RAFAEL GOMES MARTINS

ANALYSIS OF IRRIGATION SCHEDULING TECHNOLOGIES IN MAIZE

Dissertação apresentada à Universidade Federal de Viçosa, como parte das exigências do Programa de Pós-Graduação em Engenharia Agrícola, para a obtenção do título de *Magister Scientiae*.

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Araya Alemie Berhe

04/11/2018

Isaya Kisekka
(Coorientador)

Catariny Cabral Alemann
(Orientador)

"Se todos os brasileiros fossem dignos de honra e honestidade, teríamos um Brasil bem melhor"
José Silva Guerra

"As we know, there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are also unknown unknowns the ones we don't know we don't know."
Donald Rums

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BIOGRAPHY

RAFAEL GOMES MARTINS, son of José Carlos Rodrigues Martins and Maria das Graças Gomes Martins. Rafael is natural from Ouro Preto, MG, Brazil, was born on May 30 of 1992.

In 2010, the author joined the undergraduate program of Agronomy Engineer at Federal University of Viçosa (UFV). During his major, he was involved with research since the first semester at UFV. During 2013 to 2014, he was a Scientific Initiation Scholar.

In August 2014, through the Federal Government Science Without Border program, he took part in his graduation at Angelo State University and Kansas State University, USA.

In July of 2016, after completing his undergraduate degree, he enrolled at the Master's Program at the Agricultural Engineering Department at UFV, with a focus on Water Management and Irrigation. During his masters, he had the opportunity to be doing part of his studies at Kansas State University. He submitted his defense in February of 2018.

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LIST OF ABREVIATIONS

A	Empirical constant
AWC	Available water content
B	Empirical constant
BD	Bulk density
CC	Green canopy cover
CDC	Canopy decline coefficient
CGC	Canopy growth coefficient
d	Willmott concordance index
DAP	Days after planting
DSSAT	Decision Support System for Agrotechnology Transfer
Ec	Electrical Conductivity
ET	Evapotranspiration
ETa	Actual evapotranspiration
ETc	Crop evapotranspiration
ETm	Maximum evapotranspiration
ETo	Reference crop evapotranspiration
ETp	Potential evapotranspiration
F	Empirical constant
FC	Field capacity
FD	Final depth
ft	Feet
FI	Floral Initiation
GDD	Growing-degree-day
G2	Thermal time from silking to physiological maturity
G3	Kernel filling rate during linear grain filling
HI	Harvest Index
in	Inches
IWUE	Irrigation water efficiency
ID	Initial Depth
Ka	Apparent Permittivity
Kc	Crop coefficient
Ky	Response factor
LAI	Leaf area index
m	Meters
mm	Millimeters
MAE	Mean absolute error
MAD	Management allowed depletion
MBE	Mean Bias Error
NP	Neutron probe
NRMSE	Normalized root-mean square error
P1	Thermal time from emergence to end juvenile phase
P2	Photoperiod sensitivity coefficient
P5	Thermal time from silking to physiological maturity
PVC	Polyvinyl chloride
PWP	Permanent wilting point
pH	Potential of hydrogen
PHINT	Phyllochron interval
RMSE	Root Mean Square error
SHC	Saturation
SWC	Soil Water Content (SWC)
TDR	Time Domain Reflectometry
Y	Yield
Yx	Maximum yield
Ya	Actual yield

WUE	Water use efficiency
WS	Windy Speed
(θ_v)	Soil volumetric water content

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ABSTRACT

MARTINS, Rafael Gomes, M.Sc., Universidade Federal de Viçosa, february, 2018. **Analysis of irrigation scheduling technologies in Maize.** Adviser: Catariny Cabral Aleman. Co-advisers: Isaya Kisekka and Everardo Chartuni Mantovani

The global demand for food and fiber, including sources for bio-energy and industrial purposes, is expected to increase by 70 percent during the middle of this century, with water being one of the most important components to ensure the plant production. However, agriculture is by far the largest user of water among the various competing uses. Consequently, the selection of the appropriate technique, that optimizes water use is key to avoid either non-productive water use, or stress conditions that may increase the cost of irrigation or cause yield losses. Improving irrigation management techniques has a significant impact on the sustainable use of water resources. The aim of this study was to evaluate the performance of four different methods of irrigation scheduling applied on Maize (Zea Mays L.), comparing the simulated values of soil water content with Neutron Probe measurements, under a standard irrigation regime to maximize the water productivity. The irrigations were triggered based on 40% maximum allowed depletion. The specific objectives were; (1) to test, evaluate and develop the integrated Crop water management model-driven decision support tool iCrop-beta version system to schedule irrigation; (2) test and evaluate the performance of the KanSched irrigation scheduling tool widely used in Kansas; (3) test and evaluate the New Acclima TDR 310-s soil sensor performance to measure the soil water content, and check their accuracy; (4) evaluate the use of the AquaCrop model for real time irrigation scheduling and evaluate the performance as an irrigation tool. The results showed that all the techniques when calibrated well were able to follow the soil water content. The iCrop beta version was able to serve as an irrigation management tool. KanSched is a good estimation method, principally when using onsite recorded rain. The Acclima TDR-310s was not reliable for agronomic management without site specific calibration. The AquaCrop model required accurate parameters to simulate the crop growth and development under limited conditions, however, exhibited excellent performance to track the soil water content.

RESUMO

MARTINS, Rafael Gomes, M.Sc., Universidade Federal de Viçosa, Fevereiro de 2018. **Analysis of irrigation scheduling technologies in Maize** Orientador: Catariny Cabral Aleman. Coorientadores: Isaya Kisekka e Everardo Chartuni Mantovani

A demanda global por alimentos e fibras, incluindo fontes para bioenergia e fins industriais, é esperado um aumento em 70 por cento durante a metade deste século, sendo a água um dos componentes mais importantes para garantir a produção vegetal. Entretanto, a agricultura é de longe a atividade que requer maior quantidade de água entre os usos concorrentes. Consequentemente, a seleção da técnica apropriada, que otimize o uso da água torna-se chave para evitar tanto o uso improdutivo da água, ou condições de estresse, que talvez, podem aumentar o custo com irrigação, ou causar perdas de produtividade. Aprimorar as técnicas de manejo da irrigação, tem um impacto significativo no uso sustentável dos recursos hídricos. O objetivo deste estudo foi avaliar a performance de quatro métodos diferentes de manejo de irrigação aplicados na cultura do Milho (Zea Mays L.), comparando os valores simulados do conteúdo de água do solo com as medidas da Sonda de Nêutrons, sob um regime de irrigação padrão, aplicado para maximizar a produtividade da água. As irrigações foram realizadas com base em 40% da máxima depleção permitida. Os objetivos específicos foram; (1) testar, avaliar e desenvolver o sistema integrated crop water management model-driven decision support tool (iCrop beta version) como uma ferramenta de irrigação; (2) testar e avaliar a ferramenta de manejo de irrigação KanSched largamente utilizada no Kansas; (3) testar e avaliar o desempenho do sensor de solo New Acclima TDR 310 para medir o teor de água do solo e verificar sua precisão; (4) avaliar uso do modelo AquaCrop para o planejamento de irrigação em tempo real, e avaliar o desempenho como uma ferramenta de irrigação. Os resultados mostraram que todas as técnicas, quando bem calibradas, foram capazes de estimar o teor de água do solo. O iCrop beta version foi capaz de atuar como uma boa ferramenta para o manejo da irrigação. KanSched é um bom método de estimativa, principalmente utilizando dados de chuvas coletados no local. O Acclima TDR-310s não se mostrou confiável para o manejo agronômico sem uma calibração específica para o local. O modelo AquaCrop exigiu parâmetros precisos para simular o desenvolvimento da cultura em condições limitadas, no entanto, demonstrou um desempenho excelente na estimativa do teor de água do sol

1.INTRODUCTION

Studies estimate a growth in the world population by more than one billion people within the next 15 years, reaching 8.5 billion in 2030, increasing further to 9.7 billion in 2050 and 11.2 billion by 2100 (U.N., 2017). In addition, the global demand for food, feed, and fiber, including sources for bio-energy and industrial purposes, is expected to increase 70 percent by the middle of this century (FAO, 2009). However, humans have been modifying the ecosystem structure and function which has resulted in a decrease of their ability to continuously provide valuable resources such as food, forestry supplies and water (RAMANKUTTY et al., 2008). The Food and Agriculture Organization expects that most of the increase in crop production (90%) will be derived from greater crop intensity and yield rather than land expansion. Therefore, projects that focus on sustainable ways to raise food production and guarantee food security are critical nowadays.

Corn is the third largest planted crop in the world is (Zea Mays L.), after wheat and rice (THEONES, 2006) and the United States is the major producer, yielding nearest to 41% of the global total production (RAES et al., 2009). Currently, the land designated for grain production in the US is estimated around 60.49 million hectares for 2016/2017 season, where 17 million hectares is adopted for Corn. The necessity for this crop is increasing due to the several economic uses of this cereal, likewise: food, silage, biofuel and many others (HENG et al., 2009). To grow maize in semi-arid regions is difficult due to seasonal rainfall variability and thus maize often needs supplementary irrigation to meet the crop water demand especially during the critical stages of the crop (OUDA, 2016). The correlation between water and plant productivity is complex, due to the immense number of factors that are able to change or influence how the plant water relations will occur. Those requirements will change due to climatic conditions, relative maturity range, soil fertility, water availability, and by the interaction of all of these factors with each other (KRANZ, 2008). Though the desire is always to have the best condition for the crop growth, many producers are facing problems to meet the full water demands due to the lack of water resources (HEEREN et al., 2011). Water is a scarce resource with competing demands, including drinking, industrial, recreational uses and irrigation, that is by far the largest user of water among the competing uses (UPENDRAM; PETERSON, 2006). Predictions indicate that the irrigation will expand to around 32 million ha and the harvested-irrigated area would expand by 17 percent through 2050 (FAO, 2009).

To face limited water supplies and water costs, farmers need to innovate in technologies to make irrigation sustainable, both environmentally and economically (AGUILAR, ROGERS AND KISEKKA, 2015). On the same hand, there are many producers around the world that are already facing problems to irrigate their crops, due to the lack of water in some regions. One example of this deficiency nowadays is exposed by many growers in Southwest Kansas. Several producers are already facing problems to irrigate their fields, due to the fact that wells in the US Central Plains cannot no longer meet full crop water requirements due to the declines in Ogallala aquifer water levels (ARAYA, KISEKKA AND HOLMAN, 2016). The High Plains aquifer underlies 111.8 million acres (175,000 square miles) in parts of eight States— Colorado, Kansas, Nebraska, New Mexico, Oklahoma, South Dakota, Texas, and Wyoming and is the main source of water for irrigation at those states. However, the level of this aquifer is depleting and there are many concerns about the rational use of this source of water for agriculture activities, increasing the efforts to find sustainable ways to keep the production looking forward to mitigating this problem. Therefore, find technologies that can efficiently project, simulate and track the soil water content under lower soil water conditions is an essential step for irrigators.

The Irrigation scheduling is the process to predict and determine when, how much water needs to be applied to the crop in order to meet the required yield. Irrigation scheduling has various benefits: higher return, reduce of irrigation labor, reduce pumping cost, improve yields, and also, reduce loss of fertilizers due to leaching (CLARK, ROGERS AND BRIGGEMAN, 2002b). It's already proved that improvements on irrigation management techniques has a significant impact in this precious water supplies (HSIAO et al., 2009; KRANZ, 2008).

There are several techniques and ways to optimize agricultural production (FAN et al., 2012), that minimize environmental impacts and mitigate risk (HOFFMANN et al., 2017). On the other hand, the farmer is the only one that decides what equipment he will adopt, predominantly based on the costs of each technique. Choosing of the appropriate method that works well and is able show the correct and reliable conditions in the field is considered a key for sustainable production. Moreover, places with water scarcity need better irrigation scheduling techniques that maximize the water productivity and profitability (PEREIRA, OWEIS AND ZAIRI, 2002), in order to avoid either the excess of water application or stress conditions that will increase costs, yield losses and waste of water.

The aim of this study was to evaluate the performance of four different methods of irrigation scheduling applied on maize and to evaluate their performance in predicting soil water changes during the growing season. The goal was to selected the most suitable irrigation scheduling technique and recommend for implementation to guide producers water management decision in Southwest Kansas. The specific objectives were (1) evaluate and improve the integrated Crop water management model-driven decision support tool (iCrop-beta version) for use in real-time irrigation scheduling, (2) evaluate performance of the KanSched as irrigation scheduling tool, (3) evaluate the performance of new Acclima TDR 310s soil sensors as irrigation scheduling tool, (4) evaluate the validity of AquaCrop model for real-time irrigation scheduling.

2. MATERIAL AND METHODS

2.1Site Description

The experiment was conducted at the Kansas State University Southwest Research-Extension Center located near Garden City, Kansas. The coordinates of the experimental plot are 38°01′20.87″N, 100°49″26.95 W and elevation of 887 m above mean sea level (ARAYA, KISEKKA AND HOLMAN, 2016). The ago-climactic class of the study area is categorized as semi-arid with long-term mean annual rainfall of 477 mm and reference evapotranspiration (ETo) of 1810 mm (KLOCKE et al., 2011).

2.2 Soil Characterization

The soil at the site is considered as a deep well drained Ulysses Silt Loam with average pH of 8.22 and organic matter content of 1.5% (KLOCKE et al., 2011). Soil samples were collected at the same plot from the top to 1.2 meters and the texture was determinate by the hydrometer method. The lab classification was Silty Clay Loam for the top 30 cm and Silt loam from 30 to 120 cm. The permanent wilting point (PWP), field capacity (FC), available water content (AWC), saturation hydraulic conductivity (SHC) and matric bulk density(BD) were estimated using the pedo-transfer function (SAXTON et al., 1986). All the soil information obtained by the previous analyses, were compared with previous data, due to the importance of the correct soil parameters for those simulations (GIJSMAN, JAGTAP AND JONES, 2002). All the parameters were very similar with previous laboratory analyses performed for the same field by Klocke et al. (2011), including the soil bulk density.

Table 1. Soil properties at the experimental site located at Kansas State University Southwest Research-Extension Center.

ID[1]	FD[2]	PWP[3]	FC[4]	SAT[5]	AW[6]	SHC[7]	BD[8]	Soil pH[9]
cm	cm	$cm^3.cm^{-3}$	$cm^3.cm^{-3}$	$cm^3.cm^{-3}$	mm/m	in/hr	g/cm^3	1:1
0	30	18.98	35.80	49.4	168.3	0.69	1.36	8.20
30	60	13.63	32.70	48.6	190.8	1.17	1.37	8.20
60	120	12.60	31.92	48.3	193.3	1.32	1.38	8.30

1-Initial depth; 2-final depth; 3-permanet wilting point; 4-field capacity; 5-saturation; 6- Available water; 7-saturation hydraulic conductivity; 8-bulk density;9-soil pH 1:1 water/soil.

For the calculations of soil water content, we used the soil available water capacity of 0.18 $cm^3.cm^{-3}$ between field capacity (volumetric water of content of 33%) and permanent wilting point (volumetric water content of 15%)(KLOCKE et al., 2011). The values were transformed to volumetric base, using the bulk density and the interest depth of 1.2 m for the layer of interest.

2.3 Treatment Plan

The treatments were arranged in randomized complete block design, with four replications for each technique, totalizing 20 plots. Each plot measured 13.7 x 27.4 m with a total area size of 1ha including the border area. Access tubes were installed in the center rows of all the 20 plots at the depth of 2.44 m using a gidding probe (Giddings Machine Company Inc., Windsor, Colorado). The Acclima 310s sensors were installed at an adjacent rows close to the access tubes.

2.4 Agronomic Management

Plots were uniformly fertilized (LEIKAM, LAMOND AND MENGEL, 2003). The field where the experiment was conducted was under fallow. The fertilizer were applied at planting using the 10-34-00 of 187.08 L/ha. The plant density at this experiment was 8.4 plants per m^2, totalizing 84.000 seeds per hectare, using a no-till planter at 5 cm depth. Plant population was estimated for each plot by counting the emergence number of plants at 18 days after planting (DAP). The maize cultivar used in this experiment was the conventional hybrid Dekalb 62-98 VT2PRO. The cultivar had relative maturity of 118 days. The preference to work with this cultivar is related with the fact that it was the most used genetic material in the previous years, and being able to use the parameters for the modeling simulations. Weed control as pre-emergence herbicide were done by applying 7 L/ha of Lumax EZ (S-metolachlor, Atrazine, Mesotrione) and 0.21 kg/ha of Sharpen (Sa sufenacial). Post emergence was applied 2.24 kg/ha of Mad Dog Plus (Glyphosate) and Prowl H2O (Pendimethalin).

