THE FUTURE OF GROUNDWATER RESOURCES IN A WATER-ABUNDANT REGION: MODELING THE IMPACTS OF CLIMATE CHANGE AND MEASURING SOCIAL INDICATORS OF SUSTAINABILITY

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ABSTRACT

THE FUTURE OF GROUNDWATER RESOURCES IN A WATER-ABUNDANT REGION:
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As the global climate warms and the world's population grows, there will be greater pressure on water-abundant regions to maintain the sustainability of their fresh water resources and the viability of agricultural production. In the State of Michigan groundwater is a particularly important resource, as it provides drinking water for millions and irrigates much of the state's cropland. In an effort to evaluate its long-term sustainability, I modeled the potential impacts of climate change on the water table of Kalamazoo County, MI. To do this I employed the Soil and Water Assessment Tool (SWAT) and a dataset of 31 future climate projections to produce multiple estimates of groundwater recharge to the year 2100. I then used these outputs from SWAT as inputs into an existing MODFLOW groundwater model of Kalamazoo County developed by the United States Geological Survey. I was then able to simulate changes in the county's water table through the rest of the century, and under various potential future climates. Overall, the majority of climate scenarios projected an increase in water table elevation through the end of century, partly due to increases in precipitation, but also because of decreased evapotranspiration resulting from improvements in plant water use efficiency under elevated levels of CO_2.

I also explored the social context of these hydrologic simulations by measuring the awareness of groundwater sustainability threats, willingness to adopt conservation practices,

and constraints to behavior change among large quantity water users in Michigan. These metrics are collectively referred to as social indicators, and have typically been used to describe surface water quality from a social perspective. For this project, I used them to describe groundwater sustainability. I administered an online social indicators survey as part of the State of Michigan's annual online water use reporting for large quantity water users (> 378,541 liters per day). Overall, respondents exhibited high levels of awareness, were generally willing to adopt conservation, and identified cost as the principle constraint of behavior change. There were differences in the metrics for agricultural and non-agricultural respondents, but a relatively small sample size limited the analysis of additional demographic groups, including income, education level, gender, and geographic region.

I dedicate this dissertation to my wife Jamie, son Rowan, daughter Julia, and mother Christine, whose steadfast love and support motivated and carried me through this long but rewarding process.

I also dedicate it to my grandparents Julia and Edward Ryan, and great uncle John Healy, whose reverence for education inspired me to take this journey.

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KEY TO ABBREVIATIONS

CDL: Cropland Data Layer

CMIP3: Coupled Model Intercomparison Project phase 3

DEM: digital elevation model

ET: evapotranspiration

HCD: Hayhoe Climate Dataset

HRU: hydrologic response unit

IPCC: Intergovernmental Panel on Climate Change

LAI: leaf-area index

LPD: liters per day

LPM: liters per minute

MDARD: Michigan Department of Agriculture and Rural Development

MDEQ: Michigan Department of Environmental Quality

M-DIT: Michigan Department of Information Technology

ML: millions of liters

MGL: millions of liters per day

NASS: National Agricultural Statistical Service

NLCD: National Land Cover Dataset

NSE: Nash Sutcliffe Efficiency

PBIAS: Percent bias

ppm: parts per million

SIDMA: Social Indicators Data Management and Analysis System

SRES: Special Report on Emission Scenarios from the IPCC

SWAT: Soil and Water Assessment Tool

USDA: United States Department of Agriculture

USEPA: United States Environmental Protection Agency

USGS: United States Geological Survey

WCRP: World Climate Research Programme

WTP: willingness to pay

CHAPTER 1: Introduction

1.1 Background

Groundwater is a critical natural resource for much of the world. It is a source of fresh drinking water for over two billion people (UNEP, 2002). Its use for irrigation drives food systems and economic activity. The baseflow that it provides to streams and rivers helps regulate flow rates, temperature, water chemistry, and other attributes critical for properly functioning ecosystems. However, a growing global population and warming climate are threatening the sustainability of groundwater systems. Growing demand for food is driving up demand for agricultural production and, therefore, groundwater-fed irrigation. Globally, rates of agricultural water withdrawals are projected to increase through 2050 (UNEP, 2012). Rates of industrial and domestic use are also expected to increase; but, at least in the short term, the significant majority of use will continue to come from agriculture (UNEP, 2012). The growing population is also fueling urbanization, which can curb the natural groundwater recharge that feeds aquifers as the extent of impervious surfaces expands (Erickson & Stefan, 2009).

A scarcity of groundwater supplies can trigger a cascade of problems relating to water quality, land stability, and human conflict. Over-pumping could contaminate groundwater supplies by drawing up deeper, older saline water into aquifers. Furthermore, the depletion of groundwater resources has direct consequences for surface water systems. Rivers and lake levels could decline as aquifers attempt to offset the volume of water withdrawn from storage by discharging less to surface water features. These lower levels can increase the temperature and pollutant concentration in surface water bodies, affecting the aquatic species therein (M. Sophocleous, 2002). The surfaces above depleted systems could subside, creating significant risk to the structural integrity of infrastructure (Chai, Shen, Zhu, & Zhang, 2004; Galloway et al., 1998; Sun, Grandstaff, & Shagam, 1999). Populations with readily accessible fresh water could be drawn into conflict with those desperate to find sources of their own (Homer-Dixon, 1994; Postel & Wolf, 2001).

Though many of these threats are greatest in the developing world, including the regions of India, China, and North Africa (Qiu, 2010; Rodell, Velicogna, & Famiglietti, 2009a; Shahin, 2007), the United States has also seen declines in its aquifer systems. Large portions of the Plains States and Southeast have seen cumulative groundwater depletions of up to 400 km^3 over the past century, mainly due to agricultural irrigation (Konikow, 2013). The United States Geological Survey (USGS) estimates that over 44,000 square kilometers of U.S. territory have been affected by land subsidence, which it attributes mainly to groundwater use. Local and regional water conflicts have emerged over the past 20 years, including a legal battle between Alabama, Florida, and Georgia over diversions from Lake Lanier (Bluestein, Rankin, & Trueby, 2012).

The projected increases in global temperature, changing patterns in precipitation, and growing global population are expected to heighten these risks for much of the world, and exacerbate the problems of water scarcity that are already evident today (IPCC, 2014; Vörösmarty et al., 2010); all of which will put more pressure on regions with relatively abundant fresh water supplies to ensure that those resources remain viable. In particular, agriculturally productive areas in such regions will need to rely on those resources to meet a growing demand for food. But water-rich regions are not immune to the aforementioned threats to groundwater systems. Michigan is surrounded by the largest collective source of freshwater in the world, and is heavily reliant on groundwater. Half of the state's residents get their drinking water from groundwater, and Michigan has more private wells than any other state in the U.S. (State of Michigan 2004, 2013). Irrigation is used on over 162,000 hectares of agricultural land in Michigan, with 65% of those withdrawals coming from aquifers (State of Michigan 2006). Groundwater is the principle source for stream water in Michigan, with baseflow accounting for more than 80% of total flow for much of the state (Wolock 2003). It is a vital component of Michigan's economic and environmental health; but the state has had its own bouts with water scarcity. During the summer drought of 2012 a number of private, predominantly rural, wells across Michigan ran dry as water tables dropped. Some residents blamed the weather, others pointed to agriculture, as these dry periods coincided with the irrigation season for nearby farmers (Sell and Campbell 2012, Willis 2012).

Considering the future hydrological importance of regions like Michigan, and in particular its agricultural areas, it is worth exploring in greater detail what the potential impact of a changing climate and evolving landscape may have on groundwater resources there. But focusing on just the physical hydrologic characteristics does not fully delineate the threats to groundwater resources in the region, nor provide sufficient information to craft meaningful adaptive management strategies. Certain broader social characteristics can be indicative of the health and sustainability of a region's groundwater resources. These characteristics, or indicators, include a population's awareness of threats to groundwater sustainability, awareness of the consequences of excessive water use, attitudes towards water conservation practices, and constraints to adopting those practices. If, for example, a population is generally unaware of the potential impacts of excessive groundwater use, it will be difficult for policy makers to convince them to make the necessary changes to ensure the resource's sustainability in the face of the aforementioned threats. Such a situation would indicate the need for targeted public information programs in addition to implementing practical management strategies that conserve groundwater. Furthermore, identifying the principle constraints that limit a population's ability to participate in groundwater conservation can help policy makers develop comprehensive adaptation strategies that minimize those constraints and, subsequently, encourage greater adoption of conservation practices.

1.2 Statement of Problem

The projected trends of a changing climate, increased demand for agricultural production to feed a growing global population, and urbanization pose a threat to the sustainability of groundwater systems around the globe. These trends put greater pressure on water-abundant regions to ensure the viability of their systems and maintain a productive agricultural sector. Furthermore, a lack of consideration of social indicators of groundwater sustainability could hamper efforts to adapt to these threats and ensure the resource's viability.

To address this problem, I use the long-term average elevation of the water table (hydraulic head) as an indicator of the sustainability of the groundwater system. The study's primary research questions are as follows:

1. How would the water table in a water-abundant and agriculturally productive region change under multiple scenarios of future climate change?
2. How would the water table in a water-abundant and agriculturally productive region change under a scenario of future urbanization?
3. How would the water table in a water-abundant and agriculturally productive region change under a scenario of future increased agricultural production?
4. How would the water table in a water-abundant and agriculturally productive region change under a combination of the scenarios mentioned in items 1-3 above?
5. How do social indicators of groundwater sustainability vary among large-quantity water users in water-abundant regions?

1.3 Hypotheses and Expectations

1.3.1 Hydrological modeling hypotheses

For a water-abundant and agriculturally productive region:

1. The water table will rise under a future scenario of higher temperatures and greater precipitation.

H_O: $WTE_{\text{current}} \geq WTE_{\text{CC}}$

H_A: $WTE_{\text{current}} < WTE_{\text{CC}}$

where:

WTE_{current} = average water table elevation under the current climate conditions.

WTE_{CC} = average water table elevation under multiple scenarios of climate change.

2. The water table will drop under a future scenario of increased urbanization due to greater municipal water use and reduced groundwater recharge from and expansion of impervious surfaces.

H_O: $WTE_{current} \leq WTE_{URB}$

H_A: $WTE_{current} > WTE_{URB}$

where:

$WTE_{current}$ = average water table elevation under a scenario of no land cover change.

WTE_{URB} = average water table elevation under a scenario expanded urbanization.

3. The water table will drop under a future scenario of agricultural expansion due to increased water withdrawals for irrigation.

H_O: $WTE_{current} \leq WTE_{AG}$

H_A: $WTE_{current} > WTE_{AG}$

where:

$WTE_{current}$ = average water table elevation under a scenario of no land cover change.

WTE_{AG} = average water table elevation under a scenario of expanded agriculture.

4. The water table will rise under a scenario of future climate change, increased urbanization, and increased agricultural production because increasing precipitation will have a greater impact on the water table than expanded urbanization.

H_O: $WTE_{\text{current}} \leq WTE_{\text{COM}}$

H_A: $WTE_{\text{current}} > WTE_{\text{COM}}$

where:

WTE_{current} = average water table elevation under a scenario of no land cover change.

WTE_{COM} = average water table elevation under the combined scenarios.

