MODELLING THE SOIL WATER BALANCE

AND APPLICATIONS USING

A DECISION SUPPORT SYSTEM (DSSAT v3.5)

by

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DECLARATION

I hereby declare that the research results reported in this thesis are my own original investigations except where acknowledged.

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ABSTRACT

Water is a scarce resource used by various stakeholders. Agriculture is one of the users of this resource especially for growing plants. Plants need to take up carbon dioxide to prepare their own food. For this purpose plants have stomatal openings. These same openings are used for transpiration. Quantifying transpiration is important for efficient water resource management and crop production because it is closely related to dry matter production. Transpiration could be measured using a number of methods or calculated indirectly through quantification of the soil water balance components using environmental instruments. The use of models such as the Decision Support System for Agrotechnology Transfer (DSSAT v3.5) is, however, much easier than environmental instruments. Nowadays, with increased capabilities of computers, the use of crop simulation modelling has become a common practice for various applications. But it is important that models, such as DSSAT v3.5, be calibrated and verified before being used for various applications such as long-term risk assessment, evaluation of cultural practices and other applications. In this study the model inputs have been collected first Then the model was calibrated and verified. Next sensitivity analysis was carried to observe the model behavior to changes in inputs. Finally the model has been applied for long-term risk assessment and evaluation of cultural practices.

In this study, the data collected formed the basis for the minimum dataset needed for running the DSSAT v3.5 model. In addition, the factory given transmission of shading material over a tomato crop was compared to .actual measurements. Missing weather data (solar irradiance, minimum and maximum air temperature and rainfall) were completed after checking that it was homogeneous to measurements from nearby automatic weather station. It was found that factory-given transmission value of 0.7 of the shade cloth was different from the actual one of 0.765. So this value was used for conversion of solar irradiance measured outside the shade cloth to solar irradiance inside the shade cloth. Conventional laboratory procedures were used for the analysis of soil physical and chemical properties. Soil water content limits were determined using texture and bulk density regression based equations. Other model inputs were calculated using

the DSSAT model. Crop management inputs were also documented for creation of the experimental details file.

The DSSAT v3.5 soil water balance model was calibrated for soil, plant and weather conditions at Ukulinga by modifying some of its inputs and then simulations of the soil water balance components were evaluated against actual measurements. For this purpose half of the data available was used for calibration and the other half for verification. Model simulations of soil water content (150 to 300 mm and 450 to 600 mm) improved significantly after calibration. In addition, simulations of leaf area index (*LAI*) were satisfactory. Simulated evapotranspiration (*ET*) had certain deviations from the measured *ET* because the latter calculated *ET* by multiplying the potential *ET* with constant crop multiplier so-called the crop coefficient.

Sensitivity analysis and long-term risk assessments for yield, runoff and drainage and other model outputs were carried out for soil, plant and weather conditions at Ukulinga. For this purpose, some of the input parameters were varied individually to determine the effect on seven model output parameters. In addition, long-term weather data was used to simulate yield, biomass at harvest, runoff and drainage for various initial soil water content values. The sensitivity analysis gave results that conform to the current understanding of the soil-plant atmosphere system. The long-term assessment showed that it is risky to grow tomatoes during the winter season at Ukulinga irrespective of the initial soil water content unless certain measures are taken such as the use of mulching to protect the plants from frost.

The CROPGRO-Soya bean model was used to evaluate the soil water balance and growth routines for soil, plant and weather conditions at Cedara. In addition, cultural practices such as row spacing, seeding rate and cultivars were also evaluated using long-term weather data. Simulations of soil water content were unsatisfactory even after calibration of some of the model parameters. Other model parameters such as *LAI*, yield and flowering date had satisfactory agreement with observed values. Results from this study suggest that the model is sensitive to weather and cultural practices such as seeding rates, row spacing and cultivar maturity groups.

The general use of decision support systems is limited by various factors. Some of the factors are: unclear definition of clients/end users; no end user input prior to or during the development of the DSS; DSS does not solve the problems that the client is experiencing; DSS do not match their decision-making style; producers see no reason to change the current management practices; DSS does not provide benefit over current decision-making system; limited computer ownership amongst producers; lack of field testing; producers do not trust the output due to the lack of understanding of the underlying theories of the models utilized; cannot access the necessary data inputs; lack of technical support; lack of training in the development of DSS software; marketing and support constraints; institutional resistances; short shelf-life of DSS software; technical constraints, user constraints and other constraints. For successful use of DSS, the above-mentioned constraints have to be solved before their useful impacts on farming systems could be realized.

This study has shown that the DSSAT v3.5 model simulations of the soil water balance components such as evapotranspiration and soil water content were unsatisfactory while simulations of plant parameters such as leaf area index, yield and phonological stages were simulate to a satisfactory standard. Sensitivity analysis gave results that conform to the current understanding of the soil-plant –atmosphere system. Model outputs such as yield and phonological stages were found to sensitive to weather and cultural practices such as seeding rates, row spacing and cultivar maturity groups. It ha been further investigated that the model could be used for risk assessment in various crop management practices and evaluation of cultural practices. However, before farmers can use DSSAT v3.5, several constraints have to be solved.

INTRODUCTION

Ines *et al.* (2001) noted that the increasing competition for water has led to the concept of better use and management of water resources so that the needs of the stakeholders can be met properly. One of the major users of water is irrigated agriculture, especially for growing crops. Plants take in carbon dioxide through their stomatal openings in the epidermis and these same openings are used for transpiration. Quantification of this transpired water is important because it has a close relationship with dry matter production (Campbell and Diaz, 1988). This is important so that yield could be estimated with reasonable accuracy. In order to quantify transpiration, the soil water balance components, which strongly affect transpiration, have to be quantified. Alternatively, transpiration could be measured directly using any one of a number of different techniques. Environmental instruments have made the quantification of these parameters possible but the use of crop-simulation models is easier.

With increasing computer capability, the use of crop models for simulation of real processes in the soil-plant-atmosphere-system has increased significantly in recent years. Such models might be physical or empirical in nature. Models have the potential to solve many agricultural problems, one of which is efficient management of water resources.

There are a number of models that could be used for the efficient management of water resources. One of them is the Decision Support System for Agrotechnology Transfer v3.5 (DSSAT) (Tsugi *et al.*, 1994). The DSSAT models are described in Chapter 1 and application of the models presented in Chapter 2. DSSAT model uses the Ritchie (1985), based on Ritchie (1972), soil water balance submodel of intermediate complexity. It has two options for calculating potential evapotranspiration: the Priestley and Taylor (1972) and Penman-Monteith methods (Penman, 1948; Monteith, 1965). To determine the actual evaporation from potential evaporation, the model calculates the root water absorption using the law of the limiting approach in which the largest root or soil resistance determines flow rate of water into roots. Infiltration and runoff are calculated using a modification of soil conservation curve number technique and a cascading approach is used to calculate the drainage where water is allowed to move only downwards, unlike the finite difference approach (Savage, 2001a).

One of the main concerns when dealing with crop simulation models is the input data requirements. Complex models are data intensive while simpler models need less data. IBSNAT (International Benchmark Sites Network for Agrotechnoogy Transfer) recognized the importance of data availability for DSSAT model operation, calibration and evaluation. A minimum dataset was proposed to maintain a balanced set of information on weather during the growing cycle, soil characteristics at the start of the growing season, management of the crop and cultivar traits. The weather data needed as inputs to the soil water balance submodel, discussed in Chapter 4, are daily records of solar irradiance, minimum and maximum air temperature and precipitation. It has been reported that there was a tendency by some researchers to include other weather parameters such as relative humidity, wind speed and pan evaporation as part of the minimum dataset (Hunt and Boote, 1998). This was not accepted to keep the model inputs as simple as possible. Soil data such as soil texture, bulk density, root weighting factor for each depth, drained upper and lower soil water limits, soil reflection coefficient, drainage coefficient and runoff curve number are needed. In addition crop management data such as sowing or emergence dates, harvest dates, amounts and dates of irrigation and crop genetic information are also required

Hensley *et al.* (1997) reported that the soil water balance subroutines of crop models tested in the Republic of South Africa frequently give unsatisfactory results. In particular, simulation of change in soil water content, evapotranspiration, runoff and drainage are unsatisfactory. They explained that the main reason is an inadequate understanding regarding the processes in different soils and the absence of the necessary data with which to improve the models. Hence it is important to test crop models and adapt them to a particular situation. This is very important step because simulation of model outputs such as soil water balance components, yield and phenological stages of the crop have to be predicted accurately before a model is applied for a particular use. Aspects of the calibration, verification and sensitivity analysis of DSSAT v3.5 are discussed in Chapters 5 and 6.

Once a model is tested to work for a particular site and cultivars it could be applied for various purposes. For instance long-term weather data could be used to make risk assessments of yield, runoff and drainage. Hensley *et al.* (1997) used validated DSSAT v3.5 and PUTU crop growth models for risk assessment using long term weather data and four initial soil water contents (full, ¾ full, ½ full, ¼ full of the drained upper limit soil water content). In Chapter 6, a long-term risk assessment of tomato yields, runoff and drainage was carried out using 25 years of weather data and four initial soil water content values. The assessment was made for four soil water content values because initial soil water content is unknown at the start of the season for the historical weather dataset used. Crop models could also be used for evaluation of cultural practices, which will be discussed in Chapter 7.

The objectives of this work were the following:

1. discuss overview of DSSAT v3.5, general soil water balance models and soil water balance components in DSSAT v3.5. In addition, to discuss input requirements of the DSSAT model, motivation and statistical methods for model evaluation and methods for the measurement of soil water balance components;

2. literature review of the applications of DSSAT v3.5 models;

3. calibration of parameters used in the soil water balance routines of the CROPGRO-Tomato model by modifying some of its inputs and comparing simulations of soil water content, evapotranspiration, and leaf area index with actual measurements for soil, plant and weather conditions at Ukulinga, KwaZulu-Natal, South Africa;

4. sensitivity analyses of the soil water balance input parameters of the CROPGRO-Tomato model and long-term risk assessment associated with yield, runoff and drainage for soil, plant and weather conditions at Ukulinga;

4. calibration and evaluation of the soil water balance and growth routines of CROPGRO-Soya bean model and application of the model for the evaluation of soya bean cultural practices for soil, plant and weather conditions at Cedara, KwaZulu-Natal, South Africa.

CHAPTER 1

DESCRIPTION AND EVALUATION OF THE SOIL WATER BALANCE MODEL IN DSSAT v3.5

1.1 INTRODUCTION

Plants take in carbon dioxide through their stomatal openings in the epidermis and these same openings are used for transpiration. If soil water uptake by plant roots is not replenished, the soil will dry out to such an extent that plants will wilt and ultimately die. The strength at which the soil retains its water is equal to the suction that roots must exert to be able to take up soil water. An optimum range exists within which plants take up water freely. Above or below this level, plants sense stress and they react by actively reducing their daily water consumption through partial or complete closure of their stomata. The consequence is obvious: plant water stress interferes with carbon dioxide intake and reduces assimilation and dry matter production. A close relationship between dry matter production and the quantity of water transpired by the crop as explained above has been documented by Lawes (1850) and Briggs and Shantz (1913), as cited by Campbell and Diaz (1988).

Campbell and Diaz (1988) noted that it is important to determine the fraction of precipitation that is available for transpiration. They explained that transpirational water loss has little effect on the other terms of the soil water balance, except perhaps deep percolation loss. But transpiration is strongly affected by the other terms because it is the water left after the other components are satisfied. It is necessary, therefore, to determine water loss to evaporation, interception and runoff before reliable estimates of transpiration can be made. Alternatively, transpiration can be measured directly using a number of different techniques.

Hensley *et al.* (1997) stated that it is important to understand and quantify the soil water balance components because water is the most important limiting factor in crop production especially in rainfed agriculture in the Republic of South Africa. Hence the importance of determining transpiration is obvious. It is important to quantify runoff because it contributes to the water stored in dams and because it is related to erosion. Drainage contributes to ground water recharge and because of the possibility of water carrying pollutants into the ground water.

Quantifying the soil water balance components is now possible through the use of environmental instruments. Precipitation is relatively easy to measure. The change in soil water content can be measured with frequency domain reflectometry. Tipping bucket runoff meters could be used to measure runoff. Measurement of drainage is possible as described by Hensley *et al.* (1997). Although it is possible to quantify the components as described above, it is easier to use validated models to estimate their magnitude.

Hensley *et al.* (1997) clearly stated that the soil water balance subroutines of crop models currently tested in the Republic of South Africa frequently give unsatisfactory results. In particular, simulation of change in soil water content, evapotranspiration, runoff, and drainage are unsatisfactory. They explained that the main reason is an inadequate understanding regarding these processes in different soils (for instance in poorly drained soils water may move up and down and even horizontally and such processes are not well understood) and the absence of the necessary wide range of measured field data with which to improve the model.

There are a number of crop simulation models available in the world today of which the Decision Support System for Agrotechnology Transfer (DSSAT) v3.5 is one. In this Chapter an overview of DSSAT v3.5, general soil water balance models and soil water balance components in DSSAT v3.5 is given. In addition, input requirements of the DSSAT model, motivation and statistical methods for model evaluation and finally methods for the measurement of soil water balance components will be discussed.

1.2 OVERVIEW OF THE DSSAT v3.5 MODEL

The DSSAT v3.5 model (Tsuji *et al.*, 1994), a DOS-based program, has a number of crop models, with a daily time-step, executed under one shell. The crop models include: the Crop Estimation through Resource and Environment Synthesis model (CERES), based on Ritchie (1972, 1981, 1985, 1998) and Ritchie and Godwin (2002), cereals like barley, maize, sorghum, millet, rice and wheat; the CROPGRO model for legumes like drybean, soya bean, peanut and chickpea; the Simulation of Underground Bulking Storage Organs model (SUBSTOR) for potato and casava; and models for other crops like tomato, sugarcane, sunflower and pasture. The crop model architecture differs from one model to another (Ines *et al.*, 2001). However, all of the models stem from the

CERES range of crop models. The models require the following inputs: weather data, soil characteristics, crop genetic information, nitrogen inputs and management information. The inputs were standardized by IBSNAT so as to maintain a balanced set of information.

Simulation controls could be put into use before running the models. For example the model may be run with the assumption that nitrogen is non-limiting and thus none of the nitrogen transformation calculations are simulated. It is also possible to run the models assuming that water is non-limiting and thus water balance calculations are not performed. It is this capacity of the models that enables the simulation of potential production, production affected by only climate and crop characteristics affecting crop growth (carried out by disabling the nitrogen and water balance components), limited levels of production, production limited by water and nutrients like nitrogen (carried out by enabling the soil and nitrogen balance components) and reduced production, production affected by water, nutrients and other factors like pests (carried out by enabling the pest component together with water and nitrogen balance components available only for grain legumes). Another thing is that users could change weather, soil, cultivar, planting date, irrigation management, row spacing and nitrogen fertilizer management interactively to evaluate 'what if' questions. Simulated results could then be plotted from any of the simulations for comparison with real experimental treatments or for evaluation of hypothetical treatments. The models can also be operated in three modes: single treatment simulation, multiple treatment simulation and multi-year run.

All of the models under DSSAT v3.5 use the soil water balance model that is of intermediate complexity: Ritchie (1985) soil water balance model. The model allows two options for calculating potential evapotranspiration namely the Priestley and Taylor (1972) and Penman-Monteith methods (Penman, 1948; Monteith, 1965). To determine the actual evaporation from potential evaporation, the model calculates root water absorption using the 'law of limiting approach' in which the largest root or soil resistance determines flow rate of water into the roots. The model calculates infiltration and runoff using a modification of soil conservation curve number technique and uses a cascading approach to calculate drainage where water is allowed to move only downwards unlike the finite difference technique. It assumes that the soil profile is well drained, thus having no interaction with the ground water.

CERES-N model is used to simulate the nitrogen balance in the soil. Ines *et al.* (2001) reported that the nitrogen model has two forms: for upland and lowland conditions (rice). As described by Godwin and Singh (1998), processes like mineralization, immobilization, nitrification, denitrification, nitrogen uptake by plants and distribution and remobilization within the plants are simulated. The nitrogen balance model for all the other models under the shell stems from the CERES-N model.

The model has certain limitations as pointed out by Ines *et al.* (2001):

1. DSSAT v3.5 includes crop models for only a few crops and does not respond to all environmental and management factors like the effects of pests, intercropping, excess soil water and other factors on crop performance;
2. the models work in parts of the world where water, nitrogen and weather are major factors affecting crop performance. In other words it simulates three levels of production: potential, water and/or nitrogen limited and reduced production but do not consider other factors that limit yield like phosphorus availability or soil acidity;
3. the soil water balance model works well for well-drained soils. There is, however, a need for a better simulation of soil water balance in very poorly drained soils with oxygen stress as noted by Ritchie (1998);
4. furthermore, it is a daily incrementing model that does not take advantage of hourly weather data and in particular the variation of rainfall within a day. Hourly weather data is, increasingly, becoming available (Savage, 2003, personal communication).

1.3 MODELS OF SOIL WATER BALANCE

Models of soil water balance range from simple to complex ones. Simple models include for example the Keig and McAlpine model (1974). Models of intermediate complexity are those of Ritchie (1972), Reddy (1983) and Stockle and Campbell (1985). Models of complex nature are those of Norman and Campbell (1983). Although the input requirements of the models vary, they have certain common elements in that they model runoff, evaporation from the soil, transpiration, deep percolation and soil water storage in the soil. Most of the models do not estimate interception as part of the soil water balance parameters.

The model of Keig and McAlpine (1974) estimates soil water content on a weekly basis. Input requirements of the model include weekly potential evapotranspiration, weekly rainfall, initial available soil water content and available water holding capacity. Its outputs are weekly soil water content changes, water surplus, water deficits, actual evapotranspiration and the ratio of actual to potential evapotranspiration. The main limitation of such models is their low accuracy in predicting the soil water balance components (Singh, 2002).

Models of intermediate complexity include those of Reddy (1983), Ritchie (1972) and others. The model by Reddy (1983) computes daily evapotranspiration where the major inputs are easily available parameters such as rainfall and open pan evaporation. He pointed out that the model successfully differentiates between fallow and cropped areas and adequately accounts for differences in the evaporative demand as well as soil and crop factors. A data input for the model is maximum available soil water content in the top 100 mm of the soil and total profile. Potential evaporation is determined from available water in the top 100 mm at a given stage of growth. The model calculates actual evapotranspiration as a function of the time of wetting of the soil irrespective of available soil water content. Ritchie (1972) employs the Priestley and Taylor (1972) model, developed for areas of low soil water stress, to compute potential evaporation. It therefore requires modifications under dryland conditions (where there is water stress). The Ritchie (1972) model accounts for the effect of growth stage on the extractable soil water content in terms of leaf area index, that is the percentage of photosynthetically active radiation (PAR) transmission through the crop canopy while Jensen and Haize (1963) account for it in terms of crop coefficients (a simple constant multiplier). Reddy (1983) pointed out that this procedure is not valid under variable soil water content conditions. This is mainly because the crop coefficient works in situations where the plant is well watered. In general such models do not take into account upward flow or capillary rise of water in the soil. This is a limitation in poorly drained soils influenced by ground water. However, they require less computer time and input information than the complex models (Hanks and Hill, 1980). Although nowadays, compared to the 1980's, computer-processing time is less of a problem (Savage, 2002, personal communication), the availability of detailed input information is still a problem that makes such models more useful than the complex models.

Complex models such as that of Norman and Campbell (1983) generally use finite difference solutions to the soil water flow equations and they operate in hourly time steps rather than daily time steps. In addition they include details of heat and water transport within the canopy. Such models require information about thermal and hydraulic properties of the soil, and hourly meteorological data. Unlike the intermediate models, these models require wind speed and relative humidity data as inputs. It is, however, possible to estimate hourly relative humidity based on the hourly air temperature. Also, it is possible to categorise the wind speed (Savage, 2003, personal communication). The disadvantage of the more complex models is that they need maximum input of data and greater computer time than the other models.

Table 1.1 shows crop growth models used in other parts of the world and in South Africa and their complexity, input requirements and methods used for calculation of evapotranspiration.

Table 1.1 Different types of selected local and international models, their input requirements, complexity and ET calculation methods

Models	Input requirements	Complexity	ET calculation method	Comments
ACRU	Daily / monthly	Intermediate	P, H-S, L, B-C, T	Agrohydrological model
SWB	Daily	Intermediate	FAO-P-M	Irrigation scheduling model
PUTU	Daily	Intermediate	P-M, FAO-P, P-T	Crop growth model
CROPSYST	Daily	Intermediate	P-M, P-T	Crop growth model
DSSAT	Daily	Intermediate	P-T, P-M,	Crop growth model
EPIC	Daily	Intermediate	H-S, P, P-T, P-M	Erosion-Productivity impact simulator

where ACRU stands for Agricultural Catchments Research unit, SWB for soil water balance, CROPSYST for cropping systems simulation model, EPIC for Erosion-Productivity Impact Simulator, DSSAT for Decision Support System for Agrotechnology Transfer. And FAO-P-M stands for Food and Agricultural Organization of the United Nations-Penman-Monteith (Allen, 1998), P-M for Penman-Monteith (Monteith, 1965), P-T for Priestley and Taylor (1972), H-S for Hargreaves and Samani (1985), (1982) and P for Penman (1948), L for Linacre (1991), (1984), and (1977), B-C for Blaney and Criddle (1950) and T for Thornthwaite (1948)

1.4 SOIL WATER BALANCE COMPONENTS IN DSSAT v3.5

1.4.1 Infiltration and Runoff

The water balance subroutine calculates runoff using a modification of the United States Department of Agriculture (USDA) Soil Conservation Service (SCS) curve number method. This method uses total precipitation from one or more storms that occur in a single day to estimate runoff, and excludes time as an explicit variable (Ritchie and Godwin, 2002). Williams (1991) noted that that the curve number technique is a reliable procedure because it has been used for many years in the USA, it is computationally efficient, the required inputs are generally available and it relates runoff to soil type, land use and management practices. He further pointed out that that rainfall data with time increments of less than one day are not available. Also, daily rainfall data manipulation and runoff computation are more efficient than similar operations that use shorter time increments.

Ritchie (1998) stated that the runoff curve number concept is not expected to provide accurate runoff and infiltration information for a specific storm. He explained that the concept was derived to approximate runoff volume when only daily rainfall data are available. For greater accuracy, rainfall data with time increments of less than one day would be required. Infiltration and runoff could be accurately modelled if frequent measurements of rainfall are taken because this parameter varies spatially and temporally.

Campbell and Diaz (1988) used a runoff model similar to the SCS curve number concept shown in Fig. 1.1. Runoff increases as rainfall increases but is different for various soil surface conditions. Dry soils, which have high soil surface condition value, retain more water than wet soils and have lower runoff for a given rainfall. On the other hand wet soils, having low soil surface condition value, retain less water for a given rainfall and therefore have higher runoff than otherwise. The concept assumes that runoff increases as daily precipitation increases provided that precipitation is greater than some value representing initial infiltration and surface drainage. The soil water balance subroutine in DSSAT v3.5 uses a modification of SCS curve number technique.

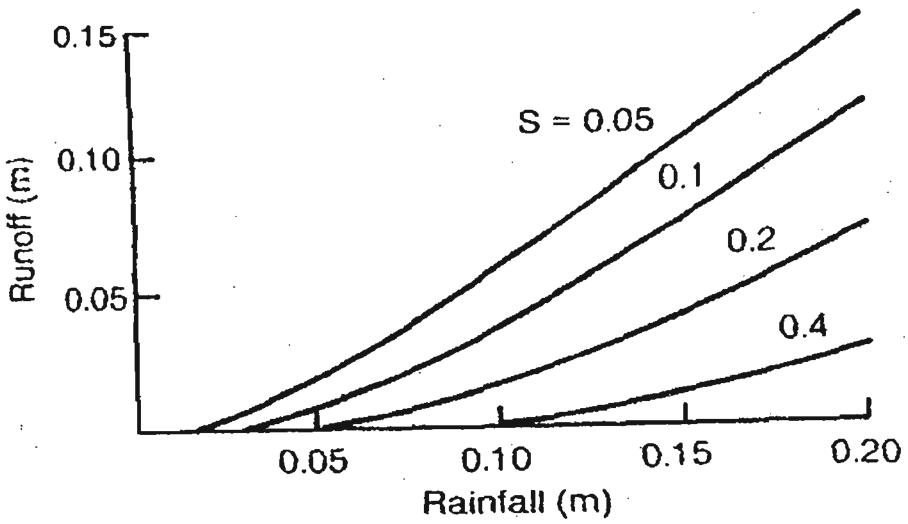


Fig. 1.1 Runoff (m) as a function of daily rainfall (m) for several soil surface condition values (S) (after Campbell and Diaz, 1988)

Unlike the DSSAT model, the CropSyst model (Stockle and Nelson, 2000) allows three options for determining runoff. The first option is where CropSyst tries to infiltrate all non-intercepted precipitation and irrigation. The second option is the SCS curve number technique. The third option is a numerical solution that is available with the finite difference infiltration model. The latter could be used where frequent rainfall data are available.

1.4.2 Drainage

Ritchie (1985) stated that the drained upper limit of soil water content is not always the appropriate upper limit of soil water availability because plants can take up water while drainage is occurring. He further explained that many productive agricultural soils drain quite slowly, and may thus provide an appreciable quantity of water to plants before drainage stops. Ritchie's multiple layer model (Ritchie, 1985) employs the cascading approach where water is moved downward from the topsoil layer to lower layers. Drainage from a layer takes place when the soil water content is between field saturation and drained upper limit. Unlike the soil water balance discussed above, CropSyst model allows the user to choose between the cascading approach and finite difference technique. The latter is more detailed and can transport water both up and down (Stockle and Nelson, 2000). One of its advantages is that drainage can be estimated with greater accuracy as compared to the cascading approach where water is assumed to move only downwards. The disadvantage, however, is that it increases simulation time and needs greater number of inputs as compared to other models.

1.4.3 Evapotranspiration

For reliable estimation of the soil water balance, it is important to accurately estimate evaporation from soil and plants. Ritchie (1981) cites the American Society of Civil Engineers (ASCE, 1973) who evaluated the accuracy of several maximum evaporation equations (E_{max}) (mm) from a wide variety of locations. He noted that the society tested energy balance and aerodynamic combination equations, humidity, irradiance and air temperature based equations and some miscellaneous equations. The well-known combination equation of Penman and two other equations, somewhat similar to it were superior because they reportedly had small errors. But some other equations like Priestley and Taylor (1972) were found to be impressive in their estimation of maximum evaporation.

In the DSSAT model of which CERES, CROPGRO and other models are a part, the equations used to predict evaporation are those employed in the model of Ritchie (1972) and Ritchie (1985). In those models the user has two options for the estimation of potential evaporation: (1) Priestley-Taylor (1972) equation for potential evapotranspiration, which needs daily solar radiant density, minimum and maximum air temperature and (2) Penman-Monteith equation which additionally requires water vapor pressure and wind speed inputs. It is claimed that both methods provide the same accuracy in their estimation of maximum evaporation under many circumstances (Ritchie and Godwin, 2002).

Priestley and Taylor (1972), cited by Ritchie (1981), found a correlation between maximum evaporation (E_{max}) from both moist vegetated and open surfaces and equilibrium evaporation (E_{eq}). The equation for E_{eq} (mm) (shown in eq. 1.1) is the same as the radiation term in Penman's combination equation.

$$E_{eq} = \frac{\Delta}{\Delta + \gamma}\left(R_n - G\right) \qquad 1.1$$

where Δ is the slope of the saturation vapor pressure curve at mean air temperature (kPa K^{-1}), γ is the psychometric constant (kPa K^{-1}), R_n is the net radiant density at the canopy top in equivalent units of mm/day and G is the daily total soil heat density (mm/day).

The correlation between E_{max} and E_{eq} has been reported to be as shown in eq. 1.2:

$$E_{\max} = \alpha E_{eq} \tag{1.2}$$

where α is a constant, E_{max} the maximum evaporation and E_{eq} is equilibrium evaporation. Priestley and Taylor (1972) experimentally derived an average value of 1.26 for the constant α in short grasses and humid conditions. The constant should be increased for arid and semiarid climates (Ritchie and Godwin, 2002). In DSSAT the constant is adjusted during execution depending on the value of the air temperature for each simulation day. The constant 1.1 (default value in DSSAT) is increased to account for advection when air temperature is greater than 24 ^{0}C and decreased to account for cold air temperatures below 5 ^{0}C.

The calculation of the actual rate of evaporation from soil is based upon the assumption that there are two stages of evaporation from soil: constant stage and falling rate stages (Ritchie, 1972). In the constant rate stage, the energy available at the soil surface limits soil evaporation. At this stage the soil is sufficiently wet to allow water transport to the surface at the required rate and maximum surface evaporation at a potential rate. First stage soil evaporation continues until a soil-dependent upper limit is reached. The soil hydraulic conductivity is the main cause for determining the cessation of the constant rate stage and beginning of the falling rate stage (Savage, 2001b).

Ritchie (1972) estimated soil evaporation during the constant rate stage using eq. 1.3:

$$E_s = \frac{\alpha \Delta \ln^{-0.04 LAI}}{\Delta + \gamma} \tag{1.3}$$

where α is 0.92 + 0.4 R_{ns}/R_n, R_{ns} is the net radiant density at the soil surface and R_n is the daily net radiant density at the canopy surface and LAI is the leaf area index.

During the falling rate stage soil evaporation depends on hydraulic properties of the soil and is less dependent upon the available energy. Black *et al.* (1967) estimated the cumulative evaporation (mm) using eq. 1.4:

$$E_s = k_s \sqrt{t} \qquad 1.4$$

where k_s is the hydraulic conductivity at –10 kPa soil matric potential (mm/day) and t is the time in days from the onset of falling rate stage evaporation and E_s is the soil evaporation.

1.4.4 Root Water Absorption

The importance of calculating root water absorption is to reduce potential evaporation from a potential value to an actual one. Ritchie (1985) pointed out that the CERES model calculates root water absorption using the “law of the limiting” approach in which the largest soil or root resistance determines the flow rate of water into the roots. He discussed further that the soil limited water absorption rate, q_r ($m^3\ m^{-1}$), considers radial flow to single roots and is expressed in eq. 1.5:

$$q_r = \frac{2.64 * 10^{-3} \exp[62(\theta - \theta_l)]}{6.68 - \ln L_v} \qquad 1.5$$

where θ is the actual soil water content ($m^3\ m^{-3}$), θ_l is the lower limit soil water content ($m^3\ m^{-3}$) and L_v is the root length density ($m\ m^{-3}$).

The model described above incorporates the assumption that water uptake is proportional to rooting density, soil hydraulic conductivity and the water potential difference between the root surface and that in bulk soil midway between two adjacent roots. Taylor and Klepper (1975) tested the validity of these assumptions. They found that the assumption that water uptake is proportional to the rooting density was valid. But the other two assumptions must be modified to include a large resistance in the pathway from root epidermis to root xylem.

The relationship between root water uptake and the water content difference between the actual and lower limit values is depicted in Fig. 1.2. It can be seen that

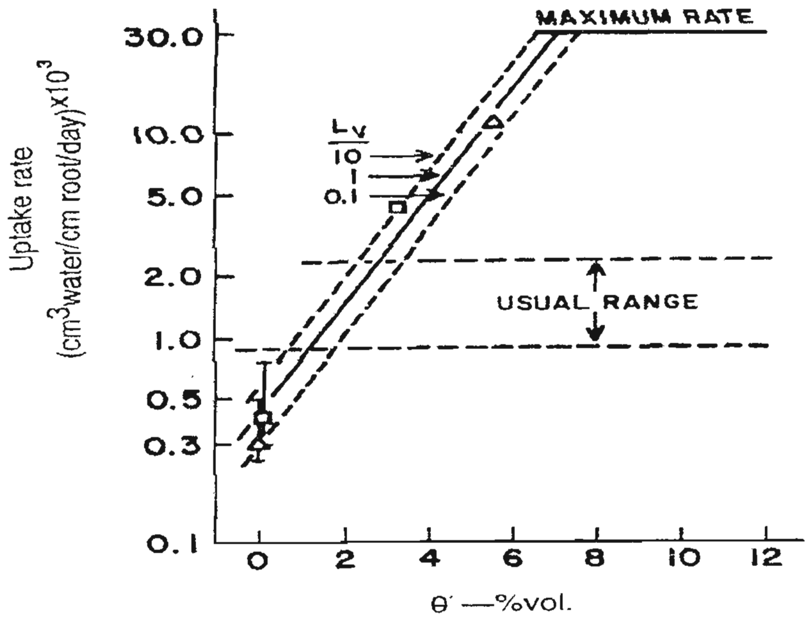


Fig. 1.2 The relationship between uptake rate q_r (m^3 m^{-1}) and actual soil water content minus the lower limit soil water content θ - θ_l (m^3 m^{-3}) with various root length density L_v (m m^{-3}) values (after Ritchie, 1985, 1998)

rooting density has a small influence on root water uptake despite the fact that water uptake is plotted on a log scale. However, different climates, crops and soils give different relationships of water uptake q_r (m^3 m^{-1}) and θ-θ_l (m^3 m^{-3}) (Hensley *et al.*, 1997). It seems unreasonable therefore to use only one relationship as proposed by Ritchie (1985). But it is also important to understand that Ritchie's relationship has been derived assuming that the hydraulic conductivity of all soils are similar when normalized to the lower limit value. It is correct when the soil water content is near the lower limit. The equation also assumes that the water potential gradient between the root and the soil remains constant, even when the soil dries out. In reality, the water potential of the roots may change considerably throughout the day.

