combination of the artificial neural networks and the crop growth simulation models have proved to be a robust technique for estimating crop irrigation water requirements in the face of limited or no daily meteorological datasets.

Keywords: Artificial Neural Networks, CROPWAT, Crop Water Requirements, Irrigation, Soil Moisture, Water Allocation, Water-Use Efficiency, Winterton

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1. Introduction

South Africa is the 30th driest country in the world and hence, it is termed a 'water stressed' country [1]. South Africa is characterized by low average annual rainfall and falls within the semi – arid and arid region of the world. The current water demand is more than the available water for supply within the country. The diverse uses of available water include: domestic, irrigation, industrial, recreation purposes and hydropower [2].

According to a report by [3], it was confirmed that irrigation uses more than 50% of the consumptive water supply in South Africa and yet, it has the lowest water use efficiency when compared with other uses. This poses a need to optimize the available water resources in a judicious and beneficial manner for agricultural purposes. Good irrigation management practices could lead to optimum food production with less water use. According to [4], one of the ways of achieving sustainable irrigation management is to develop irrigation schedules according to the actual water need of the crops. Irrigation scheduling is concerned with decisions concerning when, where and how much water to apply to an irrigated cropland in a particular growing season [5].

The scheduling and management of irrigation are essential to ensure that crop water requirements are met, crops are prevented from wilting and also maximize crop yields [6]. Crop water requirements (CWR) are the amount of water required for evapotranspiration, as well as water needed by a specific crop from planting to harvest date [7]. Computer – based models have been used to predict the future impacts of water management policies [8]. Several studies developed mathematical models and algorithms to optimize irrigation water management for different irrigation systems [9; 10].

Irrigators must optimally allocate the available water for irrigation purposes, in order to amplify the annual net profits and increase farm efficiency by preventing excess water that may cause surface runoff, groundwater drainage and leaching of the fertilizers applied. Numerous simulation and optimization modeling approaches have been developed and used, and the results derived from such studies have shown that optimization models perform excellently when used in conjunction with simulation models [11].

In allocating adequate water among crops, simulation models, optimization models or a combination of both techniques can be adopted [12]. According to [13], one of the limitations associated with optimisation models when used for irrigation scheduling is its inability to provide irrigation dates. All they can provide is the irrigation quota. In addition, the optimisation models simplify the changes in soil moisture and evapotranspiration for the convenience of optimization. Simulation models on the other hand, include models of soil water balance, crop growth simulations and soil water dynamics. Simulation models are therefore more advantageous, because they provide an in-depth detail of the crop growth and evapotranspiration.

Simulation modeling techniques assist in the design, creation and evaluation of complex systems. They help to understand and evaluate 'what if' case scenarios within a system [11]. They can model a real or proposed system, using computer software and is useful when changes to the actual system are difficult to implement, involve high costs, or not possible. Simulation models are helpful to determine the effect of water stress on crop yield [14]. Categories of simulation models as spelt out by [15] include discrete, continuous and mixed models.

Several simulation models have been developed for the purpose of adequate irrigation scheduling operations around the world. However, some of the models require highly detailed input data and information about the crop growth, which are limitations in areas with limited or no datasets available [16].

A simulation model, called IrrigRotation was developed by [17]. IrrigRotation is a soil water balance simulation model, which uses the dual crop coefficient methodology. The model uses a daily time step in performing a continuous soil water balance simulation and this helps to overcome the uncertainty of knowing the initial amount of water present in the soil profile at the beginning of the simulation [17]. IrrigRotation has been tested in the Beja region, in Alentejo South of Portugal, and it provided irrigation requirements information based on the soil, crop, rotation scheme, climate and irrigation systems data.

Another simulation model used in irrigation scheduling operations is Isareg. Isareg is an irrigation scheduling simulation model that simulates the soil water balance at the field scale. A detailed description of the model is given by [18]. It was applied to the irrigation schedule of wheat in Beijing, China and the performance was robust.