2.5 Irrigation Management

Irrigations were applied using a linear move sprinkler model 8000, Valmont Corp, Valley, NE (ARAYA; KISEKKA AND HOLMAN, 2016). The system efficiency adopted was 90% due to the fact that the pressure was always checked and all the nozzles were cleaned at the beginning of the season. All the irrigations were 25.4 mm per irrigation event, following the pressure and velocity previous calculated to apply this lamina design flow chart. The decision about when to irrigate was based on the neutron probe (NP) readings in the top 1.2 m, when management allowable depletion (MAD) reached 40 %(RINALDI and HE, 2014). Kisekka et al. (2016) pointed that keeping the MAD over 50% in the top 1.2 m can be considered as full irrigation treatment, and is the most advantageous strategy for the highest water use efficiency. However, Chai et al. (2015) defines this strategy of irrigation as a Moderate Water Deficit. The MAD of 40% was selected based on several studies, proved that this is the optimized threshold to maximize the net returns on corn and with a good potential to preserve the hydrological resources, principally for Southwest Kansas (ARAYA, KISEKKA AND HOLMAN, 2016; KISEKKA et al., 2016; RUDNICK et al., 2017). Moreover, adopting this strategy we were able to see how those models works near to the deficit irrigation strategy (CHAI et al., 2016; HENG et al., 2009; RUDNICK et al., 2017). However, on July 13th, the pump presented some problems and this problem suspended the irrigation for 18 days. Later it was defined that the problem was related not with the pump, but was linked with the depletion at the water Table. We applied 279 mm in 11 irrigations events, presenting approximately 251 mm of net irrigation. During the growing season (May to October), 16 Neutron Probe (NP) water measurements were performed to a depth of 2.4 m in 0.3 m increments. The soil water content was measured using the NP (EVETT; STEINER, 1995) before the irrigation event. The NP readings were taken every week between emergence and physiological maturity. The NP readings were suspended only at 92 DAP due to the conditions being too wet and muddy to walk on the field.

2.6 Irrigation Techniques Evaluated

2.6.1 Neutron Probe

The neutron probe (NP) is considered one of the most accurate methods to determine soil water content (EVETT AND STEINER, 1995). The water content is estimated by the amount of water in a certain volume of soil by the measurement of the number of hydrogen molecules in the soil (USDA-NRCS, 2004). Although, it has the highest precision, this technique requires a lot of operational control, due to the radioactivity safety control and the laborious access tubes installation. Moreover, the equipment has a high cost, making the technique not widely used for irrigation management at the farm level, restricting the method only for research. On the other hand, due to the reliable measurements, non-destructive readings, the NP was selected to serve in this experiment as a control technique, to compare with the others irrigation methods. In this experiment, we used the Model 503 DR Hydroprobe manufactured by CNP International. The NP calibration were laborious and difficult to be performed as reported by (REICHARDT et al., 1997)

The calibration of NP is extremely necessary to achieve good results. The calibration is based on the correlation between the count ratio with the volumetric soil water content. In 2013, the neutron probe was calibrated for this site, under saturated and very dry soil conditions. The numbers obtained by the calibration preformed in 06/06/2013 were A=0.212 and B=-0.0917. In order to check this calibration curve (RAWLS AND ASMUSSEN, 1973) that was developed, and used during the last 4 years for this specific soil at the site, it was desired to had a good variation in the soil water content (SWC) at the soil profile. For this particular site, the goal was to work with increments of 30 cm, from 0 to 240 cm, collecting and weighing the 4 samples at each layer and do the neutron probe reading at the nearest time as possible that the samples were being collected and weighted. The numbers of access tubes installed were 4 in total, with 2 at each border. The first-round sampling was done using the soil coming from the tube installation. The second collection (wet samples) was made at the nearest location to the NP access tubes two days later with the wet soil. According to Grote et al. (2003), the difference between the soil collected where the access tube is installed, with the soil collected at the nearest area later, doesn’t make difference in the errors.

The soil saturation was done with a water tank (Figure 1c), applying the water near the tube location using the soil as border to provide a homogeneous infiltration near the access tubes. All the 64 samples were identified on the soil water cans, and dried for 48 hours at 105ºC, until constant dry weight. The minimum of samples suggested is between eight to sixteen for the calibration (GRISMER; BALI; ROBINSON, 1995). The soil water content was calculated for each layer using the bulk density data present previously in (Table 1).

To take readings during the season, 20 access tubes were installed at 16 DAP. Those access tubes were installed in all 20 plots, along the middle crop row, at 2,44m depth, offering the possibility to have readings at different depths. The experiment required measurements before each irrigation event up to 2.4 m depth, with increments of 0.3 m. Fifteen NP readings were done between the planting date and the irrigation termination at the physiological maturity after planting

(DAP). The last reading was done at the full maturity at 146 DAP, totalizing sixteen readings over the season.

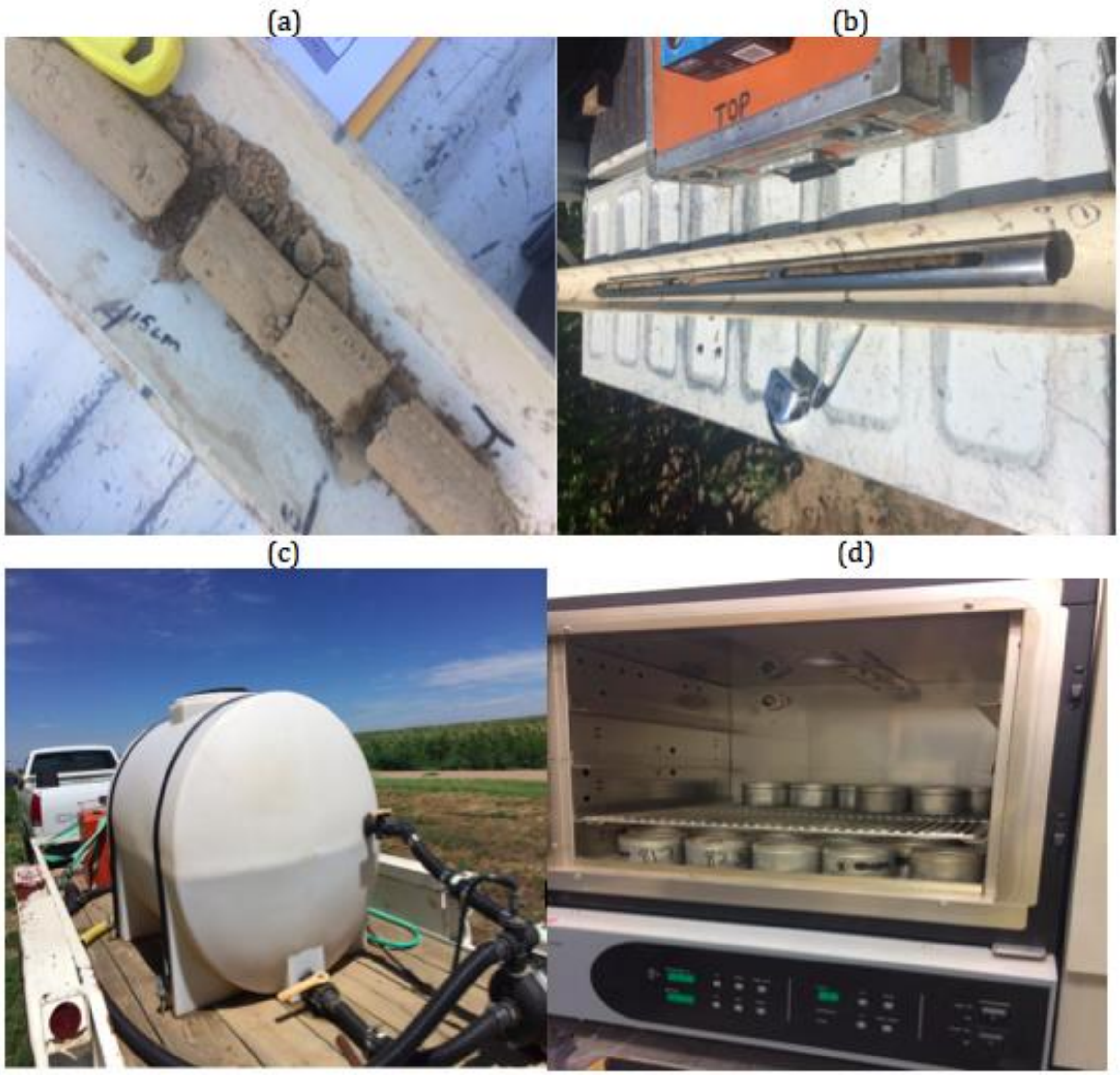

Figure 1. Soil samples with 10 cm long for the different soil layers (a), probe used to remove the soil samples (b); water tank used to saturate the soil for the second readings(c); oven used to dry the soil for 48 hours at 110 ºC (d)

2.6.2 iCrop-beta version

Models have been proved to be a useful tool for agriculture(ABEDINPOUR et al., 2012; Jones et al., 2017; MA et al., 2001; WIBOWO et al., 2017). A decision support system (DSS) is a software-based developed with the goal to compile useful information with the objective to support the decision making process (RINALDI AND HE, 2014). The Crop Estimation through Resource and Environment Synthesis (CERES-Maize) (JONES et al., 2010) is one of those crop models within the Decision Support System for Agrotechnology Transfer Cropping Systems Model (DSSAT-CSM) (HOOGENBOOM et al., 2003; JONES et al., 2003). As reported by HENG et al., (2009) those simulation models that are able to assess the effect of water effect on yield, are a very convenient instrument for the irrigation management. Several studies already proved the potential of those models to simulate the crop conditions under different irrigation regimes (ARAYA, KISEKKA AND HOLMAN, 2016; KISEKKA et al., 2016; RINALDI AND HE, 2014). However, most of those models usually require previous calibration and many parameters related with the weather, soil and crop (MA et al., 2009). The challenge to spread this technology to the farmers is related with this data requirements and the complexity of those models. The idea about the *Integrated Crop Water Management Model-driven Decision Support Tool* (iCrop), was to offer to the farmers, an option to use the modeling programs to do their irrigation and fertility management without many complexity and previous knowledge of modelling**.** The CERES model is based on the solar energy as the engines of growth (RINALDI AND HE, 2014). The way that the program simulates the soil water content and growth and development of the crop are summarized in Figure 2 proposed by Yang et al. (2006).

The iCrop decision support tool has the DSSAT v4.6.5 program inside a web server and automatically links to weather networks and soil databases and prepares the input files required to run DSSAT. iCrop allows the user to predict growth stage, yield, soil water content, water stress, nutrient stress, crop development and many other characteristics based on cultivar coefficients for each crop and management inputs. The ET was estimated using the FAO-56 method (ALLEN et al., 1998) The water balance and soil infiltration can be simulated by the program (RITCHIE, 1998 ; SULEIMAN AND RITCHIE, 2003).

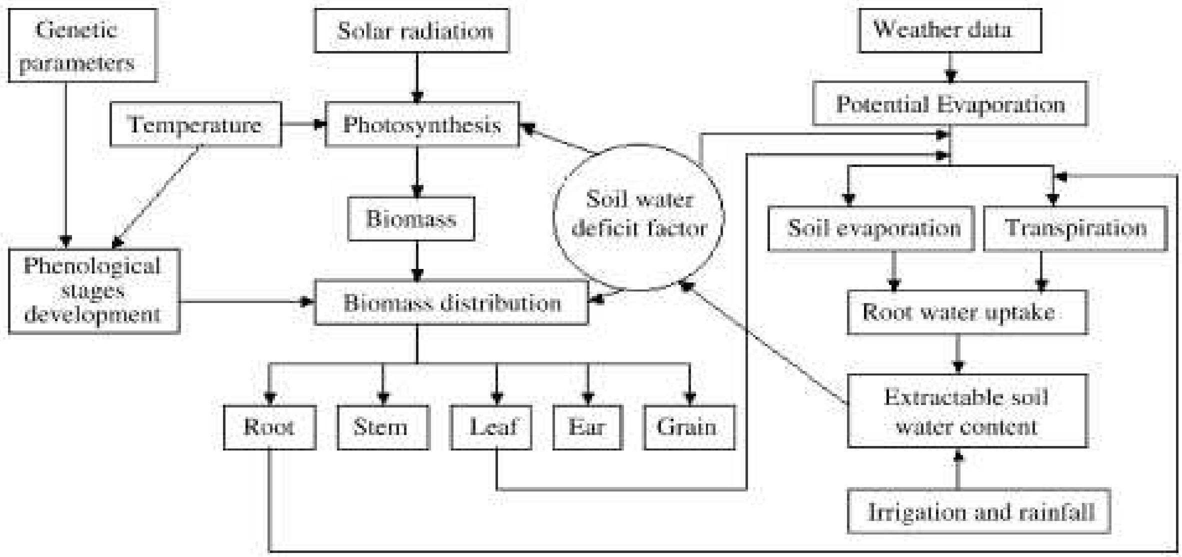

Figure 2. Conceptual diagram illustrating the influencing factors in DSSAT model. (Source: YANG et al., 2006).

The main goal with this tool is to offer and facilitate the use of those complex and robust modeling programs in an easier and applicable way. Furthermore, because this is the first occasion that the program has been used, the objective of this treatment was to test the quality of the simulation as one method to schedule irrigation under the standard irrigation strategy proposed to increase the water productivity. The model ability to predict the soil water dynamics is essential for successful predictions (HOFFMANN et al., 2017). Consequently, we evaluated the performance of this tool to predict the soil water content during the season and we were able to improve and adjust the tool, as the simulations were performed during the experiment, checking their functioning, and identifying and fixing the errors inside the program.

To make simulations, some initial information was required. Parameters related with the soil and crop were necessary to represent the real condition of the crop in the field. Those coefficients associated with the crop required by iCrop can be based on the range of degree days needed by the crop to reach each physiological stage, or custom calibrated values can be input under the customized cultivar window, using parameters from previous studies. For this specific hybrid, all crop parameters were already calibrated and validated for the same site with similar cultivar and similar conditions (ARAYA, KISEKKA AND HOLMAN, 2016). Those parameters are presented in the Table 2, offering more reliable results for the simulations. The DSSAT model requires under the soil parameters the root growth factor, those parameters were estimated based on the function proposed (HANKS et al., 1991).

Table 2. iCrop calibrated parameters used to simulate the crop site condition: Source: (ARAYA, KISEKKA AND HOLMAN, 2016)

Coefficient		Value	Unit
Thermal time from emergence to end juvenile phase	P1	230	Degree-days
Photoperiod sensitivity coefficient (0-1.0)	P2	0.78	Days
Thermal time from silking to physiological maturity	P5	990	Dregree Days
Maximum number of kernels per plant	G2	920.4	Unitless
Kernel filling rate during linear grain filling	G3	7.3	mg d-1
Phyllochron interval	PHINT	65.9	degree-days

The weather data was automatically obtained from the Mesonet system, as provided by the program with the objective to facilitate the user in gathering the all the weather information. The soil information was inserted to represent the soil at the site based on the parameters presented in Table 1. iCrop is linked to the Web Soil Survey, offering the user the possibility to use all the soil parameters from a database as well. The parameters from the web soil service were very similar with the others gathered at the site. Irrigation dates and amount per event were input into the system as well. The nutrient and tillage process were selected based on previous field information. Two simulations were performed, one with the Mesonet rainfall and another one with the recorded rainfall to check the importance to track the rain at the field and the effect of those simulations on the water content estimation. The output data was downloaded and compared with the measured data.

2.6.3 KanSched

The water balance based on evapotranspiration (ET) is one of the most common techniques to track the irrigation. This technique is associated with the sum of the transpiration and evapotranspiration (JONES et al., 2010). The ET is affected by the weather parameters, mostly by the radiation, air temperature, wind speed and humidity (TESTA, GRESTA AND COSENTINO, 2011a). The ETc is the crop estimated evapotranspiration, and needs to be compensated somehow by the rain or irrigations in order to guarantee the crop production. According to Allen et al. (1998)

the irrigation requirement is basically represented by the difference between crop water requirement and effective precipitation.

Looking forward to enhance the irrigation management, Kansas State University Research and Extension developed an ET-based irrigation scheduling tool with the objective to help the farmers to determine when and how much water to apply (CLARK, ROGERS AND BRIGGEMAN, 2002b). KanSched is computer software to monitor the soil water content that was proposed with the objective to help farmers to track the root zone soil profile water balance and scheduling their irrigation by themselves. At the beginning, this technique was just an excel spreadsheet that evolved into the current tool called KanSched3 (Available at www.bae.ksu.edu/mobileirrigationlab). This tool requires some information such as: reference ET, emergence date, crop root depth, crop canopy coverage at different growth stages, soil water holding capacity, permanent wilting point and system efficiency and climatic zone that will further customize the crop coefficients to their location (ROGERS, 2012; VÁZQUEZ-ÁLVAREZ et al., 2010). The objective was to test the KanSched tool under the standard irrigation regime to improve the water productivity and check the model accuracy to track the SWC over the season. To do that, the program was adjusted to the crop and field conditions.

The Crop coefficient (Kc) used were the same as suggested by the program, 0.25, 1.20, and 0.60 for the beginning, peak growth, and maturation stages of the corn crop (USDA, 1993). According to Dorgan (2003), many studies show that the active root zone for corn is near to 60 cm. Hsiao et al. (2009b) indicated that the root for corn should be between 1.5 and the 1.8 m. Therefore, the root depth was set for 1.2 m.