There are certain difficulties in the estimation of the total root water uptake that involves determination of root density, water potential gradient between the root and the soil hydraulic conductivity. Taylor and Klepper (1975) showed that about a 30% standard error might occur when determining root density. Similarly Ritchie (1985) commented that simulation of the dynamics of root growth in the soil is a weak part of CERES and more quantitative root growth information is required before major improvement can be made in the root growth part of CERES model.

1.4.5 Model Inputs

As described in Section 1.2, there are several kinds of soil water balance models that differ in complexity, operation and purpose. Simple models require minimum input data while complex models like that of Norman and Campbell (1983) require maximum data.

The data need of Ritchie's multiple layer model (1985), which is a submodel of DSSAT group of models, is weather data, soil data, plant data, management and other data. Most of the following information has been taken from Singh (2002).

(a) *Weather data*: daily inputs of solar radiant density (MJ m^{-2}), minimum and maximum air temperature (^{o}C) and rainfall (mm) are required primarily to calculate daily potential evapotranspiration. There are two ways for calculating daily potential evapotranspiration: Ritchie (1972) and Ritchie (1985). The main difference between the two is that the former employs the Priestley and Taylor (1972) model to calculate evapotranspiration, which does not need wind speed and relative humidity data while the latter uses the Penman-Monteith equation for calculating evapotranspiration.

(b) *Soil data*: according to Ritchie (1998) several soil factors affect the soil water balance. The factors are described below:

USDA curve number (CN2): DSSAT v3.5 uses a modification of Soil Conservation Service (SCS) (Williams, 1991). The procedure uses total precipitation in a calendar day to estimate runoff. Runoff curve numbers are specified by numbers that vary from 0 (no runoff) to 100 (all runoff). A list of runoff curve numbers for various hydrological soil groups and soil cover complexes can be found from Internet or SCS handbook. To determine the runoff curve number for cropland soils, it is necessary to decide which of the four hydrological soil groups best describes the soil. The curve number is determined from the soil texture and slope of the site. It can further be modified for the degree of conservation practices followed.

Drainage Coefficient (SWCON): Since water can be taken up by plant while drainage is occurring, the drained upper limit is not the appropriate upper limit of soil water availability. The drainage property of soils varies greatly. Some agricultural soils may provide appreciable quantities of water to plants before drainage stops because they drain quite slowly (Ritchie, 1985). SWCON varies between 0 and 1 and represents the fraction of water between the actual soil water content and drained upper limit that drains in one day. Thus for a coefficient of 0.5 with the soil water at saturated soil water content, the water content would decrease to half of the difference between the two limits in one day. On the second day, half of the remaining water between the limits would drain and so on.

Soil reflection coefficient: is the reflectance of solar radiant flux density from the soil surface. Ritchie (1998) calls this term soil albedo and is considered to affect the soil water balance because different soils have different reflection coefficients. The reflection coefficient is required to calculate potential evaporation. Its values are claimed to be not very sensitive to influencing the soil water balance. To verify this, sensitivity analysis is needed. Of particular note is that the soil reflection coefficient varies, depending mainly on the water content at the soil surface (Savage, 2003, personal communication).

Upper limit of stage one soil evaporation (U): Ritchie (1972) divided soil evaporation (mm) into constant stage and falling rate stages. The former is energy dependent while the latter depends on soil hydraulic conductivity. The upper limit of stage one evaporation can have important influence on the amount of soil evaporation during periods when the soil surface is frequently wetted by rainfall. The upper limit of stage one soil evaporation can be calculated in eqs. 1.6, 1.7 and 1.8.

$$U = 8 + 0.08 * \%\ clay \qquad Sand < 80\ \%,\ Clay < 50\ \% \qquad 1.6$$

$$U = 5 + 0.15 * (100 - \%\ Sand) \qquad \text{Sand} > 80\ \% \qquad 1.7$$

$$U = 5 + 0.06 * (100 - \%\ Clay) \qquad Clay > 50\ \% \qquad 1.8$$

As defined by USA soil classification system, clay has a particle size less than 0.002 mm, silt between 0.002 mm and 0.05 mm and sand between 0.05 mm and 2 mm. The South African soil classification is similar to the USA except that silt is taken to be between 0.002 mm and 0.2 mm and sand between 0.02 mm and 2 mm.

Extractable soil water limits: the inputs required are the drained upper limit ($m^3\ m^{-3}$), lower limit ($m^3\ m^{-3}$) and plant extractable soil water. The drained upper limit, according to Ratliff *et al.* (1983), has been defined as "the highest field measured water content of the soil after it has been thoroughly wetted and allowed to drain such that drainage becomes practically negligible", while the lower limit is "the lowest field measured water content of a soil after it has stopped extracting water and were at or near premature death or became dormant as a result of water stress". Savage *et al.* (1996) found that – 1.5 MPa soil water potential is the appropriate lower limit for water balance calculations and corresponds closely to the field lower limit of soil water availability. Despite the above finding, Ritchie (1981) reported that the pressure extraction equipment used on soil samples removed from field often fail to provide reliable estimates of the limits of soil water availability when comparing it to observations in the field. He further pointed out that upper and lower limits have to be measured in the field for accurate soil water balance modelling.

Saturated soil water: to calculate the saturated soil water (m^3 m^{-3}) we assume that it is equal to 0.85 of the total porosity (eq. 1.9). In the USA instead of 0.85, the effective porosity is taken to be 0.92. The Agrohydrological South African model ACRU does not have this factor, although effective porosity is mentioned. Schulze (1995) lists total and effective porosities from which the effective porosity ratio could be derived. But most of these data are from USA. Hence 0.92 is a good estimate for South Africa although the factor depends on the soil type (Lorentz, 2003, personal communication).

$$SAT = (1 - D_f / 2.65) * 85 \qquad 1.9$$

where D_f is the measured bulk density (g cm^{-3}) at - 0.03 MPa

Initial conditions of soil water content: the initial soil water content is required for various depths within the soil profile. If such data is not available the model may be run beginning at a time when the initial conditions are at the lower limit or drained upper limit. The model may be run assuming that the entire profile is at the lower limit in regions where the soil water supply is almost depleted at the end of a season. The approximated off-season water balance becomes the initial condition at the sowing date. The input values can be assumed to be at drained upper limit at or just before sowing in regions where the precipitation is almost always sufficient.

Root weighting factor (WR): it is generally known that root growth is more dominant near the surface under optimum water contents with the weighting ratio decreasing exponentially with increasing soil depth as shown in eq. 1.10. For each depth increment (i), a value of between 0 and 1 is calculated:

$$WR_i = exp\ (-0.02 * z_i) \qquad 1.10$$

where z_i is the depth (m) of the centre of layer *i*.

Management and other data: information such as sowing or emergence date (day of year), harvest data (day of year), dates (day of year) and amounts of irrigation (volume of water per unit area (mm)), leaf area index or percent photosynthetically active radiation (PAR) (the number of photons in the radiant energy between 400 nm and 700 nm) interception, extinction coefficient (a measure of the rate of the reduction of transmitted light through a plant), radiation use efficiency (relates biomass production to the PAR intercepted by a crop or plant) is required.

1.5 MEASUREMENT OF SOIL WATER BALANCE VARIABLES

1.5.1 Measurement of Soil Evaporation

To measure soil evaporation, the microlysimetric method has been employed (Boast and Robertson, 1982; Savage *et al.*, 1997; Kizito, 2001). To carry out measurements of evaporation from the soil, microlysimeter (ML) plastic cylinders about 125 mm long and 73 mm internal diameter and a wall thickness of approximately 3 mm can be used. To facilitate insertion into the soil, the walls of the cylinder should be tapered at. Firstly, to insert them easily into the soil. Secondly, to determine the mass of the microlysimeter (ML) on precision balances. After weighing the ML, it should be put in a zip lock plastic bag in order to protect the outside part of the cylinder from the surrounding soil.

One of the advantages of using the plastic MLs as compared to steel MLs is that the former conducts less heat and its surface is significantly cooler during the day and warmer at night. Savage *et al.* (1997) recommends that the walls of the ML should be designed to maximize thermal transfer between the soil inside and below the ML. A length of at least 300 mm is recommended if measurements are needed at the same location for several days. The one edge should be sharpened and sprayed with liquid Teflon spray.

Boast and Robertson (1982) reported that MLs could be used to take measurements of evaporation at a large number of locations for just a few days for a situation where the cost of large lysimeters is prohibitive. In cases where the resolution of large lysimeters is too large, MLs could be used to measure evaporation as a function of distance from a crop row, under conditions of partial cover and partial shading.

Aside from modelling soil evaporation, there are no other methods for the measurement of soil evaporation. The method is time consuming and destructive and often not used.

1.5.2 Estimates of Drainage

To determine drainage, Hensley *et al.* (1997) used a drainage curve determined in the field to provide information about the rate at which water moves through each layer at any specified water content above the drained upper limit. They made use of the concept that drainage occurs when water content of the deepest layer of the root zone exceeds drained upper limit. Then they identified the periods and extent during the growing season when this situation occurred and the necessary estimates were made by studying the water content graphs. They combined this information with the drainage curve data to make an estimate of drainage based on measured soil water content data.

1.5.3 Measurement of Runoff

Runoff can be measured using an automatic tipping bucket raingauge under rainfed cropping situations if the water can be collected to the point of measurement. However, for irrigated crops it is usually assumed to be negligible. This may not be a reasonable assumption for all circumstances in South Africa and if the crop is exposed to heavy rainstorms.

1.5.4 Measurement of Soil Water Content

Soil water content: To measure soil water content frequency domain reflectometry could be employed. The sensor output depends on the frequency shift or ratio between the oscillator (for a 100 MHz signal) voltage and that reflected by rods installed in the soil. The ratio of the two voltages is dependent essentially on the apparent dielectric constant of the soil, which is determined by the soil water content. The dielectric constant of pure water is around 80 at 20^0C, which is much larger than that of soil materials (~ 2.5). Hence the soil water content predominantly determines dielectric constant of moist soil (Schelde, 1996).

Measurements of soil water content at three locations within KwaZulu-Natal, South Africa using ThetaProbes (FDR sensor) gave good results, even when using the factory-supplied calibration factors, and were found to be insensitive to temperature, bulk density and clay content variations in the soil (Ripley *et al.*, 1998). Delta-T devices (2001) suggest that a soil specific calibration curve is necessary if one of the following applies:

a) if the soil is heavy clay, highly organic or in some respect "extreme";

b) if one is working to high levels of accuracy, or if one needs a controlled error figure rather than a "typical" error figure. It is also assumed that the soil is not very stony and that it does not crack when it dries.

This method was chosen because the sensors could be attached to conventional dataloggers so that unattended measurements could be taken. It has a disadvantage in case of the access tube models where there should have to be good sensor-tube-soil contact because the readings are influenced by soil water content and air gaps in the soil volume nearest the sensor.

1.5.5 Additional Measurements

Leaf area index: The LAI-2000 (LI-COR Inc., Lincoln, Nebraska, USA) plant canopy analyzer can be used to measure the LAI of a tomato crop. A minimum of ten measurements need to be performed either at sunset or before sunrise. Five measurements are taken when the optical sensor is above the canopy and the remaining five are taken when the sensor is below the canopy. The sensor can then calculate the relative foliage area (leaf area index) and foliage orientation (mean foliage tilt angle) from the transmittances at all zenith angles.

This method is non-destructive, rapid, cost effective and used for canopies ranging from grasses to forests as compared to direct measurements with an area meter. In addition, it can be used under a variety of sky conditions.

Soil temperature: measurements of soil temperature can be taken at various depths within the soil profile using thermocouples and data can be stored automatically into a datalogger.

Potential evapotranspiration: ET-gauge (ET-gauge company, model E, Loveland, USA) connected to a datalogger for automatic data storage, can be used to measure this parameter.

Other direct methods such as the weighing lysimeters, Bowen ratio and eddy flux measurements are not suitable because of their cost, complexity and because of limited area of the enclosures does not allow the water loss from a representative surface to be measured (Stanhill, 2002). Class A pan evaporation pan is inexpensive and easy to install, maintain and monitor. However, a free water surface responds differently from a crop surface in reflectivity, heat storage, day night temperature fluctuation, and water transmissivity and aerodynamic roughness of the plant canopy. In addition rainfall may occur during the season and may add water to the pan or thirsty animals wandering in the area may drink from the pan. The ET-gauge evaporimeter was chosen because it doesn't have most of the problems mentioned above and because it can be attached to a datalogger for continuous measurements.

1.6 EVALUATION OF THE SOIL WATER BALANCE IN DSSAT v3.5

1.6.2 Model Evaluation

1.6.2.1 Motivation

Whisler *et al.* (1986) explained that model building is an enjoyable if arduous task whereas model testing can be demoralizing despite the fact that model testing is an important part of modelling. This might be the reason why so many crop models are published without being tested. According to them, validation takes two main forms: validation in which the predictions are verified using field observations, and sensitivity and uncertainty analyses which test how responsive the model is to changes in certain variables and parameters. Levels of validation are also classified into two: one is at the level of predictions using field data or at the level of assumptions using controlled environment data. They explained further that both types of evaluations build confidence in the predictive ability of models. However, our confidence increases more rapidly with validation at the level of assumptions than at the level of predictions. It is important to note, though, that validation of a model is never accomplished. In fact most models are calibrated and not validated (Savage, 1993).

Savage (1993) explained the importance of modelling as follows; "a model without proof of validity is an exercise in abstract logic". He defined the validation process as a process whereby the modeller compares the model outputs with experimental data and states that ideally there should be exact agreement. In practise, however, there may be deficiencies in the model or/and in the experimental data. In addition, the different subroutines as well as the whole model should be validated and the validation of the timing of phenological events is important because they are preconditions for accurate simulation of yield.

Boote *et al.* (1996) defined validation as; "determining whether the model works with totally independent data sets, i.e. does it accurately predict growth, yield, and processes?" He cited Dreskes *et al.* (1994) saying that a model can never be validated. He further pointed out that one of the problems with model validation is that modeller's find poor prediction for some of the cases; they attempt to correct errors in the models and thus have a non-validated model that awaits new independent test data. Monteith (1996) states that when a model tested for a situation fails, it should be welcomed as a stimulus for the development of a new hypothesis and as a guide to improvement rather than trying to identify and correct the model by the introduction of arbitrary coefficients or what are called site factors.

Although the soil water balance subroutine of CERES-Wheat provided reliable estimates of soil water throughout the growing season in several tests (Otter and Ritchie, 1984), it required certain improvements. The CERES-Wheat crop simulation model has been tested in South Africa, Free State province (du Toit *et al.*, 1997). They found that a detailed study was necessary with the poor estimation of the soil water content in comparison with the actual measurements. Inaccurate simulation of soil water content resulted in errors in the simulation of plant and yield components. Similarly Hensley *et al.* (1997) found that the PUTU and DSSAT crop simulation models they used gave unsatisfactory estimates of the soil water balance variables like drainage, soil water storage, evapotranspiration and runoff. de Vos and Mallet (1987) also found that CERES-Maize and CORNF models performed poorly in predicting soil water content at Cedara, Kwazulu-Natal, South Africa. Hence it is important to test models and adapt them to a particular situation.

1.6.2.2 Statistical evaluation

Predicted results of evapotranspiration, soil evaporation, leaf area index, soil water content and drainage can be compared using graphical and statistical methods as described by Wilmott (1982) and supported by Savage (1993). Ideally, regressing the simulated data against the actual data should have an intercept of zero and slope of one (Savage, 1993). In addition, Wilmott (1982) stated that the commonly used correlation measures such as Pearson's correlation coefficient (r) and coefficient of determination (r^2) and tests of significance in general are often inappropriate or misleading when used to compare model predicted and observed variables. This is because the magnitudes of r and r^2 are not consistently related to the accuracy (the degree to which model predicted observations approach the magnitudes of their observed counterparts) of prediction. It is also possible for "small" differences between observed and predicted observations to occur with low or even negative values of r. There is also a possibility for "high" or statistically significant values of r and r^2 to occur when infact the differences between predicted and observed observations are high. Hence they should not be part of an array of model performance measures. An array of complementary measures was recommended by Wilmott (1982) for the testing of the performance of models.

Quantitative measures that Wilmott (1982) suggested such as observed value (O), predicted value (P), the average predicted value (P_a), the average observed value (O_a), the standard deviation of the predicted value (S_p), the standard deviation of observed value (S_o) and the intercept (a) and the slope (b) of the least squares regression between the predicted and observed values, systematic and unsystematic root mean square error ($RMSE_u$ *and* $RMSE_s$) and the index of agreement (d) can be used to compare different models.

One of the arrays of complementary measures used by Wilmott (1982) is the index of agreement. This index tells us something about the accuracy of the model considered. A model is considered accurate if it has an index approaching one. Other measures include the systematic and unsystematic root mean square errors. An ideal model should have a zero systematic error and unsystematic error of one. However, all of the arrays of complementary measures are necessary for evaluating model performance and no single index can adequately describe model performance.

In addition to the array of complementary measures, data display graphics can be extremely helpful in identifying the pattern of the differences between the predicted and observed values as well as extreme values. Moreover, scatterplots can represent the relationship between predicted and observed values as well (Wilmott, 1982).

1.7 THE USE AND EVALUATION OF THE MODEL IN SOUTH AFRICA

Most of the models under the DSSAT v3.5 shell, stemming from the CERES family of models, have been used, tested and improved in the USA and other countries. In South Africa, some workers have used and evaluated the models. For example Vos and Mallet (1987) carried out preliminary evaluations of the CERES-Maize and CORNF models. du Toit *et al.* (1994 a) evaluated and calibrated the CERES-Maize model. du Toit *et al.* (1997 a) used linear regression and a correlation matrix to evaluate the CERES-Maize. The genetic parameters were determined using a non-linear regression for the model (du Toit *et al.*, 1994 b). du Toit *et al.* (1997 b) evaluated CERES-Wheat v2.1 for soil water content under rainfed conditions. Hensley *et al.* (1997) used the DSSAT v3.5 to model the soil water balance of Benchmark ecotopes in South Africa. du Toit *et al.* (1998) calibrated the CERES3 (Maize) to improve silking date prediction values for South Africa. MacRobert and Savage (1998) used the CERES-Wheat for irrigation management. du Toit *et al.* (2002) compared fitted (calculated) and determined (measured) genetic coefficient G2 in CERES-Maize. du Toit *et al.* (2002) incorporated a water-logging routine into CERES-Maize and did some preliminary evaluations. Pakendorf *et al.* (1999) reported that the CROPGRO-Soya bean was used to determine biological yield potential for soya bean producing areas in South Africa; to compare observed field performance with simulated data; and simulate soya bean yield for the 1946 water catchment areas. Zhou *et al.* (2003) studied physiological parameters for modeling differences in canopy development between selected sugarcane cultivars because the ability of the models such as the CANEGRO (sugarcane model) to accurately predict yields of different cultivars may depend largely on accurate descriptions of the canopy. Little literature exists verifying the use of other models under the DSSAT v3.5 shell such as the CROPGRO-Tomato in South Africa.

1.8 CONCLUSIONS

Models of different complexity and hence accuracy have been used to estimate the soil water balance components besides environmental instruments. Simple models have limitations in that their accuracy in predicting the soil water balance components is low. Models of intermediate complexity like that of the Ritchie (1985) model do not take into account upward flow or capillary rise. However, they require less computer time and input information than the complex models. They have advantages in that they tend to maintain balance in the level of detail of their various routines. Ritchie and Godwin (2002) pointed out that a model could not be made accurate by including information from disciplines that are better understood. For instance hourly inputs of weather data might not be worthwhile while if other inputs like rooting depth of a plant are not available throughout the growing season. They noted that the output of the model would be determined by the least understood part of it. Complex models require maximum input of data and greater computer time than the other models. They estimate most of the soil water balance variables like drainage with greater accuracy because they use finite difference techniques which transports water both up and down the soil profile. But they fail to maintain balance between the various parts of the model. To evaluate the Ritchie (1985) soil water balance model in DSSAT v3.5, statistical methods described by Wilmott (1982) and supported by Savage (1993) could be used and that the commonly used measures such as Pearson's correlation coefficient (r) and the coefficient of determination (r^2) are misleading when used to compare model predicted and observed values since the bias of the model is not indicated by r^2. For the sake of comparison with model predictions, drainage could be derived from a drainage curve, soil water content measurements using frequency domain reflectometery, soil evaporation could be measured using a microlysimeter, reference evapotranspiration could be measured using an ET-gage evaporimeter, and leaf area index using a LAI-2000 leaf area index meter.

CHAPTER 2

APPLICATIONS OF THE MODEL

2.1 INTRODUCTION

Before a model is applied for a particular use, it has to be verified to see whether it simulates model outputs such as the soil water balance components, yield and phenological stages of the crop accurately. But to achieve this objective, the model has to be first calibrated for the particular site and cultivars. Once the model is calibrated, it should be verified. The model can be applied for various purposes, only after it gives satisfactory results of the output components.

A model verified to work for a particular site and cultivar can be applied for various purposes. For example Decision Support Systems for Agrotechnology Transfer (DSSAT), which consists of a number of models under its shell, has been applied in precision farming (e.g. Paz *et al.* 1999), a farming system where management practises are carried out taking three things into account: the question of where, when and what (Paz *et al.*, 1999). The model can also be used in crop management (e.g. Algarswamy *et al.*, 2000; de Vos and Mallet, 1987). Under conventional farming, a trial consisting of a few combinations of factors can take many years. However, this can be done within a short time using crop simulation models. The model has also been applied, for example, for irrigation management (e.g. MacRobert and Savage, 1998), tillage management, climate change and variability and their impacts on agriculture, crop improvement, crop yield forecasting, nutrient management, pest and disease management, weed management, harvesting, evaluating sustainability, land use planning, yield gap analysis (Jones, 2002, Matthews, 2002).

It was not practical to exhaustively review all model applications. Hence the objectives of this study were to review only some of the successful applications of models that have agricultural significance.

2.2 YIELD-GAP ANALYSIS

Matthews *et al.* (2002) noted that knowledge of the gap between potential yield of a crop and its actual yield obtained is crucial before any improvements in crop management practices are made. Yield gap has been defined as the difference between climatic potential yield and actual yield (Aggarwal and Karla, 1994). Similarly Pinnschmidt *et al.* (1997), as cited by Matthews *et al.* (2002), defined yield gap as the difference between an attainable yield level and the actual yield. Crop models could be used to determine the potential yield of a crop and the limiting factors could be identified by a stepwise analysis of the various inputs.

An example of a crop model used for yield gap analysis is that of Aggarwal and Karla (1994). They employed the WTGROWS model to predict potential wheat yields across India. This was then compared to economic and optimum actual yields across a range of latitudes. It was reported that yields increased with increasing latitude and distance from the sea primarily because of variation in air temperature. Average actual yields were less than 60% of potential yield. The yield gap was at 2000 kg ha^{-1} despite the fact that actual wheat yields had increased considerably over the preceding 25 years to 3000 kg ha^{-1}. They attributed about 35% to 40 % of this gap, after further analysis, to delayed sowing. Other factors like irrigation inefficiencies and variability in fertilizer use were also limiting wheat yields.

Bell and Fischer (1994) also used a crop growth model to assess wheat yield gains over time in a region of Mexico. They reported that farmers' actual yields in the region had increased by 57 kg ha^{-1} between 1968 to 1990. The increase in yield has been attributed to the introduction of high yielding semi-dwarf varieties, improved agronomic practices and weather variation. Potential yield was estimated using the CERES-wheat model assuming no change in cultivar or management over the time period. They found that yields would have declined by 46 kg ha^{-1} because of increased air temperatures and that the true yield gain, attributed to improvements in genotype and crop management was in fact 103 kg ha^{-1} yr^{-1}. Despite the potential yield gains, average farmers' yields have risen from 50% to 75%

over the time period in question. This was considerably lower than the potential yields predicted by the model, which indicates that there is still more scope for improvement.

2.3 FERTILIZER MANAGEMENT

Variations in climate and soil conditions are usually observed across space and time. These variations would in turn result in differences in the availability of nitrogen to the crop and hence the efficiency of use of nitrogen fertilizers by crops. If water is a limiting factor in a certain environment, uptake of nitrogen by the crop and nitrogen mineralizations will be reduced. On the other hand nitrogen will be lost by leaching and denitrification if water is excessive. Differences in soil types would also result in variations in nitrogen uptake. For instance in highly alkaline soils nitrogen is lost by volatilization. A combination of differences in weather and soil conditions means that it would be a difficult task to actually define a single fertilizer strategy optimum for all seasons. Due to this reason there is always a mismatch between supply and demand of nitrogen that consequently reduces yield or wastes fertilizer. Unlike field experiments that are unreliable in situations where there is high climatic variability, crop models may be used to assess long-term risks of particular options (Matthews *et al.*, 2000). The following paragraphs will discuss some of the applications of crop models for the management of fertilizers.

Gabrielle *et al.* (1996) adapted the CERES-Nitrogen Maize model to study the impact of climatic hazards on nitrogen losses and yield of winter oil seed rape. The aim of the experiment was to study the large nitrogen fertilizer inputs needed by the crop and its long growth cycle. CERES-Rape, the model adapted from CERES-N Maize model, was used to predict crop carbon and nitrogen budgets throughout the growth cycle including losses from leaves by senescence. The model had been calibrated on a one-year experiment with three nitrogen levels and was tested using an independent data set. It simulated the time course of biomass and nitrogen accumulation in the various plant components reasonably well during the vegetative phase. But after the onset of flowering, simulated nitrogen was not satisfactory. They concluded that the simulation effects of fertilizer on the dynamics of crop and nitrogen uptake were judged sufficiently satisfactorily to allow an investigation of nitrogen losses from rapeseed-cropped soils with the CERES-Rape model.

For accurate fertilizer nitrogen recommendations, determination of the amount and distribution of nitrate nitrogen and water in the crop-rooting zone of the soil profile is important. Crop models have been used for this purpose for instance Beckie *et al.* (1994). They tested the effectiveness of four simulation models for estimating nitrates and water in two soils. The models compared were CERES-Wheat, Erosion/productivity impact simulator (EPIC) (Williams *et al.*, 1984) and two other models. They found that all the models estimated nitrate nitrogen and water levels in the crop-rooting zone of the soil profiles similarly. They concluded that the user's objective, model versatility and ease of use, and the type of data input required versus what has been measured would determine which model was best suited for predicting nitrate nitrogen levels and water distribution in the soil profile.

Models have also been used to simulate nitrogen losses as a result of excessive rainfall or alkaline soil conditions. Gabrielle and Kengini (1996) employed a functional model (CERES) to do the simulation. They compared three models namely: CERES, CERES-SLIM (for solute transport), and CERES-NCOSIL (for nitrogen mineralization). They found that when the CERES model was linked with NCOSIL, it showed a good potential for simulating nitrogen dynamics in the soil.

One of the main limitations of DSSAT group of crop models had been their inability to simulate more than one cropping season at a time (Thornton *et al.*, 1995). To solve this problem a computer program to analyse multiple season crop model outputs had been developed by Thornton *et al.* (1995). Such a utility that enables the user to accurately simulate crop rotations can be used in the assessment of management options like application of fertilizers with time given certain environmental conditions and resource constraints at the farm level. Using this utility, one may assess a number of replications across different sequence years to quantify the production risk associated with different weather patterns.

2.4 PRECISION FARMING

Precision farming has been defined as the spatial and temporal optimization of farm management to increase productivity or reduce the use of agrochemicals (Booltink *et al.*, 2001). It tries to answer the question of what, when and where should the management practices be applied. Traditional farming assumes that that the field is homogeneous which results in inefficient use of resources. It tries to answer only the question of what and when. Crop simulation models have the potential to play an important role in applications such as precision farming. A number of workers have applied models for precision farming as will be discussed below.

Paz *et al.* (1999) used the CERES-Maize model to determine variable rate nitrogen for maize. They calibrated the model using 3 years of data from 224 grids in a 16 ha field. Yield trends along transects in the field have been predicted accurately explaining approximately 57% of yield variability. Optimum nitrogen rate were prescribed for each grid cell using 22 years of historical weather data. They found that this technique used lower amounts of fertilizer, gave higher yields and was more profitable than either transect or field level fertilizer application. In the economic analysis soil sampling and analysis costs were not included.

Seidl *et al.* (2001) developed a GIS-crop model based on a decision support system to evaluate corn and soya bean prescriptions (such as plant population, row spacing and other crop management practices) and to analyze causes of yield variability. The interface developed consisted of three modules: a crop growth model, a database, and the GIS module. The crop growth models predicted the growth of corn and soya bean on each day of simulation based on field management, weather, and soil inputs. The database managed most of the data required for simulation including model input and output files. It was also used to generate the hundreds of files needed for optimum prescription determination and to process the many predicted outputs. The GIS module connected the database for map creation and data visualization. It was also used for interactive testing of hypotheses with the crop growth models. They applied the system to find the optimum soya bean population using 21 years of data. They found that lower populations on hilltops and higher population on low-lying areas was a better choice than otherwise.

Paz *et al.* (2001) used CROPGRO-Soya bean (Hoogenboom *et al.*, 1994) to quantify the effects of spatial soya bean yield limiting factors. They first identified three factors affecting soya bean yield variability namely: water stress, soya bean cyst nematode (SCN) and weeds. They found that among many factors including soil properties, weather, pests, fertility and management, water stress had a big impact on yield variability. Other factors like SCN and weeds had their impacts but were lower than the impact of water stress.

Booltink *et al.* (2001) described tools for managing spatial variability along with tools to optimize management in environmental and economic returns. They illustrated the tools in five case studies namely: low technology approach using participatory mapping to derive fertilizer recommendations for resource poor farmers in Kenya which uses user's expertise and expert knowledge, backward modelling to analyze fertilizer applications and restrict nitrogen losses to the groundwater in the Netherlands involving use of simple comprehensive methods including modeling, a low technology approach of precision agriculture developed for banana plantation in Costa Rica to achieve higher input use efficiency and insight in spatial and temporal variation involving use of simple comprehensive methods including modelling, high technology, forward modeling approach involving detailed methods including modelling focusing on one aspect only to derive fertilizer recommendations for management units in the Netherlands and a high technology approach to detect the relative effects of several factors on soya bean yield involving detailed methods including modelling which focus on one aspect only often with a disciplinary approach. They concluded that precision agriculture is not limited to the high-technological approaches. Low-technological participatory approaches can be used very well to apply site and temporal-specific forms of agriculture. The main challenge lies, according to the authors, in the quantification of spatial and temporal variation in crop performance, soil conditions and pest and disease pressure. Precision agriculture is claimed to manage fields with resolution as small as 1 m. However, a resolution as small as 0.1 ha was found to be unnecessary as it could increase the costs of implementing site-specific management practices. They concluded that a resolution of 0.1 ha could describe observed field variation.

One of the main problems in precision farming is estimating the spatial soil inputs required to calibrate crop models to historic yields. The calibration procedure requires excessive time when applied over many grid points within a field. Irmak *et al.* (2001) developed an efficient procedure for estimating spatially variable soil properties for the CROPGRO-Soya bean model. To estimate the spatially variable soil properties, the model was run to create data bases of predicted yields for combinations of soil parameters and a search algorithm was used to select the optimum sets of coefficients for each grid to minimize the root mean square errors in the predicted and measured yields. They demonstrated its use in diagnosing areas in the field where excess water or water stress reduce soya bean yield.

2.5 CLIMATE CHANGE

A number of models have been used in climate change research because the use of modelling is the only feasible way of predicting the likely impact that climate change might have on crop production in the future (Matthews *et al.*, 2002). Amongst other crop models, DSSAT v3.5 as reported by Hoogenboom *et al.* (1995) responds to changes in air temperature, solar radiant density and carbon dioxide concentration. They noted that the models under the DSSAT shell could be used to study the potential impacts of climate changes on agricultural production but further tests have to be carried out to improve the response of the models. Some examples illustrate where crop models, under the DSSAT shell and other models, have been applied for climate change research.

Brown and Rosenberg (1997) used Erosion productivity impact calculator (EPIC) to simulate climate change induced changes in air temperature, relative humidity, solar radiant density and carbon dioxide concentration and their impacts on yield and water use in corn, soya bean, winter wheat and sorghum. They found that increases in air temperature resulted in increases in phenological development for all crops, shortened time to maturity, lowered yields and decreased water use efficiency. In addition, increases in precipitation and water vapour pressure resulted in increases in yield (positive correlation) for all crops. Solar radiant density was also found to have positive correlation to changes in yield. Crop yield increased as carbon dioxide concentration increased provided that the negative effects of changes in air temperature, precipitation, water vapour pressure and solar radiant density were removed. The interactions between different climate variables resulted in a multiplicative decrease when humidity and precipitation are decreased and reduction in yield when solar radiant density is increased. They suggested that future studies of climate impacts should take into account all the climatic variables and atmospheric carbon dioxide and not just air temperature and precipitation.

Rosenzweig and Iglesias (1998) studied the effect of climate changes on precipitation and air temperature and their impacts on world crop production using CERES-Wheat, CERES-Maize, CERES-Rice and SOYGRO-Soya bean crop models. They reported that an increase in concentration of greenhouse gases induces climate change. This in turn affects crop yields differently from region to region across the world. Mid-and high-latitude regions are affected less in terms of crop yields compared to low latitude regions according to the climate change scenarios used. They tested certain adaptations like shifts in planting date, switch of crop variety and change in fertilizer applications and irrigation. They concluded that those adaptations were effective in lessening the detrimental effects of climate change.

Tubiello *et al.* (1999) used the CERES-Wheat model, modified to include leaf level photosynthesis, to study the effect of elevated carbon dioxide concentration on agricultural production. They tested whether model predictions of crop yields for climate-induced changes in weather variable scenarios are reliable or not. They found that crop phenology was not simulated accurately whereas dry matter and grain yield were simulated to within 10% of measured values. Evapotranspiration was undercalculated by 15% under well-watered conditions and simulated evapotranspiration was too low for the site considered. Simulated reductions in water loss due to elevated carbon dioxide concentration were found to be in agreement with measurements. They concluded that the ability of the model to simulate carbon dioxide concentration-water interactions is an important attribute of models used to project crop yields under elevated carbon dioxide concentrations.