In 2009, the Food and Agricultural Organization (FAO) developed a multi-crop simulation model, called AquaCrop to address the above limitation. AquaCrop models both the crop growth and crop water requirements. [14] adopted the AquaCrop model to estimate the crop water requirement of maize planted under deficit and full irrigation in Portugal. The objective was to assess water stress impacts on crop yield. The results from this study showed the adequacy of AquaCrop in estimating maize biomass and yield under deficit irrigation conditions, mainly when an appropriate parameterization is adopted.

In this study, the combined application of an artificial neural network and a crop – growth simulation model in estimating crop irrigation water requirements and irrigation scheduling at Winterton irrigation scheme, South Africa was developed and evaluated.

2. Materials and Methods

2.1. Study Area

The study area for this research study was Winterton irrigation scheme (WIS) in South Africa. The WIS is located at the main access point to the Drakensberg, with latitude 28°91′ N and longitude 29°55′E in the Kwazulu-Natal province of South Africa. The scheme was constructed by the colonial government in 1905 but named Winterton in 1910. A weir was constructed along the Little Thukela River, which feeds the irrigation scheme and this river is one of the 19 designated water management areas in South Africa [19]. The Little Thukela River has its confluence with another river called the Thukela River, located downstream of WIS. This area has a mean annual rainfall of 790mm and mean annual temperature of 17℃ and a high irrigation demand [20].

The Department of Water Affairs and Forestry in South Africa classified this catchment area as a water stressed zone, due to the limited water resources in the catchment and large irrigation requirements [20]. The range of annual net irrigation requirements is between 500 and 1200mm per annum [20]. The major irrigated crops grown throughout the year in WIS include maize, wheat and soybeans [21]. The total farmland area under irrigation is about 3692 hectares, and this scheme currently supplies irrigation water to 55 commercial farmers and other small-scale farmers. Irrigated land area used by commercial farmers vary between 30 and 50ha [19]. Meteorological and weather data for this scheme was collected from Agricultural Research Council, South Africa. Fig. 1 indicates the geographical location of Winterton irrigation scheme (WIS).

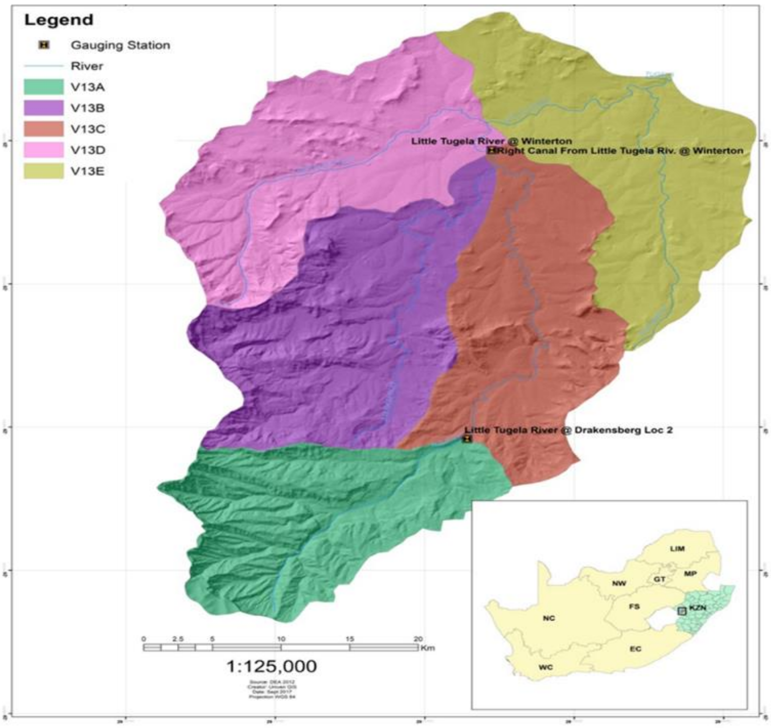

Figure 1. Location of Winterton irrigation scheme

2.2. *Artificial Neural Network (ANN)*

In this study, five feed –forward backward propagation Artificial Neural Network (ANN) predictive models were developed with varied number of neurons and hidden layers and evaluated. The optimal ANN model was evaluated and applied to produce a non-linear relationship between the input and output variables of ET and also to predict the real – time ETo for the study area. ANNs are non-linear data – driven networks, which are based on the capabilities of the human brain to predict and classify problem domains hence, the name 'neural' [22]. ANNs are mathematical models, which are widely adopted for predicting and forecasting in diverse fields of research, such as finance, medicine, engineering and sciences and also to solve extraordinary range of problems [23]. ANNs are specifically useful when the relationships between both input and output variables are discrete [24]

