SOIL MOISTURE AND TEMPERATURE SIMULATION USING THE VERSATILE SOIL MOISTURE BUDGET APPROACH

By

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A Thesis submitted to the Faculty of Graduate studies of the University of Manitoba in partial fulfilment of the requirements for the degree of

MASTER OF SCIENCE

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ABSTRACT

Akinseloyin, Taiwo Ige. M.Sc., The University of Manitoba, March 2015. SOIL MOISTURE AND TEMPERATURE SIMULATION USING THE VERSATILE SOIL MOISTURE BUDGET APPROACH.
ADVISOR: Professor Wole Akinremi.

Soil moisture and temperature are two important soil parameters that influence many vital agronomic, environmental, engineering processes within the soil. Due to the difficulties arising when measuring these parameters in the field as well as the cost of instrumentation, many models that yield accurate and timely estimation of these parameters on a large scale have been developed as reliable and efficient alternatives. The Versatile Soil Moisture Budget model can be used to stimulate the vertical, one dimensional, water balance in a soil profile. Originally the model was designed to use air temperature and precipitation data to simulate soil water content within the root zone of a cereal crop. It has since undergone modifications and the model can now output, potential evapo-transpiration, actual evapo-transpiration, and surface temperature. The temperature algorithm simulates temperature at the soil surface and has not been rigorously tested for cropping systems. In this study, a simple empirical equation that simulates soil temperature at depth of up to 90 cm was introduced into the model. The model was evaluated and the accuracy of predicted soil moisture and temperature under both perennial and annual cropping systems were tested using two years of data collected at the University of Manitoba Research Station at Carman using soil water and temperature probes. The model's accuracy in simulating soil moisture was also tested. Observed R^2 comparing modelled temperature with observed was greater than 0.90 at the soil surface but decreased to about 0.40 at soil depth greater than 30-45 cm layer. The model was shown to be better at estimating soil temperature than soil moisture. The accuracy of the model was also shown to decrease with depth. These results can be used to improve soil temperature modeling at depth as well as improve farm management planning, irrigation schedules, nutrient management, fertilizer application and drought monitoring.

ACKNOWLEDGEMENT

I am most grateful to God Almighty, who has been my strength, shield and source of help through the course of this MSc. work. I sincerely appreciate everyone that has contributed, helped, advised and assisted me while carrying out this work. Of particular note, I want to say a big thank you to my advisor, Dr. Oluwole Akinremi for his unrelenting efforts, suggestions, corrections and directions. Your wealth of experience and knowledge amaze me and has made me to improve in my education as an individual. I am also grateful to every member of my advisory committee: Dr. Paul Bullock and Dr. Trish Stadnyk. Every bit of advice you gave to me during my time doing this work was highly valuable. Your efforts made me see the need to improve this work to a great level. Thank you so much.

I will like to thank the IDRC and NSERC for the fund given to me to support my M.Sc research here in University of Manitoba. Special thanks to Bo Pan for providing technical support and guidance to me during my field work. Thanks to the soil physics and chemo-dynamics team of the department, particularly Mrs Bameke Mulikat. Also, I like to thank Rotimi Ojo for always being there to guide when working on VSMB.

I sincerely appreciate my siblings, fiancée, her parents and siblings, my friends and well wishers for all their words of encouragement and supports always. For my late parents who were staunch supporters of child education before their death, I owe it to you. Thank you for your investment on us.

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LIST OF ABBREVATIONS

ε	Real dielectric permittivity
EPIC	Erosion Productivity and Impact calculator
FDR	Frequency domain reflectometers
MBE	Mean Bias Error
RMSE	Root Mean Square error
TDR	Time domain reflectometers
VSMB	Versatile Soil Moisture Budget
VWC	Volumetric water content
%M.D	Percentage mean difference

1.0 Introduction

Soil temperature and moisture at the surface and sub-surface influence many agronomic, environmental, and agro-climatology processes within the soil. Because of this, models that can estimate soil parameters such as temperature and moisture are becoming more relevant. Good knowledge and timely prediction of the soil surface temperature and moisture status are useful for understanding factors that affect crop development, crop root condition and many physical and biological processes influencing crop growth and development within the soil such as soil N-mineralisation (Wang et al., 2006), crop canopy development and biomass (Stone et al., 1999)

According to Jia et al., (2006), soil temperature and moisture influence soil respiration and this relation can be expressed using linear, quadratic, and exponential models. Boonkerd and Weaver, (1982) studied the response of Cowpea Rhizobia to soil temperature and moisture. They showed that temperature above 35^{o}C decreased the activities of the Rhizobia species. Modelling of soil temperature and moisture can play a significant role in irrigation and other farm operations. Accurate measure of soil temperature and moisture is thus important for planning farm operation, drought monitoring and crop emergence prediction. Estimates of these parameters can be used to determine the best possible period for field operations.

1.1 Soil Water

Knowledge of soil water status such as dry or wet conditions plays an important role in many agricultural management decisions including optimisation of fertilizer rates, time of application of pesticides, herbicides, and water for irrigation. Information from soil moisture mapping has become a powerful tool for farmers in improving awareness of moisture conservation through improved soil management practices (Howard et al., 1992). Knowing the water status in the spring influences farmers' decisions to crop or fallow in a flex-cropping system (Brown et al, 1981).

Many processes of agronomic importance such as surface run-off, leaching, seedling emergence, evapo-transpiration, mineralisation of organic matter cannot be quantified without the knowledge of the moisture status of the soil (Akinremi and McGinn, 1996). Irrigation scheduling or forecast of the onset of drought also requires detailed knowledge of soil water status (Woodward et al., 2001)

Precipitation is the major component of weather through which water is added to the soil surface. Part of the water added to the soil as rainfall or snow melt flows down vertically through infiltration and is either held within the root zone for crop use or lost to underground water bodies and some of it is made available to plants while some is lost on the surface as run-off causing soil discharge and nutrient loss to streams and surface water.

Measuring soil water status directly using the thermo-gravimetric method which involves taking soil sample directly from the field and subjecting it to heat to remove the moisture before the heat loss is calculated is difficult due to spatial variability of soil water in the field (Reynolds, 1970). It is also labour intensive, time consuming and expensive. It involves destructive sampling which makes it impossible to have repeated measurement on a given sample.

In order to overcome the limitations of field measurement, research into model development that could yield timely estimates of soil water have been conducted as documented by Jackson, (1986). Models that estimate soil water have been useful in the design of irrigation and drainage systems (Bailey and Spackman, 1996). Most often, these models use a combination of soil, crop and weather parameters to estimate soil moisture distribution (Guswa et al., 2002).

1.2 Soil Temperature

Soil chemical and biological processes such as rate of decomposition and mineralisation of organic matter are directly influenced by daily and annual fluctuations in soil temperature (Giargina and Ryan 2000). Temperature affects plant growth directly through its impact on the crop's physiological activity and indirectly through its influence on soil nutrient availability (Koerselman et al., 1993). Soil temperature affects crop growth during germination of seed and emergence (Stoller and Wax, 1973). On the field, incoming solar radiation is converted to sensible heat at the soil surface resulting in a temperature gradient between the surface and the deeper layers and between the soil surface and the layers of air above it. On a bare soil without cover, heat flows from the soil surface downward by conduction during the day and soil surface temperature is usually warmer than air temperature during the day near the soil surface but it is usually cooler than air temperature at night because of the time lag in temperature fluctuation between the air and the soil. But if the soil surface is covered, air temperature is usually warmer than the soil surface temperature at night. Also, the diurnal amplitude of soil temperature declines with depth due to the damping effect (Hu and Islam, 1995).

The assessment of soil temperature is of fundamental importance to most environmental simulation models because soil temperature affects rates and directions of soil physical and chemical processes (Davidson and Janssens, 2006), energy and mass exchange (Sellers et al., 1997) with the atmosphere which are employed in most algorithms used in environmental simulation modelling.

It is understood that soil temperature influences crop growth and development at every stage of crop growth and correspondingly affects final yield (Prasad et al., 2000). For example, Raich and Schlesinger (1992) obtained a good linear correlation between soil respiration rate and net production rate of carbon dioxide flux using the relation between soil respiration and temperature. Also, Hayhoe and Dwyer (1990) used the percentage of emergence of corn in relation to varying seed bed growing degrees days (10^{o}C base) to formulate the empirical functions that are used in temperature-growth response simulation and concluded that soil temperature affects the date of corn emergence. In a similar vein, Cutforth and Shaykewich (1989) investigated the relationship of the development rates of grain corn hybrids to air and soil temperatures in south-eastern Manitoba and showed that silking and maturity were affected by soil temperature.

Soil temperature models are designed with the aim of accurately estimating daily soil temperature at the surface and sub-surface by using daily weather parameters and some soil physical properties like soil colour and texture and thermal properties such as thermal conductivity, volumetric heat capacity and thermal diffusivity.

Measurement of Soil Temperature

Soil temperature can be measured using a liquid-in-glass thermometer. It uses the principle of rising liquid in a tube in close contact with the soil or any other substance. The conduction of heat between the thermometer and soil causes a change in the volume of the liquid in the glass thermometer which is read on a scale (Childs et al, 2000, Scott, 2000). Temperature can also be measured by a bimetallic thermometer using electrical resistance principle, which is based on the thermoelectric effect of temperature or change in resistance of a metal with a change in temperature. The bimetallic thermometer uses two metal strips (with different thermal expansion coefficients) that are joined together. The strips are connected to a pointer through a wire that moves when the strips are deformed due to change in temperature when brought in contact with the soil or a medium to be measured.

The most widely used soil temperature instrument is the thermocouple (Mathew and Towey 2010). It has two wires of different metals usually copper and constantan that are welded together at two places with the welds kept at different temperatures. The thermoelectric effect converts a temperature difference to electric voltage that is generated when temperature differences cause a proportional electric potential difference between the welds and causes current to flow through the circuits formed by the connecting wires. A galvanometer is used to measure the thermoelectric current between the welds. When using thermocouples to measure soil temperature, one of the welds is kept as a reference while the other is in contact with the soil. Thermocouples are robust, economical and can sense temperature between -27^{o}C and 3000^{o}C (Childs et al, 2000, Scott, 2000)

Measuring soil temperature in the field is laborious and time consuming and is not suitable for wide scale coverage. As such, many models have been designed to estimate soil temperature. One of these models is the Air-to-Soil Temperature Transfer Model (Gehrig-Fasel et al., 2008) that uses air temperature to calculate the soil temperature. The Air-to-Soil Temperature Transfer model estimates the daily mean temperature of the root zones of the crop 10 cm below the soil surface using exclusively daily mean air temperature. The reliability of the model was tested using temperature data obtained in 2004 and 2005 in Switzerland (Gehrig-Fasel et al., 2008). The model accurately estimated soil temperature from air temperature and it was found to agree with the work of Brown et al, (2000) that showed that soil temperature can be exclusively estimated from daily mean air temperature though the study was not extended to other deeper depths. Other models such as the Simultaneous Heat and Water (SHAW) model (Flerchinger et al., 1998) and Forest Soil Temperature Model (FORSTEM) (Yin and Arp, 1993) simulate daily mean soil temperatures based on the solution of soil heat flow equations and energy balance. These models require large amounts of data such as humidity, cloudiness and other parameters that are difficult to obtain, especially on a large scale (Paul et al., 2004, Bond-Lamberty et al., 2005).

Empirical models such as the air to soil temperature model (Gehrig-Fasel, 2008, Brown et al., 2000) that require readily available parameters can be widely used if accuracy and performance is reproduced across different regions.

There is a need for validated models that can provide accurate estimates of surface and sub-surface soil temperatures.

The heat equation is usually employed in predicting soil temperature from the surface to the sub-surface (Lei et al., 2010). In order to obtain soil temperature from the solution of the heat equation, the physical conditions at the boundary of the soil must be specified. It is common for air temperature at the soil surface set to be equal to soil temperature and the heat flow measured from the energy balance in Equation 1.1 (Thunholm, 1990; Grant et al., 1995) to be used as boundary conditions while determining soil temperature as a function of time and depth

$$Rn = LE + H + S. \qquad 1.1$$

Rn is the net radiation, LE is the latent heat flow from the soil surface to the air, S is the movement of heat into the soil while H is the sensible heat flow from the soil surface into the air. When estimating soil temperature in the laboratory, both boundary conditions can be controlled easily but this is very difficult in field studies because laboratory studies always assume static conditions of flow boundaries unlike the realities under field condition. Also, there is a problem with limited data on soil surface temperature and heat flow. Consequently, meteorological data are often used to estimate the upper boundary conditions in field situations. For example, Gupta et al, (1981) stated that air temperature can be used as the driving variable in numerical modelling of soil temperature under field conditions (Akinremi et al., 1996). The simplest way is to set the soil temperature equal to the air temperature. Though the air temperature deviates considerably from the soil temperature during the daytime when the net radiation is considerably high, fairly accurate results can still be obtained by applying a correction factor accounting for thermal resistance above the soil surface (Thunholm, 1990).

Function T = T(z,t) where T is the temperature at time t(s) and depth z(m) can be modelled by taking the partial derivative of the heat flow equation. In the work of van Wijk and de Vries (1963), they formulated a one dimensional vertical model (Equation 1.2).

$$\frac{\delta T}{\delta t} = \frac{K\delta^2 T}{\delta z^2} \qquad 1.2$$

Where K ($m^2s\text{-}^1$) is the soil thermal diffusivity. They assumed that K is constant with time and depth and that two boundary conditions must be satisfied to successfully get a solution that can estimate soil temperature.

A solution (Equation 1.3) for estimating soil temperature at a corresponding depth that satisfies Equation 1.2 above using air temperature at the soil surface and heat flow downward from the soil surface as two boundary conditions is found in (Elias et al., 2004, van Wijk and de Vries, 1963)

$$T(z,t) = Ta + A\exp\left(\frac{-z}{D}\right)\sin\left[\omega t\text{-}\left(\frac{z}{D}\right) + \phi\right] \qquad 1.3$$

T is the soil temperature in degree Celsius at depth z in cm and particular time t in seconds during the day, Ta is the average daily temperature, A is the daily amplitude at the soil surface in degree Celsius, ω is the radial frequency in (rad s^{-1}), ϕ is a phase constant (radian)

D is the damping depth = $\sqrt{\frac{2K}{\omega}}$ 1.4

where K is the soil thermal diffusivity in m^2s^{-1}.

An alternative method to extensive field measurement of soil temperature is to develop and apply a soil temperature transfer model that can estimate soil temperature from the readily available air temperature that is continuously being recorded from weather stations (Brown et al., 2000).

At the moment, very few models have estimated soil temperature from the air temperature alone. For instance, (Toy et al., 1997) used monthly mean air temperature to predict monthly mean soil temperature. Ahmad and Rasul (2008) also used air temperature to estimate soil temperature from a 17 year temperature data series. Zheng et al. (1993) also used air temperature and precipitation to estimate soil surface temperature. However, in all these cases, the estimated soil temperature is for the soil surface only. Models that make use of sophisticated algorithms require many parameters such as surface cover, soil thermal diffusivity and surface energy balance to estimate soil temperature. (Thunholm 1990, Yin and Arp 1993)

Most weather stations collect air temperature and precipitation data but very few of these measure soil temperature. The use of a simple method to estimate daily mean soil temperature from daily mean air temperature will be very useful in filling the gap that currently exist in soil temperature data across several regions.

1.3 Versatile Soil Moisture Budget Model (VSMB)

This model was formulated by Baier and Robertson (1966) to simulate the vertical one dimensional water balance in a soil profile that is divided into arrays of layers at a daily time step. The model was originally designed to use air temperature and precipitation data to simulate soil water content within the root zone of a cereal crop. This model has gone through different stages of modifications since it was first developed. For example, Dyer and Mack (1984) modified this model by incorporating a drainage algorithm and a field performance appraisal. Another modification was undertaken by Boisvert et al., (1992) to include a water table function. It has also been widely used to evaluate soil moisture conditions on croplands and for scheduling irrigation (Boisvert et al., 1990). Akinremi et al., (1996) used the model to improve the water balance estimate of the Palmer Drought Index (PDI)

The VSMB has been used to estimate soil moisture in prairie grassland areas of Canada (Hayashi et al., 2010). In the VSMB, the soil surface receives water from rainfall and snowmelt after accounting for run-off. Water is extracted for evaporation and transpiration from individual layers at different rates depending upon the crop growth stage.

Baier et al. (1972) were the first to describe the computerised version of the model which was later revised by Baier et al. (1979). Akinremi et al., (1996) modified several components of this model to improve the estimation of soil water. These authors adapted an algorithm from the Erosion and Productivity Impact Calculator (EPIC) model (Williams, 1995) to calculate the surface soil temperature using a 3-day running mean. Other models such as SHAW (Simultaneous Heat and Water Model)(Flerchinger et al., 1998) and HYDRUS 1D model(Zhao et al., 2008) simulated soil heat and water movement within the soil but they usually require many inputs such as plant canopy, snow residue, air temperature, wind speed, solar radiation, relative humidity and precipitation. Some of these inputs are not readily available in the weather stations especially at deeper soil depths. Thus, the physics involved in simulating soil temperature and moisture content using these models is very complex. VSMB was chosen for this work because it is robust in nature and gives users the ability to define the depths of interest based on horizon differences and differing soil water characteristics which is a common attributes in the prairie region while simulating soil moisture content through the root zones. The model has been reportedly used and demonstrated across the Canadian prairie for various purposes(Hayashi et al., 2010).

Objectives

Even though some of the models mentioned previously simulated soil temperature well at the soil surface, they sometimes require parameters that might be difficult to obtain. A model which can simulate soil temperature beyond the soil surface to depths using easily obtained parameters such as air temperature is desired. Knowing the temperature of the soil at various depths especially at root zones will help to know the physical condition of the soil moisture during simulation's studies. For instance, at a temperature of below 0^oC and lower, freeze-thawing may occur and as a result of frozen, water movement to the next layer might cease. Since VSMB computes soil moisture in various depths based on soil moisture balance equation, it is desirable to know if indeed there is movement of water to the next layer or not. The overall goal of this study is to evaluate the VSMB and to modify the soil temperature algorithm so that it can simulate soil temperature beyond the soil surface in a Manitoba soil.

To achieve this goal, three objectives were formulated. The first objective of this study was to determine the accuracy of the Stevens' hydra probe sensors. This becomes necessary as these sensors provide continuous soil moisture readings that can be used to evaluate the performance of the VSMB.

The second objective of the study was to modify the temperature algorithm of the Akinremi version of the VSMB (Akinremi et al, 1996) to be able to simulate soil temperature at depth throughout the growing season.

The third objective is to validate the new temperature algorithm using the soil temperature data from the hydra probes and also to validate the soil moisture outputs from the VSMB against measured data from the field. Validation of the model against experimental data across different locations is an important aspect of model development.

In this study, model results are compared and evaluated based on its ability to predict measured soil temperature profiles and moisture in 4 experimental plots during a 2-year of field study.

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2.0 Performance Testing for Frequency Domain Reflectometry Probes.

2.1 Abstract

Soil water and temperature play important roles in the soil-plant ecosystem. Different kinds of sensors have been developed to measure soil moisture and temperature in the field. Frequency domain reflectometers (FDR) are sensors that measure soil moisture status based on changes in the dielectric permittivity of the soil. The sensor employed in this study measures temperature by using a thermistor.