Alexander and Hoogenboom (2000) used CERES- Maize and Wheat to study the impact of climate variability and change on crop yield in Bulgaria. They found that under the current levels of carbon dioxide (330 $\mu l\ l^{-1}$), the global circulation models (GCM) scenarios resulted in decreased yields of winter wheat and especially maize due to higher air temperature and lower precipitation. When elevated carbon dioxide concentration was used all the GCM scenarios resulted in an increase in winter wheat yield. They pointed out that shifts in planting date and hybrid selection had been reported to lessen the detrimental effects of climate change.

Rosenzweig and Tubiello (1996) employed CERES-Wheat, modified to include physiological effects of air temperature and carbon dioxide concentration on canopy photosynthesis, investigated the effects of changes in minimum and maximum air temperature on wheat yields in Central US. They were motivated to do the project by the recent observations and general circulation models indications that future air temperature shifts associated with global warming might be characterized by higher increases in nighttime minimum air temperature and lesser increases in day time air temperatures. They found that when minimum air temperature is increased more than maximum air temperature, the negative effects of air temperature on simulated wheat yields are reduced. Under current carbon dioxide concentration, air temperature changes were found to have negative impacts on yield whereas elevated carbon dioxide concentrations resulted in yield responses ranging from positive to negative.

Singh and Padilla (1995) simulated the response of rice to climate change using CERES-Rice crop simulation model. They concluded that carbon dioxide enrichment was found to have beneficial effects such as increased grain yields, reduced transpiration, increased water use efficiency, improved use of intercepted radiation, reduced nitrogen losses and increased nitrogen use efficiency. These beneficial effects were reversed with an increase in air temperature for all of the above parameters. They recommended that the negative effects of air temperature increase in warmer regions of the world could be offset by using rice varieties tolerant to high air temperature induced spikelet sterility and planting varieties with longer growth duration, particularly longer grain filling duration.

Baethegen and Magrin (1995) assessed the impacts of climate change on winter crop production in Uruguay and Argentina using CERES-Barley and CERES-Wheat crop simulation models. They found that crop simulation runs using the GCMs generated weather and sensitivity analysis indicated that wheat and barley production was more sensitive to an air temperature increase than rainfall change. They reported further that under expected climate change conditions in Uruguay, barley and wheat yields were lower, more variable and presented lower response to nitrogen fertilizer than under current conditions. A barley cultivar with a lower sensitivity to photoperiod length used was better adapted to increased air temperature than the wheat cultivar with higher sensitivity to photoperiod for late planting dates. The reverse was true for early planting dates. They also used the model to see the difference in grain yield between potentially high yielding areas and potentially low yielding areas.

Muchena and Iglesias (1995) studied the vulnerability of maize yields to climate change generated by global circulation models in different farming sectors in Zimbabwe. Similar to the findings of other workers, temperature increases of 2 °C and 4 °C reduced maize yields. However, maize yields decreased when the beneficial effects of carbon dioxide were included in the simulation under the global circulation models climate change scenarios. They noted that farming system changes like additional fertilizer, seed supplies and irrigation were found to compensate for some of the yield reductions under climate change but were reported to be costly.

Rao *et al.* (1995) studied the impact of climate change on sorghum productivity in India using CERES-Sorghum model with climate change scenarios generated by GCMs. The simulated results, like previous findings, showed that season lengths are shortened under climate change scenarios due to increases in air temperature. This would result, as reported by them, in decreased yield and water use. They found that these decreases in yield could be offset by direct enrichment of carbon dioxide, up to a 5 °C air temperature increase.

Seino (1995) used CERES-Rice, CERES-Wheat and CERES-Maize models to study climate change scenarios generated from three GCMs in Japan. They found that increased air temperature resulted in a reduction of simulated crop yield in many regions under present management systems. The beneficial effects of carbon dioxide concentration increases had been compensated in some parts of Japan and not others. Early planting and irrigation have been used as adaptation strategies. For most cases early planting increased simulated yield under climate change scenarios.

2.6 CROP MANAGEMENT

Alagarswamy *et al.* (2000) evaluated the CROPGRO-Soya bean model on Vertic Inceptisols in a climatologically variable semiarid tropical condition. They found that the model predicted the temporal changes in leaf area index, biomass and grain yield reasonably. In addition the model was used to develop a yield-evapotranspiration relationship and to assess the influence of soil water storage capacity on yield. They concluded that yield is linearly related to evapotranspiration and was reduced non-linearly as soil depth decreased. A soil depth reduction from 900 to 670 mm reduced yield minimally. Severe yield reductions were simulated when soil depth decreased below 450 mm and that 370 mm was found to be the threshold soil depth below which crop productivity cannot be sustained even in good rainfall years. Soya bean being an emerging commercial crop and the existence of a market driven economy which implies the need to grow more soya bean and to sustain more productivity, they recommended identification of niche areas for growing soya bean and developing appropriate and sustainable natural resource management technology in the soils studied.

Savin *et al.* (1995) assessed strategies for wheat cropping in the monsoonal climate of the Pampas using the CERES-Wheat simulation model and making use of 24 years of daily weather records. They found that there is a strong interaction amongst sowing date, site, cultivar, weed and year. It was noted that without limitations in nitrogen, maximum yields could be achieved by early sowing of the intermediate cycle cultivar. The reason for this was attributed partially to the greater water consumption of the crop during the crop cycle. In the lowest yielding years of both sites considered, the intermediate cultivar sown early did not appear to be the best option. In terms of stability of grain yield, latesowing of the short cycle cultivar was found to be effective. In years of low yield, for weedy fallows, the yield of the short cycle cultivar was more affected than the intermediate one.

Egli and Bruening (1992) evaluated the effects of planting date on yield of soya bean using a crop simulation model called SOYGRO using 17 years of weather data. They noted the interaction between nine planting dates, two cultivars and two row spacings and with natural rainfall or without water stress. The model accurately predicted observed yield responses for a planting date experiment at Lexington, USA and the combined general responses of other planting date experiments from several locations in Kentucky, USA. When there was no water stress, decreases in simulated yields from June plantings of one of the cultivars were reduced but not eliminated. When maximum and minimum air temperature was increased by 20% during reproductive growth simulated yield of 'williams' cultivar decreased in June planting dates but increased the yield of 'Essex' cultivar. It was explained that one of the causes of lower yields in delayed plantings is lower solar radiant density during the reproductive growth. For the late maturing cultivar low air temperatures contributed to lower yields.

de Vos and Mallet (1987) evaluated CERES-Maize and CORNF maize growth simulation models developed in the USA using data from South Africa. They found that both models agreed well with observed values of total above ground plant dry mass, leaf area index and soil water content. Realistic estimation of soil water content and leaf area index had been achieved by CERES-Maize as compared to CORNF. Both models, however, performed poorly in predicting soil water content at Cedara, Kwazulu-Natal, South Africa. They concluded that before those models can be used for general crop management decision making in South Africa, further validation works would have to be undertaken. It has also been suggested that modifications of the models to take into account specific local situations like the use of very wide row spacings in the western maize growing areas is necessary. In addition genetic coefficients, needed as inputs to the CERES-Maize model, are not available for local cultivars and need to be determined experimentally. They further pointed that soil parameters, inputs required to run the models, need to be compiled for South Africa's summer grain cropping region.

Jintrawet (1995) used the CERES-Rice model to simulate rice based cropping alternatives in Thailand. A process oriented rice model was employed and an analytical tool for answering several 'what if' questions. The validated model was able to simulate low yields obtained by farmers in north-east Thailand areas and relatively higher grain yields in northern Thailand areas. He concluded that the model could be used to find alternative ways to improve farm performance with regard to rice production. However, he points out that the effect of pests on yield loss has to be taken into account to improve the performance of the model. To be able to use the model for decision-making, he recommends, at the farm to policy levels, minimum data set of soil, crop and weather should be assembled for the country as a whole.

Jame and Cutforth (1996) pointed that traditional/conventional experience based on agronomic research have certain weaknesses because crop production functions are derived from statistical analyses instead of referring to the underlying biological or physical principles. They noted that the advent of computers and in-depth knowledge of plant growth processes led to the development of decision support systems like the Decision Support Systems for Agro-technology Transfer (DSSAT) which has the capability of assisting in making decisions for field level crop management. They pointed out that after proper validation, models can be used to test alternative crop management options and to predict crop responses to different environments that are either the result of global change or induced by agricultural management.

2.7 OTHER APPLICATIONS

Besides the applications mentioned in this chapter, the models under the DSSAT shell have been applied for some other applications. Jones (2002) listed the following workers and the area where the crop models were applied. He reported that Castrigano *et al.* (1997) and Andales *et al.* (2000) used the models for tillage management. Others such as Hoffmann and Ritchie (1993) used the model for sustainability issues. Booltink and Verhagen (1997), Gerakis and Ritchie (1998) employed the models in environmental pollution applications. Ferreyra *et al.* (2001), Chipansi *et al.* (1997) and Chipansi *et al.* (1999) used the CERES-Maize and CERES-Wheat models respectively for yield forecasting. Mavromatis *et al.*

(2001), Piper *et al.* (1996), Piper *et al.* (1998) and Colson *et al.* (1995) used CROPGRO-Soya bean and SOYGRO models respectively for variety evaluation. MacRobert and Savage (1998) used the CERES model for irrigation management.

2.8 CONCLUSIONS

The models under the DSSAT v3.5 shell have been applied successfully for various applications. Such successful applications which have agricultural significance include: yield-gap analysis, fertilizer management, precision farming, climate change and variability, crop management, and for other applications such as tillage management, sustainability issues, environmental pollution applications, yield forecasting, variety evaluation and irrigation management.

Any model used for a different purpose or at a different location needs to be calibrated and verified. To this end, the following chapters are concerned with: calibrating the soil water balance routines of the CROPGRO-Tomato (Ukulinga, KwaZulu-Natal, South Africa) and CROPGRO-Soya bean (Cedara, KwaZulu-Natal, South Africa) by modifying some of its inputs and verification of some of the model outputs; sensitivity analyses of the soil water balance input parameters; application of the CROPGRO-Tomato for long term risk assessment for soil, plant and weather conditions at Ukulinga; and use of the CROPGRO-Soya bean for evaluation of Soya bean cultural practices using long term weather data for soil, plant and weather conditions at Cedara, KwaZulu-Natal, South Africa.

CHAPTER 3

GENERAL MATERIALS AND METHODS

3.1 SITE DESCRIPTION AND INTRUMENTATION OVERVIEW

UKULINGA

A tomato crop (*Lycopersicon esculentum*) was grown at Ukulinga (latitude $\approx$ 29.67^{o}S, longitude $\approx$ 30.4^{o}E and altitude $\approx$ 775 m above sea level), KwaZulu-Natal, South Africa. The field had a slope of 1% in the E-W direction. It was bordered on the north by a farm road, on the south by a gooseberry crop, on the east by a fallow land and on the west by a farm road. The average annual rainfall, average maximum air temperature and average minimum air temperature of the site are approximately 724 mm, 38^{o}C and 3^{o}C respectively. Further details are described in Appendix 1.

Weather variables like minimum and maximum air temperature, relative humidity, solar irradiance, wind speed, wind direction and rainfall were measured using an automatic weather station system to use them as inputs for running the DSSAT model. In addition photosynthetic photon flux density inside and outside the shade cloth was measured, which is an optional input to the model. Besides soil water content was measured at two depths using ThetaProbes (Delta-T Devices, type ML1, Cambridge, UK). Thermocouple averagers (copper-constantan) were installed to measure soil temperature at four depths in the soil profile. Moreover, ET-gage (ET-gage company, model E, Loveland, USA) was also used to measure referenece evapotranspiration. An infrared thermometer (Everest Interscience Inc., 4000 ALCS model, Fullerton, CA, USA) was mounted together with the other sensors to measure crop surface temperature. A Campbell Scientific 21X datalogger was used for automatic measurement of outputs from all the sensors. Two batteries were used to power the sensors and another two batteries to power the datalogger.

To make sure that the tomato crop (Plate 3.1) grows without fungi, a fungicide called Dathane was applied every week and to prevent pests, a pesticide called Cypemerthrin was applied every week. In addition fertilizer was applied to avoid nutrient deficiency.

Plate 3.1 The experimental area planted with tomatoes and shaded with a white net having 70 % transmittance to solar irradiance (Photo MJ Savage)

The soil at Ukulinga is a poorly drained clay soil with high swelling potential. Soil properties such as drained upper and lower soil water content, bulk density, soil texture and others which are important as model inputs, were also determined in the laboratory, and some of them using models. Bulk density was determined for seven depths of the soil profile using conventional laboratory procedures. Soil texture and organic matter were also determined using laboratory procedures. Upper and lower limits of soil water availability were determined using models that need soil texture, bulk density and organic matter as inputs and using laboratory methods (Appendix 3).

CEDARA

Soya bean (*Glycine max* L. Merr.) was grown at Cedara (latitude ≈ 29.53°S, longitude ≈ 30.28°E and altitude ≈ 1076 m above sea level), KwaZulu-Natal, South Africa. The field had a slope of 6% in the N-S direction. It was bordered on the north by a maize planted field, on the south by another soya bean planted field, on the east by a farm road on the west again by a farm road. The average annual rainfall, average maximum air temperature and average minimum air temperature of the site is approximately 874.2

mm, 30.6 °C and 4.7 °C respectively (Agricultural Research Council, Institute for Soil Climate and Water, Pretoria).

Weather data for Cedara research station was collected from an automatic weather station installed nearby the soya bean field. Soil data such as drained upper limit and lower limit, bulk density, soil texture and the like were collected from the site following the same procedures used at Ukulinga research station. Other plant and soil related data collection procedures are described along with that of Ukulinga experiment site.

3.2 DATALOGGER AND POWER SUPPLY

The 21X datalogger (Plate 3.2) was placed in a small metal box housed in a bigger container. It was made sure that the logger was at all times prevented from direct entry of solar irradiance by keeping the box closed. The key to the box was always closed to avoid theft and the interior of the logger was kept dry using silica gel.

A number of sensors were connected to the logger and hence differential measurements were not possible. Instead, the single-ended option that is less accurate than the differential measurement but which allows more sensors to be used was employed for the trial.

The data recorded by the datalogger was retrieved every week to a storage module (SM 192). The SM was connected to the 9-pin serial input/output port on the datalogger for retrieving data. The command used was *9 30 A 1A A 3A. The peripheral storage device was left connected to the datalogger to avoid loss of data in case of power failure or in cases where the data logger memory was full. To transfer program to/from the logger to/from SM, the command *D 71 A 28 A was used for storage in SM area 8.

Regarding power supply, two batteries were connected in parallel to power the 21X datalogger and another two batteries were used to power the sensors. This was done to increase the lifetime of the batteries. An electronic circuit connected to the batteries ensured that the sensors were powered for only a fraction of the total scan rate of the datalogger. This increased the lifetime of the batteries appreciably. When replacing old batteries, one battery was left connected to

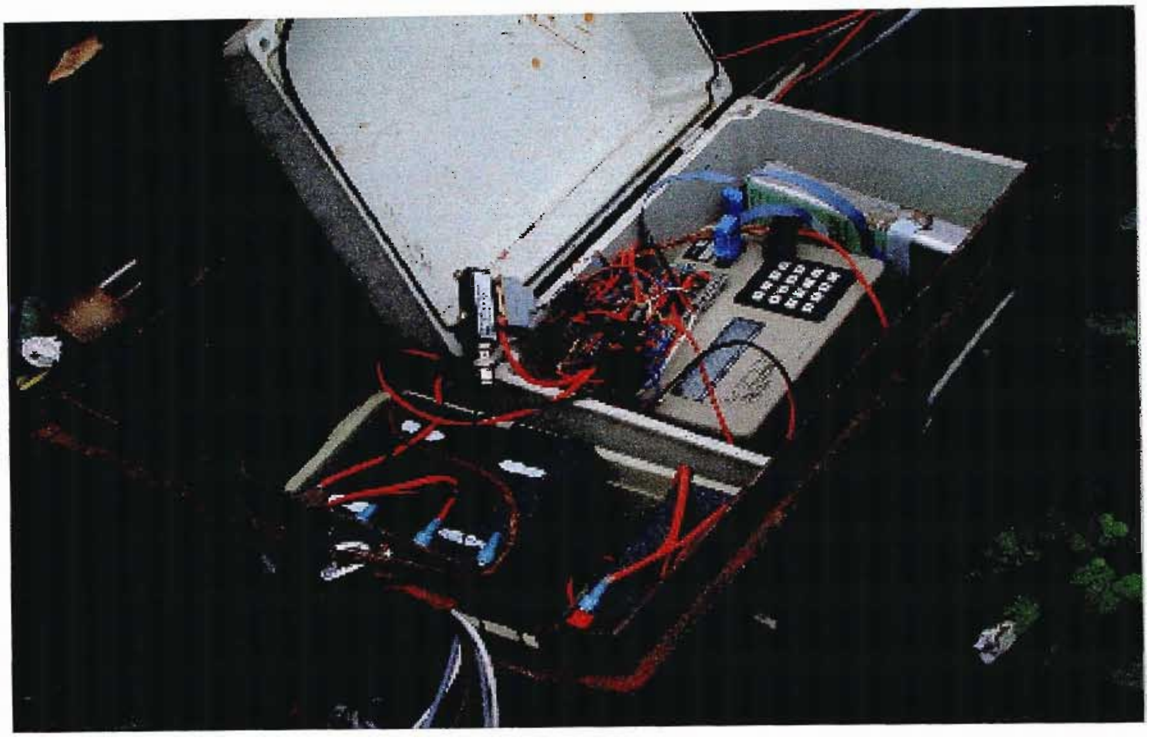


Plate 3.2 The 21X data logger with SM 192 storage module, batteries, wires from the sensors and the metal box (Photo MJ Savage)

the logger to avoid loss of a program and the same procedure was followed when changing batteries for the sensors. To protect the sensors from lightning, the ground of the datalogger was earth grounded using a lightning rod.

Appendix 2 gives the programs used for field measurements of the various meteorological and soil water-measuring instruments.

3.3 MEASUREMENT OF WEATHER VARIABLES

3.3.1 Solar Irradiance

Two pyranometers (Kipp and Zonen, model CM3, Delft, Holland), one inside and the other outside the shade cloth, were used to measure solar irradiance. One of them was installed inside the shade cloth at Ukulinga on September 11, 2002 replacing the Middleton solarimeter (Plate 3.3 in the middle upper part), installed inside the shade at the out set of the experiment. The other CM3 sensor was installed outside the shade for comparison to the inside one. To ensure that no shadow was cast on the sensors, they were mounted facing south because the sun comes from north. The sensors were

Plate 3.3 An automatic weather station system for the measurement of solar irradiance, air temperature, relative humidity, wind speed, wind direction, rainfall and additionally for the measurement of soil temperature and soil water content (Photo MJ Savage)

mounted at a height of 2 m above the soil surface to avoid shading effects of the instrument on the soil and to promote spatial averaging of the measurement.

The CM3 sensor consists of a thermopile sensor coated with a black absorbent coating, a housing, a glass dome and a cable. The principle of measurement is that the paint absorbs the radiation and converts it to heat. The resulting heat flow causes a temperature difference across the thermopile. The thermopile generates a voltage output (Kipp and Zonen, 1999).

A solarimeter (Middleton Instruments, model EP207, Melbourne, Australia) was also used at the outset of the experiment at Ukulinga. The sensor has glass domes used to remove long wavelengths and reduce the influence of wind. To dry the atmosphere inside the dome, dried silica gel was used. The silica gel was replaced when its colour changed from blue to white pink.

3.3.2 Photosynthetic Photon Flux Density (PPFD)

PPFD was measured using two quantum sensors (Li-Cor, Inc., model line quantum, USA), one inside the shade and other outside the shade at Ukulinga. The sensor is ideal for measuring photosynthetically active radiation in plant canopies where radiation is non-uniform. It has a one-meter length sensing area to achieve this. The sensor was used to permanently monitor PPFD within the canopy and it was left unattended because it is fully weather proof. The sensor was mounted on a 1500 mm stand in an east-west orientation. In addition it was maintained in a level position as much as possible.

3.3.3 Rainfall

Spoon rain gauge (Pronamic Co. Ltd, model Rain-o-matic, Silkeborg, Denmark) was used to measure rainfall inside the shade cloth at Ukulinga and in the open field at Cedara. It is like a tipping bucket rain gauge in the sense that the rain collector's measuring spoon is automatically tipped and emptied when the pre-adjusted water weight has been reached. It has a magnet attached to the tipping mechanism that activates a switch. One activation is equal to one tip or 1 mm of rainfall. It has three parts namely: the funnel, the box and the base plate. The smallest possible reading that it can detect is 1 mm. Pronamic Co. Ltd (2002) noted that it is one of the most accurate rain gauges available on the market.

The sensor was mounted at the top of a 1 m stand firmly buried into the ground. During installation the sensor was not obstructed by any of the sensors nearby and foreign elements. It was leveled as accurately as possible using a spirit level.

3.3.4 Air Temperature and Relative Humidity

Temperature and relative humidity sensor (Campbell Scientific Inc., model HMP45C, USA) (Plate 3.3 middle lower part) was used to measure air temperature and relative humidity. It contained a Platinum Temperature Detector (PTD) and a Vaisala HUMICAP 180 capacitive relative humidity sensor. It can measure temperature between $-40\ ^{0}C$ to $+60\ ^{0}C$ and from 0 to 100% non-condensing relative humidity. In the field, the sensor was housed in a Model 41002-12-plate Gill radiation shield. The sensor and hence the shield were mounted on a 1500 mm high stand. It was connected to the data logger according to the sensor's instruction manual. Both air temperature and relative humidity could be measured using single ended voltage measurements, as was used for this experiment, but the accuracy is less than differential voltage measurements.

Two HOBO H8 data loggers (Onset Computer Corporation, model RH/Temp/ 2×External, Bourne, MA, USA) have been used to measure and compare air temperature and relative humidity inside and outside the shade at Ukulinga. An interface cable has been connected into the 3.5 mm jack on the logger and into the serial port of the computer to launch the logger. Then the sensor was mounted by sticking a wire on the back of the HOBO H8 and attaching it to the top inside part of the Stevenson Screen. After the required measurements were taken, the HOBO data logger was reconnected to the interface cable and BoxCar Pro software was started and then under the menu bar '*readout*' was selected.

The HOBO H8 data logger consists of a thermistor temperature sensor, light intensity sensor, relative humidity sensor enclosed in a plastic box containing a small battery and electronics to keep time and store temperature, relative humidity, and light intensity. The logger has also an external port for temperature or voltage measurement (Onset Computer Corporation, 1997-1998).

The HOBO H8 datalogger is inexpensive and user friendly as compared to automatic weather station system. It has limitations of memory capacity where there is a need for high frequency measurements and is also limited by the absence of data telecommunications capability. The logger can also be affected by radiation, humidity and rain and hence necessitating a radiation shield.

3.3.5 Wind Speed and Wind Direction

Wind speed and direction sensor (RM Young company, model 03001 wind sentry, USA) (Plate 3.3 on the left hand side) was used to measure wind speed and direction at Ukulinga. Both of the sensors were mounted at the top of 2 m stand. When the wind direction was installed, it was made sure that it read 0° or 360° when facing to magnetic north. Blowing air near the wind speed sensor was used as means to check whether the sensor was working. The sensor was used using the manufacturer's calibration.

The principle of measurement of wind speed by the cup anemometer is that the rotation of its cup wheel produces an AC sine wave that is directly proportional to wind speed. The datalogger pulse channel measures the frequency of AC signal and converts it to m s^{-1}. The minimum wind speed that the sensor can detect is 0.5 m s^{-1}. It can measure wind speed between 0 and 50 m s^{-1} and can survive a wind speed as much as 60 m s^{-1}. The wind direction sensor has a potentiometer that is supplied with precision excitation voltage from the datalogger. The output signal, an analog voltage, is directly proportional to the azimuth of the wind direction sensor. It has a mechanical range of 360° and electrical range of 355° with 5° open.

3.3.6 Reference Evapotranspiration

ET-gauge (ET-gage company, model E, Loveland, USA) was used to measure reference evapotranspiration at Ukulinga (inside the shade cloth) and Cedara. The number 54-canvas cover, made to resist escaping water vapor and that gives ET-gage readings 10-15 % greater than the number 30 canvas cover, was used as recommended for agricultural crops by the manufacturer. To protect the ceramic cup from contamination, a disposable ET-gage 'wafer' was used between the canvas cover and the ceramic evaporator surface. Any residues left from the evaporating surface would accumulate in the wafer instead of on the surface of the ceramic cup. The instrument was installed in an irrigated location making sure that it was not obstructed from wind and sunlight. It was mounted so that the canvas covered evaporation surface was 1000 mm above the ground level. To avoid birds from perching on the instrument, two six inch 'bird wires' were inserted under the silicone rubber band and into a hole.

The ET-gauge evaporimeter was chosen because it doesn't have problems of rainfall adding water or thirsty animals wandering in the area drinking from the pan as is the case of Class-A pan evaporimeter. It has a canvas cover instead of a free water surface that responds similarly to a crop surface. It can also be attached to a datalogger for continuous measurements.

3.4 MEASUREMENT OF SOIL PARAMETERS

3.4.1 Soil Bulk Density

Bulk density was determined using a core sampler that comprises of long tubes 1000 mm in length. Undisturbed soil cores, with diameter of approximately 48 mm, length 50 mm were taken at 100 mm, 200 mm, 300 mm, 400 mm, 500 mm, and 600 mm at Ukulinga. Similarly, at Cedara soil cores were taken at 100 mm, 200 mm, 300 mm, 400 mm, 500 mm, 600 mm, 700 mm, 800 mm, 900 mm, and 1000 mm. In the latter case, samples were taken to a depth of 1000 mm because rooting depth of soya bean extends to 1000 mm, while for tomato rooting depth is quite shallow, not exceeding 600 mm. Dalgliesh *et al.* (1998) pointed out that in soils which exhibit shrink/ swell characteristics, bulk density should be measured at its drained upper limit soil water content. Therefore, the core samples for both sites were taken when the soil water content was approximately at its drained upper limit because the soils considered exhibit shrink/ swell characteristics. This was done to avoid complications associated with accounting for cracks at lower water contents (Dalgliesh *et al.*, 1998). The core samples were oven dried at 105°C for 24 hours and the mass was determined. As shown in Appendix 3 bulk density (kg m^{-3}) was then calculated for all the samples from Ukulinga by dividing the mass of the oven-dried soil (kg) by volume of the core (m^3). The same procedure was followed for calculating bulk density for the samples from Cedara.

3.4.2 Soil Texture and Organic Carbon

Both soil texture and organic carbon were analyzed at KwaZulu-Natal Department of Agriculture and Environmental Affairs, Soil Fertility and Analytical Services.

3.4.3 Drained Upper Limit and Lower Limit

A porous plate and hanging water column could be used to determine drained upper limit. To do this, suction is applied to the water-saturated core. Then the water content of the sample could be determined by taking the mass when equilibrium with that particular suction has been reached. In the field drained upper limit could be determined using a drainage curve. The soil water content at which decreases in soil water with time is negligible is taken to be the drained upper limit (Ratliff *et al.*, 1983). All of the above methods are time consuming and laborious and hence the use of models to estimate the limits becomes necessary to facilitate the application of crop model technology. A texture and bulk density based regression equation, developed by Schulze *et al.* (1985) to estimate the soil water content at various matric potentials, has been used to determine the drained upper limit. For purposes of comparison, the regression equation developed by Hutson (1986) has also been used to estimate the drained upper limit. Appendix 3 shows the calculated results from those equations.

The models mentioned above have been also used to estimate the lower limit (Appendix 3). However, it can also be determined in the laboratory using pressure plate extractors housed in a pressure chamber. The chamber is sealed and the required pressure applied. Then water will move out in response to the applied pressure until the negative pressure of the soil water matches the positive air pressure. The chamber can then be dismantled and the water content of the core measured. The positive pressure applied is taken to be -1500 kPa (Savage *et al.*, 1996) for lower limit determinations. In the field lower limit could be taken as field measured water content of a soil after plants had stopped extracting water and were at or near premature death or become dormant or became dormant as a result of water stress (Ratliff *et al.*, 1983).

3.4.4 Soil Temperature

Type T thermocouple (copper-constantan thermocouples) have been used to measure soil temperature at 150 mm, 300 mm, 450 mm and 600 mm depth with in the soil profile at Ukulinga. The individual sensors were placed with depth ensuring that a greater length of wire than at the measurement depth was buried to reduce heat transfer along the wires to the point of measurement . Like the other sensors, it was connected to a 21X datalogger to take 15-minute measurements of soil temperature.

The temperature range for this type of thermocouple is between –200 and 350°C (Savage, 1999).

3.4.5 Soil Water Content

Soil water content was monitored for certain months of the growing seasons for tomato and soya bean crops. For this purpose ThetaProbe (Delta-T Devices, type ML1, Cambridge, UK), a frequency domain reflectometry sensor, was used for tomato grown at Ukulinga while a PR1 Profile Probe (Delta-T Devices, type PR1, Cambridge, UK) was used for the soya bean crop at Cedara.

Two ML1 ThetaProbes were used to take measurements of soil water content at two depths (150 to 300 mm and 450 to 600 mm) for the tomato crop at Ukulinga.

The ML1 ThetaProbe's output depends on the frequency shift or ratio between the oscillator (for 100 MHz signal) voltage and that reflected by rods installed in the soil. The ratio of the two voltages is dependent essentially on the apparent dielectric constant of the soil, which is determined by the soil water content. The dielectric constant of pure water is around 80 at 20°C, which is much larger than that of soil materials (~ 2.5). Hence the soil water content predominantly determines dielectric constant of moist soil (Delta-T Devices, 1995; Schelde, 1996).

Delta-T Devices (1995) pointed that a fifth order polynomial of the sensor analog output voltage V (in volts) could be used to estimate the square root of the dielectric constant of the soil as follows:

$$\sqrt{\varepsilon} = 1 + 6.19V - 9.72V^2 + 24.35V^3 - 30.84V^4 + 14.73V^5 \qquad 3.1$$

The soil water content θ_v ($m^3\ m^{-3}$) is calculated from the square root of the apparent dielectric constant by using soil calibration constants a_0 and a_1.

$$\theta_v = (\sqrt{\varepsilon} - a_0)/\ a_1 \qquad 3.2$$

where $a_0 = \sqrt{\varepsilon_0}$ is the square root of the apparent dielectric constant obtained using Theta Probe voltage measured in air-dry soil. The term $a_1 = (\sqrt{\varepsilon} - \sqrt{\varepsilon_0})/\theta_{vs}$ where θ_{vs} is the soil water content at saturation, $\sqrt{\varepsilon}$ is the square root of the dielectric constant of saturated soil and $\sqrt{\varepsilon_0}$ is the square root of dielectric constant of a dry soil.

For the soil water content measurements at Ukulinga, factory values for a_0 and a_1 of 8.4 and 1.6 for mineral and 7.8 and 1.3 for organic soil were used respectively. This was done because the sensor gives precise results without soil specific calibration. To substantiate this fact, measurements of soil water content at three locations within KwaZulu-Natal, South Africa using ThetaProbes (FDR sensor) gave good results, even when using the factory-supplied calibration factors, and were found to be insensitive to temperature, bulk density and clay content variations in the soil (Ripley *et al.*, 1998). Delta-T devices (2001) suggest that a soil specific calibration curve is necessary if the soil is heavy clay, highly organic or in some respect "extreme". In addition, site specific calibration is needed if one is working to high levels of accuracy or if one needs a controlled error figure rather than a "typical" error figure and that the soil is not very stony and does not crack when it dries.

Delta-T Profile Probe type PR1 was used to take measurements of soil water content, θ_v (m^3 m^{-3}) at six points (100 mm, 200 mm, 300 mm, 400 mm, 600 mm and 1000 mm) within the vertical profile at different depths for soya bean crop at Cedara. The sensor was used in access tubes (28 mm in diameter) for rapid insertion and removal. The diameter of the access tubes is small and hence minimizes soil disturbance. To ensure maximum soil contact when installing the access tubes, holes were augured slightly undersize (25 mm in diameter). The sensor was then moved from one access tube to another collecting instantaneous measurements by connecting it to an HH2 meter.

3.5 MEASUREMENT OF PLANT PARAMETERS

3.5.1 Leaf Area Index Measurements

The LAI-2000 plant canopy analyzer (PCA) estimates LAI based on a model developed by Miller (1967). The model uses a canopy gap fraction method to relate leaf area to the probability that a ray of light from a given zenith angle will pass uninterrupted through a plant canopy. Foliage elements are assumed to be small as compared to the canopy dimensions and are randomly distributed.

LAI-2000 plant canopy analyzer (PCA) developed by Li-Cor (Lincoln, NE) was used to measure leaf area index (LAI). The PCA is not to be used to make LAI determinations in direct sunlight because leaf reflectance and transmittance of light will result in an overestimation of LAI (Li-Cor, 1990). In this study measurements of LAI were made at midday despite direct sunlight by shading both the sensor and sampling area with a white umbrella (2560 mm in diameter) that was manually held in place to block the direct rays of the sun. Measurements with the PCA were obtained throughout the season at the same marked locations.