1.3.2 Social indicator expectations

I based my expectations for how social indicators might vary upon studies that explored the willingness of individuals to adopt conservation practices for surface water protection (Prokopy, Floress, Klotthor-Weinkauf, & Baumgart-Getz, 2008), the willingness of individuals to pay for groundwater protection (Jordan & Elnagheeb, 1993; Lichtenberg & Zimmerman, 1999a; Shultz & Lindsay, 1990), attitudes and awareness of water quality issues (de Loë, Giantomasso, & Kreutzwiser, 2002; Ekmekçi & Günay, 1997; Hamilton, 1985; Lichtenberg & Zimmerman, 1999b; Napier & Brown, 1993), water use conservation (Bekkar, Kuper, Errahj, Faysse, & Gafsi, 2009; Gilg & Barr, 2006) and broader studies of environmental awareness (Kaiser, Wölfing, & Fuhrer, 1999; Schahn & Holzer, 1990) (Table 1).

Table 1: Social indicator expectations.

	Social Indicators of Groundwater Sustainability			
Population variables	Awareness	Attitudes	Willingness to adopt conservation	Constraints to adoption
Age			-	+
Gender	F > M	F > M	F > M	F = M
Education	+	+	+	-
Income		+	+	-
Sector	A > N	A > N	A > N	A = N
Operation Size			+	-

Where:

+/- : positive/negative relationship between variable and social indicator

X > Y : group X's social indicator scores will be greater than group Y's

X = Y : group X's social indicator scores will be equal to group Y's

F : female

M : male

A : agriculture

N : non-agricultural

A blank cell means that I did not have an expectation.

I expected female, highly educated, and agricultural water users to exhibit greater awareness of threats to groundwater sustainability and to the impacts of excessive groundwater use. I expected the same groups, in addition to those with higher incomes, to express more positive attitudes towards groundwater conservation, and also be more willing to adopt those practices. I expected that those who tended to use more water might be more willing to adopt conservation practices, because I assumed that their larger operations might be better able to absorb the cost of adoption than a smaller operation. I expected that the older water users might be more entrenched in their current practices and less willing to try new and more efficient approaches, and that the physical abilities needed to install and maintain these practices might add to the constraints preventing them from adopting conservation practices. I also expected the more highly educated, wealthier, and larger volume water users to be better able to absorb the costs of adopting conservation practices, and therefore indicate low constraints. I expected there to be no difference in constraints among agricultural and non agricultural water users, and male and female water users.

1.4 Scope of Work

Modeling water-table fluctuation at a sufficient resolution for all water-abundant regions of the globe is beyond the scope of this study. As I mentioned earlier, in relation to the rest of the world, Michigan is a relatively water wealthy region; however it would still prove too large an area to feasibly model the proposed changes in water-table elevation. Kalamazoo County, Michigan is an appropriate location to carry out this study. It is small enough in spatial extent to facilitate the necessary modeling, and contains landscape and physiographic characteristics that support the transferability of the study's findings. The concentration of agriculture in Kalamazoo County and its reliance on irrigation make it an appropriate site to evaluate the potential impacts of expanded agricultural land. It is also one of the most agriculturally productive areas in the Great Lakes region, which makes it a critical location for meeting the high food demand brought on by climate change and a growing population. The fact that Kalamazoo County's urban core has, unlike many other Michigan communities, steadily grown makes it an attractive location to study the potential impacts of urbanization.

To answer research questions 1-4, I utilized groundwater recharge outputs from the surface water model SWAT (Soil and Water Assessment Tool) (Arnold et al., 2012) with the groundwater model MODFLOW (Harbaugh, Banta, Hill, & McDonald, 2000) to simulate changes in hydraulic head from multiple future climate projections. SWAT is arguably the most widely utilized surface water model within academia, with a publication record of over 2,400 peer reviewed articles (CARD & Iowa State University of Science and Technology, 2016), and MODFLOW is the principle groundwater modeling tool utilized by the USGS. Long-range models of future climate can vary widely depending on their underlying assumptions, such as the concentration of atmospheric CO_2. Relying on only a single climate model to project surface and groundwater hydrology risks missing potentially significant outcomes, and masks the inherent uncertainty that climate projections introduce into derivative products. To avoid these issues, I employed a readily accessible climate dataset which included 31 different climate projections through the year 2100.

To answer research question 5, I administered a social indicator survey of groundwater sustainability to a sample of large quantity water users (> 378,541 LPD) throughout the State of Michigan. I then calculated indicator scores among the respondents and divided them into sub-groups.

In the next chapter, I discuss previous relevant research in hydrology and social indicators, and argue how this effort fills a gap in both of those fields. In Chapter 3, I describe the data and methods I employed in preparing the SWAT and MODFLOW models, followed by a discussion of my efforts to calibrate them in Chapter 4. I discuss the future climate projections and how I employed them within SWAT and MODFLOW in Chapter 5. I present the hydrologic modeling results in Chapter 6. Because it was less complex than the hydrologic modeling, I discuss the social indicator methods and survey results in single chapter, Chapter 7. I discuss the limitations, uncertainties, and implications of the hydrologic model outputs and social indicator survey results, and evaluate my research hypotheses in Chapter 8. Lastly, in Chapter 9 I summarize my key findings and discuss next future research topics.

CHAPTER 2: Background

Groundwater sustainability is a well-studied topic within the fields of hydrology and water resource management. W.M. Alley, Reilly, & Franke (1999), Fetter (2001), and Heath (1983) provide thorough overviews on the subject. Groundwater sustainability is often defined in terms of what rate and for how long can groundwater be withdrawn without depleting the resource. However, this approach to sustainability has been deemed a water balance myth, because groundwater systems will seek to establish balance in reaction to any withdrawal. Removal of water from any portion of an aquifer will necessitate an increase from other sources; either by removing water from storage or decreasing groundwater contribution to surface water features. A particular rate of withdrawal may be sustainable over a long period of time, but it will typically have environmental and ecological consequences for the surrounding environment (William M. Alley, Healy, LaBaugh, & Reilly, 2002; W.M. Alley & Leake, 2004; Sophocleous, 1997; Zhou, 2009).

For this project, I sought to explore how those consequences might evolve in the future for a water-rich region by simulating changes in groundwater resources under climate and land cover change. I also sought to estimate the degree to which large quantity water users were aware of those consequences and willing to take action to mitigate them. My approach involved three main tracks. The first was developing future recharge estimates through surface water modeling in the region of Kalamazoo County, MI. The second was applying those outputs to project water table fluctuations through groundwater modeling. The third was calculating social indicators of groundwater sustainability among large-quantity water users across the State of Michigan through a survey. I will illustrate the uniqueness of this approach, and its contribution to our overall understanding of groundwater sustainability by discussing previous research along those three tracks.

2.1 Previous Surface Water Modeling Efforts

A large number of studies have explored the potential impacts of climate change on surface water. All of the Assessment Reports from the Intergovernmental Panel on Climate Change (IPCC) have included detailed discussions of potential impacts on water resources, particularly river systems, lake levels, and ocean levels (Australian Government Publishing Service, 1990, Australian Government Publishing Service, 1992; Field, Barros, & Intergovernmental Panel on Climate Change, 2014; McCarthy & Intergovernmental Panel on Climate Change, 2001; Parry & Intergovernmental Panel on Climate Change, 2007; Watson, Zinyowera, Moss, & Intergovernmental Panel on Climate Change, 1996). Some, like this project, have focused on impacts in agricultural areas of the U.S. Midwest (Bekele & Knapp, 2010; Chien, Yeh, & Knouft, 2013; Schilling, Jha, Zhang, Gassman, & Wolter, 2008), while others have focused regionally within the Great Lakes Region (Auld et al., 2006; Barlage, Richards, Sousounis, & Brenner, 2002; Bruce, 1984; de Loë & Kreutzwiser, 2000; International Joint Commission, 2003; Kling et al., 2003; Lofgren et al., 2002).

The studies listed above are primarily concerned with streamflows. While much published research evaluates the quantity of surface water that infiltrates the soil and becomes groundwater recharge, like I propose to do in this project, there is wide variability among the techniques that have been utilized. A common approach estimates recharge through general water balance analysis (Dripps & Bradbury, 2007; Finch, 1998; Harbor, 1994; Hart, Schoephoester, & Bradbury, 2008; Kendy et al., 2003; Sophocleous, 1991; Stoertz & Bradbury, 1989; Sun & Cornish, 2005). This method was attractive due to its conceptual and computational simplicity. As processing power improved and automated baseflow separation programs became available, such as those developed by Arnold, Allen, Muttiah, & Bernhardt (1995) and Arnold & Allen (1999), more studies started to approximate recharge as a function of the ratio of stream baseflow to surface runoff (Dumouchelle & Schiefer, 2002; Gebert, Radloff, Considine, & Kennedy, 2007; Neff, Piggott, & Sheets, 2005; Santhi, Allen, Muttiah, Arnold, & Tuppad, 2008; Szilagyi, Harvey, & Ayers, 2003; Szilagyi et al., 2003; Szilagyi, Harvey, & Ayers, 2005; Wittenberg & Sivapalan, 1999). While these approaches may be effective at estimating recharge for large areas at relatively low processing costs, they are not well-suited for mapping it at finer spatial resolutions. By focusing on the stream hydrograph, baseflow separation techniques can only estimate overall recharge for a particular stream catchment. Other efforts have linked baseflow separation results to locations on the landscape through a multiple regression on physical characteristics (Holtschlag & U.S. Geological Survey, 1997; U.S. Geological Survey, Michigan Water Science Center, Michigan Department of Environmental Quality, Michigan State University Institute of Water Research, Michigan State University RS&GIS, & Michigan State University Biosystems and Agricultural Engineering, 2005). While this is an improvement over assuming recharge is uniform throughout the contributing areas above a particular flow gage, it is still a relatively coarse spatial representation because it fails to account for critical spatial variables that affect local recharge, such as well proximity, irrigation rates, tile drainage, and specific crop rotations. Other modeling approaches have generated more spatially explicit recharge estimates. Ficklin, Luedeling, & Zhang (2010) used HYDRUS to simulate changes in central California, a distinctly different region hydrologically than Kalamazoo County. For most of these recharge studies the impact of climate change was not a primary focus. Eckhardt & Ulbrich (2003) and Ficklin et al. (2010) evaluated the impact of climate change on recharge, but neither evaluated results from a broad range of climate models, and the latter did not include changes in precipitation at all.

2.2 Previous Groundwater Modeling Efforts

As with surface water, there has been considerable interest in the potential impact of climate change on groundwater resources. The aforementioned assessment reports from the IPCC also discuss the potential consequences that climate change may have on the world's aquifers (Bates, Kundzewicz, & Intergovernmental Panel on Climate Change, 2008). Bouraoui, Vachaud, Li, Treut, & Chen (1999), Dragoni & Sukhija (2008), Green et al. (2011), Holman (2006), Loaiciga (2003, 2009), and Taylor et al. (2012) provide concise discussions of the threats to groundwater resources from climate change and how to model them. Interest has often been in areas that are currently water stressed (Döll, 2009), such as the Middle East (Voss et al., 2013), Australia (McCallum, Crosbie, Walker, & Dawes, 2010), India (Nayak, Rao, & Sudheer, 2006; Rodell, Velicogna, & Famiglietti, 2009b), the U.S. Plains states (Rosenberg et al., 1999; Sophocleous, 2005), California (Faunt, 2009; Tanaka et al., 2006), and Texas (H.A. Loáiciga, Maidment, & Valdes, 2000). But modeling climate change impacts on groundwater systems in more water-abundant regions has also generated interest (Jyrkama & Sykes, 2007; Oude Essink, van Baaren, & de Louw, 2010; Rozell & Wong, 2010).