The total growing cycle recorded was 146 days. The reference ET was based on the MESONET grass. Two simulations were performed with KanSched. The first one with Mesonet rainfall data and the second, with field recorded rainfall data. Both simulations considered the initial and final root depth of 48 inches (121.92 cm) (CLARK, ROGERS AND BRIGGEMAN, 2002b). Those simulations were done to check the importance to the farmer to track their own rainfall data at the field. Growth stages were calibrated based on field observations. The soil information was set following the attributes in Table 1. At the beginning of the simulation, the water content was calculated based on the NP reading and assumed to be 81.7 %. The unit transformation was done using the same soil parameters (Table 1). The crop type selected was corn with 146 days. The reference ET system was the Grass based on climate zone number 1, representing Garden City-KS area. All the simulations were compared and submitted with statistical evaluation.

2.6.4 Acclima TDR 310 Soil Sensors

The use of time domain reflectometry (TDR) to measure in situ volumetric water content, has been widely accepted and used as an irrigation management tool due to its many advantages, e.g., superior accuracy to within 1 to 2 % of volumetric content, minimal calibration requirements, lack of radiation hazard, spatial and temporal resolution, nondestructive measurements, and are able to provide continuous measurements (SKIERUCHA et al., 2012). With advances in microcomputer and communication technology, a variety of soil sensors are gaining momentum of irrigation tools (AGUILAR, ROGERS AND KISEKKA, 2015). The idea initially was to only measure the dielectric of fluids (SCHWARTZ et al., 2016). Later, with the development of the research, were concluded the potential use of this technique to measure the soil water content was verified (TOPP, DAVIS AND ANNAN, 1980). Kome (1996) confirmed that the measurements of soil water content were not influenced by the bulk density, temperature, salinity or mineral composition, eliminating the requirement of site-specific calibrations. The TDR estimation is performed by the dielectric constant which is achieved by the measurement of the capacitance between the stainless waveguide and the soil moisture based on a step-pulse transit along the TDR probes (TOPP, DAVIS AND ANNAN, 1980). There are several papers explaining the principle of the TDR measurements (SERRARENS et al., 2000; SKIERUCHA et al., 2012; TOPP AND DAVIS, 1985; TOPP, DAVIS AND ANNAN, 1980). However, still many questions and doubts about the use of this technology for irrigation purposes, principally regarding to the requirement of sensor calibration for each soil type, making this equipment not very widely used for the irrigation management.

In this study, we selected and tested the TDR-310S SDI with rounded form factor (Figure 3a), commercialized by Acclima, Inc. This sensor is already factory calibrated for most types of soils, based on the mixing model created by the company, being able to follow the Topp equation (TOPP AND DAVIS, 1985). According to some information in the TDR brochure, this genuine time domain reflectometer sensor has a geometric parameter included at the calibration that represents most soil types. It is also reported that the pore water EC is based in the Hilhorst model. Looking at the literature, Hilhorst (2000) concluded that the calibration using this method is not necessary for each soil type, if the soil water content measured still higher than 10%. Furthermore, these sensors came with the differential option to be installed at the vertical position. This new feature, will allow the farmer to easily attach the sensor to a 1" PCV pipe (Sched. 40) and insert it into the soil at a specified depth, and remove the sensor at the end of the season, or use the sensor at different field later, that is not able to happen with the regular TDR available on the market.

Acclima sensors were able to provide information’s on several parameters e.g., volumetric water content (θv) from 0 to 100% with 0.1 % resolution, apparent permittivity (Ka) from 0 to 80 with 0.1 unit resolution, soil electrical conductivity a. Bulk EC (µS/cm), soil temperature (Celcius) and pore water electrical conductivity. In order to find similar results that the irrigators and farm managers would find in their fields, no previous calibrations were performed, using just the factory calibration to estimate the soil water content.

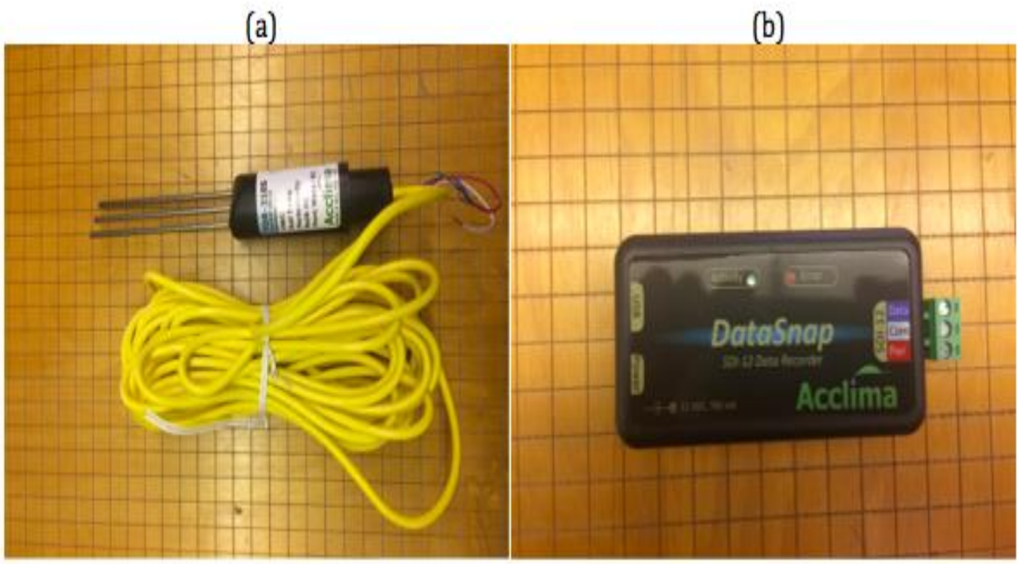

Figure 3. Pictures illustrating the type of sensor and data logger used in this experiment. Acclima TDR sensor (a) and DataSnap (b).

To collect and store the readings, we installed the SDI-12 Acclima DataSnap (Figure 3b). Two sensors were installed at each DataSnap. Before the field installation, all sensors were linked at their specific data logger and synchronized with the Irrigation manager software (Version 1.4.5.8b), available at (http://www.acclima.com/products.html). The name of each sensor was altered, according to the depth and plot that they were installed. The frequency of time readings was established to record the readings at gaps of 30 minutes. Each data logger required 8 alkaline batteries AA to work, that were plentiful for entire season.

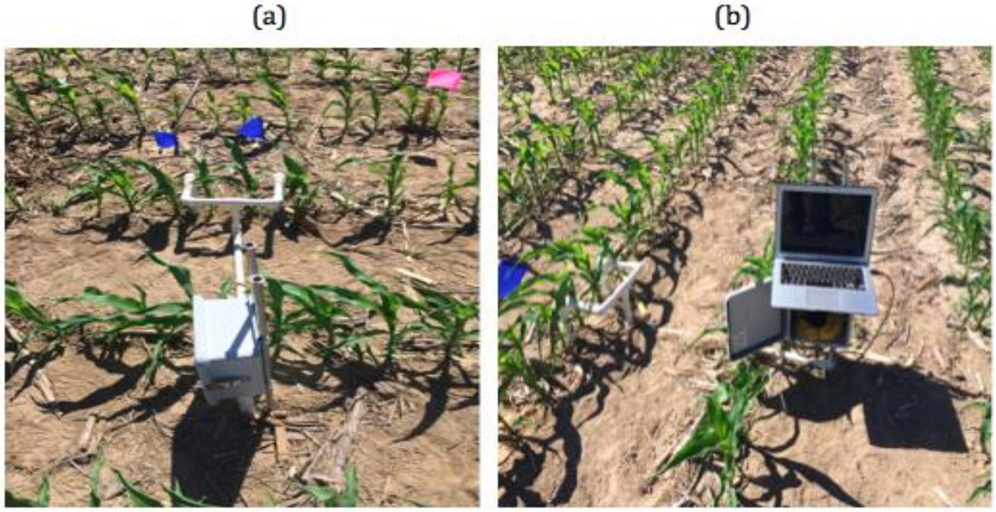

Figure 4- Acclima TDR sensors installed in the field (a) and the data download process (b).

The sensors were installed (Figure 4a) on June 12, 2017. They were installed at two depths (30 cm and 90 cm) in each treatment plot, totalizing 8 sensors in this study. In each block, one electrical box was installed in order to avoid problems with rodents and weather conditions. The data were downloaded every week from the data logger direct to the computer (Figure 3b). The initial readings started at 35 DAP and the last download was done at 146 DAP.

To improve the results delivered by the Acclima TDR 310s with the NP readings, a calibration was performed with the objective to get better results**.** There are different ways to calibrate the instrument to a specific soil (MALLANTS et al., 1996). According to Quinones (2001), several relationships can be performed with the data, by linear o polynomial functions. The calibration were performed based on the methodology used by Huisman et al. (2003), where 60% percent of the available TDR data was used to fit the calibration, and the other 40% was used for validation. The Acclima TDR 310s data were compared with the NP values during the season and evaluated goodness-of-fit before and after the calibration.

2.6.5 AquaCrop

The AquaCrop model (RAES et al. 2009; HSIAO et al. 2009; STEDUTO et al. 2009) is a water-driven model by FAO with the objective to work in a balance between simplicity, accuracy, and robustness (FARAHANI, IZZI AND OWEIS, 2009) for many different crops, including vegetables, grain and forage (HSIAO et al., 2009). For this specific work, we used the AquaCrop v.6.0, provided by FAO (http://www.fao.org/aquacrop/en/). The present model has the ability to predict the relations between the crop yield with the water, based on the followed function developed by Doorenbos and Kassm (1979).

$$\left(1-\frac{Y_a}{Y_x}\right) = K_Y\left(1-\frac{ET_a}{ET_m}\right)$$

Eq.(1)

Where:

Yx maximum yield

Ya actual yield

ETm maximum evapotranspiration

ETa actual evapotranspiration,

Ky is a yield response factor representing the effect of a reduction in evapotranspiration on yield losses

There are some Crop-specific parameters required as an input to simulate the crop development to run the AquaCrop model. Because the experiment was conduct for one season, those initial parameters were retrieved from a similar cultivar at the same site under similar conditions (ARAYA et al., 2017). Some of those parameters are: harvest index (HI), plant density, yield, biomass, effective rooting depth, crop growth stages and green canopy cover (CC), while user-specific parameters required are crop cultivar, timing of crop cycle, water management, and agronomic practices (FARAHANI, IZZI AND OWEIS, 2009). According to Hsiao et al. (2009), there are some of those parameters that are user-specific, and need to be measured by the user in order to validate the model for those conditions.

The climate file was created and updated with the information obtained by the Mesonet weather station located in Garden City, KS. As one input to run the model for all year, another file was created with the long term daily information from 1950 to 2016. The daily average for ETo, rain, maximum temperature and minimum temperature were calculated. The climate file was updated with the 2017 data, every time that the simulations were performed during the season.

Preliminary crop file was generated with crop parameters calibrated for similar conditions and cultivar for the same site by ARAYA et al. (2017). Those parameters were refined (RAES et al., 2009) based on the collected information from CC, phenology, and above ground biomass over the season with the higher and lower soil water content treatment to calibrate and validate the model. The irrigation file was created and updated as the irrigations were done. Fertility effect was not considered. The soil file was formed based on the information referred in Table 1 and inserted into the program. According to WIBOWO et al. (2017), the use of those daily crop simulations can be a good way to estimate the water stress during the crop system.

The goal of this treatment was to compare the robustness and operation of this model in simulating the water balance, looking to future implementation of this model into an online platform to deliver the simulation as an easier way to the farmers in the future, offering more option and information about their crops over the season. In this study, the water balance outputs were compared with the field measurements, looking at the potential goal to use this program as an irrigation management tool based on soil water content simulations. The output files were compared with the observed data.

2.7 Cultivars and Growing Season Information

2.7.1 Phenology and Degree Days

Phenology is one of the very important data for AquaCrop and iCrop, principally for the validation process when we use data from previous studies. The phenological stages were recorded over the season by field observations and are presented in Appendix 2.

The Growing degree days were calculated as well based on field observations of each phenological stage. The calculation were performed by subtracting 50 degrees Fahrenheit from the average daily temperature, then adding the daily growing degree days over time (LANGEMEIER, 2004)

2.7.2 Biomass

Biomass is the other key for the modeling calibration and validation (RAES et al., 2009). However, measuring biomass is a very laborious process and demands a lot of time. Four samplings were performed during the season on: June 22th, July 14th, August 02th and August 26th. The samples were collected during different physiological stages. The samples were randomly selected in one adjacent roll where the NP access tube was installed. The methodology used was to collect 6 plants in the field, take the fresh weight of all 6 plants, crash the samples, take the paper bag tare, collect a sub ample from the total sample, and take the sub samples to the oven at 80 ^{o}C until constant dry weight.

2.7.3 Canopy Cover

Canopy Cover (CC) is a key variable to evaluate and validate when using crop modeling programs (HSIAO et al., 2009; RAES et al., 2009). The CC was measured in all treatments during the crop season by two methods. The first method we used was the app developed by the Oklahoma State University, called Canopeo (http://www.canopeoapp.com/). The mobile application the allows users to take overhead pictures from the desired crop and instantly estimate the values for CC by selecting the picture of interest. Pictures were taken by using an iPhone 5s linked with a Bluetooth remote control. The phone was inserted on pedestal constructed with PVC pipes, measuring 2,4 m of height and 1,0 m of length. The pictures were taken at different times during the season. The second method used to measure the canopy cover utilized the Ceptometer Accupar. To convert the CC to LAI, that was used the methodology suggested by Hsiao et al. (2009).

2.7.4 Yield

The yields were collected for each treatment by hand harvesting. The information was used to compare the accuracy and model simulations. Two 3 m rows were hand harvested to form a 15.25 m^2. Samples were shelled using a David Bradley electric corn sheller. All the samples were weighed using a Mettler Toledo model SB32001DR scale. Moisture content and test weight were measured using a Dickey-John model GACII moisture tester.

2.8 Weather Information

For this study, we used the set of climate data, from a weather station Hinged 9.2 m tower, located near to the site (37.99292, -100.81218). The data recorded included precipitation, minimum and maximum temperatures, wind speed, solar radiation, and relative humidity. The data that was accessed at the MESONET website (http://mesonet.k-state.edu/).

The rainfall information contains data collected at the field for every single rain event during the season. The precipitation for the site was obtained from the average of the total numbers of all the rain gauge readings that are installed around the field at specifics points, in order to better represent the total amount of rain at the plot. All data were downloaded and organized in an Excel spreadsheet. Also, the crop measurements used to validate the program were compared as well. The Evapotranspiration were obtained by the Mesonet and the ETo FAO calculator and compared, using the same weather daily inputs.

2.9 Statistical Analyses

The goodness-of-fit of statistics were performed to compare the ability of each method to simulate moisture measurements. The main goal when comparing the soil water content was to estimate the precision and accuracy of each technique. However, some of those statistics were also used to test the biomass and canopy cover.

The root-mean square error [Eq. (2)] (RMSE) was used to indicate the accuracy between the observed and simulated, where Si= simulated, Oi= observed values, n=number of observation. Values less than 0.035 cm^3 cm^{-3} were considered accurate for agricultural purposes (ADEYEMI et al., 2016). The normalized root-mean square error (NRMSE) [Eq. (3)] indicated the agreement with values more near to zero, where MM=mean of the measured values. If NRMSE is <10% (excellent), 10–20 (good), 20–30 (fair) and >30% (poor).

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{\mathbf{I=1}}^{\mathbf{n}} (\mathbf{Si} - \mathbf{Oi})^2}{\mathbf{n}}}$$

Eq. (2)

$$\mathbf{NRMSE} = \left[\frac{\mathbf{RMSE}}{\mathbf{M_M}}\right] \mathbf{x\ 100}$$

Eq. (3)

The mean absolute error (MAE) [Eq. (4)] and mean bias error (MBE) [Eq. (5)] are methods to measure the error between the simulated (S) and the observed (O). The MAE is less sensitive to disperse values. The MBE provided information about the over estimation or under estimation of the observed values. The MBE values needed to be between -0.02 to 0.02 $cm^3\ cm^{-3}$ to consider the technique accurate according to the IAEA (2008)**.**

$$\mathbf{MAE} = \sqrt{\frac{\sum_{I=1}^{n} |\mathbf{Si} - \mathbf{Oi}|}{\mathbf{n}}}$$

Eq. (4)

$$\mathbf{MBE} = \frac{\sum_{i=1}^{n} (\mathbf{Si} - \mathbf{Oi})}{\mathbf{n}}$$

Eq. (5)

The Willmott (1982) index of agreement (d) [Eq. (6)] estimates the degree of agreement between the simulated values and the observed values. This index ranges below zero to one, where, one is the highest agreement.

$$\mathbf{d} = \mathbf{1} - \frac{\sum_{i=1}^{n} (\mathbf{Si} - \mathbf{Oi})^2}{\sum_{i=1}^{n} (|\mathbf{Si} - \bar{\mathbf{O}}| + |\mathbf{Oi} - \bar{\mathbf{O}}|)^2}$$

Eq. (6)

Linear equations by regression analyses were done for each method to indicate the goodness of fit and the relative variability explained by the model. Values near to 1 indicate a good agreement between measured and observed data [Eq. (7)].

$$\mathbf{R^2} = \left[\frac{\sum(\mathbf{Oi} - \bar{\mathbf{O}})(\mathbf{Si} - \bar{\mathbf{S}})}{\sqrt{\mathbf{Oi} - \bar{\mathbf{O}})\mathbf{x}\sum(\mathbf{Si} - \bar{\mathbf{S}})}}\right]$$

Eq. (7)

One way ANOVA at 1% level of significance were performed as well to compare the values of biomass, available water content, canopy cover and yield.

