QUANTIFYING GROUNDWATER RECHARGE DYNAMICS USING A PROCESS-BASED DISTRIBUTED HYDROLOGIC MODEL

By

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ABSTRACT

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Groundwater – the lifeblood of groundwater-dependent ecosystems and societies is facing unprecedented threats from over-extraction, contamination, and changing climate. Groundwater recharge provides a sustainable source of water for aquifers and plays an important role in both surface and sub-surface domains. Understanding and accurately estimating the rate, location, and timing of major recharge events and their seasonal and inter-annual variability is key to safely matching societal needs of water and to maintaining healthy groundwaterdependent ecosystems. This work attempts to understand and quantify recharge dynamics in an agricultural watershed in the Ottawa County, Michigan using field observations of baseflows, groundwater heads, satellite-based evapotranspiration (ET) products and an integrated, process-based hydrologic model. Specific objectives of the work are to: (1) understand the spatial and temporal distribution of high- and low-recharge events and (2) assess the relative impacts of climate, land use, soils, and topography on the spatiotemporal distribution of recharge within the region. County-wide synoptic and time-series baseflow data collected from over 40 small streams between July and November of 2015 were used to quantify the uncertainties in recharge estimation. Precipitation data represent important inputs to hydrologic models and have a

major influence on model performance and the estimated recharge. Compared to data from a typical network of rain gauges, the Next-Generation Weather Radar (NEXRAD) provides precipitation data at a much higher spatial resolution. NEXRAD data were blended with traditional rain gauge data to estimate recharge and to evaluate differences relative to recharge estimated using rain gauge data alone. Results indicate that caution should be exercised in using NEXRAD precipitation data for recharge estimation. The representation of recharge and its variability within a numerical model are closely related to the representation of meteorological forcing fields and their spatial structure, land use and land cover, the hydraulic properties of underlying soils and aquifers as well as topography -all of which are represented to varying degrees of accuracy depending on the mesh resolution employed and the algorithms used to represent sub grid-scale processes. To understand the effects of grid resolution on recharge and to identify optimal resolution relative to the size of the watershed, models were setup with different grid resolutions. Recharge patterns follow precipitation patterns more closely at coarse grid sizes since the characteristics of LULC, terrain and hydraulic properties are smoothed at this resolution. Insights gained from the study are expected to aid in the sustainable management of natural resources, particularly groundwater-dependent ecosystems.

In loving memory of my grandmother, Zhufeng Wang

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TABLE OF CONTENTS

LIST OF TABLES	viii
LIST OF FIGURES	ix
CHAPTER 1 Quantifying the High-Resolution Spatiotemporal Dynamics of Recharge in a Great Lakes Watershed	1
1.1 Introduction	2
1.2 Materials and Methods	7
1.2.1 Site Description	7
1.2.2 Field Work	10
1.2.3 PAWS Model	12
1.2.4 Data Sources	15
1.2.5 Criteria for Model Assessments	17
1.3 Results and Discussion	19
1.3.1 Streamflow	20
1.3.2 Evapotranspiration	30
1.3.3 Groundwater Heads	34
1.3.4 Spatial Variation in Recharge	36
1.3.5. Temporal Dynamics of Recharge	38
1.3.6. Recharge Dynamics for Various LULC	43
1.4 Conclusions	45
CHAPTER 2	49
A Comparison of Groundwater Recharge Estimated with gauge and NEXRA	AD
Precipitation Data Using a Physically-Based Hydrologic Model	49 50
2.2 Materials and Methods	53
2.2.1 Study Area	53
2.2.2 Meteorological Data	56
2.2.2.1 Weather Station Data	56
2.2.2.2 NEXRAD Precipitation Data	57
2.2.3 Model Implementation	59
2.3 Assessment of the NEXRAD MPE precipitation 2.3.1 Comparisons of the Gauge and NEXRAD MPE Precipitation 2.3.2 Comparisons of the Streamflow	61
2.4.1 The Spatial Distribution of Recharge 2.4.2 Temporal Change of the Areal Recharge Using Two Precipitation D	72 72)ata
2.4.3 Water Budget	79

2.5 Discussions and Conclusions	81
CHAPTER 3	85
Effects of Grid Resolution on Groundwater Recharge Estimation Using a	
Physically-Based Hydrologic Model	85
3.1 Introduction	86
3.2 Materials and Methods	90
3.2.1. Site Description	90
3.2.2. Model Descriptions and Setup	94
3.3 Results	98
3.3.1. Grid-size Effects on the Spatial Pattern of Recharge	98
3.3.2. Grid-size Effects on the Temporal Pattern of Recharge	100
3.3.3. Grid-size Effects on the Average Annual Water Budget	103
3.3.4. Grid-size Effects on Recharge over Different LULC	104
3.3.5 Scaling Effects on Annual Recharge	109
3.4 Discussions and Conclusions	111
APPENDICES	115
APPENDIX A	116
APPENDIX B	117
BIBLIOGRAPHY	121

LIST OF TABLES

Table 1.1 U.S. Geological Survey (USGS) gauging stations	16
Table 1.2 Model calibration parameters 2	20
Table 1.3 Summary of one-time streamflow sampling	30
Table 2.1 U.S. Geological Survey (USGS) gauging stations	61
Table 2.2 Statistical analysis of MPE precipitation based on the gauge precipitation at the three USGS gauges	64
Table 2.3 Statistical analyses of the discharge simulation performance at three USGS gauges for the period from January 2011 to November 2015	72
Table 2.4 Statistical analyses of the discharge simulation performance at three USGS gauges for the period from January 2011 to December 2014	72
Table 2.5 Annual water budgets (%P, percent of annual precipitation)	81
Table 3.1 Ottawa County watershed characteristics at different grid sizes	97
Table 3.2 Average annual water budgets (%P, percent of annual precipitation) 10	04

LIST OF FIGURES

Figure 1.1 Map of the modeling domain showing the major streams, National Climatic Data Center (NCDC) and Michigan Automated Weather Station Network (MAWN) weather stations, U.S. Geological Survey (USGS) gauging stations, National Hydrography Dataset (NHD) streams and the sampling locations for the streamflow.
Figure 1.2 Map of the land use and land cover for the modeling domain10
Figure 1.3 Process flow diagram13
Figure 1.4 Water budget in a soil column14
Figure 1.5 Comparisons between the simulated and observed daily streamflow rates at three USGS gauging stations. Dark-blue lines represent the observed streamflow rates; dark-red lines represent the simulated streamflow rates, and the black bar represents precipitation. The hydrographs of a1, b1, and c1 are presented on a linear scale from 2011 to 2015. In a2 to c2 and a3 to c3, close-up views are presented for the selected simulation period represented within the dark-blue dashed lines. In a2 to c2, the enlarged plots are on a linear scale, and in a3 to c3, enlarged views are plotted on a semi-log scale
Figure 1.6 Comparisons between the simulated and measured daily flow at sampling locations. Red lines represent the simulated streamflow rates, and the blue dots represent the measured streamflow rates. The hydrographs are presented on a semi-log scale
Figure 1.7 Maps of the average annual evapotranspiration for 2011–2014 based on (a) MODIS ET and (b) simulated ET32
Figure 1.8 Monthly time-series of MODIS and simulated ET for 2011–2014. (Unit: mm/month)
Figure 1.9 Comparison between the simulated groundwater head and the wellogic database for the period of 2011-2015
Figure 1.10 Map of the average annual recharge for the 4-year period of 2011– 2014
Figure 1.11 Monthly recharge in different land uses throughout four hydrological years: September 2011–September 201541
Figure 1.12 Dynamics of monthly areal recharge for the 4-year period of September 2011–September 201543

Figure 2.6 The spatial maps of average annual precipitation and average annual recharge based on gauge and gauge-MPE precipitation over period 2011-2014.

Figure 3.1 Climate and hydrologic stations in the study domain......92

Figure 3.2 Map of land use and land cover in the watershed94
Figure 3.3 The spatial patterns of (a) average annual ET; and (b) average annual recharge over period 2011–201499
Figure 3.4 Monthly areal precipitation with 300 m grid size and monthly areal recharge over all the grid sizes of the period 2011-2014. (Units: mm/month)101
Figure 3.5 Annual areal recharge over all the grid sizes between 2011 and 2014. 102
Figure 3.6 Comparison of daily discharge over all the grid sizes at USGS 04108800 station
Figure 3.7 Comparisons of annual recharge among all the grid sizes in different land types in the drought year of 2012107
Figure 3.8 Comparisons of annual recharge among all the grid sizes in different land types in the wet year of 2013108
Figure 3.9 Comparisons of annual recharge (mm/year) between (a) the upscaled from 700 m to 1 km and 1 km grid size; (b) the upscaled from 500 m to 1 km and 1 km grid size; (c) the upscaled from 300 m to 1 km and 1 km grid size; and (d) the upscaled from 300 m to 500 m and the 500 m grid size for the period 2011–2014
Figure A1 Comparisons between observed and simulated discharge at USGS 04118800116
Figure A2 Comparisons between observed and simulated discharge at USGS 04108600. Dark green line depicts the simulation conducted with gauge-MPE precipitation; Dark blue dash line describes the observed discharge
Figure B1 Comparison between daily discharge over four grid sizes with parameters calibrated at 300 m grid size and daily discharge at 1 km grid size with parameters calibrated at 1 km from 2011 to 2014. (Units: m³/s) (g300, g500, g700 and g1K indicate the parameters estimated at 300 m grid size, g1K_1K indicates the parameters estimated at 1 km grid size)
Figure B2 Comparison between monthly areal recharge over four grid sizes with parameters calibrated at 300 m grid size and monthly areal recharge at 1 km grid size with parameters calibrated at 1 km from 2011 to 2014.(Units: mm/month) (g300, g500, g700 and g1K indicate the parameters estimated at 300 m grid size, g1K_1K indicates the parameters estimated at 1 km grid size)

Figure B3 Comparison between annual areal recharge over four grid sizes with parameters calibrated at 300 m grid size and annual areal recharge at 1 km grid size with parameters calibrated at 1 km over the period 2011-2014. (Units: mm/year) (g300, g500, g700 and g1K indicate the parameters estimated at 300 m grid size, g1K_1K indicates the parameters estimated at 1 km grid size).....120

CHAPTER 1

Quantifying the High-Resolution Spatiotemporal Dynamics of Recharge in a Great Lakes Watershed

Groundwater recharge is a sustainable source for recharging and cleaning the groundwater and aids the integration of the surface and sub-surface water resources. Understanding and estimating the natural recharge rate, locations, and timing of major recharge events in the groundwater system are essential to meet human consumption and maintain a healthy groundwater-dependent ecosystem. This study attempts to understand and quantify the recharge dynamics in an agricultural watershed in Ottawa County, Michigan with an integrated, process-based hydrologic model with field observations of the streamflow rates, USGS streamflow rates, groundwater heads information, satellite image-based evapotranspiration (ET) products. The study objectives lie in: (1) guantifying the spatial and temporal distributions of large- and smallrecharge events in the focal region; and (2) assessing the impact of climate, LULC, soil, and topography factors on the spatiotemporal distribution of recharge events in the region. The spatial variation of the simulated recharge reveals that the geographical pattern of the simulated recharge follows a general trend whereby high or low values of recharge coincide with locations with high or low elevations, respectively, and high or low recharge locations also have low or high values of evapotranspiration, respectively. The temporal dynamics of the recharge

illustrate that recharge rates are dependent on the year-to-year climate variation corresponding to the hydrological year. Further, the recharge values are also affected by different land types and various soil types, whereby the recharge values were relatively high in agricultural land and low in the forested and impervious land.

1.1 Introduction

Groundwater resources worldwide are under increasing pressure as a result of rapid population growth, agricultural usage, industrial demands, and inefficient water management. Ensuring a reliable groundwater supply and minimizing groundwater contamination and its environmental impact are critical and urgent challenges for groundwater management (Comte et al., 2016; Gorelick and Zheng, 2015). As water levels decline in groundwater systems globally, quantifying the spatiotemporal variability of natural recharge has become key to protecting and managing both the guality and guantity of groundwater (Scanlon et al., 2006; Simmers, 2013). Further, understanding the spatial and temporal patterns of recharge is vital to evaluating contaminant transport in aguifer management and protection and further to managing the waste site (Glenn et al., 2016; Healy and Scanlon, 2010; Niazi et al., 2017; Scanlon and Cook, 2002). However, estimating the temporal and spatial variability of recharge has been a challenge (Vries and Simmers, 2002), because the occurrence and spatialtemporal variations is responsive to climatic factors, topography, the nature of the land use/land cover (LULC) types, and the hydraulic properties of the underlying soils (Arnold et al., 1998; Chinnasamy et al., 2015; Crosbie et al., 2013; Freeze

and Cherry, 1979; Hunt et al., 2008; Jyrkama et al., 2002; Kendy, 2005; McMahon and Böhlke, 2006; Memon, 1995; Turkeltaub et al., 2014). Understanding the impact of these climatic and physical factors on recharge can provide a basis for improving groundwater flow analysis and for promoting recharge estimation in large-scale water balance studies, groundwater models, and climate models more generally (Bresloff et al., 2013; Kim et al., 2012).

Because of the landscape variability in vegetation and soil, estimations of the spatial and temporal variability of recharge come with a high level of uncertainty, especially when the land surface and subsurface conditions are heterogeneous (Glenn et al., 2016; Niazi et al., 2017). To reduce the level of generalization in using low spatial and temporal resolution data, high-spatial-and-temporalresolution recharge estimation has the potential to help us model the reality of recharge explicitly. Physically-based, surface-subsurface integrated hydrologic models, which quantify all the relevant hydrologic processes contributing to recharge, play an essential role in estimating the spatial and temporal patterns of recharge (Awan and Ismaeel, 2014; Dakhlalla et al., 2016; Jyrkama et al., 2002; Scanlon and Cook, 2002). Models of this kind are viewed to be either semidistributed or fully distributed models, with either sequential coupling or full coupling schemes. Semi-distributed models lump the climatic factors and physical parameters into sub-basins or hydrologic response units (HRUs) and predict the average behavior of a catchment based on several small homogeneous units, e.g., HEC-HMS (U.S. Army Corps of Engineers, 2000) and SWAT-MODFLOW (Bailey et al., 2016). The finest spatial resolution depends on

the HRUs, and the temporal resolution is limited to the lumped and simplified conceptual model, which often proceeds at a regular and fixed time interval (Kampf and Burges, 2007). Fully distributed models discretize the watershed into grid cells, with the model parameters determined based on climatic factors, physical properties of the soil type, and the land use of the given cell, e.g. ,CATHY (Camporese et al., 2010; Paniconi and Wood, 1993; Paniconi et al., 2003), ParFlow (Ashby and Falgout, 1996; Kollet and Maxwell, 2006), InHM (VanderKwaak and Loague, 2001), MIKE-SHE (DHI, 2004), and PAWS (Shen and Phanikumar, 2010). Therefore, fully distributed models are capable of describing the hydrological processes at various spatial and temporal scales and quantifying the hydrologic responses of the watershed to the variations in climatic, LULC, soil, and topographical factors (Biftu and Gan, 2001). Also, the coupling scheme is a criterion for selecting an appropriate integrated hydrologic model for a given application (Kampf and Burges, 2007). Sequential coupling scheme has a non-iterative coupling approach such as PAWS, HEC-HMS, and an iterative coupling approach such as CATHY. These two coupling approaches (especially the non-iterative one) are computationally efficient such that they can be applied to large-range watersheds (Dagès et al., 2012; Shen and Phanikumar, 2010). However, the sequentially coupled models are sensitive to temporal discretization (Bailey et al., 2017; Camporese et al., 2010; Dagès et al., 2012). Theoretically, full coupling scheme is more accurate than sequential coupling (Furman, 2008). However, this does not necessarily mean that full coupling is superior to sequential coupling. The fully coupled models are often

restricted to short simulation periods and small catchments ranging from just a few kilometers to several hundred kilometers, e.g., InHM, (VanderKwaak and Loague 2001). Furman (2008) argues that the full coupling method is more suitable for academic application studies than in the practical applications. Building a reliable and verifiable physically-based hydrologic model with a high spatiotemporal resolution is challenging as quantifying recharge entails substantial execution time and might also cause overparameterization (Beven, 1996). PAWS + CLM (Common Land Model) in this study is a seamless integration of all the important processes of the hydrological cycle to account for the entire hydrology of a watershed/aquifer system. Moreover, PAWS+CLM is grid-based, which allows each component in water balance to be produced at very fine spatial scales and addresses problems at a local scale. Each process in the non-iterative method in PAWS has its own time step so that this model is considerably more computationally efficient than using a uniform time step for all the hydrologic processes involved. These processes vary in terms of their respective response time. For example, regarding rainfall events, surface flows respond very quickly, evapotranspiration (ET) reacts quite slowly, and groundwater responds even more slowly. Multiple datasets, such as streamflow rates (discharge) from USGS gauges streamflow rates measured between July and November in 2015, wellogic groundwater heads, and MODIS ET products were used to validate the model. USGS gauges were installed in relatively large streams in the area. County-wide spatially distributed data of streamflow rates and time-series streamflow rates were collected from small streams. Such small

streamflow rates measured in small streams were used to reduce parameter uncertainties and limit overparameterization in the model. Streamflow in the summer can be considered the baseflow given that it approximately equals the recharge (Arnold et al., 2000; Cherkauer and Ansari, 2005; Gebert et al., 2007; Zomlot et al., 2015). The factors that influence recharge, such as the groundwater table, precipitation, vegetation, and soil texture, can be examined in detail in PAWS as well. Previous studies on various watersheds in Michigan (Niu et al., 2014; Riley and Shen, 2014; Shen and Phanikumar, 2010; Shen et al., 2013) show that PAWS performs very well in terms of simulating the major components of the water budget for large- and small-scale watersheds.

