Spatial interpolation of improved groundwater recharge estimates on coarse textured soils

By

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Abstract

Groundwater recharge estimation is of fundamental significance to meet the agricultural water requirements, optimize water budget management, and further the sustainable development of water resources, particularly on coarse textured soil due to their rapid drainage behaviour. The objectives of the study were to evaluate the feasibility and robustness of groundwater recharge estimation using one-dimensional physically based modelling coupled with weather stations and to interpolate the point estimates of recharge to a regional scale. Installation of weather stations with soil moisture and temperature observation sensors and soil sampling were conducted at representative positions in the studies areas: Abbotsford, BC and La Broquerie, MB, Canada. The depth of the soil sensors ranged from 10 cm to 100 cm and covered the entire root zone of pasture. Groundwater level (GWL) loggers were installed in the multi-level wells in order to record the groundwater fluctuation during the study period, and the historical GWL data of the study areas were obtained from governmental agencies. GWL, soil properties, soil moisture, soil temperature, weather variables, and vegetation data were used as one-dimensional recharge modelling input and calibration data. Under free drainage condition (GWL > 10 m depth) in Abbotsford, BC, the mean annual recharge estimated at two stations was in average 840 mm (56% of annual total precipitation) and 854 mm (58% of average annual total precipitation) for a 1-year observation period and 27-year period, respectively. During the hydrologic winter period, 80% of recharge occurred due to the precipitation events. Under a variable water table condition (GWL < 2 m depth) in second study area of La Broquerie, MB, the recharge estimated at nine stations varied from 104 mm (55% of total precipitation during year 2014 to 2015) to 161.9 mm (85% of total precipitation during year 2014 to 2015), and the maximum recharge (57% of the

total recharge) was obtained from June to July due to the intensive precipitation in June. Since the modelling results from different study areas coincided well with other studies, this method is feasible and robust to produce reliable point estimates of recharge universally. Four methods of recharge interpolation were applied in the second study area and were cross-validated by means of true percent error between the simulated and predicted recharge. All methods consistently showed a mean recharge of approximately 130 mm during the study period and a changing trend. The best prediction (7.8% true percent error) was obtained by ordinary kriging. Therefore, the methods of using physically based vadose zone modelling and kriging to estimate both points and regional recharge on coarse textured soil are feasible and extendable.

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Contributions of Authors

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   b. Wang, Z.: Conducted the lab measurements and the model simulation, further development of methodology (part sensitivity analysis), paper writing, and correction
   c. Assefa, K.A.: Paper correction
   d. Woodbury, A.D.: Project monitoring and paper correction
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   b. Singh, N.: Field sampling and conducted laboratory experiments on particle size distribution soil parametrization using pedotransfer functions
   c. Holländer, H.M: Research idea initiation and supervision, field instruments installation, paper writing, and correction

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List of Nomenclature

d: distance between the interpolated points and the known points [m]

i: index of the interpolation points

Ks: hydraulic conductivity [cm/d]

n: van Genuchten-Mualem model empirical shape parameter

p: power parameter

t_j: secondary regionalized variable that is co-located with the primary regionalized variable z_i

u: interpolation value (recharge) [mm]

w: weight to the interpolated point

x: known point (recharge) [mm]

z_0*: estimate at the grid node (recharge) [mm]

z_i: regionalized variable at a given location (recharge) [mm]

α: van Genuchten-Mualem empirical model shape parameter [1/cm]

β_j: undetermined weight assigned to t_j and varies between 0 and 1

λ_i: undetermined weight assigned to the primary sample z_i and varies between 0 and 1

σ: standard deviation (soil water content) [cm^3/cm^3]

θ_r: residual water content [cm^3/cm^3]

θ_s: saturated water content [cm^3/cm^3]

List of Acronyms

1D: one-dimensional

API: American Petroleum Institute

ASTM: American Society for Testing and Materials

BCs: boundary conditions

CK: cokriging

D: depth from soil surface to groundwater table

FAO: Food and Agricultural Organization of the United Nations

FDR: Frequency Domain Reflectometry

GWL: groundwater level

IC: initial condition

IDW: inverse distance weighting

ME: mean error

NSE: Nash–Sutcliffe Efficiency

NN: natural neighbor

OK: ordinary kriging

P: precipitation

PET: potential evapotranspiration

PTF: Pedotransfer function

R: recharge

RMSE: root mean square error

USDA: United States Department of Agriculture

USGS: United States Geological Survey

UTM-14: Universal Transverse Mercator coordinate system, zone 14

VGM: van Genuchten-Mualem

1. Introduction

1.1 Overview

Groundwater, which is stored in the subsurface aquifers of the Earth, is considered one of the most important available natural resources. Worldwide, over 30% of the water used by cities for residential and industrial porpuses, and over 90% of water use in rural or agricultural land use areas is from groundwater (FAO 1993). Groundwater is often the sole source of water for major cities in Central America and Europe. However, with a rapidly increasing world population and industrial development, there is often greater pressure of utilization of groundwater. Strategies for monitoring groundwater storage are required that are practical, can help manage groundwater more sustainably. Groundwater recharge, as a primary hydrological process in the subsurface, replenishes groundwater through deep drainage of the soil. Commonly, the natural recharge source is precipitation, streamflow that is mainly from a surface water body, and snowmelt in cold regions. By downward percolation from the soil surface into the vadose zone, the deep drainage that enters the groundwater becomes recharge water. The accurate quantification of recharge rates is not easy since the whole process depends on many different factors of environment conditions, such as weather, soil, vegetation, and groundwater.

Groundwater recharge is highly variable in space and time. However, it is possible to estimate recharge amounts using vadose zone models. Modelling requires information and observations of weather, soil, and groundwater. However, weather, soil and groundwater observations are usually obtained at point based stations or boreholes, which limits the application of three-dimensional models of recharge. Additionally, such models are very computation and calibration intensive. Point estimates of recharge do not reflect the recharge condition of the entire watershed because of soil heterogeneity and uneven distribution of precipitation and vegetation. Therefore, two concerns have to be addressed in improving groundwater recharge estimates: how reliable is the recharge estimated by one-dimensional vadose zone modelling, and if it is reliable, how to upscale the results to the regional scale. Additionally, how to collect relevant data and use to validate models scaled to regions or watershed is uncertain.

1.2 Scope

As the primary data triggering the observation of groundwater recharge, the precipitation data is usually collected from weather stations. However, due to its complex distribution, the data is often not reliable for study areas located far from a station. Therefore, the installation of portable weather stations can help to overcome spatial shortcomings in reliable weather data. In addition to being low cost, using portable weather stations with soil sensors benefits collecting customized local weather and soil data. They can be installed, e.g., on the farm or specific research site. Vadose zone modelling has been widely applied to soil water movement studies since it has the advantages of physically-based nature, high efficiency, using on-site measurable input data, and scalable application and calibration of key parameters (Holländer et al. 2016). These are enough reasons to believe that coupling vadose zone model with soil sensor equipped portable weather station is able to produce reliable, one-dimensional (1D) recharge. In addition, very few studies using these methods were conducted and evaluated for 1D recharge estimation so far. In previous studies conducted on groundwater level interpolation, the comparison was made among different interpolation methods including local interpolation and geostatistical interpolation (Tonkin and Larson 2002; Xiao et al. 2016; Yao et al. 2014). However, recharge interpolation is more complex than that of groundwater level due to its relation to multiple parameters being mentioned in the last paragraph, which has not been done in the past.

This thesis is comprised of two manuscript-styled chapters (sandwiched thesis), and each of them contributes towards the main objectives. Chapter 3 has been peer-reviewed and published in Groundwater (Holländer, H.M., Wang, Z., Assefa, K.A., Woodbury, A.D., 2016. Improved Recharge Estimation from Portable, Low-Cost Weather Stations. Groundwater, 54(2): 243-254). The feasibility and robustness of recharge estimation were evaluated using physically-based modelling procedures, and data from a low-cost weather station with soil sensors in Southern Abbotsford, British Columbia, Canada. The manuscript presented as Chapter 4 is submitted to the journal Groundwater currently under review for publication (Wang, Z., Singh, N., Holländer, H.M., submitted. Spatial Interpolation of Groundwater Recharge Estimates on Coarse Textured Soils. Groundwater, GW20161027-0272). In this study, short-term groundwater recharge was estimated on sandy soils in southeastern Manitoba, Canada using 1D physically-based modelling and point estimates were scaled to the regional scale using two local and two geostatistical interpolation techniques.

1.3 Objectives

The main objective of the study was to estimate and spatially interpolate the groundwater recharge on coarse textured soils. The specific objectives of the study were:

i. To evaluate the feasibility and robustness of groundwater recharge estimation using one-dimensional physically-based modelling coupled with weather stations;

ii. To interpolate the point estimates of recharge to a regional scale using different interpolation methods.

2. Literature Review

2.1 Recharge Estimation on Coarse Textured Soil

Seasonal climatic variability produces extreme changes the spatial and temporal distribution of recharge on coarse textured soils, which usually happens in fast downward drainage. Due to the complexity of surface geology and hydrology, groundwater recharge is almost impossible to measure directly (USGS, 2015). Therefore, accurate recharge estimation on coarse textured soil can be a difficult task (Scanlon et al. 2002). The methods of recharge quantification can be classified into five general categories: i) water budget methods, ii) groundwater methods, iii) streamflow methods, iv) tracer methods, and v) vadose zone methods (Scanlon et al. 2002). Applying water budget methods, which has similarities to vadose zone methods, proposed to estimate the quantity of the main hydrological processes, such as infiltration, surface runoff, evapotranspiration, to determine the recharge by subtracting them from precipitation (Lee et al. 2008; Melo et al. 2015; Lee et al. 2006a). It is a commonly used straightforward method for regional recharge estimation. However, its main limitation is that the accuracy of the result strongly dependent on the accuracy of the other components. Specifically, on coarse textured soil, the accuracy depends more on the availability of the short time interval data and the quality of soil data, such as heterogeneity, due to the fast drainage in the soil profile comparing with finer soils. Additionally, this method is not recommended due to its data-based calculation mechanism (Scanlon et al. 2002). Surface water techniques, including physically-based groundwater method and streamflow methods, and tracer based method, were developed to investigate the degree of connections between surface water and groundwater systems (Scanlon et al. 2002; Taylor and Howard 1996). For instance, the increase of surface water level is considered as groundwater discharge to streams and lakes, and vice versa (Arnold and Allen 1999; Meyboom 1961). By analyzing the gauging data and the hydrograph of the groundwater table, the transmission at the interface of unsaturation and saturation can be statistically determined (Sophocleous 1991; Healy and Cook 2002; Moon et al. 2004). The range of recharge rates can be measured based on the transmission difference (loss) between systems in a long-term calculation. Since these methods are based on the assumption that the soil water retention and evapotranspiration are negligible, there is a potential to overestimate actual recharge due to the disregard of the seasonal soil water storage change and the subsequent evapotranspiration. Scanlon et al. (2002) pointed out that the application of the streamflow method was limited on fine soils or where low permeable layers exist, such as lake/river bed in a humid region for a long-term study. Another physically-based technique is analyzing the water budget of the vadose zone (Allison et al. 1994). The various soil water components can be accurately measured using lysimeters (Allen and Fisher 1991). In order to measure the soil water change, lysimeters are installed to hydrologically isolate the soil by a container and were placed under the same environmental conditions as the surrounding area. Recharge can then be determined by drainage collection at the base (deeper than the root zone) and can be estimated at time scales from minutes to years depending on the recording frequency. Therefore, the vadose zone method can produce comparatively high accuracy recharge estimation on a variety of time scale unconditionally on soil types. However, lysimeters are difficult to construct and to manage so that high costs are associated with local measurements.

2.2 Numerical Modelling

With the continuous development of computer simulation technology and the popularity of many aforementioned methods have been developed further using numerical methods that can simulate the groundwater recharge based on the original principles. However, the reliability of the recharge estimates strongly depends on the accuracy of the input data, the certainty of the parameters, the validity of assumptions, and the mechanism of the selected model (Scanlon et al. 2002). The recognized reliable input data can be collected, e.g., from government documents, samples, and data recorded by observation instruments. Through analyzing the quality and the properties of the samples by laboratory and field experiments, the properties of data recorded by observation instruments, and the parameterization of the model can be initialized. Usually, the data or the parameters which are difficult or expensive to obtain, are assumed by expert guess or using literature values. Therefore, assumptions on parameters are commonly identified as a major source of the model uncertainties, which leads to the necessity of the model calibration. Model calibration is explained in detail in the case studies (Chapter 3 and Chapter 4). The uncertainty caused by the model mechanism can be minimized by understanding the strengths and the limitations of the selected model regarding the detail research condition. After all, numerical modelling of vadose zone is a feasible way to utilize the principle of lysimeters method to estimate recharge instead of physical construction. Thus, the cost and time-consuming problems were solved.

One of the most commonly used physically-based vadose zone models HYDRUS-1D can be used to simulate various hydrological processes in the vadose zone, such as deep drainage (recharge) (Xiao et al. 2016; Šimůnek and van Genuchten 2008). The mixed form of Richards equation, which combines head-based and saturation-based formulations are applied to minimize the mass balance error without affecting modelling capability near saturation using Galerkin linear finite element schemes (Šimůnek and van Genuchten 2008). As discussed before, accurate data such as weather, vegetation, and soil data in terms of soil temperature and soil moisture are necessary as model input (Holländer et al. 2014; Bormann et al. 2011). HYDRUS-1D is also equipped with other physically-based key functions officially recognized by international organizations and governments: the van Genuchten-Mualem model (van Genuchten 1980; Mualem 1976) for determining water retention behaviour in the soil; Penman-Monteith equation combined with Feddes-type uptake functions and Chung and Horton equation for determining water content changes due to the root water stress and heat transport within the soil media (Feddes 1978; Allen 1998; Chung 1987; Pulido-Velazquez et al. 2007). Numerical modelling has the advantages of lower cost, less uncertainty, more flexibility, scalable and higher efficiency compared to the aforementioned methods (Pulido-Velazquez 2007; Zhou and Li 2011). Above all, there are enough reasons to believe that the physically-based vadose zone numerical model is able to produce reliable estimates on groundwater recharge.

2.3 Interpolation

Groundwater recharge is highly variable in space and time (Frances 2008; Holländer et al. 2016). The accurate and robust results from physically-based modelling are point estimates of recharge. Therefore, extending the attempt using the same parameters might not result in reliable recharge values at other locations within the watershed due to heterogeneity at different scales. Spatial interpolation is a complex operation taking observations, neighborhood distribution and uncertainties of interpolation models into account to interpolate the estimates to any spatial scale (Healy 2010b). Interpolation techniques can be applied to determine spatially distributed recharge for an entire watershed. One of the most widely used and easiest approaches for estimating recharge are simple empirical models which calculate the fraction of recharge into precipitation at sample locations and estimate the recharge using the precipitation data (where available) at the other locations (Saghravani et al. 2013a). However, this method is only effective at low heterogeneity (Healy 2010b). Regression techniques are another widely used approach. Linear regression equations are generally used to extrapolate the historical recharge estimates.

Besides the precipitation, additional parameters, such as specific yield and vegetation data are usually required for equation formulation (Lorenz and Delin 2007), which is considered inconvenient for limited and no data area. In recent decades, geostatistics has been used in a variety of hydrologic applications including recharge estimation (Lee et al. 2006b; Hevesi et al. 1992). One approach of geostatistics is kriging (Krige and Matheron 1967; Matheron 1967) which is an interpolation method that allows estimating recharge at any location in a watershed if point estimates of recharge are obtained at fixed locations within the same watershed (Journel and Huijbregts 1978). Specifically, the interpolated recharges are modeled by a Gaussian process governed by prior covariances, as opposed to a piecewise polynomial spline chosen to optimize smoothness of the fitted values. By setting up a grid over a watershed and determining kriging estimates of recharge at each grid point, an estimate of recharge integrated over the entire watershed can be obtained (Healy 2010b).