The input variables in this study include minimum and maximum temperature (°C), rainfall (mm), relative humidity (%), windspeed (m/s) and the output variable was reference evapotranspiration (ETo). Five feed-forward back propagation ANN models were developed and evaluated. However, in the design of this ANN models, five basic steps were followed as specified by [25]. These were: (1) collecting data, (2) pre-processing of data, (3) building the network, (4) training the network, and (5) test performance (evaluation) of the model. A major limitation of the study was the unavailability of daily values for most of these parameters, therefore monthly average data was used for this study.

The average monthly data, which covers a 40-year period (1981 – 2020) and has 480 records per dataset were provided by the Agricultural Research Council (ARC), South Africa. The monthly dataset was first normalized and randomized as specified by [26]. In building the ANN network, different structures with different number of hidden layers, neurons in each layer, transfer function in each layer were selected. MATLAB tools were adopted in writing scripts that helped to develop the ANN models. Five different models, with different number of neurons and layers were designed and evaluated to determine the optimal model (Table 1). The actual numbers of hidden neurons were estimated based on trial and error. The MATLAB built-in transfer functions, which were used for the network input is Logistic Sigmoid (tansig), while a linear (purelin) function was used for the network output.

Table 1. Developed ANN models based on different numbers of neurons and hidden layers.

Model No	No of input elements	No of hidden neurons	No of hidden layers
1	5	5	1
2	5	10	1
3	5	15	2
4	5	20	2
5	5	25	2

In training the model, twenty-eight years of data (1981 – 2008), which comprised of 336 records per dataset were used and the training algorithm used was the Levenberg-Marquardt algorithm (LM), because it applies to small and medium – size networks [27]. This LM algorithm is one of the most effective training algorithms for the feed-forward neural networks. In evaluating the network performance of the five ANN models developed, data for ten years (2009 – 2018) were used for validating the network while data for two years (2019 and 2020), which comprised of 24 records per dataset was used to test the network.

The performances of the developed ANN models were evaluated by statistical model error parameters. The three statistical error parameters used in this study were Pearson coefficient of correlation (r), root mean square error (RMSE) and coefficient of determination (R^2). Pearson correlation coefficient (r) indicates the strength and direction of a linear relationship between two variables (for example model output and observed values). It is obtained by dividing the covariance of the two variables by the product of their standard deviations. If there are n observations and n model values, then the Pearson correlation coefficient can be used to estimate the correlation between model values and observed values. The mathematical expression is given in Equation 1:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \cdot \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

The Root Mean Square Error (RMSE) is a frequently used statistical procedure that provides the difference between predicted and observed values. The lower the RMSE, the more accurate the estimation capacity of the developed model. The RMSE of a model prediction with respect to the estimated variable Xmodel is defined as the square root of the mean squared error. Equation 2 shows the mathematical expression for RMSE.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \tag{2}$$

where Xobs is observed values and Xmodel is modelled values at time/place i.

The coefficient of determination (R^2) is the summary measure in a two-variable regression model that indicates the magnitude of this 'goodness of fit'. It is defined by equation (3):

$$R^2 = \frac{ESS}{TSS} = \frac{\Sigma\, \hat{y}_i^2}{\Sigma y_i^2} \tag{3}$$

But TSS = ESS + RSS

The Total Sum of Squares (TSS) is equal to the sum of the Explained Sum of Squares (ESS) and the Residual Sum of Squares (RSS). It is known the “decomposition of variance”. The percentage of the total variation in Yi is explained by the regression model and is always between 0 and 1. A larger R2 means higher explanatory power for the explanatory variable.