Li-Cor (1991, pD1-3), cited by Hicks and Lascano (1995), described a sampling method for heterogeneous canopies. This method was used for the measurements of LAI throughout the season. It involves taking below-canopy measurements on two transects with a 45° field of view cap. The first transect was obtained by making one above canopy and four below canopy measurements parallel to the row direction. The below canopy readings were obtained directly underneath the row and at one-quarter, one-half and three quarters of the distance between the rows in a diagonal transect. The field-of-view cap was then turned perpendicular to the row direction and above-canopy and below-canopy measurements were obtained in the same locations for the second transect. As described by Hicks and Lascano (1995), the LAI was then calculated from the logarithmic average of the canopy non-interceptance (below-canopy reading divided by above-canopy reading) for each zenith angle class measured within a transect. The two transects were then averaged to obtain a LAI value for the sampled site. This method allowed the sparse and dense portions of the canopy to be measured in separate below-canopy measurements and natural logarithmic averages obtained.

The parallel-to-row transect was made with the sensor's 45^{o} azimuthal field-of-view facing east and the perpendicular transects were made facing south while sampling from south west to north east. This was done because the rows of the tomato crop were oriented east west.

3.6 DATA HANDLING AND ANALYSIS

The raw data from the data logger were retrieved to SM 192 storage module. This data were in turn extracted using PC208 datalogger support software (Campbell Scientific, 2001). The data collected this way throughout the growing season were merged into large input files for use in the data-processing module of the PC-208 software. This procedure allowed the creation of the minimum weather parameters required for model operation, evaluation, and calibration.

For model evaluation and calibration statistical parameters such as the correlation coefficient (r^2), root mean square error (*RMSE*), systematic and unsystematic root mean square error ($RMSE_s$ and $RMSE_u$), index of agreement (d) and the bias were calculated. For calculating these statistical parameters, a spreadsheet for model evaluation (Savage, 1998) was employed.

To fill the missing data points, the data were first tested for homogeneity with a nearby weather station at the Cedara Agricultural College. To do the test regression analysis, available in Excel (Windows 2000), was used.

CHAPTER 4

INPUT REQUIREMENTS OF THE MODEL

4.1 INTRODUCTION

The International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT) has recognized the importance of availability of data for model operation, calibration and evaluation. They emphasized the need for a minimum dataset to maintain a balanced set of information on weather during the growing cycle, soil characteristics at the start of the growing season, management of the crop and cultivar traits. The weather data needed as inputs to the soil water balance sub model include daily records of solar radiant density, minimum and maximum air temperatures and precipitation. It is reported that there was a tendency by some workers to include other weather parameters such as relative humidity, wind speed and pan evaporation as part of the minimum data set (Hunt and Boote, 1998). This was not accepted so as to make the model inputs as simple as possible. Soil data required are soil texture, bulk density, root weighing factor for each depth, drained upper and lower soil water limits, soil reflection coefficient, drainage coefficient and runoff curve number. Crop management data like sowing or emergence dates, harvest dates, amounts and dates of irrigation and the genetic coefficients are also required.

The objectives of this chapter are:

1. to complete the missing data sets of the weather parameters from nearby automatic weather station namely that of Cedara and Ukulinga meteorological stations for use with DSSAT group of models;
2. to compare the factory given transmission of the shade cloth to actual measurements;
3. to create the minimum data set (weather, soil and crop management parameters) necessary to run the soil water balance model for DSSAT v3.5.

4.2 THEORY

The inputs needed to run the soil water balance sub model in DSSAT v3.5, as mentioned in the introductory part of this Chapter, are required in the model because of their significant contribution to plant growth and development. The importance of each input is discussed in the following paragraphs.

Daily records of solar radiant density are required in the soil water balance sub model of the DSSAT group of crop models primarily because it is used for the estimation of potential evapotranspiration either in the Priestley-Taylor (1972) or Penman-Monteith equations. It is needed in the crop growth and development part of the crop models because it is the energy source for photosynthesis. It has been experimentally shown that at lower irradiance levels, the rate of photosynthesis and hence production increases linearly with increase in photosynthetic irradiance. But at higher irradiance levels, the rate of photosynthesis levels off and beyond certain levels it does not have positive effect on photosynthesis. Boote *et al.* (1998) found that daily solar radiant density showed a gradual saturation of daily photosynthesis starting at 20 MJ m^{-2} for an hourly model using soya bean parameters and conditions.

The maximum and minimum air temperature data are also used for the calculation of potential evapotranspiration in the soil water balance subroutine of the model that uses the Priestley-Taylor (1972) equation or the Penman-Monteith equation. It controls most plant biochemical processes including photosynthesis, respiration, and the rates of organ initiation and expansion or plant growth and development (Acock and Acock, 1991; Weikai and Hunt, 1999).

Rainfall is a very important input in crop growth models. It indirectly affects plant processes in that it determines the amount of water available for transpiration and evaporation from the soil surface (Acock and Acock, 1991; Hoogenboom, 2000). When the soil surface is dry due to low rainfall, the leaves will loose turgor pressure. This will consequently result to closure of stomata and hence reduction of assimilation and transpiration. The ultimate result will be changes in partitioning of biomass and hence reduction in yield. Hoogenboom (2000) mentions factors such as the potential evapotranspiration, extractable soil water content in the rooting zone, root distribution, canopy size, and other plant and environmental components as some of the factors affecting drought. The degree to which plants are affected by drought is dependent upon the species or cultivar. If there is excess water in the soil due to intense rainfall events, it might result in the leaching of nutrients. Also, it could result in a lack of oxygen in the rooting zone, required for root growth and respiration. As a result root activities might slow down and thus cause increased root senescence and root death rates. The ultimate result of this would be the reduction of water uptake and hence reduction of plant growth and development. Contrary to the situations discussed above Penman (1971) noted that some plants like sugar beet and kale, after a certain period of dormancy due to drought, could show signs of growth.

Plant available water is taken to be the difference between drained upper and lower limits of soil water availability. It is important to note, however, that water above the drained upper limit can be taken up while drainage is occurring. In addition plant growth can be retarded before the lower limit is reached or in other cases water extraction by roots may continue beyond the -1.5 kJ kg^{-1} range (Ritchie, 1981). Despite these shortcomings the two limits are very important for many agronomic applications and for the development of plant growth and crop management models (Cassel *et al.*, 1983) such as the DSSAT group of crop models.

Soil texture is needed to determine the drained upper and lower limits of soil water availability in cases where field measurements of those parameters are not available. Bulk density inputs are important because of their effect on root growth and movement of water (Acock and Acock, 1991).

The soil water balance sub model of the DSSAT group of crop models requires calculation of potential evapotranspiration from the soil and plant surfaces. Calculation of potential evapotranspiration in turn requires an approximation of daytime air temperature and the soil-plant reflection coefficient for solar irradiance. The Ritchie (1985) soil water balance model calculates the combined crop and soil reflection coefficient from the model-calculated leaf area index (LAI) and the input of the bare soil reflection coefficient. As pointed out by Hanks and Ashcroft (1980) the value of this reflection coefficient for most natural conditions varies from about 0.10 to 0.30 with an average value of 0.20.

It has already been described that the drained upper limit soil water content is not the appropriate upper limit of soil water availability because plants can take up water while drainage is occurring. Although the drainage rates of soil vary greatly, most agricultural soils especially clay soils drain quite slowly and may provide an appreciable quantity of water to plants before drainage stops. Soil water conductivity or the drainage coefficient varies between 0 and 1. It represents the fraction of water between the actual water content and the drained upper limit that drains in one day. As described in the Ritchie (1985) soil water balance model, water content would decrease to half of the difference between saturated water content and upper limit soil water content in one day if the coefficient were 0.5. Half of the remaining water content between the limits would drain on the second day and so forth (Singh, 2002).

Runoff is one of the important components in soil water balance calculations especially under rainfed agriculture. In irrigated agriculture and particularly drip irrigation systems runoff can be taken to be zero because almost all of the water supplied seeps into the ground. This may not be a reasonable assumption for all circumstances in South Africa and if the crop is exposed to heavy rainstorms.

Boote *et al.* (1998), cited by Mavromatis *et al.* (2001), explained that cultivar specific coefficients are required to predict daily growth and development as the plant responds to weather, soil characteristics and management practices. Other parts of the model are expected to work properly if and only if the phasic development in the model is correct because the duration of crop growth is directly proportional to productivity. The dates of flowering or similar phenological events usually come from an experiment where air temperature was measured. If the simulated event does not match the measured event, one has to make sure first that there was no error in the measurement of air temperature due to bias in the measuring equipment. In some instances, the assumption that tissue temperature is similar to air temperature may be inaccurate (Acock and Acock, 1991;

Ritchie and NeSmith, 1991). Besides the instrument may be some distance away from the experimental site and this is of importance where the elevation between the sensor and the field is different (Ritchie and NeSmith, 1991).

Crop management data such as sowing or emergence dates and harvest dates are required mainly for the start and end of simulation. If the crop is irrigated, data on dates and amounts of irrigation are important for the simple reason that irrigation influences soil water and hence water use by the plant. Other inputs like leaf area index or percent photosynthetically active radiation (PAR) interception, extinction coefficient and radiation use efficiency are required if the Ritchie (1985) soil water balance model is run on its own. The parameters are estimated if the model is a sub model of larger crop growth model such as CERES, CROPGRO and others (Singh, 2002).

4.3 MATERIALS AND METHODS

A tomato crop (*Lycopersicon esculentum*) was grown at Ukulinga (latitude ≈ 29.67°S, longitude ≈ 30.4°E and altitude ≈ 775 m), KwaZulu-Natal, South Africa. The field has a slope of 1% in the E-W direction. It is bordered on the north by a farm road, on the south by a gooseberry crop, on the east by fallow land and on the west by a farm road. The average annual rainfall, average maximum and minimum air temperature of the site is approximately 724 mm, 38°C and 3°C respectively (Agricultural Research Council, Institute for Soil, Climate and Water, Pretoria).

Two pyranometers (Kipp and Zonen, model CM3, Delft, Holland), one inside the shade cloth where the tomato crop was grown and the other outside the shade cloth, were used to measure solar irradiance. A spoon rain gauge (Pronamic Co. Ltd, model Rain-o-matic, Silkeborg, Denmark) was used to measure rainfall at the site. An air temperature and relative humidity sensor (Campbell Scientific Inc., model HMP45C, Logan, USA) was also used to measure air temperature and relative humidity (Plate 4.1 middle part). The sensors were connected to a 21X datalogger programmed to take 15-minute interval measurements (based on a 10-s sample period) throughout the crop-growing season. In addition, two HOBO H8 data loggers (Onset Computer Corporation, model RH/Temp/

2×External, Bourne, MA, USA) were used to measure 15-minute interval air temperature and relative humidity inside and outside the shade at Ukulinga. The Campbell scientific PC208 software (Split version 1.7) was used to merge the 15-minute data into a daily data as required by the DSSAT group of models. The missing data points which resulted due battery failure or problems with the sensors during the course of the growing season were completed using procedures described by Allen *et al.* (1998).

Bulk density was determined using a core sampler that comprises of long tubes 1000 mm in length. Undisturbed soil cores, with diameter of approximately 48 mm, length 50 mm were taken at 100 mm, 200 mm, 300 mm, 400 mm, 500 mm, and 600 mm at Ukulinga because tomato has a rooting depth that is quite shallow, not exceeding 600 mm. The core samples were then oven dried at 105 °C for 24 hours and the mass was determined. Bulk density (kg m^{-3}) was then calculated for all the samples by dividing the mass of the oven-dried soil (kg) by volume of the core (m^3).

Soil texture was analyzed at the KwaZulu-Natal Department of Agriculture and Environmental Affairs, Soil Fertility and Analytical Services. This was then used to estimate the drained upper and lower limits of soil water content using a texture and bulk density based regression equation, developed by Schulze *et al.* (1985) and Hutson (1986). For purposes of comparison, an algorithm developed by Ritchie *et al.* (1999), has also been used to estimate the limits.

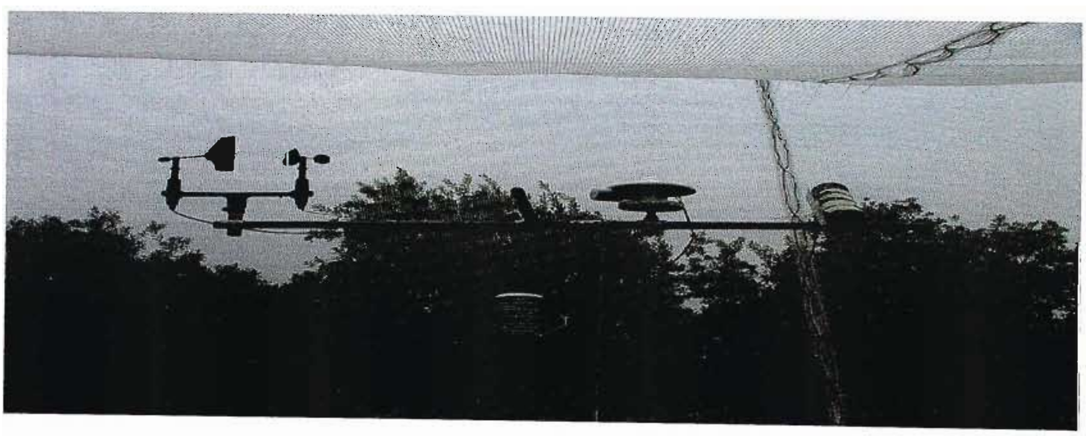


Plate 4.1 An automatic weather station system installed inside the shade cloth where the tomato crop was grown – Ukulinga experiment site (Photo MJ Savage)

4.4 RESULTS AND DISCUSSION

Solar Irradiance

The recorded solar radiant density at Ukulinga was incomplete due to short interruptions in observations, battery failure and/or memory overflow of the 21X datalogger. The missing observations were completed using a nearby weather station, Cedara Agricultural College and Ukulinga meteorological station.

Measurements inside and outside the shade at Ukulinga were used to derive a relationship that could be used later for conversion of inside solar irradiance to outside solar irradiance or vice versa. The factory given transmission of the shade cloth was 0.700. However, the actual value was found to have a 0.765 slope and an intercept of 1.048 (Fig. 4.1a). Solar irradiance outside the shade, calculated using equations shown in Fig. 4.1a, was then regressed against solar irradiance data for Cedara Agricultural College. This was done mainly because the correlation between inside solar irradiance at Ukulinga experimental site and solar irradiance at Cedara Agriculture College was poor. The relationship between those two datasets, outside solar irradiance at Ukulinga experimental site and Cedara Agricultural College shown in Fig. 4.1b, is in agreement with what Allen *et al.* (1998) recommended. According to Allen *et al.* (1998), $r^2 \geq 0.7$ and a value of the x-intercept (b) within the range ($0.7 \leq b \leq 1.3$) indicates good conditions and sufficient homogeneity for replacing missing data in the incomplete data series. Then the data for the missing periods were computed using the regression equation shown in Fig. 4.1b. The solar irradiance, completed for missing observations, throughout the growing season is shown in Fig. 4.2.

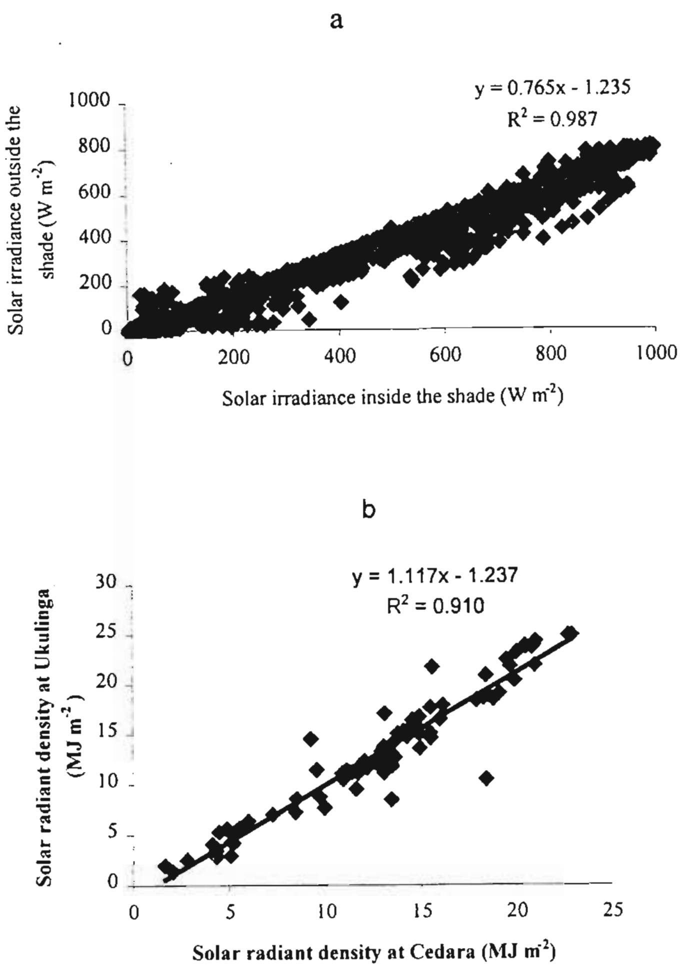


Fig. 4.1 (a) Sub-hourly solar irradiance inside and outside the shade at Ukulinga experimental site from day of year 254 to 304 (2002) and (b) daily solar radiant density at Cedara Agricultural College versus solar radiant density at Ukulinga experimental site (outside the shade cloth) from day of year 181 to 276 (2002)

Minimum and maximum air temperature

Before completing the missing air temperature observations, measurements of air temperature (using HOBO data loggers) inside and outside the shade cloth at Ukulinga experimental site were checked whether they have significant difference or not. As shown in Fig. 4.3 a and b, there is a one to one relationship between minimum and maximum air temperature outside and inside the shade cloth respectively. This could be substantiated by

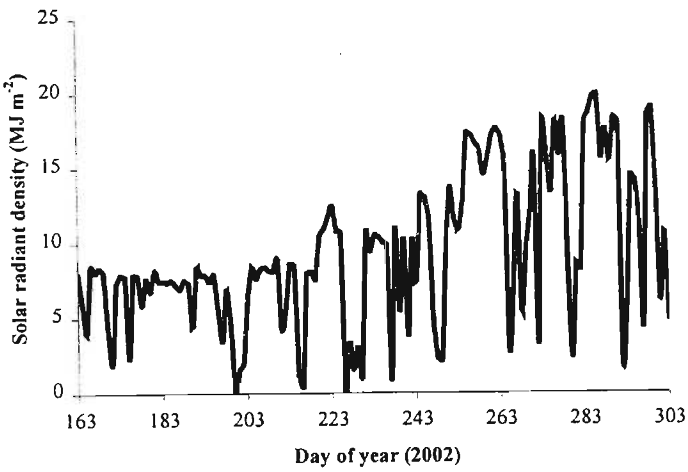


Fig. 4.2 Daily solar irradiance under shade for Ukulinga throughout the crop-growing season used for simulation

the statistical results shown in Table 4.1 that tells us that there is a one to one relationship between measurements inside and outside the shade cloth at 95% confidence.

As shown in Fig. 4.3 c and d, minimum and maximum air temperature data at the Ukulinga experiment site were regressed against the data from Ukulinga meteorological station. The relationship between those two datasets is in agreement with what Allen *et al.* (1998) recommended, which indicates good conditions and sufficient homogeneity for replacing missing data in the incomplete data series.

Regression statistics for minimum and maximum air temperature relationships are shown in Table 4.1. It can be observed that the slope and the intercept is within 95% confidence for both maximum and minimum air temperatures and hence the two datasets, that of Ukulinga experiment site and Ukulinga meteorological station, could be used interchangeably for the creation of a minimum dataset needed to run the model. The data for the missing periods were computed using the regression equations shown in Fig. 4.3 c and d. The air temperature data, completed for missing observations, throughout the growing season is shown in Fig. 4.4.

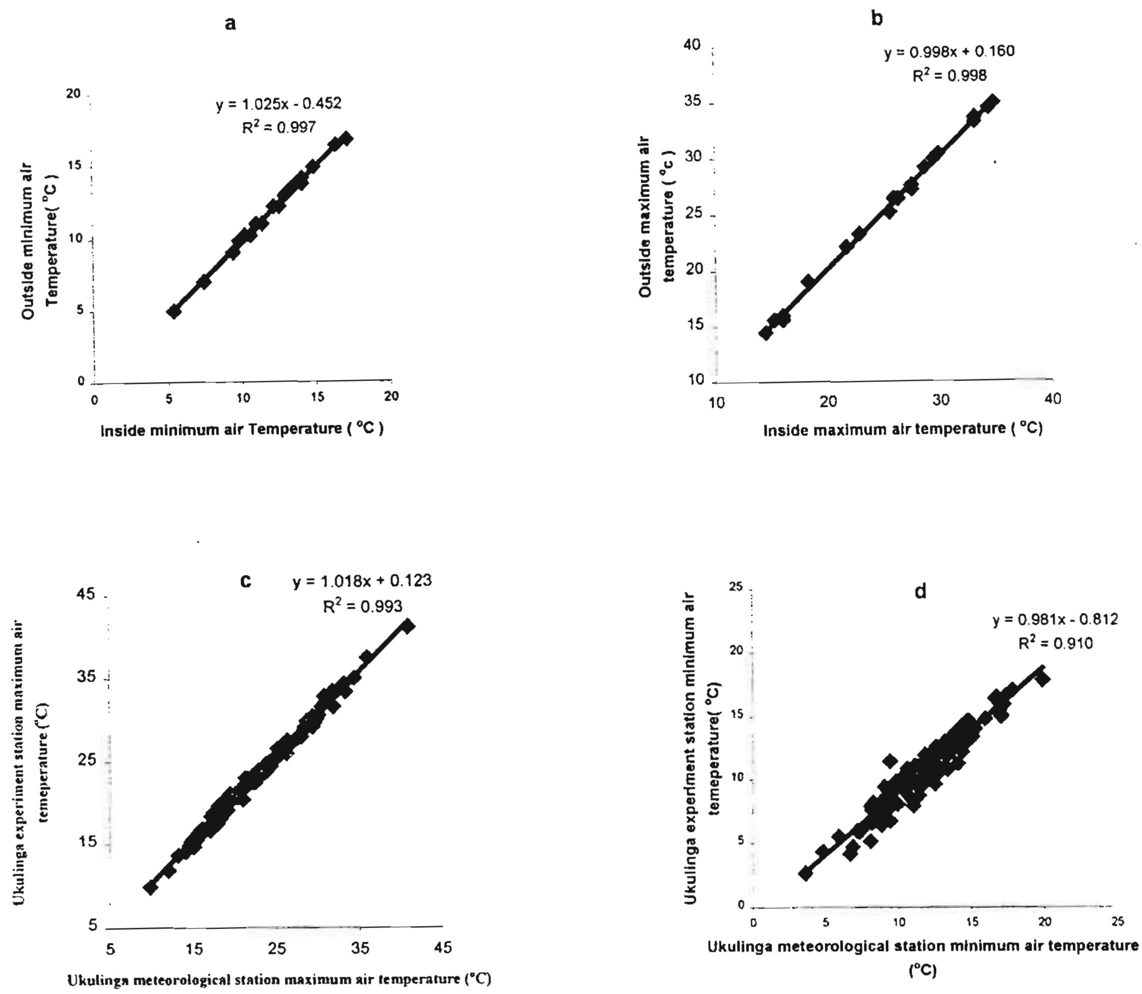


Fig. 4.3 (a and b) Daily minimum and maximum air temperature inside and outside the shade cloth at Ukulinga (Horticultural Science experiment site) and (c and d) daily minimum and maximum air temperature at Ukulinga experiment site, y-axis and Ukulinga meteorological station, x-axis from day of year 178 to 301 (2002)

Table 4.1 Summary output of the regression statistics.

Comparison		Slope	Intercept (°C)	S_{yx} (°C)*	n*	Lower 95%		Upper 95%	
						Slope	Intercept (°C)	Slope	Intercept (°C)
Inside and outside the shade cloth at Ukulinga experiment site	Maximum air temperature	0.998	0.160	0.338	99	0.974	-0.474	1.022	0.793
	Minimum air temperature	1.025	-0.452	0.186	99	0.995	-0.822	1.054	-0.0817
Ukulinga experiment site and meteorological station	Maximum air temeperature	1.018	0.123	0.205	99	1.002	-0.266	1.035	0.513
	Minimum air temeperature	0.977	-0.753	0.371	99	0.920	-1.432	1.033	-0.07446

* n refers to the number of data points (in this case daily air temeperature data)

* S_{yx} is the standard error

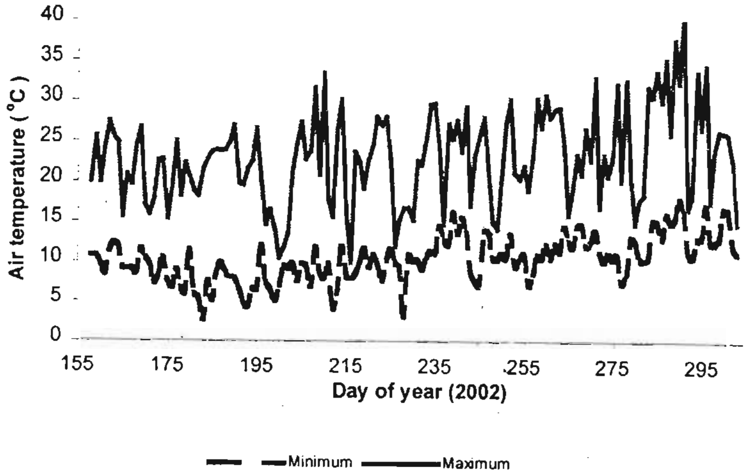


Fig. 4.4 Daily maximum and minimum air temperature under shade throughout the crop-growing season used for simulation at Ukulinga experiment site

Rainfall

To complete the missing rainfall data, the data collected at Ukulinga experiment site was compared with that of the Ukulinga meteorological station. Rainfall was collected automatically using a data logger for the former while for the latter rainfall was recorded manually. The two sets of data have the same total amount of rainfall taking the missing data points out. However, day-by-day (from midnight to midnight) comparison of the two datasets showed certain differences in some days of the year probably because the latter was collected manually. Despite such discrepancies, the missing data for the former dataset was completed using data from the latter assuming that they are homogeneous. The completed rainfall data for Ukulinga experiment site for the crop-growing season is shown in Fig. 4.5.

Soil characteristics

Soil characteristics such as the soil texture, bulk density, and organic carbon were used to determine the soil water limits like the drained upper limit and lower limit of soil water availability. To do this, regression equations developed by Schulze (1985), Hutson (1986)

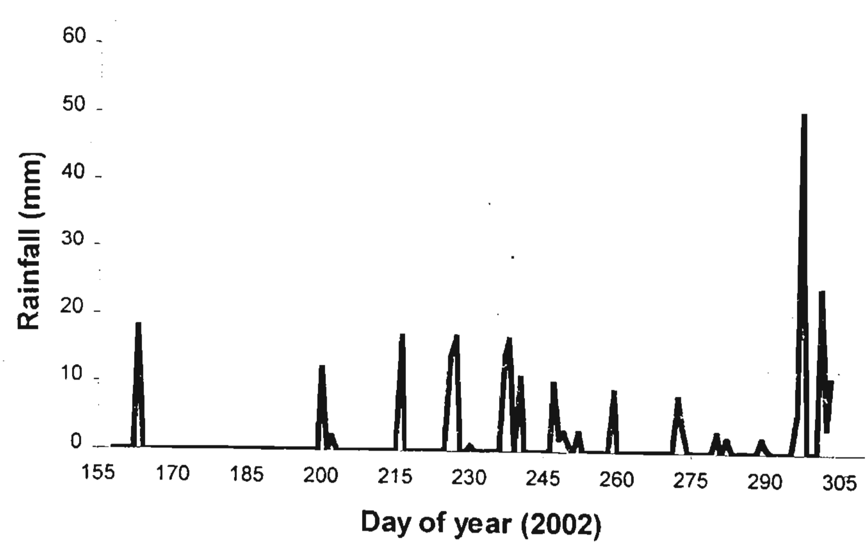


Fig. 4.5 Daily rainfall recorded throughout the crop-growing season at Ukulinga experiment site

and Ritchie *et al.* (1999) were employed. The results of such calculations are shown in Tables 4.2, 4.3 and Appendix 3.

For clay soils, upper drained limit is attained at –33 kPa whereas for sandy soils it is attained at –10 kPa. The soil from Ukulinga is clay in texture and hence its drained upper limit is attained at –33 kPa. Therefore, for simulation purposes drained upper limit at –33 kPa was considered. The reason for this is that the difference in soil water content is not much as the matric potential drops from –10 kPa to –33 kPa for clay soils. For sandy soils, however, as the matric potential drops from –10 kPa to –33 kPa the soil water drops rapidly as the larger pores will soon be emptied. This happens because it is the pore size distribution which determines the relationship between matric potential and soil water content in the wet range.

The soil water limit calculations carried out using the three equations have been compared to identify which pair of those equations shows good agreement. Since no field measurement of those limits have been taken, it has not been possible to identify which one of the equations performs better than the others. Equations developed by Hutson (1986) and Schulze *et al.* (1985) gave similar estimates of the soil water limits. As shown in Table 4.3, comparison of Hutson (1986) and Schulze *et al.* (1985) gave the lowest bias (-0.0110 and 0.0271 for drained upper limit and lower limit respectively), greatest r^2 (0.962 and 0.987 for drained upper limit and lower limit respectively) and lowest mean square error (MSE_s). This indicates that the deviation between those two methods is quite small. However, the bias and RMSE for comparisons between Ritchie *et al.* (1999) and Schulze *et al.* (1985) were bigger as compared to Schulze *et al.* (1985) versus Hutson (1986) comparisons indicating that the methods have poor agreement. The index of agreement was, however, very good for all of the comparisons carried out. Such comparisons, however, do not tell us which of these methods is good or bad because not one of them is a direct method of determining the soil water limits.

Other soil properties needed for simulations of the soil water balance are not required for each depth. These properties include soil reflection coefficient (*SALB*), the upper limit of first stage soil evaporation (*U*), the runoff curve number (*CN2*) and the

Table 4.2 Drained upper limit (DUL) and lower limit (LL) calculated using three different equations for the soil at Ukulinga experiment site

	Hutson (1986)		Schulze *et al.* (1985)		Ritchie *et al.* (1999)	
Layer thickness (mm)	DUL ($m^3 m^{-3}$)	LL ($m^3 m^{-3}$)	DUL ($m^3 m^{-3}$)	LL ($m^3 m^{-3}$)	DUL ($m^3 m^{-3}$)	LL ($m^3 m^{-3}$)
100	0.37	0.30	0.41	0.27	0.35	0.20
200	0.26	0.19	0.24	0.18	0.31	0.16
300	0.25	0.19	0.23	0.17	0.29	0.15
400	0.35	0.29	0.39	0.25	0.33	0.18
500	0.39	0.31	0.41	0.28	0.35	0.21
600	0.36	0.29	0.37	0.26	0.30	0.16

Table 4.3 Statistical parameters associated with the comparisons of the various equations for estimating soil water limits

		Hutson (1986) *vs* Schulze *et al.* (1985)	Schulze *et al.* (1985) *vs* Ritchie *et al.* (1999)	Hutson (1986) *vs* Ritchie *et al.* (1999)
DUL	r^2	0.962	0.633	0.618
	MSE_u (m^3m^{-3})	0.000	0.000	0.000
	MSE_s (m^3m^{-3})	0.001	0.005	0.002
	MSE (m^3m^{-3})	0.002	0.006	0.002
	RMSE (m^3m^{-3})	0.040	0.075	0.046
	d-index	0.999	0.999	0.999
	Bias b	-0.011	0.024	0.013
LL	r^2	0.987	0.681	0.637
	MSE_u (m^3m^{-3})	0.000	0.000	0.000
	MSE_s (m^3m^{-3})	0.002	0.006	0.012
	MSE (m^3m^{-3})	0.002	0.007	0.012
	RMSE (m^3m^{-3})	0.043	0.081	0.111
	d-index	0.999	0.999	0.998
	Bias b	0.027	0.060	0.087

DUL is the drained upper limit, *LL* is the lower limit, r^2 is the coefficient of determination, MSE_u is the unsystematic mean square error, MSE_s is the systematic mean square error, *d-index* is the index of agreement and *b* is the bias drainage coefficient *(SWCON and SWCON2)*. The values of these parameters have been calculated to be 0.09, 11.92, 76.00, 0.18, and 58.61 respectively.

Management factors

The tomato seedlings were transplanted on June 2002 and were harvested on 28 October 2002. These data are important to start and end the simulation. Irrigation water (1.42 mm) was applied daily starting from the date of planting till 18 September 2002. Later starting from 19 September 2002, 1.07 mm was applied daily until harvest time. The gross irrigation requirement per cycle was calculated (mm) by multiplying the standing time with the emitter discharge and dividing it by the lateral spacing (m) and emitter spacing (m). The calculated low application rate is possible using drippers.

4.5 CONCLUSIONS

In this study it has been possible to successfully create daily solar radiant density data from sub-hourly measurements throughout the crop-growing season. The missing data sets were completed after checking that they were sufficiently homogeneous to that of Cedara Agricultural College. In addition the factory given transmission value (0.700) of the shade cloth has been found to be different to the one found in the experiment (slope 0.765 and intercept of 1.048). As expected, air temperature data inside and outside the shade cloth has been found to be correlated. The missing air temperature data was completed using data from Ukulinga meteorological station. Then daily air temperature data for the crop-growing season was generated. Daily rainfall data was also infilled using similar procedures. Creation of certain soil physical and chemical properties was possible by carrying out conventional laboratory procedures. Estimation of the soil water limits was carried out using three equations: Schulze *et al.* (1985), Hutson (1986) and Ritchie *et al.* (1999). The former two equations, tailored for South African situations, gave similar results while the latter showed certain differences from those two equations. Hence the former were used to create the soil file. Other soil inputs have been calculated using the model DSSAT. Crop management inputs such as irrigation amount and dates have also been documented to create the experimental details file.