A total of 24 FDR sensors, known as hydra probe, were deployed to a study-site in Carman in order to acquire soil moisture and temperature data on a daily basis during the growing seasons of 2012 and 2013. Six probes were installed in four experimental plots at the depths of 0-10 cm, 10-20 cm, 20-30 cm, 30-45 cm, 45-60 cm, 60-90 cm. We used factory suggested calibration equation for each depth range by fitting the real dielectric permittivity of the probes to the volumetric moisture content obtained in the laboratory during the first growing season. In order to test the accuracy of the probe for temperature, thermocouples were installed during the first growing season and the outputs from the thermocouples were compared with the hydra probe outputs. The coefficient of determination for soil moisture are 0.96, 0.51, 0.51, 0.51, 0.41 and 0.41 for the 0-10 cm, 10-20 cm, 20-30 cm, 30-45 cm, 45-60 cm, 60-90 cm, depths respectively. The RMSE was 0.045m^3m^{-3} and 0.048m^3m^{-3} for the 0-10 cm and 60-90 cm depth, respectively. The coefficient of determination obtained for temperature were 0.53, 0.96, 0.96, 0.96, 0.96 and 0.91 at the 0-10 cm, 10-20 cm, 20-30 cm, 30-45 cm, 45-60 cm, 60-90 cm, depths respectively. The RMSE were 3.91^{o}C 1.06^{o}C, 0.78^{o}C, 0.75^{o}C, 0.76^{o}C and 0.91^{o}C at the 0-10 cm, 10-20 cm, 20-30 cm, 30-45 cm, 45-60 cm, 60-90 cm, respectively . The results showed that the Hydra probe performed well for

temperature measurement especially at depth. The study also reinforces the need for site specific calibration before using hydra probe for measuring soil water content.

2.2 Introduction

2.2.1 Soil moisture

Soil moisture refers to the water that is held between the pore spaces of the soil. It is the water that is in the vadose zone between the soil surface and the water table. Although the amount of soil water is small compared to other components of the hydrological cycle, it is nevertheless important to many agronomic, hydrological, ecological and environmental processes. Government agencies and private companies working on weather and climate, estimating the risk of run-off and soil erosion, flood control, and water quality require detailed knowledge of soil water status. Soil moisture limits crop productivity in the semi-arid region of Canadian prairies as seasonal moisture in the rooting zone of crops is often inadequate to meet the crop demand for adequate biomass production and yield.

Estimating soil water status is a very important aspect of crop yield modeling (Hanks et al, 1991). Many agricultural management decisions such as irrigation scheduling, fertilization and pesticide-use optimization and rate of application, drainage system design, soil conservation system such as zero or reduced tillage, cropping system types, require prior knowledge of soil water status.

Field based hydrological or ecological research requires accurate measurement of soil moisture. The techniques that should be employed must be simple, reliable, dependable, non-destructive and cost-effective.

2.2.2 Soil Temperature

Many important microbial processes such as decomposition and mineralization of organic forms of nitrogen increase as soil temperature increases. This accounts for the reason why tropical soils under high temperature usually have smaller levels of organic matter compared with temperate soils that are under low temperature.

The temperature of an object is a measure of the heat content of the object. The temperature of an object changes when the object loses or gains heat through any of conduction, convention, radiation or evaporation mechanism.

Soil temperature is useful for timing spring seeding operations as cold soils delay germination which may lead to non-uniform growth during early germination and inadequate seedling emergence (Tang and Long, 2008). The importance of soil temperature to seedling emergence of perennial shrubs has been previously demonstrated (Huang et al., 2004; Zia and Khan, 2004). Soil temperature affects many processes that are vital for plant growth such as nutrient uptake, plant transpiration and the form and availability of soil water (Reimer and Shaykewich, 1980). Soil temperature affects the rate and duration of vegetative growth of plant and also the activity of plant roots (Gavito et al., 2001; Weih and Karlsson, 2001).

The surface soil temperature (0-10 cm) changes in response to changes in atmospheric conditions such as solar radiation and rainfall. A better understanding of above- and below-ground development of the crop and the activities of pests affecting root crops, requires information on the surface and sub-surface soil temperature.

Soil temperature at different depths is routinely measured using standard soil thermometers. These thermometers are often expensive, fragile and are subject to breakage. The Hydra probe, on the other hand, is a robust instrument that measures both soil moisture and soil temperature. For this study, it is important to confirm that the soil temperature that is measured by the Hydra probe accurately reflects actual soil temperature. While several studies have been conducted to test the soil moisture measurement by the hydra probe, we are not aware of any report on soil temperature evaluation using the hydra probe.

2.3 Method

2.3.1 Hydra Probe Description

Although the thermo-gravimetric method remains the most accurate method of measuring soil water content, it nevertheless has a lot of drawbacks that has lead to the development of several indirect methods of measuring soil water content. Early in-situ determination of soil water status can be done through the use of radioactive materials such as Neutron scattering probes (Chanasyk and Naeth, 1996; Hu et al., 2009) and Gamma ray attenuation methods (Pires et al., 2005). Though these methods are non-destructive and accurate, they require soil-specific calibration and special training and caution to avoid harmful health hazards. Based on the procedure outlined by Fellner-Feldgg, (1969), an alternative non destructive method using time domain reflectometry (TDR) was developed by Davis and Chdobiak (1975). The TDR uses simple electrodes inserted into the soil to determine the dielectric constant of the soil. The empirical relationship between dielectric constant and volumetric water content of soils with different textures has been evaluated by (Topp et al., 1996; Noborio, 2001). When using the TDR, the measurement of the time interval for propagating a wave signal to and from the electrodes has some level of uncertainty that introduces error into the soil water determination (Lin, 2003). TDR requires relatively sophisticated electronics and distances that the sensors can be installed away from the instrument are limited. This thus makes TDR relatively expensive for many applications.

In order to overcome the limitations of the TDR, the capacitance probe was developed. Frequency domain reflectometer (FDR) probes were developed as an improvement to time domain reflectometry and to reduce the instrument cost (Dean et al, 1987). The working principle of FDR probe is based on the electrical capacitance of a capacitor that uses the soil as a dielectric medium by measuring the dielectric permittivity which is related to soil water content. An oscillator is used to generate an alternating current field which is applied to the soil such that changes in the soil water content cause a shift in the operating frequency of the instrument.

The hydra probe is a type of FDR probe. They are fast, safe and cost-effective means of measuring relative permittivity of the soil which is subsequently used in estimating soil water content.

The Hydra probe (Figure 2.1) has been found to be robust under a wide variety of field conditions and it provides in-situ measurement of many soil parameters simultaneously. The probe can provide simultaneously the values of soil moisture, temperature, electrical conductivity, and the dielectric permittivity (Seyfried et al., 2005). Hydra probes have proven to be accurate and precise in fluids of known dielectric properties in (Malicki et al., 1996 and Blonquist et al., 2005) and the strong correlation between results obtained and soil moisture (θ) suggest that it has great potential for soil moisture measurement (Seyfried and Murdock, 2004). The hydra probe though has been reported to be limited in frozen soil, lower temperature, gravelly textured soil and soils with high alkalinity (Wall et al., 2004, Seyfried and Murdock, 2004). The calibration procedure following manufacturer suggested equations for different soil types showed that the hydra probe varies in soil water content determination with respect to soil types and both studies affirmed the need for soil specific calibration procedures for hydra probe.

Figure 2.1 Hydra Probe

The sensing device has four 0.3 cm diameter stainless tines that are 5.7 cm long (Stevenson watering monitoring systems Inc. 2008), three tines form a circle of 3.0 cm diameter around a central tine on a 4.2 cm diameter cylindrical head. The tines protrude from the cylindrical head which produces a 50-MHz signal that is transmitted to the tines. The soil between the tines represents the sensing volume, which is the measuring region of the instrument in the soil. The probe comes in 3 configurations (SDI-12, RS-485 and the Analog) based on the way the generated information is transferred. The SDI-12 and RS-485 makes use of a microprocessor to process the data from the probe into readable data. The Analog uses an attached meter to measure the voltage that is produced by the instrument. The hydra probe was used in this study because it has proven accurate for soil moisture measurement in sandy loam soil(Chow et al., 2009).

2.3.2 Site Description:

This study was conducted at the Carman research station of the University of Manitoba, Canada located on latitude degree 49°29'53.200" N and longitude 98°01'47.100" W. Two cropping systems (Annual and Perennial) were used in the study. The study site (Figure 2.2) was established in 2009 and is seeded to Barley, Wheat or Canola in the annual plots while the adjacent perennial plots have been maintained in a mixture of timothy and orchard grass. Two plots that were treated with liquid pig manure were selected from each cropping system for a total of four plots for the study. The perennial plots were about 20m away from the annual plots.

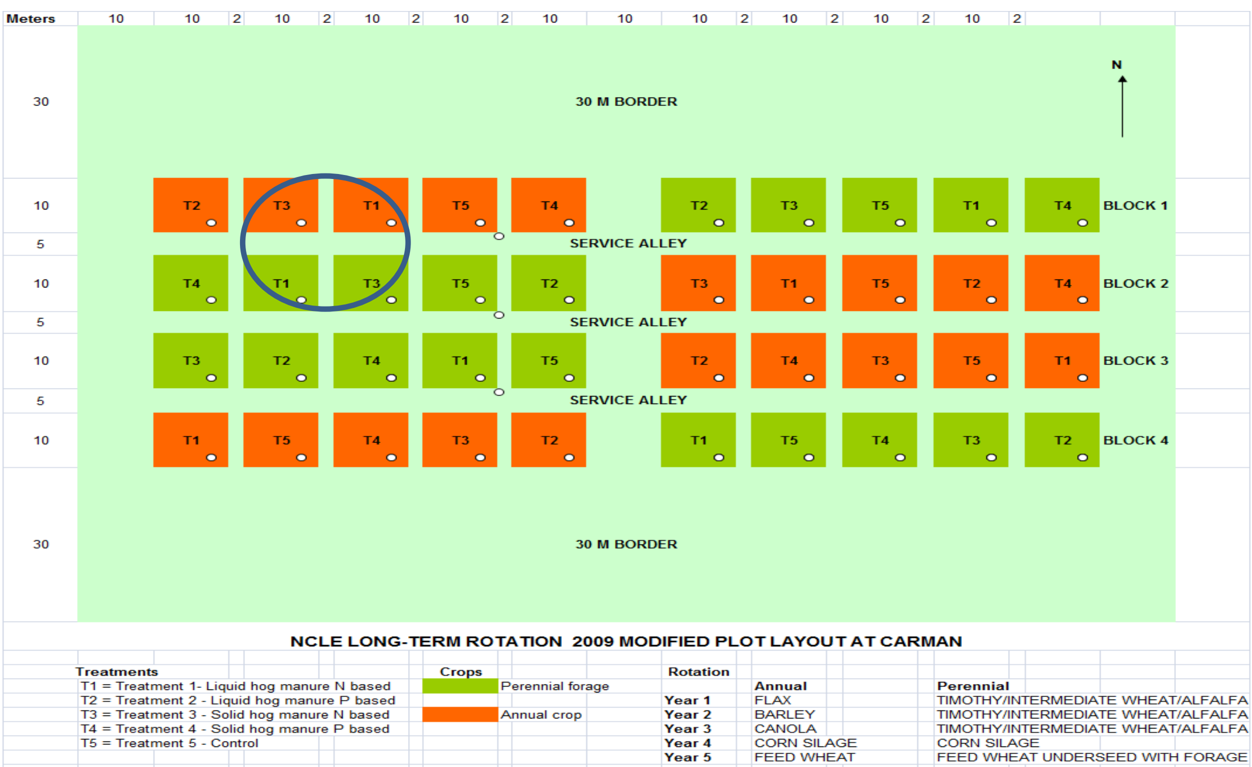


Figure 2.2: Experimental plot layout. The four circled plots were used for this study

2.3.3 Soil Classification

The Carman soil at this study location is an Orthic Black Chernozem, a loamy sand that is moderately well drained and on a gentle slope. Table 2.1 below shows the physical and chemical properties of the soil used. The soil texture was similar from the surface of the soil to the depth of interest considered in this study and the properties of the soil are within the range of limits of hydra probe's applicability according to the manufacturer specification.

Table 2.1 Physical and chemical properties of soil at Carman (adapted from Sayem et al 2014)

Characteristics	Carman soil
Soil Series	Orthic Black Chernozem
Soil pH	5.8
Soil texture	Loamy sand (Sand, Silt and Clay-86.75%, 5.02% and 8.23%, respectively)
Bulk density	1.2 (15 cm depth)
WHC	High (33 % on volume basis)
Drainage	Moderately to slow permeability
Organic matter	6.52%
Runoff	Slow surface runoff
Total C:Total N	20
Olsen P (mg kg^{-1})	20

2.3.4 Soil Moisture Measurement

To test the performance of the probes, the soil moisture content in each of the plots at each depth was determined gravimetrically during the growing season of 2012, the first year of the study. Soil samples were collected eight times during the growing season for gravimetric soil moisture determination at a distance of about 1 m away from the installed probes using a dutch auger. The samples were collected at the depths of 0-10 cm, 10-20 cm, 20-30 cm, 30-45 cm, 45-60 cm and 60-90 cm. These depth intervals correspond to depth of the installed hydra probes. Collected samples were carefully kept in a cooler to prevent moisture loss while transferring it to the laboratory. Samples were weighed and oven dried at 105°C for 24 hours or more to determine the gravimetric water content. The determined gravimetric water contents were converted to volumetric water content (VWC) using the bulk density at each depth.

$$\Theta v = \Theta g \; X \; \frac{Þb}{\rho w} \qquad 2.2$$

Θv is the volumetric water content in cm cm^{-3} while *Θg is* the gravimetric water content in gg^{-1}. *Þb* is the bulk density in g cm^{-3} while density of water assumed to be 1 g cm^{-3}

A flat bucket auger was used to take two representative bulk samples from each of the six depth layers in the four plots under study in the year 2012 and 2013. Samples were taken to the laboratory for bulk density determination. The bulk density of the soil sample was calculated as the total mass of dry soil (M_S) in each depth divided by the volume it occupies (VT).

$$Þb = \frac{\mathrm{MS}}{\mathrm{VT}} \qquad 2.3$$

M_S is gram while V_T is in cm^3

The average of the bulk density of two representative samples in each depth layer was used as the bulk density of the layer.

2.3.5 Hydra Probes Installation

For this study, four plots were selected, two each of the replicated Annual and Perennial plots. Six hydra probes were installed in each plot by digging a pit wide enough to permit the installation of the probes horizontally into a face of the pit at 5 cm, 15 cm, 25 cm, 37.5 cm, 52.5 cm, and 75 cm. The pits were dug close to the edge of each plot to provide easy access to the instruments but far enough into the field to represent the soil moisture content and temperature of the field without an edge effect. Probes were installed on the same day in all plots, just immediately after seeding. The hydra probes were firmly pushed into the side of the pit at the depth of interest to completely bury the tines into the soil. The excavated soil in the different soil layers (0-10, 10-20, 20-30, 30-45, 45-60, 60-90 cm) were kept separately to allow them to be returned into the pit and maintain the original soil layers. Efforts were made to carefully arrange the cables of the probes in such a way as to prevent channels that can convey water directly along the cable lines on the pit wall where the probes were installed (Figure 2.3). After installing the probe, the pit was back-filled with the soil from each of the layers gradually to avoid compaction. To give room for farm machinery operations, the cables were buried along a shallow 30 cm deep trench back to the data logger.

Figure 2.3 Hydra probe installation in the field

In the second year of the study (2013), two probes were installed at the same depth adjacent to each other and separated by a distance of about 10 cm in the same hole at the depths of 25 cm, 52.5 cm to test the predictability and repeatability of the probes.

2.3.6 Thermocouple Description

In order to ascertain the accuracy of the probes for soil temperature measurement, the data-logger outputs obtained from the probes were compared to recorded temperature outputs from the installed Thermocouples during the first growing season. Thermocouples haves been used in soil plant water relations for temperature measurement in laboratory and field studies (Fonteyn et al., 1987) A thermocouple is an inexpensive instrument used to measure a wide range of temperatures and made up of two different metal wires that are joined together. Common combinations of metal wires could be iron paired with copper-Nickel alloy, or rhodium paired with Platinum. A reference temperature is created at the junction where the thermocouple makes contact with the soil when installed. Changes in soil temperature create a voltage when there is a difference in the temperature at the junction connecting the metallic conductor together from the reference temperature at the other part of the circuit. The voltage reading is then converted to temperature reading using a polynomial function (Quinn, 1990). The relationship between the junction temperature difference and the generated voltage is given as:

$$T = \sum_{n=0}^{N} a_n v^n \qquad 2.1$$

Where T is in degree celsius, and *v* is in volts, a_n are polynomial coefficients.

Thermocouples are durable, rugged and accurate in their measurements. They were used in the first year of this study to test the performance and accuracy of the temperature measurements by the hydra probes.

2.3.7 Thermocouples Installation:

Low cost k-type thermocouples were installed at corresponding depths with the hydra probes on the four plots late in the growing season during the first year of study (1st August, 2012). Efforts were made to install the thermocouples close to the points where hydra probes were installed but farm activities on the field limited our ability to really bring these sensors side by side though we made effort to ensure that they were installed within five meter to ten meter distance apart. The thermocouples were installed by digging a hole big enough to permit the horizontal insertion of the metal strips of the thermocouples into the soil. A 100 cm rod was used to guide the arrangement of the thermocouples down the profiles at respective depths of 5 cm, 15 cm, 25 cm, 37.5 cm, 52.5cm and 75 cm in each of the plot under study. The thermocouple connectors that protruded from the thermistors of the thermocouples were connected to a data-logger to record the temperature readings. These connectors were housed in a plastic tote to avoid water from infiltrating into the conduits. Using a Campbell data-logger, temperature measurement was taken from the thermocouple on a weekly basis between August and October 2012. Three samples of temperature reading were taken at each depth on the day of sampling and the average was used for that hour.

2.3.8 Weather station and meteorological data

For the purpose of this study, weather data such as air temperature (^{o}C), and precipitation (mm) were obtained from the nearest Environment Canada or Manitoba Agriculture Food and Rural Initiatives (MAFRI) meteorological station located less than 1 km from the study site. These data from the Environmental Canada and MARFI stations were downloaded from their websites.

2.3.9 Statistical Procedure

Root mean square error (RMSE) was used to evaluate the performances of the hydra probe sensors in estimating soil moisture and temperature following equation 2.5.

$$\mathrm{RMSE} = \left(\frac{\sum(\text{Probe-observed})^2}{\mathrm{n}}\right)^{0.5} \qquad 2.5$$

Where **n** is the number of observation, probe is the default calibrated values, while observed is the measured value of the water content determined in the laboratory. The RMSE was normalised by dividing the RMSE by the lowest number in a plot in order to compare from one plot to the other. An nRMSE of 0-10% was considered excellent while 10-20% was considered good. A nRMSE of 20-30% is considered fair but anything higher is not considered as having good relationship.

The mean bias error (MBE) was calculated to assess the average difference between the records from the hydra probe and observed value. Positive values of MBE were taken as an overestimation while negative value indicates an underestimation by the Hydra probe. A zero value of MBE signifies that there is equal distribution of positive and negative differences.

$$\mathrm{MBE} = \frac{1}{n} \sum_{i=1}^{N} [(\text{Probe-Observed})] \qquad 2.6$$

A low MBE is usually desired for testing the long term performance of the probes.