As a part of a project studying water resources in general in Ottawa County, Michigan, the county relies heavily on its groundwater for drinking water and for agricultural and industrial usage. A declining static water level in the glacial aquifer (south-central part of the county) and increasing chloride concentrations have been reported in the county (IWR, 2013:85). We observed that many small groundwater-dependent streams in the region dried up during our fieldwork in the summer of 2015. This loss in the groundwater table indicates that the volume of groundwater in Ottawa County is not sustainable. Understanding the spatiotemporal dynamics of recharge, therefore, is of the utmost importance in groundwater resource management in Ottawa County. Results from this study provide much-needed preliminary support for the management decision making. The primary objectives of this study are (1) to quantify the spatial and temporal distributions of large- and small-recharge events in the focal region between

2011 and 2015; and (2) to assess the relative impact of climate, LULC, soil, and topography on the spatiotemporal distribution of recharge in the region.

Herein, we report on using PAWS + CLM to estimate recharge over five years at a fine spatial and temporal resolution. The study is organized as follows: Section one provides a general background of the motivation for this highspatiotemporal-resolution groundwater study and a review of physically-based hydrologic models. Section two specifies the study area, methods, methodology, and data sources. We further show the details of the model calibration and validation in section three. While section four presents the results, and section five summarizes conclusions and discussions for the recharge estimation in Ottawa County.

1.2 Materials and Methods

1.2.1 Site Description

Ottawa County, MI is located in the west-central part of the Lower Michigan (Figure 1.1). The primary river in the county is the Grand River, which drains westward into Lake Michigan. Streams in the southeast region of the county converge into the Rabbit River, as a tributary of the Kalamazoo River to the south of Ottawa County. The area on the southwest side of the county is drained by the Macatawa watershed. Therefore, in Ottawa County, the modeling domain, marked by a dark blue line in Figure 1.1, comprises part of the lower Grand River watershed, the Macatawa River watershed, and the Rabbit River watershed. The

modeling domain is approximately 1,900 square kilometers, and the elevation within its boundary ranges from 175 m to 325 m.

Lake Michigan has a strong influence in the climate of the Ottawa County. During the winter time, a massive lake effect leads to an average of 1800 mm snow in Ottawa County each year. The county's average annual rainfall is around 900 mm (miOttawa.org), and the primary uniform rain season is between May and October. The lake effect climate is essential to the county given that agricultural land accounts for about 50% of the county's total land mass and provides opportunities for diversified agricultural practices (Census of America, 2012). Before the lumber industry developed in Michigan, the county was almost entirely covered by forests. Today, large areas of forests can only be found along Lake Michigan, wetlands and rivers and scattered patches of forests intersperse with farmland. Most wetlands in the county are associated with the Grand River and its tributaries, while some wetlands are distributed along the Macatawa and Pigeon Rivers, scattered inland from the shoreline area, in the northeast. Figure 1.2 presents the spatial variabilities of land use and land cover (LULC) for the entire modeling domain.



Figure 1.1 Map of the modeling domain showing the major streams, National Climatic Data Center (NCDC) and Michigan Automated Weather Station Network (MAWN) weather stations, U.S. Geological Survey (USGS) gauging stations, National Hydrography Dataset (NHD) streams and the sampling locations for the streamflow.



Figure 1.2 Map of the land use and land cover for the modeling domain.

1.2.2 Field Work

In this study, the SonTek RiverSurveyor M9 system and the OTT MF Pro current flow meter were used to measure the streamflow rates of small streams in Ottawa County. As a robust and highly precise Acoustic Doppler Current Profiler (ADCP), RiverSurveyor M9 can measure streams with a minimum depth of 20 cm. OTT MF Pro is a low-maintenance discharge measurement system with an electromagnetic current meter that has a sensor head ideal for use in low-flow environments with a measurable depth range from 0 to 3.05 m. The RiverSurveyor M9 system collected the streamflow rates of streams with a depth of more than 20 cm, while the OTT MF Pro was primarily used to collect the streamflow rates of shallow streams with a depth of less than 20 cm, but a width of at least 1.5 m.

We performed two types of streamflow sampling in small streams in Ottawa County in 2015: "synoptic" or one-time streamflow sampling over ten days in late July and a time-series sampling over six months from June to November. Streamflow rates were collected in multiple shallow segments of the four major rivers (Grand River, Macatawa River, Pigeon River, and Rabbit River) and 44 of their tributaries. The one-time streamflow sampling between July 22nd and July 31st was undertaken with the purpose of providing a snapshot of the spatial variations in the flow. In this 10-day period, 48 streamflow rates were collected, including 22 measurements collected by the SonTek RiverSurveyor M9, nine measurements collected by the OTT MF Pro current flow meter, and 17 dried-up streams recorded as streamflow rate of 0 (sampling locations presented in Figure 1.1). The time-series sampling data for the small streams were collected for two principal reasons: (1) to provide a validation dataset in the form of discharge as a function of time; and (2) to provide a basis for examining the model's performance for small streams. Channel width and depth measurements were also collected at the sampling locations to help correct the river properties in the model. Time-series streamflow rates were collected at 14 locations at either monthly or biweekly intervals, including 13 measurements collected by the

SonTek RiverSurveyor M9 ADCP and one measurement collected by the OTT MF Pro current flow meter.

1.2.3 PAWS Model

PAWS incorporates the overland flow, channel flow, unsaturated vadose zone, and saturated groundwater flow that cover various flow paths after a rainfall event (Shen and Phanikumar, 2010). In addition, PAWS, coupled with CLM, provides detailed, process-based vegetation dynamics (Niu et al., 2014; Thornton and Zimmermann, 2007), including factors, such as canopy interception, snowpack, biomass, depression storage, and evapotranspiration (Lawrence et al., 2011; Shen et al., 2013). Based on the entire hydrology of a watershed/aquifer system, PAWS makes it possible to capture the dynamic nature of surface and groundwater exchange as driven by the head gradient, thereby providing opportunities to evaluate the sensitivity of recharge rates to climate, land use, water use, and other natural and anthropogenic factors. Figure 1.3 briefly describes the modeling framework, including the model calibration, the model evaluation, and the major results produced by each process of the model. Physical and weather data were the input for the model. We used the streamflow rates from the USGS gauging stations between August 2009 and December 2010 to calibrate the model. We then use the streamflow rates from the USGS gauging stations from January 2011 to November 2015, streamflow rates measured during the fieldwork, and the wellogic groundwater data and MODIS ET to evaluate the model's performance.

Although recharge observations are rarely available, recharge can be constrained based on an overall water budget through the surface water, vadose zone, and groundwater system. While precipitation and ET are the critical factors controlling recharge (Cao et al., 2016; Kendy et al., 2003; Tan et al., 2013), recharge estimates are reliable when the primary processes are determining the water budget, i.e., discharge and ET, are simulated accurately. An illustration of the water budget theory is presented in Figure 1.4.



Figure 1.3 Process flow diagram.



Figure 1.4 Water budget in a soil column.

Here, $D = P - ET - Q - \Delta S$ is the recharge; *P* is the precipitation, which is the model input; *Q* is the runoff; *ET* is the evapotranspiration; and ΔS is the changes in the soil water. *Q*, *ET*, and ΔS are computed by PAWS. Compared with the values of *ET* and *Q*, the value of ΔS is small and for this reason the latter is neglected in some studies (Lee et al., 2007; Mo et al., 2009; Coelho et al., 2017). LU1, LU2, ...N refer to the types of land use in one cell. In this study, the three dominant types of land use in each discretized cell are selected to represent the combination of the land use in one cell.

We applied the model at a 300 * 300 m² spatial resolution across the entire study area, with an hourly time step for weather, vegetation, and evapotranspiration simulations, a minutely time step for channel flow and overland flow, and adaptive time steps ranging from 2 min to 1 h for the unsaturated vadose zone. We aggregated the results to daily, monthly, and yearly time steps for this analysis. Twenty-two vertical layers were used to discretize the vadose zone, and two layers were defined for the saturated groundwater domain where the top layer represents the unconfined aquifer, and the bottom layer is the confined aquifer.

1.2.4 Data Sources

The meteorological forcing data for the model are daily precipitation, maximum and minimum air temperature, wind speed, and relative humidity. The values for each of these were obtained from gauge observations collected from 54 stations provided by the National Climatic Data Center (NCDC,

https://www.ncdc.noaa.gov/cdo-web/) and 18 stations provided by the Michigan Automated Weather Station Network (MAWN,

http://www.agweather.geo.msu.edu/mawn/) around the study region over the study period (Locations of the weather stations in Figure 1.1).

The 30 m resolution National Elevation Dataset (NED) from the U.S. Geological Survey (USGS, <u>http://nationalmap.gov/elevation.html</u>) was processed to generate average cell elevation and lowland-storage bottom elevation in the computational grid and used to calculate the slope and surface runoff routing of the watershed. The National Hydrography Dataset (NHD) from the USGS

(<u>http://nhd.usgs.gov/data.html</u>) provided the channel flow network and stream properties (Figure 1.1). The soil data were obtained from the Soil Survey Geographic Database (SSURGO) distributed by the U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS). The soil data were processed by Rosetta to provide soil water retention and unsaturated conductivity information for the model (Schaap et al., 2001).

The streamflow rates (discharge) for calibrating and validating the model were obtained from the U.S. Geological Survey, National Water Information System (USGS-NWIS, http://waterdata.usgs.gov/nwis/rt). Additional streamflow rates were collected by fieldwork to better estimate the model parameters. There are four USGS gauging stations for the simulation period in the study domain, of which three were used to calibrate and validate the model (USGS04119400, USGS04108800, and USGS04108600). The other station (USGS04119000), which is on the Grand River and close to the eastern boundary of the modeling domain, provided upstream inflow data for the model. Table 1.1 shows the locations of the four USGS gauges.

Gauge Number	Gauge Name	Latitude	Longitude
04119000	Grand River at Grand Rapids, MI	42.9644	-85.6764
04119400	Grand River near Eastmanville, MI	43.0242	-86.0264
04108800	Macatawa River near Zeeland, MI	42.7792	-86.0183
04108600	Rabbit River Near Hopkins, MI	42.6422	-85.7219

Table 1.1 U.S. Geological Survey (USGS) gauging stations

Groundwater head information was collected from the Wellogic database, which includes information such as the static water level (SWL), the depth of the well, and the aquifer type, as well as a vertical description of the sediments. The LULC data used in the model are from the Integrated Forest Monitoring Assessment and Prescription (IFMAP) dataset (Figure 1.2) through the Michigan Department of Natural Resources (MDNR). IFMAP is derived from the classification of Landsat Thematic Mapper (TM) imagery for the period of 1997 to 2001 and has a 30 m spatial resolution. Land use data were reclassified into several model classes, called plant functional types (PFTs) (Thornton and Zimmermann, 2007) based on the land use classification percentile values reported in previous studies (Jia et al., 2001; Lu and Weng, 2006; Niu et al., 2014). Because the model cell size (300 m) is coarser than the IFMAP spatial resolution (30 m), a model cell possesses a mixture of land use/land cover types so three dominant PFTs were recorded and used in the model cells.

Moderate resolution imaging spectroradiometer (MODIS) Global ET (MOD16) products were compared with the ET simulated by the PAWS model spatially and temporally. The MOD16 global ET datasets offer 1 km spatial resolution land surface ET data for global vegetated land areas at 8-day, monthly, and annual intervals for the 2000–2014 period. It should be noted that these datasets do not account for ET from either open water or urban areas. Data can be obtained from http://www.ntsg.umt.edu/project/modis/mod16.php.

1.2.5 Criteria for Model Assessments

Krause et al. (2005) recommend a combination of efficiency criteria for evaluating model performance. Accordingly, in this study, in addition to graphical techniques, the following statistical criteria were selected for model assessments: the coefficient of determination (R^2 , Eq. 1.1), the square-root-transformed NASH

metric (*RNASH*, Eq. 1.2) (Shen and Phanikumar, 2010) and the root-meansquare error (*RMSE*, Eq. 1.3).

 R^2 is defined as the squared value of the Pearson's product-moment correlation (Legates and McCabe, 1999) representing the percentage of the data closest to the line of best fit. Typically, values of R^2 greater than 0.5 are considered acceptable (Moriasi et al., 2007). The square-root transformed NASH (RNASH) was employed as a second criterion because NASH coefficient tends to give too much importance to the peak flows, while RNASH metric is designed to emphasize the baseflow (Shen and Phanikumar, 2010). In this study, examining baseflow simulation is more important than assessing the peak flows because baseflow is the groundwater contribution to streams and is, therefore, associated with recharge. RMSE is further used to estimate the difference between the measured and the simulated values:

$$R^{2} = \left(\frac{\sum_{i=1}^{n} ((O_{i} - \overline{O})(S_{i} - \overline{S}))}{\sqrt{\sum_{i=1}^{n} (O_{i} - \overline{O})^{2}} \sqrt{\sum_{i=1}^{n} (S_{i} - \overline{S})^{2}}}\right)^{2}$$
(Eq. 1.1)

$$RNASH = 1 - \frac{\sum_{i=1}^{n} (\sqrt{O_i} - \sqrt{S_i})^2}{\sum_{i=1}^{n} (\sqrt{O_i} - \overline{\sqrt{O_i}})^2}$$
(Eq. 1.2)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2}$$
(Eq. 1.3)

Where, O_i is the *i*th observed value, \overline{O} is the mean of the observed data, S_i is the *i*th simulated value, \overline{S} is the mean simulated value, and *n* is the total number of events.

1.3 Results and Discussion

The daily streamflow rates for the period of 08/01/2009–12/31/2010 from the USGS 041190400, USGS 04108800, and USGS 04108600 gauges were used to calibrate the PAWS model. The parameters estimated during calibration are listed in Table 1.2. The parameter optimization using the Differential Evolution (DE) algorithm (Price et al., 2005) was performed at the High-Performance Computing Center (HPCC) at Michigan State University. We used the streamflow rates at these USGS gauges from 01/01/2011 to 11/22/2015 to validate the model. Further, the measured streamflow rates from fieldwork spatially are used to validate the model performance on the streamflow rates in small streams. Also, the MODIS ET products are used to validate the simulated ET in both spatial and temporal terms. The comparison between the simulated and wellogic groundwater head is further used to verify the model performance for subsurface flow processes.