CHAPTER 5

CALIBRATION AND VERIFICATION OF THE MODEL

5.1 INTRODUCTION

Lawes (1850) and Briggs and Shantz (1913), cited by Campbell and Diaz (1988), documented that crop production has a close relationship with transpiration. Therefore, quantification of transpiration is very important. To do this the soil water balance components, which strongly affect transpiration, have to be quantified first before reliable estimates of transpiration can be made. Environmental instruments have made the quantification of evaporation, transpiration, runoff and other parameters possible. However, it is easier to use models to estimate their magnitude.

There are a number of models that could be used for the estimation of the soil water balance parameters. One of them is the Decision Support System for Agrotechnology Transfer (DSSAT). This model uses the Ritchie (1985) soil water balance sub-model of intermediate complexity. The model allows two options for calculating potential evapotranspiration: the Priestley and Taylor (1972) and Penman-Monteith methods. To determine the actual evaporation from potential evaporation, the model calculates the root water absorption using the law of limiting approach in which the largest root or soil resistance determines the flow rate of water into roots. The model calculates infiltration and runoff using a modification of soil conservation curve number technique and uses a cascading approach to calculate drainage where water is allowed to move only downwards unlike when using the finite difference technique. The data inputs of the model include weather, soil and management inputs amongst others.

Previous studies (for instance du Toit et al., 1997; Hensley *et al.*, 1997) have shown that the soil water balance subroutines of crop models including the Ritchie (1985) model tested in the Republic of South Africa have shown unsatisfactory results. Hence it is important to test models and adapt them to a particular situation. This chapter is concerned with: the calibrating of the soil water balance sub-model of the DSSAT v3.5 crop simulation model, by modifying data inputs; simulating soil water content, cumulative evapotranspiration and LAI and comparison with actual field measurements.

5.2 BACKGROUND

5.2.1 Model Calibration

Model calibration can be defined as an iterative process in which the model parameters are adjusted, within known limits, until the simulated and observed outputs agree. The Newsletter of Agro-ecosystems Modelling (1995) defines calibration as the adjustment of some parameters such that model behaviour matches a set of real world data. In the following paragraphs the importance of calibration of models, the procedures and methods employed for calibration will be discussed.

The soil water balance sub-model of the model DSSAT v3.5 simulates soil water content, soil evaporation, transpiration, drainage, etc., throughout the growing season of the crop considered. But such output variables cannot be simulated precisely if the model is not calibrated. This is because the model might have been developed for situations other than its use. In addition, calibration is necessary to account for the empiricism that is often at the base of the relations used in the model (Donatelli and Stockle, 1999). Besides the accumulation of errors in the different parameters, possible errors in the model equations could lead to model results that are quite far from measured field data (Wallach *et al.*, 2001). It is further explained that there is no such thing as a universal biophysical model that will work with an unaltered set of parameters for all conditions. It is therefore necessary to alter some of the parameters to ensure that the model works for the situation under consideration. But the model does not have to be run many times by changing the parameters haphazardly because it will be degraded and will be more like a statistical multiple linear regression model rather than a physical model (Acock and Acock, 1991; Sinclair and Seligman, 2000). The procedure should involve changing of the parameter values within the range known for the parameters (Donatelli and Stockle, 1999).

In most instances actual field observations are used to calibrate a model simulation. The simulated and observed values are compared and if it is found that they are different, then the values of the parameters that relate the response of the model to the environmental data are changed and the model is restarted to produce a new simulation (Maas, 1993). The new simulation is also compared with the observations to determine if the parameter values need further changing. The sequence of activities forms a repetitive cycle and is supposed to be stopped when the simulations and observations are judged to be the same.

As clearly stated by Refsgaard (1997), there is no universally accepted methodology for calibration of models. Also general methodologies related to model calibration, verification and validation have been subject to considerable dispute. Different workers have used various methods to calibrate models. Hanson *et al.* (1999) used a cascade approach where few parameters are adjusted in each step. They first adjusted some parameters of the soil water balance, then other parameters of the soil nutrient data and finally parameters related to plant production data. This approach is necessary where the parameters to be adjusted are large in number. In a model for predicting flowering date (Grimm *et al.*, 1993), have been able to adjust all the parameters because there were few in number. In cases where the numbers of parameters are large, some researchers have first used a sensitivity analysis of the model and adjusted the most sensitive parameters (Yan and Han, 1991; Gribb, 1996). Sumner *et al.* (1997) started with a set of three parameters to estimate and then they added further parameters one at a time if they reduced the residual variance. Nogueiera *et al.* (2001) calibrated growth rate and yield by modifying parameters proposed to affect them. They varied each of their proposed variables and minimized root mean square error (RMSE) for some of the outputs they were interested in. Hunt and Boote (1998) reported that IBSNAT emphasized the use of a systematic approach of calibration. Such an approach involves evaluation of parameters in a logical sequence. Keeping the calibrated parameters low, and thus decreasing the errors, was emphasized by Refsgaard (1997). It was also mentioned that parameters, which need to be assessed from field data and those, which need some kind of calibration should be evaluated carefully.

5.2.2 Model Verification

To verify the model, statistical methods described by Wilmott (1982) and supported by Savage (1993), as clearly stated in Chapter 1 of this thesis, could be used.

5.3 MATERIALS AND METHODS

A tomato crop (*Lycopersicon esculentum*) was grown at Ukulinga (latitude ≈ 29.67°S, longitude ≈ 30.4°E and altitude ≈ 775 m), KwaZulu-Natal, South Africa. The field has a slope of 1% in the E-W direction. It was bordered on the north by a farm road, on the south by a gooseberry crop, on the east by fallow land and on the west by a farm road. The average annual rainfall, average maximum air temperature and average minimum air temperature of the site is approximately 724 mm, 38°C and 3°C respectively (Appendix 1). The soil at the experimental site was found to be clay in texture. Other soil characteristics such as bulk density, organic carbon, soil water limits of all the soil depths considered are shown in Table 5.1. Row spacing, the space between plants and plant population was 1000 mm, 650 mm and 3.12 plants m^{-2} respectively. The plant was transplanted on June 12, 2002 and harvested on October 25, 2002. Irrigation was applied four times a day for three minutes (1.42 mm per day) until September 18, 2002. From September 19, 2002 onwards, irrigation was applied three times a day for three minutes (1.07 mm per day) until harvest time.

Table 5.1 Summary of soil input parameters used for running the model

Soil depth (mm)	Lower limit (m^3 m^{-3})	Upper limit (m^3 m^{-3})	SAT SW (m^3 m^{-3})	EXTR SW (m^3 m^{-3})	Initial SW (m^3 m^{-3})	Root distribution weighting factor	Bulk density (kg m^{-3})	pH	Org C %
0 to 50	0.270	0.410	0.420	0.140	0.410	1.00	1520	6.40	3.20
50 to 150	0.225	0.325	0.420	0.100	0.328	0.75	1510	6.45	3.20
150 to 300	0.173	0.233	0.433	0.060	0.236	0.75	1480	6.43	3.00
300 to 450	0.260	0.397	0.413	0.137	0.394	0.75	1510	5.80	2.13
450 to 600	0.267	0.383	0.460	0.117	0.384	0.75	1400	6.07	1.80
600 to 800	0.280	0.400	0.410	0.120	0.402	-	1520	7.00	1.10
800 to 1000	0.280	0.400	0.410	0.120	0.402	-	1520	7.00	1.10

Soil water content was monitored throughout the growing season of the plant. For this purpose ThetaProbe (Delta-T Devices, type ML1, Cambridge, UK), a frequency domain reflectometry sensor, was used. Two sensors were used to take measurements of soil water content at 150 to 300 mm and 450 to 600 mm soil depths.

LAI-2000 plant canopy analyzer (PCA) developed by Li-Cor (Lincoln, NE, USA) was used to measure leaf area index (LAI). The PCA should not be used in direct sunlight because leaf reflectance and PAR transmittance result in an overestimation of LAI (Li-Cor, 1990). In this study measurements of LAI were made at midday despite direct sunlight by shading both the sensor and sampling area with a white umbrella (2560 mm in diameter) that was manually held in place to block the direct rays of the sun. Measurements with the PCA were obtained during the growing season at the same marked locations.

ET-gauge (ET-gage company, model E, Loveland, USA) was used to measure reference evapotranspiration. The number 54-canvas cover for agricultural crops, made to resist escaping water vapour was used as recommended for agricultural crops by the manufacturer. The number 30 canvas cover gave measurements that were 10 to 15 % greater than those for the 54 cover (data not shown).

Weather variables such as minimum and maximum air temperature, relative humidity, solar irradiance, wind speed, wind direction and rainfall were measured using an automatic weather station system.

Soil water limits were estimated using soil texture and bulk density regression-based equations developed by Schulze *et al.* (1985) and for purposes of comparison, equations developed by Hutson *et al.* (1986) were also considered.

The CROPGRO model, one of the models under the DSSAT group of models, was used for the simulations. To ensure that the estimated soil water contents match the measured values, some of the model parameters such as drained upper limit, drainage coefficient and runoff curve number were modified. To avoid overestimation of soil water content runoff curve number was increased and drainage coefficient decreased to ensure less water percolates into subsoil layers. Underestimation of soil water content was avoided by decreasing the runoff curve number and increasing the drainage coefficient thus ensuring more water percolates into subsoil layers. Modifications were also made to the drained upper limit. To do this, the first half of the soil water content data was used for calibration and the other half was used for evaluation of the model using the parameter values obtained during the calibration process.

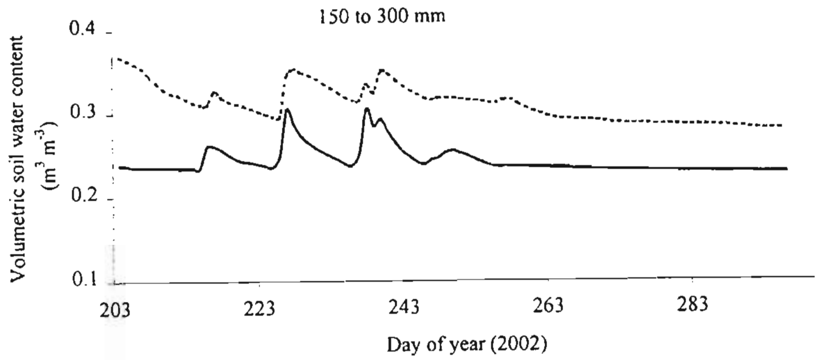
The model was run assuming that the initial soil water content was at its drained upper limit. Further it was run starting from the date of transplanting (June 12, 2002) right up to its harvest time (October 25, 2002).

5.4 RESULTS AND DISCUSSION

5.4.1 Calibration

With the unmodified set of model parameters, the simulated volumetric soil water content for both depths namely 150 to 300 mm and 450 to 600 mm followed the general trend of increment and decrement of the measured soil water content (Fig. 5.1). When compared with the measured volumetric soil water content, simulated volumetric soil water content for 150 to 300 mm depth was underpredicted throughout the growing season (root mean square error ($RMSE$) = 0.502 m^3 m^{-3}, r^2 = 0.529, index of agreement (D) = 0.321, and % systematic root mean square error ($RMSE_s$) = 98.0). This is probably because the drained upper limit for that layer (0.233 m^3 mm^{-3}) is too low because it was estimated using regression equations rather than from being measured in the field. For the 450 to 600 mm depth, the simulated volumetric soil water content overpredicted the observed values ($RMSE$ = 0.308 m^3 m^{-3}, D = 0.342, r^2 = 0.538 and % systematic root mean square error ($\mathrm{RMSE_s}$) = 96.1). This might be attributed to relatively high drainage coefficient of 0.400 and high drained upper limit specified for that layer (0.383 m^3 m^3).

As discussed above model simulations were unsatisfactory with the unmodified set of model parameters. To improve simulations of soil water content, modifications were made to the drained upper limit, drainage coefficient, and runoff curve number. Each of these variables was varied and $RMSE$- soil water content was minimized. It was made sure



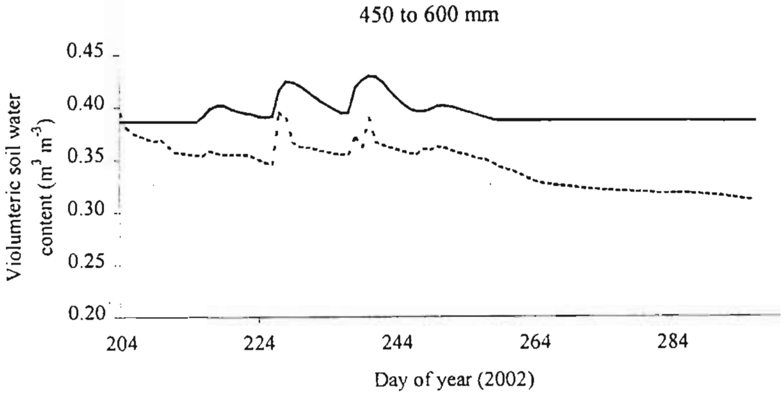


Fig. 5.1 Measured and simulated volumetric soil water content of soil layer 150 to 300 mm and 450 to 600 mm respectively at Ukulinga during the 2002 winter season using the unmodified set of model parameters

that the variables were varied within the limits known for them and as well for the site under study. The three parameters were varied in combinations of two at a time and the improvements in *RMSE*- soil water content was graphed against variation of one while also varying the other parameter.

The drained upper limit (*DUL*) for layer 150 to 300 mm, as calculated using equations developed by Schulze *et al.* (1985), was 0.238 m^3 m^{-3}. This value was very low compared to the other layers. This is mainly because the silt percentage for that layer is very low (< 5 %) and hence *DUL* is low. So the first thing done during the calibration process was to increase *DUL* along with the drainage coefficient while holding all other parameters unchanged. As shown in Fig. 5.2, the *RMSE* for soil water content decreases until 0.305 m^3 m^{-3} and then increases again beyond 0.315 m^3 m^{-3} *DUL* values for almost all drainage coefficients (*DR*) considered. The minimum *RMSE* achieved was 0.0798 m^3 m^{-3} for *DUL* of 0.307 m^3 mm^{-3} and *DR* of 0.35. Thus increasing the *DUL* and decreasing the *DR* has minimized the *RMSE* - soil water content. But this could not be taken as the optimum *RMSE*-soil water content because other combinations have to be considered.

The next step was to vary *DUL* with runoff curve number (*CN*). As the case for variation of the DUL with DR, the minimum *RMSE*-soil water content was observed between 0.305 m^3 m^{-3} and 0.315 m^3 m^{-3} for almost all runoff curve numbers considered. But for *DUL* of 0.312 m^3 m^{-3} and *CN* of 94, *RMSE*-soil water content was minimized the most (0.0757 m^3 m^{-3}) (Fig. 5.3).

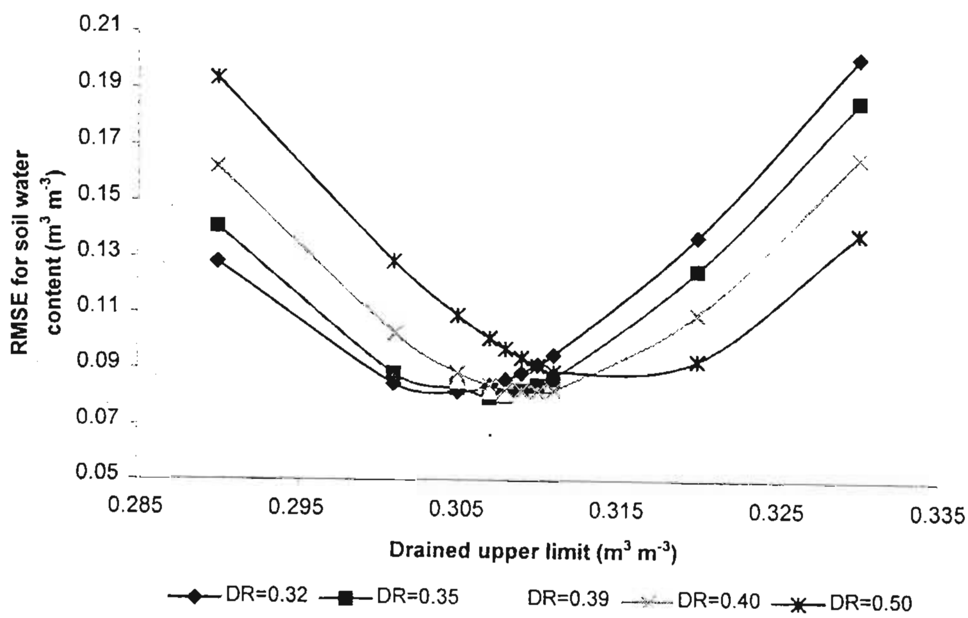


Fig. 5.2 Root mean square error for soil water content (150 to 300 mm) simulation for 2002 winter season experiment at Ukulinga for different drained upper limit values and drainage coefficients (*DR*)

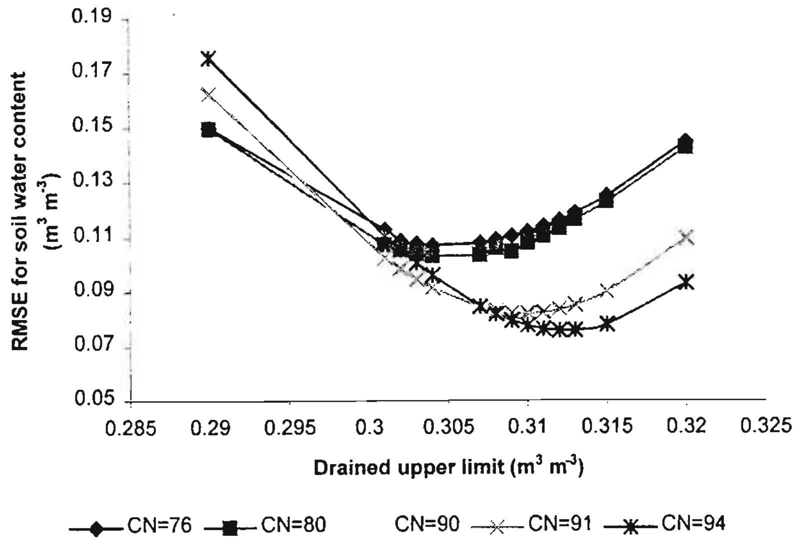


Fig. 5.3 Root mean square error for soil water content (150 to 300 mm) simulation for 2002 winter season experiment at Ukulinga for different drained upper limit values and runoff curve numbers (*CN*)

The last combination of parameters considered was variation of *CN* with *DR*. For almost all the drainage coefficients considered, *RMSE*-soil water content was minimized as runoff curve number was increased from 76 to about 90 and it started to go up beyond 95. However, *RMSE*-soil water content was minimized the most for runoff curve number (*CN*) value of 95 and drainage coefficient of 0.32. Other *CN* values like 93 and 94 and *DR* values like 0.33 gave similar *RMSE*-soil water content (Fig. 5.4). For clay soils with high swelling potential like the soils at Ukulinga and planted with row crops and poor management, the *CN* can reach as high as 91. This is very close to what is found through calibration.

Once the *CN* and *DR* coefficients were optimised, the next step was the optimisation of *DUL* for the 450 to 600 mm soil layer. There was no need to modify the *CN* and *DR* coefficients again because those parameters are the same for all the soil layers. So for the 450 to 600 mm soil layer only the DUL was modified keeping the other optimised parameters constant. As shown in Fig. 5.5, *RMSE*-soil water content was minimized most for *DUL* of 0.346 m^3 m^{-3}. Thus decreasing the *DUL* from 0.383 m^3 m^{-3} to 0.346 m^3 m^{-3} has minimized the *RMSE*-soil water content. The three optimised parameters namely the *DR*, *CN* and *DUL* for 150 to 300 and 450 to 600 mm were kept for verification of the model.

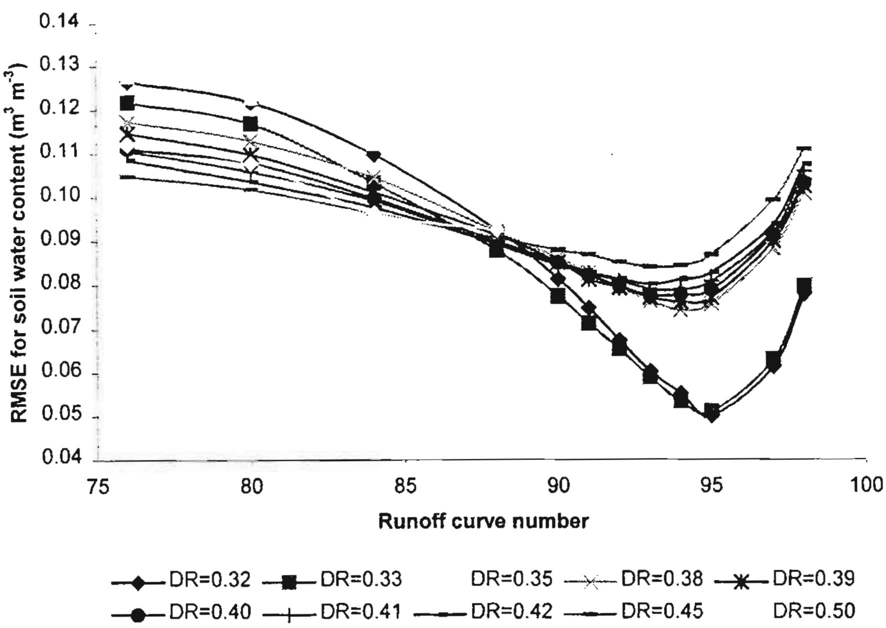


Fig. 5.4 Root mean square error for soil water content (150 to 300 mm) simulation for 2002 winter season experiment at Ukulinga for different runoff curve numbers and drainage coefficients (*DR*)

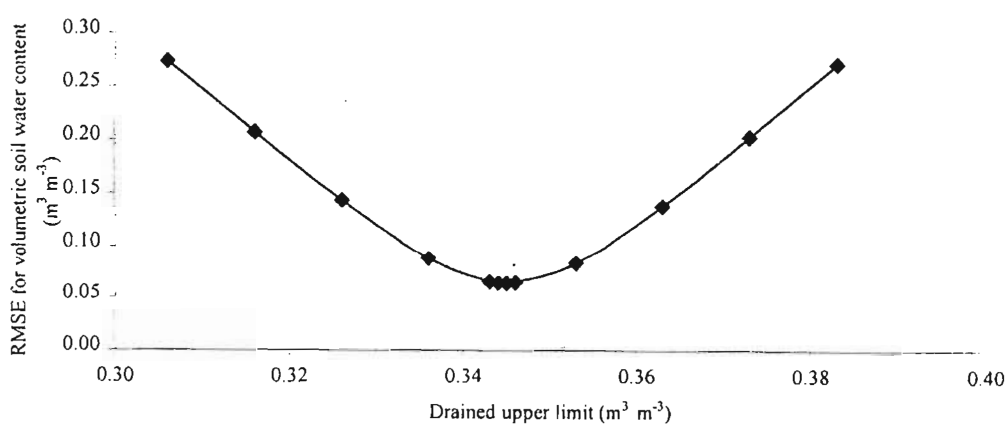


Fig. 5.5 Root mean square error for soil water content simulation (450 to 600 mm) for 2002 winter season experiment at Ukulinga for different drained upper limits (450 to 600 mm) and fixed runoff curve number (94) and drainage coefficient (0.32).

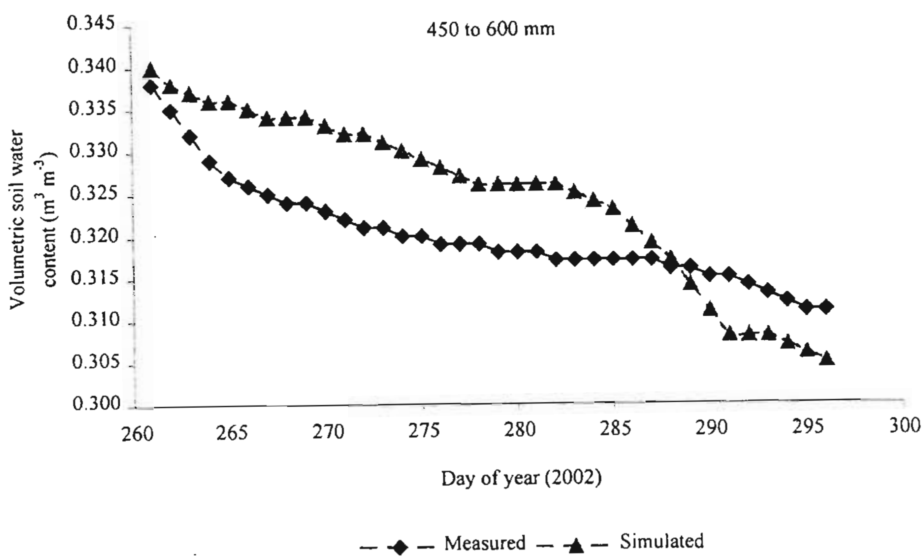
5.4.2 Verification

Model parameters such as *CN*, *DUL* and *DR* that were found to affect simulations of soil water content were optimised to minimize the *RMSE*-soil water content. Those optimum values were kept for verification of the model with the dataset for that purpose.

After modifications of some of the model parameters, simulations of soil water content for 150 to 300 mm soil layer as compared to observed values (Fig. 5.6a) were still unsatisfactory ($RMSE$ = 0.289 m^3 m^{-3}, r^2 = 0.744, D = 0.505, and % $RMSE_s$ = 90.5) despite certain improvements from the unmodified set of model parameters. The statistics mentioned here show that the *RMSE* value is relatively high and % $RMSE_s$ is quite close to the *RMSE* which indicates bias. In other words the unsystematic root mean square error ($RMSE_u$) is not close to *RMSE* which implies that that the deviations of simulated from measured values are not random. The *D*-index is also not favourable.

Simulations of soil water content for 450 to 600 mm soil layer after modifications of certain parameters were also compared with observed values (Fig. 5.6b). Considerable improvements ($RMSE$ = 0.044 m^3 m^{-3}, r^2 = 0.751, D = 0.816, and % $RMSE_s$ = 52.6) were observed as compared to the simulated soil water using the unmodified set of model parameters. The statistics as shown above are all favourable. The *RMSE* is now considerably smaller than before, r^2 has increased appreciably, the *D-index* is good compared to 0.342 value found from the unmodified set of model parameters and now it could be inferred from the $RMSE_s$ values that the deviations of the simulated from the measured soil water content are random.

Daily simulated cumulative evapotranspiration (*ET*) as compared to the calculated *ET* (crop coefficient of tomato multiplied to ET-gage reference ET) from day of year 178 to 193 was, however, not satisfactory ($RMSE$ = 13.436 mm, r^2 = 0.987, D = 0.964, and % $RMSE_s$ = 93.7) (Fig. 5.7). The statistical parameters like D and r^2 are favourable while the *RMSE* is quite large and % $RMSE_s$ is also close to the *RMSE*. This indicates that the deviations of simulated from the calculated *ET* are not random. Such deviations are



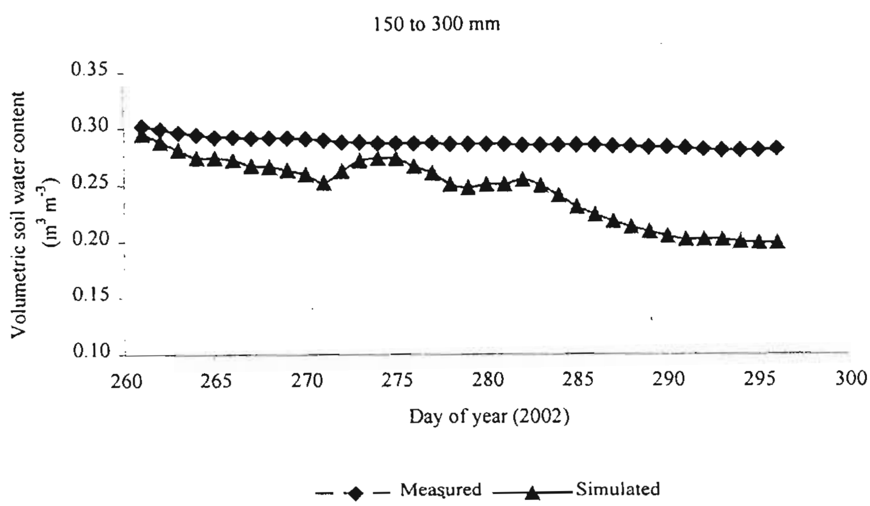


Fig. 5.6 (a and b) Measured and simulated volumetric soil water content for soil layer 150 to 300 mm and 450 to 600 mm respectively at Ukulinga during the 2002 winter season using the modified set of model parameters. Of particular note is that the dataset used for verification is an independent one starting from day of year 261 to 296

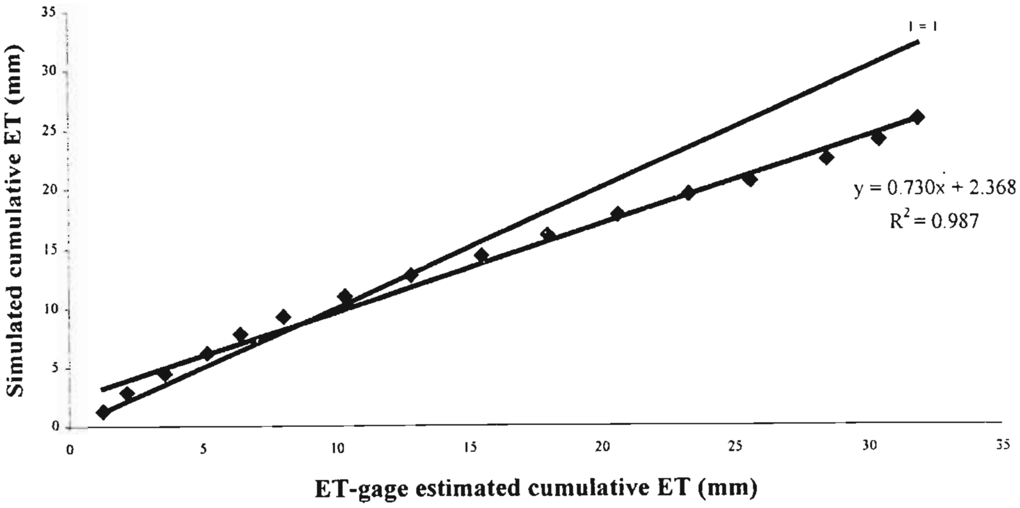


Fig. 5.7 Measured and simulated cumulative evapotranspiration from day of year 178 to 193 at Ukulinga during the 2002 winter season

inevitable due to the fact that the model simulated *ET* is modified by the potential *ET* with leaf area index of the plant each day, that is the percentage of photosynthetically active radiation (PAR). However, calculated *ET* was modified with a constant crop (tomato) multiplier, the so-called the crop coefficient. Such a procedure was found to be invalid under variable soil water content conditions (Reddy, 1983). This is because crop coefficient values are for non-stressed crops under excellent agronomic and water management conditions. This indicates that model simulations of *ET* could be improved if seasonal variations in leaf area index are simulated with reasonable accuracy. It is important to note that the datasets were serially correlated.

Simulations of LAI have been found to be satisfactory ($RMSE$ = 0.872, r^2 = 0.943, D = 0.974, and % $RMSE_s$ = 50.05) (Fig. 5.8) for the periods of time where actual field measurements were taken. The first two measurements were reasonably close to the simulated ones (slight under-prediction of 0.08 and 0.20 respectively) while the next two measurements over predicted the simulated *LAI* by 0.6 and 0.57 respectively. The last measurement was close to the simulated *LAI* (over-prediction by 0.17). The statistics as shown above are all favourable. The *RMSE* is reasonably low, r^2 and D are close to one and

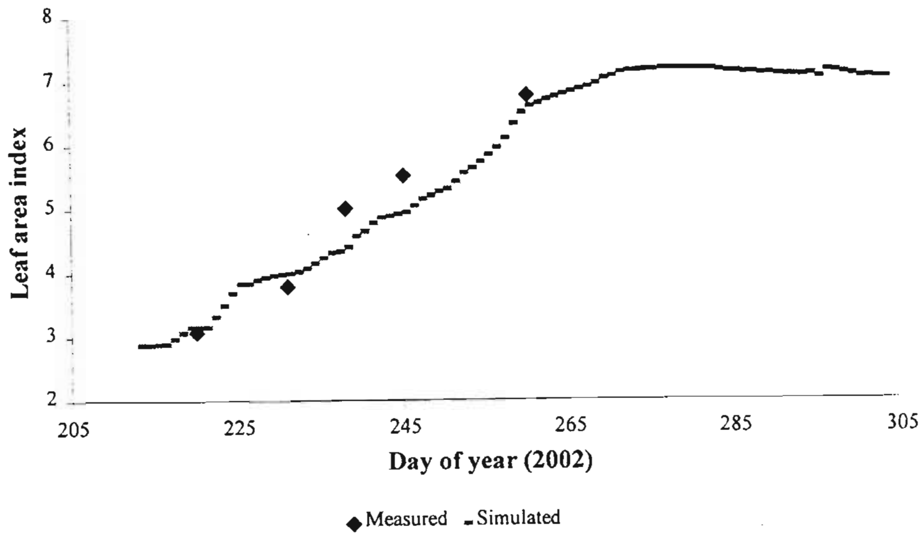


Fig. 5.8 Measured and simulated tomato leaf area index at Ukulinga during the 2002 winter season

$RMSE_s$ and $RMSE$ are quite different which might indicate that the deviations of simulated and measured *LAI* are random. Such a comparison is important to test the accuracy of the canopy development provided the soil components are known.