3. Improved Recharge Estimation from Portable, Low-Cost Weather Stations*

Abstract

Groundwater recharge estimation is a critical quantity for sustainable groundwater management. The feasibility and robustness of recharge estimation was evaluated using physically-based modelling procedures, and data from a low-cost weather station with soil sensors in Southern Abbotsford, British Columbia, Canada. Recharge was determined using the Richard's based vadose zone hydrological model, HYDRUS-1D. The required meteorological data were recorded with an HOBO^{TM} weather station for a short observation period (about 1 year) and an existing weather station (Abbotsford A) for long-term study purpose (27 years). Undisturbed soil cores were taken at two locations in the vicinity of the HOBO^{TM} weather station. The derived soil hydraulic parameters were used to characterize the soil in the numerical model. Model performance was evaluated using observed soil moisture and soil temperature data obtained from subsurface soil sensors. A rigorous sensitivity analysis was used to test the robustness of the model. Recharge during the short observation period was estimated at 863 mm and 816 mm. The mean annual recharge was estimated at 848 mm/year, and 859 mm/year based on a time series of 27 years. The relative ratio of annual recharge-precipitation varied from 43% to 69%. From a monthly recharge perspective, the majority (80%) of recharge due to precipitation occurred during the hydrologic winter period. The comparison of the recharge estimates with other studies indicates a good agreement. Furthermore, this method is able to predict transient recharge estimates, and can provide a reasonable tool for estimates on nutrient leaching which is often controlled by strong precipitation events and rapid infiltration of water and nitrate into the soil.

3.1 Introduction

*Holländer, H.M., Wang, Z., Assefa, K.A., Woodbury, A.D., 2016. Improved Recharge Estimation from Portable, Low-Cost Weather Stations. Groundwater, 54(2): 243-254

Estimation of groundwater recharge, which is a fundamentally transient and spatially variable process, is a difficult task, and values are often associated with a high degree of uncertainty. A commonly used method to estimate recharge is physically based vadose zone modelling, using the one-dimensional Richards equation (e.g., Jimenez-Martinez et al. 2009; Keese et al. 2005). These studies pointed out that vadose zone modelling is effective in the estimation of reliable recharge estimations. Reliable recharge estimates are defined in this paper by estimates which can be reproduced by other methods on recharge prediction. In order to determine reliable recharge estimations using physically-based vadose zone modelling, accurate weather, vegetation, and soil data, such as soil temperature and soil water content are needed (Holländer et al. 2014; Bormann et al. 2011). Specifically, the HYDRUS-1D finite element code was developed to solve the Richards equation in the vertical direction (Simunek et al. 2008). Assefa and Woodbury (2013) and Chen et al. (2014) pointed out that the HYDRUS-1D can provide acceptable results of the infiltration rate and cumulative infiltration at different scales.

Most soil moisture measurements were carried out in the uppermost part of the vadose zone, and especially in the root zone due to the common installation of sensors at this depth (Rimon et al. 2007). This indirectly addressed uncertainties in distinguishing between deep percolation and recharge due to the lack of information below the root zone (Leterme et al. 2012; Rimon et al. 2007). Deep percolation is defined by water that moves down through the soil profile below the root zone and cannot be utilized by plants (Hillel 2004), and recharge is defined by water which reaches the groundwater table (Fetter 2001). Installing sensors to measure soil moisture content is a critical step for recharge estimation. We believe that the best results can be achieved using data logger to measure all required field data. Using cellular data logger provides: (i) an inexpensive and rapid method of acquiring up-to-date information (ii) the ability to obtain data from remotely accessible areas (iii) reduced travel to observation sites, and (iv) compatibility with existing computer devices and software, e.g. combined with GIS. An automated data recorder can be installed with a weather station which records detailed climate data (e.g., air temperature, precipitation, wind speed, solar radiation) and thus, adds valuable data to any project. The additional transfer of data using a cellular network allows frequent delivery of the data and early warnings on malfunctions of the sensors. This data package allows for numerical modelling, using the observed soil moisture for calibration, while simulating the recharge with climate data as input. Of major importance for the acceptance of such a method are cost and robustness.

This paper is a follow-up to Hejazi and Woodbury (2011) and Assefa and Woodbury (2013). These works showed how detailed field measurements can be combined with high resolution numerical simulations to produce accurate calculations of recharge. Neither of these works though, had detailed measurements of all pertinent soil parameters at the exact same location as observed dependent variables, such as moisture and temperature. This new study shows how data from a low cost weather station, with additional soil moisture and soil temperature sensors from short-term observations can be used for robust recharge predictions. A robust recharge prediction is defined in this paper as the ability of our method to provide a reliable recharge estimate although most input data are derived from a low-cost weather station. In order to calculate the relevant long-term recharge estimates, data from a short-term measurement campaign are temporally interpolated using additional weather data from Environment Canada (2013). Finally, we will apply the aforementioned monitoring-modelling approach to a site in the Abbotsford aquifer. An intensive agricultural use of nutrients and a high annual precipitation can trigger leaching, which is a key factor for endangering the groundwater quality within this trans-boundary aquifer.

3.2 Study Area

This study was conducted in Southern Abbotsford, British Columbia, Canada (Figure 3.1). The mean daily maximum and minimum temperatures recorded from 1971 to 2000 were 14.7°C and 5.3°C, respectively (Environment Canada 2013). The study area is affected by the Pacific Ocean climate, which has mild and moist winters so that the majority of precipitation (~70%, Environment Canada (2013)) falls in the fall and winter. The mean annual precipitation is 1507 mm (1984-2013). Most of it (96.5%) is rainfall and the rest, snowfall (Environment Canada 2013).

Most of the Southern Abbotsford area is situated over the Abbotsford-Sumas Aquifer which is an unconfined trans-boundary aquifer (Figure 3.1). The aquifer covers 260 km^2 and groundwater flows in a southwest direction. The soil type is generally a sandy soil. The groundwater table at the edges of the aquifer is 0 to 5 m below the surface. While at the central portion, where this study area is located, it is at least 30 m below the surface (Abbotsford-Sumas Aquifer International Task Force 2014). The area has the largest agriculture production and the heaviest concentration of agriculture-related goods in British Columbia.

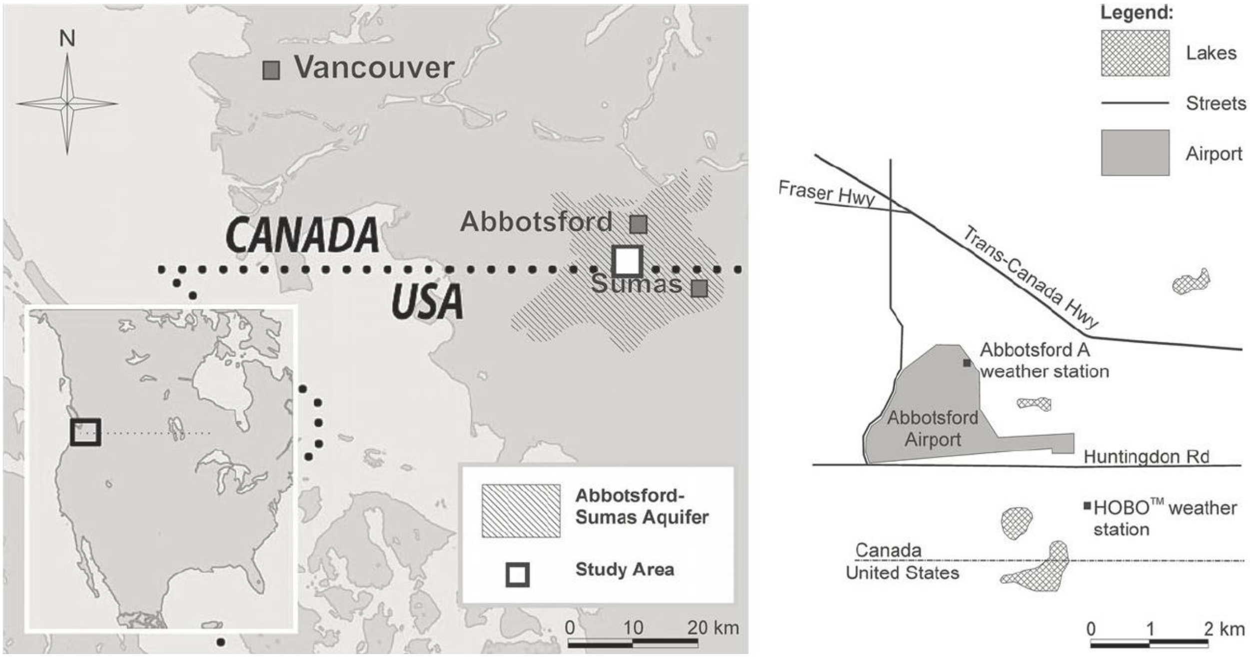


Figure 3.1: Map of Abbotsford-Sumas Aquifer across the Canada-U.S. Border

3.2.1 Data

A HOBO^{TM} U30 weather station at (49.010441 N, -122.33256 E) was installed on 18th April 2012 and dismantled on 19th March 2013. It was located 2800 m southwest of a government weather station (Abbotsford A) to provide weather and soil observations, which is generally needed for short-term studies. The HOBO^{TM} weather station provided “plug-and-play” smart sensors for measuring soil temperature, soil moisture and climate data including air temperature, precipitation, solar radiation, wind speed, relative humidity and atmospheric pressure (Table 3.1). Trenches were excavated to install soil temperature and FDR (Frequency Domain Reflectometry) soil moisture probes which are to measure the operating frequency of an oscillating circuit to obtain the dielectric constant of a certain volume water around the sensor. The sensors were installed horizontally into a vertical trench face to record soil moisture and soil temperature data at different depths. The recording time step was set to 30 minutes to receive comprehensive information on the soil moisture using FDR (Frequency Domain Reflectometry) and the soil temperature. Three sensors were installed vertically to record soil temperature and soil moisture at 10 cm, 37 cm and 100 cm depth. Therefore, the entire root zone of grass, the dominant vegetation on the site, was represented.

Table 3.1: Sensors specifications

Parameter	**Instrument**	**Installation**	**Range**	**Accuracy**
Barometric Pressure	S-BPB-CM50	1 m height	600 - 1070 mbar	±3.0 mbar
Solar Radiation (Spectral Range):	S-LIB-M003 300 to 1100 nm	2 m height	0 - 1280 W/m^2	±10 W/m^2
Air temperature	S-THB-M008	2 m height	-40 - 75°C	±0.13°C
Relative humidity	S-THB-M008	2 m height	0 - 100%	±2.5%
Rainfall	S-RGB	1 m height	0 – 127 mm/h	±1% <20 mm/h
Soil temperature	S-TMB-M006	10 cm depth	-40 - 100°C	±0.2°C
Water content	S-SMC-M005	10 cm depth	0 - 0.55 m^3/m^3	±0.031 m^3/m^3
Wind speed	S-WSA-M003	2 m height	0 - 45 m/s	±1.1 m/s

The costs of the weather station including the additional soil sensors was CA$ 4,890 and the annual costs of CA$ 300 for the cellular telemetry. API (1996) reported on the costs for recharge estimations and considered the following cost brackets: low cost: less than US$ 10,000; moderate cost: US$ 10,000 ~ US$ 50,000; high cost: greater than US$ 50,000 ($ 10,000 ≈ CA$ 13,600 in year 1996). The inflation rate from 1996 to 2012 is 43% according to the Bureau of Labor Statistics (BLS 2014). Therefore, the investment costs of CA$ 4,890 in 2012 has to be considered as low. Additionally, one day (each) for installing, dismantling of the weather station and for maintenance and installing of an additional soil moisture sensor at 100 cm depth (15th August 2012) was required. This results in a total time of about three working days for the weather station. The instrumentation faced no maintenance during that year or after return from the measurement campaign from the field since no noticeable drifts was found when all sensors were tested after their return.

The mean temperature recorded by the HOBO^{TM} weather station was 10°C and the mean daily temperatures ranged from -3°C to 25°C (Figure 3.2). Any precipitation falling as snow could not be recorded due to the nature of the available sensors (Table 3.1). This is not judged to be a major shortcoming with our experimental setup as will be shown later in the paper. Note, due to the Pacific influence on the climate, nearly 60% of the total precipitation (1375.8 mm) within the observation period, as obtained from the HOBO^{TM} weather station, was contributed during the hydrologic winter period, from 1st November 2012 to 19th March 2013.

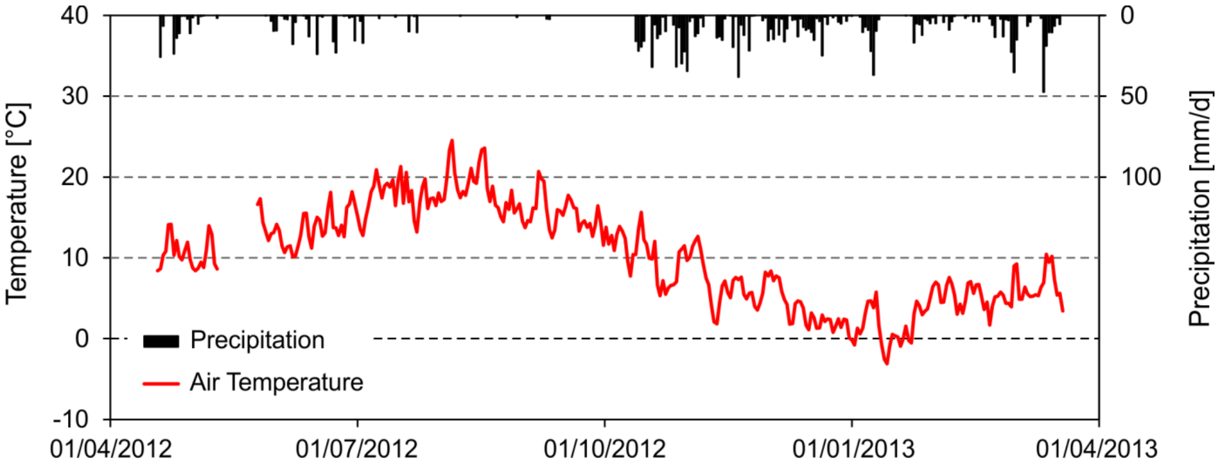


Figure. 3.2: Daily average of observed air temperature and precipitation at the HOBO™ U30 weather station (April 2012 – March 2013)

Additional weather data from the Abbotsford A weather station were obtained from Environment Canada (2013) to determine recharge estimation on a long-term basis. Daily maximum temperature, minimum temperature, total precipitation, wind speed and solar radiation from 1984 to 2010 (27 years) were available. The mean temperature was 10°C, and the annual mean precipitation was recorded as 1529 mm/year with a standard deviation σ of 223 mm/year in the 27-year period. The total precipitation recorded during the observation period by the HOBO™ weather station was 1375.8 mm, which was virtually the same as the precipitation recorded at the Abbotsford A weather station (1360.4 mm).

3.2.2 Laboratory Measurements

Two soil cores, named site 1 and site 2, were taken down to 61 cm and 91 cm with a same diameter of 6.35 cm, respectively next to the weather station at the time of removal. Sieve analyses and constant-head permeability testing were conducted to determine the properties of soil samples. The sieve analysis was carried out according to ASTM C 136-06 (ASTM 2006a). The resulting data have been applied to the USDA textual classification to determine the sand, silt and clay composition of all samples. The soil samples were characterized by a major fraction of sand (55-87%), a silt fraction between 5 and 42% and a clay fraction of 1 to 22% (Table 3.2). The permeability testing was in accordance with ASTM D 2434-68 (ASTM 2006b). All soil samples were tested three times at five different inflow hydraulic heads. The resulting hydraulic conductivity ranged from 7 cm/d to 109 cm/d. The standard deviation of the hydraulic conductivity was in all cases <10% (Table 3.2).

Table 3.2: Soil texture and hydraulic conductivities of soil samples

Soil samples	Depth [cm]	Sand [%]	Silt [%]	Clay [%]	Ks [cm/d]	σ [cm/d]
Site1 0"-6"	0 – 15.2	87.1	4.9	8.0	27.8	0.7
Site1 10"-16"	25.4 – 40.6	55.2	41.8	3.0	7.0	0.2
Site1 18"-24"	45.7 – 61.0	58.0	39.0	3.0	29.5	1.1
Site2 0"-6"	0 – 15.2	63.2	31.8	5.0	96.4	8.8
Site2 10"-16"	25.4 – 40.6	66.2	32.4	1.3	105.4	7.3
Site2 18"-24"	45.7 – 61.0	55.9	22.1	22.0	36.5	1.5
Site2 30"-36"	76.2 – 91.4	84.1	5.9	10.0	108.8	6.2

3.3 Vadose Zone Modelling

3.3.1 Governing Equations

Physically-based vadose zone modelling using HYDRUS-1D version 4.16 (Simunek et al. 2008) was used to estimate recharge. To minimize the large mass balance errors without affecting modelling capability near saturation, the mixed form of the Richard equation, which combines head-based and saturation-based formulations was applied by HYDRUS-1D, using Galerkin linear finite element schemes (Simunek et al. 2008; Celia et al. 1990).