2.3. CROPWAT crop growth simulation model

The predicted ETo from the optimal ANN predictive model was one of the inputs of a crop and irrigation water simulation model, called CROPWAT [28]. CROPWAT is a decision support tool for estimating ETo, CWR and crop irrigation requirement [29]. It was designed by the Food and Agriculture Organisation (FAO) for the design and management of irrigation schemes. It helps to plan irrigation schedules under different water supply conditions, either rain-fed or deficit irrigation [30].

CROPWAT uses the daily soil-water balance to evaluate irrigation management practices and also develop irrigation schedules. The model is based on the FAO Irrigation and Drainage papers No. 56 “Crop evapotranspiration” and No. 33 “Yield response to water" [31]. Calculations of the crop water requirements and irrigation requirements are carried out with inputs of climatic, crop and soil data.

According to [29], in order for CROPWAT to estimate CWR, the model requires the following information or data: (a) ETo values measured or calculated using the FAO Penman-Montieth equation based on decade (10 days) /monthly climatic data, such as minimum and maximum air temperature, relative humidity, sunshine duration and windspeed; (b) Rainfall data (daily/monthly/decade data); (c) Cropping Pattern which consists of the planting date, crop coefficient data files (including Kc values, stage days, root depth, depletion fraction) and the area planted (0-100% of the total area).

Determining the irrigation schedules, CROPWAT model requires information on: (a) soil type: total available soil moisture, maximum rooting depth, initial soil moisture depletion (% of total available moisture); (b) Scheduling criteria; several options can be selected regarding the calculation of application timing and application depth, or irrigate to return the soil back to field capacity when all the easily available moisture has been used. [32] provides a description of the formula used by CROPWAT model to calculate the CWR in Equation (4) as follows:

$$CWR = ETo * Kc * area\ planted \tag{4}$$

Where Kc is the crop coefficient. This shows that the peak CWR in mm/day can be less than the peak ETo value when less than 100% of the area is planted in the cropping pattern. Equation. (5), given by [33] calculates CWR as follows:

$$CWR = ETo * Kc - Pe \tag{5}$$

Where Pe is the effective rainfall, calculated as follows:

$$Pe = SF \times [0.70917 \times (Pr / 25.4) \wedge 0.82416 - 0.11556] \times 10 \wedge 0.000955 ETc \tag{6}$$

$$SF = 0.531747 + 0.295164\ (D/25.4) - 0.057697 \times (D/25.4) \wedge 2 + 0.003804 \times (D/25.4) \wedge 3 \tag{7}$$

Where D is the usable soil water storage (mm) and Pr is the monthly rainfall (mm).

The Total available soil water (TAM) is the maximum available water (mm) in the root zone of the crop, while the readily available soil water (RAM) is the amount of water (mm) in the root zone that a plant can easily extract from the soil. These are calculated as follows:

$$TAM = 1000\ (\theta FC - \theta WP) Zr \tag{8}$$

$$RAM = \rho * TAM \tag{9}$$

Where θFC is the soil water content at field capacity, θWP is the soil water content at wilting point, Zr is the root zone depth and ϱ is the soil water depletion fraction.

Furthermore, CROPWAT adopts linear interpolation to estimate the average values of Kc in between each crop development stages within the growing season. The "Crop Kc" values are calculated as Kc*Crop Area, thus if the crop covers only 50% of the area, the "Crop Kc" values will be half of the Kc values in the crop coefficient data file. In estimating the CWR, CROPWAT distributes the monthly total rainfall into equivalent daily values by using a continuous polynomial curve. The model also assumes that monthly rain falls into 6 rainstorms, one every 5 days. In this study, three decades (30 days) and four stages of plant growth were adopted in CWR determination. The crop growth stages are initial, development, mid-season and late season stages.