A number of studies have developed relatively detailed groundwater models for areas in Michigan. Reeves (2010) provides a thorough review of groundwater research in the Lake Michigan basin, including regional groundwater flow models (Buchwald, Luukkonen, & Rachol, 2010; Feinstein, Hunt, & Reeves, 2010; Hoard, 2010). Both Lofgren et al. (2002) and (Croley & Luukkonen, 2003) explored the potential impacts of climate change on Lansing, MI through groundwater modeling. Luukkonen, Blumer, Weaver, & Jean (2004) developed the detailed MODFLOW model for Kalamazoo County, which I utilized in this research project, and approximated climate change impacts through a relatively simple increase in present-day recharge estimates.

2.3 Previous Social Indicators Research

A number of studies have explored how environmental awareness and attitudes towards conservation vary among groups. Schahn & Holzer (1990) studied knowledge of environmental problems and attitudes towards conservation in Germany. The authors found positive relationships with conservation attitudes by age and education, and that women tended to exhibit more willingness to adopt conservation than men; but they also noted that men exhibited greater awareness of environmental problems. Kaiser et al. (1999) showed environmental attitude to be a strong predictor of ecological behavior.

Other efforts have focused specifically on water. Hamilton (1985) found wealth and motherhood had positive relationships with levels of concern regarding groundwater contamination. Gilg & Barr (2006) measured attitudes towards water conservation in a British city and found the group least inclined to adopt this behavior was generally comprised of young males with lower relative incomes and education. Several studies have evaluated a population's willingness to pay (WTP) for groundwater protection. Shultz & Lindsay (1990) found a positive relationship with income and WTP and a negative relationship with age. Jordan & Elnagheeb (1993) discerned a rural/urban divide in Georgia with WTP, with private well-owners (rural) more inclined to pay for groundwater protection than residents on public supply (urban). A similar divide was found by (Lichtenberg & Zimmerman, 1999a) in the Mid-Atlantic states of the US. Bekkar et al. (2009) showed that even in developing countries farmers are keenly aware of the threats to groundwater sustainability. Whereas Napier & Brown (1993) found that farmers who planted larger fields, carried more debt, and focused on grain production were less likely to deem groundwater pollution a problem.

Numerous studies have also explored the relationship between socio-economic factors and individuals' willingness to adopt water-quality related land conservation practices. Prokopy et al. (2008) evaluated 55 of these studies by counting the number of times a particular demographic variable, such as age, income, education was a significant predictor of conservation adoption. Though there was no variable that was exhibited a consistent result across the studies, the authors found that higher levels of education, income, and operation size (in the case of agriculture) indicated higher rates of adoption more often than not.

Despite the apparent lack of clear and fundamental relationships within this field, the U.S. Environmental Protection Agency (USEPA) has promoted the measuring of targeted populations' attitudes towards, awareness of, willingness to, and capacity to adopt water conservation practices as an alternative means of measuring water quality. USEPA funded the development of an online system whereby users can develop and administer surveys to quantify these social indicators of water quality (Genskow & Prokopy, 2009; Prokopy et al., 2009). The tool is called the Social Indicators Data Management and Analysis System (SIDMA) and has been utilized by numerous groups across the U.S., including local watershed groups, consultants, and federal, state, and local government agencies.

SIDMA was designed to aid local stakeholders in the management of USEPA-funded projects tasked with reducing non-point source pollution at watershed scales. Projects typically administer a SIDMA pre-survey within a watershed, then carry out some form of outreach or public education, and finally conduct a post-survey to measure changes in social indicators among the population. This approach provides groups with an alternative means of exploring threats to water quality within a watershed, in lieu of the time and funding needed to support comprehensive modeling and monitoring projects.

2.4 Why this Research is Unique

While many of the hydrological modeling studies listed above simulated surface water and groundwater, most did not explicitly connect the dynamic aspects of surface landscape functions with a detailed groundwater model to fully simulate the hydrologic system. Often, the groundwater models incorporated recharge from the surface in a manner that was spatially homogenous, either through broadly defined zones or spatially coarse estimates from baseflow separation efforts. In this project, I ran MODFLOW with SWAT-generated recharge outputs that were much more spatially heterogeneous than in previous studies, reflecting the spatially variable nature of land cover, soil type, and slope. Coupling these two models has been done before, for a study in Kansas (Sophocleous & Perkins, 2000), and several in Asia (Chung, Kim, Lee, & Sophocleous, 2010; Ke, 2013; Kim, Chung, Won, & Arnold, 2008), but not for an evaluation of climate change impacts. For the aforementioned hydrological studies that do address climate change, most use a single climate model, some use several, while others artificially modify observed climate data to simulate future change. For the Kalamazoo County MODFLOW study, Luukkonen et al. (2004) only considered a potential reduction in recharge, and simulated it by lowering average precipitation inputs by 30% to match rates during a relatively recent dry period in 1999. In this study, I evaluated 31 different future projections of climate, which included both increases and decreases in recharge, allowing me to paint a clear range of potential hydrologic impacts to both surface and groundwater from climate change.

While a number of SIDMA projects have been carried out across the U.S., with particular focus on the Great Lakes Region[1], most have been targeted at a specific population within a particular watershed. Because SIDMA was designed to aid in reducing non-point source pollution, these projects have almost exclusively dealt with surface water; and most of the previously mentioned studies of awareness and attitudes towards groundwater focused on

[1] The team that developed SIDMA was comprised of researchers from universities in the Midwestern U.S., with funding from US EPA Region V, which is located in Chicago, IL.

pollution. For this study, I utilized SIDMA to measure social indicators of sustainability of groundwater supply among large quantity water users across the State of Michigan.

CHAPTER 3: Preparing the Hydrologic Models

This project contained two main tracks of research. The first was computer modeling of the water table in Kalamazoo County, Michigan under various climate and land cover change scenarios. The second was an assessment of social indicators of groundwater sustainability through a state-wide survey of large-quantity water users in Michigan. This chapter details the methods employed in modeling the water table, including the selection of the study area, preparing the surface water model with the Soil and Water Assessment Tool (SWAT) (Arnold et al., 2012), and configuring the groundwater model with MODFLOW (Harbaugh et al., 2000).

3.1 Study Area

3.1.1 Physical and Demographic Characteristics

My primary geographic focus for modeling the water table was on Kalamazoo County, located in the southwest portion of Michigan's Lower Peninsula, covering an area of approximately 1,500 km^2 (Figure 1). Cropland is the dominant land cover in the county, accounting for roughly 40% of the area, with forest (21%), urban (20%, 6% impervious), and wetlands (11%) representing the next largest land cover classes (Fry et al., 2011). Corn (25,900 hectares) and soybeans (10,900 hectares) are the main crops harvested from those agricultural lands (Michigan Agricultural Statistics Service, 2013). Topographic relief is moderate, with an elevation range of 110 meters over a distance of around 40 km (Gesch, Evans, Mauck, Hutchinson, & Carswell Jr., 2009). The depth to the water table generally follows the spatial trend of the surface topography, with depths of over 55 meters in the hillier northwest portion of the county. The major hydrologic feature of the county is the Kalamazoo River, which runs westward before turning and exiting the county's northern border and continuing its path to Lake Michigan. The northern portion of the county falls within the Kalamazoo River watershed (42% of the county's area), while the remaining portion (58%) lies within the headwaters of the St. Joseph River watershed. The county's sub-surface geology consists of coldwater shale bedrock, overlain by sand and gravel glacial outwash that varies in depth from 30 meters in the southeast to 183 meters in the west (Forstat, 1983; Luukkonen et al., 2004). Soils in the county are primarily sandy, with an average profile of roughly 55% sand, 15% clay, and 30% silt; which makes for well draining soils. Most of the county's soils belong to the B hydrologic soil group (69%), followed by A (23%), C (5%), and D (3%) (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture, 2009). The average annual precipitation at the Kalamazoo Battle Creek International Airport over the period of 1980-2010 was 91 cm, with about 13 cm of liquid precipitation in winter, and the remaining 79 cm evenly spread among the other seasons. Average annual low temperature over that period was 4.4°C (-6.7°C in winter), while the average annual high was 14.4°C (27.2°C in summer) (National Climate Data Center, 2013).

As of 2012 Kalamazoo County had a population of around 254,000 residents (U.S. Census Bureau, 2012), and is one of the few areas of Michigan that has been able to sustain population growth through the state's economic downturn over the past decade (Mack, 2011; Monacelli, 2013). The adjacent cities of Kalamazoo and Portage represent the main urban core of the county, with populations of around 75,000 and 47,000 respectively. The county's population is expected to grow steadily through 2040 (Grimes & Fulton, 2012).

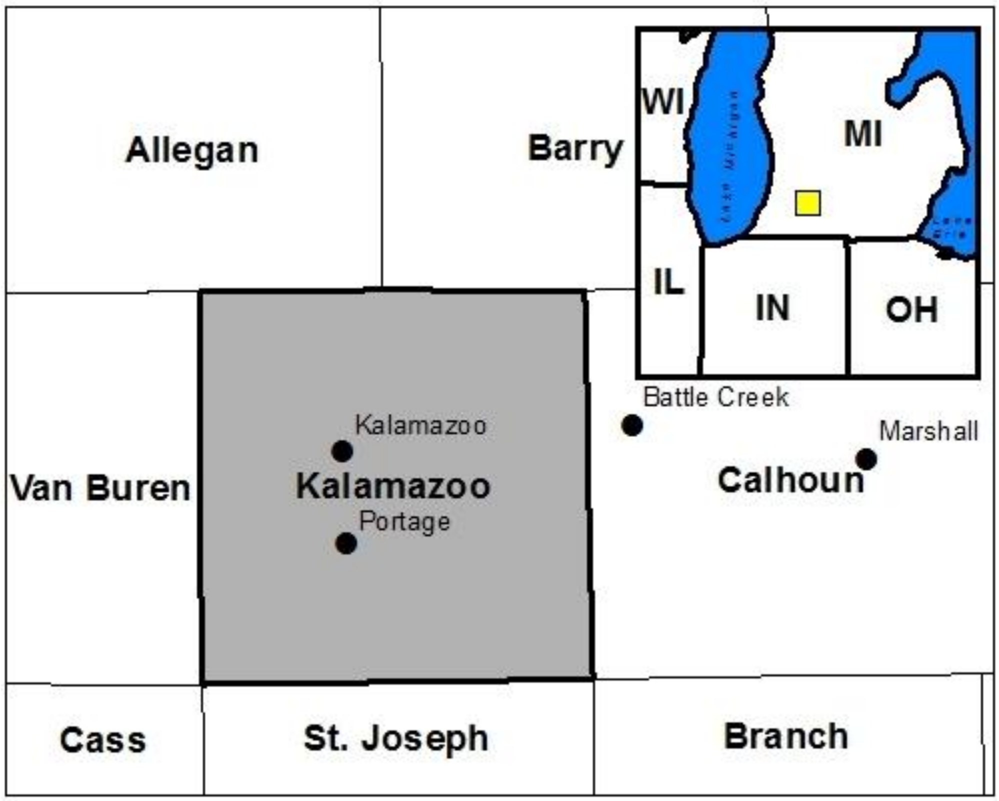

Figure 1: Kalamazoo County location.