2.4 Results and Discussion

2.4.1 Hydra probes Field evaluation for Soil Moisture

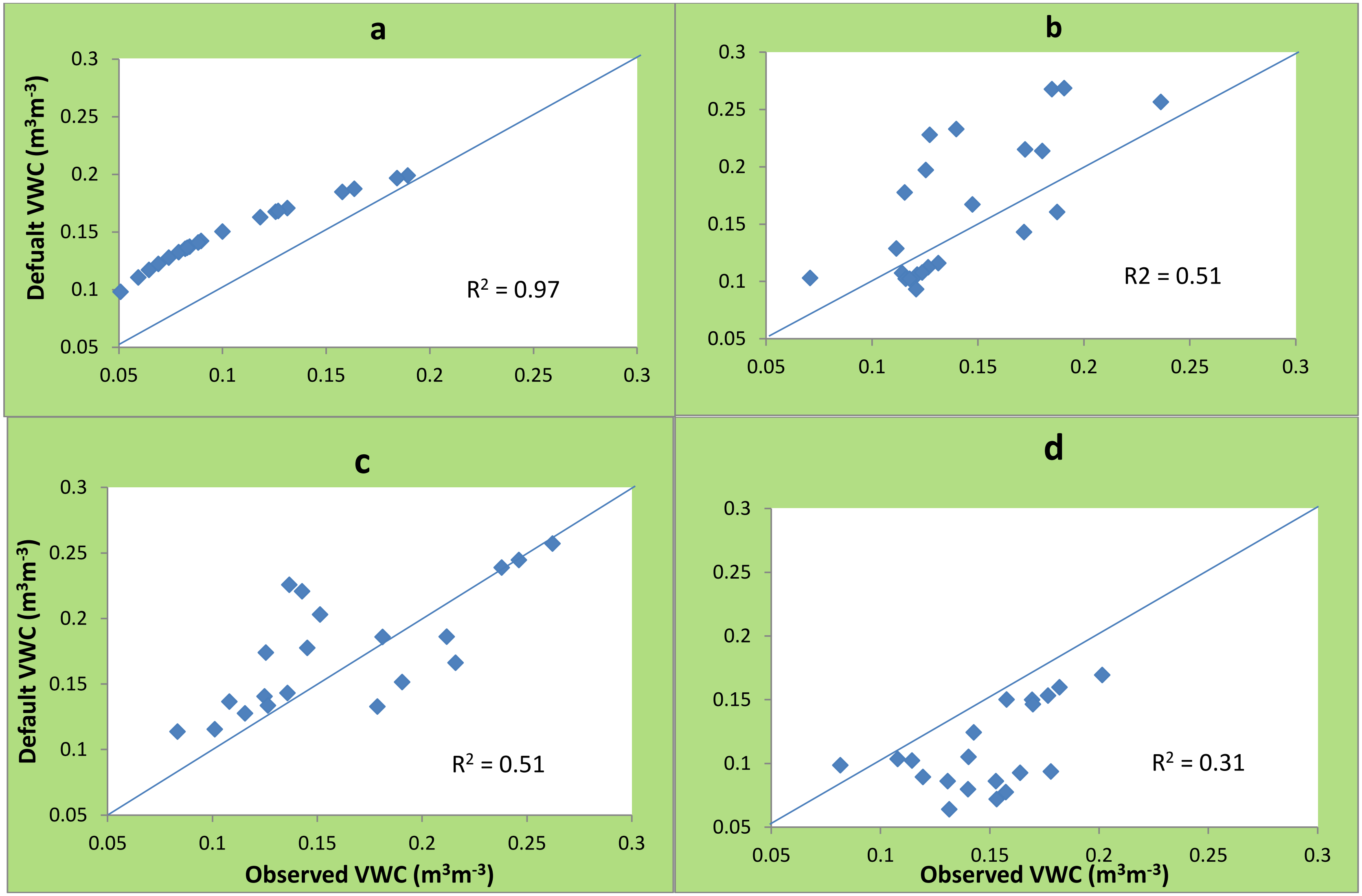
When the volumetric water content obtained from the factory default parameters for the hydra probe were compared to the gravimetric water content, the result showed poor agreement between the two data set (data not shown). Following the procedures outlined in the manufacturer's manual for calibrating the instrument in a well drained soil, default moisture values were marched against the square roots of dielectric permittivity which were used to derive the equation of best line fits used in the determining the moisture contents used in the study.

The bulk density of the soil at various depths is shown in Table 2.2. The soil is predominantly loamy sandy with the bulk density in the range of 1.03 g cm^{-3} to 1.69 g cm^{-3}. The highest values obtained in some depths might be due to compaction while taking the samples with the bucket auger. Unfortunately, these results were used for converting gravimetric moisture content to volumetric moisture content and this accounts for while the results of calibration only seems appropriate at the surface.

Table 2.2 The bulk density of the different soil layers and experimental treatment in the fall of 2012 and 2013.

	0-10cm	10-20cm	20-30cm	30-40cm	40-60cm	60-90cm
				($g\ cm^{-3}$)		
Canola 1 2012	1.31	1.31	1.12	1.36	1.39	1.39
Canola 2 2012	1.07	1.67	1.41	1.34	1.41	1.25
Forage 1 2012	1.03	1.37	1.44	1.07	1.47	1.32
Forage 2 2012	1.13	1.36	1.40	1.54	1.69	1.54
Canola 1 2013	1.13	1.66	1.46	1.51	1.35	1.32
Canola 2 2013	1.13	1.57	1.46	1.46	1.37	1.15
Forage 1 2013	1.15	1.41	1.46	1.45	1.46	1.54
Forage 2 2013	1.15	1.58	1.61	1.54	1.42	1.54

Figure 2.4 compares the results from the hydra probes using factory calibration and the thermo-gravimetric moisture content in the first year of the study (2012) in Carman. The coefficient of determination (R^2) was 0.96 (Figure 2.4a) and 0.41 (Figure 2.4f) for the 0-10 cm and 60-90 cm depth, respectively suggesting that the probe performed better at the surface than at depth in the first year of the study. The depths in between showed R^2 in the range of 0.51 to 0.31 though the 1:1 line suggested that the relationship might be fairly correlated as it is in figure 2.4b, 2.4c and 2.4f. The RMSE for the probe at 0-10 cm was 0.043 m^3m^{-3}, 0.027 m^3m^{-3} and 0.038 m^3m^{-3} at 10-20 cm and 20-30 cm, respectively while that of 45-60 cm and 60-90 cm was 0.047 m^3m^{-3} (Table 2.3). The RMSE/Avg is the normalised value of RMSE using the mean value of each depth range to normalise. Usually, at 0-10%, nRMSE is considered excellent and any result above 30% is not considered as having good relationship. Only two depths 10-20cm and 20-30cm slightly showed good relationships. Others are somewhat above 30% though none is up to 40%.



a
Defualt VWC (m3m-3)
0.3
0.25
0.2
0.15
0.1
0.05
0.05
0.1
0.15
0.2
0.25
0.3
R2 = 0.97
b
R2 = 0.51
c
Default VWC (m3m-3)
R2 = 0.51
Observed VWC (m3m-3)
d
R2 = 0.31
Observed VWC (m3m-3)

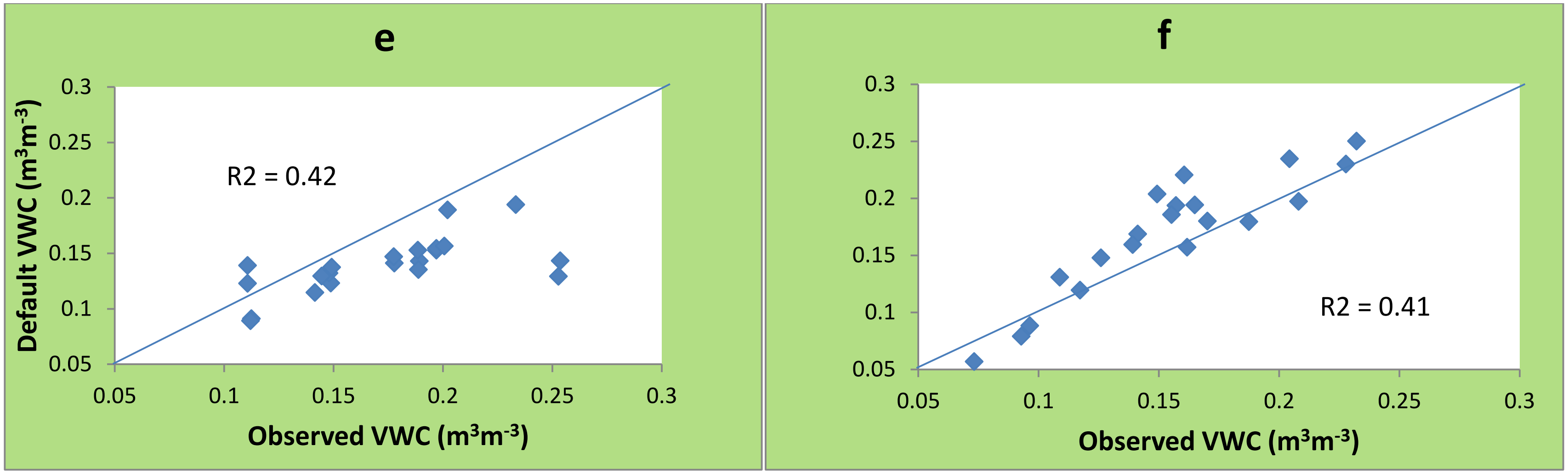


Figure 2.4 Comparison of observed field moisture and hydra probe moisture using the factory default calibration at different depths (2012) (a) 0-10cm (b) 10-20cm (c) 20-30cm (d) 30-45cm (e) 45-60cm (f) 60-90cm

The result of the study is similar to what Bosch, (2004) reported when he obtained up to 75% deviation using a similar probe in the field. These large deviations could also be as result of errors in the measurement of bulk density.

The higher moisture content variability observed from the hydra probes output when two probes are compared across different depth layer might be due to depth interval effect which arises due to varying responses of measuring probe to different soil thickness (Kristensen 1973) and the slope of the site isn't perfectly flat, so installing precisely even with meter rule in different hole might be difficult and this could account for the observed differences obtained for the moisture.

Table 2.3 Statistical parameters for comparing agreement between the thermo-gravimetric and hydra probe water content in six soil layers

	Depth Range (cm)					
	0-10	**10-20**	**20- 30**	**30-45**	**45-60**	**60-90**
N	20	22	20	20	21	21
RMSE(m^3m^{-3})	0.045	0.027	0.038	0.049	0.047	0.048
nRMSE	0.3	0.16	0.22	0.34	0.34	0.3
MBE	0.0433	-0.027	0.013	-0.038	-0.034	0.0057
T(<=t)One tail	0.00028*	0.081	0.21	0.000177*	0.001852*	0.36
R^2	0.96	0.51	0.51	0.31	0.41	0.41

*Depths showing significant differences in moisture content between installed probes and observed at alpha level of 0.05

Figure 2.5 shows the results comparing the soil moisture outputs from two hydra probes installed at the same depth in same hole and also two hydra probes installed at the same depth in two different holes. It was observed that the soil moisture values obtained using these probes at the same depth in the same hole do not perfectly fit each other (Figure 2.5a). More surprising was the fact that the measurements observed from the probe in the different holes at 20-30cm depth in Figure 2.5b has higher correlation than that in the same hole in Figure 2.5a. At 45-60cm depth, although the R^2 was high (figure 2.5c), there seems to be a wide variation in the values obtained either in same hole or in different holes. In similar way to the result observed in 20-30cm depth, the measurement obtained from the probe installed at different holes at 45-60cm depth (Figure 2.5d) though has lesser R^2 than the results from the same hole at same depth, has better fit in the 1:l line. Also, the results in Figure 2.5d shows that lower values were obtained from the probes installed at different holes compared to the probes installed in same holes which further confirmed that probes were not returning same values for moisture even at close range.

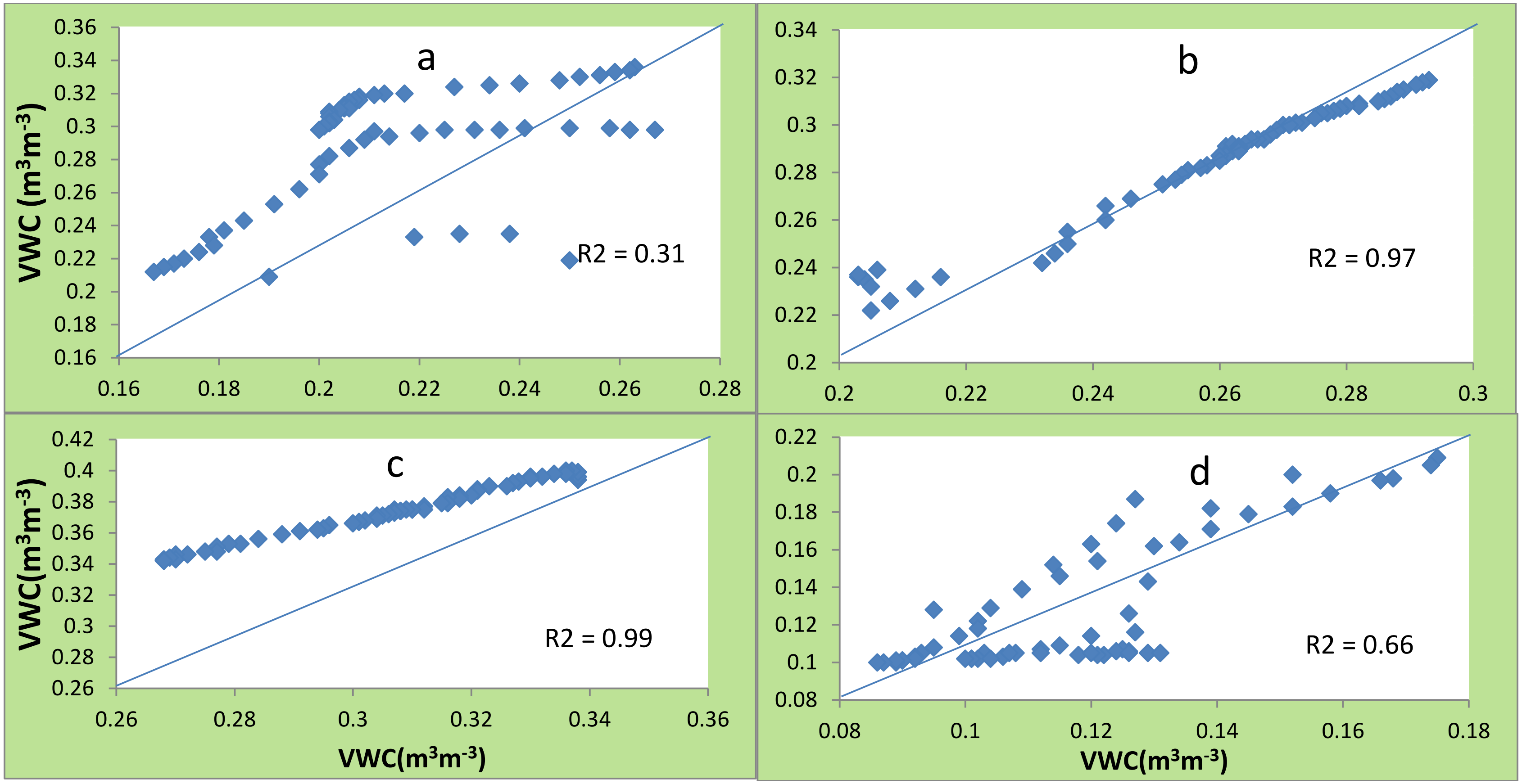


Figure 2.5 Comparison of soil water content measure by two hydra probes in the same hole and in different holes at the same depth in 2013 annual plot (a) measurements taken in one probe against another probe in same hole at the 20-30 cm depth (b) measurements taken in one probe against another probe in two different holes at the 20-30 cm depth (c) measurement taken measurements taken in one probe against another probe in same hole at the 45-60 cm depth (d)measurements taken in one probe against another probe in two different holes at the 45-60 cm depth

Aside from the natural variability of soil moisture on the field, the reason for this discrepancy is not easily well defined judging from the fact that these instruments are the same and were installed at same time. These results further attest to the fact that soil moisture is highly variable both in space and in time (Dubois et al., 1995). The reason why the two probes in the same depths were different from each other could be as a result of a shift in either of the probe as a result of pressure induced movement such as depression on the field that makes the probes to shift on move in the course of the growing season(Martinez et al., 2008) and this might make the sensing area of the hydra probes to soil completely different in moisture content from the other probe even at same hole. For two probes in same depth, since the sensing volume of the hydra probe is smaller compare to the distance between these probes, it will be logical to assume that the soil they will sensing will not be the same as the soil moisture content of the soil that will be in contact with each probe will not be the same.

2.4.2 Hydra probes Field evaluation for Soil Temperature

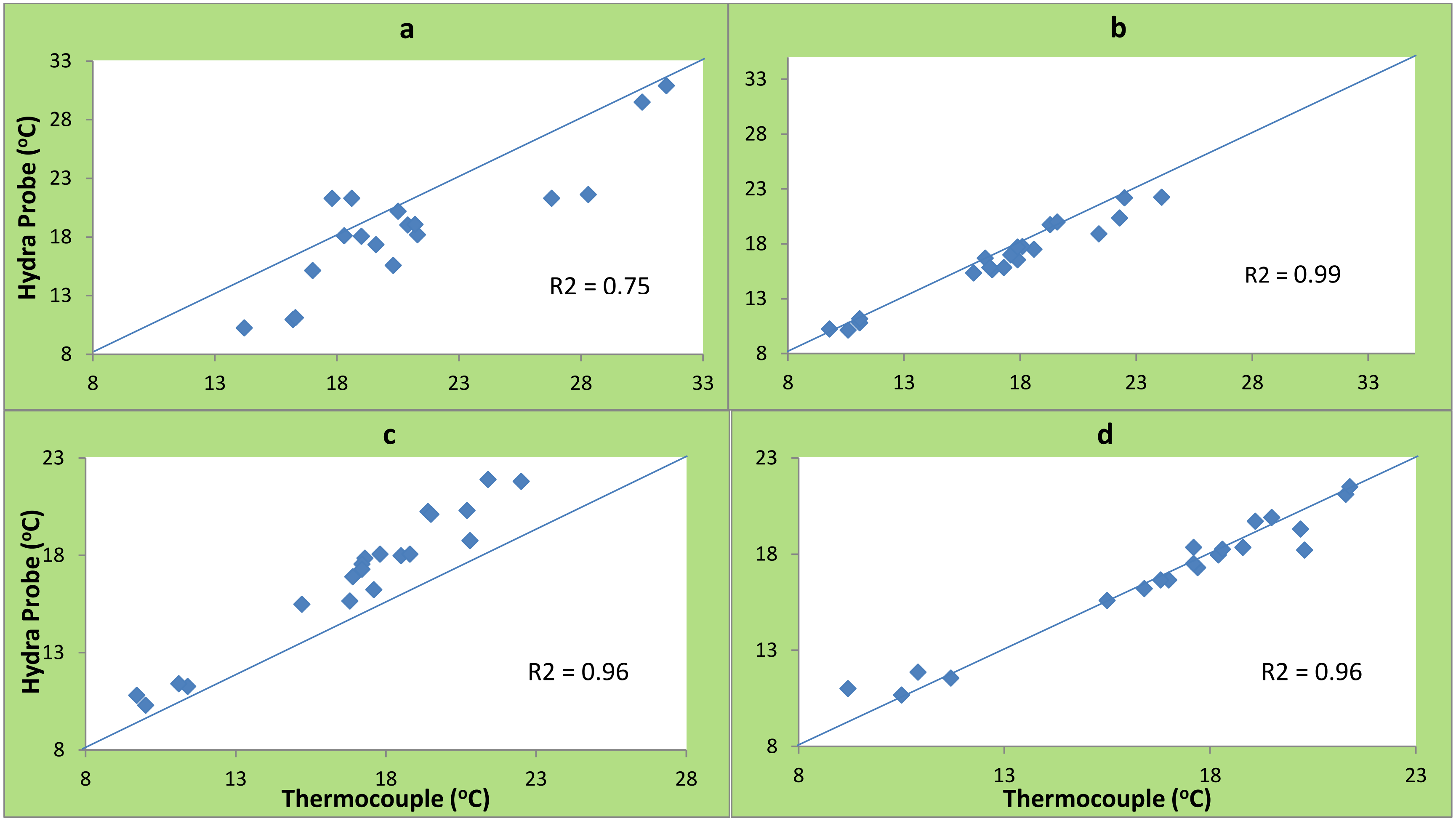
The measured temperature values obtained from the thermocouple on days of sampling were compared against hourly temperature outputs from the hydra probes. The recorded time of the day when measurement was taken from the thermocouple was used to represent the hour of the day and these were taken to be the values for the sampling days. The results of our comparison of temperature from the Hydra probe with that from the thermocouple indicated that R-square was least (0.76) at 0-10 cm depth of all depths considered in this study while the R^2 values of the remaining depths were above 0.90 (Table 2.4 and Figure 2.6). The lower R-square values in the first layer (0-10cm) was not unexpected as this layer experiences the greatest fluctuation in soil temperature. Unfortunately, these results cannot be compared with any other work because to the best of my knowledge, this is the first independent evaluation of soil temperature measurement using a hydra probe (Bellingham and Fleming, 2007). The time series comparing soil temperature from the hydra probe and the thermocouple is shown in Figure 2.7. It was noted that the hydra probes measurements correlated well with the measurements from the thermocouple.