3. RESULTS AND DISCUSSION

3.1- Weather Conditions

3.1.1- Temperature

Maize is a C4 plant, and originated from climates with warm summers (RAES et al., 2009). Thermic exigencies for Maize regulates the growth stages and the total duration of the cycle growth (GADIOLI et al., 2000). The data of maximum temperature, minimum and average temperature are presented in Figure 5.

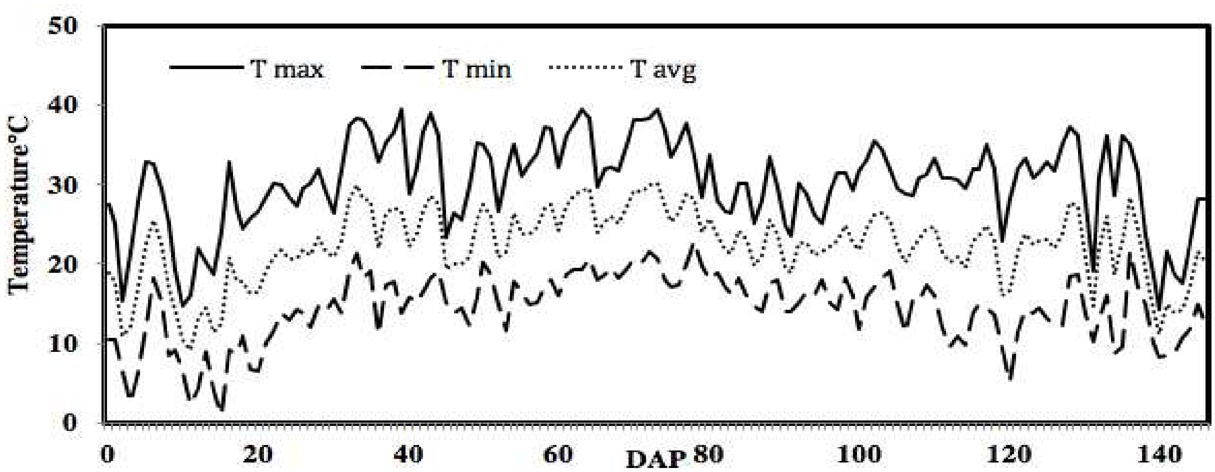

Figure 5. Maximum temperature, minimum temperature and average temperature during the growing season (May, 9^{th} to Oct, 2^{th}) in near Garden City-KS United States.

The optimum temperature for corn depends on each phenological growth stage (PAYERO et al., 2008). The mean observed during the season (May to Oct.) had a maximum of 39.5°C (July, 7^{th}) and minimum of 0.9 °C (May, 24^{th}). Lower temperatures happened more frequently at the beginning of the season. It was observed that the crop required 12 days for emergence, probably, due to lower temperatures at the beginning of the season. According to Sánchez et al. (2014) the lower temperatures that can cause damage to steam, leaf and ear need to be lower than -2.2°C. Singh et al. (2014) analyzing the Maize response to temperature, concluded that temperatures above 30°C and below to 22°C can affect the leaf photosynthesis. Hsiao et al. (2009) suggested for Maize on AquaCrop simulations, the basal temperature for corn to be set at minimum of 8°C and maximum of 30°C. For the CERES-Maize the optimum temperature is 26°C (SÉRGIO et al., 2001). Harterfield and Prueger (2015) concluded that the exposure to high temperatures during the reproductive stages has the highest impact to the crop. We can observe that during the silking stage, from 70 to 85 DAP at the Pre-Blister stage, the maximum temperature ranged from 39.5°C to 33.5 °C and the minimum 22.8°C to 17°C. Therefore, the high temperature during the pollination could have had some impact on the final yield.

3.1.2- Solar Radiation

The solar radiation (SR) can affect the Maize both by the intensity and the duration of the solar radiation. The SR through the season is presented in Figure 6. The maximum value recorded was 31.3 MJ/m² on May 12th. The lowest value was 3.5 MJ/m² on September 25th. Observing the graphic of solar radiation, it’s clear that the radiation decreased over the season. Those values of radiation are very important for the models AquaCrop and DSSAT (CERES-Maize), due to the fact that they utilize this information to predict the yield and crop growth. To explain how important is the SR in the model, according to Sérgio et al. (2001), the CERES-Maize under optimum conditions of temperature and soil water content, 5.0 g of biomass is produced for each MJ of radiation intercepted.

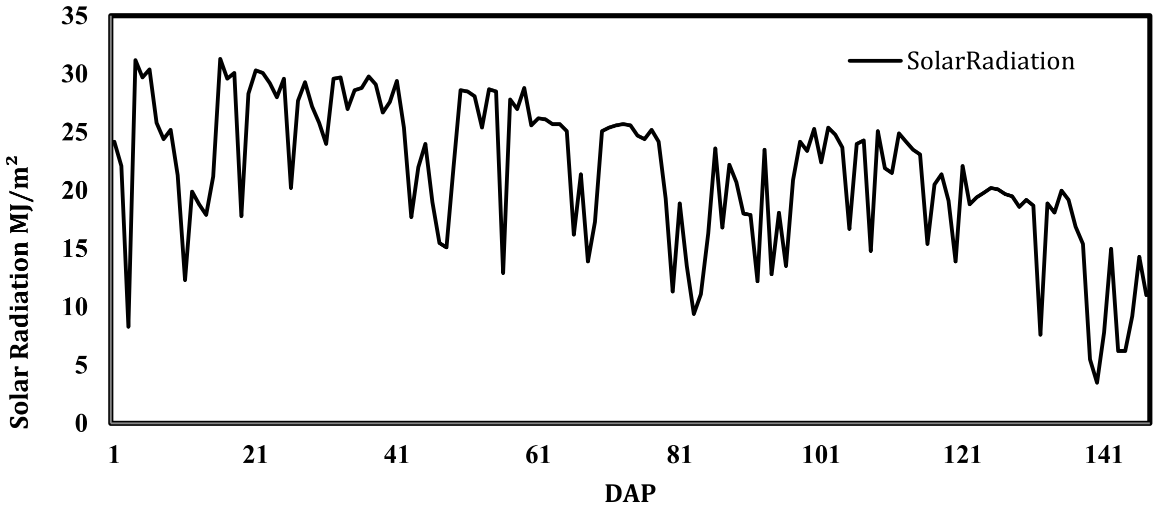

Figure 6. Solar radiation (a) during the growing season (May, 9th to Oct, 2th) near Garden City-KS United States in 2017.

3.1.3- Relative Humidity

The average Relative Humidity (RH) (Figure 7) was 62.15%. The maximum was 96.6% at 140 DAP, and minimum was 36.8% at 46 DAP. During the pollination (70-85 DAP) the average RH was 62.0%. According to Cantele (2009), the optimum RH during the flowering and grain fill stages needs to be more than 70%. We observed some values near to this ideal range, but, was not above 70% during all the previous stage . This might have had some effect during the pollination, upsetting the final yield as well.

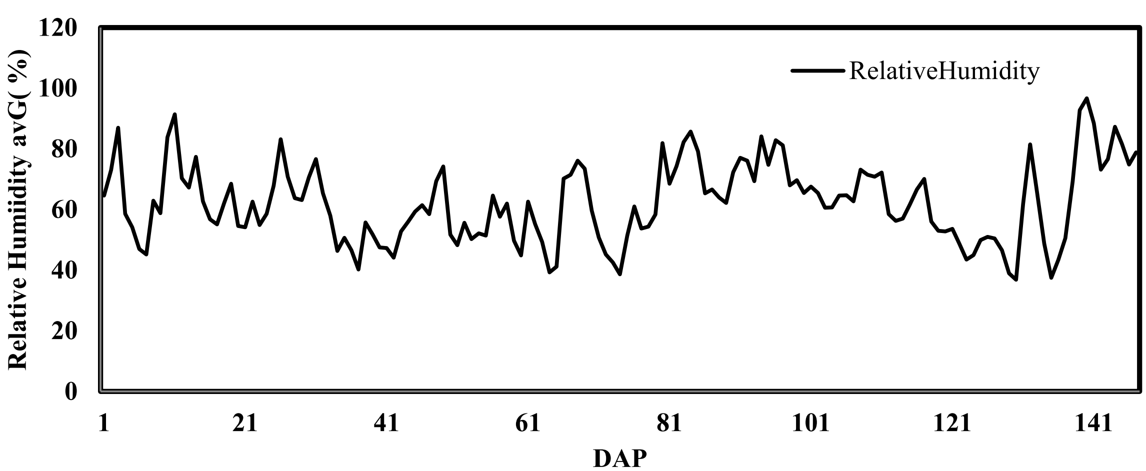

Figure 7. Average daily relative humidity during the growing season (May, 9th to Oct, 2th) in near Garden City-KS, United States.

3.1.4- Windy Speed

Figure 8 shows the wind speed (WS) during the growing season. The maximum value was 6.5 m/s, minimum of 0.9 m/s, and average of 3.1 m/s. The high WS could help with pollen dispersion and heat distribution, however, can contribute to excessive transpiration, leaf area reduction (MOURA et al., 2009), and affect the water distribution under higher values, as evidenced by Grote et al. (2003).

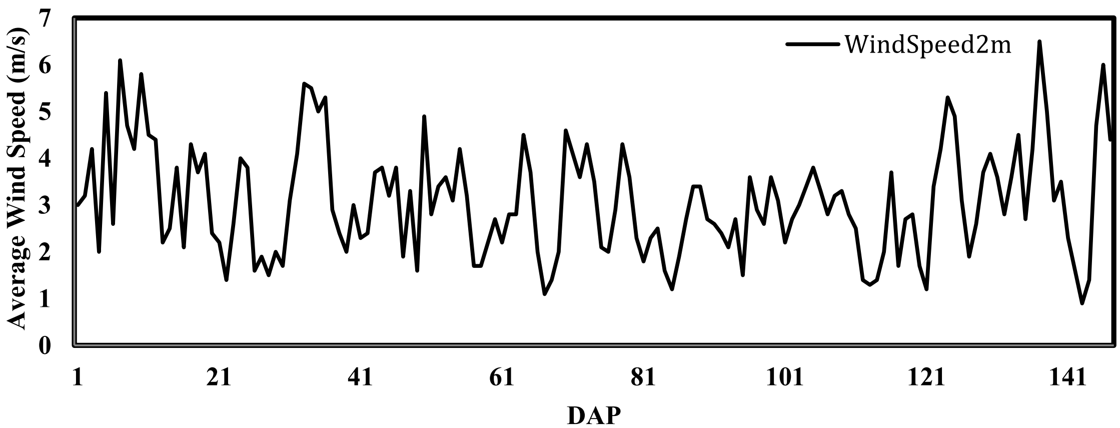

Figure 8. Average wind speed (m/s) during the growing season in near Garden City-KS, United States.

3.1.5- Evapotranspiration (ETo)

The recommended method FAO-56 (ALLEN et al., 1998) to estimate the reference evapotranspiration (ETo) was obtained with the help of ETo calculator (RAES, 2009) and the results compared with the Mesonet ETo values. This comparison was performed due to the uncertain about the way that the ETo were calculated by Mesonet. The results are shown in Table 3 and Figure 9.

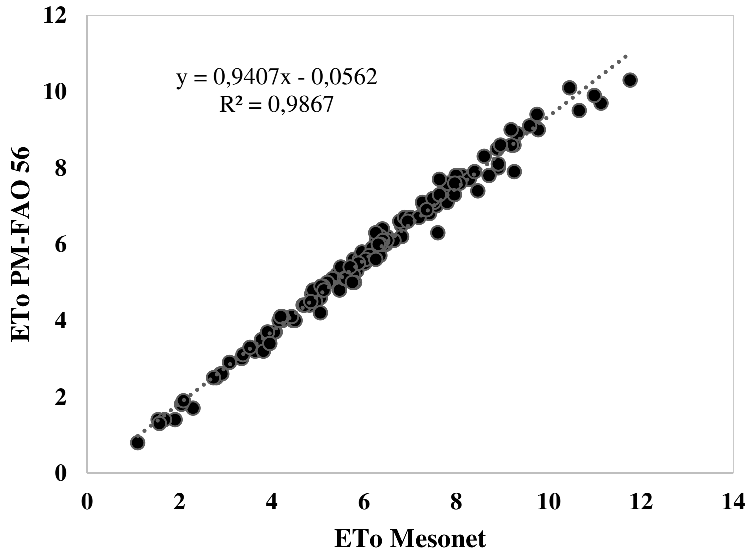

Figure 9. Reference evapotranspiration estimated by Penman-Monteith in AquaCrop and Kansas Mesonet.

The results agreement the two calculations resenting the coefficient of determination of 0.99. The Pearson correlation coefficient (r) was calculated as well, and presented the value of 0.99, providing confidence in the two calculations. The NMRSE proved that the Mesonet system is considered excellent to predict the values of ETo.

Table 3. Statistical results comparing the Reference Evapotranspiration (ETo) estimated by Mesonet and FAO-56.

ETo Calibration					
n[1]	RMSE (mm)[2]	NMRSE (%)[3]	MAE[4]	MBE[5]	d[6]
147.00	0.49	8.74	0.64	0.41	0.99

1-Number of observations; 2-root mean square error; 3- normalized root mean square error; 4-mean absolute error; 5-mean bias error; 6-wilmott concordance index;

Figure 10, demonstrates that the ETo by FAO-56 and Mesonet performance of both are very similar during the crop season. However, it is notable that the FAO-56 in AquaCrop overestimates estimates ET at some points. The reference evapotranspiration during the experimental period were approximately 6.05 mm/day. The maximum ETo occurred at 33 DAP, 11.77 mm by the FAO 56 method and 10.3 mm at the Mesonet. The cumulative ETo by Mesonet was 887.97 mm. The long-term (1950–2013) seasonal (May to Oct.) average ETo is 962 mm (ARAYA et al., 2017) and the 1034 mm was observed for the same time at this year.

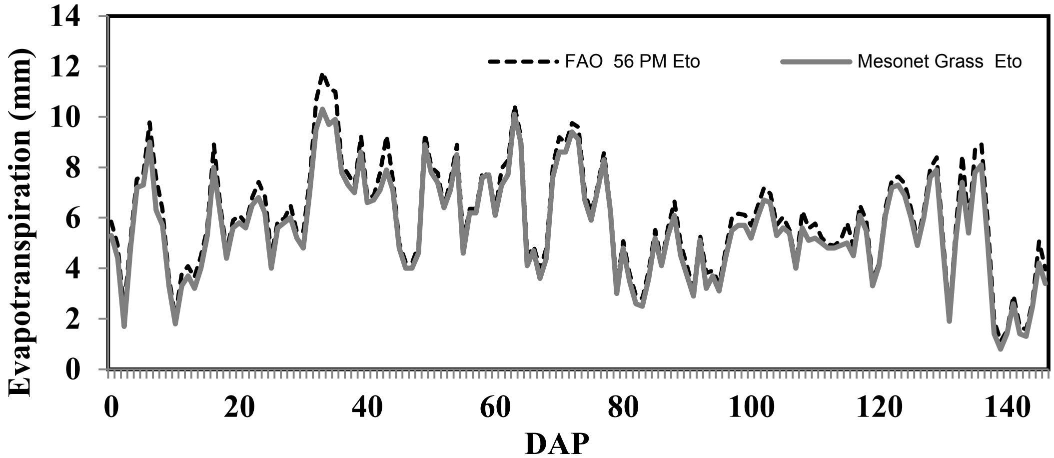

Figure 10. Comparison of the reference evapotranspiration (ETo) estimated by Penman-Monteith calculations in implemented in AquaCrop and Kansas Mesonet.

3.1.6- Irrigation and Rainfall

Eleven irrigations were performed over the season at 45, 52, 59, 65, 84, 100, 104, 108, 114, 121 and 128 DAP based on the NP readings. The rainfall during the experiment were measured at the field and compared with the values recorded by the weather station (Figure 11). The recorded total rain at the site was 262.4 mm over the 2017 season (May, 9th to Oct, 2th) and the total by Mesonet was 239.25 mm. The long-term average, between 1950-2013 is 349 mm (ARAYA et al., 2017) and the observed was 296.4 mm, for the same range of time, proving that the season was almost 50 mm lower than the average rainfall.

The values recorded by the rain gauges, were not able to divide the rain hourly, or on daily basis. When the rain happened on consecutive days at night, the total amount of rain was recorded by just the last day. The evaluations always happened in the early morning, explaining some huge differences between the recorded and Mesonet values when the rain event occurred at night. The recorded rain by Mesonet and the rain gauges, was considered the same amount of the effective rain because any values lower than 0.02 mm was reported, and on any day during the season the available water content (AWC) water was higher than 100%.