Symbol	Parameter Meaning (unit)	Adjustment method*	Upper Bound	Lower Bound
α	van Genuchten parameter Alpha (1/m)	3	4	1.0e-01
γ	Empirical fitting parameter for root efficiency function (Lai and Katul, 2000)	1	1	1.0e-06
D	Average distance from ponding domain to flow domain (m)	1	300	20
h_{o}	overland flow ground interception (m)	1	5	0.1
Κ	Groundwater hydraulic conductivity(m/day)	3	60/10**	1.0e-10
K_r	River Leakances (m/day)	3	50	0.5
K_{S}	Soil saturated hydraulic conductivity (m/day)	3	10	1.0e-08
Ν	van Genuchten parameter N	2	5	1.03
R_h	River bed rise (m)	1	2	0
$r_{k/k}$	Anisotropy ration for the bottom conductivity between unconfined and confined aquifer	1	0.05	1.0e-10
S_{y}	Specific yield for unconfined	3	20	5.0e-05

 Table 1.2 Model calibration parameters

*: Adjustment method: 1, Assign the value to the parameter; 2, add the value to the parameter; 3, multiply the parameter by the value

**: 60 and 10 are the upper bounds of the groundwater hydraulic conductivities of unconfined aquifer and confined aquifer respectively

1.3.1 Streamflow

We compared the daily observed and simulated streamflow data over five years at three USGS gauging stations (Figure 1.5). The zoom-in hydrographs at each station in both semi-log scale and linear scale are shown for the period of July 1st, 2013–December 31st, 2013. The coefficient of determination, RNASH, and RMSE were used to examine the model performance for streamflow simulation. The coefficients of determination for all three stations were higher than 0.5, which is an acceptable value. The RNASH values ranged from 0.4 to 0.98. The lowest

RNASH was at USGS 04108600, and we think that might be partially because it is close to the watershed boundary. The values of RMSE at these three USGS gauges were small compared to the streamflow rates at corresponding USGS gauges. The comparison at USGS 04119400 (Grand River, Eastmaville) showed an outstanding performance on streamflow simulation because of the contribution of the upstream inflow input provided by UGSG 04119000, which is at the intersection of Grand River and the watershed boundary. All the statistics indicate that the model performed to an acceptable standard in simulating streamflow, especially during the low flow periods of 2011-2015. The mismatches in the hydrograph are primarily due to the underestimation of streamflow peaks in the spring. An examination of the weather records shows that the precipitation values are low for the underestimated peak periods, indicating that precipitation is not the direct cause of the high streamflow rates. And we also need to take into account that the county is affected by heavy lakeeffect snow during the winter time. Therefore, the mismatches identified may be correlated with the effects of melting snow. A close inspection of Figure 1.5 (b1) shows that the simulated streamflow at USGS 04108800 (Macatawa River, Zeeland) was underestimated at the peak every spring during the entire simulation period because the lake-effect snow was severe at this location, which is close to Lake Macatawa and Lake Michigan. There are two possible reasons for the uncertainties on the snow-melting periods: (1) the uncertainty of the measured snowfall depth induced by the measurement methods at the weather stations, and (2) the deficiency of the snow energy balance routine of the current

CLM model. The snowmelt events have the potential effects of reducing the correlation coefficient as well as the RNASH values.



Figure 1.5 Comparisons between the simulated and observed daily streamflow rates at three USGS gauging stations. Dark-blue lines represent the observed streamflow rates; dark-red lines represent the simulated streamflow rates, and the black bar represents precipitation. The hydrographs of a1, b1, and c1 are presented on a linear scale from 2011 to 2015. In a2 to c2 and a3 to c3, close-up views are presented for the selected simulation period represented within the dark-blue dashed lines. In a2 to c2, the enlarged plots are on a linear scale, and in a3 to c3, enlarged views are plotted on a semi-log scale.

Figure 1.5 (cont'd)


Figure 1.5 (cont'd)



The time-series comparisons between the simulated and field-measured streamflow rates were analyzed, and the comparisons at six sampling locations scattered throughout the watershed are presented in Figure 1.6. As the streamflow rates in these small streams were very small ($0\sim10 \text{ m}^3/\text{s}$), the comparisons of the streamflow rates were plotted in the semi-log scale to examine the streamflow rates closely. Value 0.1 m³/s was added to the simulated and measured data at location M22 and M38 for plotting in semi-log scale due to the zero or close to zero values for some simulation periods. Overall, the simulated streamflow reached a good agreement with the measured streamflow at these sampling locations. One-time sampling was performed in July 2015 to measure the "baseflow," as the ET values were high in the summer. The measured and simulated streamflow rates for the collected streamflow data are summarized in Table 1.3. The simulated streamflow rates are close to the measured streamflow rates. The results of the time-series sampling data and the one-time sampling indicate that the proposed model has (1) the ability to capture "baseflow;" and (2) the potential to accurately simulate recharge because baseflow can be considered a proxy for the recharge (Arnold et al., 2000; Risser et al., 2005; Zomlot et al., 2015).



Figure 1.6 Comparisons between the simulated and measured daily flow at sampling locations. Red lines represent the simulated streamflow rates, and the blue dots represent the measured streamflow rates. The hydrographs are presented on a semi-log scale.





Figure 1.6 (cont'd)



SiteID	Obs	Sim	Instrument	SiteID	Obs	Sim	Instrument
G7	0.16	0.12	M9	P7	0.1	0.04	OTT
G9	0.11	0.06	M9	P12	0.44	0.26	M9
G13	0.005	0.008	OTT	R25	0.11	0.11	OTT
G18	0.06	0.1	OTT	M6	0.01	0.02	M9
G20	0.05	0.03	OTT	M16	0.07	0.05	M9
G31	0.006	0.007	OTT	M18	0.03	0.01	M9
G49*	0.11,0.06	0.06,0.01	OTT	M101	0.05, 0.05	0.02,0.06	OTT
G66	0.12	0.15	M9	M71*	0,0,0	0,0,0	
G69	0.25	0.33	M9	M81*	0,0,0	0,0,0	
G77	0.03	0.05	M9				
G5, G34, G37, G38, G39, G41, G42, G54, G75;				Observed		Simulated	
M5, M7, M8, M28, M51, M54				0		0	

Table 1.3 Summary of one-time streamflow sampling

*more than one measurement was collected at this location. M9: RiverSurveyor M9. OTT: OTT MF Pro.

1.3.2 Evapotranspiration

To evaluate the performance of our model, we also used the monthly and yearly MODIS ET products over the four-year period of 2011 to 2014 to validate the simulated ET temporally and spatially. The comparison between the 4-year average annual MODIS and the simulated ET of the spatial map is presented in Figure 1.7.

The simulated ET with a spatial resolution of 300 m provides more details than does the MODIS ET with a cell size of 1 km. For the simulated ET, the highest values occurred along the major rivers and in the wetlands, while the lowest values were found in urban areas. The spatial variation in the MODIS ET values was relatively moderate compared with those of the simulated ET because ET's coarser resolution smooths the spatial variabilities of ET. Moreover, the MODIS ET products do not include the ET from open water or wetlands, where ET values appear to be the highest in our model. In addition, the MODIS ET is not

available for urban areas where our model estimates the lowest ET values (Mu et al., 2013) (The blank areas in the MODIS ET map in Figure 1.7 represent the urban areas). But in an overall comparison, the spatial pattern of the simulated average annual ET is similar to that of the average annual MODIS ET. In the study area, two regions showed significant differences in their average annual ET values. First, the northeast part of the modeling domain shows higher average annual simulated ET values than the MODIS ET. The Rough River, a wetland associated with Rough River, and the forested land cover in the northeast region lead to high ET values. The other region that showed a significant difference in its average annual ET values from the MODIS ET is in central Ottawa County where the percentage of sand in the soil is high. Water is readily brought up to the surface to produce high ET values in sandy soils. Also, the values of precipitation were higher than the values of precipitation in the surrounding areas. While the simulated ET values are high in most cells in this area, the MODIS ET has high ET values only in some cells in this area.



Figure 1.7 Maps of the average annual evapotranspiration for 2011–2014 based on (a) MODIS ET and (b) simulated ET.

With a time-series ET constraint, the uncertainty of the recharge estimation decreases as compared to when a constraint of this nature is not included in the model (Xie et al., 2017). Thus, a comparison between the simulated and MODIS monthly ET was examined in this study. We aggregated the time series of the daily ET output to a time interval by months to compare with monthly MODIS ET products. The comparison of the areal average monthly simulated ET and the monthly MODIS ET is presented in Figure 1.8. The results for the simulated ET resemble the MODIS ET values. The R² value for the 4-year comparison is 0.79. As expected, the highest value for both the simulated and the MODIS ET accrued during the summer each year and the lowest values accrued during the winter time. The 2012 drought leads to the low ET value shown for the summer of 2012.

The primary reason for the differences between the simulated ET and the MODIS ET may have arisen because of the different ET algorithms used in PAWS-CLM and in producing MODIS ET. PAWS-CLM uses a resistance approach to simulate ET based on the two-big leaf model (Dai et al., 2004), whereas the MODIS ET is produced by the revised Penman-Monteith formulation (Mu et al., 2011). The second reason is that the areal monthly MODIS ET does not account for ET from either open water or urban areas. However, the areal monthly simulated ET includes the ET from both open water and urban areas.



Figure 1.8 Monthly time-series of MODIS and simulated ET for 2011–2014. (Unit: mm/month)

1.3.3 Groundwater Heads

We derived the observed groundwater heads data from over 400 wells installed in unconfined aquifer within the Ottawa County. The estimated groundwater heads were extracted for the computation cells where the wells are located. The comparison between the estimated and the observed groundwater heads is presented in Figure 1.9. The scatter plot shows the groundwater heads in distinct colors for different years against the reference 1:1 45-degree line. The overall R² value is 0.88, indicating a good match both in spatial and temporal terms. Given the close match between the estimated and wellogic groundwater heads data, we argue that the performance of the PAWS model also provides good estimates on the ground heads for this study.



Figure 1.9 Comparison between the simulated groundwater head and the wellogic database for the period of 2011-2015

Thus, based on the comparisons in the three fields of the streamflow, the evapotranspiration, and the groundwater heads between our estimated data and the published data from various sources, we are confident that the PAWS model performs well in estimating these variables. Meanwhile, the similar geographical and time-series patterns between the estimated and the published data further approve the capability of the PAWS model at producing good estimates both in a finer geographic scale (300 m) and temporal dynamics of various hydrologic

factors (daily temporal resolution). Despite that recharge is not the factor that we can use to compare between the estimated and real values, the water balance at the pixel level allows us to argue that if streamflow, ET, and groundwater heads are relatively close to the actual situation, recharge estimates should match with the actual recharge condition in our study area. Therefore, in the following sections, we are going to present the estimated recharge data without further justification for the quality of our modeled values.

1.3.4 Spatial Variation in Recharge

Figure 1.10 shows the spatial pattern of the average annual recharge over the four-year period of 2011–2014. The spatial distribution of the simulated recharge followed the general pattern whereby high and low recharge values occurred at high and low elevations, respectively. And the opposite relationship was found between the spatial patterns of ET and recharge except for urban areas where both ET and recharge values are low. The primary recharge areas for the glacial aquifer occurred in the northeastern and southeastern parts of the county, where the primary land use is agriculture and elevation is high. The central area of the county showed low recharge values for two main reasons. First, the high ET values were found in this area. Second, the elevation in this area is relatively low. The groundwater replenished by the recharge in the northeastern region of the county discharged to the Grand River. Also, the groundwater replenished by the recharge in the southeastern area of the county mainly discharged to the Rabbit River. Therefore, the primary recharge areas did not contribute much

groundwater into the central part of the county where has experienced the highlevel, unsustainable groundwater usage.

The unexpected high values of recharge along the top eastern boundary of the computational domain, which we think are due to boundary issue that the watershed was composited based on the surface watershed composition so that the groundwater table at the boundary might have been affected by the groundwater flow outside of the model domain. And this is the only region in the study we think shows slightly different patterns of recharge from our impression in the study area.



Figure 1.10 Map of the average annual recharge for the 4-year period of 2011–2014.

1.3.5. Temporal Dynamics of Recharge

Recharge is related to factors such as precipitation, land use types, soil types, topography, and the ways these factors are combined. The non-linear relationship between recharge and these climatic and physical factors is complex. Figure 1.11 presents the monthly dynamics of recharge with different types of soil for four kinds of land use. In this study, each pixel in the LULC map consists of three dominant LULC types expressed as a percentage, which means different cells might have different combinations depending on their specific three dominant types. Soybean, corn, broadleaf, and needleleaf are the dominant land types in the selected cells for Figure 1.11. Agricultural land (soybean/corn) accounts for 90% of the selected cells, and forested land (broadleaf/needleleaf) takes 80–90% of the selected cell. Three major soil types—sand, clayloamy, and loam—were defined based on the relative proportions of sand, clay, and silt (NRCSS, USDA). The soil in the soybean land and broadleaf forest land for the selected cells was mostly sandy, whereas in the corn and needleleaf forest cells it mainly was clay loamy.

The time series of the estimated monthly recharge based on various vegetation and soil types illustrate the various responses of recharge to different conditions of vegetation, soil, and rainfall. In agricultural land, the simulated monthly recharge generally had a late response to the monthly precipitation and increased after intense precipitation during the simulation period except for the year of 2012 (Figure 1.11(a) and (b)). Precipitation for the year 2012 was below average, which had a more significant impact on reducing the recharge in the soybean land with sandy soil than in the corn land with clay loamy soil, indicating that recharge in sandy soil was more responsive to precipitation. Also, high ET values are more often observed in sandy soils. The fluctuation of the monthly recharge values was greater in the forested land than in agricultural land. Further, the monthly recharge values in the forested land were low, especially in 2012 due to a period of drought that took place in late spring to fall. The temporal fluctuation of recharge in forested land may have arisen at least in part of the

fluctuation in ET, which took a large portion of the precipitation (about 60% in this study area). The temporal pattern of ET is primarily affected by precipitation and the growing season in the agricultural land, as ET in the forested land is more dependent on precipitation given that forests do not have a clear growing season. Therefore, we argue that the temporal fluctuation of ET is correlated to the temporal fluctuation of recharge in the forested land. Further, the recharge in the forested land is also affected by the types of land use because the forested area accounted for 80–90% of the selected forested cell. As the model cell is 300 m * 300 m, 10-20% of the other land use types could potentially cause noticeable impacts on recharge.



Figure 1.11 Monthly recharge in different land uses throughout four hydrological years: September 2011–September 2015.

Figure 1.11 (cont'd)



Figure 1.12 presents the time series of the average areal monthly recharge for the period of September 2011–September 2015. The cycle of the monthly recharge dynamics is responsive to the cycle of a hydrological year. However, the temporal distribution of the average areal monthly recharge for each hydrological year was different. For example, extremely high precipitation values were found in April 2013, which contributed to the peak values of recharge. However, the effect is not as strong in other hydrological years.



Figure 1.12 Dynamics of monthly areal recharge for the 4-year period of September 2011–September 2015.

1.3.6. Recharge Dynamics for Various LULC

Boxplots of the annual recharge for four major land use types were created for the drought year of 2012 and the wet year of 2014 to examine the impact of LULC on recharge (Figure 1.13). We used these two years because the climatical factors represent a typical condition of the area as 2012 experienced significant drought, 2014 showed more of an average condition in the area. As noted in section 2.4, three dominant PFTs were modeled in each cell in this study. For example, one cell might be composed of 70% of soybean, 20% of corn and 10% of the broadleaf forest. In the boxplots, X-axis noted the percentage of one dominant LULC type in a cell. Taking soybean as an example, 10% in the X- axis represents that the cell contains between 0 and 10% of soybean, and 20% means that soybean constitutes to between 10 and 20% of the cell, and so forth. The 90% of soybean indicates that the cells have larger than 80% but smaller than 100% of soybeans. In each box, the central horizontal line indicates the median, and the bottom and top of the vertical bar indicate the first and third quartile metrics, respectively. The outliers are plotted individually using a "+" symbol.