The van Genuchten-Mualem (VGM) model (van Genuchten 1980; Mualem 1976) was chosen as an indirect method for water retention behaviour determination on the given soil samples. Besides saturated hydraulic conductivity Ks, which was measured during the laboratory measurement period, actual measurements of soil unsaturated hydraulic properties are time-consuming, complex, and costly. Therefore, the other four parameters (saturated water content θ_s, residual water content θ_r, and the van Genuchten empirical shape parameters α and n) within the VGM model were estimated using ROSETTA (Schaap et al. 2001) and used as initial parameterisation. ROSETTA uses pedotransfer functions (PTF) to predict the VGM parameter by using the soil texture distribution (Table 3.2). The soil properties of each sample were applied to the same soil depth in the model. Mean soil properties were assigned to model cells below the observations.

The Chung and Horton equation (Chung and Horton 1987), which is also dependent on the soil texture, was used to estimate thermal conductivity. In this study, parameters have been determined from the default values based on the dominant soil class of sand.

The effect of evapotranspiration and root water uptake on the water distribution in the vadose zone was represented by Feddes-type uptake functions (Feddes et al. 1978a). The flux due to root uptake was estimated as a function of potential transpiration and the pressure head. The vegetation at weather station was observed as pasture. The default parameterization of pasture from the database integrated into the HYDRUS-1D code was therefore used. The potential evapotranspiration PET [LT^{-1}] was calculated by Penman-Monteith equation (Allen et al. 1998) which requires climate data as input, such as daily mean temperature, wind speed, relative humidity and solar radiation; all of these data were recorded by HOBO™ weather station. A detailed description of the Penman-Monteith method can be found in Allen et al. (1998).

3.3.2 Boundary and Initial Conditions

Boundary conditions (BCs) are related to external forcing in this study, such as precipitation, distinct temperature differences between summer and winter, and the existing soil moisture conditions. The upper BC was defined as "atmospheric BC with surface runoff" in order to address the high precipitation volume and available daily meteorological data. Additionally, snow accumulation and thawing was accounted for. The lower BC is considered free drainage at a depth of 2 m since this depth was below the effective root zone from where water can enter vertically due to a plant-relevant capillary rise within the soil. This lower BC is most appropriate for situations where the water table lies far below the domain of interest (Simunek et al. 2008). For this study, the depth to the groundwater table was greater than 30 m in the central part of the study area (refer to Study Area).

The outflow at the lower boundary out of the model (at 2 m depth) yields the rate for deep percolation. Vaccaro (2007) showed that the soil moisture content below that depth has to be at least at field capacity without further losses. Therefore, the same amount of water which leaves the model at the 2 m level will recharge the aquifer as soon it reaches the groundwater level at 30 m below the soil surface. The initial condition (IC) of soil moisture and soil temperature was linearized between the observed soil temperature and moisture at difference depths.

3.3.3 Calibration

The prediction of the VGM parameters using ROSETTA was described in the Governing Equations section. However, ROSETTA was developed based on a set of soil samples obtained from USA and European countries. Thus, it could cause inaccurate predictions when applied on soil samples from other geographical regions. For these reasons, the HYDRUS-1D parameter estimation module was also used, and this can be described as an “inverse option” (Simunek et al. 2008), to improve estimates of soil properties by a Marquardt-Levenberg type parameter optimization algorithm. The Marquardt nonlinear minimization method is a weighted, least-squares approach based on Marquardt's maximum neighborhood method (Marquardt 1967). Only the saturated hydraulic conductivity Ks was determined directly during the laboratory measurement and was considered “fixed”. The other VGM parameters (θ_s, θ_r, α, and n) were initially estimated by ROSETTA (Table 3.3a). As a consequence, these parameters were used for calibration versus the observed soil moisture and soil temperature data at different depths. The calibrated VGM parameters were used afterwards to model the long-term recharge estimates (Table 3.3b).

Table 3.3a: VGM parameters predicted by PTF

Soil Samples	**Depth [cm]**	**θ_r [m³/m³]**	**θ_s [m³/m³]**	**α [1/cm]**	**n [-]**
Site1 0"-6"	0 – 15.2	0.05	0.37	0.03	2.07
Site1 10"-16"	25.4 – 40.6	0.03	0.41	0.02	1.45
Site1 18"-24"	45.7 – 61.0	0.03	0.41	0.02	1.43
Site2 0"-6"	0 – 15.2	0.03	0.39	0.03	1.41
Site2 10"-16"	25.4 – 40.6	0.03	0.41	0.04	1.43
Site2 18"-24"	45.7 – 61.0	0.06	0.39	0.02	1.36
Site2 30"-36"	76.2 – 91.4	0.05	0.37	0.03	1.80

Table 3.3b: Calibrated VGM parameters after inverse method excluding Ks was measured by permeameter test

Soil Samples	**Depth [cm]**	**θ_r [m³/m³]**	**θ_s [m³/m³]**	**α [1/cm]**	**n [-]**	**Ks [cm/d]**
Site1 0"-6"	0 – 15.2	0.03	0.35	0.01	1.30	28.0
Site1 10"-16"	25.4 – 40.6	0.01	0.30	0.01	1.43	7.0
Site1 18"-24"	45.7 – 61.0	0.03	0.45	0.01	2.50	30.0
Site2 0"-6"	0 – 15.2	0.04	0.36	0.01	1.13	96.4
Site2 10"-16"	25.4 – 40.6	0.01	0.31	0.01	1.35	105.0
Site2 18"-24"	45.7 – 61.0	0.03	0.45	0.01	2.50	36.5
Site2 30"-36"	76.2 – 91.4	0.07	0.30	0.05	1.65	108.8

Various performance criteria were used in the soil moisture and soil temperature calibration of the HYDRUS-1D vadose zone model to determine and minimise the error between observations and model simulations. Three performance criteria were applied on the calibration results: (i) ME (Mean Error), determines over- or under-prediction, (ii) RMSE (Root Mean Square Error), a measure of the calibration accuracy (Hyndman and Koehler 2006), and (iii) the Nash–Sutcliffe Efficiency NSE (Nash and Sutcliffe 1970), used to assess the predictive power of hydrological models. For RMSE analysis, zero is the best value, meaning simulations perfectly match observations. An NSE of 1 corresponds to a perfect match of modelled value to the observed data, while a value of zero indicates the modelling results are as accurate as the mean of the predictor.

3.3.4 Sensitivity Analysis

A sensitivity analysis is typically required to identify the strength and relevance of the inputs in determining the variation in the output (Saltelli et al. 2008), and to identify sensitive parameters as a way of screening parameters for calibration. In this work, the sensitivity analysis was used to test the robustness of the simulated results. Robustness is defined as the ability of our method to provide a reliable recharge estimate although most input data are derived from a low-cost weather station and therefore subject to uncertainty. Therefore, changes in parametrization should not result in larger impact on the recharge estimate. The tested variables are primarily the recharge, temperature and the soil moisture content. The sensitivity analysis was limited to soil moisture as a fundamental target since the calibration showed that the model outputs were much more sensitive to the changes in regard to soil moisture than to soil temperature. The VGM parameters were varied to determine their influence on the calculated water retention and recharge amount. The key parameters involved in the VGM model were chosen in the sensitivity analysis: empirical shape parameters α and n and saturated hydraulic conductivity Ks to estimate the robustness of the numerical model. Liu et al. (2013) and Holländer et al. (2009a) showed that the parameterisation of vegetation has a smaller impact on recharge estimates than changes to the VGM parameterization. Therefore, the vegetation parameters were not included in the sensitivity analysis.

A common approach is changing one-factor-at-a-time to identify the effect produced on the output (Czitrom 1999), and this is roughly equivalent to a partial derivative. Recent studies have testified the feasibility and applicability of this method on evaluating the sensitivity of the variant cross-correlation parameters (e.g., Oostrom et al. 2013). To increase the comparability of the results, the calibration result was considered as the baseline while α and n were changed by ±5%, ±10% and ±25% at each time. Two main goals were sought while testing the sensitivity of Ks: (i) to test the local sensitivity at that point where the soil samples were taken and (ii) to identify the sensitivity analysis on a larger scale to account for soil heterogeneity. Therefore, Ks was changed by ±σ which was derived from the laboratory measurements (Table 3.2) to test the local sensitivity. Changing Ks by ±σ covered therefore 74% (= 2σ) of all possible Ks values derived from the original soil samples. Finally, Ks was increased and decreased by a factor 2 and 4 to account for larger heterogeneity on a larger scale.

3.4 Results

3.4.1 Calibrations

When comparing VGM parameters estimated by the PTF and those derived using the inverse calibration method, θ_r and θ_s showed only small differences while larger departures in n and in α were observed (Tables 3.3a and 3.3b). While α was reduced to 0.01 1/cm for depths up to 61 cm

(PTF-estimated n = 0.02-0.04), the n-parameter was increased in some cases and decreased in others. Ks was not calibrated since the values were directly determined from the laboratory tests.

The soil moisture content at 10 cm, 37 cm and 100 cm depth (Figure 3.3 a-c) and the soil temperature at 10 cm and 37 cm depth were used for the calibration. The difference in simulated and observed soil moisture and soil temperature were by means of RMSE between 1 and 2% and between 1.06 and 1.91°C respectively, and by means of NSE 0.90 to 0.97 and 0.91 to 0.96, respectively (Table 3.4). The MEs showed that there is no tendency for over- or under-prediction since the values were nearly zero. All of these measures represent values which were much better than the calibration standard for hydrological models (Moriasi et al. 2007).

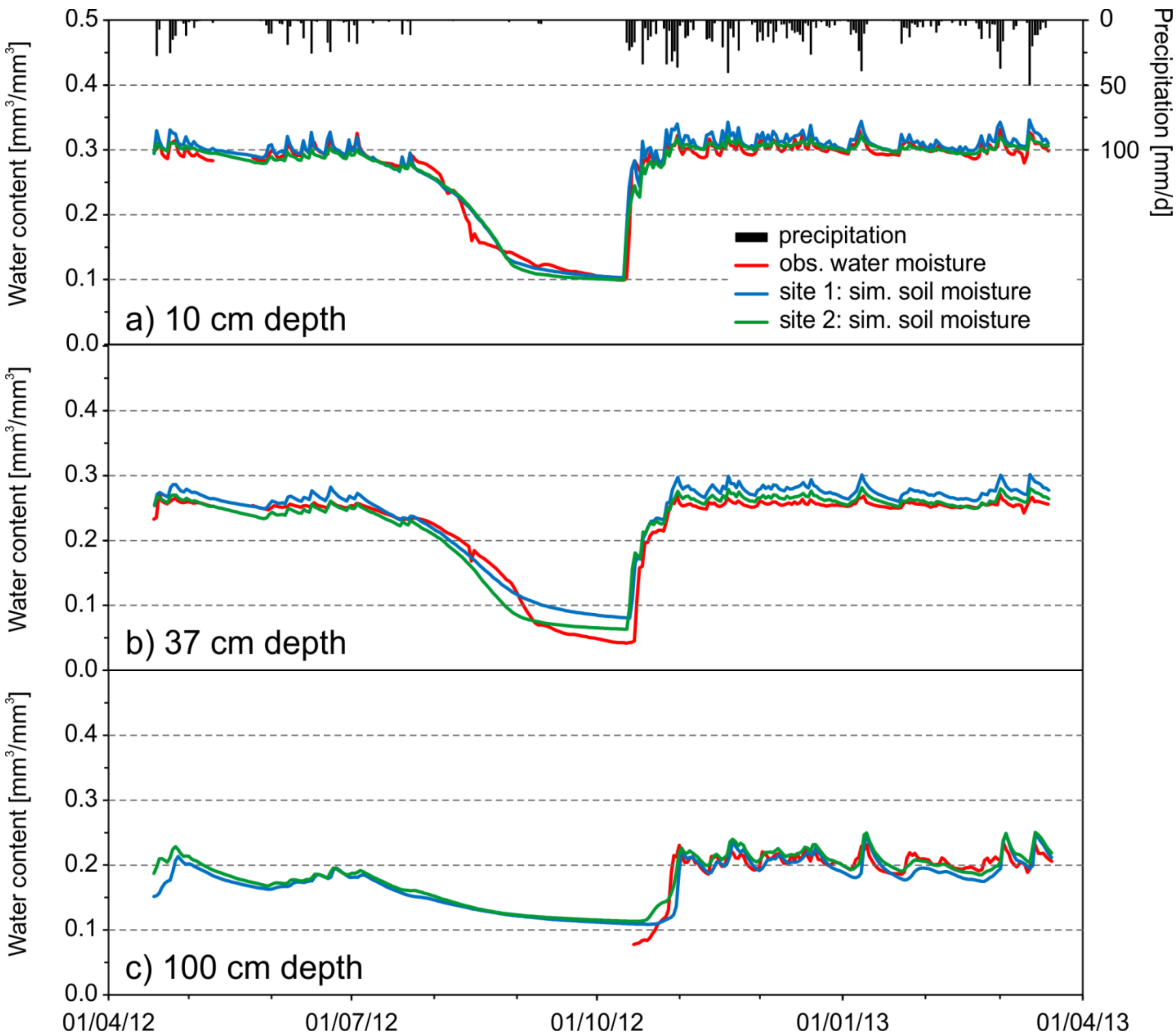


Figure 3.3a, b, and c: Calibration of the soil water contents at 10 cm, 37 cm, and 100 cm depth using the inverse-derived VGM parameter, the temperature sensor at 100 cm was later installed on Oct 10th 2012

Table 3.4: Calibration performance testing by RMSE, ME and NSE (inverse solution)

			Site 1			Site 2	
	Depth [cm]	10	37	100	10	37	100
Soil moisture	RMSE [m^3/m^3]	0.014	0.022	0.018	0.012	0.018	0.015
	ME [m^3/m^3]	0.007	0.016	-0.004	-0.001	0.001	0.007
	NSE [-]	0.961	0.898	0.916	0.970	0.932	0.942
Soil temperature	RMSE [°C]	1.90	1.07		1.91	1.06	
	ME [°C]	1.27	0.59		1.24	0.59	
	NSE [-]	0.92	0.96		0.91	0.96	

The mean air temperatures were below 0°C on six days, between the 11th and 22nd January 2013. Therefore, no precipitation was observed by the HOBO™ weather station. The soil temperatures at 10 cm were below 0°C on seven days. However, a minimum soil temperature of -0.5°C was observed, which had no obvious impact on the soil moisture content and its measurement. The weather station recorded precipitation of 16.8 mm and a soil moisture increase of 2% one day after the freezing period (23rd January). The numerical model reacted to this precipitation amount by predicting a 2% moisture increase. The data from Environment Canada showed that there was no snow fall recorded between 11th and 22nd January 2013.

3.4.2 Sensitivity Analysis

The VGM parameters α, n, and Ks were evaluated further during the sensitivity analysis. The parameter n showed the largest sensitivity. Taking analysis results at 37 cm depth as an example, the empirical shape parameter n (Figure 3.4) showed the largest sensitivity on soil moisture estimation, followed by α and Ks at the point scale. The impact of Ks on soil moisture increased if Ks was varied on a larger scale so that the soil moisture was more sensitive to Ks than to n. For example, changing the parameter n from -25% to +25% impacted the moisture content from -44% to 283% (Figure 3.4). The sensitivity analysis for sample site 1 showed that changes of the VGM parameter n impacts the recharge estimates by -0.9% / +1.2%, -1.5% / +2.9%, and -2.3% / +12% if n was varied by ±5%, ±10% and ±25%, respectively. Therefore, the changes in recharge estimates were at least one magnitude smaller than the impact on the soil moisture.