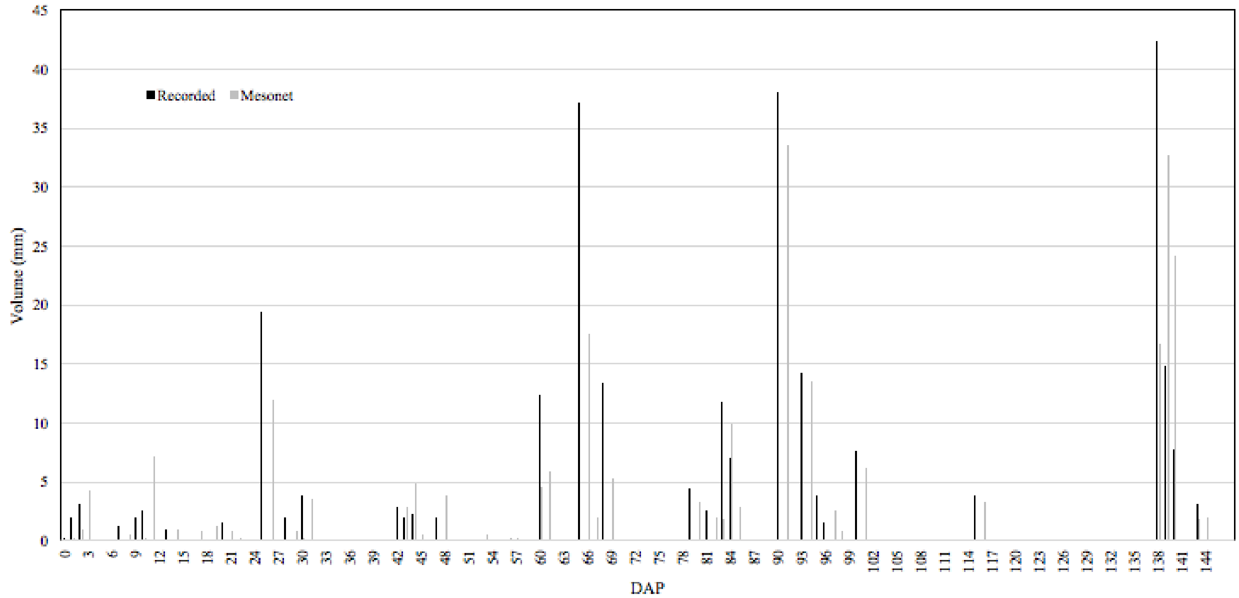

Figure 11. Recorded rain at the experimental plot and Mesonet rain data over the season.

Observing the rain data during the simulations, we observed the importance of the equipment to be able to measure the rainfall hourly, or at least daily. Rain events that starts in the afternoon or occurring during the night were recorded just on the next day, generating some errors due to the fact that the total rain was recorded for all the previous day. The simulation programs like AquaCrop and iCrop-beta version could take in consideration some factors based on the values of recorded rain and the Mesonet rain that could affect the simulation as well, likewise: runoff and deep percolation

3.2 Neutron Probe

3.2.1- Neutron Probe Calibration Check

The readings of Neutron Probe (NP) were done from the top to the 2.4 m depth. At first glance the calibration check showed how well the calibration curve performed and the equipment were adjusted for the soil existing at site. According to IAEA, (2008) direct soil water measurements will result in error margin, usually 0.01 cm^3 cm^{-3}, considering the multiple source of errors in this process. The RMSE of 0.022 cm^3 cm^{-3} and NMRSE of 10.62 % proved how well the NP is able to predict the soil moisture. The regression on Figure 10, shows the R^2 of 0.85, proving the agreement between the values. The error will increase due to the changes in bulk density over the soil depth (PARKES AND SIAM, 1979). According to Vachaud et al. (1977) most of the NP calibrations occur with the range between 0.12 to 0.28 $cm^3\ cm^{-3}$. As represented by the Figure 12, the calibration checking was able to range from 0.15 to 0.33 $cm^3\ cm^{-3}$, near to the permanent wilting point and field capacity.

Table 4. Statistical results comparing the Neutron probe (NP) soil water content versus the volumetric soil water content from a gravimetric method from the top to 240 cm depth.

Neutron Probe Calibration Check (240 cm)					
n[1]	RMSE ($cm^3\ cm^{-3}$)[2]	NMRSE (%)[3]	MAE [4]	MBE[5]	d[6]
53	0.02	10.62	0.12	-0.01	0.93

1-Number of observations; 2-root mean square error; 3- normalized root mean square error; 4-mean absolute error; 5-mean bias error; 6-wilmott concordance index.

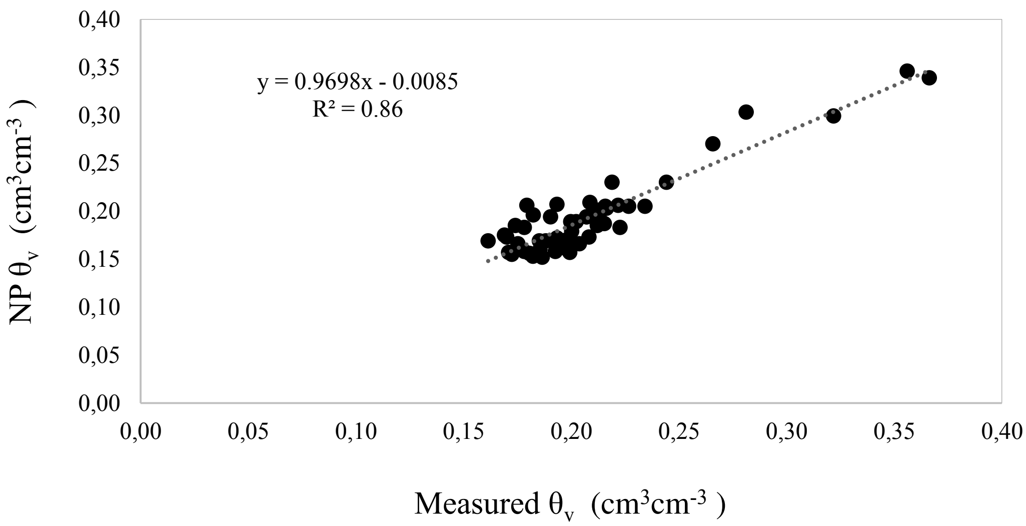

Figure 12. Regression between volumetric water content values obtained from gravimetric and neutron probe volumetric water content at the total profile of 240 cm.

As reported before, the interest depth of this experiment was to measure soil water content in the top 120 cm of soil profile. Results from the evaluation of 30 samples from 0 to 120 cm depth are presented in Figure 13. The statistical analysis showed R^2 of 0.90, RMSE of 0.017 $cm^3\ cm^{-3}$ and Wilmott equal to 0.96, resenting better agreement than the values founded at the total profile using 53 samples. Reichardt et al. (1997) found a R^2 of 0.90 between the count ratio and volumetric content. According to Grote et al. (2003), to perform a good calibration curve, it is recommended to review the data and remove some data that appear some error. Therefore, some outliers points were removed from the data to get reliable correlation due to the high chances of errors during the physical measurements (FALLEIROS, 1994). In field conditions, there are numerous factors that can influence the readings, e.g., plant roots, soil compression and soil variability. Results of RMSE of 0.017 cm^3 cm^{-3} and the correlation do of 0.9, proved that the NP performed very well for this specific site, being able to serve as the control to compare diverse techniques to estimate the soil water content in this experiment.

Table 5- Statistical results comparing the Neutron probe soil water content versus the volumetric soil water content from a gravimetric method from the top to 120 cm depth.

Neutron Probe Calibration (120) cm					
n^1	RMSE (cm^3 cm^{-3})^2	NMRSE (%)^3	MAE ^{4}	MBE ^{5}	d^6
30	0.017	9.65	0.098	-0.0098	0.96

1-Number of observations; 2-root mean square error; 3- normalized root mean square error; 4-mean absolute error; 5-mean bias error; 6-Wilmott concordance index.

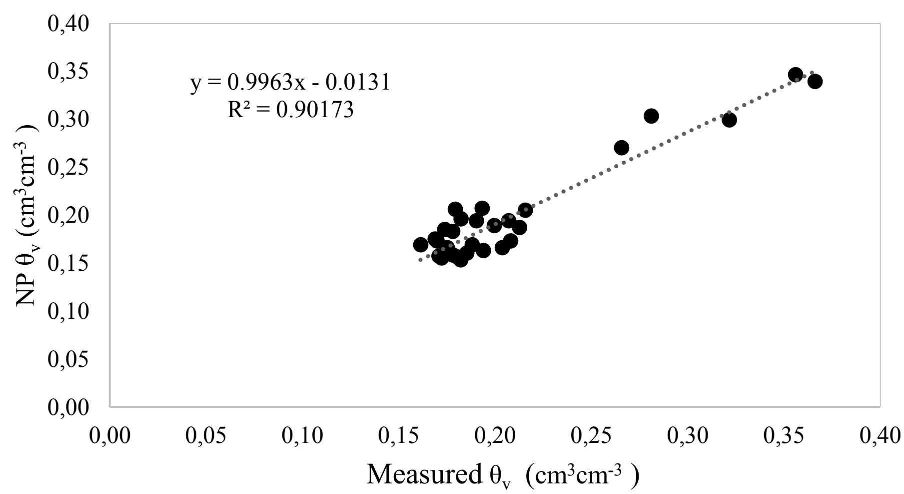

Figure 13. Regression between volumetric values obtained from gravimetric and neutron probe volumetric water content at the top profile of 120 cm.

3.2.2-Neutron Probe Results

The readings over the season show the θ_v changing from 0.31 to 0.165 cm^3 cm^{-3} in the control treatment. The 15 neutron probe readings were used to manage the irrigation over the season. The average θ_v observed was 0.258 cm^3 cm^{-3} approximately 60% of the available water was in the top 120 cm. All treatments received the same amount of irrigation over the season, there were some variations in the θ_v. Ladekarl (1998) comparing the TDR vs neutron probe techniques, concluded that the variations at the same field is presumed by the heterogeneous wetting and dry patters in the soil. The soil variability is also reported by Reichardt et al. (1997), comparing the readings of 20 access tubes we did not find the same values of θ_v. Those differences can be explained by the soil variability, amount of previous crop material, differences in evapotranspiration as well. However, the AWC were analyzed using one way ANOVA, proving that there is any significant difference between the readings (*p-value* >0.01).

The lower water content resented at 77 DAP was related with the pump problems during the season, however, this lesser SWC was good to test the accuracy of the methods to estimate this huge variation of AWC. The variation of the AWC is expressed by the Figure 14. It's notable that the iCrop beta version plots was able to keep the θ_v higher, expecting more yield.

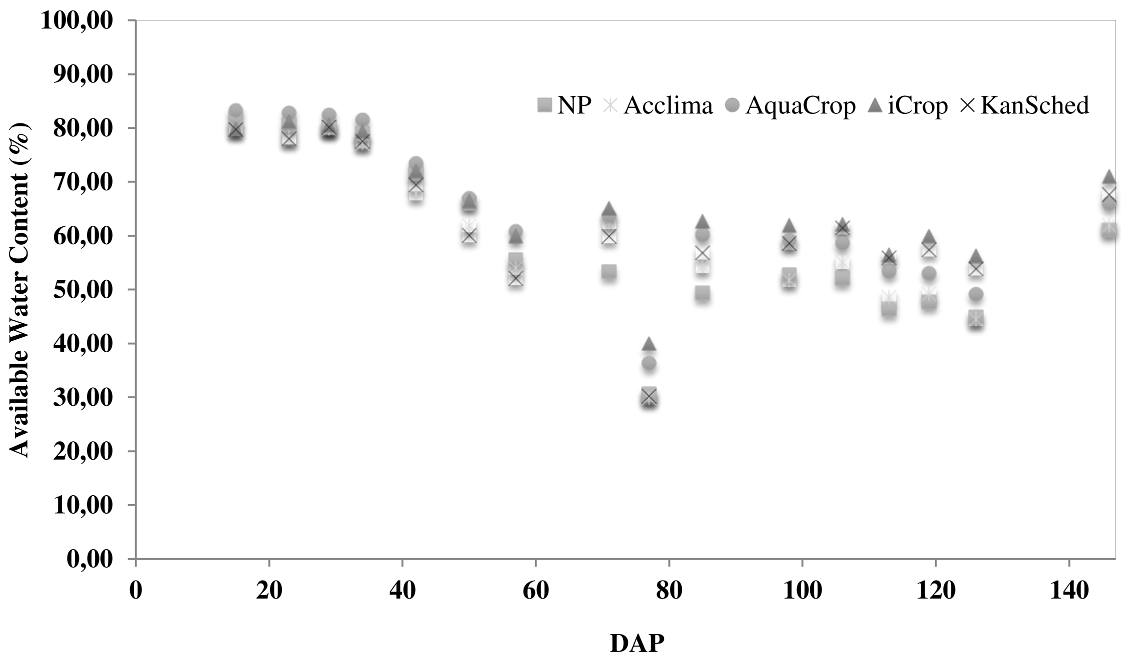

Figure 14. Neutron probe readings converted to available water content (%) over the season to manage the irrigation in in each treatment.

3.3 iCrop beta version

3.3.1 iCrop Soil Water Content estimation

The simulations performed with the recorded rain and the Mesonet rain were very similar. Both simulations were able to predict the floral initiation, 75% silking and physiological maturity in a reliable way with the previous calibrated parameters. The emergence was predicted on both simulations on May 17th and the observed was May 21th. As commented before, the temperature was lower during the emergence time, varying from of 8.6 °C to 24.5°C minimum and maximum average. According to Langemeier (2004) a mid-season maturity corn hybrid requires an average of 125 growing degrees days (GDD) for emergence. Observing the calculated GDD, the range of 120-212 degrees happened from 8 to 12 DAP, matching with the model prediction. However, the thermal-unit methods can largely differ due to the differences between the minimum and maximum temperature (WARRINGTON AND KANEMASU, 1983). The floral initiation and 75% silking with the Mesonet data was 1 day later when compared with the recorded rain simulation, that matched with field observations. The physiological maturity in both simulations data was at October 4, only two days later than the observed at the field.

Differences between the outputs related to the collected rain at the field and water content simulations resented differences mainly in the Runoff. The recorded rain generated 17.46 mm more runoff when compared with the Mesonet simulation. One possible reason for that, is due to the recorded rain values was not recorded hourly, resenting some accumulated values for more than one rain event, as was explained in the rain data discussion before. The simulations of soil water content in iCrop beta version started on January 1st since that the program uses the weather from the weather station system, so the precipitation is the sum of all the year. As observed in Figures 15 and 16 below, representing the water balance below, the iCrop-beta version with collected rain was able to predict better the θ_v over the season.

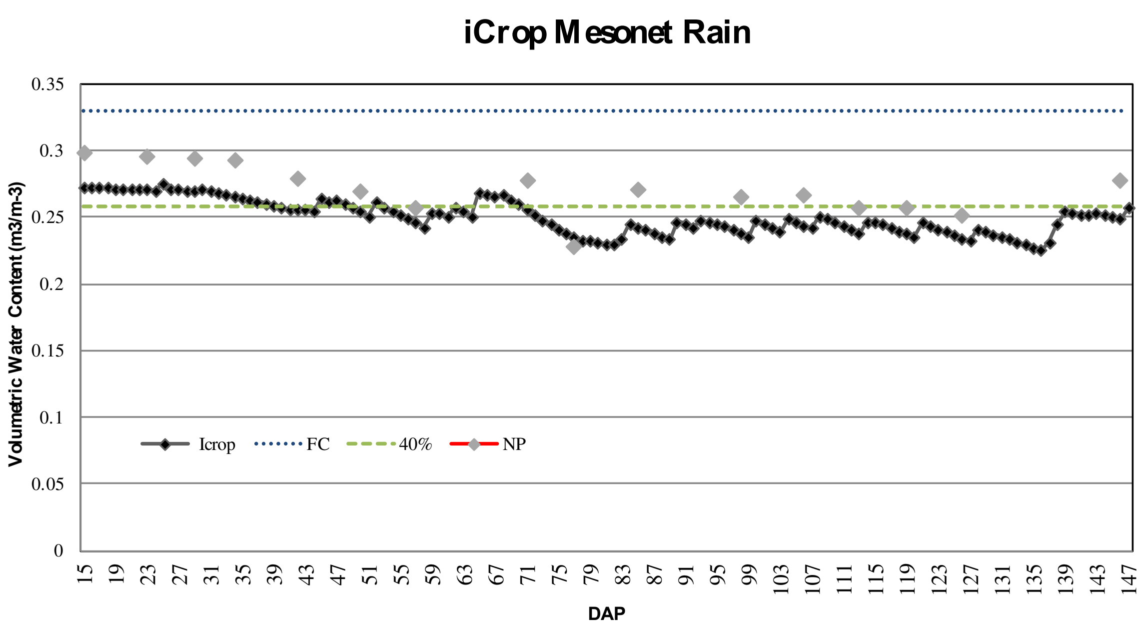

Figure 15. iCrop beta version soil water content simulated with Mesonet weather and rain data over the season versus Neutron Probe measurements.