Table 2.4 Evaluation of the temperature measurements by the Hydra probe

Soil Sampling Layer (cm)	Hydra probe point of installation (cm)	Thermocouple point of installation (cm)	R^2
0-10	5	5	0.75
10-20	15	15	0.96
20-30*	25	25	0.96
30-45	37.5	37.5	0.96
45-60*	53	53	0.96
60-90	75	75	0.91

* Two extra probes were installed at these depths in the second growing season in same hole adjacent to the original holes previously established during the first growing season.

A comparison of measurements from the extra probes installed during the 2013 growing season to the one already installed during the 2012 growing seasons showed that the hydra probes were working but still shows variability even when installed close to each other. Figure 2.8 shows the comparison of the hydra probes output against each other from the same hole at same depth and also results obtained from two closely dug different holes at same depths for soil temperature. The probes that were installed at the same depth and in the same hole had similar soil temperature readings showing a higher correlation (Figure 2.8a) with a R^2 of 0.99. This is an indication of the reproducibility of these probes when measuring soil temperature.


a
b
c
d
R2 = 0.75
R2 = 0.99
R2 = 0.96
R2 = 0.96
Hydra Probe (ºC)
Thermocouple (ºC)

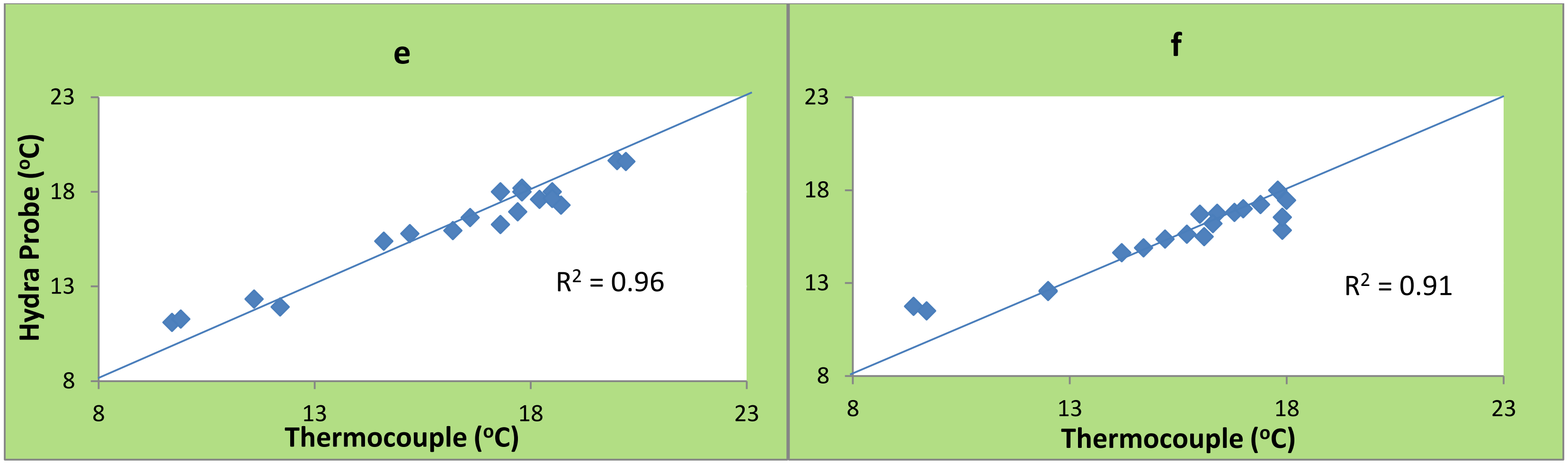


Figure 2.6 Comparison of observed soil temperature from thermocouple and hydra probe at different depths (a) 0-10cm (b) 10-20cm (c) 20-30cm (d) 30-45cm (e) 45-60cm (f) 60-90cm

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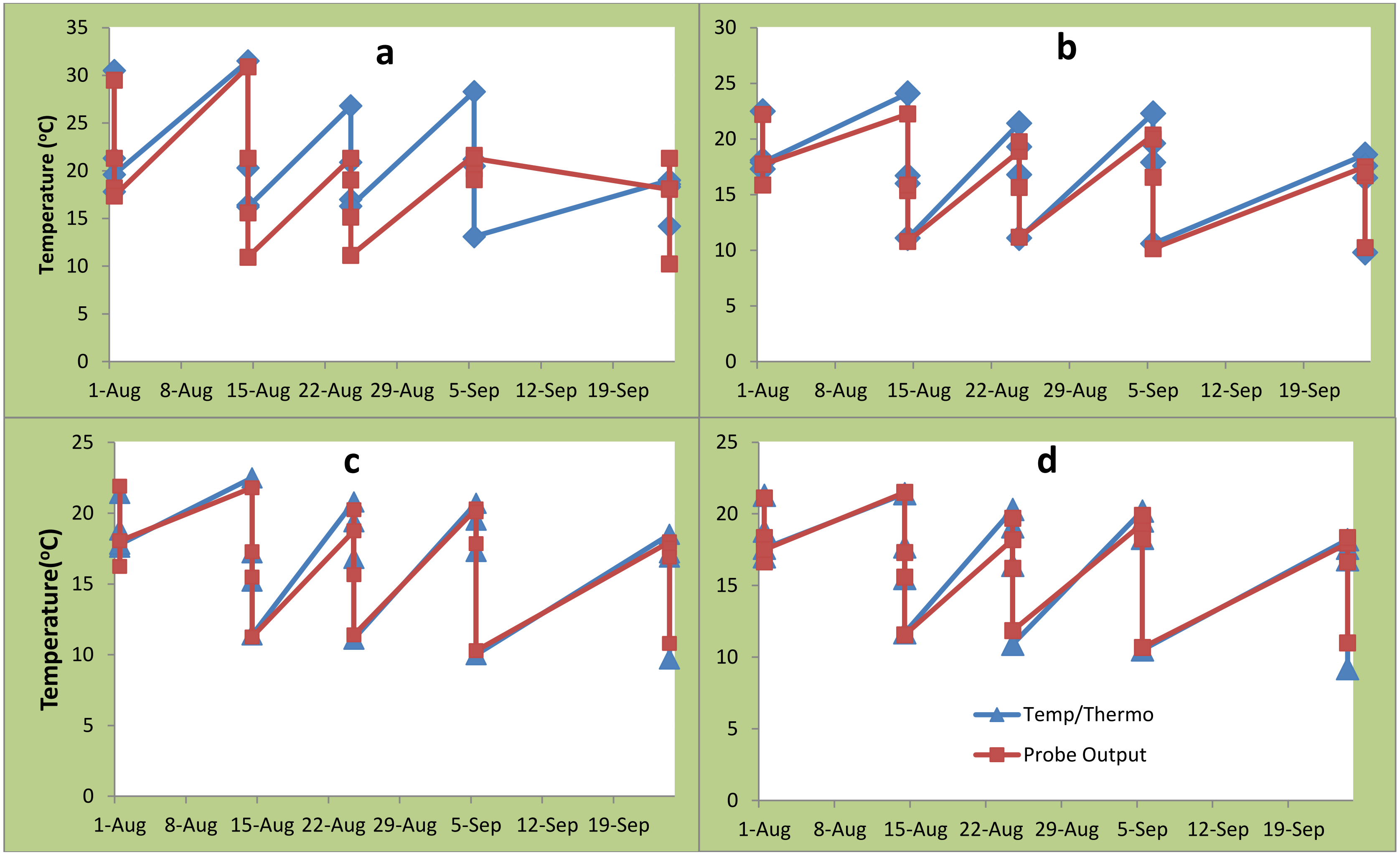
a
b
c
d
Temperature (ºC)
Temperature(ºC)
1-Aug
8-Aug
15-Aug
22-Aug
29-Aug
5-Sep
12-Sep
19-Sep
Temp/Thermo
Probe Output

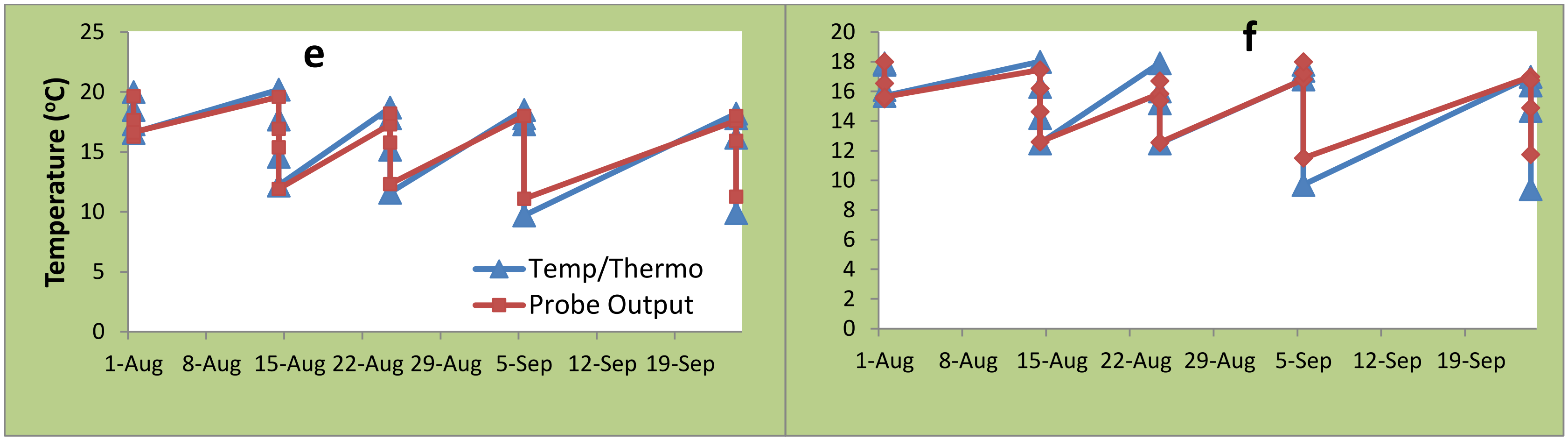

Figure 2.7 Comparison of soil temperature from the hydra probes to the values obtained from the thermocouples at different depths (a) 0-10 cm (b) 10-20 cm (c) 20-30 cm (d) 30-45 cm (e) 45-60 cm (f) 60-90 cm

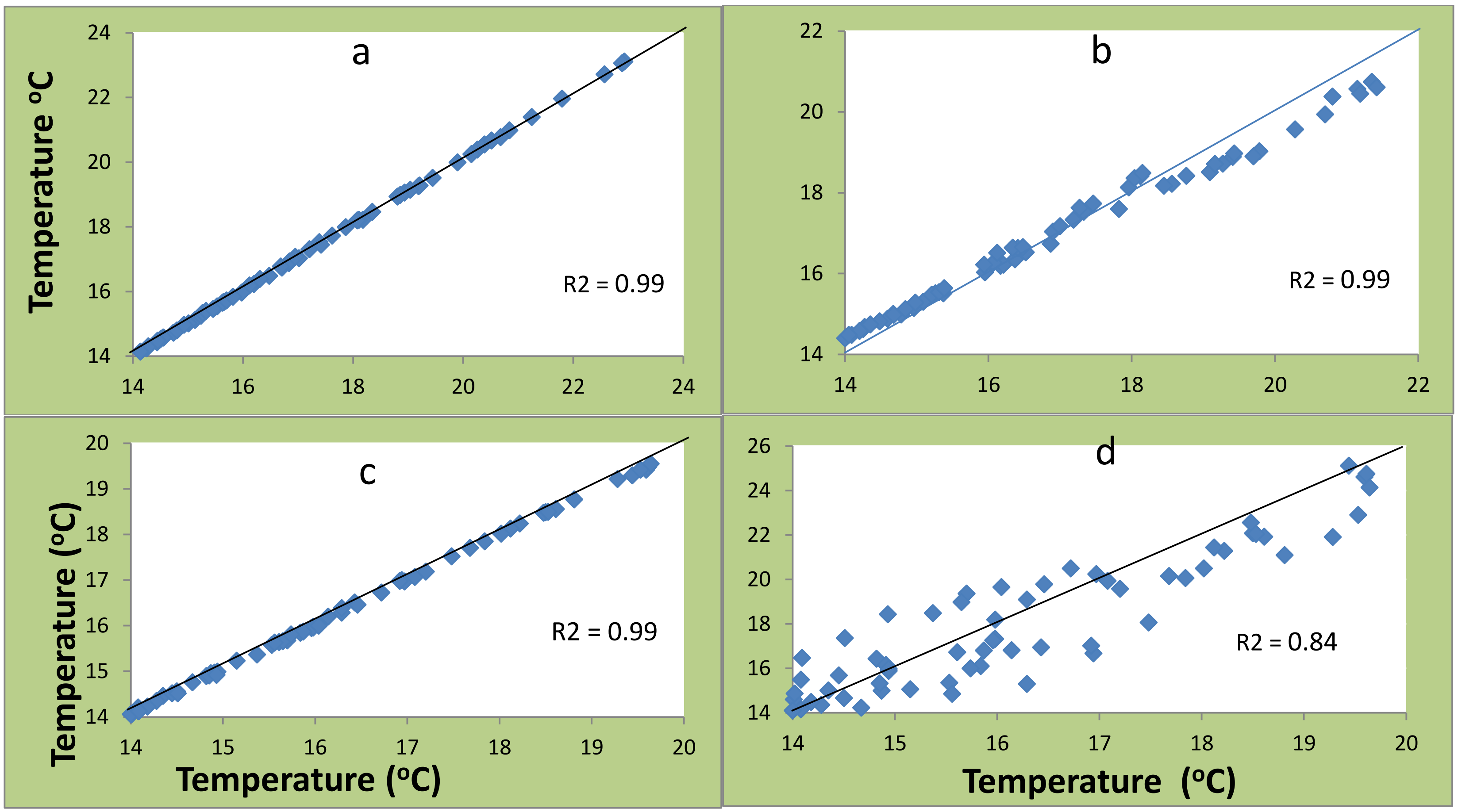

Figure 2.8 **Hydra probe versus hydra probe comparison for soil temperature (2013) (a) two probes in the same hole at the 20-30 cm depth (b) two probes in two different holes at the 20-30 cm depth (c) two probes in the same hole at the 45-60 cm depth (d) two probes in two different holes at the 45-60 cm depth.**

However, R^2 of 0.84 was observed when the probes were in two different holes at the same depth (Figure 2.8d). The differences obtained in the performance of the probe from one hole to the other could be due to the fact that soil temperature dynamics is spatial and temporarily variable (Kammerer et al., 2014). So, the probes placed side by side in the same hole gave temperature data that are nearly perfectly fit to one another in contrast to the probes placed at same depth in another hole. Spatial variation induced by topography and moisture content differences might have been responsible for these observed differences. The results obtained from this study agreed with the work of Bellingham and Fleming (2007) of Stevens's water monitoring system on the evaluation of hydra probe temperature measures. They found hydra probe to give accurate temperature outputs at temperature between -30^oC and 40^oC.

At the depth of 0-10 cm, the thermocouple has an average value of 20.4 ^oC with a maximum temperature of 31.5 ^oC and a minimum value of 13.1^oC (n =18) between 1st of August and 24th September 2012 (Table 2.5). The hydra probe has an average value of 19.1 ^oC with a highest value of 30.9 ^oC and a lowest value of 10.3 ^oC. The smaller R^2 value at the 0-10 cm depth could be as a result of high rate of fluctuation at the surface during the warm period that the temperature data were collected. Soil temperatures measured using the thermocouple at the 10-20 cm depth had smaller average of 17.3 ^oC with a highest value of 24.1 ^oC and lowest value of 9.8 ^oC compared to the soil surface temperature.

Table 2.5 Average, maximum and minimum soil temperature measured using the thermocouple and Hydra probes at different depths during 8 weeks of measurement (1st August to September 24th, 2012.

	Thermocouple			Hydra probe		
	Highest (ºC)	**Lowest(ºC)**	**Average(ºC)**	**Highest(ºC)**	**Lowest(ºC)**	**Average(ºC)**
0-10cm	31.5	13.1	20.4	30.9	10.3	19.1
10-20cm	24.1	9.8	17.3	22.3	10.3	16.6
20-30cm	22.5	9.7	17.0	21.9	10.3	16.9
30-45cm	21.4	9.2	16.9	21.5	10.7	16.9
45-60cm	20.2	9.7	16.3	19.7	11.1	16.3
60-90cm	18	9.4	15.5	18	11.5	15.5

Table 2.6 Statistical comparison of thermocouple and hydra probe soil temperature in six soil layers

	0-10cm	10-20cm	20-30cm	30-45cm	45-60cm	60-90cm
N	20	20	20	20	20	20
RMSE	3.91	1.06	0.78	0.75	0.76	091
RMSE/Avg	0.20	0.064	0.046	0.044	0.046	0.058
MBE	-1.31	-0.67	-0.10	-0.02	-0.007	0.08
P(T<=t)one tail	0.21	0.29	0.47	0.02*	0.50	0.46

*Depth showing significance difference in thermocouple reading to probe reading at alpha level of 0.05

In comparison, the hydra probes in this layer (10-20cm) have an average value of 16.6 ^{o}C with a maximum of 22.3 ^{o}C and a minimum of 10.1 ^{o}C. It can generally be seen, as expected, that the soil temperature, as measured by both instruments, decreased with soil depth (Table 2.5). The RMSE was greatest at the surface layer and decreased considerably with soil depth (Table 2.6). The RMSE/avg which is the normalised RMSE are all less than 10% inferring that observed temperature data from thermocouples have excellent relationship with the measurements from the probe except at the surface which is 20%, statically regarded as a good relationship. The MBE values shows that the hydra probes gave slightly lower values than the installed thermocouples. The t-test carried out on the data shows that there were no significant differences between the data from the hydra probes and the thermocouple except at the soil layer of 30-45cm (Table 2.5). The difference in the depth range of 30-45cm might be due to error from improper placement of the thermocouples when being installed at this particular depth.

2.4.3 Limitations

The conversion of gravimetric water content to volumetric water content requires a measure of the soil bulk density at different depths. There is a great deal of uncertainty with the soil bulk density measurement creating uncertainty in the measured volumetric water content. Previous researchers (Holmes et al, 2011, Huang et al., 2004) have reported the challenges of accurately determining soil bulk density especially at depth and its impact on soil moisture content since observed field moisture content is a product of gravimetric moisture content and bulk density. In essence, errors associated with the bulk density measurement automatically affect the volumetric moisture content that is used to evaluate the performance of the hydra probe.

The second limitation was that the gravimetric soil moisture samples had to be taken from distances of about 1-2 meter away from the installed probes and were different from the soils that are directly in contact with the sensing volume of the probe. The Hydra probes have already shown how soil water can be different from adjacent holes separated by a distance of 1 m. As such, soil moisture content observed from the probes might be different from the thermo-gravimetrically determined moisture content due to spatial variability of the soil.