5.5 CONCLUSIONS

Model simulations with unmodified set of model parameters gave unsatisfactory results because of certain errors in quantifying some of the sensitive model parameters such as the *DUL, DR* and *CN* and possible errors in model equations. After calibration of certain model parameters, simulations of soil water content showed significant improvement especially for the lower soil layer (450 to 600 mm). It was observed that accurate values of *DUL* are necessary if simulations of soil water content are to match measurements. Estimating DUL using models (as was used in this experiment) is not advisable. Instead the *DUL* should be measured under field conditions. The model gave satisfactory results as far as simulations of *LAI* is concerned. Deviations of simulations of actual *ET* with ET-gage estimated *ET* were found to be not random. This was mainly because ET-gage estimated *ET* was multiplied with a constant crop multiplier, the crop coefficient for tomato. Such a procedure was found to be invalid under variable soil water content conditions. The model, however, takes the seasonal variations in LAI into account. Hence it could be inferred that model simulations are superior than otherwise.

CHAPTER 6

SENSITIVITY ANALYSIS AND LONG -TERM RISK ASSESSMENT

6.1 INTRODUCTION

Savage (2001a) defined sensitivity analysis as the evaluation of the sensitivity of the model output to changes in input values. Sensitivity analysis was used for various purposes. Gabrielle (1995) used the analysis to investigate the precision required for the input parameters of a model. Chopart and Vauclin (1990) and Singh *et al.* (1993) applied the analysis to determine the sensitivity of model outputs to changes in their input value because some model parameters were not precisely known. Others have used the analysis to guide future research by highlighting the most important processes (e.g. Walker *et al.*, 2000) and for parameter estimation by showing which combination of parameters lead to realistic model behaviour.

One of the valuable uses of crop models such as the DSSAT is their ability to make use of long-term weather data for simulations of yield and other model output parameters which aids in assessing risk. Hensley *et al.* (1997) used two models namely the DSSAT v3.5 and PUTU (de Jager et al., 1983) crop growth models for risk assessment of yield, runoff and drainage. They concluded that models have to be reliable before they could be used for such a purpose. However, such an assessment is of great importance for comparison of relative yield and other model output parameters.

As previously mentioned Decision Support System for Agrotechnology transfer (DSSAT) v3.5 has many models under its shell of which CROPGRO-Soya bean model developed by Hoogenboom *et al.* (1994) is a part. This model has been modified to simulate the growth and development of tomatoes. Input requirements, calibration and evaluation of the CROPGRO-model, which shares the same water balance sub-model like the other models in the DSSAT shell, have been studied in the previous chapters. In this chapter sensitivity analyses of the soil water balance will be conducted with respect to runoff curve number, drainage coefficient, drained upper limit and lower limit for all soil layers. Moreover, parameters of the model such as the drained upper limit, first stage evaporation from the soil surface, soil reflection coefficient and their effects on model output will be investigated. Furthermore, input changes in weather data such as rainfall, minimum and maximum air temperatures and solar radiant density and their sensitivity to output will be investigated. Historical weather data were used to assess the long-term risks associated with yield, runoff and drainage for soil, plant and weather conditions at Ukulinga.

6.2 MATERIALS AND METHODS

To see the sensitivity of each output to changes in input, the relative sensitivity index used by Nearing *et al.* (1989), as cited by Walker *et al.* (2000), was employed. The relative sensitivity index was calculated as follows:

$$S = \frac{O_2 - O_1}{I_2 - I_1} * \frac{I_{avg}}{O_{avg}} \qquad 6.1$$

where I_2 and I_1 are the smallest and greatest input values tested for a given parameter, I_{avg} is the average of I_2 and I_1, O_1 and O_2 are model output values corresponding to I_1 and I_2 and O_{avg} is the average of O_1 and O_2. Walker *et al.* (2000) reported that an index of 1 indicates that the output ranges about the average output to the same degree as the tested input ranges about the average input. A negative value indicates that input and output are inversely related. The greater the absolute value of the index, the greater the impact an input parameter has on a particular output. The index is unitless and hence provides a basis for comparison with other input variables.

A sensitivity analysis of 22 model input parameters was carried out. Each of these input parameters was individually varied to determine the effect on seven model output variables. Then the sensitivity index was calculated using Eq. 6.1.

In addition, sensitivity analysis of the model was performed using combinations of six solar radiant density and six air temperature regimes. The model allowed changing of those parameters by a constant multiplier of 1.0, 1.1, 1.2, 1.4, 1.3 and 1.5 for solar radiant density and 0.8, 0.9, 1.0, 1.1, 1.2, and 1.3 for air temperature from their respective base values. The sensitivity of those input parameters was evaluated graphically for some output parameters such as yield on a dry weight basis and biomass at harvest. Sensitivity analysis with respect to certain management practices such as row spacing and plant population for tomato were also carried out. For this purpose six values, above and below the base value of 1000 mm, were chosen for row spacing and eight values below the base value of 3.1 plants m^{-2} was chosen for plant population.

Long-term weather data was used to simulate yield (dry weight basis), biomass at harvest, runoff and drainage probabilities. Such an assessment was carried out using four initial soil water content values: full, ¾, ½, and ¼ of drained upper limit at planting. Long-term simulations were repeated four times for the site for each and every soil water content at planting. As far as weather data was concerned, the data available were only minimum and maximum air temeperature and rainfall. The missing data points were infilled according to the procedures suggested by Allen *et al.* (1998). Solar radiant density was simulated using the Campbell-Donatelli model available as part of the RadEst v3-model (FAO-SDRN Agrometeorology group and ISCI-Crop Science, 2001). Details of the model are given in Appendix 5.

6.3 RESULTS AND DISCUSSION

The sensitivity index defined in Eq. 6.1 was computed for each combination of input and output parameters shown in Table 6.1. The outputs considered for this purpose were runoff, soil water content at the end of the season, drainage, soil evaporation, transpiration, and evapotraspiration and the inputs were the runoff curve number (CN), drainage coefficient (DR), soil reflection coefficient (SALB), soil water evaporation constant (U), drained upper limit (DUL) and lower limit (LL) for soil layers 0 to 50 mm, 50 to 150 mm, 150 to 300 mm, 300 to 450 mm, 450 to 600 mm, 600 to 800 mm, and 800 to 1000 mm respectively. In addition, rainfall, minimum and maximum air temperature and solar radiant density were also considered.

Modelled runoff was found to be primarily sensitive to runoff curve number (CN) and rainfall. As shown in Fig. 6.1, runoff increases with increases in CN for a given rainfall regime. For a given CN, as rainfall is altered by a multiplier of 80%, 90%, 100%, 110% and 120% of the base value, runoff progressively increases. The rate of increase for the runoff, however, is less than that of the rainfall (the sensitivity index is 1.042 for rainfall as opposed to 1.136 for CN) (Table 6.1). Other parameters like the DUL also affect runoff but to a lesser extent (Table 6.1).

Soil water content at the end of the season was found to be most sensitive to DUL for soil layer 600 to 800 mm, 450 to 600 mm, 800 to 1000 mm, 300 to 450 mm,

Table 6.1 Sensitivity index results for soil, plant and weather conditions at the Ukulinga experimental site during the 2002 winter season

Parameter	Range tested	Base value	Runoff	Soil water(303)*	Drainage	Soil evaporation	Transpiration	Evapotranspiration
CN	6 to 94	94.000	1.136	-0.034	-0.441	-0.025	-0.017	-0.011
DR	0.01 to 0.99	0.320	-0.141	-0.074	0.424	-0.116	0.174	-0.047
SALB	0.090 to 0.260	0.090	0.088	0.001	0.195	-0.165	0.007	-0.111
U	0 to 50	12.000	-0.001	0.000	-0.007	0.005	0.000	0.004
DUL1	0.050 to 0.420	0.410	0.388	0.011	-0.471	1.107	-0.276	0.387
DUL2	0.050 to 0.420	0.325	0.677	0.043	-0.538	0.060	0.231	0.307
DUL3	0.050 to 0.430	0.310	0.332	0.075	-0.503	-0.121	1.030	0.109
DUL4	0.050 to 0.410	0.375	0.036	0.104	-0.288	-0.039	0.179	0.022
DUL5	0.050 to 0.460	0.346	0.004	0.157	-0.350	-0.002	0.020	0.005
DUL6	0.050 to 0.410	0.400	0.005	0.189	-0.379	0.000	0.001	0.000
DUL7	0.050 to 0.410	0.400	0.000	0.119	-0.278	0.000	0.000	0.000
LL1	0.008 to 0.300	0.270	0.033	0.001	0.032	0.015	-0.089	-0.019
LL2	0.008 to 0.301	0.225	-0.060	0.005	0.096	0.043	-0.229	-0.043
LL3	0.008 to 0.302	0.173	-0.267	0.012	0.189	0.130	-0.789	-0.092
LL4	0.008 to 0.303	0.260	-0.018	0.001	0.050	0.006	-0.076	-0.021
LL5	0.008 to 0.304	0.267	0.000	0.000	0.001	0.000	-0.002	-0.001
LL6	0.008 to 0.305	0.280	0.000	0.000	0.000	0.000	0.000	0.000
LL7	0.008 to 0.306	0.280	0.000	0.000	0.000	0.000	0.000	0.000
Rainfall	*	UNUK0201.wth	1.042	0.065	0.353	0.020	0.037	0.021
Min air T	*	UNUK0201.wth	-0.003	-0.035	-0.265	-0.251	0.216	0.146
Max air T	*	UNUK0201.wth	-0.014	-0.139	-0.847	-0.798	0.883	0.528
SRAD	*	UNUK0201.wth	-0.057	-0.223	-1.153	1.024	0.815	0.848

* A multiplier of 0.60 and 1.40 was used for all the weather parameters as the smallest and largest ranges in the sensitivity analysis tests. Soil water (303) refers to soil water at the end of the season

where CN stands for runoff curve number, DR for drainage coefficient, SALB for soil refection coefficient, U for first stage soil evaporation limit, DUL (1 to 7) and LL (1 to 7) for drained upper limit and lower limit soil water content for soil layers 0 to 50 mm, 50 to 150 mm, 150 to 30 mm, 300 to 45 mm, 450 to 600 mm, 600 to 800 mm, 800 to 1000 mm respectively, min air T for minimum air temperature, max air T for maximum air temperature and SRAD for solar radiant density.

150 to 300 mm, and sensitive to rainfall and DUL for soil layer 50 to 150 mm, 0 to 50 mm. The DR and CN coefficients were also found to be inversely related in their respective orders to soil water content at the end the season (Table 6.1). In Chapter 4, calibration of simulated soil water content was carried out with respect to the three parameters that the model was found to be sensitive.

As shown in Table 6.1, drainage was found to be directly related to DR and rainfall. However, an inverse relationship was noted with solar radiant density,

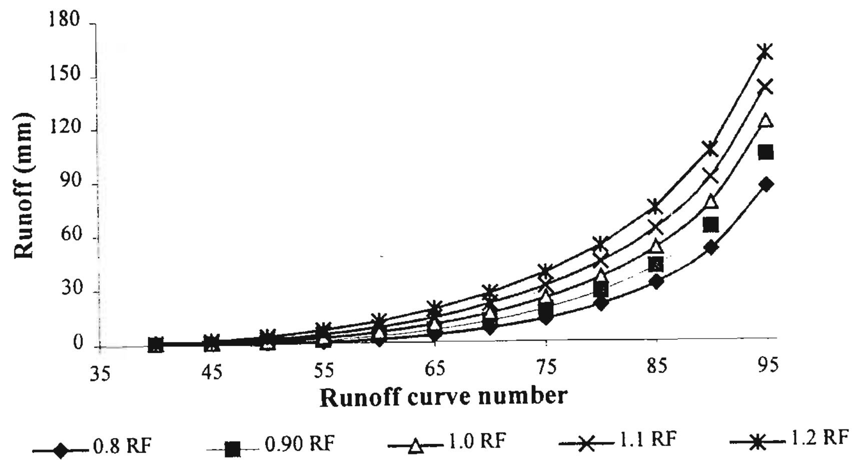


Fig. 6.1 Modelled runoff as affected by rainfall and runoff curve number for soil, plant and weather conditions at Ukulinga during the 2002 winter season. RF stands for base value rainfall

maximum air temperature, DUL for soil layer 50 to 150 mm, 150 to 300 mm, 0 to 50 mm, CN, DUL for 600 to 800 mm, 450 to 600 mm, 300 to 450 mm, and 800 to 1000 mm respectively. The latter could be explained as follows: coarse textured soils, with low drained upper limit soil water content, such as sandy and sandy loam soils have much larger particles and larger voids between the particles. Hence water drains easily in these soils unless there is an underlying restrictive layer or upward water movement which restricts water movement. Fine-textured soils such as clay soils have relatively higher drained upper limit soil water content than otherwise. Such soils have smaller voids and hence drain quite slowly. The results found here conform to the current understanding of the soil-plant-atmosphere relationships.

The results shown in Table 6.1 also indicate that the model simulated soil evaporation is most sensitive to DUL for soil layer 0 to 50 mm and solar radiant density respectively. Hillel (1980), as cited by Wallace *et al.* (1999), reported that the total soil water evaporative loss is the sum of the losses in the energy limited phase (that is dependent on the net solar radiant density at the soil surface and canopy surface) and the hydraulically limited second phase of evaporation. Total soil evaporation for a given season would therefore depend on the total amount of time the soil spends in the first and second stage drying which itself is a function of the soil type, solar radiant density and the frequency at which the surface is wetted by rainfall (Wallace *et al.*, 1999). This understanding of soil evaporation is in conformity to the above sensitivity analysis results. Maximum and minimum air temperatures were found to have an inverse relationship with soil evaporation probably because of their effects in increasing transpiration.

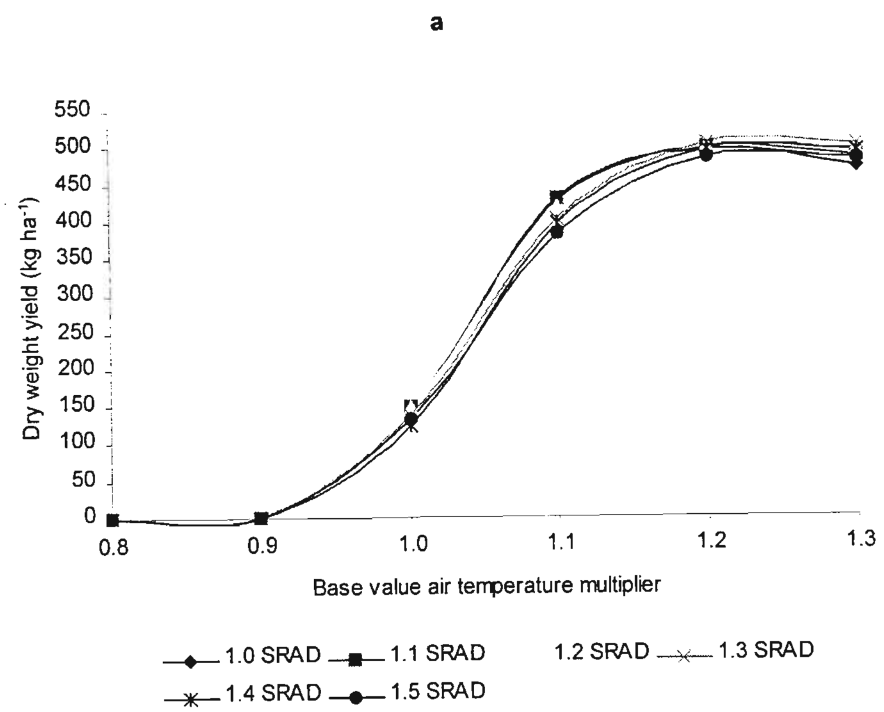
Plant evaporation was found to be most sensitive to DUL for soil layer 150 to 300 mm, and maximum air temperature, and solar radiant density respectively. Denmead and Shaw (1960, 1962), as cited by Saxton (2002), found that as plant available water and hence DUL increases actual plant transpiration increases from potential transpiration in a non-linear pattern. However, the lower limit soil water content (LL) was found to be inversely related to plant transpiration. This is because of the fact that the LL soil water content is a situation that causes plant decay and death if it persists. In actual fact plant transpiration is near zero at that point (Saxton, 2002). Other factors also affect transpiration but to a limited extent.

Evapotranspiration was sensitive to solar radiant density, maximum air temperature, DUL for the first four soil layers, minimum air temperature and rainfall in that order. Allen *et al.* (1998) found that soil water content is a very critical factor affecting evapotraspiration as was found from the sensitivity analysis results. This is simply because if there is no water in the soil, evaporation cannot take place. If there is enough water present in the soil, other factors like the weather will determine the rate of evapotranspiration. The results, depicted in Table 6.1, showed that other parameters such as SALB, although not very sensitive, have inverse relationships to evapotranspiration.

Simulation of yield, on a dry weight basis to changes in air temperature and solar radiant density is shown in Fig. 6.2. To do such simulations all the input model parameters were kept constant. An increase in solar radiant density resulted to corresponding increases in dry weight yield of tomato up until solar radiant density was increased by a factor of 30% from the base value solar radiant density (i.e. the solar radiant density at Ukulinga during the 2002 winter season). Increasing the solar radiant density beyond that resulted in decreased dry weight yield of tomatoes. Similarly Boote *et al.* (1998) found that daily solar radiant density showed a gradual saturation of daily photosynthesis starting at 20 MJ m^{-2} for an hourly model using soya bean parameters and conditions.

For all the solar radiant density regimes considered, maximum dry weight yield of tomatoes was observed for an air temperature regime 20% warmer than the base value (i.e. the air temperature at Ukulinga during 2002 winter season) (Fig. 6.2). Air temperature lower or higher than that decreased the dry weight yield. This might be attributed to reduced photosynthetic efficiency for lower air temperatures and increased respiration at higher air temperatures and shortening of fruit setting period. The minimum air temperature during the 2002 winter season and particularly during the first flower and first seed stage was 12.1 °C. This is far below the minimum air temperature requirement of tomato (18 °C). Air temperatures less than 13°C for several hours when flowers are open during pollination usually result in little or no fruit set (Bodnar and Garton, 1994).

For all the solar radiant density regimes considered, biomass at harvest was maximum for an air temperature regime 10% greater than the base value (Fig. 6.2). This explains why biomass at harvest needs less air temperature increases to reach its maximum as compared to dry weight yield that needs air temperature 20% greater than the base value to reach its maximum.



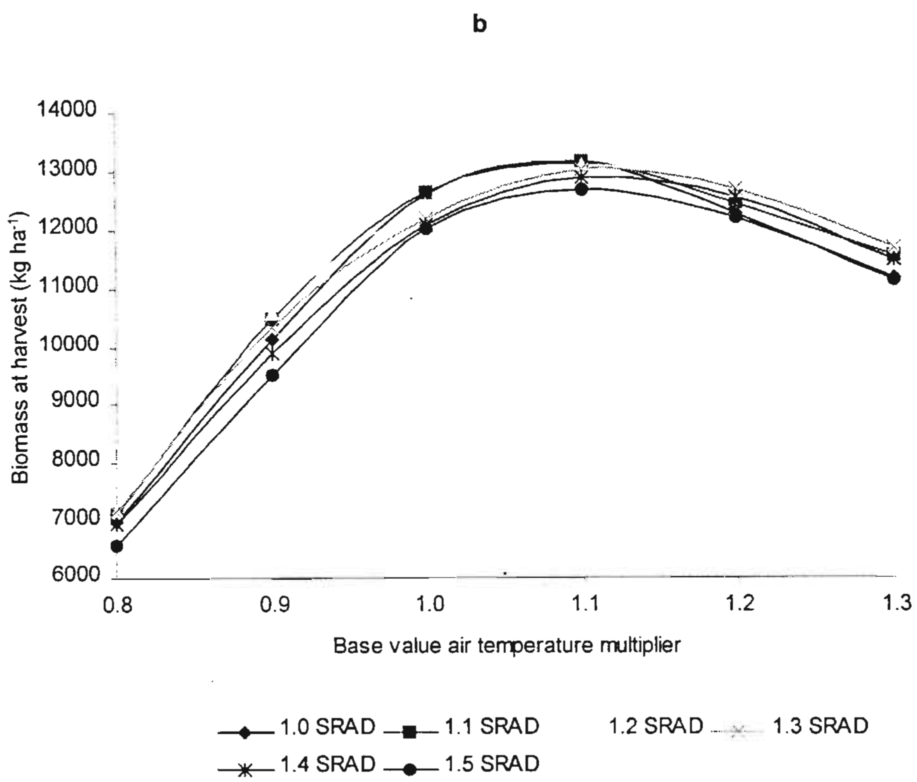


Fig. 6.2 Response of the DSSAT model to (a) dry weight yield and (b) biomass at harvest to changes in air temperature and solar radiant density for soil, plant and weather conditions at Ukulinga during the 2002 winter season. The legend at the bottom indicates base value solar radiant density multiplied with 1.0, 1.1, 1.2, 1.3, 1.4, and 1.5 respectively

For almost all plant populations considered dry weight yield of tomatoes increased as the space between rows was decreased from 1.5 m to 0.6 m and to 0.8 m for others (Fig. 6.3). This is because a decrease in row spacing causes a decrease in crop extinction coefficient that would consequently result in increased intercepted solar radiant density (Maas and Arkin, 1980). This would maximize photosynthesis and total plant biomass production and hence would result to higher yield. However, reducing the space between rows below 0.8 m resulted in lower yields probably due to plant stresses such as late season soil water deficiency. Although significant interaction was observed between different combinations of row spacing and plant population, an increase in plant population from 1.0 to 1.4 plants m^{-2} resulted in higher yields due to greater interception of solar radiant density. However, increasing the plant population further did not result in increases in dry weight yield probably due to the presence of other factors such as water and nutrient deficiency.

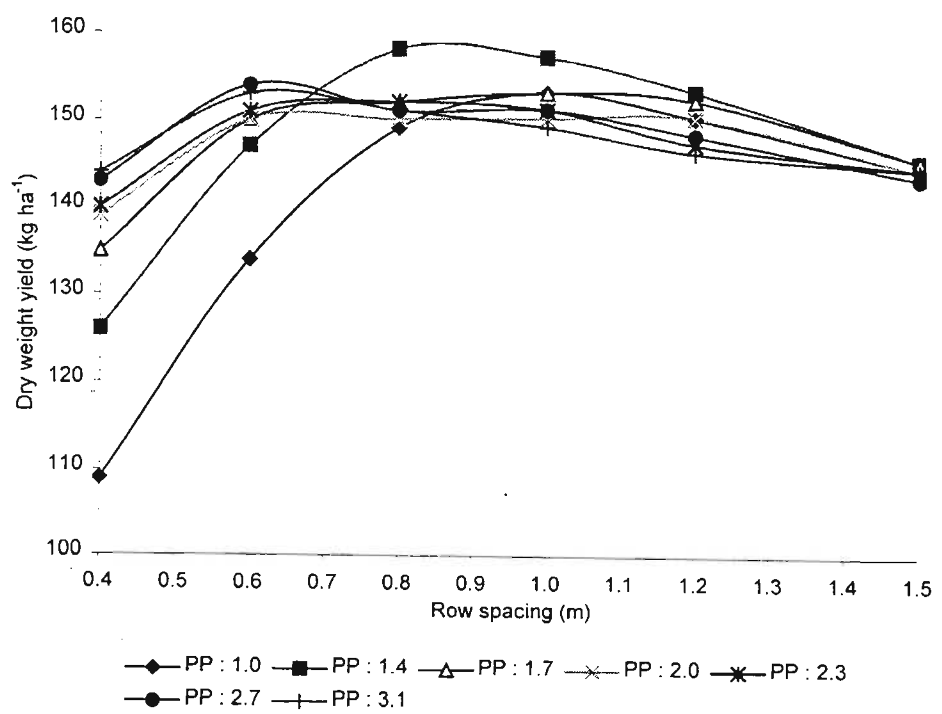


Fig. 6.3 Response of the DSSAT model to changes in row spacing and plant population for soil, plant and weather conditions at Ukulinga during the 2002 winter season. The legend at the bottom stands for plant population of 1.0, 1.4, 1.7, 2.0, 2.3, 2.7, and 3.1 plants m^{-2} respectively

The probability of a complete crop failure is 88 % for full initial soil profile water content at planting as simulated using the 25 years weather data for Ukulinga (Fig. 6.4). The probability of crop failure progressively increases as the initial profile soil water content decreases from full to ¼ of drained upper limit values. This implies that growing tomatoes during winter season is risky even when the initial soil water content of the profile is full and therefore a farmer would be better growing the crop during other times of the year when the minimum air temperature is above 13°C. The year 2002 had a relatively warmer winter than other years considered and hence the yield was, surprisingly, higher than the other years (150 kg ha^{-1} for full initial soil water content at planting) (data not shown).

The probability that drainage will be less than 10 mm is 76% for full initial soil profile water content. As expected, the probability that drainage will be less than 10 mm

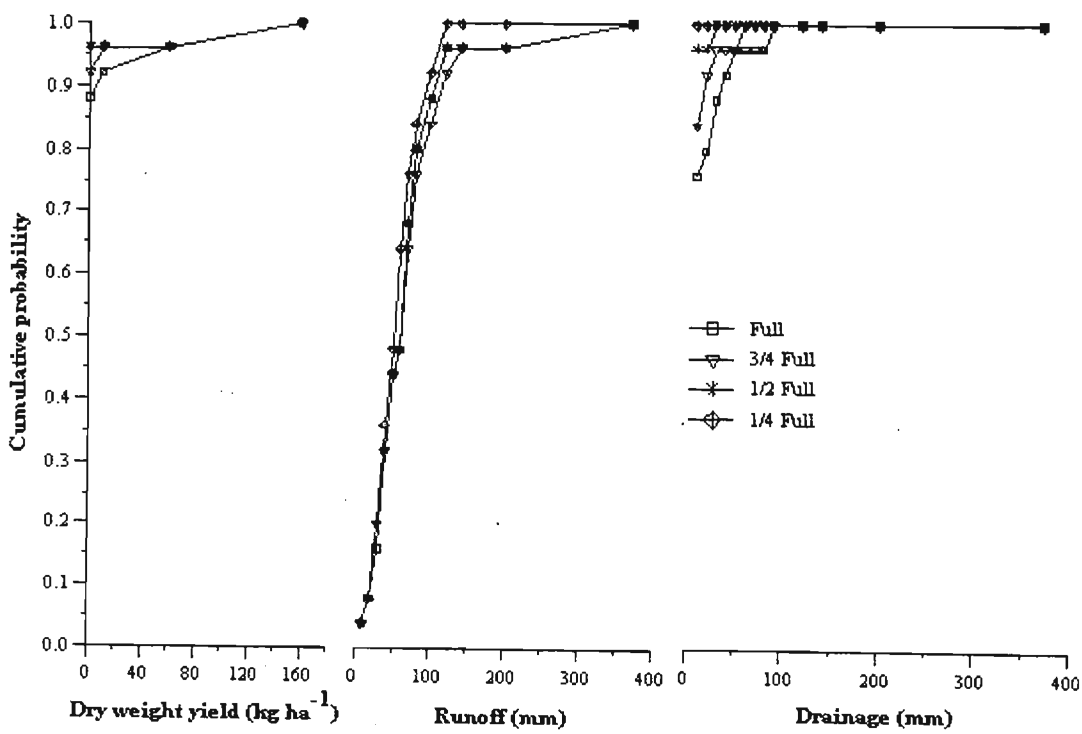


Fig. 6.4 Cumulative probability as a function of yield (dry weight basis), drainage and runoff simulated for different initial soil profile water contents and long-term weather data at Ukulinga

progressively increases as the initial soil water content is decreased (84%, 94%, 100% for an initial soil profile soil water content of full, ¾, ½, and ¼ of the drained upper limit values respectively). This would mean that drainage losses in terms of water and important nutrients are quite low for low initial profile soil water content during the season for most of the historical weather dataset considered. The significance of such a low drainage is that the crop would be utilizing most of the incoming water and if salts were present within the water, rising water tables that might have contributed to salinity effects would be avoided.

For 50% probability, runoff did not exceed 44 mm for most of the initial soil profile water contents considered. This implies that the initial soil profile water content had little effect on runoff over the crop-growing season (Fig. 6.4). The lower the initial soil water content, the higher is the infiltration rate (a parameter which behaves exactly the opposite to runoff). The higher the initial soil water content the lower is the infiltration rate. Long term risk assessment using the four soil water contents gave similar results probably because the effect of the initial soil water content was limited for the early stages of the crop growth. The effects of soil water content on runoff for the whole crop growing season might have been masked due to changes in soil water content as a result of rainfall and irrigation.

6.4 CONCLUSIONS

Sensitivity analysis carried out for model output parameters such as soil water content at the end of the season, runoff, drainage, soil evaporation, plant transpiration and evapotranspiration gave results that conforms to current understanding of the soil-plant-atmosphere relationships. In addition dry weight yield of tomatoes were studied with respect to variable solar radiant density regimes. It was found that an increment by as much 30% from the base value was found to maximize the yield. Beyond that, yield progressively declined. In a similar fashion an air temperature regime 20% higher than the base value gave maximum yield. However, below and above that, the yield declined. It was observed from such results that it is not advisable to grow tomatoes during the winter season in the open environment. Similar results were also obtained for biomass at harvest. As expected dry weight yield increased as the plant spacing was decreased due to higher intercepted solar radiant density. Reduction of spacing between plants below 0.8 m resulted in reduced yield. In a similar fashion, an increase in plant population gave higher yields for the same reason mentioned above. An increase in the plant population above 1.4 m did not result in higher yields probably due to factors such as water, nutrient and radiation deficiency. Such an analyses has great importance for farmers in optimizing management practices with increased reliability of models. The long-term risk assessment carried out showed that it is risky to grow tomatoes during winter season at Ukulinga irrespective of the initial soil water content in the open environment. However, one could grow tomatoes under cover in winter. One might question the reliability of models for such an analysis in this study because the genetic coefficients have not been determined experimentally and as well the soil inputs such as drained upper and lower limits have been determined from soil texture and bulk density regression based equations. However, at least the relative values are reliable even if absolute values might vary to a certain extent from field situations.

CHAPTER 7

APPLICATION OF THE MODEL FOR EVALUATION OF CULTURAL PRACTICES

7.1 INTRODUCTION

The interaction of soya bean genotypes with environmental factors such as air temperature, solar radiant density, rainfall, soil characteristics and cultural practices such as seeding rate, planting date, and row spacing necessitate on-site cultivar evaluation for that particular environment. A particular soya bean cultivar may do well in some environments, but cropping of that cultivar in another environment may not be successful. Hence cultivar evaluation is a common practice in soya bean producing countries (Pakendorf *et al.*, 1999).

There is limited information available to identify the optimum seeding rate and row spacing for a particular environment especially for recently released cultivars. Allard and Bradshaw (1966), as cited by Rosenthal and Gerik (1990), suggested that a long-term history of observations is needed to adequately evaluate the cultural and environmental interactions on grain yield. However, it is not practical to empirically assess cultural practices in the long run.

Some crop simulation models may be very useful in evaluating cultural practices over extended periods of time using historical weather information or computer generated weather information. For instance the DSSAT v3.5 decision support system (Tsugi *et al.*, 1994), which has a number of models under its shell, is a daily incrementing model that can predict crop growth and development through the interactive relationships of soil (soil type, drained upper limit, lower limit, soil depth, slope, rooting distribution), weather (solar radiant density, air temperature, and rainfall) and cultural practices (row spacing, plant population, planting date, cultivar maturity group). However, other models such as the soil water balance model (SWB) (Annandale *et al.*, 1999; Annandale *et al.*, 2000), a multi-soil layer, daily time step, generic crop, mechanistic, irrigation-scheduling model and the CropSyst model (Stockle and Nelson, 2000) are not sensitive to cultural practices such as row spacing because they need crop growth parameters for different row spacings as the canopy radiation extinction coefficients difference is not accounted for in the model. Therefore, unlike the DSSAT suite of crop models, crop growth parameters for SWB have to be determined or fitted for soya bean grown in different row spacings (for example Jovanovic *et al.*, 2002).

The objectives of this study were to first evaluate the performance of soil water balance and growth routines of the CROPGRO-Soya bean model, one of the models under the DSSAT v3.5 group of crop models and then to evaluate the effect of row spacing, seeding rate and cultivars on simulated yield of soya bean using thirty-three years of historical weather information at Cedara.

7.2 MATERIALS AND METHODS

Soya bean (*Glycine max* L. Merr.) was grown at Cedara (latitude ≈ 29.53°S, longitude ≈ 30.28°E and altitude ≈ 1076 m above sea level), KwaZulu-Natal, South Africa. The field had a slope of 6 % in the N-S direction. It was bordered on the north by a maize planted field, on the south by another soya bean planted field, on the east by a farm road and on the west by a farm road. The average annual rainfall, average maximum air temperature and average minimum air temperature of the site is approximately 874.2 mm, 30.6 °C and 4.7 °C respectively (Agricultural Research Council, Institute for Soil, Climate and Water, Pretoria). Weather data was collected from an automatic weather station installed nearby the soya bean field for the year 2002-3. Thirty-three years of historical weather data set for Cedara (Agricultural Research Council, Institute for Soil, Climate and Water, Pretoria) were used to evaluate the effect of row spacing, seeding rates and cultivars on simulated yield of soya bean. The soil at the experimental site was found to be clay in texture. Other soil characteristics such as bulk density, organic carbon, soil water limits of all the soil depths considered are shown in Table 7.1. The experiment considered three row spaçings: 225 mm, 450 mm, and 900 mm; four seeding rates: 200000 plants ha^{-1}, 300000 plants ha^{-1}, 400000 plants ha^{-1}, 500000 plants ha^{-1}; and three cultivars: prolific (upright bushy), LS555 (upright) and CRN5550 (bushy). The experiment also contained sprayed and unsprayed treatments. The three cultivars were planted on November 1, 2002 and harvested on April 3, 2003. The field was rainfed.