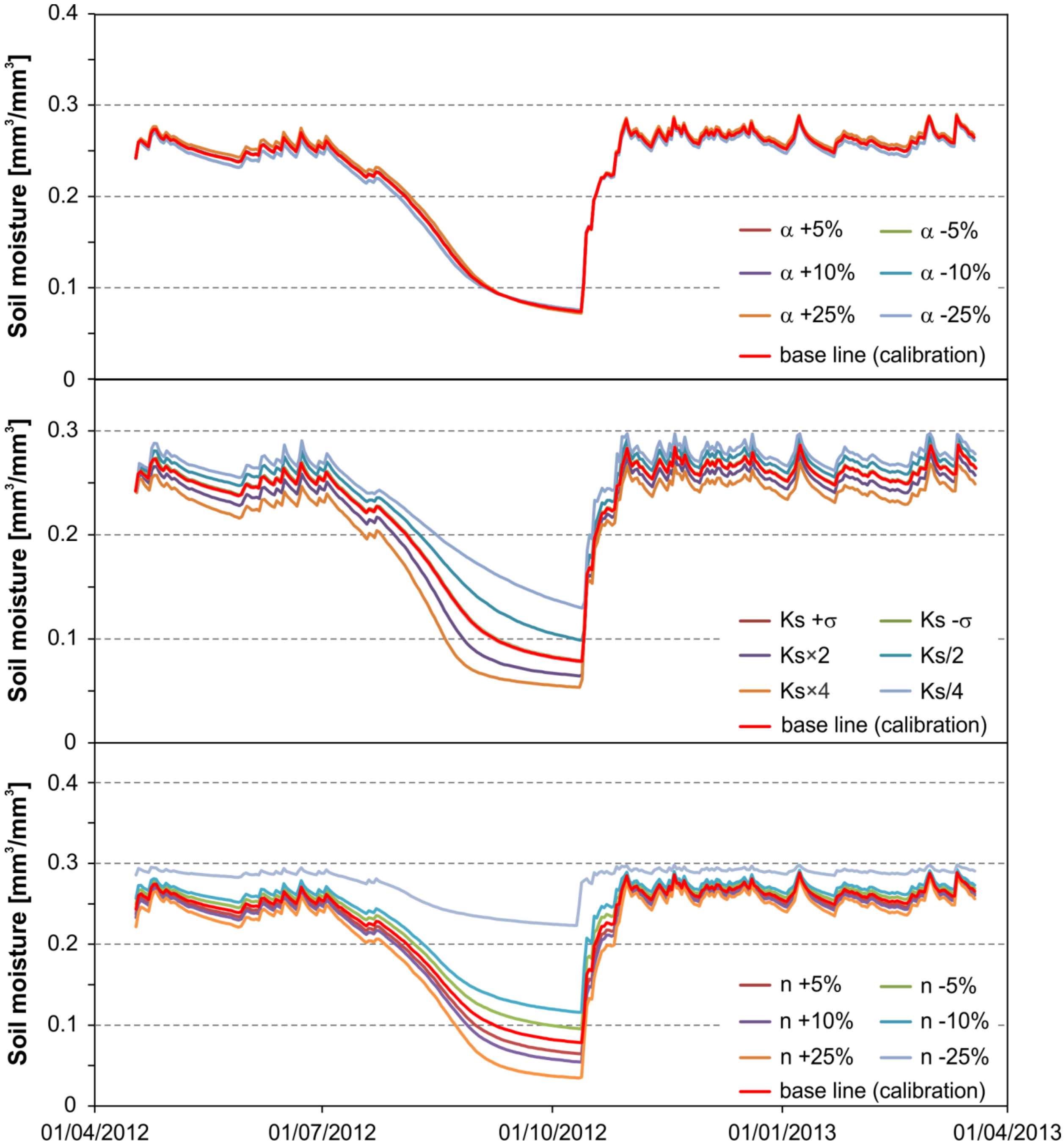


Figure 3.4: Sensitivity of n, α, and Ks on soil water content at 37 cm depth (Note: the soil temperature curves of the sensitivity analysis are nearly equal to the baseline)

The VGM parameter α was slightly less sensitive than n. In addition, all changes are relatively small. The changes are nearly constant which approximately shows a linear behaviour of the changes. Final cumulative recharge is stable at ± 5% of the baseline (Figure 3.5) at the point scale. Focusing on a large heterogeneity of soil due to its representation of a larger plot, resulted in changes of the recharge by +10.0% and -13.9% while increasing/decreasing Ks by a factor of 4.

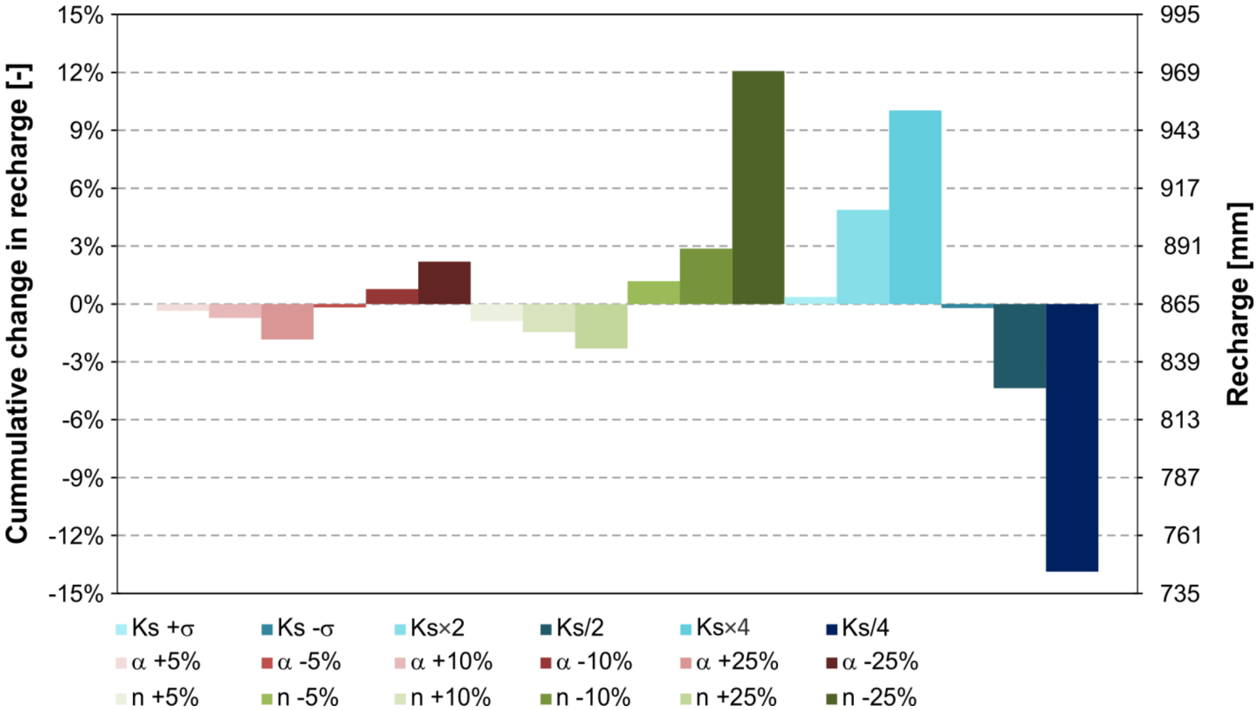


Figure 3.5: Impact of parameter changes on the cumulative recharge (site 1)

3.4.3 Recharge

The recharge using the VGM parameters after inverse calibration during the observed period was simulated as 863 mm and 816 mm for sites 1 and site 2, respectively. The ratio of recharge-precipitation was calculated as 63% and 59%, for each site respectively. For the long-term study, the recharge was estimated in the 27-year period to 848 mm/year with σ of 206 mm/year and 859 mm/year having σ of 208 mm/year for each site, respectively (Figure 3.6). The recharge estimated directly using the PTF-derived VGM parameters (Table 3.3a) were 892 mm/year with σ of 197 mm/year and 915 mm/year with σ of 204 mm/year each site, respectively. These recharge estimates were about 5% larger than the estimates using the inverse calibration method. For verification of the finding by Vaccaro (2007), the lower BC was lowered to 30 m. The recharge estimate was within 0.1% the same of the estimate using the lower BC at 2 m over the 24 years period. The differences during the short time period were larger since the initial condition has a large impact since the soil moisture was initialized using field capacity. There was a lag between the arrival of the recharge at the lower BC at 30 m compared to the lower BC at 2 m. However, all the modelling results below the 2 m depth are vague to evaluate the lag fully due to insufficient data.

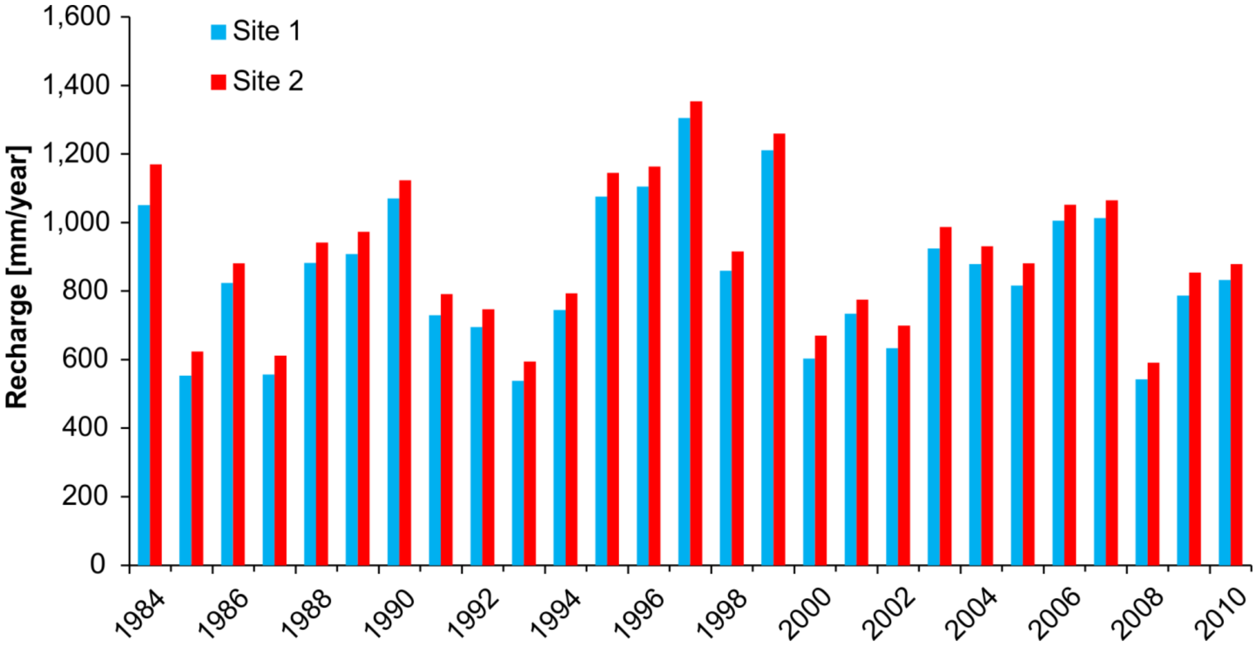


Figure 3.6: Annual recharge estimated from the long-term (27-year) weather data from Abbotsford A weather station

Monthly recharge statistics were derived from the long-term study. The maximum recharge occurred in December and January with means of 177 mm/month with σ of 82 mm/month, and 185 mm/month with σ of 72 mm/month, respectively (Figure 3.7). According to the monthly mean recharges, there was a nearly-linearly decreasing rate of 21 mm/month from January to October. During the period from October to December, the recharge increased by a rate of 57 mm/month (Figure 3.7).

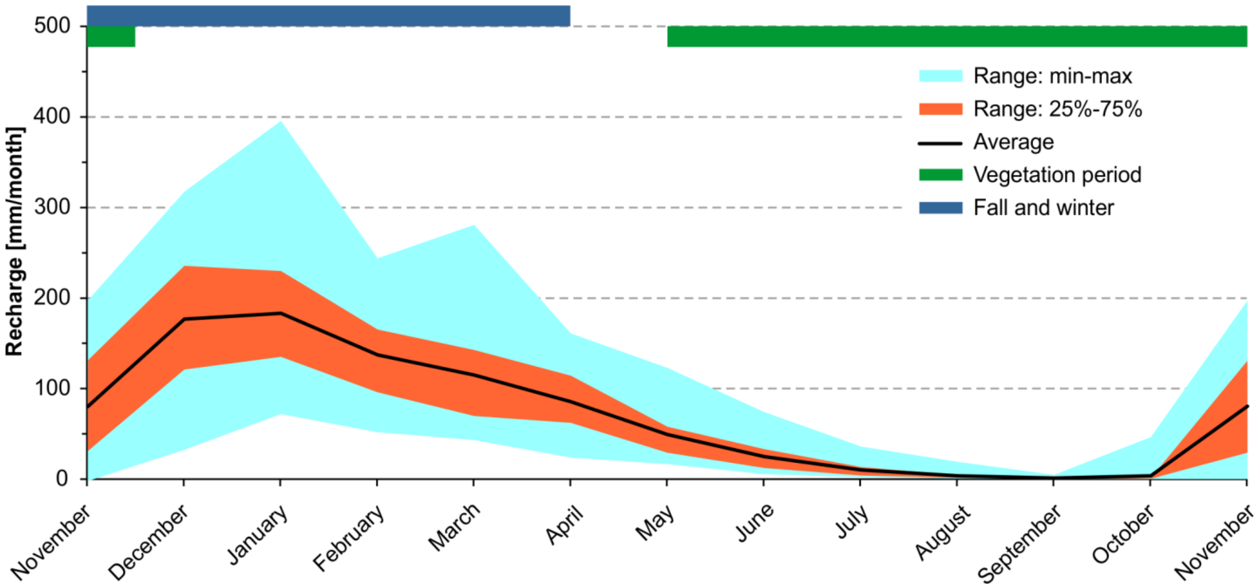


Figure 3.7: Monthly estimated recharge distribution in long-term period

3.5 Discussion

The overall error of 1-2% in soil moisture estimation by HYDRUS simulation expressed by RMSE (Table 3.4) was within the same range as the measurement error of the soil moisture sensors (3.1%, Table 3.1). However, the simulation vs. observed soil temperature had a RMSE of 1.1 to 1.9°C (Table 3.4) which was significantly larger than the measurement error of the temperature sensors (0.2°C, Table 3.1). The NSE and the ME verified the good agreement between estimated values and measured data since the NSE was in all cases ≥ 0.9 and the ME was nearly zero (Table 3.4).

Overall, soil water content (Figure 3.3a-c) showed the largest variation at 37 cm below the soil surface. There are two reasons for this: (i) root density is correlated with root water uptake. Since the root density decreases with depth (Fryrear and McCully 1972), the transpiration effect also decreases with depth, thereby evapotranspiration decreases and (ii) the unsaturated hydraulic conductivity decreases non-linearly as soil moisture content decreases. Therefore, the variations in soil moisture decrease with increasing soil depth.

The sensitivity analysis was used to test the robustness of the simulated results. The less sensitive the results are to parameter changes, the more robust is the result (recharge). The empirical shape parameter n was found to be the most sensitive. However, figure 3.5 indicates that the changes to any VGM parameter (α, n, and Ks) results in small changes in recharge (<5%). An exception to this case is lowering the VGM parameter n by 25%: where, the recharge estimate is 12% larger than the baseline using the model with inverse calibrated VGM parameters. Table 3.3b shows that n is rather small for the first two layers (1.30 and 1.43) so that a reduction by 25% results in very low n values. Ippisch et al. (2006) showed that small n-values ($n \leq 1.1$) can cause uncertainties in the recharge estimation. Therefore, the larger changes in recharge can be satisfactorily explained and do not impact the robustness of the method itself. Therefore, no significant changes could be found in the recharge estimates which prove that the observation-simulation model is robust in terms of recharge estimation. The recharge estimates of both VGM parameterisations (Tables 3.3a and 3.3b) are quite similar and differ by about 5% due to the low sensitivity of the model to the VGM parameter. Looking at a larger scale implies larger heterogeneity which was represented by increasing the changes in Ks. This resulted in larger changes in recharge (up to 14%) which are significantly larger than any of the measurement uncertainties. However, Assefa and Woodbury (2013) showed by using soil data on a 500 m by 500 m grid that recharge estimates are still reliable and can be of advantage for questions regarding water resources management.