Reported average daily water use for agriculture in Kalamazoo County was around 98 million liters per day (LPD) in 2004, while 2003 non-agricultural use (primarily for industry and golf courses) was around 19 million liters per day (Groundwater Inventory and Mapping Project, 2005a, 2005b). Michigan Department of Agriculture and Rural Development (MDARD) reported that the county was the largest irrigator in the state for 2010 (MDARD, 2012). Community water use reported to the Michigan Department of Environmental Quality (MDEQ) for the cities of Kalamazoo and Portage from 2005-2009 averaged 72 million and 23 million liters per day, respectively. These estimates do not include use from small (< 378,541 LPD) private wells.

3.1.2 Kalamazoo MODFLOW Model Boundary

Modeling hydrology often requires looking beyond political boundaries to define a study area, because those boundaries frequently do not follow the contours of a watershed or a groundwater divide. The existing USGS MODFLOW model for Kalamazoo County developed by Luukkonnen et al. (2004), which I will refer to as the original MODFLOW model from here on, defined a model boundary well outside of the county border. This extended boundary generally followed surface water features (Figure 2), and minimized the potential issue of failing to account for large water fluxes into and out of the model's aquifers. Because the ultimate goal of this part of the project was to evaluate the potential changes in those aquifers as a result of climate change and land cover change, this extended MODFLOW boundary defined the effective project study area; even though the primary geographic focus was on Kalamazoo County. Despite the larger study area, the county was still the central feature of the original MODFLOW model. The three-dimensional grid cells that comprised it had varying definitions of length, width, and height. The cells in model's interior had finer resolutions in the planar dimensions (201 by 201 meters) than the cells closer to the exterior (up to 792 by 792 meters); therefore those areas were able to represent the model inputs like recharge, conductivity, and withdrawals less homogenously than the border areas (Figure 3).

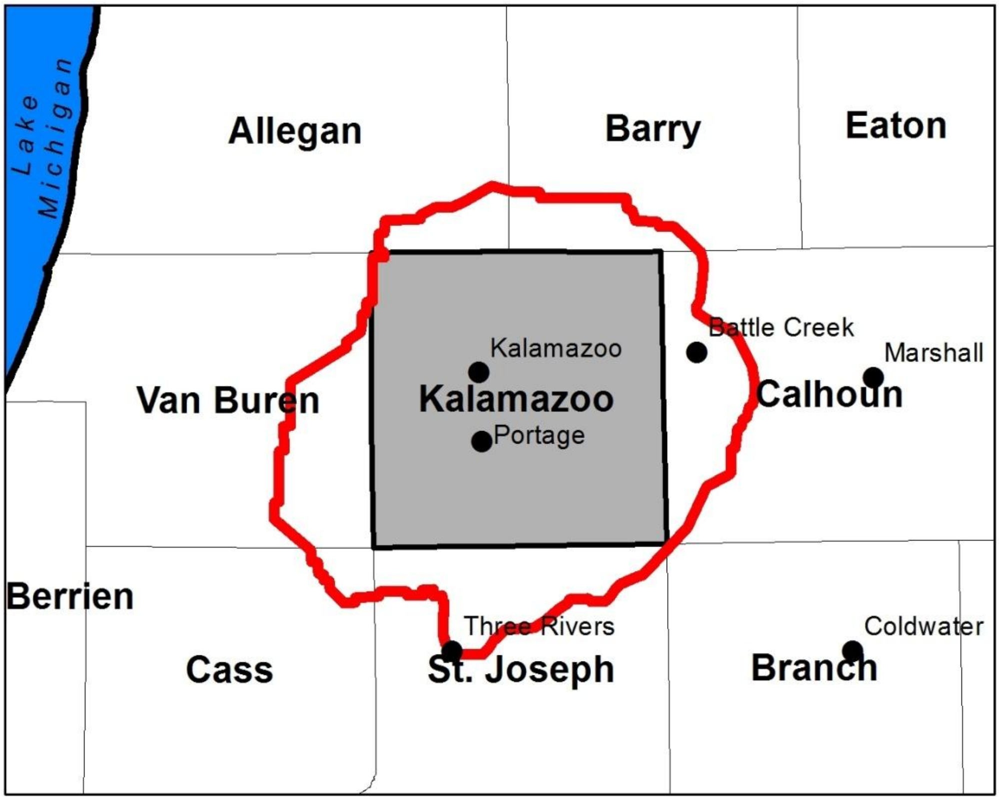

Figure 2: MODFLOW model boundary in red.

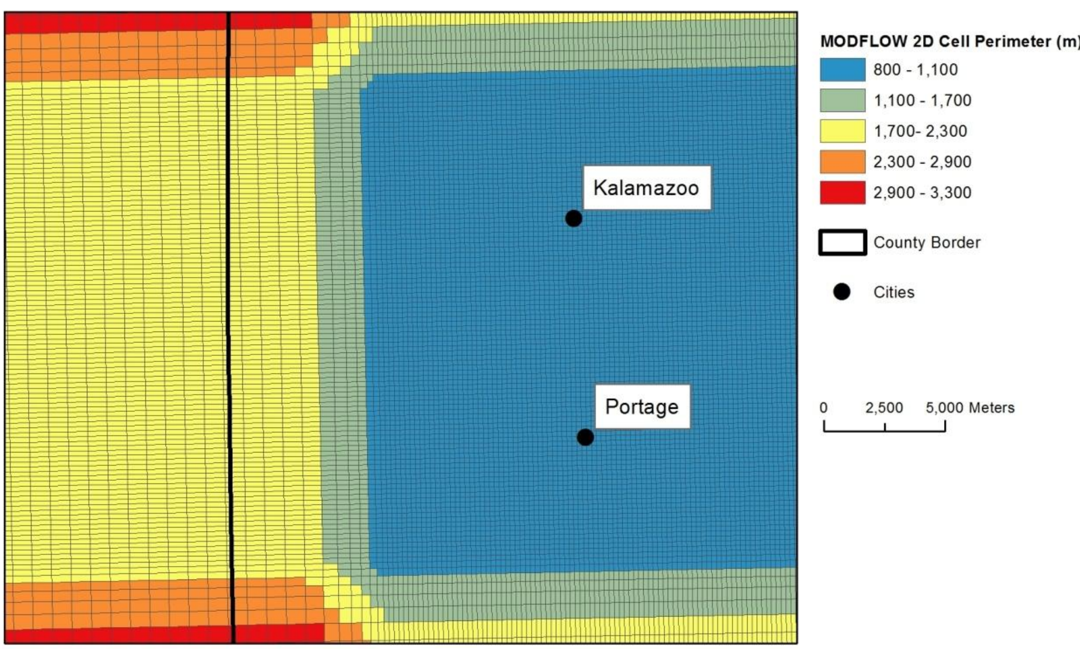

Figure 3: Varying MODFLOW 2D cell sizes.

3.1.3 SWAT Watershed Boundaries

As a model designed to simulate surface water hydrology, SWAT requires a study area defined by watersheds. Because I utilized spatial outputs from SWAT as inputs to MODFLOW, those watersheds had to cover the MODFLOW boundary defined in Figure 2. Because the MODFLOW boundary was roughly defined by surface water features, it would have been possible to create a SWAT study area that approximated this boundary. However, in order to calibrate SWAT model outputs, the study area watersheds had to be extended to the locations of stream gages with daily flow observations, creating a much larger SWAT study area than the one used in MODFLOW. Furthermore, in order for SWAT to computationally process such a large area, I had to break up the SWAT study area into five separate models. These five models represented the watersheds of the Kalamazoo River, the headwaters of the St. Joseph River, the upper portion of Thornapple River, the Paw Paw River, and the Upper Dowagiac River (Figure 4). The Kalamazoo and St. Joseph models were so large that they were further divided into sub-models by the multiple stream gages within them. These sub-divisions improved the model calibration for these areas because I was able to make more local parameter adjustments, as opposed to trying to calibrate an entire model solely based upon observations at the outlets of the Kalamazoo and St. Joseph rivers. This delineation ultimately yielded twelve SWAT models, corresponding to the USGS gage locations that had daily data available for the relatively recent past (Figure 5) (Table 2). For the remainder of this manuscript, I will refer to the various SWAT models by their respective USGS gage identifiers in Table 2.

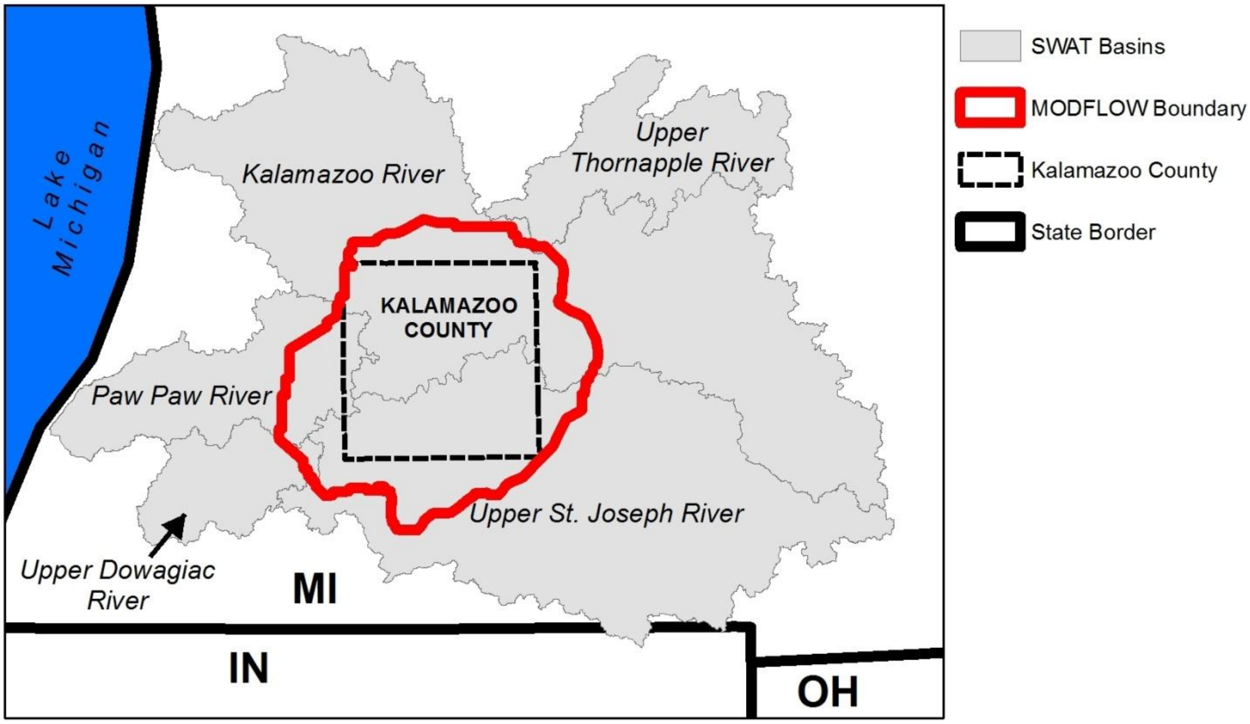

Figure 4: SWAT model basins.