2.5 Conclusion

This study showed that hydra probe produces acceptable results for soil temperature measurement but have limited capacity for soil moisture measurement in the field without site specific calibration. The sensor was found to be more reliable for soil temperature because soil moisture exhibited greater spatial variability with associated sampling errors. As observed, soil temperature that was measured by the hydra probe did not require specific field calibration for inorganic soil while field specific calibration is needed for soil moisture. This is due to the fact that soil moisture is more spatially variable naturally. The manufacturer's suggested equation for a soil with less than 20% clay was found to be inadequate for the soil used in this study. This study further reinforces the need for site specific calibration for hydra probe before it can be used to measure or monitor soil moisture content.

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3.0 VSMB MODEL MODIFICATION AND MOISTURE SIMULATION EVALUATION

3.1 Abstract

Soil temperature influences many biological systems and as such has very important applications for many agronomic and environmental models. The measurement of soil temperature with instruments has limited spatial and temporal coverage. Other methods such as modelling are appealing as they can be applied where point measurement might be limited. Therefore, soil temperature models that use weather variables and other soil properties have been formulated. The VSMB, a model that simulates soil moisture has been used to simulate soil surface temperature using daily maximum and minimum air temperature as inputs. Because of the importance of soil temperature within the root zone, a simple empirical equation was incorporated into the VSMB to simulate soil temperature at soil depths of up to 90 cm. Comparison was made between observed data from the field of two cropping systems (annual and perennial) and the simulated results during the 2012 and 2013 growing seasons. The model captured the trend in daily soil temperature up to a depth of 45 cm, however, the new algorithm was found to overestimate soil temperature as depth increases and the discrepancies between simulated and observed increased as the depth increased. The percentage mean difference for the top soil layers was less than 10% while it was highest at the 45-60 cm depth with a percentage mean difference of about 40%. The model also gave a better estimate of soil temperature from the annual cropping system (RMSE 1.96^{o}C) than the perennial cropping system (4.01^{o}C). The results from another field site (Carberry, Manitoba) used in validating the model were similar to those obtained at Carman. This model can be used to give first approximations of soil temperature at depths and demonstrates that empirical equations have limited capacity to reproduce soil temperature at various depths.

3.2 Introduction

3.2.1 Soil Temperature

Soil temperature is an important parameter for many agronomic and environmental applications such as drought monitoring, irrigation scheduling, and drainage practices among others (Parton, 1984; Jackson et al., 2008). Agronomic processes such as soil water movement, nutrient uptake and availability, crop root respiration and transpiration are affected by soil temperature (Reimer and Shaykewich, 1980; Soltani et al., 2006). Measuring soil temperature, especially when point measurement is insufficient can be laborious and time consuming and sometimes very difficult to carry out under certain field conditions. Because of the challenges and limitations confronting the direct measurement of soil temperature, the need for predictive models that can simulate soil temperature become very important (Reimer and Shaykewich, 1980; Lei et al., 2010)

Three major modeling techniques are used for simulating soil temperature. First is the empirical models that make use of statistical relationships between soil depth and air temperature with climatological variables (Toy et al., 1997). A second technique makes use of physically based processes and Fourier's law to predict the soil surface temperature and sub surface temperature (Flerchinger et al., 1998). These are known as mechanistic models. The third type employs a combination of empirical and mechanistic model that uses a heat flow equation to simulate deeper layer temperature while using an empirical method to determine the temperature at the upper boundary of the soil (Sándor and Fodor, 2012). This latter method takes advantage of the close correlation that exists between soil temperature and air temperature to develop predictive practical models of soil temperature (Lei et al., 2010).

Research efforts have been made to develop models that can simulate soil temperature, however, many of these models require lots of inputs that are not readily available except through remote sensing. For instance, (Mahrer and Katan, 1981) employed in their work albedo, solar radiation, air density, ground emissivity in developing a two dimensional numerical model for estimating soil temperature. Mihalakakou (2002) used in addition to air temperature, relative humidity, global solar radiation and soil surface temperature, which are difficult to obtain, to develop a model for estimating daily and annual variations of soil surface temperature. A semi-empirical model that accounts for forest canopy and litter was described by (Kang et al., 2000). It made use of thermal diffusivity which is highly variable due to bulk density and soil moisture content changes but the model was inadequate at the depth of 20 cm where the majority of microbial activities take place. Paul et al., (2004) used this concept to estimate soil temperature for a range of surface soils using modifiers that account for litter cover and canopy. The limitation of this model was that it required too many input parameters. Dardo et al., (2001) developed a model to predict soil temperature and heat flow as functions of time and depth in a sandy soil. They took into account the relationship between changes in thermal conductivity and volumetric heat capacity which are very difficult to measure especially in the field due to spatial variability with respect to water content.

Because of the complexities and challenges involved in using the aforementioned models, there is need for a pragmatic and flexible soil temperature model that requires minimal and easily obtained input variables such as air temperature for routine field applications. It has been argued that prediction based on the Fourier heat equation only applies to homogenous and isotropic soil as their outputs tend to vary widely due to the effect of noise arriving from the initial data employed in the equation (Elias et al., 2004). However, these models still have the potential to accurately estimate soil temperature when the proper damping factor is employed for the region of interest (Reimer and Shaykewich, 1980).

The heat conduction equation (Equation 1.2) expresses the temperature of a homogenous and isotropic soil with respect to time t(s) and changes in temperature with respect to soil depth z (cm). This equation was used by Lei et al. (2010) who assumed K to be a constant with time and depth though not a good assumption considering the fact that K is very unstable and varies rapidly both in time and space especially on the field. They used two boundary conditions to solve the equation. The first boundary condition was to set the soil surface temperature to be equal to the air temperature which as a sinusoidal wave that is given as: $T(0, t) = Ta + Ao\sin(wt+\phi)$ (Lei et al., 2010). The second boundary condition is an assumption that the soil temperature is the same as the mean air temperature at infinitely large depth. (Lei et al, 2010). The solution of Equation 1.2 above using the two stated boundary conditions is given by Equation 1.3 (Elias et al., 2004) that was used for estimating soil temperature at any depth using the surface air temperature and soil thermal diffusivity.

Equation 1.3 was found to have some deficiencies such as: (i) it is not easy to know whether the equation can simulate successive days accurately when there is large variation in weather and (ii) the equation assumes diurnal temperature variation to be symmetrical with time whereas, in the general term, the rate of heating is greater than that of cooling for a given diurnal change in temperature. (Lei et al, 2010).

Since thermal conductivity and diffusivity are highly variable and difficult to obtain, the purpose in this study is to introduce a simple parametric algorithm into the versatile soil moisture budget to simulate soil temperature at varying depths from the top of the soil down to a depth of 90 cm.

3.2.2 Soil Moisture

Soil moisture is a vital resource for a wide range of agricultural and environmental applications. Irrigation scheduling and management, drainage planning, pasture production are agronomic practices that require adequate knowledge of soil water status (Santisopasri et al., 2001; Wang et al., 2001). Soil moisture is known to influence the potential of a soil to support optimal crop yield since crop yield has a direct relationship with spring soil moisture and precipitation during the growing season (Qian et al., 2009). Different crops have varying soil moisture requirements hence, it is necessary to have an understanding of the moisture supplying capacity of a soil with regards to the moisture demand of the crops that will be grown in a soil (Döll and Siebert, 2002). With adequate and timely information about soil water status and fluctuations especially at the onset of the growing season at hand, farmers are able to make informed decision with regards to seeding, time to apply fertilizer, herbicide and pesticides, and when to irrigate. Soil moisture stress can result in loss of crop productivity most especially during the key stages of growth leading to poor yield. The incident of drought increases the chances of pest infestations on a field (Porter et al., 1991). On the other hand, excess moisture can also affect crop yield through its impact on root respiration. Different soil moisture simulation models exist in the literature ranging from the simple water balance approach to the detailed mechanistic models that make use of the Richard's equation (Akinremi and McGinn, 1996; Baier and Robertson, 1996; De Jong and Bootsma, 1996; Chapman and Malone, 2002). We have selected the versatile soil moisture budget for this study. Although the VSMB has been widely used for simulating soil water across the prairies (Akinremi et al., 1996, Akinremi et al, 1997 and Hayashi et al., 2010), virtually all the previous users of the model have pointed to the need for site specific evaluation if accurate results are desired.

The objectives of this chapter were: to incorporate a soil temperature algorithm requiring minimal inputs into the VSMB so that the model can be used to estimate soil temperature at depth. To evaluate this new algorithm with field measured soil temperature data during two growing seasons. The parameters that the proposed temperature algorithm was the most sensitive to were identified and these in turn guided the parameterisation of the model for estimating soil temperature at depth. To also compare observed thermo-gravimetric determined soil moisture content measured against soil moisture content outputs from the VSMB.

3.3 Methods

3.3.1 VSMB Model Overview

The Versatile Soil Moisture Budget was a model initially developed to simulate the vertical one dimensional water balance in a soil column that is divided into arrays of layers at a daily time step (Hayasi et al., 2010). Baier et al., (1979) described the improved computerized version of the model with the input control data that are required to run the computer program. Boisvert et al., (1992) introduced a sub-model to simulate water table depth. Akinremi and McGinn, (1996) while conducting a study on drought climatology coupled the Palmer drought index model with the VSMB to improve soil moisture simulation. Akinremi et al., (1996) replaced the algorithm used by Baier and Robertson (1996) to estimate potential evaporation with the Priestley-Taylor equation that uses solar radiation due to a widespread access to solar radiation. They also introduced a simple cascade algorithm from the Ceres-Wheat model to describe the vertical flow and redistribution of moisture between zones. Hayashi et al. (2010) used the model to estimate evaporation and modified the drying curve functions, radiation scheme and growth rate parameters to obtain a good agreement between simulated evaporation and measured evaporation. The VSMB has been reasonably tested for many applications and the results have been verified against lysimeter readings, crop yield estimates, irrigation scheduling and soil moisture condition with an acceptable accuracy of estimates for moisture distribution (Hayashi et al.,2010, Hayhoe et al., 1993; Akinremi and McGinn, 1996; Baier and Robertson, 1996). Akinremi et al., (1996) used a simple equation with daily air temperature input to estimate surface (0-5 cm) soil temperature. An evaluation of this simple soil temperature algorithm showed that it simulates soil surface temperature with a reasonable degree of accuracy (Akinremi et al. 1996). However, the model did not simulate soil temperature at depth.

3.3.2 Soil Temperature Estimation

3.3.2.1 Introduction and Development

Soil temperature is a measure of soil internal energy or heat content and changes in the heat gained or loss by the soil will result in subsequent change in soil temperature. Soil temperature modeling could be achieved by solving the Fourier equation or by generating an empirical mathematical model from observed soil temperature over several years (Mihalakakou, 2002). Because of the difficulties involved in obtaining the required inputs for soil temperature simulation on the field, a simple algorithm that can reasonably and accurately give soil temperature profiles both at the surface and at depth is desirable by soil-plant interaction model developers.

3.3.2.2 Soil Surface Temperature estimation

Surface soil temperature is influenced by many factors including meteorological (e.g. solar radiation, air temperature), soil surface condition such as albedo and soil properties (e.g. thermal conductivity, diffusivity). The variability of these factors accounts for the variable nature of soil temperature at the soil surface. Models for estimating soil surface temperature can be developed by using the daily minimum and maximum air temperature together with the plant biomass (Parton

1984). This author tested a large number of models and selected the model that has the best fit with minimum input requirement for predicting daily minimum and maximum temperature in a short-grass prairie location. He used the equation $Ts^{mx} = Ta^{mx} + E^{T}.E^{B}$ to predict the daily maximum surface temperature and $Ts^{min} = Ta^{min} + E^{T}.E^{B}$ for minimum air temperature where Ta^{mx} is the maximum air temperature, Ta^{min} is the minimum air temperature E^{T} is the elevation of the maximum or minimum soil surface temperature above air temperature derived as a function of the maximum or minimum air temperature and E^{B} is the effect of the plant biomass. The model also accounted for leaf area index and coefficient used in the Beer-Lambert Law describing solar radiation interception through the canopy. They obtained a good fit between predicted and observed daily, maximum and minimum temperature but the model only works effectively where there is a high level of solar radiation. A simple algorithm for estimating soil surface temperature is found in the erosion and productivity impact calculator (EPIC) model that takes into consideration the insulating effect of snow cover and plant biomass (Akinremi et al., 1996).

Many plant-soil interaction and nutrient recycling models require only daily average soil temperature to drive their model. Cho et al., (1979) derived daily soil temperature used in calculating denitrification intensity by using a relationship between soil temperature and soil depth at various times of the year. They derived the function T = T (z,t) where T is the temperature at time t (s) and depth z (cm) using two boundary conditions. They used the first boundary condition: $T(0, t) = Ta + Ao\sin(wt+\phi)$ suggesting that the surface temperature varies sinusoidally with time with an average value of Ta where Ao is the amplitude, w is the radial frequency while ϕ is a phase constant.

The other boundary condition is lim T (z,t) = Ta ($z \to \infty$) assuming that soil temperature remains fairly constant as the depth increases to infinity even though this is not the case as observed on the field.

A solution for estimating soil temperature at corresponding depths that satisfies these two boundaries with respect to equation 3.1 above can be found in (Elias et al., 2004;Van Wijk and de Vries, 1963; Kirkham and Powers, 1972).

Onofrei, (1986) employed a parametric approach to Equation 1.3 using a set of parameters for a research field in Manitoba region of the Canada prairies found in (Reimer and Shaykewich, 1980) to estimate the temperature at the center of a soil layer as:

$$T\left(z_{j*}t_s\right) = 5.5 + 12.5 \exp\left(\frac{-z_{j*}}{140.7}\right) \sin\left[0.5236t_s - \left(\frac{z_{j*}}{140.7}\right) - 1.964\right] \qquad 3.1$$

Tmean = 5.5 ^{o}C, Ao = 12.5 ^{o}C, dd = 140.7 cm. w = 0.5236 month^{-1} and Φ = -1.964

The term T (z_{j*}, ts) is the temperature of a soil layer (j*) at center Zj*cm at time of seeding (t_s) which is taken as 0 for the first month of the year. That is t_s is equal to 0 for January. This equation though roughly fairly predicted soil temperature at the first day of the simulation in a given location but has the limitation of predicting same values for soil temperature at a given depth from one location to the other throughout the year due to its use of a province-wide temperature average and amplitude. There is need to account for changes in temperature from one place to the other and from year to year.

3.3.3 VSMB Temperature Simulation and Modification

An algorithm adopted from the Erosion and Productivity Impact Calculator (EPIC) model was used to simulate the soil surface temperature in the VSMB (Akinremi et al. 1996). It uses a 3-day running mean of the simulated surface temperature to eliminate the variability that is associated with air temperature, a major input used by the algorithm. The surface temperature was calculated with the Equation 3.2

T_{save} = Tmean + 0.25(Tmax –Tmin) (3.2)

Where T_{save} is the average daily soil surface temperature, Tmean is daily average air temperature, Tmax is maximum daily temperature, Tmin is minimum daily temperature. A set of empirical equations that uses air temperature, the temperature of the adjacent top layer and the previous day's temperature of a particular soil layer to predict the soil temperature at depth was used in this study. This equation is given as:

$$T(z_{j*}t_s) = \left[\frac{(K_{j*}\ x\ T_{j*,i-1}) + (T_{j*,i})}{(K_{j*\ +1})}\right] \qquad 3.3$$

T_{j*}, i is the temperature of layer j* on day i (^oC)

$T_{j*,\ i-1}$ = previous day's temperature of the layer j*

$T_{j*-1,\ i}$ = temperature of the above soil layer temperature on day i.

K_{j*} is an empirical variable define as: $(z_{j*}/K_1) - K_2$

K_1 = 6 while K_2 = 0.25 (Walker 1977)

Zj* is the center point of a particular soil layer in cm

At the soil surface, the first layer where K_{j*} is usually lower than zero, the T_j* is assumed to be equal to the air temperature. The above equation assumes that as the depth increases, soil temperature depends more on the previous day temperature than on the influx of heat from the layer above. Efforts to get a standardized value for amplitude and soil diffusivity using previously available temperature data did not yield realistic values and so Equation 3.3 was introduced into the VSMB in this study to simulate the soil temperature up to a depth of 90 cm from the soil surface. Equation 3.3 above was used to simulate the surface soil temperature at a depth range of

0-10cm while Equation 3.2 was used to simulate temperatures at depths below 10 cm. The algorithms were coded in FORTRAN and adopted into the VSMB and were tested with different levels of parameters of K1 and K2.

3.3.4 Model Sensitivity Analysis

In order to understand the relationship between the input parameters used by the algorithm and the soil temperature outputs generated, a sensitivity analysis was carried out using two of these parameters (K_1 and K_2). The algorithm employed in the model used a value of 6.0 for K_1. Model simulations were made using varying values of K_1 (5.5, 6.0, 6.5, 7.0 and 8.0) while the value of K_2 remained at 0.25. Then, the value of K_1 was kept constant 6.0 while that of K_2 (the weighting factor) was varied from 0.2 to 0.4 in increments of 0.05. The root mean square error, mean bias error and coefficient of determination were used to select the most appropriate values of K_1 and K_2.

3.3.5 Soil Temperature from Hydra Probes

The data used to validate the model results are from the Hydra probes installed on the field. Six hydra probe sensors were installed at varying depths (Table 3.1). The temperature values obtained from the Hydra probes were daily average temperature values which were derived from the averages of the hourly temperature values for a particular day. The probes were tested for performance against readings from thermocouples installed at same depths in the same plots on the field during the first growing season (2012). The probes were also tested for reproducibility in the second growing season (2013) by installing two of the probes at the same depth adjacent to each other (Table 3.2).

Table 3.1 Probe Installation and the sampling depths

Soil Layer (cm)	Hydra probe installation depth (cm)
0-10	5
10-20	15
20-30*	25
30-45	37.5
45-60*	53
60-90	75

* Two additional probes were installed in each of these depths in a different hole.

Table 3.2 The relationship between two Hydra probes installed at the same depth.

Soil Sampling Layer (cm)	Hydra probe point of installation (cm)	R^2
20-30*	25	0.99
45-60*	53	0.99

* Two probes were installed at this depth on same hole adjacent to the original holes during the second growing season.

3.3.6 Statistical procedure

The R^2 values of the regression equation between the observed and the modeled variable were used to check if the observed data were well correlated with the modeled output.

In order to evaluate and test the performance of the model, the Root Mean Square Error (RMSE) between the observed and simulated variable was calculated using Equation 3.6

$$\text{RMSE} = \left(\frac{\sum(\text{Simulated-observed})^2}{\text{n}}\right)^{0.5} \qquad (3.6)$$

The simulated values are output from the model while the observed is the output from the Hydra probe. The total number of observations is n.

In order to determine if the model overestimates or underestimates soil temperature at any depth, the Mean Bias Error (MBE) was used. Zero values are desired as it signifies that there is equal distribution of positive or negative differences. A positive MBE means that the model overestimates, while a negative MBE signifies that the model underestimates soil temperature at depth of interest.

$$\text{MBE} = \frac{1}{\text{n}} \sum_{\text{i}=1}^{\text{N}} [(\text{Simulated-Observed})] \qquad (3.7)$$

A simple student t-test was also used to compare the results from the probes against the model outputs at α level of 0.05 to know if the results are significantly the same or different from each other.

In order to determine the deviation of the simulated temperature from the observed values in percentage term when the data were pooled together for 2012 and 2013 for each depth range, the percentage mean deviation from the measured values were calculated as:

$$\%MD = \frac{1}{n}[\sum_{i=1}^{N} \frac{(\text{Simulated-Observed}}{\text{Observed}} * 100) \quad (3.8)$$

The %MD gives the percentage of the deviation of the model output from the actual values from the hydra probes.