Figure 1.13 shows that the median values of recharge increased when the percentage of the soybean and corn land types in the cells increased for both the drought year of 2012 and the wet year of 2014. Conversely, the median values of the recharge decreased when the coverage percentages of the broadleaf and impervious land types in the cells increased for both years. The recharge values are lower in the cells with a larger proportion of forested land types, because the root system in the forested land retains a relatively high level of moisture in the soil and leads to a high ET value. Changes in the median recharge values over the percentage of all four land types are similar in the drought and wet years, but the recharge values for 2014 are higher than those for 2012.



Figure 1.13 Annual recharge in various types of land cover in the year of 2012 and 2014 (Unit: mm/year)

1.4 Conclusions

In this study, we explored estimating recharge at a very fine spatiotemporal resolution (300 m on a daily basis) at a watershed scale with a process-based hydrologic model (PAWS). To build a reliable and valid hydrologic model, we used the streamflow rates from USGS gauges and the county-wide streamflow rates collected from small streams to spatially and temporally validate the model. We also used wellogic groundwater heads data and MODIS ET products to validate the model's performance on recharge estimation indirectly. The results show that the model estimations are in agreement with the observations of the major hydrologic components, including streamflow, groundwater, and ET.

Further, the high spatial and temporal resolution allows us to see more local variations of these factors both in individual cells and the time series. Based on the validation with existing data, we argue that PAWS model is capable of producing a realistic representation of recharge. The capability of PAWS to simulate the hydrological process at such a fine resolution is due to two essential characteristics: (1) the model is process-based, which allows us to examine each factor individually on the fine-spatial-resolution cells; (2) the non-iterative sequential coupling method allows us to more efficiently carry out the modeling process, which enables us to run the model at such fine spatial and temporal resolution for such a long simulation period and a large watershed. The modeling process with multiple step-time intervals (from 1 min to daily) takes 3 hours for a one-year worth of analysis, which makes the total processing time to be within 24 hours for the overall project after we made our decisions about parameterization. With the PAWS model, we produced daily outputs of recharge for the Ottawa County during the five-year study period, and the data is further aggregated to monthly averaged values for analysis purposes. The occurrence of recharge and its spatial and temporal variations were examined in response to climatic factors, land use, the hydraulic properties of the underlying soils, and topography. The spatial variation of recharge shows that the primary recharge areas do not contribute much groundwater to the central part of the county, which has experienced the high-level, unsustainable groundwater usage. The results of the temporal dynamics of recharge also advance our understanding of how vegetation types and soil contents influence recharge, which is critical for

managing land types rotations to sustain the groundwater usage. Likewise, the results strengthen the field's understanding of the long-term impact of forest restoration on aquifer recharge volumes and water resource management. The temporal dynamics of the monthly recharge show that recharge rates are dependent on the year-to-year climate variation corresponding to a specific hydrological year. The analysis of the monthly recharge simulation (derived from daily recharge data) allow us to have a much closer look at the recharge values, patterns, and trends in a local 300 m by 300 m cell size. And we also hope this study opens the opportunity for further fine spatial and temporal analysis on recharge and furthers the guidance on water resource management at a very fine spatial and temporal scale.

Estimating recharge at a high spatial and temporal resolution is vital in apprehending and representing the reality of recharge at the local scale. The high spatial and temporal resolution of recharge estimation in this study not only makes it possible to design water resource management plans on a very fine local scale but also contributes to our understanding of the relationship between groundwater recharge and various climatical and physical factors at a fine resolution.

In our study, we also understand that there is a lot left yet to be done. First, the modifiable areal unit problem (MAUP) remains an important issue as the fine cell size is arbitrarily defined in this study. A follow-up study will further the discussion on MAUP to compare the cell-size effect on recharge estimation using 300 m, 500 m, 700 m, and 1 km cell sizes for the same period and same study area.

Second, we also discuss the effect of various precipitation data provided by different sources as well. Third, given the time frame of this study, we do not have the chance to carry out a study to analyze the "time-lag" between precipitation and recharge cases. We think this study will further our understanding of the relationship between precipitation and recharge, which can potentially provide more explicit guidance for the water resource management to improve the impacts of activities to increase recharge on a local scale by mimicking the precipitation-recharge process.

CHAPTER 2

A Comparison of Groundwater Recharge Estimated with Gauge and NEXRAD Precipitation Data Using a Physically-Based Hydrologic Model

This study aims to understand the differences on recharge estimation using two precipitation datasets based on a physically-based hydrologic model for Ottawa County, MI between 2011 and 2015. We first use the rain gauge data as the sole source for precipitation; and further, we combined the Stage IV NEXRAD data (also known as Multi-Sensor Precipitation Estimator, MPE) with the rain gauge data as our second data source for precipitation. With the gauge data as a reference, this study assessed the quality of NEXRAD MPE precipitation by examining the relationship between the two datasets and comparing the performance on discharge simulation at three USGS gauges. The results show that precipitation data from both sources produce a similar performance in the streamflow estimation in our model except for the year 2015. The spatiotemporal analysis of recharge shows that the spatial pattern of average annual recharge over the period of 2011-2014 was not sensitive to the different precipitation datasets and the temporal patterns of monthly recharge are also similar using the two datasets from 2011 to 2014. We conclude that NEXRAD MPE data have the

potential to be a supplemental source of precipitation data in understanding the impacts of precipitation on recharge.

2.1 Introduction

Groundwater recharge provides a sustainable source of water input for aquifers and plays an integral role in both surface and sub-surface water resources. Understanding and accurately estimating the rate, location, and timing of major recharge events and their seasonal and inter-annual variability is important to safely satisfy the societal needs of water and preserve the groundwaterdependent ecosystem. As a major component of a watershed system, groundwater recharge is challenging to quantify. A physically-based hydrologic model provides a reliable and cost-efficient way to estimate recharge with all the relevant hydrological components.

In many aspects, precipitation data remains one of the most critical factors in modeling hydrologic processes as precipitation serves as the direct driving force of the hydrologic models (Sexton-Sims et al. 2010; Xie and Xiong, 2011; Gao et al., 2017). Specifically, the spatial and temporal variation of precipitation, the spatial distribution of the stations gathering precipitation data, the spatial and temporal resolution of the precipitation data, and extreme precipitation cases all influence the performance of physically-based hydrologic models. A plethora of research (Larson and Peck 1974; Price et al., 2011; Cunha et al., 2012; Shen et al., 2015) shows that precipitation remains the primary source of uncertainty in watershed modeling, while the spatial and temporal variations of precipitation influence hydrologic responses, such as spatial and temporal dynamics of runoff,

evapotranspiration, and recharge in a watershed (Daly et al., 2002; Moore et al., 2006; Cole and Moore, 2008; Mobley et al.2012). Existing studies also found that in a physical-based hydrologic model, the responses are sensitive to the locations of the rain gauges and the corresponding spatial variability of the rainfall data (Bell and Moore, 2000; Segond et al., 2007; Pechlivanidis et al., 2017). In addition, the spatial and temporal resolutions of the rainfall data also have a great impact on hydrologic modeling (Fu et al., 2011; Vergara et al., 2013; Ochoa-Rodriguez et al., 2015). The impact of long-term spatial-temporal variabilities of precipitation on recharge was examined by Acworth et al. (2016) using gauge precipitation. Moreover, extreme precipitation plays a key role in determining recharge reported by Zhang et al. (2016) using reanalysis precipitation produced based on rain gauge data.

There are a number of different precipitation products collected using different methods, such as rain gauges, ground-based radar (Next-Generation Weather Radar, NEXRAD), and satellite-based microwave and infrared sensors. The conventional precipitation data collected from the rain gauges are typically used as the ground truth to examine the qualities of the precipitation products derived by radars and satellites (Grimes et al., 1999; Habib et al., 2009; Price et al., 2011; Serrat-Capdevila et al., 2014). As a primary source of climate data, a network of land-based National Climatic Data Center (NCDC) weather stations records the precipitation information collected from rain gauges. However, the low density of existing rain gauges and the missing data due to malfunctioning lead to large gaps in data and sometimes significant differences between the

data collected from nearby gauges. For large watersheds, the sparsely located rain gauges may not be enough to capture the overall variability of precipitation. Although radar has itsown limitations, such as range discrimination, pulse length, the radar system provides spatially continuous precipitation information at a high temporal resolution (Gao et al. 2017). The Stage IV NEXRAD data, also known as the multi-sensor precipitation estimator (MPE), is calibrated based on the data gathered by the high-accuracy rain gauges through the regional River Forecast Centers under the National Weather Service (NWS) and is further mosaicked to be a national product with a 4 km spatial resolution (Price et al., 2011). FAS crop analysts also argue that the radar-based precipitation data have superior quality compared to the other global precipitation data sets that cover the United States (Gebremichael and Hossain 2009). MPE has been widely used in hydrologic modeling (Kalin and Hantush, 2006; Habib et al., 2009; Price et al., 2011; Kitzmiller et al., 2013), but the use of MPE data in recharge estimation has not been fully explored.

This study investigates whether the use of MPE data improves the accuracy of recharge estimation, evaluated based on the simulated streamflow data, using a physically-based hydrologic model (Process-based Adaptive Watershed Simulator, PAWS). This study developed two PAWS models based on data from two sources: first, we use the conventional precipitation data collected by gauges from the NCDC and MAWN (Enviro-weather Automated Weather Station Network). Further, the MPE precipitation is combined with the conventional rain gauge precipitation to represent the second source of the precipitation data.

Section 2 explains the data and methods of this study in details, while section 3 focuses on the comparisons of the precipitation using two different data sources. We also compared the simulated and the observed streamflow to evaluate our adoption of the MPE precipitation data, as Neary et al. (2004) and Price et al. (2011) have shown that streamflow simulations can be used to evaluate the quality of MPE precipitation. Moreover, in section 4, we further investigate the simulated spatial distribution of recharge, the simulated temporal change of areal recharge, and the water budget for using two different data sources. Section 5 presents the conclusions of this study.

2.2 Materials and Methods

2.2.1 Study Area

Ottawa County, MI, located in the western-central part of the Lower Michigan (Figure 2.1), is located within a watershed (shown in Figure 2.1) that consists roughly of three sub-watersheds, including a part of the lower Grand River watershed, the Macatawa River watershed, and the Rabbit River watershed. The total area of the three sub-watersheds is about 1900 km^{2,} and the elevation ranges from 175 m to 325 m. The primary land use types of Ottawa County, MI are agriculture (about 47%), forest (about 23%), grass (about 10%), urban (about 10%), followed by water (about 4%) and wetlands (about 4%) (Figure 2.1). The agricultural products include mainly corn and soybean. This study focuses on the application of a physically-based hydrologic model to the total area of these three sub-watersheds.

Having a strong lake effect due to its contiguity with Lake Michigan, the Ottawa County has a climate that is strongly influenced by it. During the winter time, heavy lake-effect snow has introduced an average of 1800 mm of snowfall each year. The average annual rainfall in the county is around 900 mm (miOttawa.org) which is relatively uniformly distributed between May and October.



Figure 2.1 Study area. (The top right map shows the location of the Ottawa County watershed in Michigan; the top left map shows the major streams in the watershed, the weather stations inside the watershed, the NEXRAD Radar HRAP grids (4 km spatial resolution), the Radar station and the UGSG gauges; the lower left map shows the spatial variability of elevation; the lower right map shows the primary land use and land cover types inside the watershed.

2.2.2 Meteorological Data

The weather stations (NCDC and MAWN) and the NEXRAD (Next-Generation Radar) are the two sources for obtaining the precipitation information in this study. The weather stations are unevenly distributed in the watershed and are concentrated around the urban areas. There are two stations in the southeastern watershed and three weather stations located in the central and western watershed (Figure 2.1). Daily NEXRAD precipitation products (MPE) produced by the Advanced Hydrologic Prediction Service National Weather Service (NWS) offer high temporal (daily) and spatial (4 km) resolution precipitation data. Since it is based on a field view of weather, precipitation data is available at every location within the 4 km by 4 km grid cells.

2.2.2.1 Weather Station Data

As meteorological data sets are needed to drive a physically-based hydrologic model, two organizations become our main sources: the GHCN-Daily and the MAWN. The meteorological data for the model input, including daily precipitation, maximum and minimum air temperature, wind speed, and relative humidity data, were obtained from GHCN (Global Historical Climatology Network) – Daily archive at the National Oceanic and Atmospheric Administration/ National Climatic Data Center (NOAA/NCDC, <u>https://www.ncdc.noaa.gov/cdo-web/</u>). GHCN-Daily is a composite of climate records from numerous sources that were merged and then subjected to a suite of quality assurance reviews (Menne et al., 2012). However, about two-thirds of the weather stations report the precipitation data only. The additional meteorological data, such as air temperature, relative

humidity data, were collected through the Enviro-weather Automated Weather Station Network (MAWN: <u>http://www.agweather.geo.msu.edu/mawn/</u>). MAWN was built for making decisions strategically based on the weather information to improve the efficiency and productivity of agriculture. It provides detailed weather data and information, such as precipitation, air temperature, relative humidity, soil temperature, at hourly and daily temporal resolution. Putting the two main data sources together, there is a total of 72 weather stations around the study area over our simulation period (2009-2015), including 54 NCDC stations and 18 MAWN stations. The locations of the weather stations are shown in Figure 2.1. Among all the meteorological data, precipitation data collected by the rain gauges from the weather stations as precipitation depth represents the nearactual amount of precipitation at the scale of a localized point. The gauges are unevenly distributed in the study area and in our case, most of the gauges are concentrated around the urban areas, of Grand Rapids.

2.2.2.2 NEXRAD Precipitation Data

NEXRAD (Next-Generation Radar) system is a network of 160 high-resolution Doppler weather radars throughout the United States and select overseas locations. Operated by the National Weather Service (NWS), the NEXRAD system can detect the precipitation and wind using a field view based on a grid size of 4 km by 4 km. The NEXRAD precipitation products are the ground accumulated rainfall which is estimated based on a reflectivity and rainfall rate relationship (Fulton et al. 1998). The rainfall estimates are improved after 2010, due to the deployment of the Dual Polarization (Dual Pol) technology. Dual Pol

more accurately discerns the returns signal which allows the radar to better differentiate among the different types of precipitation (e.g., rain, hail, and snow) and reduce the non-weather artifacts. The KGRR (Grand Rapids, MI) site which is the closest radar site in the study domain, activated Dual Pol in December 2011.

The NEXRAD precipitation products are categorized into four product levels based on the amount of preprocessing, calibration, and quality control procedures performed (Xie et al. 2005; Sexton-Sims et al. 2010; Kang and Merwade 2014). The Stage IV NEXRAD (also known as Multi-Sensor Precipitation Estimator, MPE) daily precipitation products were utilized in this study as the main precipitation data source to be examined in this study. MPE products are the gauge-adjusted and manual quality-controlled precipitation products estimated by the NWS River Forecast Centers (RFCs) (Young et al., 2000; Price et al., 2011; Chen et al., 2013). The data can be accessed from Advanced Hydrologic Prediction Service National Weather Service (NWS, <u>https://water.weather.gov/precip/download.php</u>). The spatial resolution of the NEXRAD precipitation data is approximately 4 km by 4 km which is referred to as an HRAP (Hydrologic Rainfall Analysis Project) grid, shown in Figure 2.1 (Reed and Maidment, 1999).

NEXRAD can locate and follow precipitation up to over 400 km. However, NEXRAD signal attenuates as distance increases from the radar site (Doviak and Zrnić 1984), which can lead to poor performance on data collection. Luckily for

this study, one of the six radar stations covering Michigan is located very close to the central-eastern boundary of our study area (Station KGRR, Figure 2.1).

2.2.3 Model Implementation

PAWS is a physically-based hydrologic model, which incorporates overland, unsaturated vadose zone, saturated groundwater and channel flows (Shen and Phanikumar, 2010) that cover various flow paths in the watershed. In addition, PAWS coupled with the Community Land Model (CLM) 4.0 provides detailed, process-based vegetation dynamics (Thornton and Zimmermann, 2007; Niu et al. 2014) while taking the canopy interception, snowpack, biomass, depression storage and evapotranspiration into consideration (Lawrence et al., 2011; Shen et al., 2013). Considering the entire hydrology of a watershed system, PAWS allows us to capture the dynamic nature of surface and groundwater exchange driven by the head gradient, thus to evaluate recharge by quantifying all of the recharge-relevant hydrologic processes in the system.