The delay between a precipitation event and the corresponding soil moisture change during long dry periods (e.g., between 23.07.2012 to 12.10.2012, Fig. 3a-c) is: without any delay, with a delay of two days and with a delay of three weeks for depth of 10 cm, 37 cm, and 100 cm depth, respectively. In the rainy periods, the delay between infiltration at land surface and recharge at the groundwater table is shorter than in the transition period from dry to rainy, due to the retention of soil moisture. The lithology and the soil saturation within the vadose zone determined the time delay, and the flux harmonised the recharge rates relative to the precipitation. Therefore, the soil moisture decline at each depth showed its own characteristic.

The annual recharge estimated from the two sites in the 27-year period are very similar: the mean annual recharge estimate (site 1: 848 mm/year with σ of 206 mm/year and site 2: 859 mm/year with σ of 208 mm/year), as well as the per-year estimate (Figure 3.6). This underscores the robustness of the chosen method. These mean recharge values agree with the range 851-900 mm/year estimated by Scibek and Allen (2006) at the same location as our weather station in the

Abbotsford region. Scibek and Allen (2006) determined the recharge by the HELP model (Hydrologic Evaluation of Landfill Performance, Schroeder and Ammon (1994)). Furthermore, the variation in the estimated recharge between the two sites is within the accuracy of the measurement. HELP is a limited model allowing one-day time steps, and considers only grass or bare soil as land cover. Concerns about HELP recharge over-estimation have been duly note elsewhere (Assefa and Woodbury 2013; Berger 2000). In this particular case, limitations of HELP can be neglected since the land cover happens to be the same in our HYDRUS simulations at the study site. Our recommendation would be to use HYDRUS as a preferred simulator.

Figure 3.6 also indicates that the effect of wet and dry years is obvious on recharge estimation. For instance, the amount of recharge (site 1: 1306 mm/year and site 2: 1314 mm/year) in 1997 was more than double of that (both sites: 539 mm/year) in 1993 (precipitation of 1997: 1999 mm/year, precipitation of 1993: 1170 mm/year). The calculated ratio of annual recharge to precipitation from 43% to 69% agrees with the study by Kohut (1987). Kohut reported that annual recharge can range between 37% and 81% of the annual precipitation. This indicates that the recharge is dominated by the precipitation in the Abbotsford area. The good match between the recharge estimates of this and earlier studies is based on the successful calibration of the soil moisture contents. The soil moisture drives the water flow within the vadose zone and, therefore, the recharge estimation; the adopted method can robustly predict the recharge without increasing the error due to the measurement.

According to the monthly recharge estimates, the majority of recharge was contributed during the fall and winter from November to April (Figure 3.7). The main months of recharge accumulation are December (178 mm/month with σ of 82 mm/month) and January (185 mm/month with σ of 72 mm/month). These findings agree with the Piteau Associates

Engineering Ltd. (2006) report on the onsite climate conditions. Only small amounts of recharge were obtained during the vegetation period.

(Kaown et al. 2009) showed that nitrate leaching in correlated to recharge rates in unconfined aquifers. Therefore, the Abbotsford aquifer shows a high potential for groundwater contamination in fall and winter due to the intensive nitrogen loading from agricultural production and high recharge. Although the groundwater receives only 20% of the total recharge during vegetation period, late summer application of fertiliser which covers 33% of the whole year's fertiliser (Spectrum Analytic Inc) is not recommended. Recharge increases rapidly of about 60 mm/month from October to December. Therefore, a late fertilization can fall into a strong recharge event, which results in nutrients leaching from nitrate which may not have been completely used by the crops.

3.6 Conclusion

The study shows how data from a low cost weather station, along with additional soil moisture and soil temperature sensors from short-term (year) observations can be used for robust recharge predictions. The method yields highly accurate recharge estimation during the observation period (April 2012 – March 2013) as well from the long-term period (from year 1984 to year 2010) as it agrees with recent studies in the same area. At this point, this method implements the practise of saving time and cost by using temporal data which are extended using long-term climate data to derive profound recharge estimates. The main advantage of using these unmanned cellular data loggers is that data can be obtained from difficult or even inaccessible areas and that malfunctions can be easily detected. The vadose zone model HYDRUS-1D, which only uses soil information and climate data as input, allows for cost-effective, efficient and robust recharge estimates. The use of ROSETTA with limited additional laboratory tests resulted in an initial

VGM parameters set which, in combination with the parameter estimation function of HYDRUS-1D, significantly shortened the calibration process. As a consequence, the final calibration performance was much better than the normal standard for vadose zone modelling and, therefore, resulted in robust recharge estimation.

Due to the physically-based nature of the modelling approach, we believe this method can be applied within the context of recharge estimation from remotely accessible areas. Furthermore, being able to predict transient recharge estimates, this method can provide a reasonable tool for estimates on nutrient leaching. For example, Evans et al. (2008) showed that nitrate leaching is often controlled by strong precipitation events which result in rapid infiltration of water and nitrate into the soil. This agrees with our assumption that highly temporal recharge estimates also increase the prediction quality of nitrate leaching in the Abbotsford area.

4. Spatial interpolation of groundwater recharge estimates on coarse textured soils

Abstract

Knowledge of groundwater recharge estimation and its spatial distribution benefits groundwater sustainable management. In this study, short-term groundwater recharge was estimated on sandy soils in southeastern Manitoba, Canada using one-dimensional physically-based modelling and point estimates were scaled to the regional scale using two local and two geostatistical interpolation techniques. Calibration and sensitivity analysis were used to evaluate the reliability and robustness of the recharge point estimates. The short-term average recharge estimated at nine locations varied from 103.9 mm (55% of total precipitation) to 161.9 mm (85% of total precipitation). The maximum recharge was obtained from June to July, accounting for 57% of the total recharge. The performance of each of the four interpolation methods was evaluated and compared using cross validation by means of true percent error between the observed and predicted recharge. Ordinary kriging gave the best prediction (7.76% true percent error). All methods consistently showed a similar mean gross recharge (~ 130 mm) over four months and a general trend of decreasing recharge regionally from north to south.

4.1 Introduction

Groundwater depletion has become a common problem in many parts of world (Oki and Kanae 2006). Of the largest 37 aquifers in the world, 21 have exceeded sustainability tipping points and are being depleted, and 13 are considered significantly distressed (Richey et al. 2015). Groundwater is often overexploited to relieve water stress, and in many regions, it represents the only source for irrigated agriculture and municipal uses. Therefore, it has become increasingly important to improve region specific understanding of groundwater resources, and, more specifically, to assess the groundwater recharge in shallow aquifers. In shallow aquifers, the quantity of the recharge is considered highly variable, both spatially and temporally. Compared to deep aquifers, shallower aquifers respond faster to precipitation events, and recharge is more sensitive to root and soil characteristics (Neff et al. 2005; Holländer et al. 2016). Shallow groundwater is vulnerable to pollutants which can rapidly percolate through coarse textured soils, e.g., during strong precipitation events (Evans et al. 2000; Holländer et al. 2016). Recharge, as the main driving force of pollutants, is often the most important factor in contamination risk assessment. Therefore, accurate estimation of recharge is crucial for groundwater management, specifically during decision making on drought alleviation, for contamination risk assessment and for agricultural best practices (Holländer et al. 2009b).

Recharge can be directly measured by lysimeters. However, lysimeters are limited in their spatial extent, providing a point measurement, and are very costly. Numerous indirect methods, such as physical, statistical and mathematical equations, have been developed to estimate recharge (Healy 2010a). These methods differ in their cost, complexity and time consumption. Comparing to other methods, physically-based vadose zone modelling has the advantages of producing reliable and robust recharge estimates, being cost effective and including convenient calibration tools (Holländer et al. 2016; Assefa and Woodbury 2013). Additionally, this method enables the use of climate data, including: precipitation, air temperature, relative humidity, wind speed, and solar radiation; as well as, soil data, including: texture, soil moisture, and temperature; and vegetation data to estimate recharge. These data can be rather simple to obtain with a weather station, along with additional soil moisture and soil temperature sensors, and soil samples collected at the site (Wang et al. 2016; Holländer et al. 2016). Lastly, an unmanned cellular data logger can send the data from difficult or inaccessible areas and alarm the user if a malfunction were detected.

However, groundwater recharge is highly variable in space (Frances 2008; Assefa and Woodbury 2013). The accurate and robust results from physically-based modelling are point estimates of recharge. Extending the recharge estimation across a region using the same parameters might not result in reliable recharge estimates at other locations, due to heterogeneity in soil texture and weather distribution. Spatial interpolation is a method used to estimate data in a contiguous area and predict the unknown points with available observations (Chai et al. 2008; Losser et al. 2014). Due to its complex operation which takes omnidirectional considerations of observations, neighborhood distribution, and uncertainties of interpolation models into account, the reliability of the results from the interpolation strongly depends on the quality of the inputs, their spatial coverage and the model selection (Healy 2010a). Different interpolation methods, such as local interpolation methods and geostatistical methods have been developed to date. Local interpolation methods comprise natural neighbor (NN) (Sibson 1981), Thiessen polygons (Goovaerts 2000), inverse distance weighting (IDW) (Bartier and Keller 1996), and splines (Unser 1999). The basic approach for geostatistical methods is kriging (Krige and Matheron 1967; Matheron 1967). Kriging methods consisting of simple or ordinary kriging (OK) and universal kriging, which were originally developed for the mining industry. With further development, variants of kriging such as cokriging (CK), are now used in a variety of applications such as environmental science, remote sensing, natural resources and hydrogeology (Bayraktar and Turalioglu 2005; Chiles and Delfiner 2009; Tonkin and Larson 2002; Richmond 2002; Papritz and Dubois 1999). In recent decades, several studies were carried out on comparing and evaluating these methods on interpolation of groundwater levels; the results consistently agreed that kriging was the optimal method (Xiao et al. 2016; Yao et al. 2014; Sun et al. 2009; Kumar 2006). However, recharge interpolation is more complex than that of groundwater levels, due to recharge's cross-variation with multiple meteorological and soil parameters. For this reason, some commonly used methods were not applicable to recharge interpolation. E.g., empirical models that estimate recharge as fractions of precipitation, since this method is only effective at a low heterogeneity (Healy 2010a; Saghravani et al. 2013b).

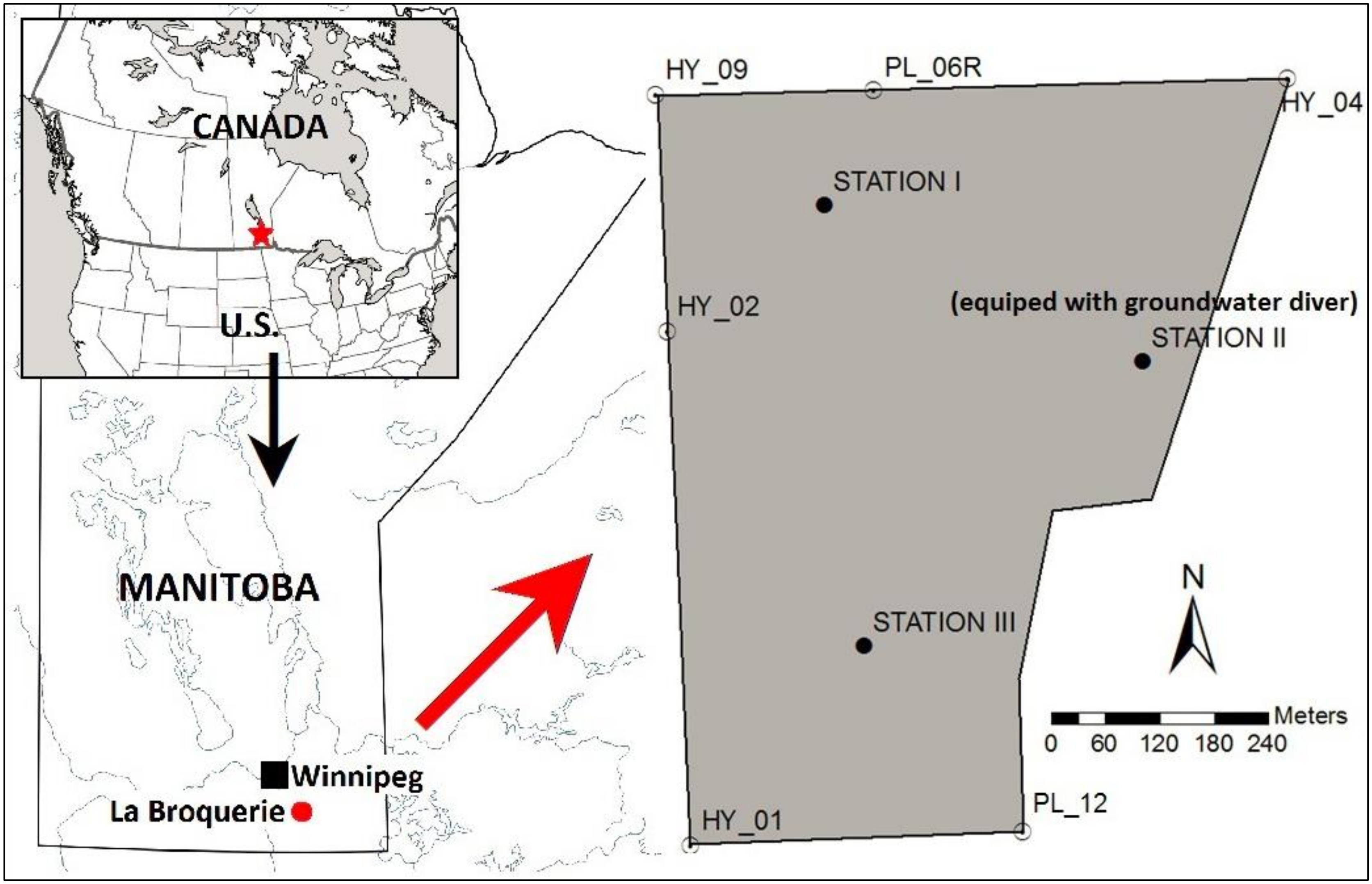
This study focuses on estimating the recharge at multiple locations on sandy soils in the same study area using 1-D physically-based modelling. Furthermore, four interpolation methods including NN, IDW, and two different kriging methods are applied to estimate areal recharge in the study area. The interpolated recharge on sandy soils by these four methods is compared and evaluated.

4.2 Study Area

This study was conducted at the La Broquerie Pasture and Swine Manure Management Study Site, a 40 ha of tame grassland in the Rural Municipality of La Broquerie, southeastern Manitoba (Figure 4.1). The field site was located on pastureland and was mainly covered by quackgrass (*Elytrigia repens L. Nevski*) and Kentucky bluegrass (*Poa pratenis L.*). The pasture's height reached up to 60 cm in the summers of 2014 and 2015. The coverage of pasture was more than 90%, excluding the traffic path across the field. The field site was established in 2003 to study the impact of hog manure application on pasture in the Canadian Prairie. Due to the field site's location in the Canadian Prairies, it had a humid continental climate (Peel et al. 2007), with a large difference between summer and winter temperatures.

The entire field site was situated over the Sandilands Aquifer, which is an unconfined trans-boundary aquifer. Groundwater flowed in a northeastern direction. The main soil type at the field site was loamy sand to gravel, while there was a clay layer at a depth of 2 meters in the western half of the field site (Coppi 2012).

Figure 4.1. Layout of the 40 ha La Broquerie Pasture and Swine Manure Management Study Site showing the locations of observation stations (●), observation wells equipped with groundwater diver (○); soil samples were taken at both stations and wells



4.2.1 Data

Three onsite observation stations, including two HOBO^{TM} U30 weather stations which were additionally equipped with soil temperature and moisture sensors (Station I: UTM-14, 5475653.6 m N, 683242.6 m E, installed in April, 2014; Station II: UTM-14, 5475488 m N, 683598 m E, installed in April, 2015) and one HOBO^{TM} U30 station only equipped with soil temperature and moisture sensors (Station III: UTM-14, 5475173 m N, 683288 m E, installed in April 2015) provided data until the end of the simulation period (31st December 2015) (Table 3.1). The HOBO^{TM} U30 weather stations provided “plug-and-play” smart sensors for measuring soil temperature, soil moisture and climate data, including air temperature, precipitation, solar radiation, wind speed, relative humidity and atmospheric pressure. The recording time step was set to 30 minutes to receive comprehensive information on the soil temperature from 10 to 90 cm depth and the soil moisture using FDR (Frequency Domain Reflectometry). FDR sensors were limited to measure soil moisture in winter seasons due to the change in dielectrically constant from water to ice. The sensors had an accuracy of ±3.1% regarding volumetric water content and 0.1°C regarding temperature. Any precipitation falling as snow was not identified due to the nature of the available sensors (Table 3.1); therefore, snow precipitation data was required. Snow data were obtained from the Winnipeg Airport climate station which is 90 km in the northwest of La Broquerie and validated by frequency and variation tests with the snow data (1st Jan 2008 to 31st December 2008) recorded by the Steinbach climate station, which was 24 km to the study area but ceased monitoring in 2009. Coppi (2012) reported the presence of a shallow water table at the field site. In order to monitor the groundwater level (GWL), seven Van Essen Micro-Divers were installed in the observation wells (one was overlapping with Station II) in 2014 (Figure 4.1).