Soil water content was monitored starting from early January 2003 until the end of March with Delta-T Profile Probe type PR1 (Plate 7.1) at six positions (100 mm, 200 mm, 300 mm, 400 mm, 600 mm and 1000 mm) within the vertical profile. The sensor

Table 7.1 Summary of soil input parameters used for running the model

Soil depth (mm)	Lower limit (m^3 m^{-3})	Drained Upper limit (m^3 m^{-3})	SAT SW (m^3 m^{-3})	EXTR SW (m^3 m^{-3})	Initial SW (m^3 m^{-3})	Root distribution weighting factor	Bulk density (kg m^{-3})	pH	Org C %
0 to 50	0.230	0.345	0.389	0.115	0.345	0.50	1530	4.20	3.20
50 to150	0.231	0.343	0.403	0.112	0.343	0.50	1490	4.25	2.95
150 to 300	0.232	0.341	0.408	0.109	0.341	0.40	1480	4.17	2.90
300 to 450	0.257	0.360	0.424	0.103	0.360	0.30	1430	4.23	1.97
450 to 600	0.268	0.371	0.419	0.103	0.371	0.20	1440	4.50	1.50
600 to 800	0.279	0.391	0.462	0.112	0.391	0.20	1320	4.50	0.80
800 to 1000	0.274	0.410	0.439	0.137	0.410	0.15	1380	4.05	0.50

Plate 7.1 The Delta-T type PR1 soil profile probe and the access tube used for measurement of soil water content

was used in access tubes (28 mm in diameter) for rapid insertion and removal. The diameter of the access tubes was small to minimize soil disturbance. To ensure maximum soil contact when installing the access tubes, holes were augured slightly undersize (25 mm in diameter). The sensor was then moved from one access tube (Plate 6.1) to another collecting instantaneous measurements by connecting it to an HH2 meter (Plate 7.2).

In a laboratory study, the PR1 sensor measurements when connected to the hand held HH2 meter and to a CR10X datalogger (Plate 7.2) were compared with gravimetric soil water content. The soil samples used were brown and dark clay from Cedara and Ukulinga experimental sites respectively. For this purpose, five plastic pipes 200 mm in diameter were used. Two of the pipes were filled with wet soil while the other two were filled with air-dry soil and the fifth one was ensured to have soil water content

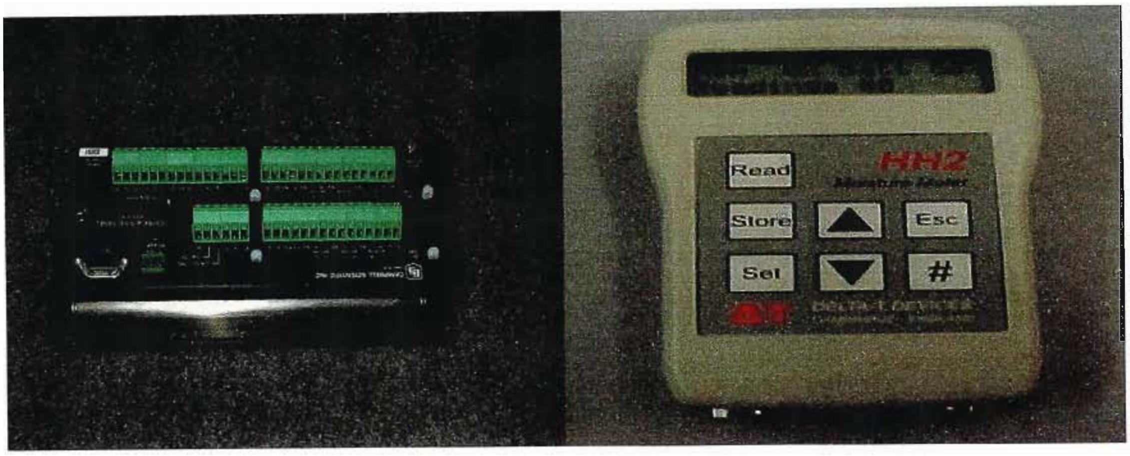


Plate 7.2 CR10X datalogger (left) and HH2 meter (right) (Photo M F Gebregiorgis) used in with the Delta-T Profile Probe type PR1 for measurement of soil water content

between the two. The pipes were made to have six openings at 100 mm, 200 mm, 300 mm, 400 mm, 600 mm and 1000 mm within the vertical profile of the pipes. These openings were used for purposes of sampling soil for gravimetric soil water content determinations. One of the pipes used for this purpose is shown (Plate 7.3).

A LAI-2000 plant canopy analyzer (PCA) developed by Li-Cor (Lincoln, NE) was used to measure leaf area index (LAI). The PCA is supposed not to be used to make LAI determinations in direct sunlight because leaf reflectance and transmittance of light will result in an overestimation of LAI (Li-Cor, 1990). In this study measurements of LAI were made at midday despite direct sunlight by shading both the sensor and sampling area with a white umbrella (2560 mm in diameter) that was manually held in place to block the direct rays of the sun.

Other plant parameters such as days to canopy, flowering date, plant height, pod height and yield were also measured for both 2001-2 and 2002-3 growing seasons (Cedara Agricultural Research Centre).

Plate 7.3 One of the pipes, 1000 mm in length and 200 mm in diameter, used in the laboratory study for the comparison of gravimetric soil water content with soil water content measurements from Delta-T PR1 soil profile probe (inside the pipe) and the seven openings along its vertical profile for gravimetric soil sampling

ET-gage (ET-gage company, model A, Loveland, USA) was installed about 200 m away from the soya bean field to measure reference evapotranspiration. As recommended for agricultural crops, number 54-canvas cover, corresponding to alfalfa reference evaporation, made to resist escaping water vapour and that gives ET-gage readings 10 to 15% greater than the number 30 canvas cover, corresponding to grass reference evaporation, was used (Cedara Agricultural Research Centre).

Soil water limits were estimated using soil texture and bulk density regression based equations developed by Schulze *et al.* (1985).

The CROPGRO-Soya bean model, one of the models under the DSSAT shell, was used for running the simulations. Calibration of the soil parameters was carried out using procedures mentioned in section 5.3. Cultivar specific coefficients (genetic coefficients), which reflect simulated differences in cultivar growth and development, were not readily available for South African soya bean cultivars. The coefficients could be determined experimentally or fitted from data on phenological events and yield components (du Toit, 2002). In this study the coefficients were fitted from data on phenological events and yield using procedures described by Mavromatis *et al.* (2001). For this purpose, flowering date and yield data collected in the year 2001-2 growing season for one of the treatments (225 mm row spacing and 200000 plants ha^{-1}) was used to estimate the model coefficients and calibration of soil water content and the other treatments were used for verification of the model. The parameters were manipulated until simulated output matched field observations of flowering date and yield. The calibrated parameters versus the default values are presented (Table 7.2).

The model was run assuming that the initial soil water content was at its drained upper limit for all the historical weather dataset used and as well for 2001-2 and 2002-3

Table 7.2 Calibrated and standard default crop specific coefficient values for soya bean maturity group VII (LS555 and CRN5550) used in CROPGRO-Soya bean

Parameter	CRN5550		LS555	
	Calibrated	Default	Calibrated	Default
Critical daylength for crop development, h	12.830	12.330	12.830	12.330
Sensitivity to photoperiod, 1/h	0.280	0.320	0.303	0.320
Time between plant emergence and flower appearance, photothermal days	20.800	20.800	20.800	20.800
Time between first flower and first pod, photothermal days	6.380	10.000	9.000	10.000
Time between first flower and first seed, photothermal days	16.000	16.000	13.000	16.000
Time between first seed and physiological maturity, photothermal days	36.000	36.000	32.000	36.000
Time between first flower and end of leaf expansion, photothermal days	18.000	18.000	18.000	18.000
Maximum leaf photosynthesis rate, mg CO_2 m^2 s^{-1}	1.030	1.030	1.030	1.030
Specific leaf area of cultivar under standard growth conditions, cm^2 g^{-1}	375.000	375.00	375.000	375.000
Maximum size of full leaf (three leaflets), cm^2	180.000	180.00	180.000	180.000
Maximum fraction of daily growth that is partitioned to seed + shell, unitless	1.000	1.000	1.000	1.000
Maximum weight per seed, g	0.180	0.180	0.180	0.180
Seed filling duration for pod cohort at standard growth conditions, photothermal days	24.000	23.000	23.000	23.000
Average seed per pod under standard growing conditions, average seeds per pod	2.050	2.050	2.050	2.050
Time required for cultivar to reach final pod load under optimal conditions, photothermal days	15.000	10.000	15.000	10.000

growing seasons. Further it was run starting from October 27, 2002 until harvest time (April 3, 2003).

7.3 RESULTS AND DISCUSSION

7.3.1 Soil Water Content Measurements

Before using the Delta-T PR1 sensor for monitoring the soil water content in the field, it was calibrated against the gravimetric soil water content measurements. Measurements with the PR1 sensor connected to a hand held HH2 meter were compared to measurements where the PR1 was connected to a CR10X datalogger (Fig. 7.1). The results showed that both methods gave statistically the same estimates of soil water measurements at the 99 % confidence (intercept + SE intercept 99% = -0.022, intercept – SE intercept 99% = -0.065; slope + SE slope 99% = 1.003, slope – SE slope 99% = 0.904).

Soil water content measurements using the PR1 sensor were then compared with gravimetric soil water measurements (Fig. 7.2). It was observed that the PR1 sensor measurements of soil water content conformed well to gravimetric soil water content in the drier range while a considerable deviation was observed in the wetter range (Fig. 7.2). For these measurements, a bulk density of 1056 kg m^{-3} was used. The gravimetric and PR1 soil water content measurements were taken after a week of application of water to ensure that change in soil water content was negligible. In other words the system was allowed to reach equilibrium before taking the soil water measurements. The relationship was then used to calibrate the actual soil water measurements taken at Cedara Agricultural College on the soya bean field trial. Of particular note is that since the soil water measurements using the PR1 and gravimetric methods conformed well in the dry range while considerable deviation was noted in the wet range, the actual soil water measurements were calibrated taking this situation into account. That is to say the two datasets were treated separately for purposes of calibration.

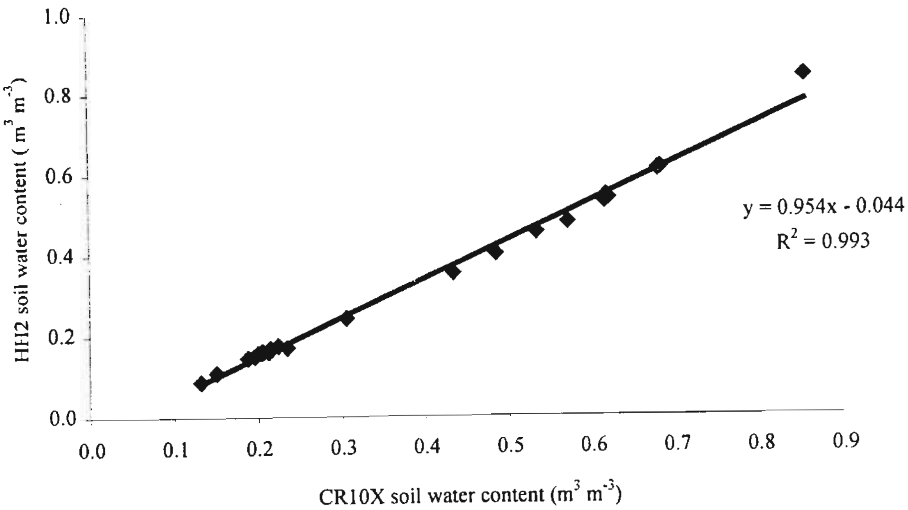


Fig. 7.1 Comparison between soil water measured using PR1 connected to a CR10X datalogger (x-axis) versus soil water measured using PR1 connected to hand held HH2 meter (y-axis)

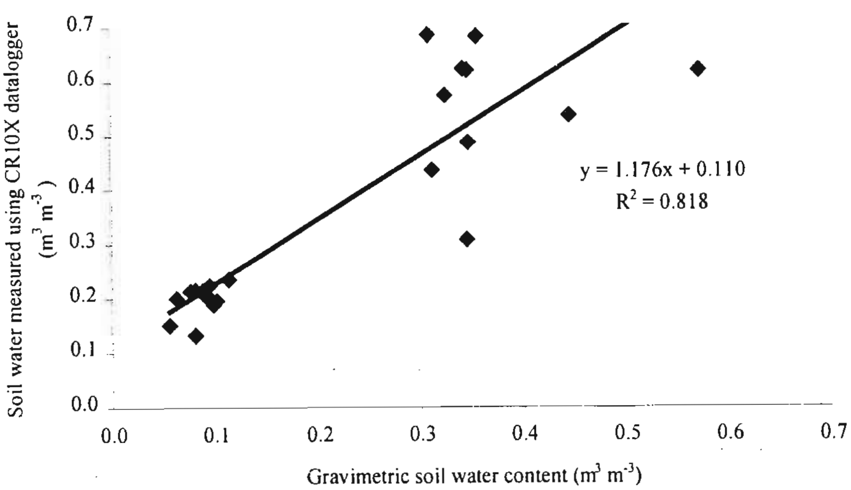


Fig. 7.2 Gravimetric soil water content versus soil water content measured using PR1 connected to CR10X datalogger for laboratory investigation using a dark and brown clay soil from Cedara and Ukulinga experimental sites respectively

7.3.2 Verification of Simulated Soil Water Content

Before verification, the same procedures were followed as in Chapter 5 to calibrate the soil parameters that are critical parameters affecting simulated soil water content. The statistics were unsatisfactory for the calibration dataset (cultivar Prolific, row spacing

900 mm and seeding rate of 500000 plants ha^{-1}) especially *d* (index of agreement) was very low (Table 7.3). One of the reasons for this might be the fact that only 12 measurements of soil water content were considered for the whole season. However, the *RMSE*-soil water content did improve considerably after calibration (Table 7.3). As shown in Table 7.3, for 300 mm, 400 mm, and 600 mm soil depth, the r^2 is fairly high whereas the index of agreement (*d*) is low and the *RMSE* is fairly low. In this instance it is not possible to say that the accuracy of the prediction is satisfactory because the magnitudes of r^2 is high. As Wilmott (1982) noted the magnitudes of r^2 are misleading and are often unrelated to the sizes of the differences between observed and predicted values. So other statistical measures like the index of agreement and *RMSE* have to be considered as well. For the independent datasets, it was expected that the statistics would not be satisfactory either. To verify this calibrated parameters were kept for verification of soil water content measurements for other treatments on the soya bean field. As shown in Table 7.4 the statistics results indicate that the simulations of soil water content using the independent datasets were also unsatisfactory. Modifications of the *DUL*, as discussed in Chapter 5 did improve the simulated soil water content to some extent. But it was not possible to improve the simulated soil water content to a satisfactory standard for the calibration dataset. This probably indicates that the sensor's access tube might have had inadequate contact with the soil and hence underestimation of soil water content for all the soil depths and treatments considered.

Table 7.3 Statistical parameters calculated for the calibration dataset for eleven soil water content measurements at Cedara Agricultural College during 2003

Soil depth (mm)	r^2	d	$RMSE$ (m^3 m^{-3})	% $RMSE_S$	% $RMSE_U$
100	0.013	0.068	0.125	99.681	0.318
300	0.846	0.000	0.118	98.857	1.143
400	0.839	0.015	0.094	98.585	1.415
600	0.727	0.013	0.111	96.869	3.131
1000	0.113	0.163	0.045	39.473	60.523

where r^2 is the coefficient of determination, d is the Wilmott's index of agreement, $RMSE$ is the root mean square error, $RMSE_s$ is the systematic root mean square error, $RMSE_u$ is the unsystematic root mean square error

Table 7.4 Statistical parameters calculated for the verification dataset for eleven soil water content measurements at Cedara Agricultural College during the 2003

Treatment	Soil depth (mm)	r^2	d	$RMSE$ ($m^3\ m^{-3}$)	% $RMSE_S$	% $RMSE_U$
Prolific 450 mm; 500000 plants ha^{-1}	100	0.784	0.000	0.206	99.732	0.267
	300	0.673	0.031	0.207	98.988	1.011
	400	0.171	0.116	0.191	98.152	1.840
	600	-	-	-	-	-
	1000	0.052	0.476	0.066	71.523	28.477
LS555 250 mm; 300000 plants ha^{-1}	100	0.762	0.068	0.115	99.047	0.953
	300	-	-	-	-	-
	400	0.835	0.063	0.3728	99.908	0.092
	600	-	-	-	-	-
	1000	0.001	0.195	0.133	92.656	7.340
LS555 450 mm; 300000 plants ha^{-1}	100	0.572	0.016	0.108	98.053	1.946
	300	0.366	0.023	0.157	99.906	0.094
	400	0.353	0.014	0.180	99.964	0.036
	600	-	-	-	-	-
	1000	0.007	0.181	0.251	97.949	2.050
LS555 900 mm; 300000 plants ha^{-1}	100	-	-	-	-	-
	300	0.089	0.285	0.094	86.661	13.338
	400	0.377	0.015	0.180	99.962	0.038
	600	-	-	-	-	-
	1000	-	-	-	-	-

The dashed lines indicate measured data excluded due to some problems

where r^2 is the coefficient of determination, d is the Wilmott's index of agreement, $RMSE$ is the root mean square error, $RMSE_s$ is the systematic root mean square error, $RMSE_u$ is the unsystematic root mean square error

7.3.3 Verification of Simulated Leaf Area Index

The model's simulations of leaf area index did respond well to changes in row spacing. As shown in Table 7.5, simulated leaf area index was the highest for 225 mm row spacing and lowest for 900 mm row spacing. This trend conformed to actual measurements of leaf are index (*LAI*). For 900 mm row spacing simulated *LAI* overestimated the measured value by 0.12 only; for 450 mm row spacing by 0.19 and for 225 mm by 0.53. However, it has not been possible to evaluate the model simulations of *LAI* from the beginning of the growing season right up to senescence.

7.3.4 Verification of Simulated Evapotranspiration

Simulated evapotranspiration was found to have unsatisfactory agreement with measured evapotranspiration (r^2 = 0.463, d = 0.822, $RMSE$ = 10.596 mm, % $RMSE_s$ = 29.372, n = 32) (Fig. 7.3). The r^2 value was not satisfactory whereas d was fairly good. Although the $RMSE$ is large, it seems that the deviations of simulated evapotranspiration from measured evapotranspiration are random because the $RMSE_s$ is low. The $RMSE$ is large probably because measured potential evapotranspiration was modified with a constant crop multiplier, the crop coefficient. As was explained in Chapter 5, such a procedure is invalid under variable soil water content conditions (Reddy, 1983). From this then it could be anticipated that model simulations of evapotranspiration might to be superior to measured evapotranspiration if seasonal leaf area index is simulated with reasonable accuracy.

Table 7.5 Comparison between simulated and measured leaf area index for LS555 cultivar with seeding rate of 300000 plants ha^{-1} and different row spacings for day of year 25, 2003 at Cedara during the summer season

Row spacing (mm)	Leaf area index	
	Measured	Simulated
900	4.66	4.78
450	6.03	5.84
225	6.39	5.86

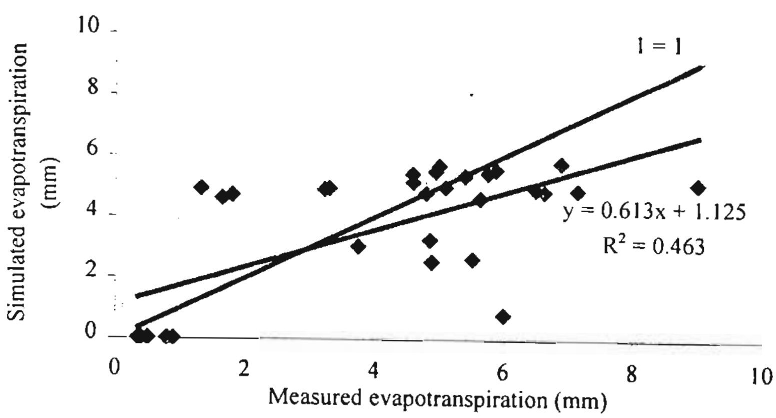


Fig. 7.3 ET-gage measured and simulated evapotranspiration from day of year 57 to 93 at Cedara during the 2003 summer season

7.3.5 Verification of Simulated Yield

In general the model was able to show yield decreases and increases in response to row spacing and seeding rates for CRN5550 cultivar (Table 7.6). Simulations of yield for CRN5550 cultivar agreed with field observations of yield satisfactorily (r^2 = 0.433, d = 0.764, $RMSE$ = 867. 782 kg ha^{-1} , % $RMSE_s$ = 39.973, n = 24). The $RMSE_s$ is quite small which indicates that the deviations of simulated from measured values are random. The d-index is also fairly good. However, r^2 is not favourable. Simulated flowering date matched field observations reasonably well (Table 7.6).

Table 7.6 Simulated and measured yield and flowering date for different row spacings and seeding rates for CRN5550 cultivar at Cedara for summer growing seasons 2001-2 and 2002-3 respectively

Year	Seeding rate (plants ha^{-1})	Row spacing (mm)	Measured yield (kg ha^{-1})	Simulated yield (kg ha^{-1})	Measured flowering date (days after planting)	Simulated flowering date (days after planting)
2001-2	200000	225	3685	3685	62	62
		450	3987	3669	62	62
		900	3417	3228	59	62
	300000	225	4270	3843	58	62
		450	4042	3821	59	62
		900	3587	3342	58	62
	400000	225	4255	3938	62	62
		450	4079	3915	61	62
		900	3433	3408	58	62
	500000	225	3506	4001	62	62
		450	3896	3976	61	62
		900	3320	3456	58	62
2002-3	200000	225	4588	3996	-	66
		450	4640	3983	-	66
		900	3949	3571	-	66
	300000	225	3996	4132	-	66
		450	4270	4115	-	66
		900	4278	3673	-	66
	400000	225	4264	4213	-	66
		450	4556	4195	-	66
		900	3959	3737	-	66
	500000	225	4262	4266	-	66
		450	3909	4268	-	66
		900	3804	3786	-	66

For cultivar LS555, the model was also able to show general yield increases and decreases like CRN5550 in response to row spacing and seeding rates. Simulations of yield using the model for this cultivar did agree with field observations to a satisfactory standard (r^2 =0.577, d = 0.773, $RMSE$ = 2395.2 kg ha^{-1} , % $RMSE_s$ = 72.0, n = 24). Although the systematic $RMSE$ is indicating bias, other parameters such as the index of agreement and r^2 are fairly good. Moreover, simulated flowering date is indicating almost perfect agreement with observed flowering date (Table 7.7)

Table 7.7 Simulated and measured yield and flowering date for different row spacings and seeding rates for soya bean LS555 cultivar at Cedara for summer growing seasons 2001-2 and 2002-3 respectively

Year	Seeding rate (plants ha^{-1})	Row spacing (mm)	Measured yield (kg ha^{-1})	Simulated yield (kg ha^{-1})	Measured flowering date (days after planting)	Simulated flowering date (days after planting)
2001-2	200000	225	3175	3316	65	64
		450	3507	3302	65	64
		900	2553	2914	65	64
	300000	225	3462	3453	64	64
		450	3343	3436	65	64
		900	3422	3010	64	64
	400000	225	4091	3531	64	64
		450	3649	3513	65	64
		900	3265	3073	65	64
	500000	225	4877	3578	65	64
		450	3454	3560	64	64
		900	3276	3120	64	64
2002-3	200000	225	4620	3972	-	67
		450	4884	3957	-	67
		900	3878	3544	-	67
	300000	225	5000	4116	-	67
		450	4983	4101	-	67
		900	3915	3649	-	67
	400000	225	4085	4188	-	67
		450	4296	4174	-	67
		900	3538	3723	-	67
	500000	225	4243	4230	-	67
		450	4211	4216	-	67
		900	3341	3781	-	67

7.3.6 Application of The Model

Although model verifications for some of the soil water balance components was unsatisfactory, the model could still be applied to evaluate the effect of row spacing, seeding rates and cultivars on simulated soya bean yield for over 30 growing seasons at Cedara.

As shown in Fig. 7.4 for cultivar CRN5550, at 50% probability level and for all seeding rates it was found that 225 mm and 450 mm row spacings were found to have greater yield than of the 900 mm row spacing. Decreasing the row spacing from 900 mm to 450 mm or 225 mm gave rise to higher yield. This is because a decrease in row spacing causes a decrease in crop extinction coefficient that would consequently result in increased intercepted solar irradiance (Maas and Arkin, 1980; Board *et al.*, 1990; Board et al., 1992; Flenet *et al.*, 1996). Greater radiation interception often increases yield (Parves *et al.*, 1989). Among the different seeding rates, the highest yield was simulated for 400000 plants per ha^{-1} seeding rate with 450 mm row spacing at 50% probability level. This might be explained by the fact that the intercepted solar irradiance increases as plant population increases. Increasing the plant population beyond 400000 plants ha^{-1} did not result to increased yield probably because of the presence of other factors such as water and nutrient deficiency. Farmers in KwaZulu-Natal use 300000 plants ha^{-1} seeding rate (Killian, 2003, personal communication). This actually indicates a room for improvement of the current cultural practices used by farmers. But the improvement can be made as far as the limitations of the model are taken into account. The model for example does not respond to the effects of pests, intercropping, excess soil water and other factors on crop performance. It works in parts of the world where water, nitrogen and weather are major factors affecting crop performance. In other words it does not take into account factors that limit yield such as phosphorus availability or soil acidity. The soil water balance model works well for well-drained soils. Good simulation of the soil water balance in very poorly drained soils with oxygen stress is not possible. The model is a daily incrementing model that does not take advantage of hourly weather data and in particular variation of rainfall within a day. Nowadays hourly weather data are becoming available. The improvements of the cultural practices, therefore, have to be carried out taking into account the limitations of the model mentioned above.

As shown in Fig. 7.5 for cultivar LS555, at 50% probability level and for all seeding rates it was found that 225 mm and 450 mm row spacings were found to have greater yield than that for the 900 mm row spacing. Decreasing the row spacing from 900 mm to 450 mm or 225 mm gave rise to higher yield for reasons mentioned before. Among the different seeding rates, the highest yield was simulated for 400000 plants ha^{-1} seeding rate with 450 mm row spacing at 50% probability level. This is quite similar observation as the other cultivar (CRN5550). Increasing the plant population beyond 400000 plants ha^{-1} did not result in further increases in yield probably because of the presence of other factors such as water and nutrient deficiency. This actually indicates a room for improvement of the current cultural practices used by farmers or suggests that the model might still need further improvement.

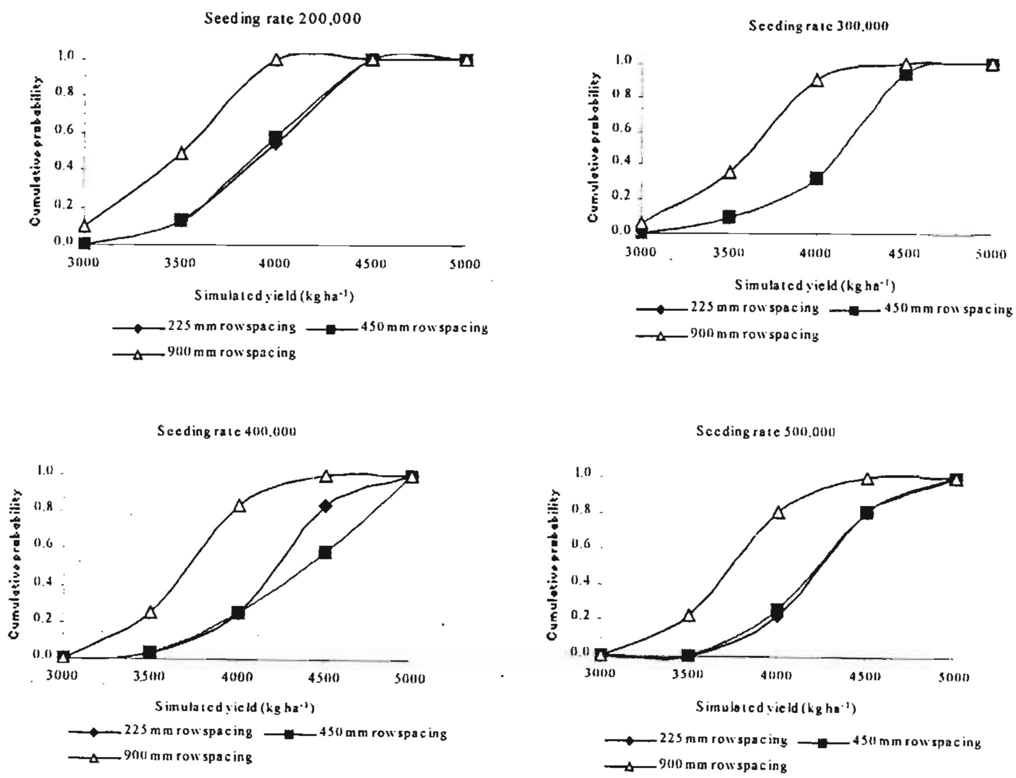


Fig. 7.4 Cumulative probability as a function of soya bean yield for different seeding rates and row spacings for cultivar CRN5550 using the 33-year historical weather dataset for Cedara

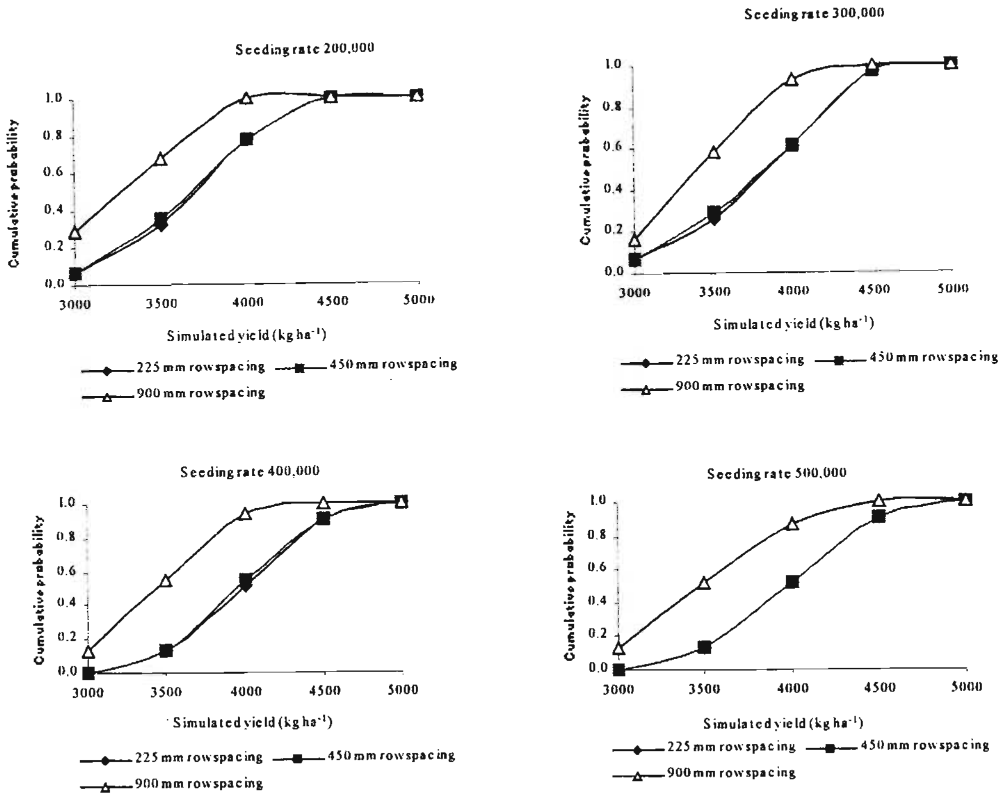


Fig. 7.5 Cumulative probability as a function of soya bean yield for different seeding rates and row spacings for cultivar LS555 using the 33-year historical weather dataset for Cedara

7.4 CONCLUSIONS

The CROPGRO-Soya bean model, one of the many models under the DSSAT v3.5 shell, simulations of soil water content were unsatisfactory even after calibration of the some of model parameters such as *DUL*, *DR* and *CN*. There is a suspicion that the measured soil water was not accurate enough probably due to inadequate contact of the access tubes with the soil. However, other simulated parameters such as the *LAI*, yield, and flowering date had satisfactory agreement with measured values. The results for both cultivars showed that reducing the row spacing from 900 mm to 450 or 225 mm resulted in higher yield because of greater interception of solar irradiance. Increasing the plant population up to 400000 plants ha^{-1} increased yields because of greater solar irradiance. Plant population increases beyond that did not result in higher yields probably because of other factors such water and nutrient deficiency. The results suggest that farmers in KwaZulu-Natal could possibly increase their yields by reducing the row-spacing and increasing plant population from their current cultural practices. The results from this study also suggest that the CROPGRO-Soya bean model is sensitive to weather, and cultural practices such as seeding rates, row spacing and cultivar maturity groups. It is recommended that further research is needed to verify the benefits that farmers can get from improving their cultural practices.

CHAPTER 8

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

8.1 INTRODUCTION

Besides environmental measurements, models of different complexity have been used to estimate the soil water balance components. Simple models have limitations in that their accuracy in predicting the soil water balance components is low. Despite the advantages, models of intermediate complexity such as the Ritchie (1985) model used in DSSAT v3.5 have limitations. The Ritchie (1985) model assumes that the soil is freely draining without oxygen stress and without interaction with the groundwater. Furthermore, the model is a daily incrementing model that does not take advantage of hourly measurements. Moreover, it has certain weaknesses in estimating the root water absorption. Such weaknesses have to be corrected before simulations of soil water balance components for South African situations (as it was found for this experiment) could be satisfactory. Similarly, previous studies by Hensley *et al.* (1997) and du Toit *et al.* (1997) showed that simulations of the soil water balance components were unsatisfactory. The conclusions reached for each chapter will be presented in their respective orders and then the recommendations for future research will follow.