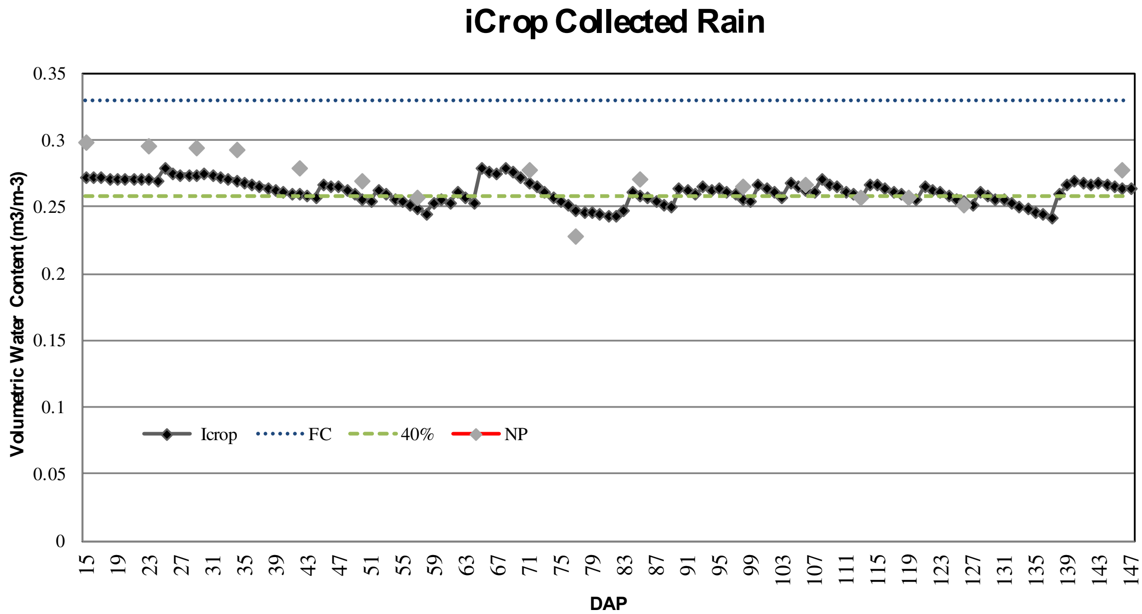

Figure 16. iCrop beta version soil water content simulated with in situ collected rainfall data over the growing season versus Neutron Probe measurements.

The predictions performed by iCrop beta version for soil water content started on January 31th and continued through the simulated maturity date. Therefore, 16 measurements were compared with the simulation, delivering the results showed in Table 6. The daily output file is expressed in extractable water, and required to be transformed to values to comparable with the NP measurements. The iCrop beta version extractable water was divided by the irrigation management depth and summed to the volumetric water content at the Permanent Wilting Point (PWP). Comparing the results from the soil water content the results were very similar, however, were a slight more efficient under the recorded rainfall, being able to represent better the water balance at the field. The NMRSE of 6.13 and 6.52 % proves the excellence of the model to predict the SWC, even with the Willmott Index was near to 0.55. The MBE suggest that the model slight underestimates the simulated values.

Table 6- iCrop beta version results simulated with Mesonet recorded rain and with recorded rainfall in situ.

	n[1]	RMSE (cm^3cm^{-3})[2]	NMRES (%)[3]	MAE [4]	MBE [5]	d[6]
Recorded	16	0.017	6.13	0.12	-0.01	0.51
Mesonet		0.018	6.52	0.12	-0.01	0.55

1-Number of observations; 2-root mean square error; 3- normalized root mean square error; 4-mean absolute error; 5-mean bias error; 6-wilmott concordance index.

The simulation of θ_v is related with the soil parameters. According to Ritchie (1998) the realistic simulation of soil water content is extremely related with the soil parameters adopted to represent each component of the soil. The Web Soil Survey, which makes possible to predict important site-specific soil parameters. However, at this study, the information regarding to the soil, were changed (field capacity, saturation point, permanent wilting point and soil depth) due to the field measurements information. Soldevilla-Martinez (2013) testing the ability of DSSAT to predict the soil water content noted that the parameterization was able to reduce the RMSE in 80% and 90% between the simulated and observed soil water measurements (SOLDEVILLA-MARTINEZ et al., 2013) finding RMSE of 0.011 and 0.006 cm^3 cm^{-3} at 10 and 40 cm depth.

The yield observed was 13264 kg/ha at the field on this treatment, 133kg more than the simulated by the iCrop beta version based on in-situ climate data (13.131kg/ha). Simulation based on in-situ and Mesonet climate data resulted in the same yield. Gijsman et al. (2002) reported that the high available soil water content does not necessary represent higher yield with DSSAT simulations, that could be the reason for any difference at the estimated yield. Also, Hurtado et al. (2005) studying the variance of yields under a spatial variability on soil, found errors between 0.9 to 23.3% with calibrated parameters for each plot, demonstrating the good performance on the yield prediction performed by iCrop beta version.

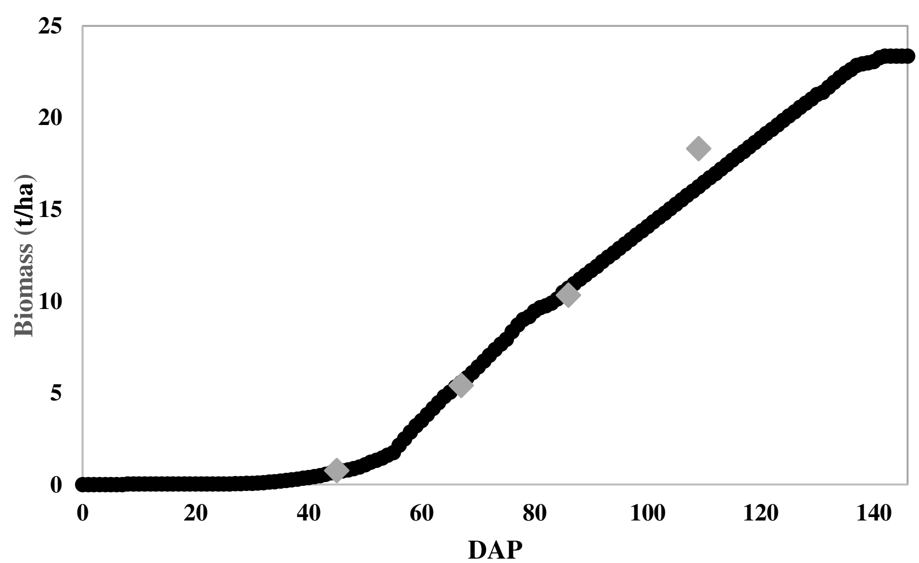

Figure 17. Biomass observed at the field (gray diamonds) versus simulated values (black dots) by iCrop beta version.

The obtained values were submitted under statistical analysis. The comparison of biomass presented the correlation coefficient of 0.99. The calculated RMSE was 1.09 t/ha and NRMSE of 12.15%. Araya et al. (2017) simulating the Corn biomass founded NRMSE of 10.76% for validation, proving the good agreement simulated by iCrop beta version.

3.4 KanSched

3.4.1 KanSched with Mesonet rain

With the Mesonet rain data, the performance of KanSched was acceptable based on the results represented by the Table 7. The RMSE of 0.026 cm^3cm^{-3}, NMRSE of 9.90 and MAE of 0.15 reflects the accuracy of this method to be used as an irrigation scheduling tool.

Table 7. KanSched statics results performed between simulated values of soil water content with Mesonet rainfall data versus measured values by Neutron probe.

KanSched (Mesonet)					
n[1]	RMSE (cm^3cm^{-3})[2]	NRMES (%)[3]	MAE[4]	MBE [5]	d[6]
16	0.026	9.90	0.15	-0.02	0.76

1-Number of observations; 2-root mean square error; 3- normalized root mean square error; 4-mean absolute error; 5-mean bias error; 6-wilmott concordance index.

Observing the water balance in Figure 18, it’s visibly that the model underestimates the SWC at conditions near to 50% of MAD. At the beginning of the season, the model was able to track the SWC very well, however, with time, the estimation was not able to track the SWC as expected.

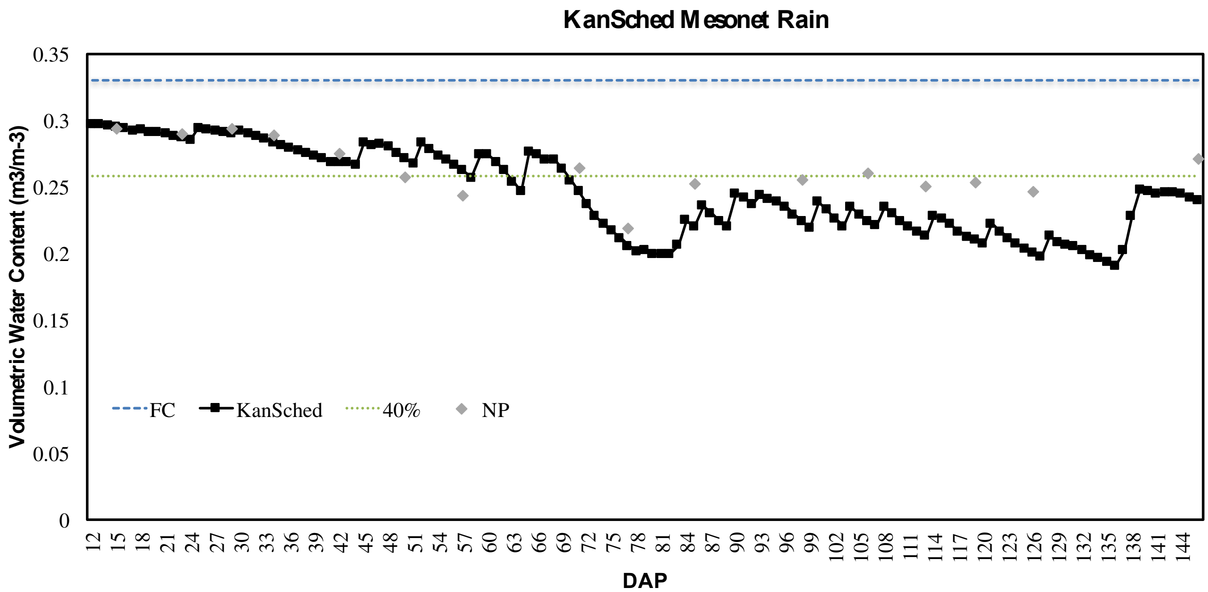

Figure 18. KanSched soil water content simulated values over the season versus Neutron Probe measurements with the Mesonet rainfall data.

According to Dogan et al. (2003) the Kc is adjusted every time that the MAD goes below 50%. This adjustment probably penalizes the SWC under estimating those values. To check this Kc adjustment, that was not able to be observed in the online version, the same information was inserted in the Excel spreadsheet of KanSched. The results confirmed that the penalization at the Kc happened under 50% MAD as represented by the Figure below. The correction of Kc is suppressed as the SWC value approaches the PWP. Therefore, if the system projects the SWC will return to the normal Kc values just when the MAD returns to some points higher than 50%.

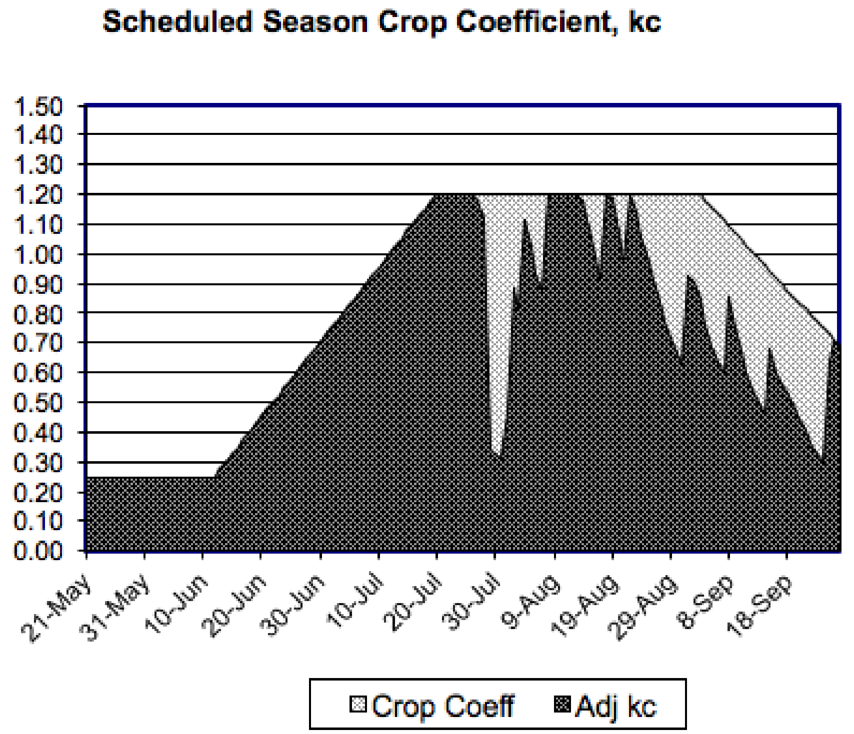

Figure 19. Figure representing the Crop coefficient (Kc) correction made by KanSched excel spreadsheet. (CLARK, ROGERS AND BRIGGEMAN, 2002a)

The evapotranspiration calculated in a correct way will develop an important task at this method, due to the direct interference at the withdraw of water from the soil. Moreover, other important input is the correct day of each growth stage. The correct date will determine the Kc, that will direct interfere at ETc, regulating the Soil water content estimation.

3.4.2 KanSched with recorded rain

The water balance using the field recorded rain is represented in Figure 20. The results as expected were better when compared with the weather station recorded rainfall. Statistical analysis results are shown in Table 8. The RMSE utilizing the rain data was 0.007 $cm^3\ cm^{-3}$ lower when compared with the previous simulation, increasing the Willmot index from 0.76 to 0.82. The NRMSE also decreased to 6.89%, reflecting the importance to track the rain at the field.

Table 8. KanSched statistical results performed between simulated values of soil water content with recorded rainfall data versus measured values by neutron probe

KanSched (Recorded Rainfall)					
n[1]	RMSE (cm^3cm^{-3})[2]	NRMES (%)[3]	MAE[4]	MBE [5]	d[6]
16	0.019	6.89	0.13	-0.01	0.82

1-Number of observations; 2-root mean square error; 3- normalized root mean square error; 4-mean absolute error; 5-mean bias error; 6-wilmott concordance index.

On the other hand, the correlation values decreased 7%. This effect probably happened due to the distribution of the data affecting the linear distribution, presenting values more dispersed when compared with the previous simulation.

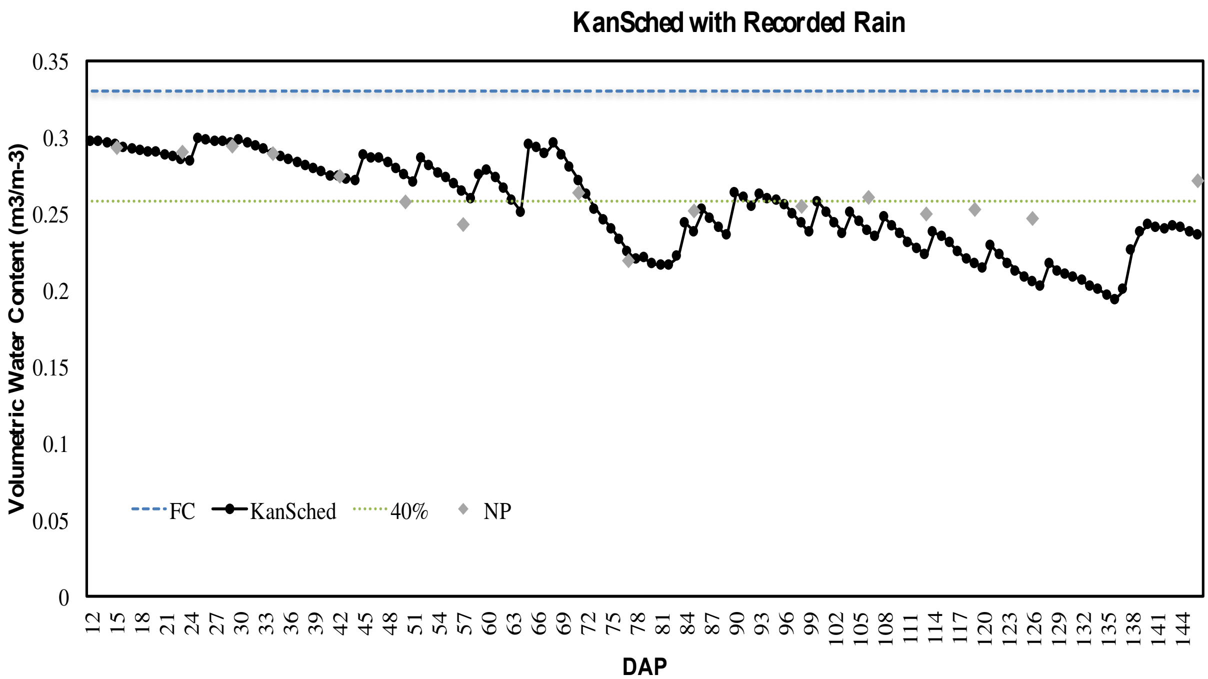

Figure 20. KanSched soil water content simulated values during the season and Neutron Probe measurements with the in situ recorded rainfall data.