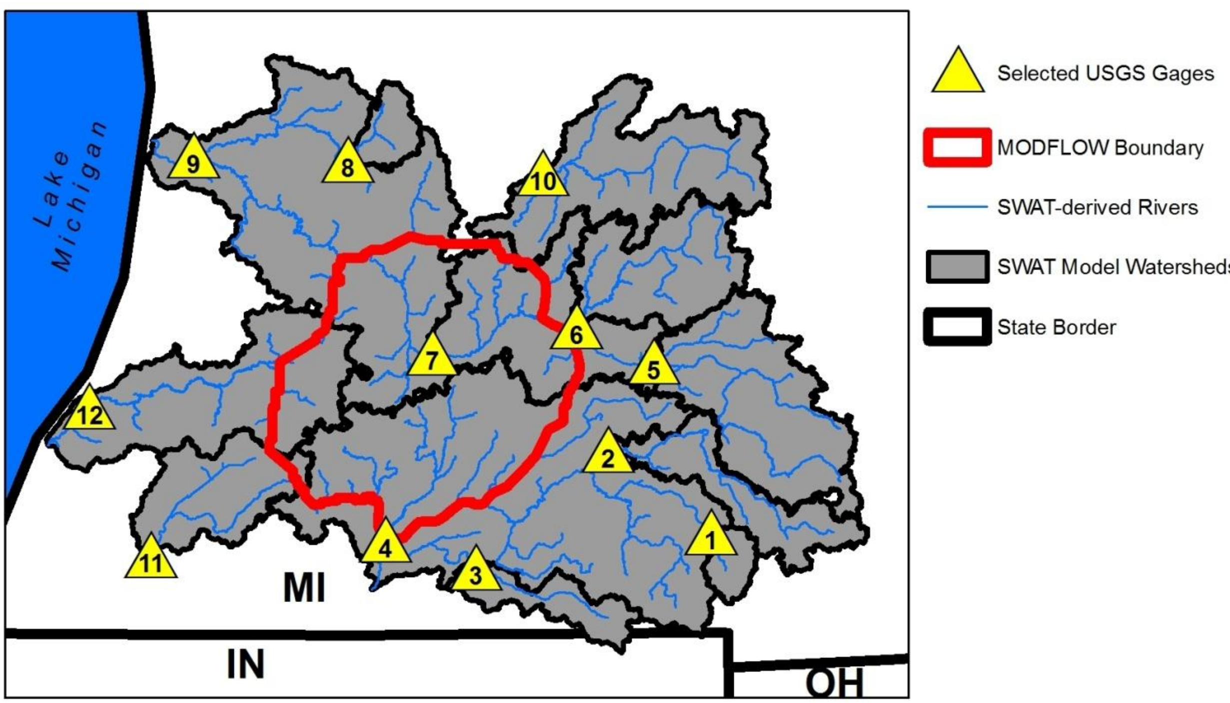

Figure 5: SWAT model watersheds. Numbers in the gage symbols correspond to records in Table 2.

Table 2: Selected USGS stream gages. Gage Number column corresponds to gage labels in Figure 5.

Gage Number	USGS Gage ID	USGS Gage Name	SWAT Basin
1	04096515	South Branch Hog Creek Near Allen, MI	Upper St. Joseph
2	04096405	St. Joseph River at Burlington, MI	Upper St. Joseph
3	04097540	Prairie River Near Nottawa, MI	Upper St. Joseph
4	04097500	St. Joseph River at Three Rivers, MI	Upper St. Joseph
5	04103500	Kalamazoo River at Marshall, MI	Kalamazoo
6	04105000	Battle Creek at Battle Creek, MI	Kalamazoo
7	04106000	Kalamazoo River at Comstock, MI	Kalamazoo
8	04108600	Rabbit River Near Hopkins, MI	Kalamazoo
9	04108660	Kalamazoo River at New Richmond, MI	Kalamazoo
10	04117500	Thornapple River Near Hastings, MI	Upper Thornapple
11	04101800	Dowagiac River at Sumnerville, MI	Upper Dowagiac
12	04102500	Paw Paw River at Riverside, MI	Paw Paw

It may seem odd to generate SWAT models for HUCs 04096515, 04096405, and 04097540 (gage numbers 1, 2, and 3, respectively) given this study's focus on the MODFLOW model and the fact that none of those SWAT model boundaries touch the MODFLOW boundary. However, those three models serve as tributaries for HUC 04097500 (gage number 4) which covers a large portion of the southern half of the MODFLOW model area. In order to adequately calibrate the streamflow of the HUC 04097500 SWAT model, I had to also simulate and calibrate the flow from the tributaries. This need to account for tributary flows during calibration was the reason that I also included HUCs 04103500, 04105000, and 04108600 in the study (gage numbers 5, 6, and 8, respectively), because they are tributaries to HUCs 04106000 and 04108660.

3.2 Surface Water Model Preparation

I developed separate SWAT models for each of the watersheds in Figure 5, which provided sufficient geographic coverage to generate calibrated model inputs to the MODFLOW model illustrated in Figure 2. I calibrated each SWAT model to baseflow conditions during the early half of the 2000-2010 decade, and validated against the later half. I then ran each calibrated model under various combinations of future climate scenarios, increased urbanization, and agricultural expansion through the end of the century. For each scenario, I stored SWAT's field-scale output of groundwater recharge for later use as an input into the MODFLOW groundwater model so that I could simulate the effect of each scenario on the study area water table.

This section will detail how I prepared the SWAT models, what inputs they needed, and how I mapped the groundwater recharge output.

3.2.1 SWAT Model Overview

SWAT is a physically based hydrologic model that runs on a daily time step, employs weather, soils, and land management as the primary inputs, and produces a broad range of outputs, including surface runoff, streamflow, evapotranspiration, biomass growth, crop yields, and groundwater recharge, to name several. SWAT was developed by scientists at the USDA Agricultural Research Service (USDA-ARS) in Temple, TX. It is one of the most broadly utilized surface water models in agricultural, civil, and environmental engineering, with a global user base and over 2,400 academic publications as of March 2016 (Center for Agriculture and Rural Development, n.d.).

A SWAT model is run at a watershed scale, though at its most granular level it calculates daily outputs for each unique hydrologic response unit (HRU) in a study area. An HRU represents a unique combination of land cover, soil, and slope within a particular subbasin of a

SWAT model. I discuss the specific inputs that I employed to create the HRUs in greater detail in the next section. However, a conceptual understanding of how an HRU is created and utilized within SWAT is essential in understanding the model's functions. I calibrated each SWAT model against streamflow outputs generated for each watershed; however, I stored HRU-scale groundwater recharge estimates as inputs into the MODFLOW simulations.

SWAT allows users to specify a broad range of model inputs, but also allows them to assume standard default values. It is easiest to discuss the various inputs used in this project as they were employed sequentially to set up the SWAT models. The steps described here are presented in the context of setting up a single SWAT model. These steps were repeated twelve times for this project, once for each of the models in Table 2.

3.2.2 Watershed Boundary, DEMs, and Sub-watersheds

The first step in setting up each SWAT model was to define the general watershed to be simulated. SWAT delineates the model's boundary from a Digital Elevation Model (DEM); but in order to prepare the other model inputs, and keep their respective geographic sizes (and therefore file sizes) manageable, I generated buffered watershed boundaries from the Watershed Boundary Dataset (WBD) (USGS, n.d.-a). The WBD contains watersheds of varying scales, from the small-scale 2-digit watersheds of the Great Lakes (*e.g.* 04) and Mississippi River basins, to the large-scale 12-digit watersheds (*e.g.* 041000030101) that ultimately feed the smaller-scale watersheds downstream. I aggregated the 12-digit watersheds of the WBD, the smallest class of features in the dataset, to define the SWAT model boundaries of Figure 5. For example, I generated an initial boundary for SWAT model 04097540 by combining the three

HUC12 watersheds in the WBD above gage number 3. I then buffered that initial boundary by 1,000 meters, and used it to clip the other SWAT input datasets, such as DEM, land cover, and soil survey map units (discussed in greater detail below) prior to their utilization in the SWAT models. I then used the un-buffered boundary to define a study area mask that governed all subsequent SWAT spatial inputs.

The next step in the SWAT preparation was to delineate model subbasins. I performed this delineation, and the majority of subsequent SWAT inputs, with ArcSWAT, a mapping interface for ArcGIS© to set-up, parameterize, and run SWAT models. I generated model subbasins with the ArcSWAT Automatic Watershed Delineation tool. I then provided ArcSWAT with the study area mask, a 10-meter DEM from the National Elevation Dataset (Gech et al., 2002) that was previously clipped by the buffered initial boundary, and stream locations from the National Hydrography Dataset (NHD) (USGS, n.d.-a) to burn in a drainage network to the DEM. These inputs enabled ArcSWAT to delineate subbasins that ultimately helped organize and parameterize the SWAT model. I refined the subbasins further by identifying large impoundments along the model area's DEM-derived river network. I used aerial photography and the U.S. Army Corps of Engineers' National Inventory of Dams (U.S. Army Corps of Engineers, n.d.) to identify areas along the river network where impoundments created large lakes or reservoirs. ArcSWAT created individual subbasins for each impoundment, which facilitated subsequent parameterization of reservoirs within SWAT and in evaluating their outflows. The number of subbasins within a model was largely dependent on the size of its study area. SWAT model 04097500 contained 72 sub-watersheds, whereas model 04108600 only contained three.

3.2.3 Land Cover

I represented Land cover in the SWAT models with the USDA Cropland Data Layer (CDL) (USDA - National Agricultural Statistics Service, 2014). The CDL is a remotely sensed land cover image that categorizes the landscape into the traditional classes from the National Land Cover Dataset (NLCD), such as deciduous forest, high-intensity residential, pasture, wetlands, and open water, but replaces the generic agricultural category with detailed crop classes. Whereas the NLCD contains the broadly defined row-crop agriculture class (NLCD code 82), the CDL sub-divides those areas into corn, soybeans, winter wheat, oats, sugar beets, and alfalfa among over 50 other classes. The spatial resolution of the CDL is 30-meters by 30-meters. A new CDL is released each year, allowing users to infer likely crop rotation schedules for each 900 m^2 area on the landscape.

I analyzed CDL images for 2010 – 2013 to create a land cover dataset that included the non-agricultural classes described above, and likely crop rotations. For example, if a particular pixel in the CDL was classified as corn in 2010 and 2012, and soybean in 2011 and 2013, then the final land cover dataset coded that pixel as “CSCS” (corn-soy-corn-soy) to represent that rotation. There were multiple possible rotations that could have been included in the final land cover dataset. Some of the most common classes among these multi-year land cover datasets were the following: alternating corn and soy rotations (CSCS and SCSC), corn-soy-wheat rotations (CSWC, SCWS, WCWS), and alternating alfalfa and pasture (APAP and PAPA). The multi-year classification also allowed for continuous growing of a single crop over the four years, including corn (CORN), soybean (SOYB), winter wheat (WWHT), and alfalfa (ALFA). For the 04097500 SWAT model, which covers a large portion of the MODFLOW study area and is representative of agriculture in most of the eleven other SWAT models, the most common agricultural land cover classifications were the following: CSCS (14% of the model landscape), SCSC (11%), PAST (continuous pasture 6%), CORN (5%), and APAP (5%).

I did not model livestock production in SWAT for three main reasons. First, livestock production accounted for only 20% of the total market value of agricultural production in 2012, versus 80% for cropland (NASS - U.S. Department of Agriculture, 2012). Second, it is difficult to identify the locations of livestock operations and represent them spatially within a SWAT model. While cropland can be readily inferred from satellite imagery products like the CDL, I was unable to locate a database that contained addresses or coordinates of livestock operations. It might be possible to infer a relationship between livestock production and areas of identified as pasture in the CDL, but not all pasture land is utilized for livestock. Third, even if I was able to locate such facilities, it would have been difficult to estimate the head counts for these operations to adequately represent their hydrologic impacts on the watershed.