3.4 Results and Discussion

3.4.1 Model Sensitivity Analysis

The results of model simulations using different values of K_1 showed that the value of 7.0 and 8.0 in Equation 3.3 produced soil temperature estimates that were closest to the observed soil temperature (Table 3.3) above 30 cm depth. K_1 value of 7 and 8 gave the highest optimal values for comparing parameters at 10-20 cm and 20-30 cm soil layer but relationship between model and observed became poor with increasing depths. At soil depths 45 cm and above, K1 of 4 gave the optimal values for MBE and RMSE but the R^2 values were considerably low. The K1 value of 7 has the highest R^2 on the average at deeper depths. The RMSE at the deeper depth of above 45cm to 90 cm was consistently lower using 7 for K_1 than K_1 value of 8 in the equation. It was also observed that the R^2 was also relatively greater compared to other values of K_1 especially at depths deeper than 45 cm signifying that the observed data fit the model better using this value of K_1. Therefore for this study, K_1 was taken to be 7 instead of 6 used in the original algorithm (Walker, 1977). Results of model simulation using various values of K_2 showed that model results were not sensitive to K_2. As such, subsequent model simulations used the value of 0.25 for K_2.

Table 3. 3: Statistical parameters on the sensitivity analysis of model parameter, K_1

Selected values of K_1	n	RMSE	MBE	R^2	RMSE	MBE	R^2
			10-20			**20-30**	
4	112	3.69	3.21	0.9	4.70	3.67	0.61
5	112	3.49	3.13	0.91	4.42	3.69	0.76
6	112	3.38	3.12	0.92	4.43	3.65	0.83
6.5	112	3.33	3.03	0.92	4.09	3.62	0.85
7	112	3.29	3.01	0.93	4.00	3.59	0.87
8	112	3.22	2.96	0.93	3.86	3.53	0.90
			30-45			**45-60**	
4	112	5.54	4.00	0.007	5.19	3.73	0.21
5	112	5.36	4.30	0.7	5.51	4.35	0.04
6	112	5.30	4.51	0.39	5.76	4.76	0.006
6.5	112	5.14	4.48	0.49	5.69	4.91	0.012
7	112	5.07	4.50	0.58	5.70	5.02	0.69
8	112	5.01	4.57	0.68	5.78	5.20	0.22
			60-90				
4	112	4.27	3.07	0.35			
5	112	4.89	3.77	0.2			
6	112	5.55	4.70	0.11			
6.5	112	5.54	4.62	0.09			
7	112	5.69	4.84	0.06			
8	112	6.14	5.55	0.009			

3.4.2 Simulated versus Observed Temperature at Carman in 2012 and 2013

The soil temperature data taken directly from the installed probes at the soil surface (0-10 cm) was compared with model simulation using the original soil temperature equation in the VSMB (Equation 3.2). This comparison was carried out for the 2012 and 2013 growing seasons under annual and perennial cropping systems. Hourly temperature values were obtained from the hydra probes and were matched against temperature measurements with thermocouples corresponding to the hours when the data were recorded. The temperature data were few because of late installation of the thermocouples in the field though recorded measurements gave enough confidence for the study. In general, the original equation in the VSMB captured the trend in average daily soil surface temperature values with an R^2 value of 0.93 (Fig 3.1) which was much better than the value of 0.79 obtained by (Akinremi et al., 1996) using the same algorithm. The RMSE was 1.92^oC (Table 3.4). However, the model overestimated the daily soil surface temperature of the annual plots with a MBE of 0.91^oC while it underestimated the daily soil temperature at the perennial plots with a MBE of -0.59^oC (Table 3.5).

The new algorithm (Equation 3.3) for simulating soil temperature down the soil profile captured the trend in the observed daily soil temperature correctly at depths close to the soil surface but couldn't simulate soil temperature effectively at depths of 45 cm and below. The new algorithm generally overestimated daily soil temperature as the depth increases (Table 3.4) because K_1 value of 7 used for the model was optimal at the surface layers. The new algorithm appears to transmit heat below the soil surface faster than what was measured, possibly due to the neglect of important physical soil processes that modulate soil temperature at depth. Changes in albedo, moisture content and particularly soil diffusivity were not accounted for in the model and these are variables that have strong influence on diurnal daily soil surface temperature.

The RMSE increased as the depth increased and the MBE showed positive values and also increased as the depth increased showing that the model overestimated soil temperature as we move down the soil profile. Table 3.4 shows the root mean square error and mean bias error for the 2012 data for the annual plot.

The estimation quality of this model decreased as the depth increased in agreement with Perreault et al. (2013) who reported that the performance of the model he employed in simulating soil temperature decreased beyond 25 cm into the soil.

Table 3.4 Statistical parameter for comparing agreement between simulated and observed soil temperature at Carman (2012 Annual plots)

	n	**RMSE**	**MBE**
0-10	49	1.92	0.91
10-20	112	3.29	3.08
20-30	112	4.00	3.97
30-45	112	5.15	4.50
45-60	112	5.80	5.02
60-90	112	5.69	5.18

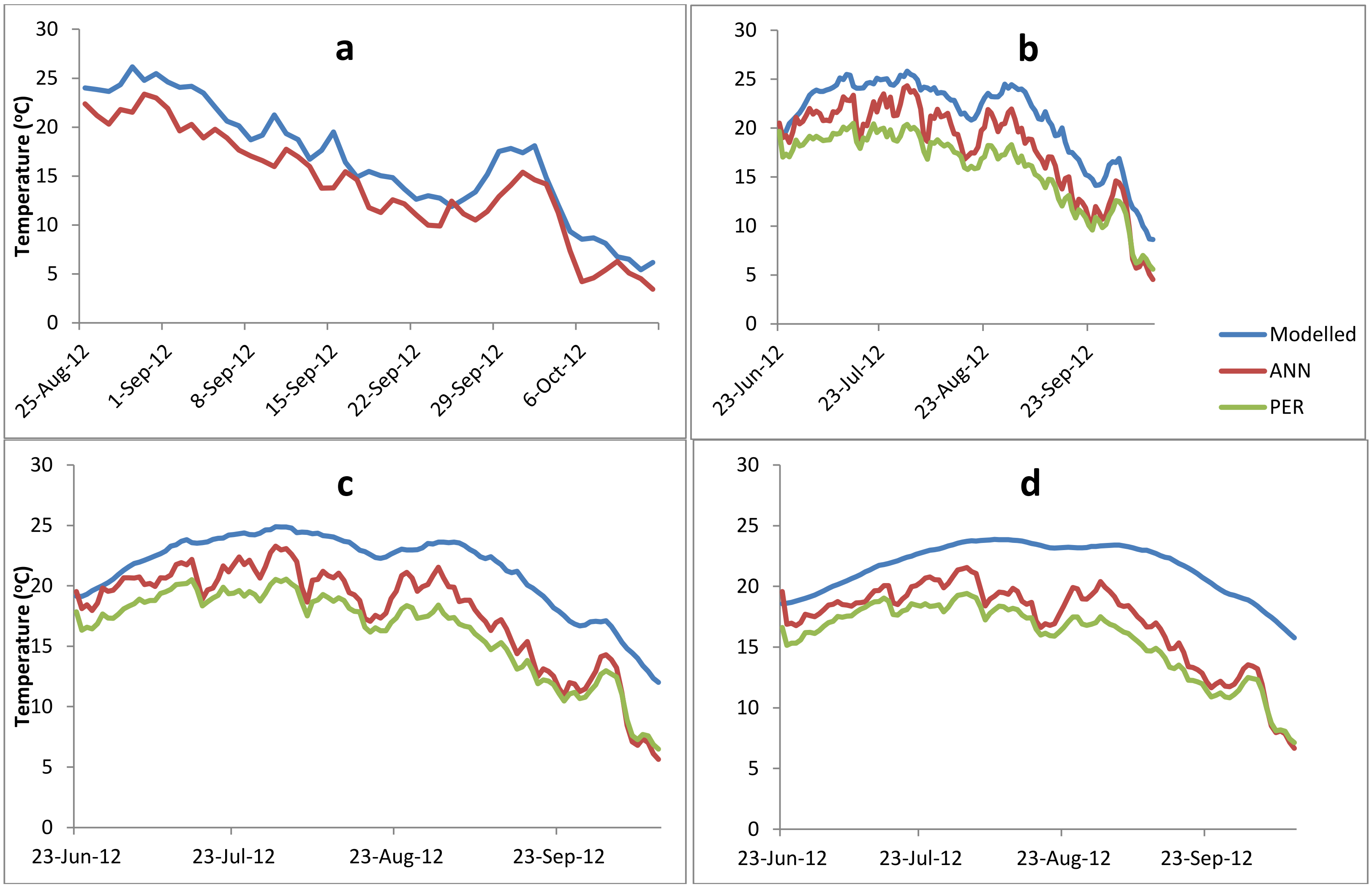
Also, the data for the perennial plot (Table 3.5) showed that the model underestimated soil surface temperatures (0-10 cm). However, below this depth, both the RMSE and the MBE increased down the soil profile signifying an overestimation of daily soil temperature. The observed soil temperature values of the perennial plots were considerably smaller compared to the annual plots as expected except at the soil surface. The initial higher temperature values observed from the perennial plots at start of the simulation might be due to heat loss reduction and reduced vegetation cover during the growing season compared to the annual plots since it takes a while before they could provide cover for the soil. This could also be due to the fact that large temperature fluctuations always occur at the surface of the soil.

Table 3.5 2012 Statistical parameter for comparing agreement between simulated and observed soil temperature at Carman (2012 Perennial Plots)

	N	**RMSE**	**MBE**
0-10	31	4.62	-0.59
10-20	112	5.23	5.07
20-30	112	5.32	5.14
30-45	112	6.81	6.53
45-60	112	7.18	6.70
60-90	112	7.05	6.51

Figure 3.1 compares the simulated soil temperature to those that were measured at various soil depths during the 2012 growing season. It shows that the level of model inaccuracy and overestimation increased with depth, although not in a predictable manner. The reason for the big discrepancy at depth is unknown and illustrates the difficulty of using an empirical equation to simulate soil temperature at depth reported by others (Kemp et al., 1992), Perreault et al., 2013).

Figure 3.2 also shows both annual and perennial observed soil temperatures were below simulated values indicating the model mostly overestimates soil temperature especially at depth.


a
b
c
d
Temperature (ºC)
0
5
10
15
20
25
30
25-Aug-12
1-Sep-12
8-Sep-12
15-Sep-12
22-Sep-12
29-Sep-12
6-Oct-12
23-Jun-12
23-Jul-12
23-Aug-12
23-Sep-12
Modelled
ANN
PER

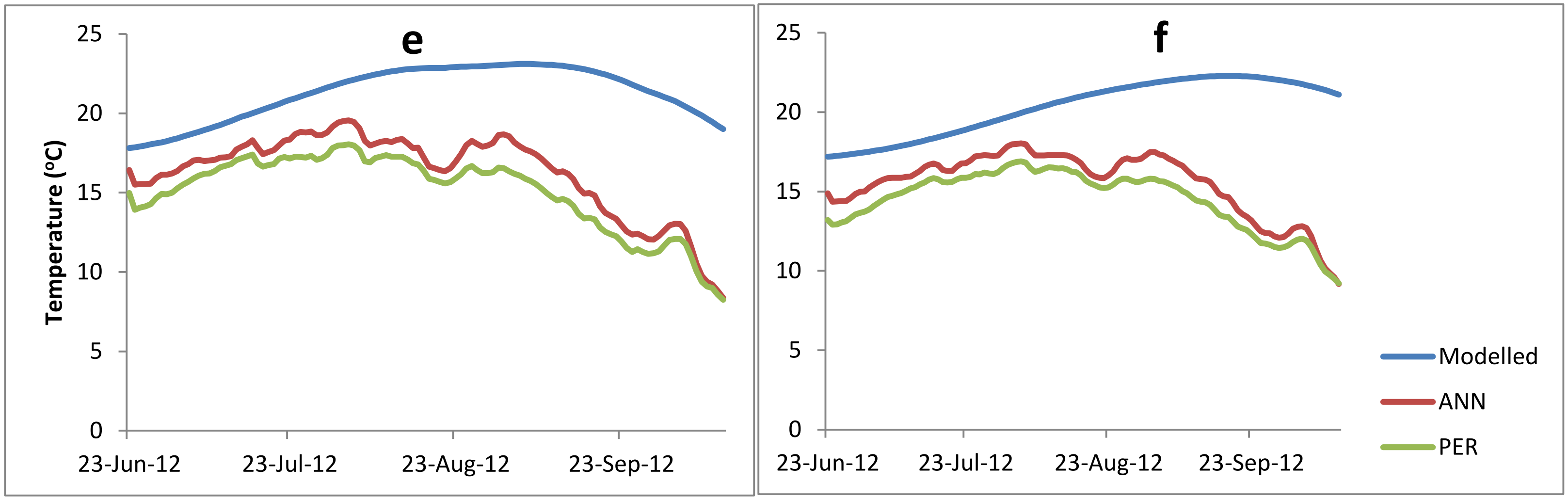


Figure 3.1 Daily soil temperature simulations versus observed at varying depths at Carman during the 2012 growing season for (a) 0-10cm (b) 10-20 cm (c) 20-30 cm (d) 30-45 cm (e) 45-60 cm (f) 60-90 cm

ANN = Annual plots

PER = Perennial plots

Measured values for the perennial plot at 0-10cm were not presented because the probe at that depth stopped working after a while there were not enough data for a comparison.

The results that we obtained for the simulation that were carried out in 2013 at Carman followed the same pattern as that of 2012 (Table 3.6). The model was better at reproducing soil temperatures close to the soil surface while it overestimated soil temperatures at depth. Nevertheless, the root mean square error and mean bias error were considerably smaller than those that were obtained in 2012 signifying an improvement of the model performance in the second year of the study. Even though the weather inputs employed in this study were obtained from the same station over the two seasons, there could be possibility of the 2013 weather data having better estimates and thus could be the reason why there was improvement in the second year of simulation. Another possible reason could be that probes contact with the soil could change due to changes the soil physical condition since the probes were left in the field through the winter months. Even though the soil

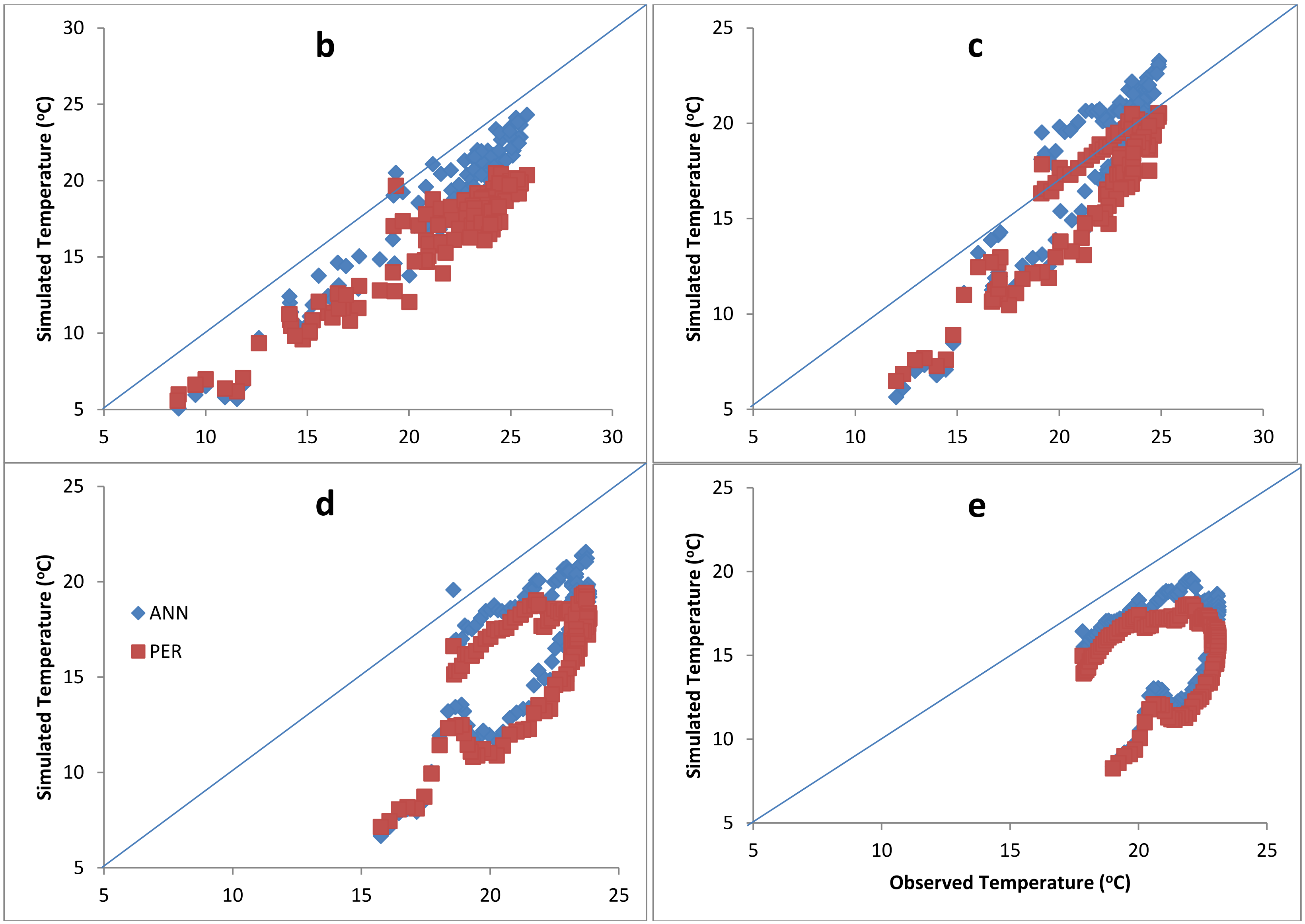
Table 3.6 Statistical parameter for comparing agreement between simulated and observed soil temperature at Carman (Annual 2013)

	n	RMSE	MBE
0-10	62	0.87	0.40
10-20	62	0.86	0.40
20-30	62	1.05	0.71
30-45	62	1.65	1.06
45-60	62	1.63	0.86
60-90	62	1.57	0.16

The perennial plots in 2013 (Table 3.7) had lower soil temperature values than the annual plots shown in Table 3.6. The overestimation of soil temperature by the model in the perennial plot in 2013 was greater than for the annual plots (compare Table 3.6 to 3.7). This could be as a result of the shading effect of the forage biomass resulting in a cooler soil temperature which was not taken into account by the model. This is in agreement with (Sándor and Fodor, 2012) who observed that crop cover and leaf area index have significant effects on soil temperature dynamics.

Table 3.7 **Statistical parameter for comparing agreement between simulated and observed soil temperature at Carman (Perennial 2013)**

		RMSE	**MBE**
0-10	62	2.73	1.75
10-20	62	2.81	1.98
20-30	62	2.74	1.99
30-45	62	2.92	2.06
45-60	62	2.74	1.76
60-90	62	1.89	0.82


b
c
d
e
Simulated Temperature (ºC)
Observed Temperature (ºC)
ANN
PER
5
10
15
20
25
30

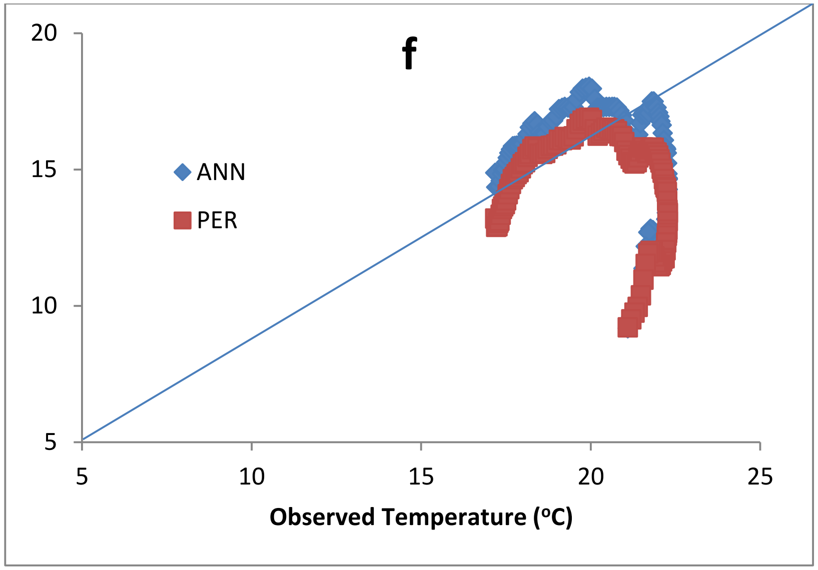


Figure 3.2 Comparison of daily soil temperature simulations and observed at Carman 2012 for (a) 0-10cm (b) 10-20cm (c) 20-30cm (d) 30-45cm (e) 45-60cm (f) 60-90cm

One of the probes at 0-10cm stopped working and so comparison between annual and perrenial are not presented.