The best way to keep the system matching with the rea SWC, even under limited conditions, is setting some soil measurements over the season. KanSched also gives the option to update the soil water availability, that will overwrite the estimated AWC in the soil profile. This option probably is the best way to use the model under limited conditions, due to the errors that happened at the middle of the season. However, those SWC measurements needs to be precise because the value will overwrite the previous simulated results and will start to count from the added value.

Another observed point running those simulations was that the MAD line offered by the KanSched is programmed wrong by the system, in an opposite way. For example, if the farmer stetted their trigger irrigation to perform at 40 % of MAD, actually he was irrigating at 60% of MAD, allowing the soil depletion to be high than he actually wanted. The developers were contacted to fix the error.

3.5 Acclima TDR 310s

3.5.1- Factory Calibration Performance

Comparing the NP readings versus the Acclima TDR 310s sensors over the season, we can observe that the sensors were able to follow the variations in the θv, using just the factory calibration. The results of θv for each depth combining the NP and Acclima 310s are expressed in Figures 21 and 22. The NP results at 30 cm (Figure 21), due to the more exposition of θv variations, presented more oscillations over the season from 0.195 cm^3cm^{-3} to 0.31 to cm^3cm^{-3}. As we can perceive, more variations are expressed by the TDR readings curve. However, this behavior was expected because TDR measurements were taken at intervals of 30 minutes, recording all the variations performed by the rain and irrigation events, expressing the sensor sensitivity to the water content change, being able to measure the trends of θv. At the 90cm depth (Figure 22), the θv ranged from 0.166 cm^3cm^{-3} to 0.279 $m^3.m^{-3}$. Even though the treatments received the same amount of irrigation, the response to irrigations and rain were more visible in rep 1 and 3 (Figure 21a and 21c). This response to the variation, could be associated with to some soil disturbance during the probe installation, soil variations and soil crop cover. The Rep 1 and 3 were installed at the North face of the field and the Rep 2 and 4 at South, that could have had the same soil characteristics and were at similar microclimate conditions. Probably in Rep 3 the water was able to infiltrate more quickly and contact the sensor easily, explaining the higher variation. The Rep 2, demonstrated that the sensors was sensitive at the soil water changes, being able to record values at high and lower SWC.

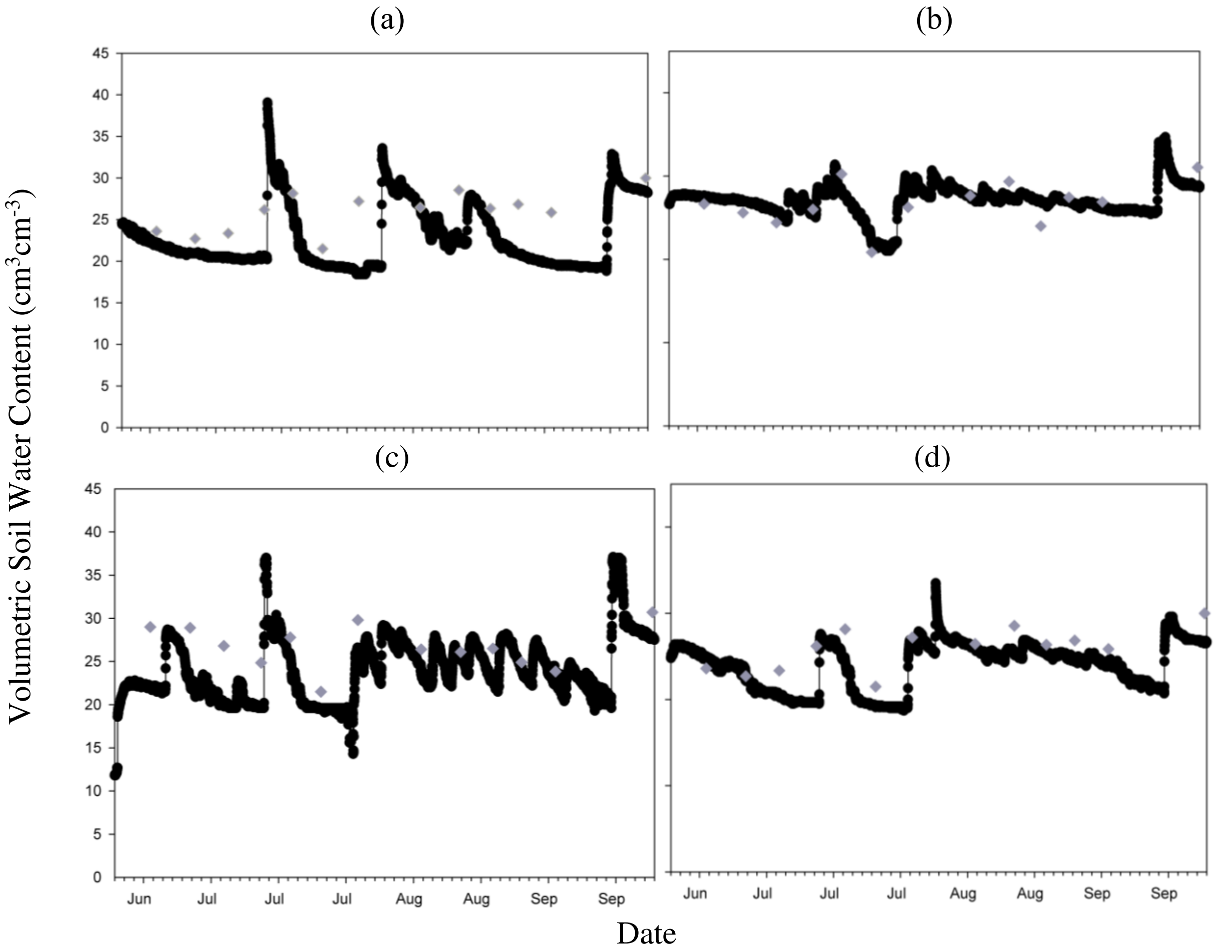

Figure 21. Volumetric soil water content of Neutron probe and Acclima for each repetition (in sequence: 1-a,2-b,3-c and 4-d) at 30 cm depth over the season**.**

Observing the sensors installed at 90 cm depth, we cannot observe huge variance at θv and any huge direct response to irrigation or rain. The same behavior was observed by Ladekarl (1998) testing TDR sensors from 0-200 cm depth. It is clear in Figure 22c that the sensor in replication 3 at 90 cm didn't work properly due to the huge difference between the simulated and observed data. The TDR failure to predict the θv could be initiated by many factors, e.g., factory sensor problem, soil variation on texture or problem during the installation. The major problem that happens with those sensors during the installation is related with the contact between the sensor and the soil. Any gap around the waveguide will cause interference at TDR measurements (WALKER, WILLGOOSE AND KALMA, 2004)

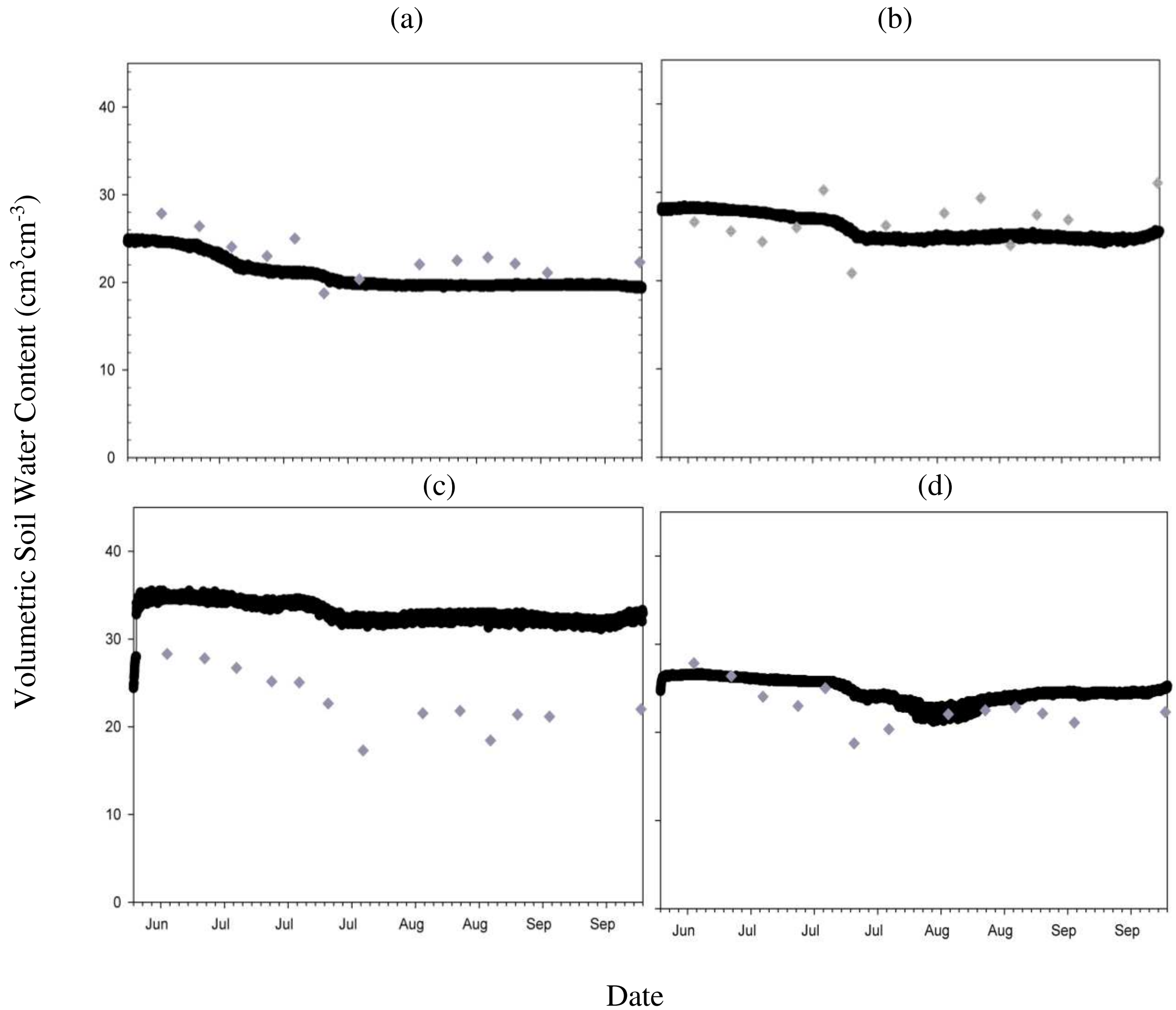

Figure 22. Volumetric soil water content of Neutron Probe and Acclima TRD 310s for each repetition (in sequence: 1-a,2-b,3-c and 4-d) at 90 cm depth over the season.

To avoid the TDR failure due to installation, and give some time to the soil fit near to the sensors, many authors suggest the installation more early as possible to give some time for the soil to interact with the sensor, avoiding those problems and delivering more reliable and realistic results. Walker et al., (2004) testing sensors to measure SWC concluded that the differences in the SWC were results of a combination of factors, including soil disturbance, volume of soil measured by each sensor be different, and air or fluid gap near to the TDR waveguide.

The statistics in Table 8 comparing the NP measurements with the Acclima 310s for the same depth and most nearly same time between their readings. The results indicate the Acclima

310s is not recommended for irrigation management by using just the factory calibration based on to the RMSE being bigger than 0.035 cm^3cm^{-3}(ADEYEMI et al., 2016). As expected, the total accuracy will not be guaranteed by the factory calibration, but relative performance could be very useful for irrigation purposes (LEIB, JABRO AND MATTHEWS, 2003). The average RMSE, excluding the rep 3 is 0.047 cm^3cm^{-3} for the top 30 cm and 0.032 cm^3cm^{-3} for the 90 cm depth. The factory calibration of TDR 315, that is a similar sensor by the same company, delivered average values of RMSE equal to 0.035 m^3 m^{-3} (SCHWARTZ et al., 2016). The best result was performed by the Rep 2 at 90 cm, with NMRSE less than 10% classifying the performance of the method as excellent. However, the average performance could be classified between good and fair. According to Adeyemi et al. (2016) TDR sensors performed well in a higher moisture range than dryer conditions (0.2-0.35 cm^3cm^{-3}), probably this is a cause of the best results at 90 cm depth as well. The MBE insinuate that sensors usually underestimates the soil water content measurements. The same was observed by Schwartz et al. (2016) testing similar Acclima TDR 315 with factory calibration.

Table 9. Statistical results of soil sensors readings with factory calibration compared with the neutron probe soil moisture values.

			30 cm				
REP[1]	N[2]	RMSE (cm^3cm^{-3})[3]	NRMSE (%)[4]	MAE [5]	MBE [6]	d[7]	(R^2) [8]
1	13	0.044	17.05	0.20	-0.03	0.37	0.47
2		0.038	14.09	0.18	-0.03	0.53	0.57
3		0.041	15.06	0.19	-0.03	0.56	0.40
4		0.065	25.18	0.23	0.05	0.38	0.78
AVG 30cm		0.047	17.85	0.05	-0.01	0.46	0.56
			90 cm				
1	13	0.026	11.20	0.16	-0.02	0.68	0.65
2		0.023	9.58	0.14	-0.02	0.67	0.65
4		0.046	22.10	0.20	-0.04	0.37	0.46
AVG 90cm		0.032	14.29	0.05	-0.03	0.57	0.59

Note:1-Replication number; 2- number of observations; 3- root mean square error; 4- normalized root mean square error; 5-mean absolute error; 6 -mean bias error; 7- willmott concordance index;8-coefficient of determination.

To confirm that the sensor was under the suggested condition by the factory to deliver the lowest error of θv, where the Bulk EC needs to be between 0 to 4000 µS/cm. The soil electrical conductivity was checked and the maximum value found was 1752 µS/cm at Rep 3, at 90 cm. The following highest value was 1238 on Rep 4 at 90 cm as well. However, the values still inside the range proposed by the Acclima 310s to provide an estimation of more or less 1% of error in the volumetric water content. As expected the factory calibration of sensors does not deliver the same results as claimed by the manufactures, due to the factory test their sensors under ideal conditions, representing the best performance of the product.

3.5.1- TDR Calibration Performance

The rep 3 at 90 cm was not considered in the calibration. Due to the number of NP readings, we opted to use 30% for calibration and 70% for validation. The results obtained during this season provide the idea about the requirement of calibration of this TDR 310s for higher accuracy and use for agronomic purposes. The following equation presented in Figure 23 was used to adjust the Acclima results. The correlation between the data was 0.96 and the linear regression presented R^2 of 94.

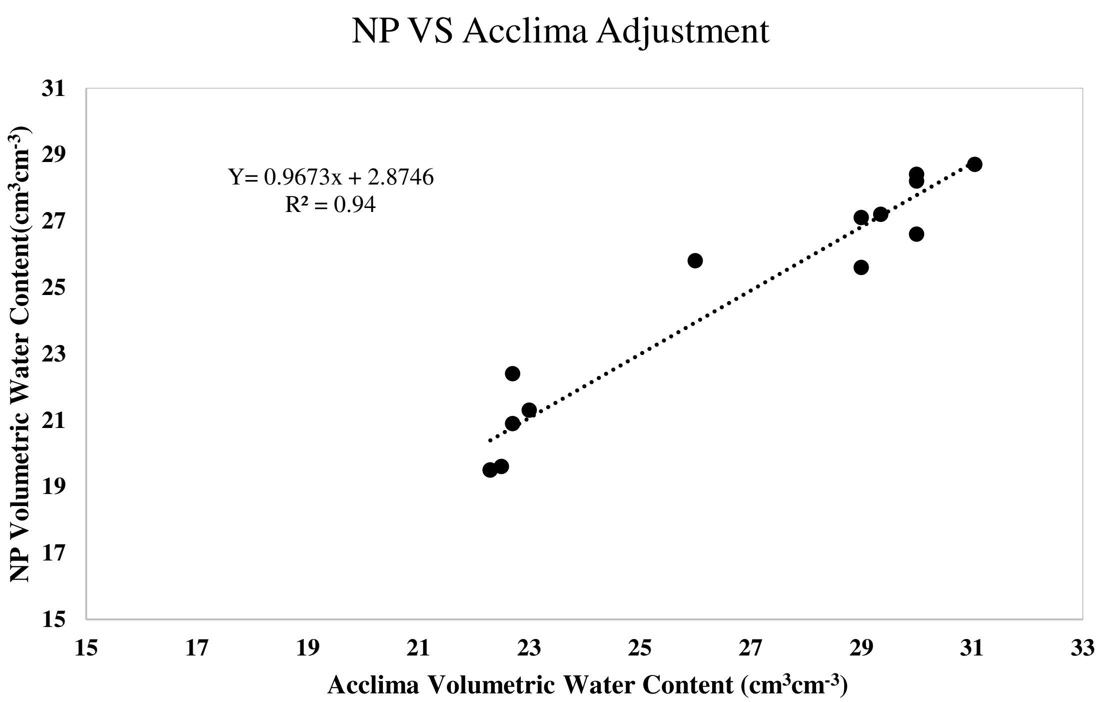

Figure 23. Linear calibration between NP and Acclima TDR 310s.