3. Results

3.1. ETo Prediction using the ANN model

The ANN model training stopped when the error starts to increase for the validation dataset. The correlation coefficient (r), root-mean-square error (RMSE) and coefficient of determination (R^2) for each of the five models were observed and recorded in Table 2.

Table 2. Statistical error parameters of developed predictive ANN models

Model No	No of hidden neurons	No of hidden layers	r	RMSE	R^2
1	5	1	0.9581	0.74	0.918
2	10	1	0.9692	0.67	0.940
3	15	2	0.9714	0.70	0.944
4	20	2	0.9517	0.76	0.906
5	25	2	0.9428	0.82	0.889

As indicated in Table 2, model 2 performed the best among all the investigated ANN models for predicting ETo, as it yields the lowest values of RMSE of 0.67 with an acceptable r value of 0.9692 and a high R^2 value of 0.94. This is in line with the recommendation of [34;35], which states that the model with the lowest RMSE gives the best model performance. The optimal model was used in predicting the monthly ET_o values for the year 2022 and this is presented in Table 3.

Table 3. Predicted monthly Evapotranspiration values for year 2022

Month	Predicted ET_o (mm/month)	Predicted ET_o (mm/day)
January	304.10	10.13
February	216.84	7.23
March	217.51	7.25
April	174.03	5.8
May	166.12	5.54
June	127.57	4.25
July	122.68	4.09
August	134.27	4.47
September	129.49	4.32
October	235.27	7.84
November	289.55	9.65
December	270.95	9.03

3.2. CROPWAT Simulation model

The values of Predicted ETo (mm/day) in Table 3 was one of the inputs to the CROPWAT model [34], alongside other required information, such as rainfall data, cropping pattern, soil type, scheduling criteria, monthly rainfall, crop parameters and soil characteristics values. Figure 2 shows the CROPWAT input values of ET_o, rainfall and effective rainfall (Pe) for the year 2022, which is the planting year for this study. The planting date for potatoes on the farmland is 1st April, 2022, while the harvest date is 23rd August, 2022, a total of 140 days.

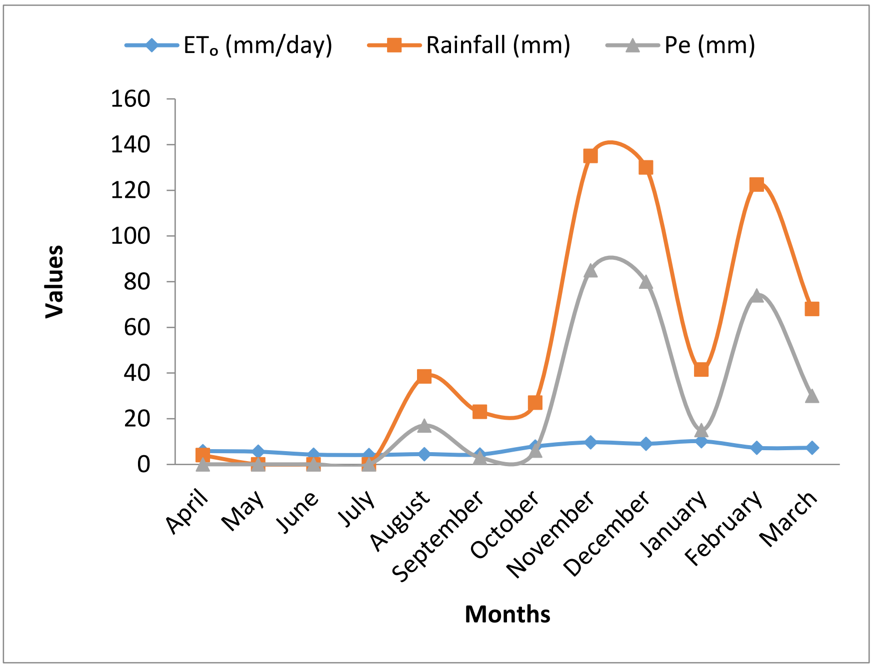

Figure 2. Values of monthly Pe, ET_o and rainfall for 2022 at WIS.