Two PAWS models were built respectively for using the gauge precipitation data, and the combined gauge and NEXRAD MPE precipitation products (also mentioned as gauge-MPE in this article). The discharge information from the USGS 04119000 station (Figure 2.1 and Table 2.1) which is located at the junction between Grand River and watershed boundary served as the upstream inflow for the model. The grid size of the model is 300 m by 300 m which enables us to capture the detailed spatial variability of the simulated recharge. We used hourly time steps for weather, vegetation, and evapotranspiration simulations, 10 minute time steps for channel flow, and overland flow, and adaptive time steps

ranging from 2 min to 1 h for the unsaturated vadose zone. The results were aggregated to daily, monthly and yearly time steps for further analysis.

In this study, we first calibrated the model based on precipitation data obtained from the weather stations only. The same calibration parameters and model inputs except for the precipitation data were used for each of the models. Therefore, deviations in streamflow, ET, and recharge can be expected to be based solely on the precipitation variations. The daily streamflow rates for the period of 08/01/2009-12/31/2010 from the USGS 041190400, USGS 04108800, and USGS 04108600 gauges (Figure 2.1, Table 2.1) which are scattered across the county were used to calibrate the PAWS model. The parameter optimization using the Differential Evolution (DE) algorithm (Price et al., 2005) was performed at the High-Performance Computing Center (HPCC) at Michigan State University. We used the streamflow rates at these USGS gauges from 01/01/2011 to 11/22/2015 to validate the model. Further, the measured streamflow rates from fieldwork spatially are used to validate the model performance on the streamflow rates in small streams. In addition, the MODIS ET products are used to validate the simulated ET spatially and temporally. The comparison between the simulated and wellogic groundwater head information verifies the model performance on the subsurface flow processes. All the analyses of this article are based on the period between January 2011 and November 2015.
Gauge Number	Gauge Name	Latitude	Longitude
04119000	Grand River at Grand Rapids, MI	42.9644	-85.6764
04119400	Grand River near Eastmanville, MI	43.0242	-86.0264
04108800	Macatawa River near Zeeland, MI	42.7792	-86.0183
04108600	Rabbit River Near Hopkins, MI	42.6422	-85.7219

Table 2.1 U.S. Geological Survey (USGS) gauging stations

2.3 Assessment of the NEXRAD MPE precipitation

2.3.1 Comparisons of the Gauge and NEXRAD MPE Precipitation

Two daily precipitation datasets were collected from the weather stations and the NEXRAD weather radars from 2009 to 2015. Twenty-two weather stations are inside the watershed area, including the NCDC and MAWN rain gauges. The rain gauges are unevenly distributed in the watershed as most are concentrated around the urban areas. And the gauges have a density of 0.012 gauges/km² in the study area, which is much better than the average gauge density in the United States (0.0013 gauges/km²) (Linsley 1992). The NEXRAD MPE daily precipitation products with a 4 km spatial resolution are adjusted by the gauge precipitation with high accuracy (Price et al., 2011). To assess the quality of the NEXRAD MPE daily precipitation data, we compared the NEXRAD MPE precipitation products with the corresponding gauge-based precipitation data close to the only three USGS gauging stations which provide streamflow data for model calibration and validation. The weather stations are US1MIOW0030, US1MIAN0001, and USW00004839, which are labeled as W3, W2, and W1 in Figure 2.1. The comparisons between the gauging precipitation and MPE precipitation products over 2011-2015 are presented in the scatterplots in Figure

2.2. The daily precipitation rate comparisons are scattered around the 1:1 line at the weather station US1MIOW0030 and weather station US1MIAN0001.

However, NEXRAD MPE shows some extreme high values of precipitation when the gauging precipitation is small. And, the precipitation comparison scatterplot at the weather station USW00004839 is also scattered around the 1:1 line but with a relatively larger cloud.



Figure 2.2 Scatter plots of the gauge and the NEXRAD MPE precipitation rates over the period of 2011-2015. (Unit: mm/day)

Further, we used several metrics to measure the relationship between the gauges and the MPE precipitation datasets. Specifically, three metrics are used: (1) Pearson's correlation coefficient (ρ , Eq. 2.1) is a measurement of the linear correlation between the two precipitation datasets; (2) percent bias (B, Eq. 2.2) is used to examine the systematic differences between the two datasets; and (3) relative normalized root mean square differences (NRMSD, Eq. 2.3) is a measure of the random differences between the two datasets.

$$\rho = \frac{\sum_{i=1}^{n} (R_i - \overline{R})(G_i - \overline{G})}{\sqrt{\sum_{i=1}^{n} (R_i - \overline{R})^2 \sum_{i=1}^{n} (G_i - \overline{G})^2}}$$
(Eq. 2.1)

$$B = \frac{\sum_{i=1}^{n} (R_i - G_i)^2}{\sum_{i=1}^{n} G_i} \cdot (100)$$

$$(Eq. 2.2)$$

$$NRMSD = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (R_i - G_i)^2}}{\overline{G}}$$

$$(Eq. 2.3)$$

Where, R_i and G_i represent the *i* th day precipitation rate of rain gauges and MPE, respectively (mm/day); \bar{R} and \bar{G} are the mean values of precipitation over the whole study period; *n* is the number of gauge and weather radar pairs. ρ is the Person's correlation coefficient; B is the percent bias; NRMSD is the relative normalized root mean square difference. Table 2.2 shows a summary of the metrics for the NEXRAD MPE precipitation data against the gauge precipitation data at the three selected USGS gauges between January 2011 and November 2015. It shows that the Pearson's correlation was high at weather station US1MIAN0001 and weather station US1MIOW0030, and relatively low at weather station USW00004839. The percent bias and the *NRMSD* presents the same trend as the Pearson's correlation, the values of bias and *NRMSD* at weather station US1MIAN0001 and weather station, the values of bias and *NRMSD* at

and the values of bias and *NRMSD* at weather station USW00004839 was the largest among these three weather stations. Generally speaking, we see a strong correlation and little bias between the two data sets at the US1MIAN0001 and US1MIOW0030 weather stations. The statistical analysis illustrates that the values of NEXRAD MPE precipitation were close to the gauge precipitation at US1MIAN0001 and US1MIOW0030 weather stations and had a significant difference from the gauge precipitation at USW00004839.

Table 2.2 Statistical analysis of MPE precipitation based on the gauge precipitation at the three USGS gauges.

	ρ	B (%)	NRMSD
USW00004839	0.70	37.84	2.07
US1MIOW0030	0.90	15.65	1.07
US1MIAN0001	0.91	15.93	1.03

This result is consistent with the processing of NEXRAD MPE precipitation products which are adjusted based on the gauge precipitation. Precipitation pairs at US1MIOW0030 and US1MIAN0001 weather stations which are about 27~33 km away from the NEXRAD site have a strong correlation. And, precipitation pairs at the USW00004839 weather station which is about 45km away from the NEXRAD Site – KGRR, has a relatively poor correlation, but the Pearson's correlation remains quite high between the two data sets. The relatively smaller correlation might be caused by the long distance away from the radar site. As mentioned earlier, NEXRAD signal attenuates as distance increases from the radar site.

2.3.2 Comparisons of the Streamflow

As discussed earlier, quantifying the uncertainties of precipitation data obtained from the rain gauges and NEXRAD MPE is not straightforward. In this study, we also compared the observed and the simulated discharge to aid in evaluating the use of these two precipitation datasets in our physically-based hydrologic model (Figure 2.3). This approach is one of the predominant approaches to evaluate precipitation data sources (Neary et al., 2004; Kalin and Hantush, 2006; Sexton-Sims et al., 2010; Price et al., 2011). Also, the base flow is a proxy of recharge and therefore, accurately simulated base flow indicates that the model has the potential to accurately simulate recharge.

The criteria used to examine the streamflow (discharge) estimation performances are (1) the coefficient of determination (R2, Eq. 2.4); (2) the root-mean-square error (RMSE, Eq. 2.5); and (3) the square-root-transformed NASH metric (RNASH, Eq. 2.6) which is designed to emphasize the assessment of the baseflow (Shen and Phanikumar, 2010) as a proxy of recharge since the NASH metric is biased toward peak flows.

$$R^{2} = \left(\frac{\sum_{i=1}^{n} ((O_{i} - \overline{O})(S_{i} - \overline{S}))}{\sqrt{\sum_{i=1}^{n} (O_{i} - \overline{O})^{2}} \sqrt{\sum_{i=1}^{n} (S_{i} - \overline{S})^{2}}}\right)^{2}$$
(Eq. 2.5)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (S_i - O_i)^2}$$
(Eq. 2.6)

$$RNASH = 1 - \frac{\sum_{i=1}^{n} (\sqrt{O_i} - \sqrt{S_i})^2}{\sum_{i=1}^{n} (\sqrt{O_i} - \sqrt{O_i})^2}$$
(Eq. 2.7)

Where, O_i is the *i*th observed value, \overline{O} is the mean of the observed data, S_i is the *i*th simulated value, \overline{S} is the mean simulated value, and *n* is the total number of events.

Figure 2.3, Figure 2.4, and Figure 2.5 show the comparisons between the observed discharge and the two sets of model-simulated discharge with the gauge precipitation data and gauge-MPE precipitation data at three USGS gauges. The metrics used to test the comparisons with the two above-mentioned precipitation datasets were summarized in Table 2.3. Both simulated sets of results of discharge with the gauge-based precipitation and the gauge-MPEbased precipitation data show agreements with the observed discharge at the USGS 04119400 station on the Grand River. The R² (0.96), RNASH (0.98) between the simulated and observed streamflow using gauge precipitation data are very high, while the R² (0.97) and RNASH (0.97) are also very high based on the gauge-MPE precipitation data. Therefore, we can argue that both models have produced outstanding performance at USGS 04119400. Close inspection of Figure 2.3 reveals that the simulation conducted with the gauge-MPE precipitation data led to an overestimated discharge value in 2015, especially in the fall. However, the discharge simulation at the USGS 04119400 station has a relatively good performance because of the significant contribution of the input upstream inflow data provided by the UGSG 04119000 station which is at the

intersection of Grand River and the watershed boundary (point of entry of the Grand River into the Ottawa County used as a boundary condition in the model). Comparing the NEXRAD MPE precipitation to the gauge precipitation for the period from January 2015 to November 2015, the values of NEXRAD MPE precipitation were consistently larger than the values of gauge precipitation (Figure 2.3). As we take the conventional gauge precipitation data as the standard input for the model, the NEXRAD MPE data are consistent with the gauge data in the years between 2011 and 2014. But we do detect some disagreement for the year 2015, further research is needed to investigate the causes and explanations of this unexpected situation.

Figure 2.4 and Figure 2.5 also illustrate that the simulation conducted with the gauge-MPE precipitation data led to an overestimated discharge value in 2015. The metrics from our statistical analyses illustrate that the discharge simulation conducted with the gauge precipitation data has a higher correlation coefficient with the observed discharge than that conducted with the gauge-MPE precipitation data at the USGS 04108800 station. The R² of the gauge precipitation simulated-observed discharge is 0.51 which is acceptable indicating a strong correlation with values larger than 0.5 (Moriasi et al., 2007). The R² is 0.42 when we use gauge-MPE precipitation data (Table 2.3). The RNASH has the same trend as the R² as the value is 0.66 for using the gauge precipitation data and 0.54 with the gauge-MPE precipitation data (Table 2.3). The USGS 04108800 station did not have discharge records for the period from January 2015 to mid-March 2015. The comparison between the simulated and observed

discharge data at the USGS 04108600 station also shows that the R² and RNASH are smaller when we combine with NEXRAD MPE precipitation data (Table 2.3). When we further recalibrated the model based on a combination of the gauge precipitation and NEXRAD MPE precipitation data, we still observe the general offsetting trend of the streamflow estimation in 2015 (APPENDIX A). We suspect that the NEXRAD MPE has some data offset in the year of 2015, but further research is needed to understand this discrepancy in the NEXRAD MPE dataset fully.

Since 2015 was the only year we observed a large offset in our analysis, we also summarized the comparison for the years between 2011 and 2014. The metrics for this period are summarized in Table 2.4. Both the R² and RNASH increase significantly based on the NEXRAD MPE precipitation data. The R² with the NEXRAD MPE precipitation increase from 0.43 to 0.53 at the USGS 04108600 station. Moreover, the RNASH increase from 0.28 to 0.38. And the R² and RNASH with the NEXRAD MPE precipitation at the USGS 04108800 station increase from 0.42 to 0.46, and from 0. 54 to 0.67, respectively.

Based on the series of comparisons drawn between the simulated discharge using two data sources and the observed discharge, we can argue that the NEXRAD MPE data leads to relatively similar performance as the conventional gauge-based precipitation data in our study area. However, in some years, the similarity is not robust as consistent overestimated results have been observed for one of the five years in the model.



Figure 2.3 Comparisons between observed and simulated discharge at USGS 04119400. (The dark green line depicts the simulation conducted with gauge-MPE precipitation; the dark red line describes the simulation conducted with gauge precipitation. The presented simulation period is from January 2011 to November 2015. The selected window period is from January 2015 to November 2015.)



Figure 2.4 Comparisons between observed and simulated discharge at USGS 04108800. (The dark green line depicts the simulation conducted with gauge-MPE precipitation; the dark red line describes the simulation conducted with gauge precipitation. The presented simulation period is from January 2011 to November 2015. The selected window period is from January 2015 to November 2015.)



Figure 2.5 Comparisons between observed and simulated discharge at USGS 04108600. (The dark green line depicts the simulation conducted with gauge-MPE precipitation; the dark red line describes the simulation conducted with gauge precipitation. The presented simulation period is from January 2011 to November 2015. The selected window period is from January 2015 to November 2015.)

	04119400		04108800		04108600	
	Gauge	MPE	Gauge	MPE	Gauge	MPE
R ²	0.96	0.97	0.51	0.42	0.53	0.43
RMSE	21.06	20.22	3.75	3.99	1.78	1.89
RNASH	0.98	0.97	0.66	0.54	0.4	0.28

Table 2.3 Statistical analyses of the discharge simulation performance at three USGS gauges for the period from January 2011 to November 2015.

Table 2.4 Statistical analyses of the discharge simulation performance at three USGS gauges for the period from January 2011 to December 2014.

	04119400		04108800		04108600	
	Gauge	MPE	Gauge	MPE	Gauge	MPE
R ²	0.98	0.98	0.54	0.46	0.55	0.53
RMSE	22.95	20.76	3.66	3.86	1.82	1.88
RNASH	0.98	0.98	0.68	0.67	0.45	0.38

2.4 Results

2.4.1 The Spatial Distribution of Recharge

The spatial maps of the average annual precipitation and the average annual recharge obtained based on the gauge precipitation data and the NEXRAD MPE precipitation data between 2011 and 2014 are shown in Figure 2.6. The spatial variabilities of recharge are affected by the spatial characteristics of precipitation, land use and land cover (LULC), terrain characteristics, and soil types. Figure 2.6 shows that the general spatial patterns of the simulated recharge using both precipitation datasets roughly follow the spatial pattern of elevation (DEM), whereby high values of recharge occur in places with high elevation. Agricultural

land generally has larger values of recharge than forested land does for the recharge maps produced based on both precipitation datasets. Also, we can clearly see that the precipitation map obtained from the NEXRAD MPE is more fine-grained than the gauge-based precipitation map. On the one hand, this situation reflects the high spatial resolution of the NEXRAD MPE dataset, and on the other hand, the NEXRAD MPE offers the possibility to study and understand the impacts of precipitation on recharge on a fine scale. And further, if NEXRAD MPE data lead to consistent results with the conventional gauging data, the fine-resolution maps on various hydrologic variables will enable various water resource management projects to be implemented on a fine scale.