Just a simple linear function was able to reduce the RMSE almost 40% than the factory calibration. The results are presented in Table 9. The sensors presented an average of 0.026 and

0.021 cm^3cm^{-3} of RMSE after the calibration for the top 30 cm and 90 cm, respectively. The MBE also decreased when compared with the previous results. The NRMSE can render the method as excellent and the Wilmott index also was higher. The coefficient of determination was satisfactory as well. Though, to achieve higher coefficient of determination probably will require more data at a bigger range of SWC to deliver higher results.

Table 10. Statistical results of soil sensors with calibrated values compared with the neutron probe soil moisture values.

30 cm							
REP[1]	N[2]	RMSE (cm^3cm^{-3})[3]	NRMSE (%)[4]	MAE [5]	MBE [6]	d[7]	(R^2) [8]
1	9	0.029	11.38	0.15	-0.02	0.7	0.44
2		0.014	5.34	0.11	0	0.92	0.76
3		0.036	13.57	0.17	-0.03	0.5	0.84
4		0.026	10.01	0.15	-0.02	0.67	0.53
Avg 30cm		0.026	10.08	0.15	-0.02	0.70	0.64
90 cm							
1	9	0.02	8.4	0.15	-0.01	0.92	0.69
2		0.022	9	0.15	0.02	0.69	0.66
4		0.022	9.8	0.13	0.01	0.82	0.55
Avg 90cm		0.021	9.07	0.14	0.01	0.81	0.59

Note:1-Replication number; 2- number of observations; 3- root mean square error; 4- normalized root mean square error; 5-mean absolute error; 6 -mean bias error; 7- willmott concordance index; 8- coefficient of determination.

The calibration for a specific soil is required for the implementation of this technology, this requirement can restrict the their use. SCHWARTZ et al. (2016) evaluating the Acclima 315 TDR, founded values ranged from 0.017 to 0.02 m^3cm^{-3}. According to Kristoph-Dietrich (2012), the most effective method to develop the calibration curve is the laboratory calibration, being able to find higher values of R^2 of 0.979, suggesting that probably better results could be acquired using this error with a laboratory calibration.

3.6 AquaCrop

3.6.1 Soil water content

The AquaCrop parametrization without any modification was not able to simulate the real condition present at the field. Some of those non conservative parameters were refined (HSIAO et al., 2009) and are presented in the Appendix 1. The possible reason for that could be related with the Araya et al. (2016b) parameterization process. In his work, even using similar crop and site with the analogous characteristics, the crop parameters were calibrated and validated to represent all the irrigation treatments. Probably, those parameters should be better represented by the optimum condition to fit the results obtained for this work. The AquaCrop estimation of SWC versus the NP readings over the season are presented in Figure 24.

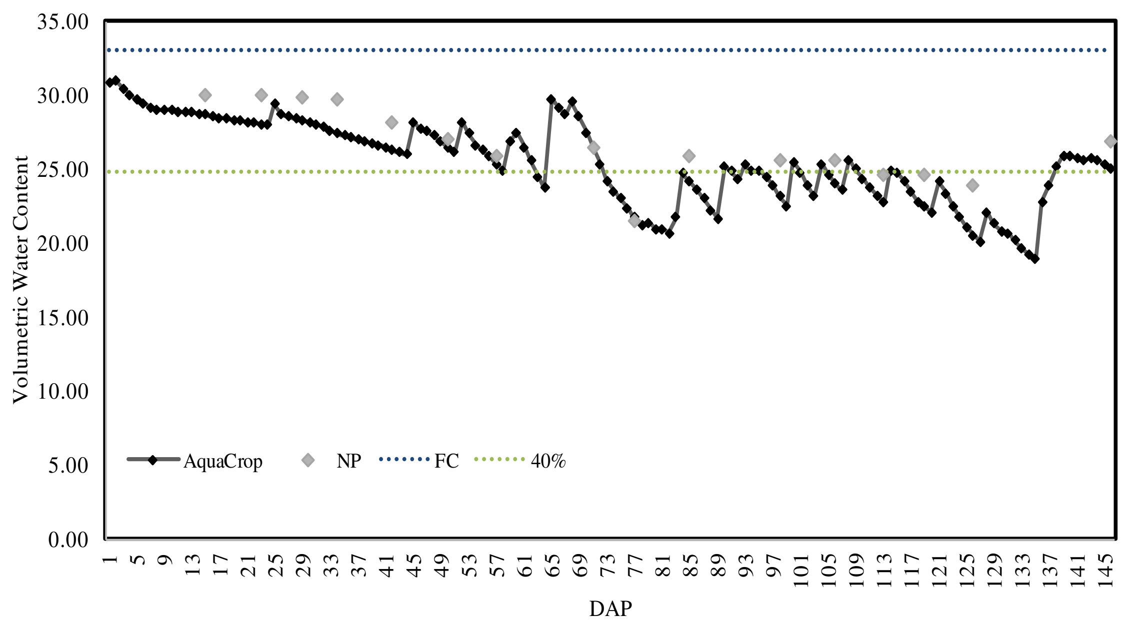

Figure 24. AquaCrop soil water content simulated with recorded rain data over the season versus Neutron Probe measurements.

The AquaCrop model proved to be able to perform very well in simulating the water dynamics over the season. Dissimilar from the others previous methods, the AquaCrop was able to keep on track the estimation of θv even under limited conditions and keep the SWC on track. This ability to estimate the θv under lower AWC shows the potential for the method to estimate the SWC under limited conditions was also observed by many authors (ANDARZIAN et al., 2011; FARAHANI, IZZI AND OWEIS, 2009; HENG et al., 2009).

Table 11- Statistical results of AquaCrop soil water content compared with the neutron probe soil moisture values.

AquaCrop 120 cm					
n[1]	RMSE (cm^3cm^{-3})[2]	NRMES (%)[3]	MAE[4]	MBE [5]	d[6]
16	0.018	6.57	0.02	-0.02	0.87

3.6.2 Canopy cover

CC had correlation coefficient of 0.94 and d of 0.93, however the RMSE of 19.11 was a little bit high. This high RMSE of CC probably is related to the two points that didn't matched at the same time at the middle of the season. Because the CC has an expressive growth in few days, if the model doesn't match with this exact time, the differences between observed and measured values can be huge. Heng et al. (2009) comparing the measured and simulated CC values under different conditions, also founded high values of RMSE, up to 33.53% under the rainfed and 15.42 % in irrigated treatment. According to Steduto et al. (2009) the water stress can have a negative impact on the crop development, principally during the flowering time, that could be the other reason for those values.

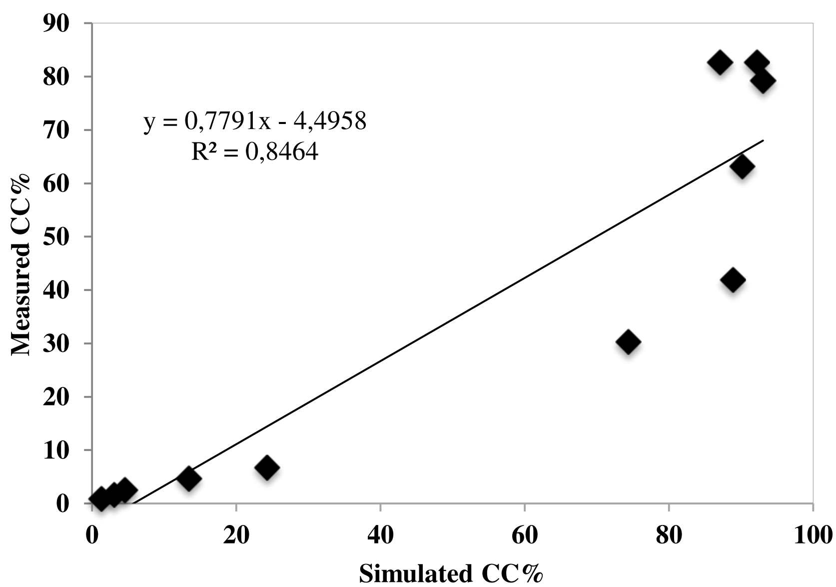

Figure 25. Canopy Cover (CC) observed at the field (gray diamonds) by the Canopeo method versus simulated values by AquaCrop.

3.6.3 Aboveground biomass

Figure 27 shows the simulated and observed biomass. It's clear shown that there were some discrepancies between the values. The RMSE was 0.65 t/ha and Wilmmott index of 0.99. The lowest error to estimate biomass by Heng et al. (2009) when comparing three sets of data was 0.49 t/ha.

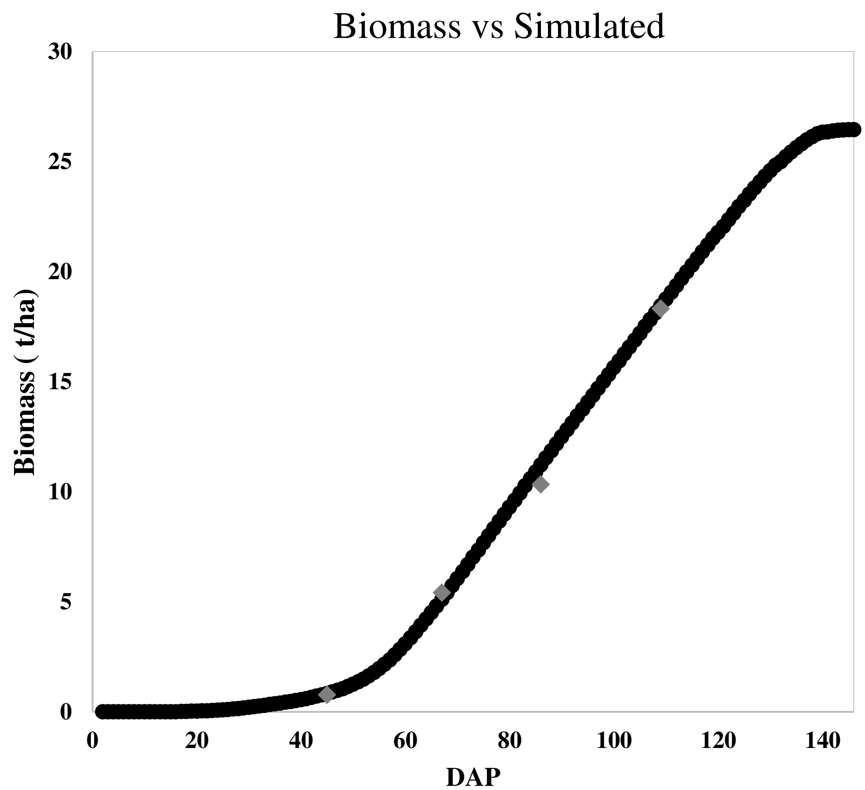

Figure 26. Biomass observed at the field (gray diamonds) versus simulated values by AquaCrop.

3.6.4 Grain yield

Our results show that the predicted yield was 13538 kg/ha, very near to the observed at the field of 13584 kg/ha, representing the accuracy of the model. The precision to predict the yield was reported by Andarzian et al. (2011) evaluating the AquaCrop under different irrigation management strategies.

4.CONCLUSIONS

All technologies indicated ability to predict the soil water content over the season in response to the irrigation management performed in Western Kansas. Though, iCrop beta version and AquaCrop indicated best performance to predict the soil water content when compared with Neutron Probe measurements. Moreover, those techniques predicted well the biomass and yield. However, iCrop beta version needs some efforts to avoid errors. AquaCrop needs to be adapted to become easier to operate, and less dependent of the parameterization, in order to operate as a consistent irrigation management tool. The Acclima TDR-310s performance was not satisfactory for agronomic management without site specific calibration.

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APENDIX 1

Appendix 1. Some of the crop parameters and values used for calibrating AquaCrop model

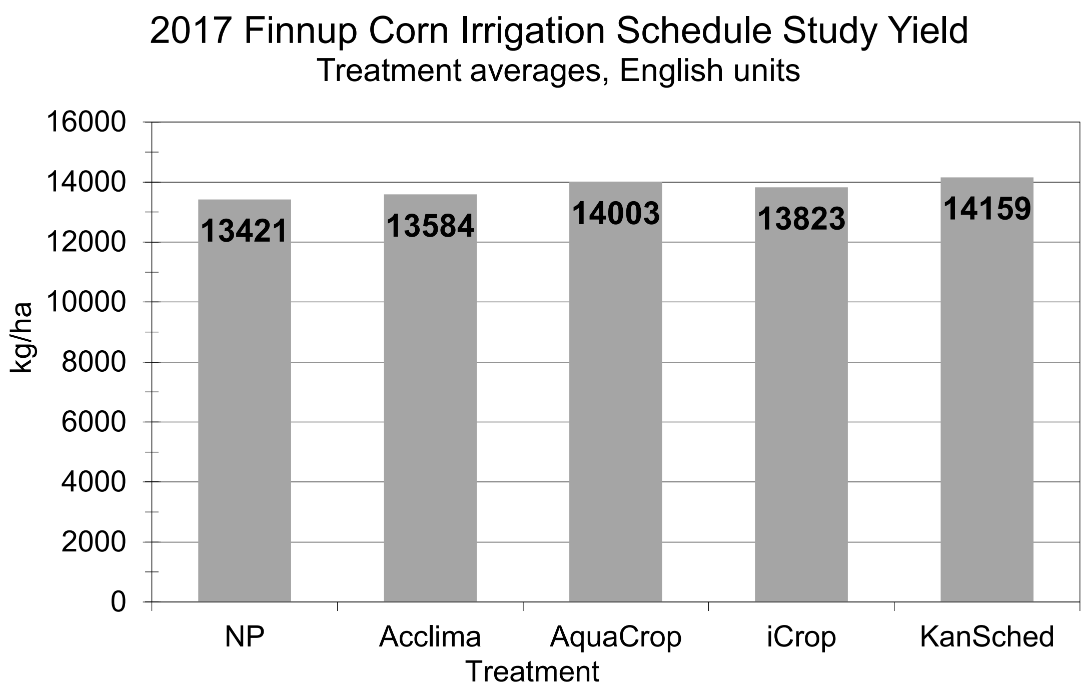
Parameters	Initial	Calibrated
Canopy cover per seedling at 90% emergence (cm2)	6.5	7
Canopy expansion (CGC) (%/day)	13.5	13.1
Maximum canopy cover (%)	80	94
Canopy decline (CDC) (%/day)	11.7	11.7
Emergence (days after planting)	20	12
Normalized Crop Water Productivity (g/m2)	33.7	33.7
Maximum canopy cover (days after planting)	76	70
Start of senescence (days after planting)	120	120
Flowering (days after planting)	80	71
Root depth (m)	2.4	1.5
Max root depth (days after planting)	115	105
Max. crop evapotranspiration	1.05	1.05
Harvest Index (HI) (%)	52	52
Canopy expansion function		
P-upper	0.1	0.16
P-lower	0.45	0.7
Shape	2.9	2.9
Stomatal closure function		
P-upper	0.65	0.65
Shape	6	6
Early canopy senescence function		
P-upper	0.45	0.45
Shape	2.7	2.7
Fertility effect	not considered	not considered

APENDIX 2

Growth Stage	Observation Date DAP					
Planted	0	0	0	0	0	0
Emerged	12	12	12	12	12	12
V 4	28	28	28	28	28	28
V 5	30	30	30	30	30	30
V 6	37	37	37	37	37	37
V 8	42	42	42	42	42	42
V 12	50	50	50	50	50	50
Pre-Tassel	69	69	69	69	69	69
Tasseled	71	71	71	71	71	71
Silked	73	73	73	73	73	73
Pre-Blister	85	85	85	85	85	85
Milk	94	94	94	94	94	94
Soft Dough	101	101	101	101	101	101
Early Dent	108	108	108	108	108	108
Dented	111	111	111	111	111	111
Late Dent- 1/4 S *	120	120	120	120	120	120
Late Dent- 1/2 S *	128	128	128	128	128	128
Mature	146	146	146	146	146	146

Planted	Crop planted
Emerged	Crop emerged
V X	Vegetative stages, V 3 = 3 fully extended leaves with full open collars, V 6 = six leaves, etc.
Pre-Tassel	Tassel and ear shoot emerging, but not yet fully emerged
Tasseled	Tassel fully extended and ear shoot exposed, but no silk showing and no pollen evident
Silked	Pollination period with silks emerged, and tassels shedding pollen
Pre-Blister	Pollination is complete, silks all brown, no fluid in seed coat, kernel looks like a pimple
Blister	Kernels are watery blisters with white color and clear fluid
Early Milk	Start of roasting ear stage, white to yellow kernels with thin milky substance
Milk	Prime roasting ear stage, full yellow color, milky kernel fluid
Soft Dough	Past roasting ear, first few dents near butt end, kernels still milky when squeezed
Early Dent	Kernels starting to dent, thick gummy kernel substance, still squirt milk when mashed
Dented	Most kernels dented or denting, can easily cut kernel with fingernail, still some milk
Late Dent	All kernels dented and drying down from top with small white starch layer forming
Mature ("Black Layer")	Physiological maturity, tip of kernel is black since dry matter production is finished

APENDIX 3



Appendix 3. Recorded yield (kg/ha) at the field statically equal by one way ANOVA (p-value>0.01)