The total rainfall precipitation, maximum mean daily temperature, mean daily temperature and minimum mean daily temperature measured from 15th May 2014 to 5th November 2015 by HOBO™ stations were 486 mm, 9.5°C, 4.7°C and -0.8°C, respectively.

4.2.2 Soil Analysis

One soil core (~1 m depth) was taken next to each of the observation stations at the time of their installation in 2014 and next to each well in June 2015 (Figure 4.1). The water content of 111 soil samples (50~100 g per sample) was determined by oven drying at 105°C for 6 hours. First, a sieve analysis was conducted, and then a secondary particle size test using laser diffraction was used to determine particle size <75μm. Sieving analysis was conducted according to the ASTM C 136-06 (ASTM 2006a), using six sieve sizes: 4.75 mm, 2.00 mm, 0.85 mm, 0.425 mm, 0.18 mm, and 0.075 mm which represented fully the gravel and sand distribution. An Oscillatap ML-4330 TS sieve shaker sieved 111 test samples for 10 minutes each. The finest portion of the test samples obtained on the bottom pan was collected to determine the silt and clay distribution using a Mastersizer 2000 (Malvern Industries) in complement with the wet sample dispersion unit, Hydro 2000S. The instruments were effective to detect particle size in a range of 0.01 to 10,000 μm with laser diffraction technique. Both tests obtained the relative proportions of different grain sizes in order to determine the soil sample types by sand, silt, and clay according to USDA textual classification. The permeability testing was in accordance with ASTM D 2434-68 (ASTM 2006b). All soil samples were tested three times at five different inflow hydraulic heads. Finally, organic carbon content was measured by drying all the test samples in the laboratory at 450°C for another 24 hours (ASTM 2009).

4.3 Vadose Zone Modelling

4.3.1 Governing Equations

Variably saturated water flow modelling software HYDRUS-1D version 4.16 (Simunek et al. 1998) was used for recharge simulation at nine locations of the field site. The database ROSETTA (Schaap et al. 2001) was chosen for determining unsaturated soil hydraulic parameters. HYDRUS-1D combined with Feddes-type root water uptake was used to simulate moisture changes in the vadose zone (Šimůnek and van Genuchten 2008; Feddes et al. 1978b). To improve the accuracy of mass balances in the water flow calculation and to minimize the corrections to the dispersion term, the mixed form Richards equation suggested by Celia et al. (1990) was applied. The van Genuchten-Mualem model (VGM) (van Genuchten 1980; Mualem 1976) was selected to determine the water flow in the soil profile using the five soil hydraulic parameters saturated hydraulic conductivity Ks, the empirical shape parameters α and n, residual soil water content θ_r, and saturated soil water content θ_s. Holländer et al. (2016) showed that the VGM parameters can be reliably predicted by ROSETTA for sandy soils and that the dependent soil moisture simulations require minimal calibration. In order to account for the effects of soil temperature on water flow and redistribution processes, the thermal conductivity was calculated using the Chung and Horton equation with the empirical parameter for sand/gravel suggested by Šimůnek and van Genuchten (2008).

4.3.2 Boundary and Initial Conditions

The specification of appropriate initial conditions (IC) and boundary conditions (BCs) is an essential part of conceptualizing and modelling the vadose zone, and plays an important role in the determination of the numerical stability and accuracy of the model. In this study, external forcing such as air temperature, precipitation and solar radiation, controlled the potential water flux across the upper boundary. Comparing to Abbotsford, soil moisture conditions were more sensitive to the large annual temperature differences and intense seasonal precipitations. The observed water table occasionally rose near to the soil surface. Therefore, an "atmospheric BC with surface runoff" best defined the upper BC with the consideration of surface ponding and post-winter soil thawing. The lower BC was defined as variable pressure head since the known GWL was less than 2 meters below ground surface during the modelling period. The IC of soil moisture and soil temperature was linearized between the observed soil temperature and moisture at difference depths. Due to the absence of observation wells at Station I and III (Figure 4.1), the GWL data used for the soil moisture simulation of Station I and III were taken from the closest observation wells (Station I: PL_06R, Station III: PL_12). The GWL observation time mismatch caused by the distance between stations and observation wells was adjusted according to the observed soil moisture dynamic at 60 cm and 90 cm depth at Station I and Station III, respectively.

4.3.3 Calibration

HYDRUS-1D uses a Marquardt-Levenberg type parameter estimation technique for inverse calculation of the VGM parameters by minimizing the error between observed and simulated soil moisture content (Šimunek et al. 2012). Additionally, the Marquardt-Levenberg method was noted as a local estimation gradient method that required initial estimates of the unknown parameters to be optimized.

Based on changes in soil texture, the soil profile of 200 cm was modeled and was divided into three layers at three observation locations Station I to III. The soil hydraulic properties of all three layers were described by the five VGM parameters. The determination of the VGM parameters formed the main part of the calibration process, as they define the characteristics of the soil model and influence the soil moisture and the pressure head (Holländer et al. 2016). Thus, the observed soil moisture values from 1st May 2014 to 5th November 2014 were used for model calibration. A constant head test was used to determine Ks. The other four VGM parameters were initially predicted by ROSETTA. Predicted parameter always contain a large uncertainty since the predictions are based on soil samples from different geographical regions and might not adequately describe the soil at the field site (Holländer et al. 2016). Consequently, the VGM parameters predicted from ROSETTA were used as the initial parameter set and were optimized during calibration (Table 4.1). Two performance criteria were applied to evaluate the calibration results: mean error (ME) to verify overestimation or underestimation, and root mean square error (RMSE) to determine the accuracy of calibration.

Table 4.1. VGM parameters (a) predicted by ROSETTA, and (b) after calibration, Ks was obtained from lab measurement, not calibrated

	Soil Sample	Depth [cm]	θ_r [-]	θ_s [-]	α [1/cm]	n [-]	Ks [cm/d]
(a)	**Station I**	0-20	0.05	0.37	0.08	1.89	0.02
		20-45	0.05	0.35	0.15	2.68	1214
		45-200	0.05	0.35	0.15	2.68	8470
	Station II	0-30	0.05	0.37	0.12	2.28	50
		30-80	0.05	0.35	0.15	2.68	1681
		80-200	0.05	0.35	0.15	2.68	1113
	Station III	0-15	0.05	0.37	0.12	2.28	70
		15-80	0.05	0.35	0.15	2.68	121
		80-200	0.05	0.35	0.15	2.68	3821
(b)	**Station I**	0-20	0.07	0.35	0.01	2.58	-
		20-45	0.04	0.38	0.19	1.11	-
		45-200	0.03	0.37	0.05	1.35	-
	Station II	0-30	0.07	0.36	0.03	1.99	-
		30-80	0.04	0.35	0.02	2.68	-
		80-200	0.03	0.30	0.06	1.74	-
	Station III	0-15	0.07	0.36	0.07	1.41	-
		15-80	0.04	0.35	0.03	2.41	-
		80-200	0.03	0.30	0.10	1.81	-

4.3.4 Validation

In order to show the comprehensiveness and the robustness of the model, validation of the HYDRUS-1D was used to confirm that the model accurately predicted soil moisture in response to the weather conditions of any other time period. After calibration, the calibrated parameters were used to simulate the data from 1st May 2015 to 5th November 2015 to validate the model of Station I. The end date of the validation period was due to the soil became frozen after 5th November 2015. The model performance was evaluated in terms of the difference between observed soil moisture and simulated soil moisture.

4.3.5 Sensitivity Analysis

Some degree of uncertainty is inherent in numerical models. The impacts of model inputs may be difficult to measure or predict, and the robustness of a model may be hard to know. A sensitivity analysis is a widely used technique to examine the degree of uncertainty and strength of the model inputs and how the inputs affect the simulation result. In this study, the key parameters involved in the VGM model were chosen in the sensitivity analysis: empirical shape parameters α, n, and the saturated hydraulic conductivity K_s to test the robustness of the simulated recharge.

4.4 Recharge Interpolation

4.4.1 Interpolation Techniques

In this study, groundwater recharge was estimated by interpolation the 1-D results at nine locations (three weather and soil observation stations and six groundwater observation wells) from HYDRUS-1D, which assumed the accumulated water flow through the bottom of the root zone became recharge. Interpolation was used to explore spatial data points within the range of a discrete set of known data points through applying deterministic and geostatistical functions.

Thus, a regional representation of groundwater recharge was obtained. Four interpolation techniques integrated in ArcGIS 10.2 were employed: IDW, NN, OK and CK. Finally, the difference among four methods were compared and evaluated.

Inverse Distance Weighting (IDW) is a typical type of deterministic interpolation method that assigns values to the unknown points with the weighted average value from the neighbor known points. The weight was calculated by the inverse value of the distance from one unknown point to one known point, in other words, the interpolated point was more weighted from the nearest known point.

$$u(x) = \frac{\sum_{i=1}^{N} w_i(x)u_i}{\sum_{i=1}^{N} w_i(x)} \tag{1}$$

$$w_i = \frac{1}{d(x, x_i)^p} \tag{2}$$

Where u is the interpolation value, x denotes a known point, i denotes the index of the interpolation points, w is the weight assigning to the interpolated point, d is the distance between the interpolated points and the known points and p is the power parameter (Bartier and Keller 1996).

Similar to IDW, Natural Neighbor (NN) is also a weighted-average interpolation method. Instead of weighting by distance, NN finds the closest known points and applies weights determined by the neighborhood proportionate areas to them in order to interpolate a value (Sibson 1981). Since the NN interpolation was carried out by local samples surrounding the interest point, this guaranteed the method would not produce peaks or valleys that were not shown from the known points.

Simple or ordinary kriging (OK) is a geostatistical interpolation method and defines the spatial correlation in terms of value and neighborhood distribution of sample points in order to explain variation in the surface. The interpolated values are modeled by a Gaussian process governed by prior covariance, as opposed to a piecewise-polynomial spline chosen to optimize smoothness of the fitted values. Traditional kriging methods are limited to map the surfaces from one data type at the target location. Therefore, they fail in using the existing spatial correlations between secondary data points and the primary attribute (Journel 1989). As the extension of kriging, cokriging (CK) is able to manage the estimation process from more than one data type to improve the interpolation performance and considered as the potential method in the La Broquerie case.

$$z_0^* = \sum_{i=1}^{n} \lambda_i z_i + \sum_{j=1}^{n} \beta_j t_j \tag{4}$$

where z_0* is the estimate at the grid node; λ_i is the undetermined weight assigned to the primary sample z_i and varies between 0 and 1; z_i is the regionalized variable at a given location, with the same units as for the regionalized variable; t_j is the secondary regionalized variable that is co-located with the primary regionalized variable z_i, with the same units as for the secondary regionalized variable; and β_j is the undetermined weight assigned to t_j and varies between 0 and 1. Specifically because of the additional cross-correlation between different parameters, CK performs better than OK (Ahmadi and Sedghamiz 2007). The main variable of interest is recharge, and both autocorrelation for recharge and cross-correlations between recharge and the other variable types in terms of soil texture, depth to the water table and precipitation will be considered to improve the prediction of the regional recharge. Since the distribution difference of precipitation at study area can be ignored due to the size of the study area (0.4 km^2), the governing secondary parameters for CK operation can be reduced to (i) the depth to the water table and (ii) the soil texture.

4.4.2 Cross Validation

Cross validation is a model validation technique mainly applied on predictions to test how accurate the prediction is at a known data point. Cross validation omits the observation at a known data point, and solves for the point using data from the rest of the observations, the prediction is then compared with the observed value. This procedure was rotated for each known position. Due to the small data population, cross validation was expected to perform better than conventional validation whose performance is dependent on a good distribution, amount and spread of data. In this study, cross validation was conducted on each of the nine points of recharge by the geostatistical analyst integrated in ArcGIS.

4.5 Results

4.5.1 Calibration and Validation

Measured hydraulic conductivity ranged from 0.02 cm/d at the surface to 8470 cm/d at a depth of 45 to 200 cm and was not changed during calibration (Table 4.1a and 4.1b). The residual moisture content was predicted by ROSETTA at 0.05 cm^3/cm^3 for all soil (Table 4.1a) and changed to 0.03 cm^3/cm^3 to 0.07 cm^3/cm^3. The saturated moisture content was changed by ± 3% except for the third layer at Station II and Station III, which were reduced to 0.30 from 0.35. VGM parameters α and n were largely changed from the ROSETTA prediction during calibration (Table 4.1b).

The calibrated VGM parameters were used to simulate the soil moisture at depths of 10, 30 and 60 cm (Figure 4.2). Agreements between simulated and measured soil moisture were achieved for both calibration and validation periods (Figure 4.2). The root mean square error (RMSE) varied from 0.01 to 0.03 cm^3/cm^3 at 10 cm depth, was consistent at 0.02 cm^3/cm^3 at 40 cm depth, and varied from 0.03 to 0.05 cm^3/cm^3 at 60 cm depth at three stations after calibration (Table 4.2). The average error (ME) for 10 cm, 30 cm and 40 cm depth showed that there was no distinct under- or overestimations by the simulation because the values were close to 0 after calibration. However, the soil moistures at 60 cm and 90 cm depth were slightly overestimated by 0.02 cm^3/cm^3 (Table 4.2). The model output from 6th November 2014 to 30th April 2015 and after 5th November 2015 for Station I was not reliable since the sensors were limited to measure the frozen soil moisture. The RMSE and ME of validation period (19th June to 5th November) indicated similar results comparing to the calibration period at Station I. The RMSE of simulated soil moisture at 10 cm and 30 cm depth were the same as 0.03 cm^3/cm^3 and 0.02 cm^3/cm^3 of calibration, respectively, and 0.03 cm^3/cm^3 less than that of calibration period at 60 cm depth (Table 4.2). The ME of validation was 0.02 and 0.01 cm^3/cm^3 more than that of calibration at 10 cm and 30 cm depth, respectively, and 0.01 cm^3/cm^3 less at 60 cm depth at Station I (Table 4.2).