Figure 2.6 The spatial maps of average annual precipitation and average annual recharge based on gauge and gauge-MPE precipitation over period 2011-2014.

The northern part of the study area with high estimated recharge values, the values of the recharge estimated with the NEXRAD MPE precipitation were consistently higher than the values of recharge obtained with the gauge precipitation data which is probably because the values of the NEXRAD MPE precipitation (between 1050 mm/year and 1200 mm/year) were much higher than

the values of gauge precipitation values (between 950 mm/year and 980 mm/year) in this area. The impact of high precipitation from the NEXRAD MPE dataset on recharge can be seen in the estimated recharge value in the northern part of the study area. The areal averaged annual precipitation based on the gauge precipitation data, and the NEXRAD MPE precipitation data were 911.0 mm/year and 968.8 mm/year, respectively. The areal averaged annual recharge obtained with the gauge precipitation and NEXRAD MPE precipitation was 112.1 mm/year and 125.0 mm/year. The values of the NEXRAD MPE precipitation were 1.06 times larger than the values of gauge precipitation. However, the values of recharge estimated with the NEXRAD MPE precipitation data were 1.12 times higher than the values of recharge estimated with the gauge precipitation data. Since all the other factors are held constant, the difference in the estimated recharge is attributed solely to the difference in the precipitation data inferring that the higher precipitation values presented in the NEXRAD MPE precipitation data lead to a higher estimation of the recharge.

2.4.2 Temporal Change of the Areal Recharge Using Two Precipitation Data

Figure 2.7 presents a side-by-side comparison of both the monthly areal precipitation (bars on the top) and estimated monthly areal recharge values (lines) of the two precipitation datasets: gauge data and the NEXRAD MPE data. The changes of the estimated recharge based on the two precipitation datasets follow the cycle of the hydrologic year starting from October and ending in September of the following year. The values of the simulated monthly areal recharge based on two precipitation datasets were similar over the period from

September 2011 to November 2013. The estimated recharge with the NEXRAD MPE precipitation data was larger than the one derived with the gauge precipitation data after December 2013. In 2014, the values of the estimated recharge using the NEXRAD MPE precipitation data were consistently larger than the values from the gauge precipitation data, while the temporal patterns of the simulated recharge remained similar. In 2015, simulated recharge with the NEXRAD MPE precipitation data for the simulated recharge remained similar. In 2015, simulated recharge with the NEXRAD MPE precipitation data kept increasing with a fluctuating precipitation data.

When we compare the values of the gauge precipitation data to the values of the NEXRAD MPE precipitation data, the values were similar from September 2011 to September 2013 (Figure 2.7). However, the NEXRAD MPE precipitation data were smaller than the values of gauge precipitation when the precipitation was heavy, while the NEXRAD MPE precipitation data were greater than the values of gauge precipitation when the precipitation was light. In previous studies, NEXRAD MPE precipitation was found to have underestimated heavy rain and overestimated light rain (Jiang et al. 2006; Skinner et al., 2009). The values of NEXRAD MPE precipitation were larger than the values of gauge precipitation starting from October 2013, the values of the NEXRAD MPE precipitation were significantly and consistently greater than the values of the gauge precipitation in 2015. The large values of precipitation made a significant contribution to the peak values of recharge. In a hydrologic year from October 2013 to September 2014, the annual gauge precipitation was 924.9 mm. The NEXRAD MPE-based areal precipitation over the period from October 2013 to September 2014 was

1092.6mm. But for the year of 2015, the cumulative precipitation from January to November was 663 mm based on the gauging data and 1217 mm from the NEXRAD MPE. The values of the NEXRAD MPE precipitation were much larger than the values of gauge precipitation in the year 2015. Given the constraint of this study, future research is needed to investigate the significant discrepancy between the two datasets.



Figure 2.7 The comparison between gauge and gauge-MPE precipitation conducted areal monthly recharge.

Figure 2.8 describes the seasonal changes of the estimated recharge based on the gauge precipitation data and the NEXRAD MPE precipitation data. Here, seasons were defined as northern meteorological seasons. A calendar year is divided into four meteorological seasons of three months each: Spring is from March 1 to May 31; Summer is from June 1 to August 31; Fall is from September 1 to November 30; and, Winter is from December 1 to February 28 (February 29 in a leap year). The seasonal changes of the estimated recharge using gauge precipitation data (Figure 2.8) indicate that winter was the primary recharge season and summer was the low recharge season except for the hydrologic year of 2012-2013 right after the drought year of 2012. The values of the estimated recharge increased from fall 2012 to spring 2013 and then decreased until fall 2013. The large values of the estimated recharge in Spring were contributed by the extremely high precipitation in April 2013, and this impact lasted until fall 2013. The seasonal changes of recharge with the NEXRAD MPE precipitation had a similar trend as one using the gauge precipitation data. But in 2015, there are large differences in precipitation from the two data sources. The intense high values of precipitation from the NEXRAD MPE precipitation data in the spring and summer of 2015 (Figure 2.7) leads to an extremely high estimated recharge values in the spring and summer of 2015. But the estimated recharge based on the conventional gauge data illustrates relatively stable and consistent seasonal changes between 2011 and 2015. We suspect errors in the 2015 NEXRAD MPE data, but further research is needed to fully understand the discrepancies between the two precipitation datasets from these two sources.



Figure 2.8 The comparison between estimated seasonal recharge based on gauge and NEXRAD MPE precipitation data. (X-axis is time, "W" indicates winter, "S" indicates Summer)

2.4.3 Water Budget

To further evaluate and compare the model performances using the gauge precipitation data and the NEXRAD MPE precipitation data, this study also calculated the water budget between 2011 and 2014. Table 2.5 summarizes the annual water budget in a typical drought year of 2012, in the typical wet year of 2014, and the average annual water budget over the period from 2011 to 2014. The annual water budget of 2012 and 2014 and the average annual water budget between 2011 and 2014 were all 5% to 20% larger than the values of precipitin which is acceptable because of the inputs/outputs or storage mechanisms in the watershed. In the drought year of 2012, the areal annual gauge precipitation was 755.1 mm/year, while the areal annual NEXRAD MPE precipitation was 728.8mm/year. The ratios of recharge (symbol – Dperc, which stands for "deep percolation" another term of recharge) to precipitation are the same in the year 2012. But, in the wet year of 2014, the ratio of recharge to precipitation based on the NEXRAD MPE precipitation (16.4%) was larger than that with the gauge precipitation data (14.3%). The areal annual gauge precipitation was 893.9 mm/year in 2014, while the areal annual NEXRAD MPE precipitation was 1072.8mm/year in 2014. This observation confirms the study by Zhang et al. (2016), who argued that the extreme values of precipitation have stronger impacts on recharge estimation.

Further, we also compared the simulated ET values in the water budget by using the two different precipitation data. The percentages of ET based on the two datasets appeared to be similar in 2012 water budget, and the averaged four-

year water budget. The annual areal gauge precipitation in 2012 was 755.1 mm/year, which is close to the value (728.8mm/year) of NEXRAD MPE precipitation in 2012. Moreover, the averaged annual areal gauge precipitation (911.0 mm/year) was also similar to the averaged annual areal NEXRAD MPE precipitation (968.8 mm/year) for the period of 2011-2014. The percentage of ET appeared to be similar smaller when we used the NEXRAD MPE data than that from the gauge precipitation data in 2014. But the values of the simulated ETs were similar based on the two precipitation datasets, 542.6mm/year with the gauge data and 560.0 mm/year with the NEXRAD MPE precipitation data which is because that annual areal precipitation of the gauge precipitation (893.9) mm/year) was much smaller than that of the NEXRAD MPE precipitation (1072.8) mm/year) in 2014. However, the ratios of recharge to precipitation conducted with the two precipitation datasets for the water budget of 2012, 2014 and the average four-year period were similar. In 2014, the high precipitation from NEXRAD MPE produced large values of recharge. To sum up, ET estimation, taking up a large portion of the water budget, was not as sensitive to the high precipitation as the estimated recharge was, but recharge has a significant response to the high values of precipitation.

	2012			2014	Ave	Ave annual	
	Gauge	MPE	Gauge	MPE	Gauge	MPE	
Р	100	100	100	100	100	100	
ET	75.9	78.6	60.7	52.2	61.9	60.9	
Dperc	13.0	13.0	14.3	16.4	12.3	12.9	
Qoc	22.3	18.4	27.2	30.9	25.8	23.7	
Qgc	1.1	2.7	1.1	2.5	1.0	2.4	
SUBM	1.9	3.4	5.8	7.5	4.1	5.5	
Total	114.2	116.1	105.1	110.9	105.1	105.4	

Table 2.5 Annual water budgets (%P, percent of annual precipitation)

P: precipitation, Dperc: percentage of recharge in the water budget, Qoc: surface runoff percentage in the water budget, Qgc: groundwater outflow percentage in the water budget, SUBM: sublimation percentage in the water budget.

2.5 Discussions and Conclusions

This study compared and examined two datasets for obtaining the precipitation data from the conventional gauge stations and the radar-based NEXRAD. We used a physically-based hydrologic model, PAWS, to test the performance of these two datasets on recharge estimation in the watershed around the Ottawa County, MI during the period of 2011 – 2015. The obvious advantages of the NEXRAD dataset lie in its high spatial and temporal resolution, with the complete coverage of the U.S. But the current research has revealed that the NEXRAD data may have discrepancies with the conventional gauge-based precipitation data during some periods. This study used PAWS, a physically-based hydrological model, to examine how NEXRAD precipitation data differed from or agreed with the conventional gauge-based precipitation data, and further to investigate how the two precipitation datasets performed in estimating the discharge, the spatial patterns of recharge, and the time-series recharge, and water budgets.

First, we compared the precipitation data from both sources at three weather stations over the period of 2011-2015. The results show that the two datasets have a high correlation at the two weather stations which are relatively close to the existing NEXRAD radar station. This confirms the general consensus of the radar-based NEXRAD data in that the farther the location is away from the radar station, the lower the accuracy of the data. However, although we have found discrepancies between the two datasets, their correlation is consistently strong at all three weather stations. Thus, we argue that NEXRAD MPE datasets would serve as a good supplement to the conventional gauge precipitation data for locations not too far away from the radar station.

Second, we compared the estimated streamflow data using two datasets with the observed streamflow data at the three USGS gauge stations. The results show that the estimated streamflows have a relatively strong correlation with the observed data. Generally, precipitation data from both sources produce a similar performance in the streamflow estimation in our model with the exception of the year 2015.

Further, the maps of the average annual estimated recharge based on the two precipitation datasets over period of 2011-2014 show very similar patterns in the study area. When we examined the average annual recharge maps, we noted that the areas with higher precipitation values from the NEXRAD MPE data caused the higher estimated average annual recharge. However, both recharge estimation maps based on the two datasets have similar spatial patterns, which further indicates that the NEXRAD data do not have a consistent spatial bias in

estimating recharge in a physically-based hydrologic model. Thus, NEXRAD MPE data opens up the possibility to study and understand the impacts of precipitation on recharge.

The examination of the time-series of the areal monthly recharge based on the two precipitation datasets shows that the two monthly recharge time-series agree with each other between 2011 and 2014. But there appears to be a sharp difference between the two in the year 2015. Further investigation reveals that the NEXRAD MPE precipitation data is systematically and consistently higher than the gauge-based precipitation data. The difference can be clearly seen in Figure 2.7, and we suspect an error in the NEXRAD MPE data for 2015, but further research is needed to understand the exact reasons for this difference. The comparison of the estimated seasonal recharge shows similar patterns in that the two estimations roughly agree with each other before 2015, but the 2015 estimation is also clearly affected by the high values in the NEXRAD MPE data. Last but not least, the total water budget is consistent within the acceptable range for both two precipitation datasets. The estimated water budget composition also reveals that the percentages of various estimated components in the water budget are similar using two precipitation datasets. However, the extreme values of precipitation have stronger impacts on recharge estimation. Thus, all in all, the precipitation datasets from the conventional gauge stations and from the radar-based NEXRAD MPE have shown a strong correlation with each other. The strongest correlation of the precipitation values occurs at locations that are closer to the radar station. Spatially, the two datasets produce

similar patterns of the estimated recharge for the study region. Also, temporally, the two datasets show a strong correlation between 2011 and 2014. Therefore, we argue that NEXRAD MPE generally provides a reasonable estimate of precipitation for hydrologic modeling in areas close to the radar stations. The high spatial resolution of the NEXRAD data also provides the possibility to help implement water management plans in the area with sparse weather stations/with weather stations which have missing records.

CHAPTER 3

Effects of Grid Resolution on Groundwater Recharge Estimation Using a Physically-Based Hydrologic Model

Results of numerical modeling based on distributed hydrologic models are sensitive to the grid size adopted, as the local climate and physical characteristics of the study area, such as precipitation, land use, and elevation can vary significantly based on different cell sizes in a physically-based hydrologic model. The grid size used in a model not only influences the overall representation of the spatial variability of the physical characteristics, but also lead to large differences in recharge estimation. The grid size in a model is also closely related to the computational efficiency and computer storage which are essential factors in numerical modeling. In this study, we used a physically-based hydrologic model, PAWS, to examine the effects of four grid sizes, 300 m, 500 m, 700 m, and 1 km on the recharge estimation in Ottawa County, Michigan between 2011 and 2014. The results showed that the values of estimated recharge were related to grid sizes while the spatial and temporal patterns of recharge remained consistent for the four grid sizes. Finer grid size can capture the detailed spatial variabilities of recharge as the baseflow comparisons showed that the recharge was more accurately simulated with a grid size less than 500 m. Moreover, the analysis of scaling effects illustrated that a finer grid size was able to represent the spatial continuity in recharge as well. These findings

demonstrated that a grid size below 500 m well captured the spatial variabilities of the recharge in the study domain. The spatial and temporal patterns of annual and monthly recharge were related to precipitation, Land Use and Land Cover (LULC) types, and topography as the recharge was more strongly related to precipitation at a coarser grid size. The analysis of the grid size effects on recharge over different LULC types demonstrated that the impacts of different LULC types on recharge were not significant across the four grid sizes.

3.1 Introduction

Groundwater is extracted for agricultural, industrial, and municipal uses globally and remains as the primary source of freshwater for approximately one-third of the world population (Alley, 2006; Giordano, 2009; Gleeson, Wada, Bierkens, & Beek, 2012; Kundzewicz & Döll, 2009; Richey et al., 2015; Siebert et al., 2010). Groundwater is also a key factor to maintain the composition and functions of groundwater-dependent ecosystems to regulate the water levels, water temperature and nutrition (Brown, Bach, Aldous, Wyers, & DeGagné, 2011; Howard and Merrifield, 2010; Murray et al., 2003). However, over-extraction and contamination of groundwater also lead to problems, such as aquifer depletion, land subsidence, cessation of base flow, and damaged natural ecosystems (Aeschbach-Hertig & Gleeson, 2012; Brown et al., 2011; Rodell, Velicogna, & Famiglietti, 2009). Groundwater recharge is the sustainable source for recharging and cleaning groundwater and plays an integral role in surface and sub-surface water resources (Hartmann, Gleeson, Wada, & Wagener, 2017; Vries & Simmers, 2002). Therefore, understanding and accurately estimating the natural

recharge is essential for sustainable management and preservation of the groundwater for the human activities and natural ecosystems. In particular, estimations of recharge are important to groundwater modelers because recharge is one of the primary inputs to groundwater modeling studies (Jyrkama, Sykes, & Normani, 2002).