8.2 CONCLUSIONS

Creation of the minimum dataset for solar radiant density, air temperature and rainfall was possible after completion of the minimum dataset from a nearby weather station. This was done after making sure that the data were homogeneous to that the nearby weather station. The factory-given transmission value for the shade cloth was found to be different from the one measured in the experiment. Conventional laboratory procedures were used to create soil physical and chemical properties. The soil water limits were calculated using regression equations developed by Schulze *et al.* (1985). Other soil inputs were calculated using the model DSSAT v3.5. Crop management inputs such as the irrigation amount and dates were also documented to create the experimental details file.

Before calibration of the soil water balance model, model simulations of soil water content gave unsatisfactory results because of certain errors in quantifying some of the sensitive model parameters such as the *DUL*, *DR*, and *CN* and possible errors in model equations. After calibration *DUL*, *DR*, and *CN*, simulations of soil water content showed significant improvement especially for the lower soil layer (450 to 600 mm). It was found that accurate values of *DUL* are necessary if simulations of soil water content are to match measurements. The model gave satisfactory results as far as simulations of *LAI* is concerned. Deviations of simulations of actual *ET* with measured *ET* were not random. This was mainly because the measured potential *ET* was multiplied by the crop coefficient. Such a procedure was found to be invalid under variable soil water content conditions. The model, however, takes the seasonal variations in *LAI* into account. Hence it could be inferred that model simulations are superior than otherwise.

Sensitivity analyses carried out on the model output parameters gave results that conform to the current understanding of the soil-plant-atmosphere relationships. Variable solar radiant density regimes were used to investigate the effect on tomato dry weight yield. An increment of the solar radiant density by 30% gave maximum yield. Beyond that yield progressively declined. Similarly, an air temperature regime 20% higher than the base value gave maximum yield. However, below and above that yields declined. It was observed that it is not advisable to grow tomatoes at Ukulinga during the winter season unless certain management measures such as plastic cover are used to increase the soil temperature. Similarly, plant population and row spacing were optimized for tomatoes for soil, plant and weather conditions at Ukulinga. Such an analysis has great importance to farmers in optimizing management practices with increased credibility of models. A long-term risk assessment has been carried out and it was observed that it was risky to grow tomatoes during winter season at Ukulinga irrespective of the initial soil water content. It was found that drainage increases as initial soil water content is decreased and hence loss of nutrients is quite low for low initial profile soil water content. This is significant because the crop would be utilizing the incoming water and if salts were present within the water, rising water tables that might contribute to salinity effects would be avoided. Initial soil water contents had little effects on runoff over the whole crop-growing season because the effects of initial soil water content was limited to early stages of the crop growth and might have been masked due to changes in soil water content as result of irrigation and rainfall.

Simulations of soil water content using the CROPGRO-Soya bean model has been found to be unsatisfactory even after calibration of some of the model parameters such as *DUL*, *DR* and *CN* at Cedara. There is a suspicion that the measured soil water content values were not sufficiently accurate due to inadequate contact of the access tubes with the soil. However, other plant parameters had satisfactory agreement with simulated values. Further, the model was found to be sensitive to weather and cultural practices such as seeding rates, row spacing and cultivar maturity groups for soya bean.

8.3 RECOMMENDATIONS FOR FUTURE RESEARCH

As mentioned in Chapter 1, the soil water balance submodel of DSSAT v3.5 works well for well-drained soils. There is, however, a need for a better simulation of soil water balance in very poorly drained soils with oxygen stress. The model's assumption that the soil is well drained and thus having no interaction with the groundwater may not always be correct. It is therefore recommended that the DSSAT v3.5 model be modified for water-logged soils especially when the interaction between crop growth and soil water are investigated.

The DSSAT v3.5 model has fewer soil, crop and weather data inputs because the principle of minimum dataset was adopted during its development and because it is a daily incrementing model. However, it does not take advantage of hourly weather data and in particular the variation of rainfall within a day. Hence the runoff curve number technique for calculating runoff and infiltration is not expected to provide accurate information for a specific storm. For greater accuracy, sub-daily rainfall data would be needed.

One of the weaknesses of the soil water balance submodel of DSSAT v3.5 is in its calculation of root water absorption. The model assumes that root water uptake is proportional to rooting density, soil hydraulic conductivity and the water potential difference between the root surface and that in bulk soil midway between adjacent roots. Taylor and Klepper (1975) tested the validity of these assumptions and they found that the assumption that water uptake is proportional to rooting density is valid whereas the other two assumptions are invalid. Furthermore, the relationship between root water uptake and water content difference between the actual and lower limit soil water content used in the model might be different for different climates, crops and soils

(Hensley *et al.*, 1997). The relationship has been derived assuming that the hydraulic conductivity of all soils is similar when normalized to the lower limit value. This assumption is valid only when the soil water content is near the lower limit value. The model also assumes that the water potential gradient between the root and the soil remains constant even when the soil dries out. In reality, the water potential of the roots may change throughout the day. It is recommended, therefore, for future research that the relationship be modified for South African soils, climate and crops.

It is also recommended that careful attention be given to determining drained upper and lower limits. Of particular note is that the soil water limits have to be determined in the field rather than estimating them using regression models as was done in this study.

Despite some of the limitations that DSSAT v3.5 may have due to its assumptions contained with it or its construction, it has been applied for various applications as discussed in Chapters 2, 6, and 7. Cox (1996) and Newman *et al.* (2000), as cited by Stephens and Middleton (2002), however, pointed out that the routine use of DSSAT v3.5 and other decision support systems (DSS) has been so poor because of: unclear definition of clients/end users; no end-user input prior to or during the development of the DSS; DSS may not solve the actual problems that the client wants solved; DSS does not match their decision-making style; producers see no reason to change their current management practices; DSS may not provide benefit over current decision-making system; limited computer ownership amongst producers; lack of field testing of the model; producers do not trust the model output due to a lack of understanding of the underlying theories of the models utilized; users often do not have the necessary data inputs for the model; lack of technical support in running the model, preparing input files and interpreting output files; lack of training in the development of DSS software; marketing and support constraints; institutional resistances; short shelf-life of DSS software; technical constraints, user constraints and other constraints.

For successful uptake of decision support systems such as the Decision Support Systems for Agrotechnology Transfer (DSSAT v3.5), the above points have to be taken into account. Furthermore, if models are to be useful in a development context, their success should ultimately be measured by the impact that they have on farming systems and natural resource management and not on the success of the model developers or the company trying to market the software (Mathews *et al.*, 2002).

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APPENDICES

Appendix 1 Long-term total rainfall (mm) and maximum and minimum air temperature (°C) at Ukulinga

Year	Total rainfall (mm)	Average maximum air temperature (°C)	Average minimum air temperature (°C)
1975	709.7	42.0	1.5
1976	963.1	38.5	2.0
1977	772.0	39.5	3.5
1978	1010.3	35.5	3.5
1979	685.5	35.0	4.0
1980	537.1	36.5	4.0
1981	526.4	40.0	2.0
1982	619.2	37.5	2.5
1983	605.2	39.0	3.0
1984	632.0	35.0	3.5
1985	580.8	36.0	5.0
1986	838.8	36.5	4.5
1987	1040.5	36.0	3.5
1988	917.0	37.5	3.5
1989	756.8	36.5	3.0
1990	765.9	39.0	2.5
1991	798.4	37.0	2.5
1992	373.7	41.1	0.2
1993	751.9	41.9	4.0
1994	588.6	40.5	0.5
Average	723.6	38.0	2.9

Source: Agricultural Research Council, Institute for Soil, Climate and Water, Pretoria.

Appendix 2 Program listing of the 21X data logger used for the measurement of weather, soil and plant parameters at Ukulinga.

```
;{21X}
*Table 1 Program
  01: 60        Execution
Interval (seconds)
;Air Temeprature (Tair)      : 1H
yellow,G purple
;Relative Humidity          : 1L
blue,G orange, red 12v, G black,
G clear(shield)
;IRT      : 2H yellow,2L white,G
black
;ThetaProbe 1   : 3H yellow,G
green,white,blue, red 12V
;ThetaProbe 2   : 3L yellow,G
green,white,blue, red 12v
;ThetaProbe 3   : 4H yellow,G
green,white,blue, red 12v
;Linequantum sensor 1 : 4L red,G
blue,clear white
;Linequantum sensor 2 : 5H red,G
blue,clear white
;Wind direction sensor : 5L
green,G clear black, lex blue
;Middleton solarimeter : 6H
red,G black
;CM3radiation sensor    : 6L
red,G red and blue
;TC 2      : 7H blue,G red
;TC 3      : 7L blue,G red
;TC 4      : 8H blue,G red
;TC 5      : 8L blue,G red

;Raingauge       : PI black, G
white, clear
;Windspeed sensor: P2 black, G
clear, white (sometimes red
pulse and Green G)

;12 V control box
;Yellow to C1; black to G; Red
to 12 V;
;Red to second 12 V; red to
strip connector for sensors

1:  Batt Voltage (P10)
 1: 1          Loc [ Batt_Volt ]

2:  Internal Temperature (P17)
 1: 2          Loc [ Tpanel    ]

3:  Volt (SE) (P1)
 1: 1          Reps
 2: 3          50 mV Slow Range
 3: 11         SE Channel
 4: 3          Loc [ KippSolar ]
 5: 121.21     Mult
 6: 0.0        Offset

4:  Do (P86)
 1: 41         Set Port 1 High

;The delay for the Everest IRT's
and Thetaprobe need to be 800 cs
5:  Excitation with Delay (P22)
 1: 1          Ex Channel
 2: 0          Delay w/Ex (units =
0.01 sec)
 3: 800        Delay After Ex
(units = 0.01 sec)
 4: 0          mV Excitation

6:  Volt (SE) (P1)
1: 1           Reps
 2: 5          5000 mV Slow Range
 3: 1          SE Channel
 4: 4          Loc [ AirTC     ]

5: 0.1         Mult
 6: -40.0      Offset

7:  Volt (SE) (P1)
 1: 1          Reps
 2: 5          5000 mV Slow Range
 3: 2          SE Channel
 4: 5          Loc [ RH        ]
 5: 0.1        Mult
 6: 0          Offset

8:  Volt (Diff) (P2)
 1: 1          Reps
 2: 4          500 mV Slow Range
 3: 2          DIFF Channel
 4: 6          Loc [ Tcanopy   ]
 5: 0.1116     Mult
 6: -3.2418    Offset

9:  Volt (SE) (P1)
 1: 3          Reps
 2: 5          5000 mV Slow Range
 3: 5          SE Channel
 4: 7          Loc [ Thetaprob ]
 5: .001       Mult
 6: 0.0        Offset

10:  Do (P86)
 1: 51         Set Port 1 Low

11:  Polynomial (P55)
 1: 3          Reps

 2: 7          X Loc [ Thetaprob ]
 3: 10         F(X) Loc [ Theta1
]

 4: 1.0        C0
 5: 6.19       C1
 6: -9.72      C2
 7: 24.35      C3
 8: -30.84     C4
 9: 14.73      C5

12:  Beginning of Loop (P87)
 1: 0          Delay
 2: 3          Loop Count

13:  Z=X+F (P34)
 1: 10      -- X Loc [ Theta1    ]
 2: -1.6       F
 3: 13      -- Z Loc [ swc1min   ]

14:  Z=X*F (P37)
 1: 13      -- X Loc [ swc1min   ]
 2: .11904     F
 3: 13      -- Z Loc [ swc1min   ]

15:  Z=X+F (P34)
 1: 10      -- X Loc [ Theta1    ]
 2: -1.3       F
 3: 16      -- Z Loc [ swc1org   ]

16:  Z=X*F (P37)
 1: 16      -- X Loc [ swc1org   ]
 2: .1282      F
 3: 16      -- Z Loc [ swc1org   ]

17:  End (P95)

18:  If (X<=>F) (P89)

 1: 5          X Loc [ RH        ]
 2: 3          >=
 3: 100        F
 4: 30         Then Do

19:  If (X<=>F) (P89)
 1: 5          X Loc [ RH        ]
 2: 4          <
 3: 108        F
 4: 30         Then Do

20:  Z=F (P30)
 1: 100        F
 2: 5          Z Loc [ RH        ]

21:  End (P95)

22:  End (P95)

23:  Volt (SE) (P1)
 1: 1          Reps
 2: 3          50 mV Slow Range
 3: 8          SE Channel
 4: 19         Loc [ LineQuan1 ]
 5: 200        Mult
 6: 0.0        Offset

24:  If (X<=>F) (P89)
 1: 19         X Loc [ LineQuan1 ]
 2: 4          <
 3: 0          F
 4: 30         Then Do

25:  Z=F (P30)
 1: 0          F
 2: 19         Z Loc [ LineQuan1 ]

26:  End (P95)

27:  Volt (SE) (P1)
 1: 1          Reps
 2: 3          50 mV Slow Range
 3: 9          SE Channel
 4: 21         Loc [ LineQuan2 ]
 5: 260.29     Mult
 6: 0.0        Offset

28:  If (X<=>F) (P89)
 1: 21         X Loc [ LineQuan2 ]
 2: 4          <
 3: 0          F
 4: 30         Then Do

29:  Z=F (P30)
 1: 0          F
 2: 21         Z Loc [ LineQuan2 ]

30:  End (P95)

31:  Pulse (P3)
 1: 1          Reps
 2: 1          Pulse Input Channel
 3: 2          Switch Closure, All
Counts
 4: 22         Loc [ Rain_mm  ]
 5: 1.0        Mult
 6: 0.0        Offset

32:  Excite Delay Volt (SE) (P4)
 1: 1          Reps
 2: 5          5000 mV Slow Range
 3: 10         SE Channel
 4: 1          Excite all reps
w/Exchan 1
 5: 2          Delay (units 0.01
sec)
 6: 5000       mV Excitation
 7: 23         Loc [ WindDir_2 ]
 8: .142       Mult
 9: 0.0        Offset

33:  If (X<=>F) (P89)
 1: 23         X Loc [ WindDir_2 ]
 2: 3          >=
 3: 360        F
 4: 30         Then Do

34:  Z=F (P30)
 1: 0          F
 2: 23         Z Loc [ WindDir_2 ]

35:  End (P95)

36:  Pulse (P3)
 1: 1          Reps
 2: 2          Pulse Input Channel
 3: 21         Low Level AC,
Output Hz
 4: 24         Loc [ WS_ms     ]
 5: 0.75       Mult
 6: 0.2        Offset

37:  If (X<=>F) (P89)
 1: 24         X Loc [ WS_ms     ]
 2: 4          <
 3: 0.21       F
 4: 30         Then Do

38:  Z=F (P30)
 1: 0          F
 2: 24         Z Loc [ WS_ms     ]

39:  End (P95)

40:  Z=X (P31)
 1: 5          X Loc [ RH        ]
 2: 26         Z Loc [ CSI_1     ]

41:  Z=F (P30)
 1: 100        F
 2: 25         Z Loc [ CSI_R     ]

42:  Z=X/Y (P38)
 1: 26         X Loc [ CSI_1     ]
 2: 25         Y Loc [ CSI_R     ]
 3: 26         Z Loc [ CSI_1     ]

43:  Z=F (P30)
 1: .6108      F
 2: 25         Z Loc [ CSI_R     ]

44:  Z=X*Y (P36)
 1: 25         X Loc [ CSI_R     ]
 2: 26         Y Loc [ CSI_1     ]
 3: 26         Z Loc [ CSI_1     ]

45:  Z=F (P30)
 1: 17.0       F
 2: 25         Z Loc [ CSI_R     ]

46:  Z=X (P31)
 1: 25         X Loc [ CSI_R     ]
 2: 27         Z Loc [ CSI_
```

```
2       ]

47:  Z=F (P30)
 1: .2694     F
 2: 25        Z Loc [ CSI_R      ]

48:  Z=X+Y (P33)
 1: 25        X Loc [ CSI_R      ]
 2: 27        Y Loc [ CSI_2      ]
 3: 27        Z Loc [ CSI_2      ]

49:  Z=X*Y (P36)
 1: 4         X Loc [ AirTC      ]
 2: 27        Y Loc [ CSI_2      ]
 3: 27        Z Loc [ CSI_2      ]

50:  Z=F (P30)
 1: 237.3     F
 2: 25        Z Loc [ CSI_R      ]

51:  Z=X+Y (P33)
 1: 4         X Loc [ AirTC      ]
 2: 25        Y Loc [ CSI_R      ]
 3: 25        Z Loc [ CSI_R      ]

52:  Z=X/Y (P38)
 1: 27        X Loc [ CSI_2      ]
 2: 25        Y Loc [ CSI_R      ]
 3: 25        Z Loc [ CSI_R      ]

53:  Z=EXP(X) (P41)
 1: 25        X Loc [ CSI_R      ]
 2: 25        Z Loc [ CSI_R      ]

54:  Z=X*Y (P36)
 1: 25        X Loc [ CSI_R      ]
 2: 26        Y Loc [ CSI_1      ]
 3: 28        Z Loc [ e          ]

55:  Volt (SE) (P1)
 1: 1         Reps
 2: 3         50 mV Slow Range
 3: 6         SE Channel
 4: 34        Loc [ CM3radiat ]
 5: 37.38     Mult
 6: 0.0       Offset

56:  Thermocouple Temp (SE)
(P13)
 1: 4         Reps
 2: 1         5 mV Slow Range
 3: 12        SE Channel
 4: 1         Type T (Copper-
Constantan)
 5: 2         Ref Temp (Deg. C)
Loc [ Tpanel    ]
 6: 30        Loc [ TC_2       ]
 7: 1.0       Mult
 8: 0.0       Offset
57:  If time is (P92)
 1: 0         Minutes into a
 2: 15        Minute Interval
 3: 10        Set Output Flag
High

58:  Set Active Storage Area
(P80)
 1: 1         Final Storage
 2: 101       Array ID

59:  Real Time (P77)
 1: 1220
Year,Day,Hour/Minute (midnight =
2400)

60:  Average (P71)
 1: 1         Reps
 2: 3         Loc [ KippSolar ]

61:  Average (P71)
 1: 2         Reps
 2: 19        Loc [ LineQuan1 ]

62:  Average (P71)
 1: 1         Reps
 2: 4         Loc [ AirTC      ]

63:  Sample (P70)
 1: 1         Reps
 2: 5         Loc [ RH         ]

64:  Average (P71)
 1: 1         Reps
 2: 6         Loc [ Tcanopy    ]

65:  Resolution (P78)
 1: 1         High Resolution

66:  Average (P71)
 1: 3         Reps
 2: 7         Loc [ Thetaprob ]

67:  Average (P71)
 1: 6         Reps
 2: 13        Loc [ swc1min    ]

68:  Resolution (P78)
 1: 0         Low Resolution

69:  Totalize (P72)
 1: 1         Reps
 2: 22        Loc [ Rain__mm   ]

70:  Wind Vector (P69)
 1: 1         Reps
 2: 0         Samples per Sub-
Interval
 3: 0         S, él, & à(él)
Polar
 4: 24        Wind Speed/East Loc
[ WS_ms      ]
 5: 23        Wind
Direction/North Loc [ WindDir_2
]

71:  Average (P71)
 1: 1         Reps
 2: 28        Loc [ e          ]

72:  Average (P71)
 1: 5         Reps
 2: 30        Loc [ TC_2       ]

73:  Totalize (P72)
 1: 1         Reps
 2: 34        Loc [ CM3radiat ]

74:  Sample (P70)
 1: 1         Reps
 2: 1         Loc [ Batt_Volt ]

*Table 2 Program
  01: 60          Execution
Interval (seconds)

1:  Serial Out (P96)
 1: 30        SM192/SM716/CSM1

*Table 3 Subroutines

End Program

-Input Locations-
1 Batt_Volt 1 1 1
2 Tpanel     1 1 1
3 KippSolar 1 1 1
4 AirTC      1 3 1
5 RH         1 4 2
6 Tcanopy    1 1 1
7 Thetaprob 5 2 1
8 Thetapr_2 9 2 1
9 Thetapr_3 17 2 1
10 Theta1    5 2 1
11 Theta1_2  9 0 1
12 Theta1_3  17 0 1
13 swc1min   1 2 2
14 swc2min   1 1 0
15 swc3min   1 1 0
16 swc1org   1 2 2
17 swc2org   1 1 0
18 swc3org   1 1 0
19 LineQuan1 5 2 2
20 LineQua_2 1 1 0
21 LineQuan2 1 1 2
22 Rain__mm  1 1 1
23 WindDir_2 1 2 2
24 WS_ms     1 2 2
25 CSI_R     1 8 8
26 CSI_1     1 4 3
27 CSI_2     1 4 3
28 e         1 2 1
29 _________ 1 0 0
30 TC_2      5 1 1
31 TC_3      1 1 1
32 TC_4      1 1 1
33 TC_5      1 1 1
34 CM3radiat 1 2 1
35 ET-gauge 1 0 0
-Program Security-

Program Trace Information File
for:  TES26082.CSI
Date: 11/26/2002
Time: 11:32:47

T = Program Table Number
N = Sequential Program
Instruction Location Number
Instruction = Instruction Number
and Name

Inst ExTm = Individual
Instruction Execution Time

Block ExTm = Cumulative
Execution Time for program
block,
                 i.e., subroutine
Prog ExTm = Cumulative Total
Program Execution Time


Output Flag High

Inst  Block   Prog     Inst
Block   Prog

ExTm   ExTm   ExTm     ExTm
ExTm   ExTm
T|N|Instruction
(msec) (msec) (msec)   (msec)
(msec) (msec)
---------------
------ ------ ------   ------ --
---- ------
1|1|10 Batt Voltage
7.6    7.6    7.6      7.6
7.6    7.6
1|2|17 Internal Temperature
14.0   21.6   21.6     14.0
21.6   21.6
1|3|1 Volt (SE)
57.2   78.8   78.8     57.2
78.8   78.8
1|4|86 Do
0.1    78.9   78.9     0.1
78.9   78.9
1|5|22 Excitation with Delay
8001.0 8079.9 8079.9   8001.0
8079.9 8079.9
1|6|1 Volt (SE)
12.1 8092.0 8092.0     12.1
8092.0 8092.0
1|7|1 Volt (SE)
12.1 8104.1 8104.1     12.1
8104.1 8104.1
1|8|2 Volt (Diff)
74.9 8179.0 8179.0     74.9
8179.0 8179.0
1|9|1 Volt (SE)
19.5 8198.5 8198.5     19.5
8198.5 8198.5
1|10|86 Do
0.1 8198.6 8198.6      0.1
8198.6 8198.6
1|11|55 Polynomial
13.2 8211.8 8211.8     13.2
8211.8 8211.8
1|12|87 Beginning of Loop
0.2 8212.0 8212.0      0.2
8212.0 8212.0
 Execution times in the loop are
 calculated for one pass only.
1|13|34 Z=X+F
0.9 8212.9 8212.9      0.9
8212.9 8212.9
1|14|37 Z=X*F
0.9 8213.8 8213.8      0.9
8213.8 8213.8
1|15|34 Z=X+F
0.9 8214.7 8214.7      0.9
8214.7 8214.7
1|16|37 Z=X*F
0.9 8215.6 8215.6      0.9
8215.6 8215.6
1|17|95 End
0.2 8215.8 8215.8      0.2
8215.8 8215.8
1|18|89 If (X<=>F)
0.4 8216.2 8216.2      0.4
8216.2 8216.2
1|19|89 If (X<=>F)
0.4 8216.6 8216.6      0.4
8216.6 8216.6
1|20|30 Z=F
0.3 8216.9 8216.9      0.3
8216.9 8216.9
1|21|95 End
0.2 8217.1 8217.1      0.2
8217.1 8217.1
1|22|95 End
0.2 8217.3 8217.3      0.2
8217.3 8217.3
1|23|1 Volt (SE)
57.2 8274.5 8274.5     57.2
8274.5 8274.5
1|24|89 If (X<=>F)
0.4 8274.9 8274.9      0.4
8274.9 8274.9
1|25|30 Z=F
0.3 8275.2 8275.2      0.3
8275.2 8275.2
1|26|95 End
0.2 8275.4 8275.4      0.2
8275.4 8275.4
```

```
1|27|1 Volt (SE)
57.2 8332.6 8332.6       57.2
8332.6 8332.6
1|28|89 If (X<=>F)
0.4 8333.0 8333.0        0.4
8333.0 8333.0
1|29|30 Z=F
0.3 8333.3 8333.3        0.3
8333.3 8333.3
1|30|95 End
0.2 8333.5 8333.5        0.2
8333.5 8333.5
1|31|3 Pulse
1.4 8334.9 8334.9        1.4
8334.9 8334.9
1|32|4 Excite Delay Volt (SE)
32.5 8367.4 8367.4       32.5
8367.4 8367.4
1|33|89 If (X<=>F)
0.4 8367.8 8367.8        0.4
8367.8 8367.8
1|34|30 Z=F
0.3 8368.1 8368.1        0.3
8368.1 8368.1
1|35|95 End
0.2 8368.3 8368.3        0.2
8368.3 8368.3
1|36|3 Pulse
1.4 8369.7 8369.7        1.4
8369.7 8369.7
1|37|89 If (X<=>F)
0.4 8370.1 8370.1        0.4
8370.1 8370.1
1|38|30 Z=F
0.3 8370.4 8370.4        0.3
8370.4 8370.4
1|39|95 End
0.2 8370.6 8370.6        0.2
8370.6 8370.6
1|40|31 Z=X
0.5 8371.1 8371.1        0.5
8371.1 8371.1
1|41|30 Z=F
0.3 8371.4 8371.4        0.3
8371.4 8371.4
1|42|38 Z=X/Y
2.7 8374.1 8374.1        2.7
8374.1 8374.1
1|43|30 Z=F
0.3 8374.4 8374.4        0.3
8374.4 8374.4
1|44|36 Z=X*Y
1.2 8375.6 8375.6        1.2
8375.6 8375.6
1|45|30 Z=F
0.3 8375.9 8375.9        0.3
8375.9 8375.9
1|46|31 Z=X
0.5 8376.4 8376.4        0.5
8376.4 8376.4
1|47|30 Z=F
0.3 8376.7 8376.7        0.3
8376.7 8376.7
1|48|33 Z=X+Y
1.1 8377.8 8377.8        1.1
8377.8 8377.8
1|49|36 Z=X*Y
1.2 8379.0 8379.0        1.2
8379.0 8379.0
1|50|30 Z=F
0.3 8379.3 8379.3        0.3
8379.3 8379.3
1|51|33 Z=X+Y
1.1 8380.4 8380.4        1.1
8380.4 8380.4
1|52|38 Z=X/Y
2.7 8383.1 8383.1        2.7
8383.1 8383.1
1|53|41 Z=EXP(X)
5.9 8389.0 8389.0        5.9
8389.0 8389.0
1|54|36 Z=X*Y
1.2 8390.2 8390.2        1.2
8390.2 8390.2
1|55|1 Volt (SE)
57.2 8447.4 8447.4       57.2
8447.4 8447.4
1|56|13 Thermocouple Temp (SE)
133.6 8581.0 8581.0      133.6
8581.0 8581.0
1|57|92 If time is
0.3 8581.3 8581.3        0.3
8581.3 8581.3
 Output Flag Set @ 157 for Array
101
1|58|80 Set Active Storage Area
0.2 8581.5 8581.5        0.2
8581.5 8581.5
1|59|77 Real Time
0.1 8581.6 8581.6        1.0
8582.5 8582.5
 Output Data 3 Values
```

```
1|60|71 Average
1.4 8583.0 8583.0        5.1
8587.6 8587.6
 Output Data 1 Values
1|61|71 Average
1.9 8584.9 8584.9        8.1
8595.7 8595.7
 Output Data 2 Values
1|62|71 Average
1.4 8586.3 8586.3        5.1
8600.8 8600.8
 Output Data 1 Values
1|63|70 Sample
0.1 8586.4 8586.4        1.0
8601.8 8601.8
 Output Data 1 Values
1|64|71 Average
1.4 8587.8 8587.8        5.1
8606.9 8606.9
 Output Data 1 Values
1|65|78 Resolution
0.4 8588.2 8588.2        0.4
8607.3 8607.3
1|66|71 Average
2.4 8590.6 8590.6       11.1
8618.4 8618.4
 Output Data 3 Values
1|67|71 Average
3.9 8594.5 8594.5       20.1
8638.5 8638.5
 Output Data 6 Values
1|68|78 Resolution
0.4 8594.9 8594.9        0.4
8638.9 8638.9
1|69|72 Totalize
1.1 8596.0 8596.0        2.1
8641.0 8641.0
 Output Data 1 Values
1|70|69 Wind Vector
21.0 8617.0 8617.0       78.5
8719.5 8719.5
 Output Data 3 Values
1|71|71 Average
1.4 8618.4 8618.4        5.1
8724.6 8724.6
 Output Data 1 Values
1|72|71 Average
3.4 8621.8 8621.8       17.1
8741.7 8741.7
 Output Data 5 Values
1|73|72 Totalize
1.1 8622.9 8622.9        2.1
8743.8 8743.8
 Output Data 1 Values
1|74|70 Sample
0.1 8623.0 8623.0        1.0
8744.8 8744.8
 Output Data 1 Values

Program Table 1 Execution
Interval    60.000 Seconds

Table 1 Estimated Total Program
Execution Time in msec 8623.0
w/Output 8744.8

Table 1 Estimated Total Final
Storage Locations used per day
3840.0

--------------- Table 2 --------
-------
2|1|96 Serial Out
2.0     2.0     2.0     2.0
2.0     2.0'

Program Table 2 Execution
Interval    60.000 Seconds

Table 2 Estimated Total Program
Execution Time in msec     2.0
w/Output     2.0

Table 2 Estimated Total Final
Storage Locations used per day
0.0

Estimated Total Final Storage
Locations used per day 3840.0
```

APPENDIX 3

General soil properties and soil water characteristics calculated using equations developed by Hutson (1986) for Ukulinga experiment site.

Soil layer	Layer thickness (mm)	% C	% Si	% Sa	Bulk density (kg m^{-3})	RD	pH	Organic carbon (%)	Field capacity (-10 kPa) (m^3 m^{-3})	Saturated water content (92%) (m^3 m^{-3})	Field capacity (-33 kPa) (m^3 m^{-3})	Wilting point (-1500 kPa) (m^3 m^{-3})
1	100	49	29	22	1522	Very common	6.420	3.200	0.408	0.426	0.374	0.304
2	200	45	3	52	1512	Common	6.540	3.200	0.294	0.429	0.255	0.194
3	300	45	1	53	1458	Very few	6.420	2.900	0.287	0.450	0.247	0.187
4	400	45	28	27	1522	No roots	5.750	2.100	0.389	0.426	0.354	0.286
5	500	60	21	19	1503	No roots	5.790	2.200	0.420	0.433	0.386	0.315
6	600	55	20	25	1349	No roots	6.160	1.600	0.397	0.491	0.362	0.293
7	1000	62	19	19	1525	No roots	7.020	1.100	0.420	0.423	0.386	0.315

%C = percent clay, %Si = percent silt, %Sa = percent sand, RD = rooting distribution, OC = organic carbon (%) and the percentage for saturated soil water content is the effective porosity.

Soil water characteristics calculated using equations developed by Schulze *et al.* (1985) for Ukulinga experiment site.

Soil layer	Field capacity (-10 kPa) (m^3 m^{-3})	Field capacity (-30 kPa) (m^3 m^{-3})	Wilting point (-1500 kPa) (m^3 m^{-3})	Saturated water content (92%) (m^3 m^{-3})	Saturated water content (100%) (m^3 m^{-3})
1	0.441	0.410	0.268	0.392	0.426
2	0.282	0.245	0.175	0.395	0.429
3	0.270	0.231	0.170	0.414	0.450
4	0.421	0.388	0.252	0.392	0.426
5	0.437	0.405	0.279	0.398	0.433
6	0.408	0.373	0.264	0.452	0.491
7	0.434	0.402	0.279	0.391	0.425

the percentage for saturated soil water content is the effective porosity.

APPENDIX 4

Additional information needed to run the soil water balance model in DSSAT v3.5 for Ukulinga experiment site.

- Hydrologic condition: high runoff potential (D)
- Modification for soil conservation services: Fair (1.04)
- Permeability class: unknown
- Colour of soil: black and hence albedo is 0.09.
- Upper limit of stage one soil evaporation (U): 34.2104
- Initial soil water content at the start of the season: field capacity
- Transplanting date: 12 June 2002
- Harvest date: 25 October 2002
- Irrigation: four times a day for three minutes till 18/09/2002. From 19/09/2002 onwards, irrigation was applied three times a day
- Soil Nitrogen: non limiting
- Row spacing: 1000 mm x 650 mm
- Sowing depth: 80 mm
- Plant population: 3.12 plants m^{-2}
- Irrigation system efficiency: 90%

APPENDIX 5 M odel Campbell and Donatelli in RADEST v 3-model

$EstRad_i = tt_i\, PotRad_i$

EstRad= Estimated radiation (MJ m^{-2})

PotRad = Potential radiation (MJ m^{-2})

i = day of the year

$tt_i = \tau [1\text{-}exp\ (-b\, f\, (T_{avg})\ \Delta T_i^{\,2}\, f\, (T_{min}))]$

tt = transmissivity

τ = clear sky transmissivity

ΔT = $Tmax_I - (Tmin_I + Tmin_{I+1}) / 2$

$f(T_{avg})$ = 0.017 * exp (exp (-0.053 * $T_{avg=}$))

T_{avg} = $(Tmax_I + Tmin_I) / 2$

$f(T_{min})$ = exp ($Tmin_I / Tn_c$)

Tmax = daily air maximum temperature (° C)

Tmin = daily air minimum temperature (° C)

Tnc = empirical parameter

b = empirical parameter