Table 4. Estimated Crop water requirement of potatoes in WIS using CROPWAT model

Month	Decade	Stage	Kc coefficient	ETc (mm/day)	ETc (mm/dec)	Pe (mm/dec)	Irrigation Requirement (mm/dec)
April	1	Initial	0.45	3.81	3.81	3.1	35.0
April	2	Initial	0.45	3.60	3.60	0.0	36.0
April	3	Initial	0.45	3.48	3.48	0.6	34.2
May	1	Deve	0.69	5.13	5.13	3.7	47.6
May	2	Deve	1.12	8.04	8.04	4.9	75.5
May	3	Deve	1.57	10.40	114.4	3.3	111.1
June	1	Mid	1.93	11.44	114.4	0.3	114.2
June	2	Mid	1.95	10.36	103.6	0.0	103.6
June	3	Mid	1.95	10.69	106.9	0.0	106.8
July	1	Mid	1.95	10.88	108.8	0.0	108.8
July	2	Mid	1.95	10.95	109.5	0.0	109.5
July	3	Late	1.87	11.94	131.3	0.1	131.2
August	1	Late	1.52	11.13	111.3	9.6	101.6
August	2	Late	1.17	9.45	94.5	14.4	80.1
August	3	Late	0.94	7.99	24.0	3.3	18.0
Total					1259.2	43.2	1213.2

*mm/dec = millimeters per decade (10 days)

Table 4 shows the values of the crop water requirements and irrigation requirements per decade (10 days), as simulated by CROPWAT crop growth simulation model. The growing period has been divided into stages of growth and the resultant crop coefficient

(Kc) was multiplied by the ETo. This provides the value of crop reference evapotranspiration (ETc). A total value of 1259.2 mm/decade is the total crop reference evapotranspiration for the study. Also, the total irrigation requirement is 1213.2mm/decade. This forms the CWR throughout the growing season. Figure 3 is a graphical chart showing the values of ETc and Irrigation requirements (IR).

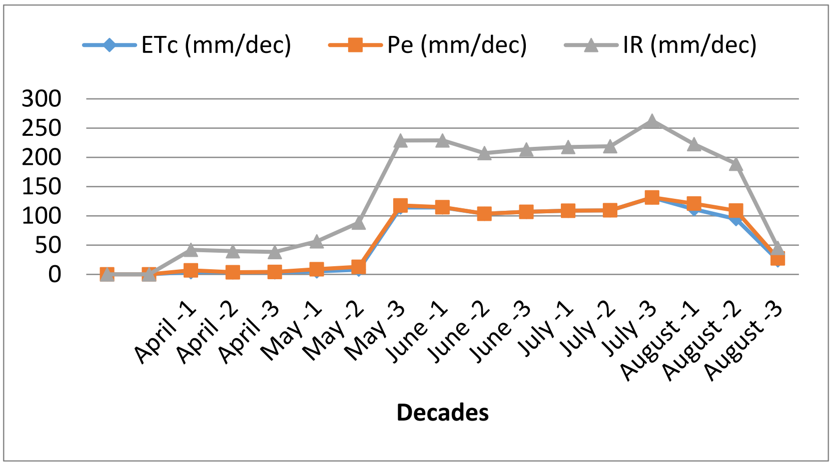

Figure 3. Values of ETc and irrigation requirement as simulated by CROPWAT model

As indicated in Figure 3, it can be observed that the values of ETc at the initial stage of potatoes is very low. This shows that potatoes require little amount of water at the initial growing stage and it increases gradually into the developmental stage and it is highest at the mid – stage of growth. Crop water requirement is at the optimal level during the mid – stage and the commencement of the late stage of growth. This is in consonance with the assertions of [36], that water are saved at the early stages of the crop growth cycle and also at the maturation and ripening stages. The resilience to water stress for the growth stages of potatoes have been identified by the model.

Figure 4 presents the values of depletion, Readily Available Water (RAM) and Total Available Water (TAM) for this study. The depletion values are the lowest at the initial stage of growth, and this increases as the crop grows. The depletion value is highest at the mid and late stages of growth with an average value of 38mm. Figure 4 shows the soil water retention in the loamy clay soil present at the study area, it also shows the level at which the crop enters the wilting point, the amount of irrigation water to be applied per irrigation time that will bring the soil moisture to field capacity.