Groundwater recharge is a difficult component to be quantified in the hydrologic budget. Sparse information and indirect interpretation of observed groundwater recharge make the determination of recharge uncertain. Moreover, the heterogeneity of the climate and the land-surface and subsurface properties, such as land use, topography, hydraulic conductivities or porosities, increases the uncertainty of the recharge estimation (Glenn, Jarchow, & Waugh, 2016; Hartmann et al., 2017; Niazi, Bentley, & Hayashi, 2017). Physically-based integrated hydrologic models offer a relatively efficient and reliable way to estimate recharge by quantifying all the relevant hydrologic properties contributing to recharge (Awan & Ismaeel, 2014; Bailey, Rathjens, Bieger, Chaubey, & Arnold, 2017, 2016; Camporese, Paniconi, Putti, & Orlandini, 2010; Dakhlalla, Parajuli, Ouyang, & Schmitz, 2016; Jyrkama et al., 2002; Kollet & Maxwell, 2006; Paniconi & Wood, 1993; Scanlon & Cook, 2002; Shen & Phanikumar, 2010; VanderKwaak & Loague, 2001). Physically-based hydrologic models describe the vegetation dynamics, overland runoff, streamflow, soil water, groundwater flow, and energy cycle as well. However, due to the inherent nonlinearity of the processes, model results are sensitive to how spatial patterns of climate, and watershed physical characteristics are defined and represented

on a grid cell in the model (Mo, Liu, Chen, Lin, Guo, & Wang, 2009; Molnár & Julien, 2000; Rojas, Velleux, Julien, & Johnson, 2008). The grid size used in a model would affect the overall representations of variability in physical characteristics (Molnár & Julien, 2000).

Grid-size effects on the major components of the hydrological cycles are complex. Existing studies have shown the grid-size effects on various hydrological components, such as the evapotranspiration (ET), soil moisture, and surface runoff, and illustrated that the sensitivity of ET to grid size is smaller than that of soil moisture and runoff to grid size (Cerdan et al., 2004; Kuo et al., 1999; Hessel, 2005; Liang, Guo, & Leung, 2004; Mo et al., 2009; Molnár & Julien, 2000). Zhang et al. (2008) focused on a 12 km² study area and illustrated that a coarser grid size (100-200 m) better captures the peak flow than a finer grid size (10-30 m) does. However, the grid-size effect on recharge is still yet to be studied.

Grid sizes also contribute to scaling issues over the heterogeneous land surface (Sridhar, Elliott, & Chen, 2003). A coarse grid size may make the spatial variation in the model hidden in the representation (Kuo et al., 1999; Schoorl, Sonneveld, & Veldkamp, 2000). In recent years, high-resolution remote sensing and GIS hydrologic products contribute to advances in hydrological modeling and provide us more options when a wide diversity of models are applied over a broad range of different scales (Sulis, Paniconi, & Camporese, 2011). The grid sizes for different scales of watersheds can vary from meters to kilometers. (Bormann, 2006) argued that there might be a critical grid size at which the scaling effects

became significant, therefore, an appropriate grid size should also take the scale of the study area into consideration.

Nevertheless, grid size choices are also closely related to the computational efficiency and may require large computer storage space, which is another essential factor in the numerical models (Molnár & Julien, 2000; Vieux, 2016). While a smaller grid size can significantly increase the accuracy to describe the surface-subsurface heterogeneity and further estimate detailed recharge in the model; as a tradeoff, a smaller grid size also requires longer computation time and a higher demand for computer storage. In general, the basic strategy to find a suitable grid size on a watershed scale is to make a proper compromise between estimation accuracy and computation efficiency.

While it is clear that understanding the effects of grid size in recharge estimation is very important especially in the physically-based hydrological models for both modeling and groundwater management practices, the grid size effect on recharge estimation remains an understudied topic in the literature. This study used an integrated surface-subsurface hydrologic model, PAWS + CLM, to evaluate the grid-size effects on recharge estimation in the Ottawa County, MI. PAWS is a grid-based hydrologic model with efficient computational algorithms, which enables the simulations ranging from coarse grid size to fine grid size. The model was calibrated using streamflow rates from USGS gauges over the period 2009-2010 and further validated using streamflow rates from USGS gauges between 2011-2015, streamflow rates measured in 2015, MODIS evapotranspiration (ET), and wellogic groundwater head datasets. The objectives

of this study are to (1) examine the effects of grid size variation on the spatial and temporal patterns of recharge simulation; (2) analyze the precipitation and LULC impacts on recharge estimation using four grid sizes of 300 m, 500 m, 700 m, and 1 km; (3) evaluate the grid size selection for physically-based hydrological model.

In the next section, we illustrate the modeling domain, the PAWS approach of modeling recharge, and the model input datasets. The third section presents our results showing the grid-size effects on the spatial and temporal patterns of recharge in the Ottawa County, MI. And, we also examine the impacts of various LULC on recharge simulation over the four grid sizes and the scaling effects on the annual recharge simulation and estimation. The conclusions and arguments are drawn in section four.

3.2 Materials and Methods

3.2.1. Site Description

In this study, Ottawa County, MI was selected as our study site where groundwater faces issues such as water table declination and contamination (IWR, 2013:85). The Ottawa County in Michigan heavily relies on its groundwater for drinking water, agriculture, and industry. To sustain the increasing demand for water accompanying the burgeoning population, pumping wells are being dug deeper and larger, which may have induced pollution into the rock formations (Sommers, 1984). And the declining water table may further elevate the concentration of contaminants. Existing studies show that the percentage of

domestic wells having chloride concentrations exceeding 250 mg/l (recommended level for drinking water) has increased from less than 4% before 2000 to 6-8% between 2000 and 2010 (IWR, 2013:95). Our fieldwork also observed that many small streams dried up in this region in the summertime of 2015.

Having a total area of 1460 square kilometers, the Ottawa County, MI is located on the west-central edge of the lower peninsula of Michigan along the eastern shoreline of Lake Michigan (Figure 3.1). Groundwater is important to the Great Lakes ecosystem because it provides a reservoir for storing water and directly replenishing the lakes in the form of base flow and indirectly as base flow to the tributaries which eventually discharge to the lakes (Sommers, 1984). Serving as the most important groundwater resource, the Marshall aquifer is an important source in the total water supply (Westjohn & Weaver, 1998). Grand River, as the primary river in the county, flows westward into Lake Michigan. The area to the north of Grand River and the immediate contiguous region to the south of Grand River are drained through the Grand River watershed into Lake Michigan. Streams in the southeast region of the county converge to Rabbit River, which further drains into Kalamazoo River watershed to the south of Ottawa County, MI. And the remaining area on the southwest of the county is drained by Macatawa watershed. Ottawa County, MI is located in the Traverse Carbonate reservoir which is one of the major Carbonate reservoirs in Michigan producing oil and gas (Catacosinos & Daniels, 1991). As significant quantities of oil and gas

produced in this region, the extractions of oil and gas may also introduce potential pollution to the groundwater system.



Figure 3.1 Climate and hydrologic stations in the study domain.

The climate in Ottawa County, MI is strongly influenced by Lake Michigan. During winter time, the county is affected by heavy lake-effect snow. Ottawa County, MI witnesses an average of 1800 mm of snow each year. Annual snowfall, typically in months between October and April, can range from less than 500 mm to

accumulations exceeding 2500 mm per year (miottawa.org). The average annual rainfall in the county is around 900 mm (miOttawa.org). The primary rain season is well distributed from May to October. Sitting on the eastern shore of Lake Michigan, the temperatures in Ottawa Country are cooler during springs and early summers and milder in falls and winters than the temperatures in the rest of the area of the county. This special climate is essential to the county where agricultural land takes about fifty percent of the county's total land mass and provides opportunities to the diversified agriculture in the county (USCB, 2012). Ottawa County, MI has a great diversity of land covers (Figure 3.2). Agricultural land dominates in the central, northwest, and southeast parts of the county. And large areas of forests and wetlands are predominant in the western portions. A

large area of forests can be found along Lake Michigan as well. Scattered patches of forest are interspersed with farmland, along with wetlands, streams, and roads. Northern and southern Michigan forest types overlap in this transition area. Four major urbanized areas, Holland, Zeeland, Grandville (extending from Grand Rapids), and Grand Haven, are located throughout the county.



Figure 3.2 Map of land use and land cover in the watershed.

3.2.2. Model Descriptions and Setup

This study uses the PAWS + CLM model to analyze the grid effects on groundwater recharge estimations. PAWS (Shen & Phanikumar, 2010) + CLM (Oleson et al., 2013) is an integration of all important processes of the hydrological cycle considering the entire hydrology of a watershed system, explicitly solving the physically-based governing partial differential equations for overland flow, channel flow, wetlands, the subsurface flow, and the interactions among these components. The model is capable of constraining the recharge simulations by using all the recharge-relevant components in the water budget. PAWS+CLM is a grid-based model allowing each component of the water balance to be produced at very fine spatial scales and addresses problems at the local scale. The non-iterative method of coupling used in PAWS makes computation efficient and each process with its individual time step also reduces the computational efforts compared to using a uniform time step for all the hydrologic processes. The non-iterative method and the adoption of a structured grid allow the applicability of the fine-grid-size model for large watersheds over a long temporal period.

The coupling between PAWS and CLM is based on the conservation of mass. Vertically and horizontally discretized topography, soil, and geology information in PAWS are ported to CLM to keep the same definitions of computational units. At each time step, climate forcing is passed into CLM to compute energy and water fluxes with ET computed based on the resistance concept. Then, the resulting ET fluxes, as a function of depths, are passed back to PAWS as a source/sink term for the unsaturated zone (Richards equation). Soil temperature, ice content, canopy storage, ground precipitation, dew, and snowmelt amounts are also passed from CLM to PAWS. The soil hydrology module in CLM is substituted by PAWS, which is the key for coupling these two models.

To analyze the grid effects on recharge simulation, PAWS + CLM was applied to estimate the recharge over Ottawa County, MI between 2011 and 2014 over four grid sizes: 300 m, 500 m, 700 m, and 1 km. As the grid size decreases, the numbers of grid cell increase dramatically. The total areas vary using different

grid sizes (Table 3.1) because a finer grid size allows the study area to capture more areas at the boundary than the total area based on a coarser grid size. For the PAWS + CLM model, seven years daily weather data (January 2009 – November 2015) were obtained from the National Climatic Data Center (NCDC) and Michigan Automated Weather Station Network (MAWN). The 30 m resolution national elevation dataset (NED) from U.S. Geological Survey (USGS) was preprocessed to generate average cell elevation, lowland-storage bottom elevation, average slope, and surface runoff routing of the watershed in the computational grids. National Hydrography Dataset (NHD) from USGS provided the channel flow network and streams properties. Soil data were obtained from the Soil Survey Geographic Database (SSURGO) which is distributed by the U.S. Department of Agriculture, Natural Resources Conservation Service (USDA-NRCS). The soil data were processed by Rosetta to provide soil water retention and unsaturated conductivity information for the model (Schaap, Leij, & van Genuchten, 2001). The land use and land cover (LULC) data used in the model is the Integrated Forest Monitoring Assessment and Prescription (IFMAP) dataset and is available from the Michigan Department of Natural Resources (MDNR). Land use data were reclassified into several model classes, called plant functional types (PFTs) (Thornton & Zimmermann, 2007) based on the land use classification percentile values reported in previous studies (Niu, Shen, Li, & Phanikumar, 2014; Jia, Ni, Kawahara, & Suetsugi, 2001; Lu & Weng, 2006). As the model cell size is coarser than the IFMAP spatial resolution (30 m), a model cell possesses a mixture of land use/land cover types and three dominant PFTs
were used in a model cell. The coverage percentage of the ten representative

LULC in the watershed for the four grid sizes are listed in Table 3.1.

Characteristic	300m	500m	700m	1km
Watershed Area (*10 ³ km ²)	1.900	1.901	1.896	1.887
Total number of grid cells	37082	13347	6818	3351
Broadleaf Forest Land	19.7%	20.4%	20.9%	21.3%
Needleleaf Forest Land	4.6%	4.3%	4.0%	3.8%
Shrub	1.6%	1.0%	0.7%	0.4%
Grass	9.7%	9.7%	9.7%	9.6%
Corn	19.1%	19%	19.4%	20%
Soybean	14%	14%	14.3%	13.6%
Forage Crops	13.9%	14.4%	14.1%	14.1%
Impervious Land	10.6%	10.1%	9.8%	9.5%
Water	2.2%	2.8%	3.2%	4.0%
Wetland	4.6%	4.3%	3.9%	3.7%

Table 3.1 Ottawa County Watershed characteristics at different grid sizes

The model calibration based on the Differential Evolution (DE) (Price, 2005) algorithm was done using the High Performance Computing Center (HPCC) resources at Michigan State University. Parameters estimated during calibration are listed in Table 1.2 in Chapter 1 Section 1.3. The model was calibrated against streamflow rates (discharge) from three USGS gauging stations at a 300 m grid size. The simulations were performed from 2009 to 2015 and the period from August 01, 2009 to December 31, 2010 was used to calibrate the model. The streamflow rates from USGS gauging stations of the period of 2011 - 2015 were used to validate the model. In addition, we carried out fieldwork between June and November of 2015 to collect streamflow data to provide a set of first-hand validation data for validating the model results. The SonTek RiverSurveyor M9 system and the OTT MF Pro current flow meter were used to measure streamflow rates of small streams at 48 sampling locations in Ottawa County, MI.

Also, we used the moderate resolution imaging spectroradiometer (MODIS) Global ET (MOD16) products to validate the ET simulated by the PAWS model spatially and temporally between 2011 and 2014.

Model calibration was carried out for 300 m grid size and the calibrated set of parameters was then transferred to the other three grid sizes, 500m, 700m, and 1km. Although there may be a bias in running all the models with various grid sizes using the same set of calibrated parameters, it was reasonable to use the same values of parameters at all the grid sizes because parameters were resampled for all the grid sizes and were adjusted using "global multipliers" within the framework of a linear transformation. We also calibrated model at 1km grid size to examine the potential bias brought by parameters. Results demonstrate that we can use the parameter set that calibrated based on 300m grid size maintain the modeling consistency.

3.3 Results

3.3.1. Grid-size Effects on the Spatial Pattern of Recharge

The spatial patterns of the average annual ET and average annual recharge over four grid sizes are shown in Figure 3.3. The simulated recharge presents obvious spatial variability over all the grid sizes. The spatial patterns of the average annual recharge were negatively related to the spatial patterns of average annual ET for all the grid sizes, whereby high ET values corresponded to low recharge values and vice versa. The spatial patterns of recharge also followed the general trend that high and low recharge values occur in high and low elevations

respectively (terrain information displayed in Figure 3.1). In Figure 3.3, the negative recharge (discharge) occurs close to the locations of stream channels and wetlands. With the grid size increasing, the stream channel boundaries became unidentifiable because coarser grid sizes averaged the spatial details of LULC. The 300 m and 500 m grid sizes offered the most details of spatial variability of recharge among all the grid sizes. The fine grid sizes indicated strong local spatial variabilities of the recharge in the watershed. Nevertheless, the general spatial patterns of recharge over the watershed were similar for all four grid sizes, indicating that the overall spatial pattern of recharge was not sensitive to the grid sizes at the watershed scale considered in this study.



Figure 3.3 The spatial patterns of (a) average annual ET; and (b) average annual recharge over period 2011–2014.

3.3.2. Grid-size Effects on the Temporal Pattern of Recharge

Figure 3.4 and Figure 3.5 display the differences in spatially averaged monthly recharge and annual recharge based on the four grid sizes between 2011 and 2014. The monthly patterns of recharge using different grid sizes had similar trends, as the values of recharge increased from fall to spring and decreased from spring to fall in a hydrologic year (Figure 3.4). However, the monthly recharge values decreased when the grid size changed from coarse to fine. The difference between the monthly recharge values with 300 m grid size and the monthly recharge values with the other three grid sizes was the greatest, whereas the differences based on 500 m, 700 m, and 1 km grid sizes were small, especially during low recharge periods. Recharge increased sharply in Spring 2011 and Spring 2013 due to the high volume of precipitation, especially with the coarse grid sizes demonstrating that recharge estimation was more sensitive to precipitation using a coarser grid size. And, by comparing the values of annual recharge for different years, the differences of the recharge values among the four grid sizes in a drought year (2012) were smaller than the differences of the recharge values in a more humid year of 2013 (Figure 3.5). The time-series of the annual recharge (Figure 3.5) also indicates that recharge has a positive relationship with precipitation for all the four grid sizes. The recharge values presented in the drought year of 2012, which had an areal precipitation of 755mm, were less than the recharge values in the other years. In addition, the recharge was the largest in 2013 when the areal precipitation was 1023mm, which was the highest among the years. The values of the average annual

recharge for all of the four grid sizes are comparable to the annual average values reported by USGS (Neff, Piggott, & Sheets, 2005). Specifically, the values of recharge at coarse grid size were closer to the values of the recharge reported by USGS because the recharge derived by USGS were represented by a coarse resolution 8-digit hydrologic unit code.