3.2.4 Soils

The soils data in the SWAT projects were derived from the USDA's SSURGO soil surveys (Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture, 2009). ArcSWAT has an interface to connect to SSURGO databases, read in the detailed survey attributes, and map them within the watershed so that SWAT can utilize the dominant soil map unit conditions to simulate surface run-off, infiltration rates, and water holding capacity. All ArcSWAT required was a GIS layer of soil map units for each SWAT model watershed, which simply entailed downloading surveys for each county that intersected the watershed, merging the features, and clipping them with the buffered boundary. ArcSWAT uses the unique SSURGO identifiers as the key field to retrieve the necessary attribute data from its built-in soil database.

3.2.5 Irrigation

In order for SWAT to be able to simulate irrigation, I had to sub-divide the agricultural classification of the CDL further. SWAT allows agricultural areas to be irrigated from surface waters, shallow aquifers (which discharge to streams), and deep aquifers (which SWAT considers water lost from the system). There is no readily available dataset that locates irrigated farm fields, or distinguishes among irrigation sources. The NRCS, Michigan Department of Agriculture and Rural Development (MDARD), and the Michigan Department of Environmental Quality (MDEQ) maintain records that could provide that information, but these are managed as confidential files. One option was to ignore irrigation entirely and cite it as a limitation of this project's analysis; but that would leave out a significant portion of the water budget for this region. As I stated earlier, agricultural irrigation was the single largest source of water withdrawals in Kalamazoo County. Therefore I had to develop a means of estimating irrigation.

The approach I took was to utilize the State of Michigan's Wellogic database of well locations and attributes, the CDL, the SSURGO soil surveys, NHD stream locations, and a report from MDEQ (Michigan Department of Environmental Quality, 2006) to identify potential irrigation locations within each SWAT model. I developed this irrigation search algorithm as a Python script. The algorithm begins by identifying wells within Wellogic that are classified as active (database field “WEL_STATUS” = ‘ACT’), used for irrigation (“WELL_TYPE” = ‘IRRI’), and have a pump capacity greater than 757 liters per minute (“PMP_CPCITY” > 200 gallons[2]). The algorithm creates a 152 meter buffer[3] for each of these wells and then analyzes that buffer to identify any intersecting CDL pixels that could be irrigated (*i.e.* agricultural classes) and that overlay soil map units classified as belonging to the A or B hydrologic soil groups in SSURGO. If the algorithm finds a qualifying combination of land cover and hydrologic soil group, it then delineates a contiguous area of CDL pixels that could be potentially irrigated by a particular well, up to a maximum distance from the well of 914 meters. I based the criteria for pump capacity and hydrologic soil group on an assessment of potentially irrigatable agricultural lands in Michigan conducted by Miller (2013). I chose the 914 meter maximum distance for a well’s reach simply based upon aerial photo interpretation of fields served by wells classified as active and irrigation in Wellogic. In summary, the algorithm identifies active wells of sufficient capacity that are used for irrigation, looks around each of well for areas where the withdrawn water would likely be applied, and tries to map those areas contiguously. Figure 6 through Figure 9 illustrate how the process worked for a sample well in SWAT model 04097500.

Figure 6 shows the approximate location of such a well. Wellogic’s records are susceptible to errors in both well attributes and location. The accuracy of the well records is typically dependent upon the thoroughness of the driller that installed it. If the driller utilized a GPS when recording the well’s location, then we have a higher degree of confidence in its placement on a map. If the well’s location was simply assigned by geocoding an address, the

[2] Wellogic volumes are reported in English units.

[3] I designed the search algorithm with English units, so the search distance was set a simpler value of 500 feet, and not a seemingly arbitrary value of 152 meters.

well may be incorrectly located along a road center line as opposed to the center of a field, which would be the more likely scenario in a central-pivot irrigation system.

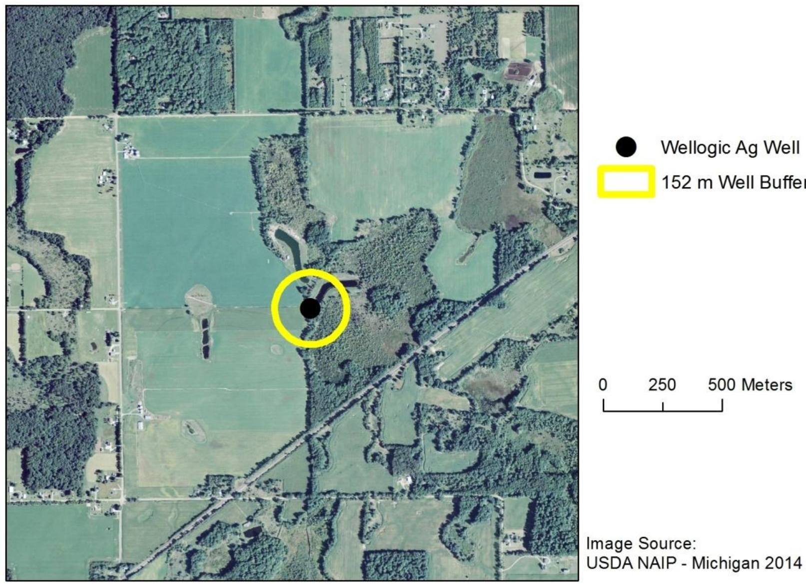

Figure 6: Active Wellogic irrigation well, with pump capacity greater than 757 LPM, in the 04097500 SWAT model watershed.

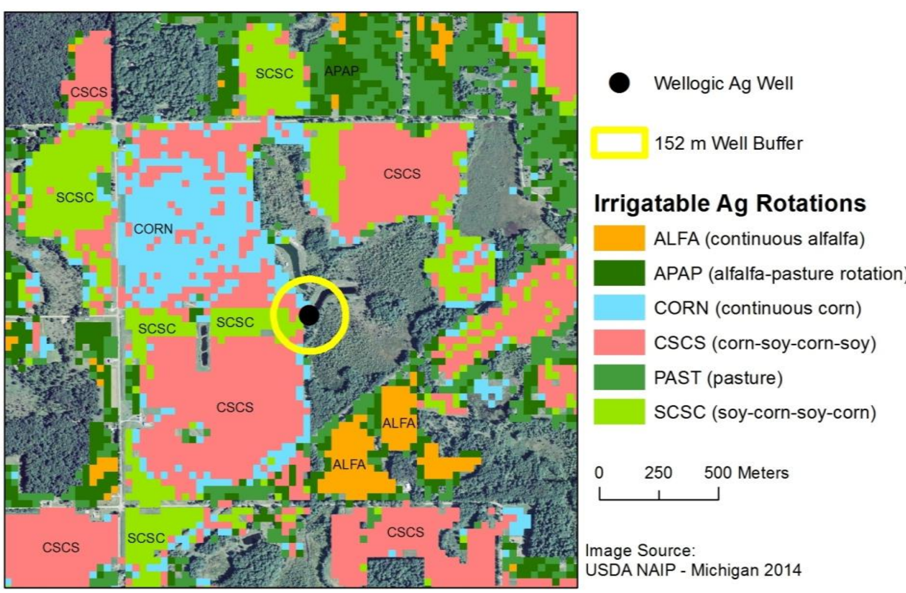

Figure 7: Crop rotations inferred from CDL images from 2010-2013. Non-shaded areas were non-agricultural pixels in the CDL.

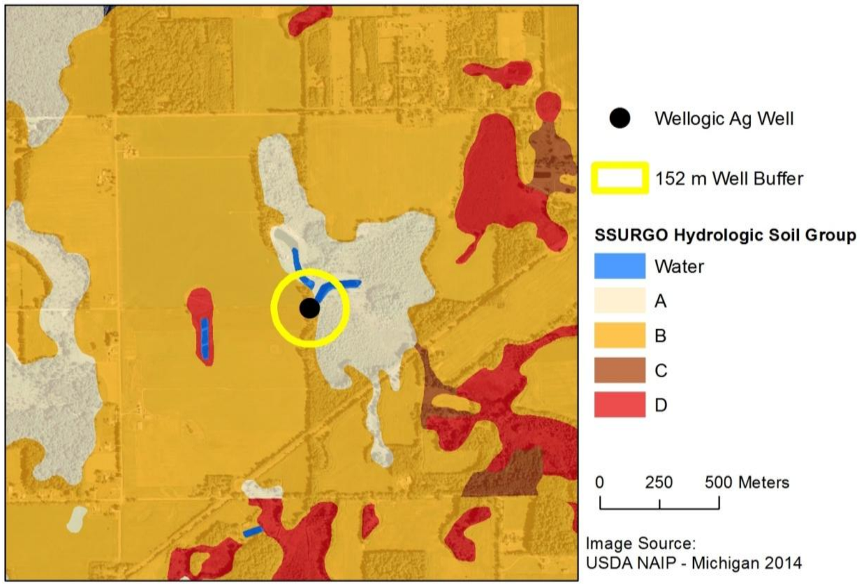

Figure 8: Hydrologic soil group classifications in SSURGO map units.

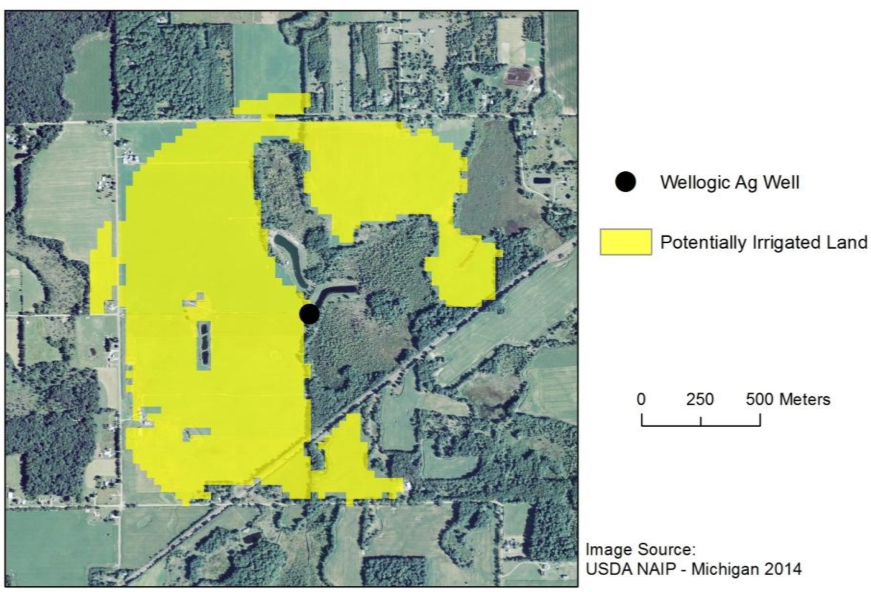

Figure 9: Contiguous land within 914 meters of the Wellogic well that is agricultural in the CDL and on soils classified as belonging to the A or B hydrologic soil groups in SSURGO.

Figure 7 shows the agricultural pixels of the CDL near a well. I interpreted the field to the west of the well as growing continuous corn in addition to corn and soybean in rotation[4]. Figure 8 shows the hydrologic soil groups, as estimated by SSURGO, in the well's area. The two figures illustrate that a portion of land within the western half of the well's buffer met the algorithm's criteria of agricultural land on A or B soils. The algorithm then searched up to 914 meters beyond the well-buffer, for other agricultural lands on A and B soils that are contiguous with the identified pixels within the buffer. This search ultimately yielded the areas shaded yellow in Figure 9.