Pooling the temperature data together from all plots for the two years, the RMSE for the soil surface (0-10 cm) was 1.98 for the annual plots while it was 4.01 for the perennial plots while the mean bias error was 1.39 and 1.69 for the annual and perenial plots, respectively. The percentage mean difference for this layer was 7.28% for the annual while it is 10.6% for the perenial. The percentage mean difference is seen to significantly increase as soil depth increased beyond 45 cm producing the highest percentage mean difference of 39.5% especially with the perennial plot. From the results, it was observed that the model seems to perform better on the annual plots. The results of the coefficient of determintaion, root mean square error and mean bias error all show that the model gave better results on the annual plot compared with the perennial plot. Overall, the model estimates were statistically different from the observed (Table 3.8)

Table 3.8 Pooled Temperature data for 2012 and 2013 (Simlated versus Observed)

	N	R^2	RMSE	MBE	%MD
			Annual		
0-10	93	0.84	1.98	1.39	7.28
10-20	174	0.85	2.72	2.19	14.6
20-30	174	0.77	3.32	2.76	18.4
30-45	174	0.37	4.34	3.61	24.4
45-60	174	0.001	4.83	3.79	26.1
60-90	174	0.15	4.73	3.22	23.1
			Perennial		
0-10	93	0.032	4.01	1.65	10.6
10-20	174	0.84	4.75	4.51	28.9
20-30	174	0.79	4.80	4.59	29.8
30-45	174	0.29	5.94	5.53	38.6
45-60	174	0.0006	6.16	5.44	39.5
60-90	174	0.05	5.86	4.72	35.9

Table 3.9 shows that the observed soil temperature showed statisctically significant differences from the simulated results when the data were pooled together for the whole of 2012 and 2013. The differences between the observed and simualted were statistically signifcant at alpha level of 0.05 on the student paired t-test carried out(Table 3.9)

Table 3.9 Paired Two Sample t-test for temperature(Simulated vs Observed)

		0-10cm			10-20cm	
	SIMULATED	ANNUAL	PERENNIAL	SIMULATED	ANNUAL	PERENNIAL
Mean	21.0	19.61	19.09	21.25	19.06	16.73
Variance	11.5	13.17	3.154	13.53	18.20	11.80
Observations	93	93	93	174	174	174
P(T<=t) one-tail		0.0038	1.6E-06		2.4E-07	1.14E-27
t Critical one-tail		1.65	1.65		1.65	1.65
P(T<=t) two-tail		0.0076	3.2E-06		4.79E-07	2.28E-27

	20-30			30-45		
	SIMULATED	ANNUAL	PERENNIAL	SIMULATED	ANNUAL	PERENNIAL
Mean	21.4	18.65	16.83	21.26	17.65	15.73
Variance	7.06	13.46	9.34	3.187	9.16	6.42
Observations	174	174	174	174	174	174
P(T<=t) one-tail		6.63E-15	1.25E-39		3.11E-34	4.2E-74
t Critical one-tail		1.65	1.65		1.65	1.65
P(T<=t) two-tail		1.33E-14	2.51E-39		6.23E-34	8.39E-74

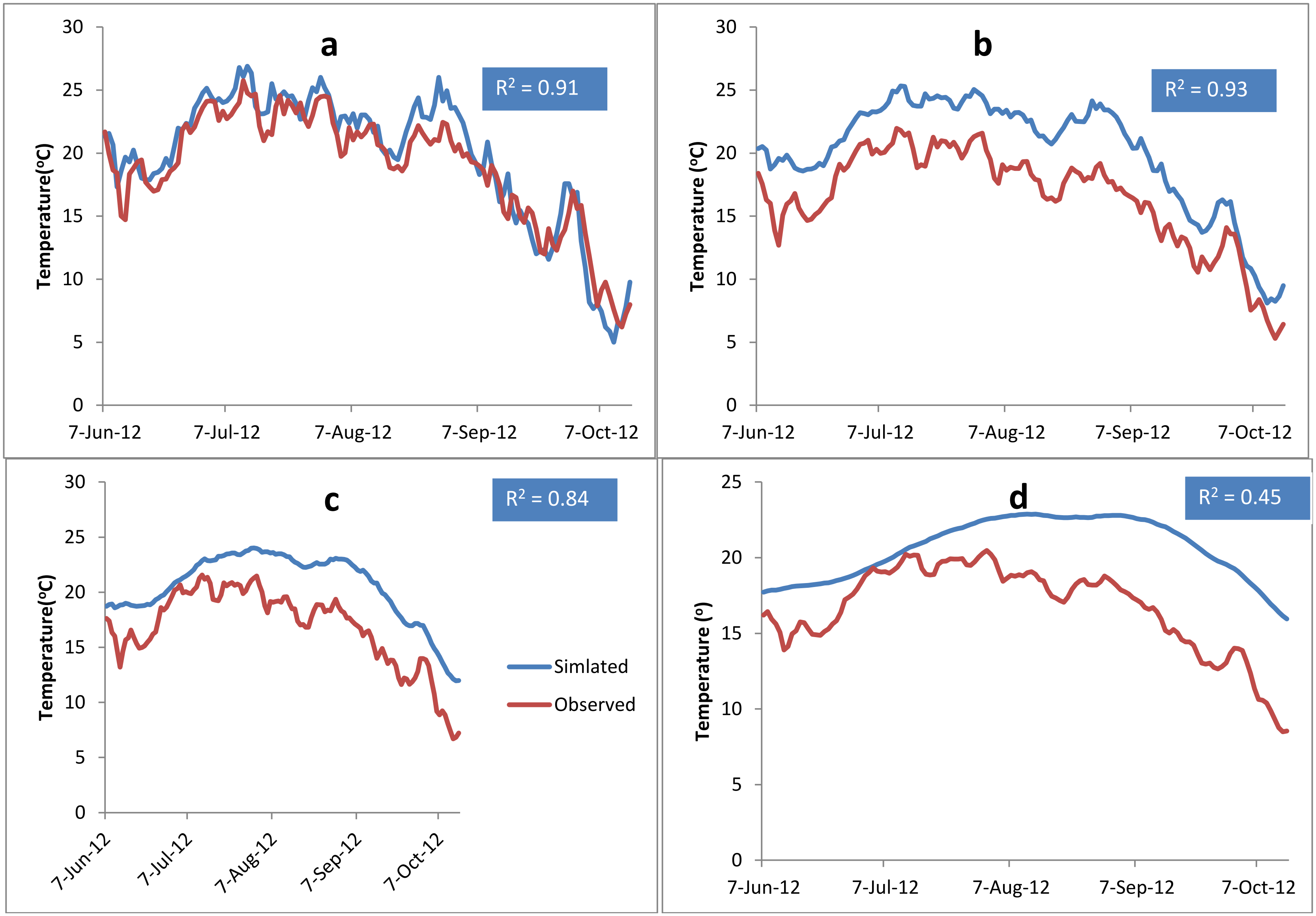
	45-60			60-90		
	SIMULATED	ANNUAL	PERENNIAL	SIMULATED	ANNUAL	PERENNIAL
Mean	20.52	16.73	15.07	18.97	15.76	14.26
Variance	3.55	5.66	4.05	6.62	3.45	2.37
Observations	174	174	174	174	174	174
P(T<=t) one-tail		1.07E-45	7.94E-84		1.76E-33	4.69E-63
t Critical one-tail		1.65	1.65		1.65	1.65
P(T<=t) two-tail		2.15E-45	1.59E-83		3.51E-33	9.37E-63

3.4.3 Model Validation Using Independent Temperature Data from Carberry, Manitoba.

This site has a history of being seeded with buckwheat alternated with canola and barley from 2003 till the time of collecting data for this study. During the time of collecting this data, barley and wheat were grown in this plot in the year 2012 and 2013 respectively. The soil in this site well drained sandy soil. The depths that were tested were 0-10cm, 10-20cm, 20-40cm, 40-60cm and 60-90cm. Daily average temperature measurements were used for both simulated and observed. The surface cover at Carberry field is similar to the annual plots of the Carman field. The model was able to capture the trend in daily soil temperature up to a depth of 40 cm (Figure 3.3). The coefficient of determination for depths below 40 cm was less than 50% signifying that more than 50% of variations in the measured soil temperature were not accounted for by model simulation. Similar to the results obtained at Carman, the model overestimated soil temperature at Carberry except at the soil surface in the year 2013. Similar to the observation made at Carman in 2013, statistical analysis of model performance at Carberry in 2013 showed that it performed better than in 2012 (Table 3.10). The mean bias error for all depths in 2013 was smaller compared to 2012 and the root mean square error was generally closer to one in 2013 compared to the year 2012. As can be seen from table 3.4, the root mean square error for depth ranges of 40-60 and 60-90 for 2012 and 2013 are 1.51, 5.91 and 1.18 and 2.63, respectively. The smaller RMSE values obtained in these higher depths agreed with the result of (Perreault et al., 2013). The mean bias error was also lower for these two depth ranges with year 2102 having 3.93 and 6.84 while in 2013, it was 0.74 and 3.34.

Table 3.10 Model simulation versus Daily observed Temperature data at Carberry in 2012 and 2013

		2012			2013		
	n	R^2	RMSE	MBE	R^2	RMSE	MBE
0-10	131	0.91	0.35	0.80	0.86	1.13	-1.90
10-20	131	0.93	1.97	3.64	0.78	0.59	2.91
20-40	131	0.84	1.11	3.76	0.33	0.99	2.23
40-60	131	0.45	1.51	3.94	0.02	1.18	0.74
60-90	131	0.2	5.91	6.84	0.04	2.63	3.34


a
R^2 = 0.91
b
R^2 = 0.93
c
R^2 = 0.84
d
R^2 = 0.45
Temperature(ºC)
Temperature (ºC)
Temperature (º)
30
25
20
15
10
5
0
7-Jun-12
7-Jul-12
7-Aug-12
7-Sep-12
7-Oct-12
Simlated
Observed

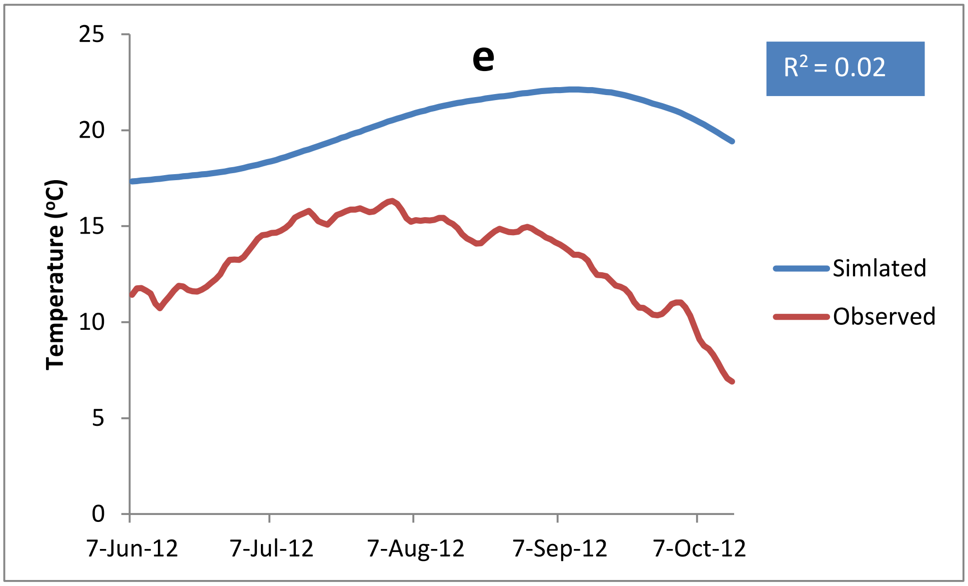


Figure 3.3. Daily field observation versus simulated temperature at Carberry in 2012 at 5 varying depths (a) 0-10 cm (b) 10-20 cm (c) 20-40 cm (d) 40-60 cm (e) 60-90 cm

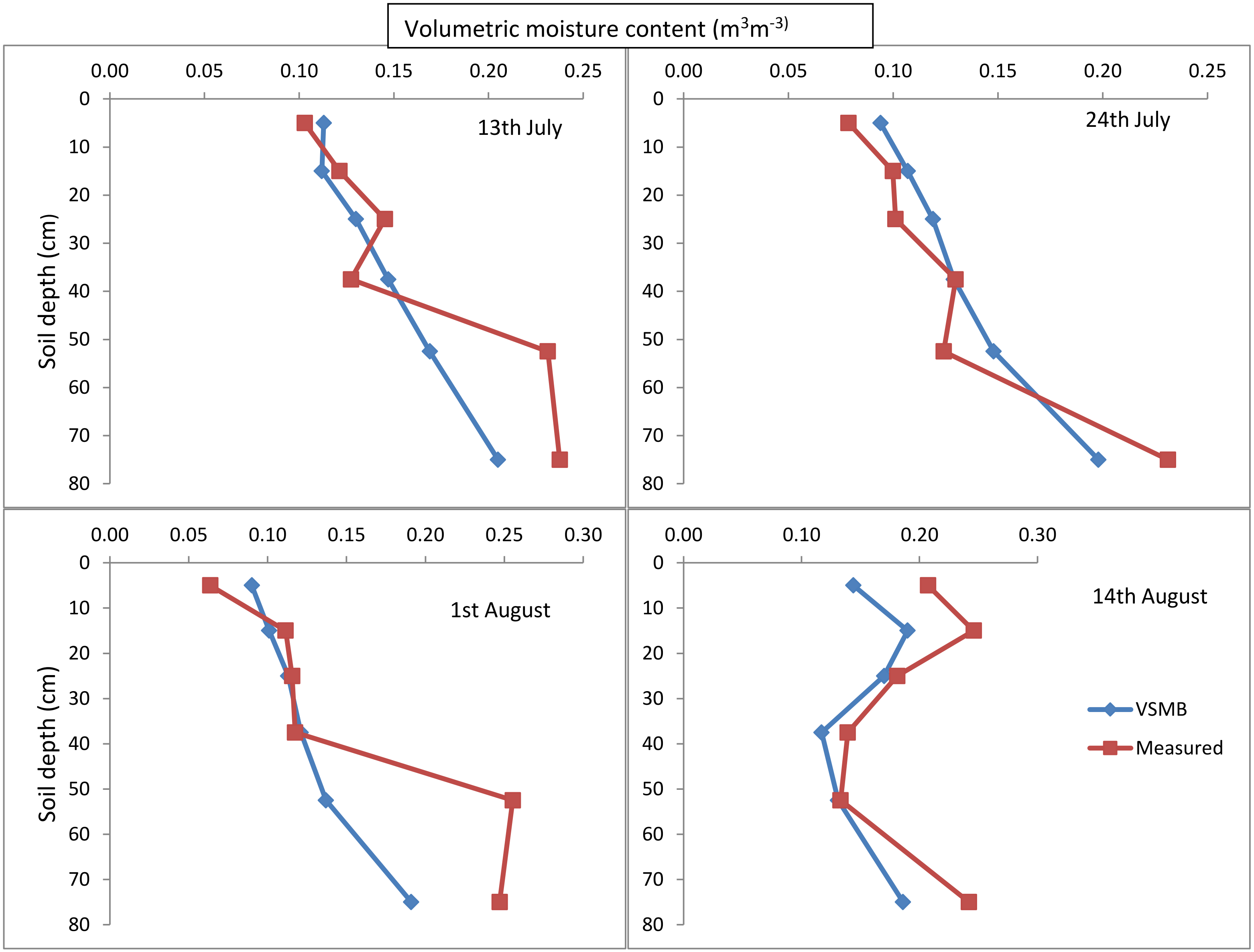
3.4. 4 Profile Comparison of Modeled Soil Moisture vs. Observed at Carman (2012).

Since the efforts to calibrate the hydra probe did not yield desirable results, thermo-gravimetric moisture content was compared with moisture content that was simulated by VSMB. This limited the comparison to the first year of study (2012). Figure 3.4 and 3.5 shows the comparison between the thermo-gravimetrically determined soil moisture and the modelled soil moisture from the VSMB from July 2012 to September 2012 at Carman, Manitoba.

Table 3.11 Statistical parameter for comparing agreement between simulated and observed soil moisture at Carman in 2012

	Annual			Perennial		
	R^2	RMSE (m^3m^{-3})	MBE (m^3m^{-3})	R^2	RMSE (m^3m^{-3})	MBE (m^3m^{-3})
0-10 cm	0.85	0.03	0.02	0.76	0.03	-0.02
10-20 cm	0.54	0.06	0.04	0.71	0.03	0.04
20-30 cm	0.42	0.04	0.03	0.48	0.04	0.02
30-45 cm	0.6	0.02	0.01	0.51	0.03	0.02
45-60 cm	0.38	0.05	0.02	0.5	0.03	0.02
60-90 cm	0.28	0.05	0.03	0.3	0.06	-0.06

The model generally overestimated soil moisture content except for two layers (0-10 cm and 60-90 cm) in the perennial plot (Table 3.11). The reason for such differences in the perennial plot could be due to the effect of vegetation on evapo-transpiration. The underestimation of soil moisture in the deepest layer in the perennial plot could also be due to the fact that the model did not transmit a sufficient amount of water to this layer especially during the growing season. The results of this evaluation further signify the necessity for the re-evaluation of the drying curve used in the VSMB.