Figure 3.4 Monthly areal precipitation with 300 m grid size and monthly areal recharge over all the grid sizes of the period 2011-2014. (Units: mm/month)



Figure 3.5 Annual areal recharge over all the grid sizes between 2011 and 2014.

Base flow is a moderate proxy of recharge. To better understand the grid size effects on recharge, comparisons of discharge among four grid sizes were generated at the USGS 04108800 station (Figure 3.6). The RNASH (squareroot-transformed NASH) metric, focusing on baseflow, was employed to examine the baseflow performance over various grid sizes. RNASH is defined below (Shen & Phanikumar, 2010):

$$RNASH = 1 - \frac{\sum_{i=1}^{n} (\sqrt{O_i} - \sqrt{S_i})^2}{\sum_{i=1}^{n} (\sqrt{O_i} - \overline{\sqrt{O_i}})^2}$$
(Eq.1)

where, O_i is the *i*th observed value; S_i is the *i*th simulated value; and *n* is the total number of events.

The values of RNASH at USGS station 04108800 are relatively high at 300 m grid size (RNASH = 0.66) and at 500 m grid size (RNASH = 0.68), whereas the values are low using a 700 m grid size (RNASH = 0.62) and at 1 km grid size

(RNASH = 0.6). The grid size of 500 m appears to be optimum from the point of baseflow simulation.



Figure 3.6 Comparison of daily discharge over all the grid sizes at USGS 04108800 station.

3.3.3. Grid-size Effects on the Average Annual Water Budget

The annual averages of the major water budget components over the period 2011-2014 using the four grid sizes are reported in Table 3.2. Spatially-averaged recharge consisted of a smaller percentage of the precipitation when the grid size changed from coarse to fine. The other components in the water budget were not as sensitive to the grid size as the recharge. The sums of ET, recharge, surface runoff and groundwater outflow, and sublimation over various grid sizes were

about 100% ~ 120% of the precipitation which was acceptable because there may be some other inputs/outputs or storage mechanisms in the watershed (Niu et al., 2014). The differences among the total budgets over the four grid sizes very well reflected the differences of the recharge percentage. The sum of the water budget at 300 m grid size was the closest to 100%, and the largest sum of the water budget occurred at a grid size of 1 km with the value of 115.6%, which was also within the acceptable range as noted earlier.

Table 3.2 Ave	erage annual	water budgets	(%P, percent o	r annual precipit	ation)
	300m	500m	700m	1km	

	300m	500m	700m	1km	
Р	100	100	100	100	
ET	61.9	61	60.6	59.9	
Dperc	12.3	17.9	19.8	22.1	
Qoc	25.8	24.8	25.2	24.1	
Qgc	1.0	3.0	3.2	5.3	
SUBM	4.1	4.2	4.2	4.2	
Total	105.1	110.9	113	115.6	

P: precipitation, Dperc: recharge, Qoc: surface runoff, Qgc: groundwater outflow, SUBM: sublimation.

3.3.4. Grid-size Effects on Recharge over Different LULC

Three representative LULC types in this study domain: corn, broadleaf and impervious land were selected to analyze the influences of LULC on recharge estimation over various grid sizes.

Boxplots of annual recharge among the four grid sizes over the three representative land types were created at a drought year (2012) and a wet year (2013) (Figure 3.7 and Figure 3.8). In this study, three dominant PFTs were modeled in each cell as noted in section 2.2. In the boxplots, X-axis noted the percentage of one dominant LULC type in a cell. For example, in the first figure

showing the land type of corn, 0.1 in the X-axis means that the percentage of corn in a cell is below 10%, and 0.2 means the percentage of corn is between 10% and 20%, and so forth. And, 0.9 includes the cells with the percentage of corn between 80%-100%. Boxes of different grid sizes are shown using distinct colors. On each box, the central horizontal line indicated the median, and the bottom and top of the vertical line of the box were the first and third quartile metric, respectively. The outliers were plotted individually using the "+" symbol. Both Figure 3.7 and Figure 3.8 show that the medians of the recharge over all the four grid sizes increased when the coverage percentages of corn land in the cells increased in both the drought year of 2012 and the wet year of 2013. Oppositely, the medians of the recharge over all the four grid sizes decreased when the coverage percentages of broadleaf and impervious land types in the cells increased in both the drought year of 2012 and the wet year of 2013. For all the grid sizes, the values of recharge remained higher in the cells with a higher coverage percentage of cropland (corn) than that in the cells with high coverage percentage of forest (broadleaf) and impervious land. The values of recharge in the wet year of 2013 were greater than those in the drought year of 2012. Thus the changes in the medians of recharge over the coverage percentage of all these representative three land types in 2013 were more significant than that in 2012.

The medians of recharge for cells with over 60% coverage of corn were similar among different grid sizes, indicating that the recharge estimations were not sensitive to the grid sizes when corn dominated the cells. Showing a similar

pattern, the medians of recharge for cells dominated by impervious land were also not sensitive to different grid sizes. When broadleaf forest land was the dominant land type in the cells (above 60% coverage percentage), the medians of recharge fluctuated over the four different grid sizes. The fluctuations of the medians in the wet year of 2013 were more significant than that in the drought year of 2012. The differences in the elevation for major broadleaf forest areas were relatively large, whereas, the differences of the elevations for corn was small. Thus, the spatial variability of terrain may need to be considered when the area experiences high volumes of precipitation.

The number of the outliers decreased as the grid size increased for all the selected land use types, which demonstrated that the spatial variation of recharge was more pronounced in the finer grid size while a coarser grid size averaged out the spatial outliers. The outliers for the cells dominated by the broadleaf forests were more than that in other land cover types due to the spatial variabilities of the terrain. Broadleaf forests were distributed mainly in the western part of the watershed (close to Lake Michigan) with a lower elevation and eastern part of the watershed with a higher elevation. Broadleaf trees can also be found in the agricultural land or wetland areas as well.



Figure 3.7 Comparisons of annual recharge among all the grid sizes in different land types in the drought year of 2012



Figure 3.8 Comparisons of annual recharge among all the grid sizes in different land types in the wet year of 2013

3.3.5 Scaling Effects on Annual Recharge

To further understand the scale effects associated with recharge, this study adopted an approach used by Mo et al. (2009) to draw four comparisons between the "resampled" recharge data and the simulated recharge data. The 2011-2014 simulated annual recharge values based on 300 m, 500 m and 700 m were resampled to 1 km grid size using the nearest neighbor resampling scheme. These three resampled 1 km recharge data were further compared with the simulated 1 km recharge data, which we assumed represented the true value from our physically-based model. We also resampled the simulated 300 m recharge data to a 500 m grid size and tested it against the simulated recharge based on a 500 m grid size. The comparison between the recharge resampled to 1 km grid size from 300 m, 500 m and 700 m and the simulated recharge based on 1 km grid size in 2011 to 2014 were illustrated in Figure 3.9(a) (b), and (c). The comparison between the simulated recharge with a 500 m grid size and the recharge resampled from a 300 m to a 500 m grid size is shown in Figure 3.9(d). The correlation coefficient (R^2) was used to analyze the scaling effects. The value of R² ranges from 0 to 1, with 1 representing the two data have a very high correlation, meaning a weak scaling effect (Mo et al., 2009). The grid size effect testing on ET (Mo et al., 2009) had observed R² values between a weak relationship of 0.6 and a strong relationship of 0.98. And, in our comparison, a relatively weak relationship ($R^2 = 0.48 - 0.62$) was revealed, which showed that the simulated annual recharge was sensitive to grid size changes. Because of the existing grid size differences in the resampling process, the R² value was

higher when the two grid sizes were farther apart. For example, the climate and physical characteristics using a 300 m grid size were more fragmented compared to ones using a 500 m, 700 m, or 1 km grid size. And interestingly, the R² between the resampled recharge from a 300 m to a 500 m grid size and the simulated recharge values based on a 500 m grid size (R² = 0.51 - 0.54) was as strong as the R² between the resampling from a 300 m to a 1 km grid size and the simulated recharge values based on a 1 km grid size (R² = 0.48 - 0.54). Therefore, the scaling effect was strong for recharge among the grid sizes we tested of 300 m, 500 m, 700 m, and 1 km, which implies that the grid size should be very carefully selected for the physically-based hydrologic model based on specific purposes of the study.



Figure 3.9 Comparisons of annual recharge (mm/year) between (a) the upscaled from 700 m to 1 km and 1 km grid size; (b) the upscaled from 500 m to 1 km and 1 km grid size; (c) the upscaled from 300 m to 1 km and 1 km grid size; and (d) the upscaled from 300 m to 500 m and the 500 m grid size for the period 2011–2014.

3.4 Discussions and Conclusions

This study used a physically-based hydrologic model (PAWS) to examine the grid-size effects on recharge estimation over the grid sizes of 300 m, 500 m, 700 m, and 1 km. Based on a watershed scale, we examined how different grid sizes impact on recharge estimation and representation. Specifically, we focused on the grid-size effects on (1) the spatial variation and representation of the simulated recharge and watershed structures, such as stream channels and

wetlands; (2) the time-series study of the recharge over humid and drought years; (3) the relation between LULC types and recharge estimation; and (4) the consistency of the annual recharge estimation across different spatial scales. First, the simulated recharge based on all of the four grid sizes showed obvious spatial variability. Fine grid sizes (300 m and 500 m) provided greater details of spatial variability of recharge and can capture the locations of major stream channels and wetlands. Therefore, the grid sizes below 500 m are recommended for simulating and presenting the detailed spatial variabilities of recharge at the watershed considered in this study. For resource management purposes on a county level, a smaller grid size also provides the feasibility to carry out detailed management plans. But any of the four grid sizes can be used to illustrate the general spatial pattern of recharge on a watershed scale as well.

Second, the time-series patterns of both monthly and annual areal recharge over the four-year period between 2011 and 2014 were similar across all of the four grid sizes. But, both the monthly and annual values of areal recharge increased as the grid size increased. The fluctuations of annual precipitation in different years did not affect the spatial pattern of recharge, but the simulated recharge maps revealed a positive relation between the recharge and precipitation. The differences in the recharge values using different grid sizes were especially strong when the precipitation was high in a particular year. This implies that in a humid year or in areas with high precipitation, recharge simulation using a physically-based hydrologic model based on a coarser grid size might produce different results from one based on a finer grid size.

Further, this study analyzed the grid-size effect on simulating recharge based on three representative LULC categories of corn, broadleaf forest, and impervious land. The analysis of recharge estimation over different LULC types demonstrated that the impacts of different LULC types on recharge showed similar effects with all the four grid sizes. The recharge values remained high when the cropland (corn) was the dominant LULC component in the cells over all the four different grid sizes. The values of recharge were low when forests and impervious land types dominated the cells. However, the relation between the recharge values and the three representative LULC types was consistent for all four grid sizes, which indicated that the grid size effect was minor in illustrating the relationship between LULC types and recharge. Therefore, a coarser grid size is recommended in investigating the impacts of LULC types for computation efficiency purposes.

Last but not least, we also tested whether the recharge estimations using different grid sizes remained consistent based on the correlation coefficient (R²) for four pairs of the "resampled" recharge values from a finer grid size and the simulated recharge values. The results showed that the resampled recharge from a finer grid size and the simulated recharge did not have a strong correlation (R² in the 0.48-0.62 range), which indicated that the resampled values of recharge might be inconsistent with the simulated recharge values. This situation implies that the scaling effect is strong in recharge estimation and the grid size needs to be carefully selected for recharge estimation based on the purpose of the study. For resource management purposes, the recharge estimation based on a

coarser grid size should be reviewed before detailed management plans can be applied to a relatively small watershed.

Based on this study, we conclude that the grid size plays an important role in estimating recharge values. And seeking and justifying a proper and robust grid size for a study or research is always challenging. Based on the results, we can see that choosing a grid size properly is very important in representing the recharge values, investigating times series of recharge estimation, and carrying out a physically-based hydrologic model for recharge estimation. And, the relationship between recharge and LULC types remains consistent across different grid sizes. Further investigations are also needed to understand the application of specific resource management plans based on the recharge estimation using various grid sizes and how finer grid sizes can assist the decision-making process in groundwater and water resource management.

APPENDICES

APPENDIX A



Figure A1 Comparisons between observed and simulated discharge at USGS 04118800. Dark green line depicts the simulation conducted with gauge-MPE precipitation; Dark blue dash line describes the observed discharge.



Figure A2 Comparisons between observed and simulated discharge at USGS 04108600. Dark green line depicts the simulation conducted with gauge-MPE precipitation; Dark blue dash line describes the observed discharge.

APPENDIX B

In this study, we calibrated our model based on 300 m and 1 km grid size and adopted the parameter set calibrated at 300 m for all grid sizes to maintain the modeling consistency based on two main reasons. First, we evaluated the model performance based on the discharge comparison on the 1 km grid size with two set of parameters calibrated at either the 300 m or the 1 km grid sizes. The comparisons with the observed data show great similarities. Second, we compared the simulated recharge at 1 km grid size with the parameter set calibrated at either the 300 m or the 1 km grid sizes and observed that the results illustrate similar temporal patterns. Thus, for modeling efficiency and consistency purposes, we adopted the parameter set calibrated at 300 m for all the models at four different grid sizes. The detailed comparison and decision-making process is illustrated here in Appendix B.

Figure B1 shows the comparisons of daily discharge over four grid sizes with parameters calibrated at the 300 m grid size and daily discharge at the 1 km grid size with parameters calibrated at 1 km at USGS 04108800. The value of RNASH between estimated discharge and observed discharge at the 1 km grid size with parameters calibrated at the 300 m grid size is 0.6, while the value of RNASH between the two at the 1 km grid size with parameters calibrated at 1 km grid size with parameters calibrated at the 300 m grid size is 0.6, while the value of RNASH between the two at the 1 km grid size with parameters calibrated at 1 km is 0.54. The RNASH comparison shows that the model performs better when we use the 300 m based parameter set than the one calibrated on the 1 km grid size. And, we conclude that the parameter set calibrated at the 300 m grid size can be used for the model with the 1 km grid size.

Figure B2 shows that the temporal patterns of the monthly areal simulated recharge based on the parameter sets calibrated at 1 km and at 300 m are similar. Figure B3 shows that both the simulated recharge at the 1 km grid size with parameters calibrated at the 300 m grid size and the 1 km grid size also show similar patterns and strong agreements when compared with recharge based on other grid sizes. So, we think the parameter set calibrated at 300 m can be used for all the grid sizes in this study for the modeling efficiency and consistency purposes.



Figure B1 Comparison between daily discharge over four grid sizes with parameters calibrated at 300 m grid size and daily discharge at 1 km grid size with parameters calibrated at 1 km from 2011 to 2014. (Units: m³/s) (g300, g500, g700 and g1K indicate the parameters estimated at 300 m grid size, g1K_1K indicates the parameters estimated at 1 km grid size)



Figure B2 Comparison between monthly areal recharge over four grid sizes with parameters calibrated at 300 m grid size and monthly areal recharge at 1 km grid size with parameters calibrated at 1 km from 2011 to 2014.(Units: mm/month) (g300, g500, g700 and g1K indicate the parameters estimated at 300 m grid size, g1K_1K indicates the parameters estimated at 1 km grid size)



Figure B3 Comparison between annual areal recharge over four grid sizes with parameters calibrated at 300 m grid size and annual areal recharge at 1 km grid size with parameters calibrated at 1 km over the period 2011-2014. (Units: mm/year) (g300, g500, g700 and g1K indicate the parameters estimated at 300 m grid size, g1K_1K indicates the parameters estimated at 1 km grid size)

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