While the algorithm identifies potential locations irrigated by Wellogic wells, the attributes in the Wellogic database help determine the source of the water withdrawal. If a well withdraws water from the drift aquifer (field name "AQ_TYPE" = 'DRIFT'), then the algorithm classifies the source of water for that well's irrigated lands as SWAT's shallow aquifer. If the well withdraws water from the bedrock (field name "AQ_TYPE" = 'ROCK'), then the algorithm classifies the source as SWAT's deep aquifer. If no value is present for the AQ_TYPE field, then the algorithm compares the well depth attribute (field name "WELL_DEPTH") to a well depth value averaged for drift and and bedrock wells in the SWAT model's geographic area in order to determine the likely source.

The algorithm applies a similar approach for estimating fields irrigated by surface water; however, without a touchstone feature like a Wellogic well to initiate an evaluation of an area's likelihood of irrigation, the results are more uncertain. Instead of starting with a well, the

[4] This example illustrates a particular limitation of the CDL; specifically that a single field, visible in the aerial image, can have a mix of land cover class pixels scattered throughout. In reality a farmer would not grow continuous corn in one 900 m^2 area, and employ a corn-soy rotation in the adjacent 900 m^2 area.

algorithm for surface water irrigation begins with the DEM-derived stream network generated by ArcSWAT when it delineates SWAT subbasins. The algorithm deems agricultural CDL classes within 91 meters of the stream network, and on soils classified as belonging to the A or B hydrologic soil group in SSURGO, as potentially irrigated. It then searches for contiguous qualified areas up to 914 meters from the stream. It avoids irrigating areas that have already been classified as irrigated by Wellogic wells. Unlike its groundwater irrigation approach, however, the algorithm works towards a target number of pixels to identify as irrigated by surface water in each SWAT subbasin. It calculates a threshold for each subbasin and, once the threshold is met, moves on to the next subbasin. Without the threshold the algorithm would over-irrigate the landscape, because there is no shortage of agricultural land within 91 meters of the stream network in this region, and most of it is not irrigated by surface water.

The algorithm calculates the surface water irrigation threshold for each SWAT subbasin based upon the average total irrigation hectares reported to the NASS Ag Census, and the ratio of surface water to groundwater irrigation in each Michigan county estimated by MDEQ in 2006. For example, the Ag Census reported that County X had on average of 100,000 hectares of agricultural land, of which 10,000 were irrigated. M- DEQ estimated that 60% of the county's irrigation was from surface water. After clipping the CDL by the subbasin of interest, the algorithm observes that 100 hectares of agricultural land, of which it assumes (based upon a ratio of 10,000 irrigation hectares to 100,000 total agricultural hectares) 10 hectares are irrigated. The algorithm then assumes that 6 of those hectares are irrigated by surface water

(60% of irrigation in the county is surface water), which becomes the subbasins target[5]. If the algorithm identifies 6 hectares worth of pixels within the subbasin of interest, it moves on to the next subbasin. Figure 10 and Figure 11 illustrate an area within SWAT model 04097500 that the algorithm identified as potentially irrigated by surface water.

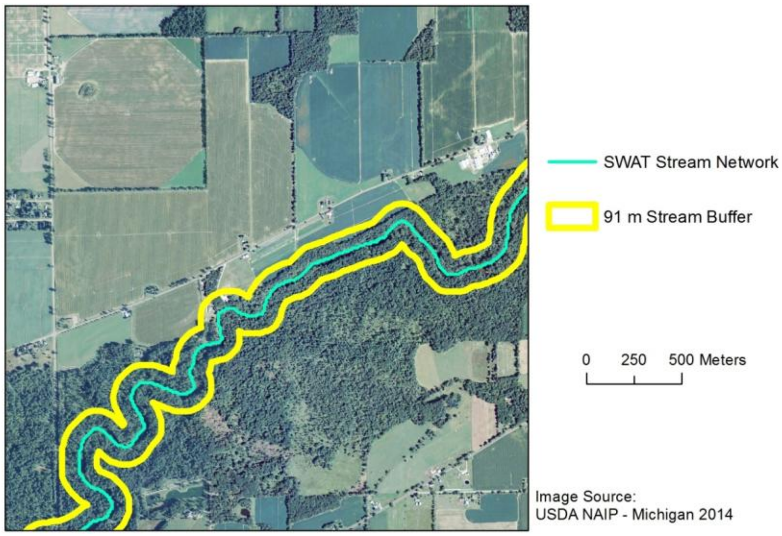

Figure 10: SWAT stream adjacent to agricultural areas in model 04097500.

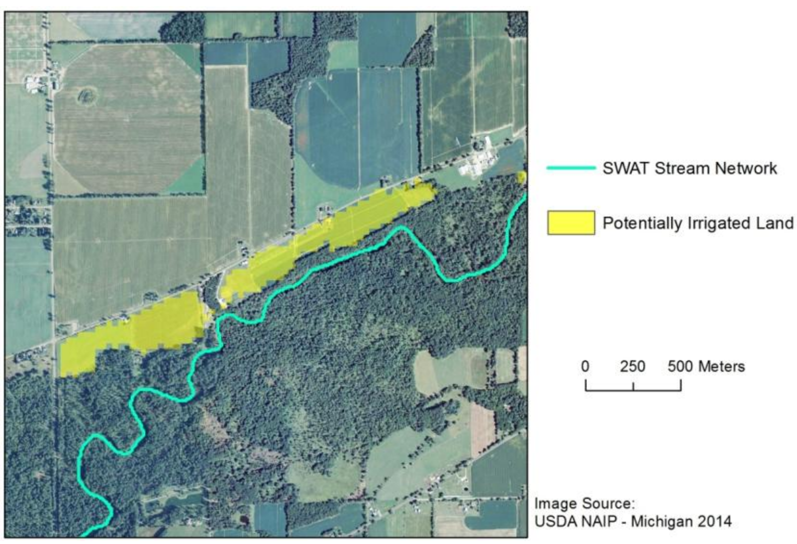

Figure 11: Contiguous land within 914 meters of the SWAT stream network, that is agricultural in the CDL, and on soils classified as belonging to the A or B hydrologic soil groups in SSURGO.

[5] Note that in this hypothetical example, I assume that the SWAT subbasin is completely contained within the borders of a single county. In an actual application, the surface water irrigation algorithm factors in the fractional area of each county in the SWAT subbasin of interest.

Neither the groundwater nor surface water algorithms yielded ideal estimations of irrigated land locations. Because the groundwater algorithm centered its search for qualifying areas around the well point, it assumed that the well was properly located. Figure 11 shows an area irrigated by the surface water search algorithm; but it is obvious that the fields to the north of the stream have central pivot irrigation systems, and the algorithm failed to identify them as irrigated by groundwater. These field were missed because there was no record of their wells in Wellogic. The algorithm also allowed neighboring fields to be irrigated by a nearby well, even though these fields may not employ any irrigation in reality. By comparing Figure 7 and Figure 9, one can see that the search carried out in that example picked up the field growing a corn-soybean rotation northwest of the well, and a field growing alfalfa to the southeast. Based upon the aerial interpretation, neither of these fields appear to be part of the farm that the well purportedly serves; though it is not uncommon for a single farmer's fields to be scattered across the landscape. The search algorithm could be improved with human interpretation of aerial photography, but the geographic scope of this project's 12 SWAT models made such an effort impractical.

I also attempted to identify the irrigated areas of golf courses. Using keyword searches for "golf" in Wellogic, I identified courses and manually digitized their boundaries from aerial imagery. I made the determination of drift or bedrock sources in the same manner as the agricultural irrigation wells.

I evaluated the results of this process against hectares of irrigation reported to the National Agricultural Statistical Service's Ag Census (NASS - U.S. Department of Agriculture, 1997, 2002, 2007, 2012). Figure 12 highlights the primary SWAT models that comprise the MODFLOW study area, and displays the county borders so that the respective portion of each model within a county can be approximated . Table 3 lists the hectares identified by the search algorithm described above for the highlighted SWAT models. The table also lists the main intersecting counties for each model, and the average sum of irrigated hectares within those counties as reported by the 1997-2012 NASS Ag Censuses. In Figure 12, one can see that the 04097500 SWAT model comprises roughly 50% of the combined areas of Branch, Calhoun, Kalamazoo, and St. Joseph counties. Table 3 shows that those three counties had a combined total of 73,936 irrigated hectares, when averaged across NASS Ag Censuses from 1997 through 2012. Table 3 also shows that the irrigation search algorithm employed for 04097500 estimated 42,506 hectares of irrigation, 57% of the total irrigated hectares reported by NASS. So for a SWAT model that comprises roughly half of those three counties, the irrigation search algorithm's hectares estimate was a little more than half of the NASS reported irrigation hectares. I observed similar algorithm results for SWAT models 04108660 and 04106000. In 04108660, the SWAT model covers a little over half of Allegan and Kalamazoo counties, and the estimated irrigation hectares are a little more than half of those reported to NASS. About one quarter of the Calhoun and Kalamazoo counties are covered by 04106000, and the irrigation search algorithm estimated about one quarter of NASS reported irrigation hectares for those two counties. Though this evaluation was not a precise assessment of the search algorithm's ability to locate irrigated fields, it demonstrated that the approach was within the ball park of likely total irrigation hectares, and a vast improvement over an alternative approach of ignoring irrigation all together.

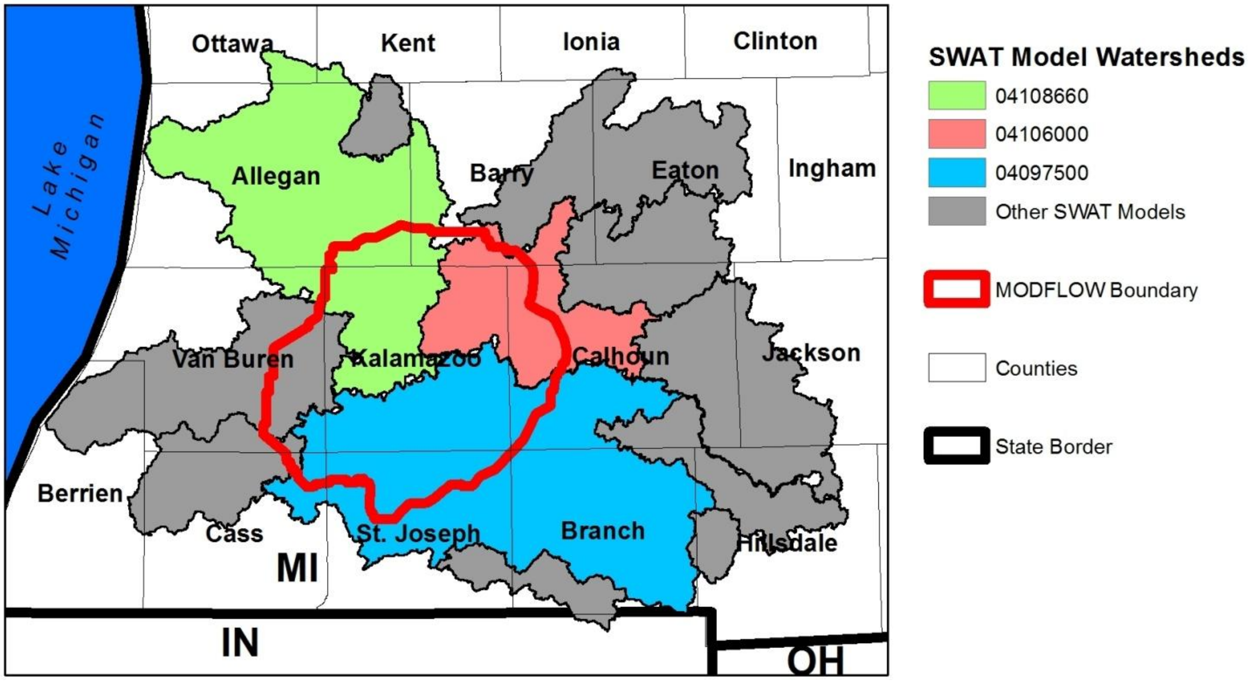

Figure 12: Highlighted SWAT models to evaluate the performance of the irrigation search algorithm.