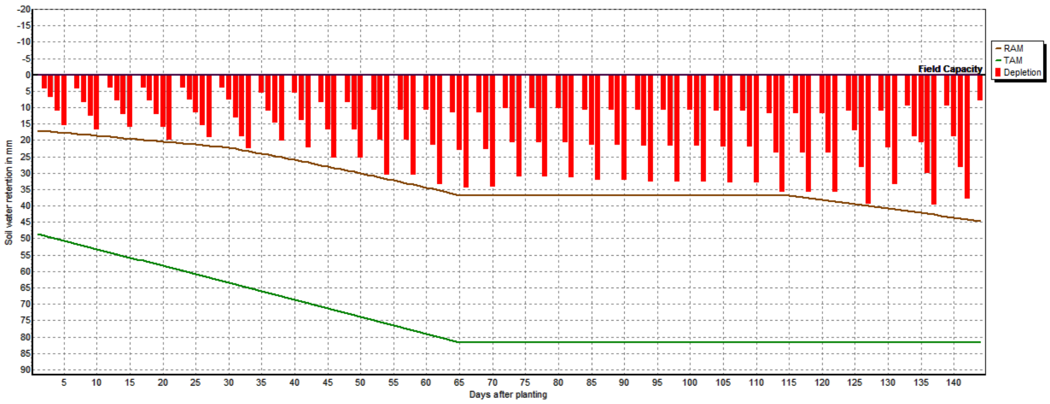

Figure 4. Irrigation schedule chart showing simulated values of RAM, TAW and depletion

The following are the summary of results obtained from the simulation operations:

Total gross irrigation = 1824.2mm; Total net irrigation = 1276.9mm; Total rainfall = 48.2mm; Effective rainfall = 35.3mm; Total rainfall losses = 13mm; Actual water use by crop = 1248.5mm; Potential water use by crop = 1251.2mm; Actual irrigation requirement = 1215.9mm; Rainfall efficiency = 73.1%. The irrigation conditions are to irrigate at critical depletion and also refill soil to field capacity.

4. Discussion

The combined application of an artificial neural network and a crop – growth simulation model in estimating crop irrigation water requirement and irrigation scheduling of potatoes grown at Winterton irrigation scheme, South Africa was demonstrated in this study. The major crops grown in the scheme are maize, wheat and soybeans.

Five feed –forward backward propagation artificial neural network predictive models were developed with varied number of neurons and hidden layers and evaluated. The optimal ANN model, which has 5 inputs, 5 neurons, 1 hidden layer and 1 output was used to predict monthly ETo in the Winterton area. Also, the CROPWAT model was able to adequately estimate the crop water requirements of potatoes, through its planting season, which is between April 1st and 23rd August, 2022. It also helped in designing the irrigation schedules for the study. It was observed that the calculated total crop water needs of this study is 1259.2mm; net irrigation water requirement is 1276.9mm and this is spread over a 5 – day irrigation time – step throughout the entire 140 days of cropping season. Potatoes are regarded as a crop that has high sensitivity to drought, hence, adequate water supply must be ensured in order to prevent wilting of the crop.

5. Conclusions

However, it can be concluded that potatoes will produce maximum yield if grown on a farmland at Winterton irrigation scheme under the simulated irrigation schedules despite the low average annual rainfall experienced in the study area. Since the net irrigation requirement is higher than the crop water requirement, there will be adequate water to sustain the crop planted. Irrigation water application must be carried out at the critical depletion point and refilled to field capacity. This will prevent the crop from reaching the permanent wilting point. Irrigation scheduling also prevents over-irrigation which could lead to wastage of the limited water resources within the study area. Future research will evaluate the maximum crop yield and benefits. The scope of this research study was limited to the weather and meteorological parameters obtained for Winterton Irrigation scheme in South Africa.

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