Figure 4.2. Measured, calibrated, and validated soil moisture content at Station I; groundwater level and the deepest sensor position

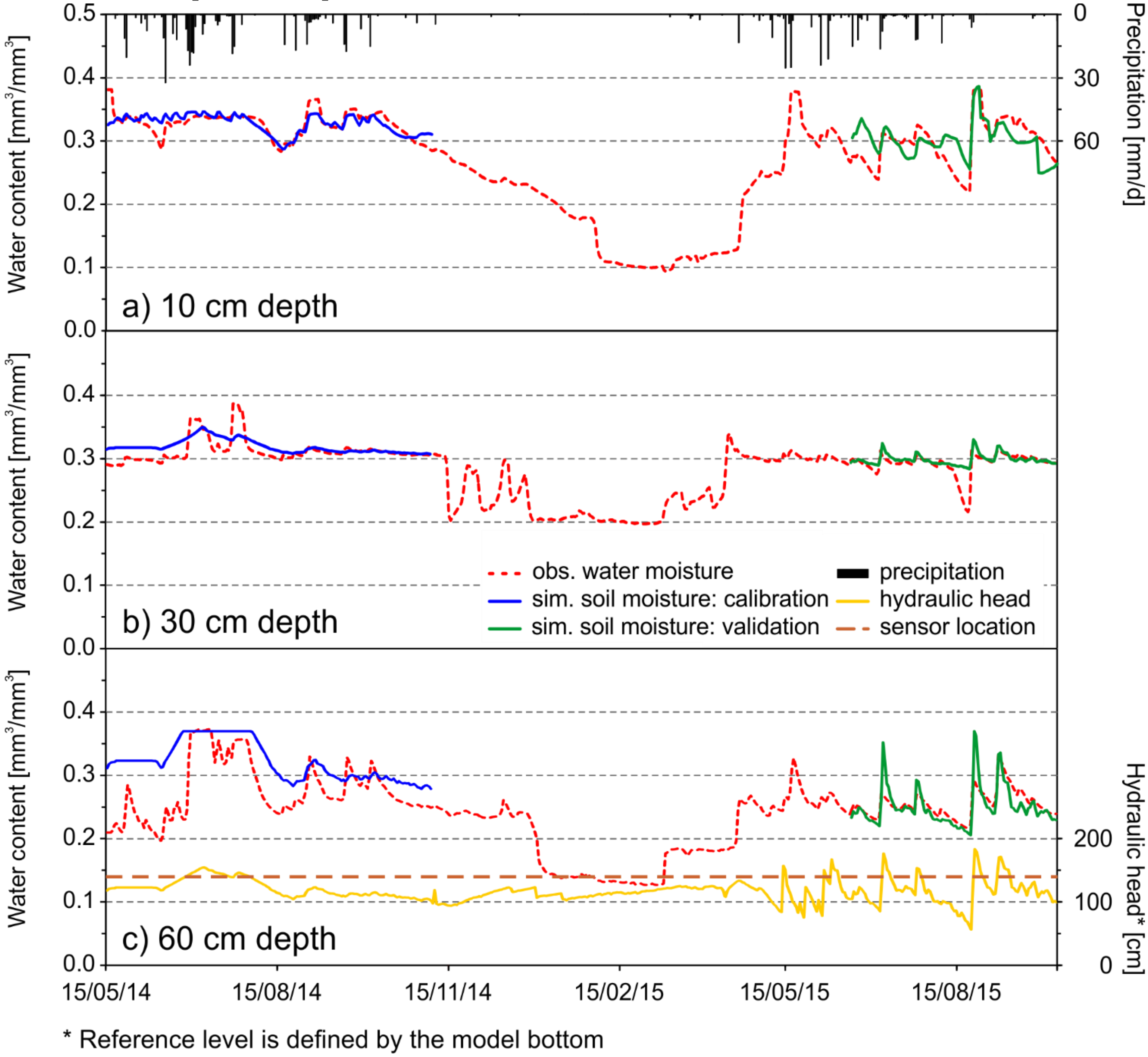


Table 4.2. Calibration and validation performance of soil moisture content of three stations

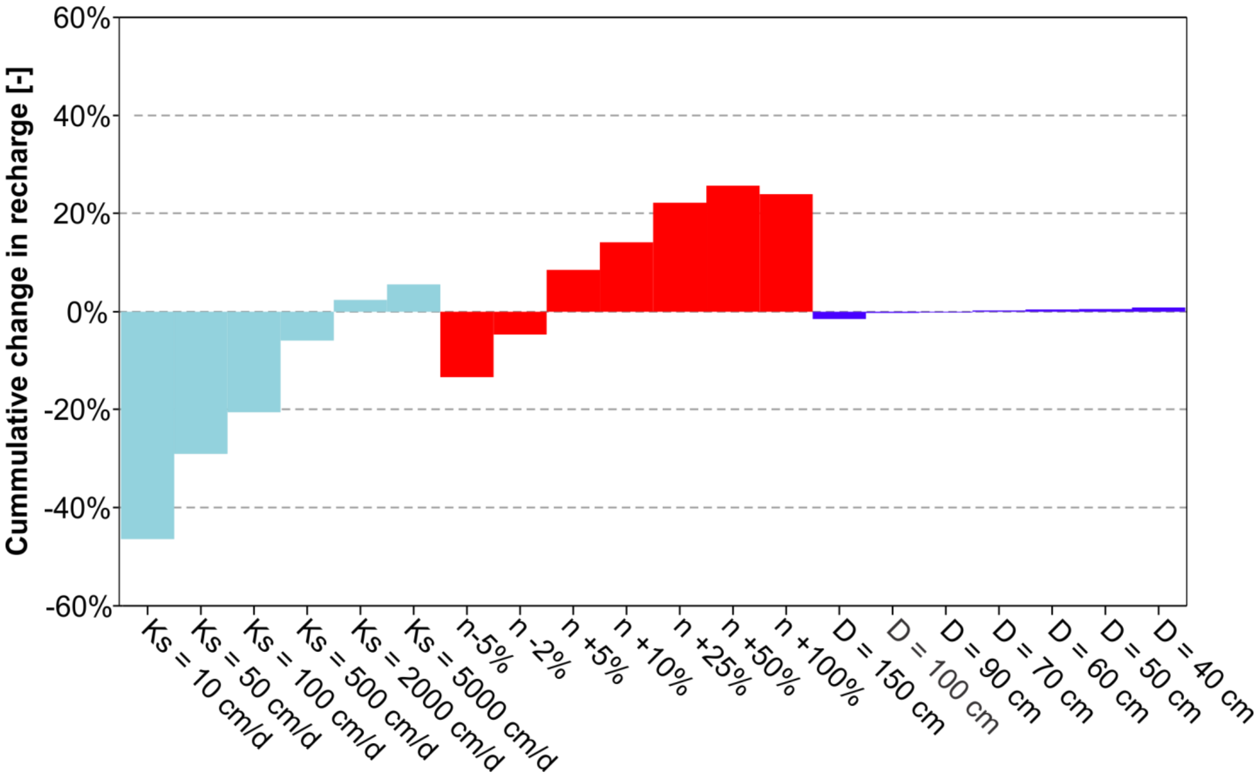
		Station I [cm^3/cm^3]			Station II [cm^3/cm^3]			Station III [cm^3/cm^3]		
		10 cm	**30 cm**	**60 cm**	**10 cm**	**30 cm**	**60 cm**	**20 cm**	**40 cm**	**90 cm**
Calibration	**RMSE**	0.03	0.02	0.05	0.01	0.02	0.03	0.01	0.02	0.04
	ME	0.01	0.00	0.02	0.00	0.00	0.00	0.01	0.02	0.04
Validation	**RMSE**	0.03	0.02	0.02						
	ME	0.03	0.01	0.01						

Mean error: ME; Root mean square error: RMSE

4.5.2 Sensitivity Analysis

The sensitivity analysis results showed that the HYDRUS-1D model, used to simulate water flow under the unsaturated soil condition with varying depths of GWL, was primarily influenced by the following parameters: the saturated hydraulic conductivity Ks, and the empirical shape parameter n (Figure 4.3). The GWL did not show an obvious impact on the cumulative recharge. Recharge changes ranged from -2% to 1% from the baseline value varying GWL depths from 150 cm to 40 cm. This result agreed with the findings of Holländer et al. (2016) on the sensitivity of soil moisture to the VGM parameters of a similar soil type. In this study, using the calibrated parameters as the standard value, results showed that Ks and n had a positive relationship with cumulative recharge. Recharge reduced by 47% and 13% using 1% of the baseline value of Ks and the 95% baseline value of n, respectively, and increased by 7% and 24% using the 500% baseline value of Ks and the 200% baseline value of n, respectively.

Figure 4.3. Sensitivity of VGM parameters and of the groundwater table on accumulated recharge, D is the depth to the groundwater table



4.5.3 Point Estimates of Recharge

The simulated groundwater recharge at the three observation stations and the six multi-level wells varied from 103.9 mm (55% of total precipitation P of modelling period) to 161.9 mm (85% P) with an average of 133.6 mm (70% P) from June 19th to July 18th, have been simulated by HYDRUS-1D using the calibrated VGM parameters (Table 4.1). In the five time periods from 19th June to 18th November using a 30-day interval, the average recharge of the nine sites were calculated as 76.5 mm, 29.7 mm, 8.8 mm, 2.9 mm and 15.7 mm corresponding to the precipitation of 68.2 mm, 43.2 mm, 12.6 mm, 22.0 mm and 43.6 mm (Table 4.3). The maximum and minimum recharge at each of the locations occurred in the time period from 19th June to 18th July and from 19th September to 18th October respectively, which encountered the maximum and minimum precipitation respectively (Table 4.3). In general, the northern part of study area received more recharge than the southern part.

Table 4.3. Accumulated recharge estimated at stations and wells, and accumulated precipitation over 30-day periods

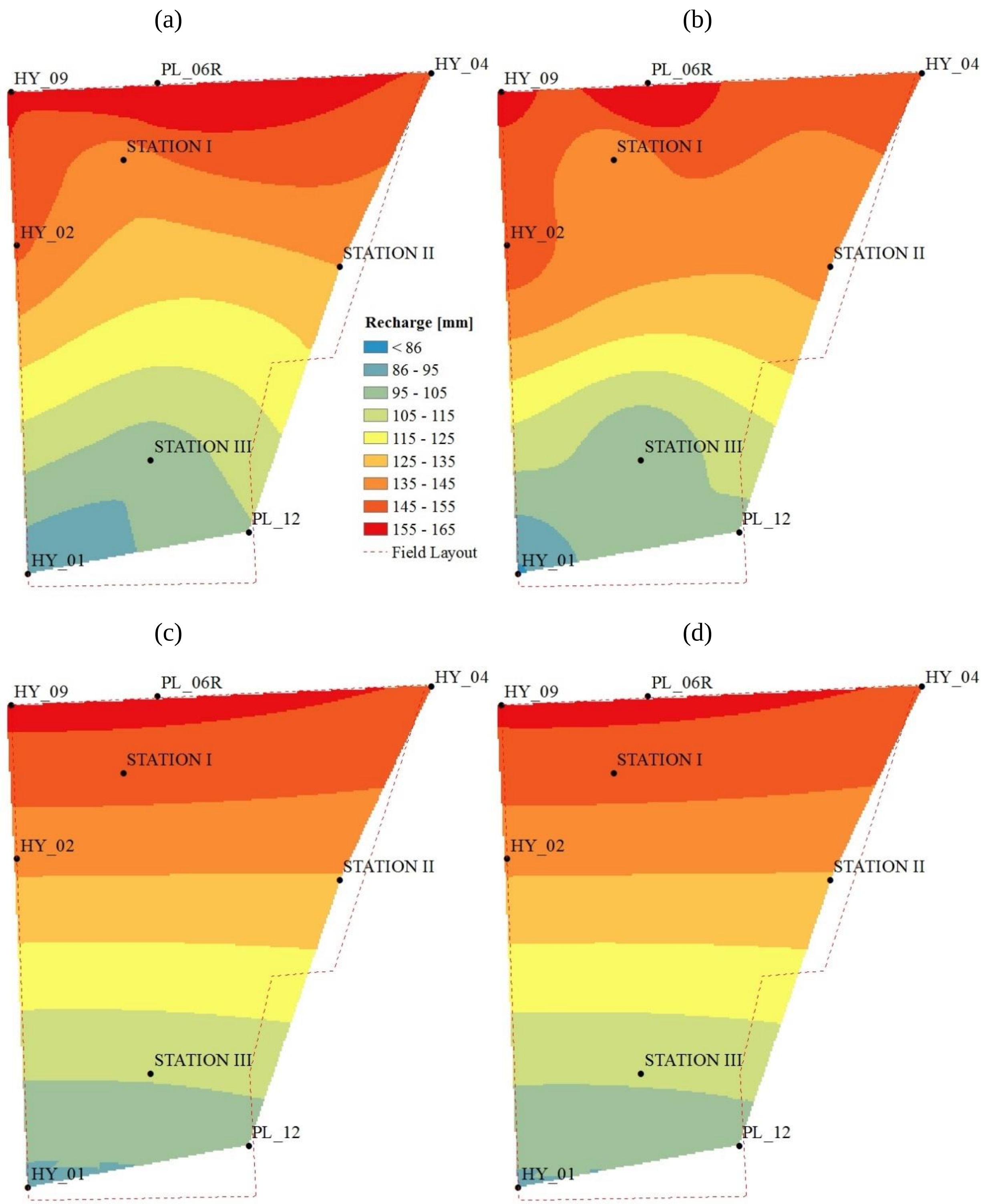
Time Period (year 2015)	**Recharge [mm]**									
	Station I	**Station II**	**Station III**	**HY01**	**HY02**	**HY04**	**HY09**	**PL06R**	**PL12**	**P**
Jun 19-Jul 18	66.7	77.4	65.4	65.4	83.8	79.3	92.3	100.0	58.0	68.2
Jul 19-Aug 18	34.5	26.9	33.9	26.8	27.1	30.4	28.9	29.2	29.8	43.2
Aug 19-Sep 18	13.9	6.0	16.5	4.6	3.6	11.3	7.6	6.8	8.9	12.6
Sep 19-Oct 18	5.5	1.1	6.5	0.4	0.2	4.5	3.9	1.4	2.5	22.0
Oct 19-Nov 18	16.9	24.4	3.3	22.0	14.7	18.7	29.2	7.2	4.7	43.6
Sum	137.4	135.8	125.6	119.3	129.4	144.2	161.9	144.6	103.9	189.6
R/P ratio	72%	72%	66%	63%	68%	76%	85%	76%	55%	

Recharge: R; Precipitation:

4.5.4 Recharge Interpolation

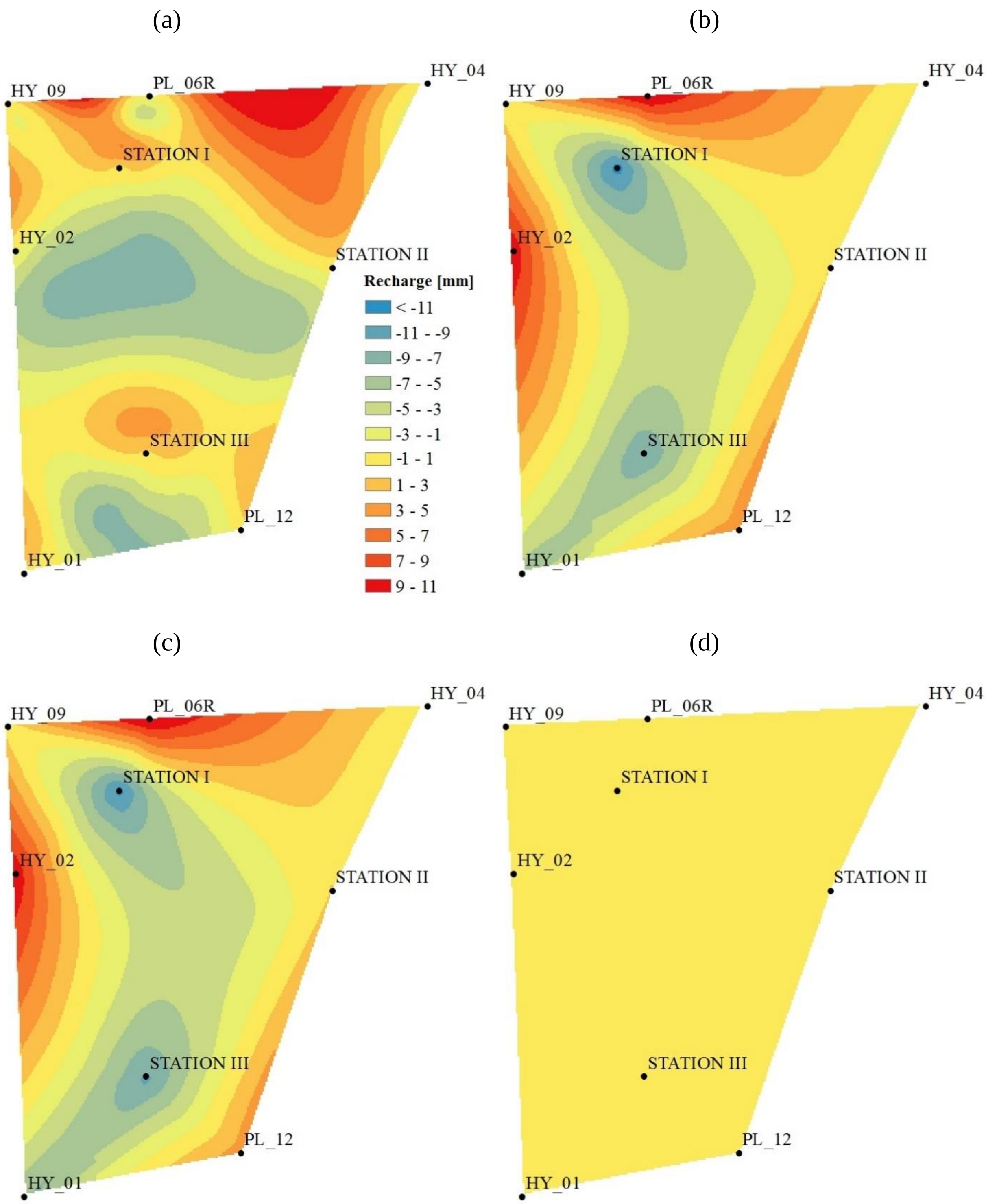
The gross groundwater recharge values, at each of the nine sites, from 19th June to 18th November were interpolated by four different methods. These methods were compared to another at a common raster resolution level and the methods were spatially consistent. The recharge patterns interpolated by NN and IDW had strong similarity, while the pattern by OK and CK were nearly identical (Figure 4.4). The curvature of the recharge contour lines determined by NN and IDW methods were larger than the ones determined by OK and CK methods. All interpolation results showed that the southern part of study area received more recharge than the northern part. The mean recharge interpolated by NN, IDW, OK and CK were 129.0 mm with a standard deviation σ of 19.8 mm, 130.0 mm with σ of 18.4 mm, 130.1 mm with σ of 18.4 mm and 130.1 mm with σ of 18.1 mm, respectively.