Volumetric moisture content (m3m-3)
Soil depth (cm)
13th July
24th July
1st August
14th August
VSMB
Measured

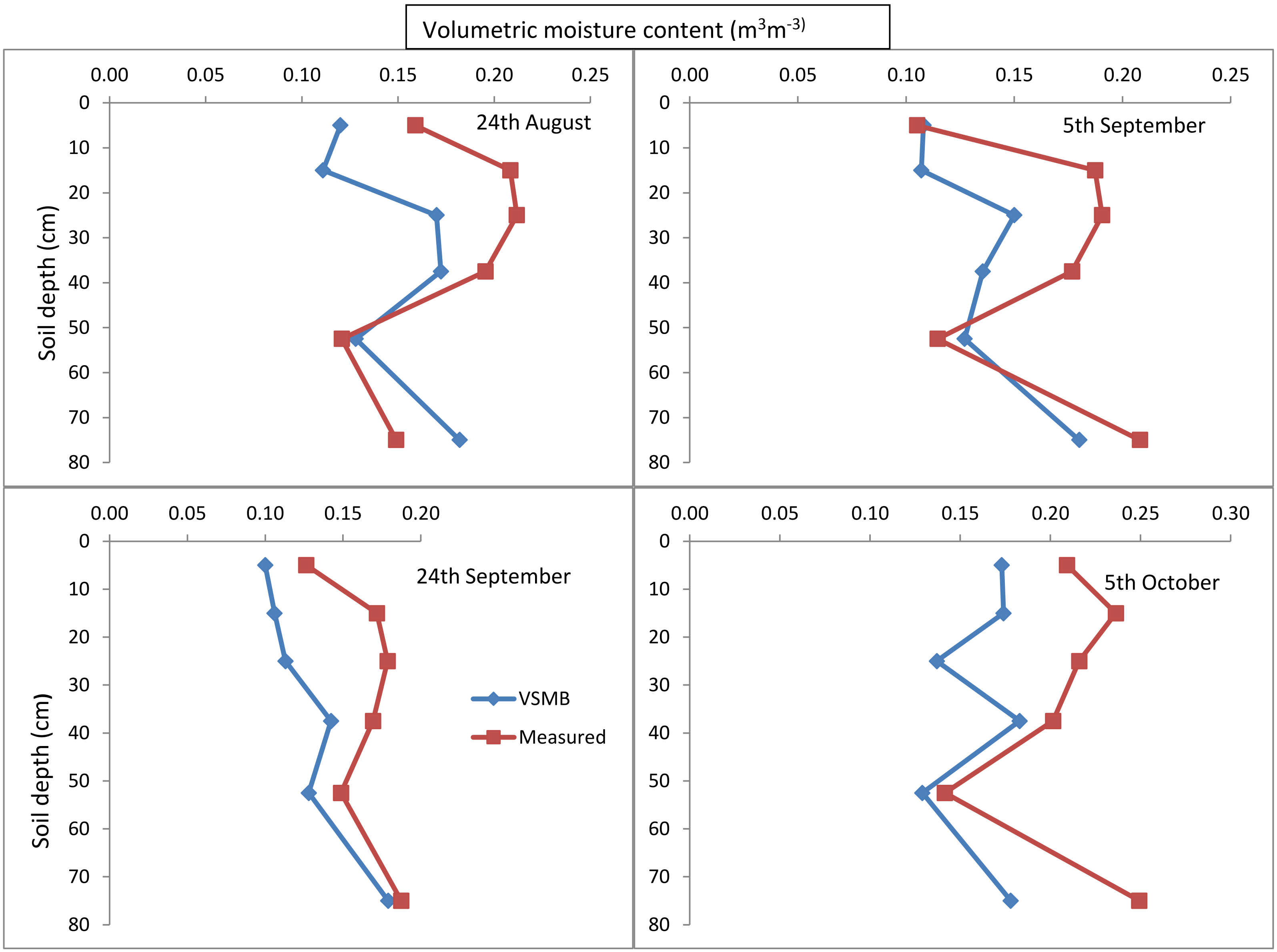
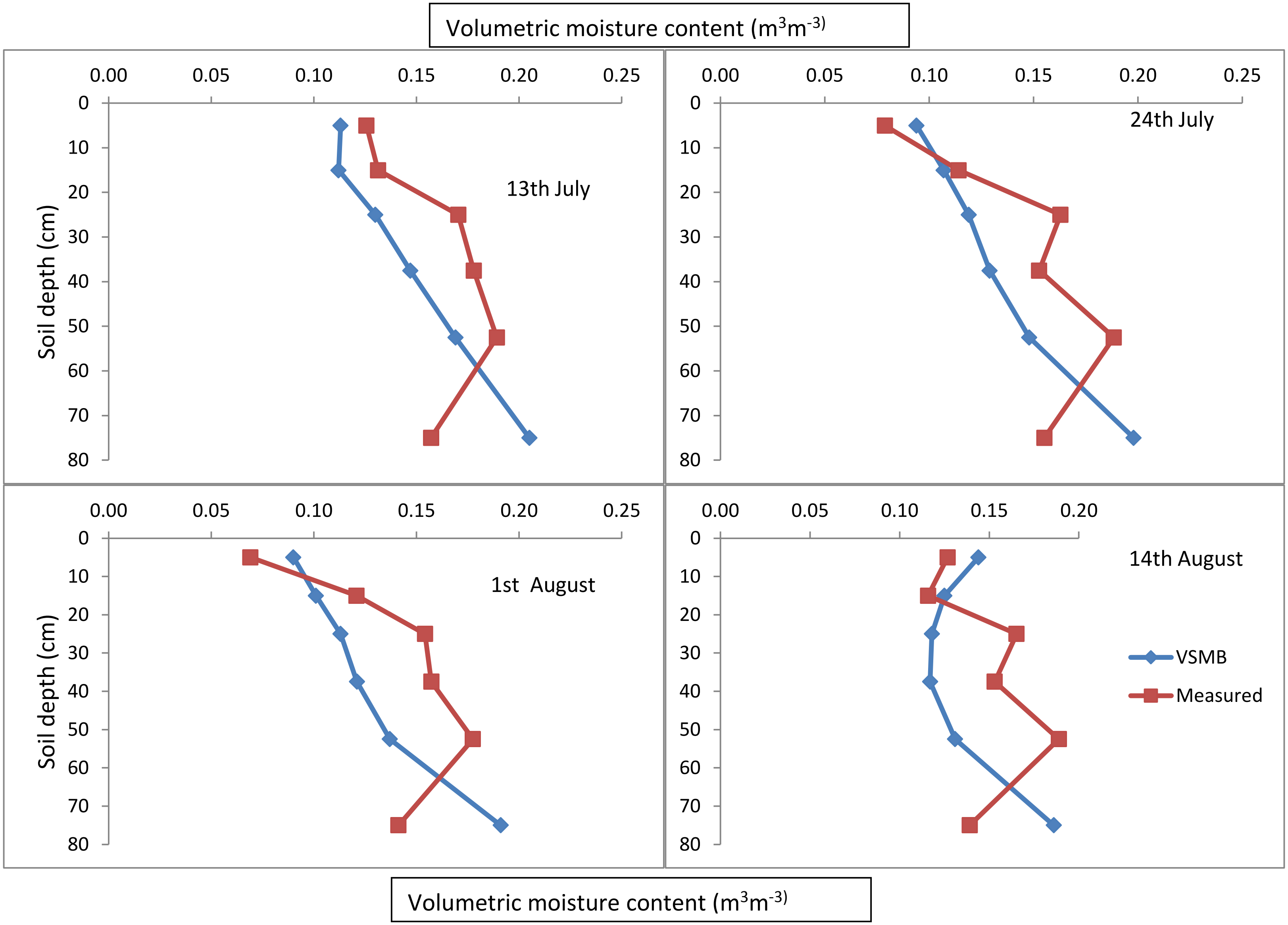


Figure 3.4 Changes in soil moisture content (simulated versus observed) between July to October 2012 at Carman (Annual)


Volumetric moisture content (m3m-3)
13th July
24th July
1st August
14th August
Soil depth (cm)
VSMB
Measured
Volumetric moisture content (m3m-3)

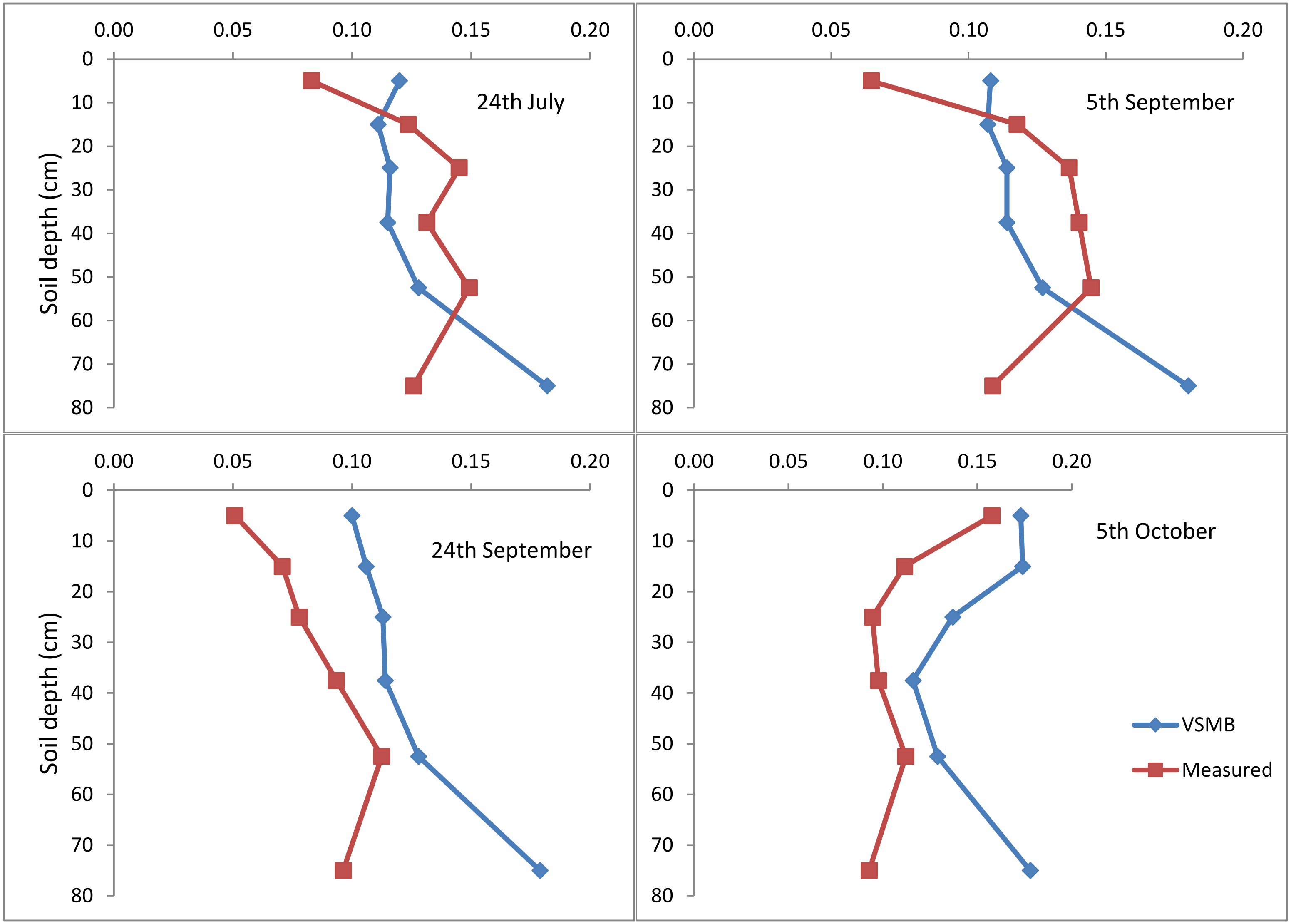


Figure 3.5 Changes in soil moisture content (simulated versus observed) between July to October 2012 at Carman (Perennial)

The model was able to capture the trend of the soil moisture especially at the surface of the soil to about 30 cm into the soil (Figure 3.4 and 3.5). These figures compared soil moisture contents that were measured 8 times in 2012 (13th July to 12th October) to model simulation for the annual plot (Figure 3.4) and Perennial plot (Figure 3.5). The results showed the performance of the VSMB in simulating soil moisture during the growing season and it was observed that performance differs at different stages with respect to depth. The smallest RMSE between model with observed values was 0.02m^{3}m^{-3} at the soil surface (0-10 cm) while the greatest RMSE was 0.081m^{3}m^{-3} at the 60-90 cm depth. The result showed that the model simulated soil surface soil moisture the best with R^2 of 0.84. This agrees with (Akinremi et al., 1996) that soil surface, though the most responsive to moisture changes because of influx of precipitation and evapo-transpiration, is the layer that is best simulated by the VSMB. Soil moisture was found to decrease with depth and so also did the coefficient of determination decline with depth.

3.5 Conclusions

The use of a model to estimate soil water and temperature has advantages and potentials. However, before these models can be used for decision making and planning purposes, there is the need to compare modeled results with observed values in the field or laboratory. Since temperature plays a major role in most environmental and agronomic models that involve soil-plant interaction because of its influence on almost all processes taking place on the soil, an assessment of the algorithm used in determining soil temperature in the agronomic models is vital. The soil temperature algorithm that was tested in this study worked fairly well on the soil surface to about a depth of 30 cm. It however failed to capture the trend of daily soil temperature at depths below 30 cm. It was also observed that the algorithm overestimated the daily soil temperature when compared with the observed. This overestimation was likely due to the fact that only the depths of interest, surface temperature and previous day temperature were used in this model and properties such as thermal diffusivity, moisture content, crop cover and amplitude changes were not factored into the model. The model nevertheless offers insight into how simple parametric equation can be introduced into the versatile soil moisture budget for soil temperature estimation down the soil profile. The VSMB also shows the need for improvement for moisture simulation that will account for a better reading of the drying curve and root extraction coefficient since it was observed that the model seemed to underestimated the observed moisture values most of the time.

Future studies that will look into how crop cover, moisture and thermal diffusivity can be introduced into the model for temperature simulation is recommended. Also, daily study of changes in the soil temperature amplitude over the course of the year is also recommended if accurate soil temperature estimation is desired.

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4.0 Overall Synthesis

Soil temperature has a significant impact on many physical, chemical and biological processes taking place in the soil and as such has a huge effect on agricultural production in general. The importance of soil temperature to crops is easily seen on its direct impact on seedling germination, emergence and growth thereby having great influence on overall crop biomass production (Weih and Karlsson, 2001). Soil temperature is very difficult to measure especially at the soil surface because of its high temporal and spatial variations. Because of the challenges and limitations with direct soil temperature measurement, there is a need for development of predictive models that can simulate soil temperature from the surface to the extent of the root. The prospect of formulating tractable models which relate soil temperature with other easily measured and accessible variable such as air temperature remains attractive (Lei et al., 2010).

In this field study, the soil surface temperature algorithm used in the versatile soil moisture budget was evaluated. An empirical equation employed in accounting for daily soil temperature at different depths of interest was introduced into the VSMB to enable it simulate soil temperature at any depth up to about 90 cm. The main objective of this research was accomplished in two parts. The first aspect included performance testing of the hydra probes which was reported in the chapter 2 of the study. This is important because of the need to verify that the outputs from the probes are comparable to the observed soil temperature and moisture. A research site was established using hydra probe sensors in Carman, Manitoba in 2012 and 2013 for the purpose of testing the VSMB soil temperature algorithm and soil moisture model. The Field calibrations were carried out in the first year of the study (2012) using the probes manufacturer's guidelines. The results of the studies show that hydra probes performed better for soil temperature than for soil moisture. The r^2 between the thermo-gravimetric moisture content and hydra probe measurements were found to be significantly low signifying a need for site specific calibration if high degree of accuracy is desired. The installed hydra probe produced a good fit with the installed thermocouple with a high r^2 greater than 0.90 in most cases suggesting that hydra probe can accurately measure soil temperature at greater accuracy with little or no specific site calibration. However, the R2 was low in the 0-10cm layer. The observed values from the probes formed the basis for which the model results were compared.

Chapter 3 focused on the evaluation and modification of the soil temperature algorithm in the VSMB model. Since the results from the instrument are point measurements and can be expensive to carry out on a large scale, models are employed to fill these gaps in a way to overcome the limitations of point specific measurements of the probes which do not incorporate measurement over time and space as is required in many agronomic applications (Akinremi and McGinn, 1996). A simple empirical equation requiring minimal inputs such as air temperature and soil depth was introduced into the VSMB model to simulate soil temperature at depth. This study showed that there are a lot of irregularities and discrepancies in using this algorithm to simulate soil temperature at depth. This research further affirms the need to account for some other variables when using an empirical equation in simulating soil temperature at depth (Kemp et al., 1992). Improving the accuracy of the VSMB in simulating soil temperature at depth holds great potential for farmers that will require accurate and immediate information about soil temperature at depth which is often time not included in data from weather station. The soil temperature algorithm in the VSMB if improved to simulate effectively at higher soil depths will help to understand the physical state of the soil at depths when VSMB is simulating soil moisture especially during the spring when snow has not fully melted. This has the potential to improve accuracy and efficiency of the VSMB. Severe soil temperature increase when combined with extreme water stress from the soil poses great danger to many agricultural applications. Thus, soil temperature monitoring and availability of real-time soil temperature estimate are vital in drought forecast and assessment, crop diseases and pest control and agronomic processes either at the provincial or national level.

4.1 Future Work

In order to improve the calibration procedure of the hydra probes especially for soil moisture, there is a need for site specific calibration procedure to increase the confidence level in the measured data. The number of laboratory determined soil moisture samples used for calibration should be increased since more data points will yield better representative calibrated equations and thus increase our confidence in the data. The different procedure for obtaining more accurate soil bulk density will improve the quality of the soil moisture estimates used in the calibration procedures.

Since comparative analysis between thermocouples and Hydra probes were weak at the surface of the soil surface above 10 cm, there needs to be some work done to improve results at the soil surface. First, a comparison needs to be run where the thermocouples and the Hydra probes are in very close proximity. The distance between them was too large in this study. There also needs to be special care taken in a comparison to ensure that the thermocouples compared to Hydra probes near the surface are at the same depth because there can be large differences in temperature with only small differences in depth near the soil surface. Finally, the comparison needs to occur where both the thermocouples and the Hydra probes have the same type of vegetative cover. Shading of the surface makes a significant impact on the energy absorbed and therefore, the temperature of the soil surface.

The algorithm that was introduced into this VSMB to simulate soil temperature at depth though performed better at the soil surface to about 30 cm. There is a need for an improvement on the algorithm or a replacement of the algorithm with another one that could simulate better than what was obtained in this study at depth. There will be a need to investigate the reason for the large discrepancies observed at depth using this algorithm. Study can look into varying K_1 and K_2 simultaneously to investigate if there will be better simulation especially at depth. Employing an algorithm that will include the soil thermal diffusivity though highly variable in space and time at different depths might provide a clue since soil temperature amplitude is dampened at depth. There is no documentation of any research at the moment that focused on using VSMB to simulate soil temperature at depth. Since VSMB is widely used, efforts should be made to study and improve its temperature simulation capacity. Knowing the temperature of the soil to a reasonable depth at anytime of the year will be helpful in determining the physical condition of model simulation site.

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APENDICES

Table A1 Field Capacity Determination for Carman

Plot 8 depth range	wt of can (g)	wt of can + wet soil(g)	Wt of oven dry soil(g)	Wt of Soil(g)	F.C in % g/g	Bulk density(g/cm3)	F.C in %Vol/Vol
0-10cm	37.96	133.7	123.9	9.8	11.40	1.31	14.90
10-20cm	38.62	157.74	143.87	13.87	13.18	1.31	17.22
20-30cm	38.35	153.55	137.99	15.56	15.62	1.12	17.49
30-45cm	38.39	177.99	157.74	20.25	16.97	1.36	23.07
45-60cm	38.08	175.48	158.44	17.04	14.16	1.40	19.78
60-90cm	38.43	131.92	117.89	14.03	17.66	1.40	24.71
Plot 9							
0-10cm	37.75	135.17	119.4	15.77	19.31	1.07	20.68
10-20cm	37.66	140	124.45	15.55	17.92	1.67	29.96
20-30cm	38.44	150.81	134.48	16.33	17.00	1.41	23.96
30-45cm	38.4	160.99	141.9	19.09	18.44	1.34	24.77
45-60cm	38.22	129.76	115.88	13.88	17.87	1.41	25.18
60-90cm	38.08	153.73	128.35	25.38	28.12	1.25	35.14
Plot 18							
0-10cm	38.18	121.44	110.2	11.24	15.61	1.03	16.08
10-20cm	38.5	121.38	111.32	10.06	13.81	1.37	18.89
20-30cm	38.14	152.65	138.373	14.277	14.24	1.44	20.56
30-45cm	38.69	131.72	120.81	10.91	13.29	1.07	14.26
45-60cm	37.88	153.38	139.48	13.9	13.68	1.47	20.15
60-90cm	38.15	158.99	147.25	11.74	10.76	1.32	14.26
Plot 19							
0-10cm	38.27	131.31	124.31	7	8.14	1.13	9.19
10-20cm	37.95	125.98	118.11	7.87	9.82	1.36	13.33
20-30cm	38.28	135.31	123.75	11.56	13.53	1.40	18.95
30-45cm	38.38	150.94	139.02	11.92	11.84	1.54	18.25
45-60cm	38.66	129.08	120.87	8.21	9.99	1.69	16.92
60-90cm	38.68	144.05	134.31	9.74	10.19	1.33	13.54