Figure 4.4. Regional (in mm) recharge using (a) Natural Neighbor, (b) IDW, (c) Kriging and (d) CoKriging



The difference in the recharge distribution between NN and each of the other methods (Figure 4.5(a), (b), (c)), and between OK and CK (Figure 4.5(d)) were compared in terms of mean value and standard deviation; no significant differences were observed. The recharge difference between NN and IDW, OK and CK varied from 12.8 mm to -7.9 mm with σ of 4.4 mm, from 11.5 mm to -11.8 mm with σ of 3.7 mm, and from 11.9 to -11.5 mm with σ of 3.8 mm, respectively; the recharge difference between OK and CK varied from 0.5 mm to -1.0 mm with σ of 0.3 mm.

Figure 4.5. Recharge (in mm) difference between: (a) Natural Neighbor and IDW, (b) Natural Neighbor and Kriging, (c) Natural Neighbor and CoKriging and (d) Kriging and CoKriging



Cross validation was applied to test the quality of the recharge prediction by IDW, OK and CK. The true percent error between the calibrated recharge (by HYDRUS-1D) and the predicted recharge (by ArcGIS cross validation) presented by IDW, OK and CK were 12.1%, 7.9% and 7.8%, respectively (Table 4.5). There was an obvious over-prediction (>10%) of recharge at Station I, Station III and HY_01, and an under-prediction (<-10%) at HY_02 and PL_06R by the three methods (Table 4.5). Additionally, the recharge predicted by IDW showed an under-prediction at HY_04 and HY_09. OK and CK showed a good match with calibrated recharge. IDW had a divergent prediction trend than both OK and CK at PL_12 (Table 4.5). In the semi-variogram model selection for OK and CK, Gaussian model resulted the best-fitted theoretical models in RMSE, mean standardized error and average standard error comparing with circular, exponential and K-bessel semi-variogram model (Table 4.4).

Table 4.4. Mean error and root mean square error of OK and CK semi-variogram model selection

	ME [mm]	**RMSE [mm]**
Gaussian	0.23	11.75
Circular	-0.03	14.96
Exponential	-0.05	16.54
K-bessel	0.21	12.00

Mean error: ME; Root mean square error: RMSE

Table 4.5. Recharge interpolation cross-validation of IDW, OK and CK

		Recharge [mm]					
Position	**Point estimate by HYDRUS-1D**	**IDW**		**Kriging**		**CoKriging**	
		Predicted	**Error [%]**	**Predicted**	**Error [%]**	**Predicted**	**Error [%]**
Station I	137.4	156.5	19.1	152.9	15.5	152.3	14.9
Station II	135.8	136.3	0.6	134.2	-1.6	134.1	-1.7
Station III	97.9	116.3	18.5	110.3	12.4	110.8	12.9
HY_01	86.3	117.8	31.5	101.6	15.4	102.6	16.4
HY_02	148.6	139.3	-9.3	132.2	-16.3	132.6	-16.0
HY_04	153.5	139.0	-14.5	154.9	1.4	154.1	0.5
HY_09	157.9	145.8	-12.0	158.2	0.36	157.3	-0.6
PL_06R	169.7	140.1	-29.6	153.4	-16.4	153.2	-16.6
PL_12	103.9	111.6	7.5	95.2	-8.6	96.5	-7.4
Average true error			12.1%		7.9%		7.8%

4.6 Discussion

The empirical shape parameters α and n were overestimated by ROSETTA in most cases (Table 4.1). Moreover, the calibrated parameters using the HYDRUS-1D inverse model resulted in a larger variation of parameter values of the nine field sites than the prediction by ROSETTA. This result indicated that the soil layers were modified to have more influence on soil water movement after the calibration. The sensitivity analysis proved that the VGM parameter n was the most sensitive parameter for the recharge, which agreed with Holländer et al. (2016). Recharge estimates increased more than 20% compared to the baseline if n increased by 25%, 50%, and 100%. Compared to the baseline value of n, the predicted n by ROSETTA was constantly larger than the calibrated n values. This would have been fostered an overestimation of the cumulative recharge in the case that the ROSETTA predicted n was directly used to estimate recharge. Therefore, the calibration process was necessary for the recharge estimation by HYDRUS-1D inverse calculation, in addition to the ROSETTA predictions.

The simulation results of soil moisture dynamics presented at 10, 30 and 60 cm depths were underlain by differences in the soil characteristics, initial soil moisture content and groundwater depth at three stations (Figure 4.2 (a) (b) (c)). The calibrated VGM parameter α had its largest value at Station I and α was lower at the other stations, having its lowest value at Station III, while n increased from Station I to Station III. As a result, the differences in the average soil moisture content at 10 cm for Station I, II and III (33%, 18% and 10%, respectively) can be attributed to the spatial variability of soil type and its effect on water movement in the soil profile, since α and n are associated with soil type. The simulated soil moisture at 10 cm and 40 cm depth for both calibration and validation periods were consistently correlated to the precipitation in terms of intensity and frequency at each of the three stations. The RMSE in the soil moisture simulation up to 75 cm depth was less than 3%. That was within the same range of the measurement error of the soil moisture sensor of 3.1% (Table 3.1). Additionally, with ME less than 2%, the result verified a good agreement between estimated values and observed data at 10 cm, 30 cm and 40 cm depths. Soil moisture showed the largest variation at 60 cm, and 90 cm depths and the RMSE and ME was at average 3% larger than at 10 cm and 40 cm depths for Stations I and III. We claim that the overestimation of soil moisture at 60 and 90 cm depths related to the transferred groundwater level data from the nearby observation wells of Station I and Station III since the GWL was not measured directly at the stations. Thus, the minimal mismatch of the soil moisture amplitude was acceptable, since the simulated soil moisture at Station I corresponded well with the groundwater table. Nonetheless, according to the sensitivity analysis, the cumulative recharge was merely affected by the depth of the groundwater table within a short-time period. The key reasons were that the root water uptake was not effective since the root density was sparsely distributed below 50 cm depth and the coarse soil texture allowed rather fast fluxes. This resulted in short temporal delays between a precipitation event and the corresponding soil moisture changes at depths of 10, 40 and 100 cm depth (1 day, 2 days and 4 days in average respectively). The responding time was longer when the precipitation event was after a long dry period (e.g. 23rd August 2015), due to the retention of soil moisture (Figure 4.2(b), (c)).

Recharge and precipitation data (Table 4.3) additionally indicated that the delayed response to precipitation affected the timing of recharge. For instance, the period from 19th August to 18th September had the least amount of precipitation comparing with the other periods, while the following period (from 19th September to 18th October) had the least recharge. Overall, the recharge temporally distributed from July to November was consistent with the amount of precipitation distributed from June to October, and the maximum amount of recharge was from June to July (Table 4.3). During this time, the recharge estimated at Station II (77.4 mm), HY02 (83.8 mm), HY04 (79.3 mm), HY09 (92.3 mm) and PL06R (100.0 mm) were larger than the precipitation amount (68.2 mm). This confirmed that the soil retention had a pivotal role in temporal recharge distribution and soil moisture dynamics (Table 4.3). The calculated ratio of cumulative recharge to total precipitation (from 19th June to 18th November) varied from 55% to 85% and agreed with the study by Cherry (2000). Cherry (2000) reported the recharge could have a high recharge to precipitation ratio (73% of average annual spring/fall precipitation or 30% of average annual precipitation) on sandy sediments on Sandilands Aquifer in southern Manitoba. The GWL was at average ~1 m below the soil surface in this study, and at ~2 m in the study of Cherry (2000). However, the sensitivity analysis showed a very small impact of depth to groundwater on the recharge. Hereby, both studies indicated that the precipitation dominated recharge on sandy soils.

The cumulated recharge, interpolated by four methods, consistently indicated that the northern side of the study area received the greatest recharge, and that the recharge gradually decreased from north to south (Figure 4.4). This result agrees with the findings of the recharge sensitivity analysis for Ks, since Ks within the root zone at Station III, which is located in the south, is one magnitude lower than at Stations I and II (Table 4.3). Due to the nature of the NN method, the curvature of the recharge contour lines was more obtuse than the ones by IDW. By contrast, the IDW spatial recharge distribution was more strongly impacted by the gradient of the recharge from north to south. For instance, the large difference in recharge over a short distance, e.g., at HY09 towards Station I (Figure 4.5(b)). The main differences in spatial recharge distribution between NN and IDW were located close to the extreme values (Figure 4.5(a)). Compared to the outcome between NN and IDW (Figure 4.5(a)), Figure 4.5(d) showed a high similarity in recharge distribution between OK and CK. This can be explained using the sensitivity analysis: the depth of groundwater table and the Ks > 500 cm/d had a marginal impact on cumulated recharge. Therefore, no obvious difference was found using OK and CK. They both presented that the cumulated recharge linearly decreased from north to south, and the contour lines seemed insensitive to the individual point recharge values that did not match to the general trend (Table 4.3). As expected, the greatest differences in recharge were shown at station I and station III, HY02 and PL06R by comparing OK and CK interpolation results with the of NN (Figure 4.5(b), (c)). Furthermore, the predictive performance of IDW, OK and CK were measured by cross validation in calculating the error between the predicted and the measured values (Table 4.5). CK had a slightly smaller error of 0.11% than OK, which indicated that CK improved the prediction on sandy soils. However, the improvement was not significant. As also shown by the sensitivity analysis, the soil moisture dynamic in the sandy soils had a negligible dependency to the hydraulic conductivity but was stronger influenced by the soil retention. On the other hand, due to the shortage of handling strong gradients by IDW, the prediction at Station I, Station III, HY01 and PL06R showed discrepancies that resulted in 5% more error compared to OK and CK. Thus, OK was the best method to interpolate the recharge on the sandy soil in terms of lower prediction error, less bias on extreme individuals and time-saving of preparing additional corresponding data compared to NN, IDW, and CK.

4.7 Conclusion

This paper presented a one-dimensional physically-based vadose zone model to predict point estimates of recharge on sandy soils and with a shallow groundwater table and compared different interpolation techniques in La Broquerie in southeastern Manitoba. The performance criteria of the recharge estimation at point scale showed a good match between observed data and simulated result for the calibration and the validation period. This extends the conclusion by Holländer et al. (2016) that the use of weather station along with additional soil moisture sensors from short-term observations can be used for robust and reliable recharge prediction on sandy soils in situations where the groundwater table is shallow.

Four spatial interpolation methods to simulate spatial distribution of recharge based on ArcGIS were compared and evaluated in this study. Owing to the similarities in sandy soil characteristics and the uniformity of meteorological condition over the nine locations, all four methods were able to present a similar mean, minimum and maximum recharge in the study area over a short-term observation period, despite the spatial distribution. Regional recharge was found to be decreasing from north to south for all interpolation techniques. The period from June to July and from September to October yields the maximum and minimum recharge, respectively. OK and CK had the least cross-validation error of all methods. OK estimates had the advantages of fewer input data requirement and no obvious prediction difference compared to CK. Therefore, OK was considered as the optimal method for recharge interpolation on sandy soils and with shallow groundwater table in La Broquerie. In the case of more complex metrological conditions and high heterogeneity in soil characteristics and vegetation distribution, CK is recommended, since it estimates a lower prediction variance and cross-validation error than OK. To this point, being able to predict and interpolate transient recharge estimates spatially, this method is able to predict the recharge at unknown locations and reveal reliable overviews on spatial recharge distribution on sandy soils. Consequently, this method can provide guidance for groundwater resources management and protection.

5. Summary

Two recharge estimation studies were carried out on coarse textured soil in Abbotsford, BC and La Broquerie, MB. The method of using one-dimensional physically based vadose zone numerical model with data from a portable weather station to estimate recharge on coarse textured soil at the point scale was developed. HYDRUS-1D was able to produce reliable point estimates of groundwater recharge on coarse textured soils using data from the portable weather station. The recharge estimated in both studies agreed with governmental documents, and previous studies in the same area. The model integrated non-linear least squares inverse calculation function significantly shortened the calibration process, and the calibration performance of both studies increased significantly compared to the standard for vadose zone modelling. The sensitivity analyses on key parameters of the water retention function verified the numerical robustness of the method and of the recharge estimates. Moreover, due to the reliable recharge estimates from two study areas having different climate conditions, the universality of the method was verified for coarse textured soil. Thus, HYDRUS-1D, only using weather and soil information as input, was realized for the cost-effective and efficient recharge estimation. Additionally, the usage of portable weather stations equipped with unmanned cellular data loggers allows obtaining the data from difficult or inaccessible areas without traveling and labor force.

Four ArcGIS based spatial interpolation methods to simulate spatial distribution of recharge were compared and evaluated in this study. Due to the interpolation data having spatial similarities in the soil characteristics and the high uniformity of weather condition at all observation locations on the study area, all the methods were able to predict a regional recharge with similar average value and spatial changing trend. OK is considered as the optimal method for recharge interpolation since they require fewer input data and their estimates resulted in a better performance of the cross validation compared to NN, IDW, and CK. In a case of higher heterogeneity in soil, groundwater, vegetation and weather conditions, CK is recommended since it additionally estimates the covariation relationship between the recharge and the secondary parameters, which can reduce the cross-validation error and prediction variance.

Both studies resulted in a high recharge-precipitation ratio (50% to 87%) on coarse textured soil, and the time delay between precipitation events and the recharge observation varied with the depth of groundwater and the amount of a precipitation event. In other words, recharge can be larger than the amount of precipitation in a single month. The majority of the recharge was observed in the hydrological winter period with heavy and intensive precipitation events in the Pacific Ocean climate in Abbotsford, while, the humid continental climate in La Broquerie receives the majority of recharge in spring and fall because of the snow melts in spring and intensive precipitation events. The sensitivity analysis on different parameters related to recharge showed that the parameter importance was: empirical water retention parameters which govern the soil moisture dynamic, followed by the saturated hydraulic conductivity, and finally the depth to groundwater. Since root water uptake was not effective below the root zone, it results in fast recharge on coarse textured soils. Therefore, the recharge amount was merely affected by the groundwater depth as long as the groundwater was located below the root zone. Finally, the precipitation amount dominates the recharge on coarse textured soils.

6. Recommendations for Future Research

1. Since the soil water movement is the fundamental process in the vadose zone, this method can be applied to further studies and problems, such as solute transport, irrigation management, and thawing and freezing process in cold regions.
2. Due to the physically-based nature of the model mechanism, through coupling HYDRUS-1D with weather forecast models, this method has a great potential to predict reliable recharge for the near future. Once the model is calibrated, the cost for the installation of the weather station can be saved.
3. Another potential of the method is to couple the recharge estimation model with the groundwater models. Instead of collecting recharge data as an input for modelling groundwater, combining HYDRUS-1D with kriging will be able to simulate the regional recharge based on the geological data and on the weather data, which are also typical inputs of groundwater models.

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