Table 3: Irrigation hectares estimated by the search algorithm versus county-level estimates reported by NASS Ag Census.

SWAT Model	Estimated Irrigated Hectares	Intersecting Counties	Average Irrigated Hectares in Intersecting Counties (NASS Ag Census)
04097500	42,506	Branch, Calhoun, Kalamazoo, St. Joseph	73,937
04106000	4,249	Calhoun, Kalamazoo	16,077
04108660	13,153	Allegan, Kalamazoo	20,142

I recoded the land cover pixels in these irrigated areas to distinguish them from the non-irrigated land cover classes prior to their input into ArcSWAT. For example, I reclassified the pixels in Figure 7 classified as “CSCS” (corn-soy-corn-soy four year rotation) to “CSCH”. The four year corn-soy rotation was maintained, but the “H” at the end indicated that the pixels were irrigated with water from the shallow aquifer. Similarly “CSCD” would inidicate that the pixels were irrigated with water from the deep aquifer, and “CSCU” would indicate that irrigation was from surface water. See Appendix A for full listing of SWAT land cover classifications used in this project.

3.2.6 HRU Definition

With subbasins delineated, and land cover, DEM, and soil inputs processed, ArcSWAT was able to define the hydrologic response units (HRUs) that drive SWAT's simulations. The HRU is the finest geographic scale at which the model simulates hydrology and plant growth. ArcSWAT created an HRU for each unique combination of land cover, soil type, and slope class within each SWAT sub-watershed. I broke slope into three classes: less than 2%, between 2% and 5%, and greater than 5%. For example, SWAT modeled areas classified as CORN in the land cover dataset, on soil map features classified as Kalamazoo loam in SSURGO, on DEM pixels where the slope is between 2% to 5%, and in SWAT subbasin 2 of model 04106000 as a single HRU. SWAT stored the area of those locations within subbasin 2, retrieved weather inputs from the station closest to that subbasin (discussed in greater detail later), and utilized default and user-customized parameter values for CORN and Kalamazoo loam soils to calculate daily values of precipitation, run-off, infiltration, groundwater recharge, evapotranspiration, and biomass production for each day in a model simulation time period. SWAT made these daily calculations for each HRU in the model, and summed them to calculate annual totals.

Though some HRUs may be confined to a precise location, a single farm field for example, most are distributed throughout a subbasin. Figure 13 and Figure 14 illustrate the spatial distribution of HRUs for a sample of areas in SWAT model 04106000. Table 4 provides details on the composition of the selected HRU IDs displayed in Figure 13. Figure 14 demonstrates how a single HRU (in this case ID 2566) does not necessarily have to represent a single geographic feature. Note how the subbasin boundaries created distinct HRUs. HRU IDs 3215 and 5330 share the same land cover classification (SCSC), SSURGO soil ID (187069), and slope class (< 2%), but are located in separate subbasins. The practical implication of this distinction is that if the respective subbasin centroids are closer to different weather stations, then the HRUs will be modeled with different daily precipitation and temperature values.

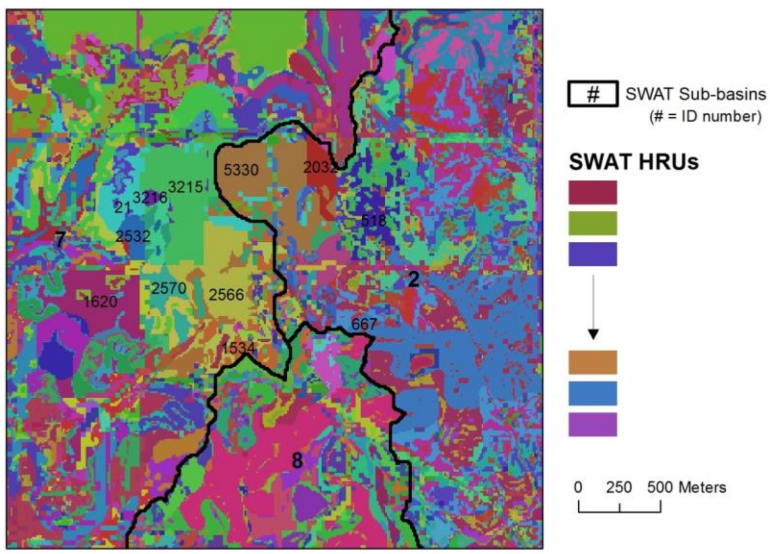

Figure 13: Sample of SWAT HRUs in model 04106000, with selected HRU IDs displayed.

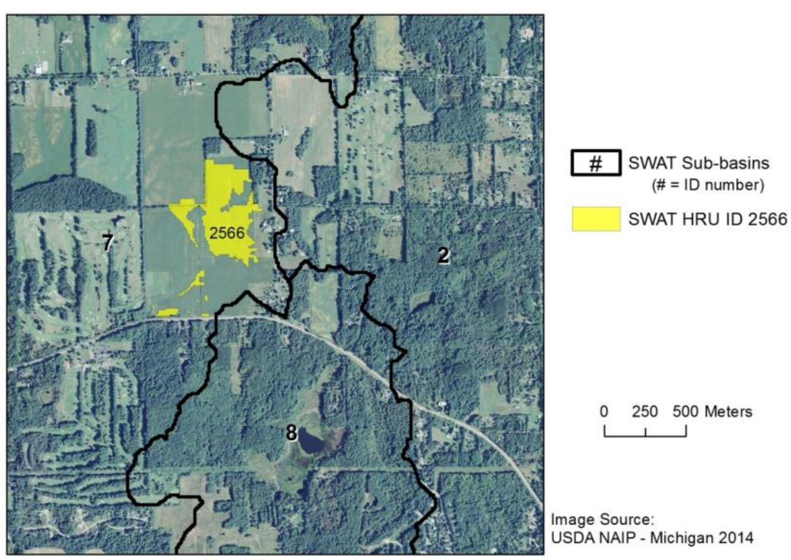

Figure 14: Selected HRU in SWAT model 04106000.

Table 4: Sample of SWAT HRUs.

HRU ID	SWAT Subbasin	Land Cover	SSURGO Soil ID	Slope Class
21	2	CORN	187069	< 2%
518	2	ALFA	186087	> 5%
667	2	FRSD	187074	2% - 5%
1534	7	PAST	187069	< 2%
1620	7	GOCH	187071	< 2%
2032	2	URML	187069	> 5%
2532	7	CORN	187071	< 2%
2566	7	CORD	187069	< 2%
2570	7	CORD	187071	< 2%
3215	7	SCSC	187069	< 2%
3216	7	SCSC	187069	2% - 5%
5330	2	SCSC	187069	< 2%

ArcSWAT offers an option to reduce the number of HRUs within a model, and therefore improve the processing time required to complete a simulation. A user can do this by specifying separate HRU definition thresholds for land cover, soil type, and slope class. For example, a land cover definition threshold of 5% means that ArcSWAT will identify any land cover class within a subbasin that accounts for less than 5% of its total area, and then reapportion that land cover's area among the more dominant classes of the subbasin. If alfalfa (ALFA) only accounts for 2% of total land area in subbasin 7, and deep-aquifer irrigated corn-soy (CSCD) and corn-wheat (CWCD) land covers comprise 25% and 20%, respectively, of subbasin 7's area, then the 2% of ALFA area may be apportioned over those two classes. Similar aggregations can be applied to soil type and slope classes.

There is no rule of thumb in selecting threshold definitions. A SWAT modeler must weigh costs and benefits of selecting a threshold. The lower the value the higher the processing time and storage requirements; the higher the value the more limited the analysis that can be done on model outputs. I evaluated several values and ultimately settled on 3% thresholds for land cover, soil type, and slope. These values provided the best detail for SWAT's spatial output given the time and resources available to conduct the study. For comparison's sake, the 3% threshold created 13,818 HRUs in SWAT model 04108660; whereas a test-case threshold value of 2% created 25,598 HRUs, effectively doubling the processing time and storage requirements. The primary drawback of employing the thresholds was that spatial detail in model outputs was lost. Continuing the example in the preceding paragraph, SWAT will not produce recharge outputs for alfalfa areas in subbasin 7. Not employing threshold definitions would generate outputs for alfalfa in that example, but at tremendous cost to computing resources. The challenge of accounting for these aggregated areas when connecting SWAT's recharge output with MODFLOW as an input will be discussed in greater detail in 3.3.2: HRU Mapping and Output.

3.2.7 Point Sources

SWAT accepts point source inputs at the subbasin scale. I downloaded discharge records for point source loadings from both MDEQ and US EPA. I obtained National Pollutant Discharge Elimination System (NPDES) locations through a website hosted by MDEQ (MDEQ, n.d.)[6,7]. For the locations that intersected the SWAT model watersheds, I downloaded detailed discharge data from US EPA's Permit Compliance Database (US EPA, n.d.), an online warehouse for NPDES data. I calculated average daily values of water and pollutant discharge for each permit in the downloaded records, and then calculated totals across all the permits within a particular subbasin to generate a total discharge input for SWAT. Though point source discharges are not

[6] The website is no longer available.

[7] NPDES locations were also available through US EPA, however a comparison to the MDEQ locations revealed that the latter's records were more accurate spatially.

indicative of recharge or other components of groundwater hydrology, I had to account for all of the primary sources of streamflow in order to properly calibrate for baseflow at gage locations, which was the goal of the calibration efforts described in the next chapter.

3.2.8 Weather

The primary goal in the SWAT modeling for this project was to generate groundwater recharge outputs under various future climate and land management scenarios, and then input those data into MODFLOW to see what impacts those scenarios may have on the water table in Kalamazoo County. I will discuss the methods I used in representing those scenarios in greater detail in Chapter 5: Future Hydrologic Model Scenario Preparation, but I must first discuss the structure of the future climate data in order to explain the weather inputs used to set up the SWAT models.

A team of researchers led by Katherine Hayhoe downscaled and organized over 30 future climate scenarios into a standard format (2013). The research team stored daily climate projections at 1/8 degree grid points. These locations align with a previous climate study by Maurer (Maurer, Wood, Adam, Lettenmaier, & Nijssen, 2002) in which researchers interpolated observed daily weather data (from 1949 through 2010) from a network of National Climate Data Center (NCDC) stations to 1/8 degree grid points. The spatial alignment of these two datasets facilitates comparisons of observed and projected climate outputs by minimizing the potential impacts that highly local weather patterns may have on weather outputs at daily resolutions.

For the initial preparation and calibration of the SWAT models, I used the weather data from Maurer as daily inputs of precipitation and temperature. The 1/8 degree grid points effectively served as weather stations. For each SWAT subbasin centroid, ArcSWAT identified the closest Maurer grid point and used that station's weather data to drive the HRU calculations within the particular subbasin (Figure 15). An alternative approach would have been to utilize the actual locations and observations of the NCDC dataset. But this could have created problems when conducting the future climate scenario simulations, because I would have had to change the locations of each model's weather stations and, therefore, could have introduced additional spatial uncertainty into the final outputs.

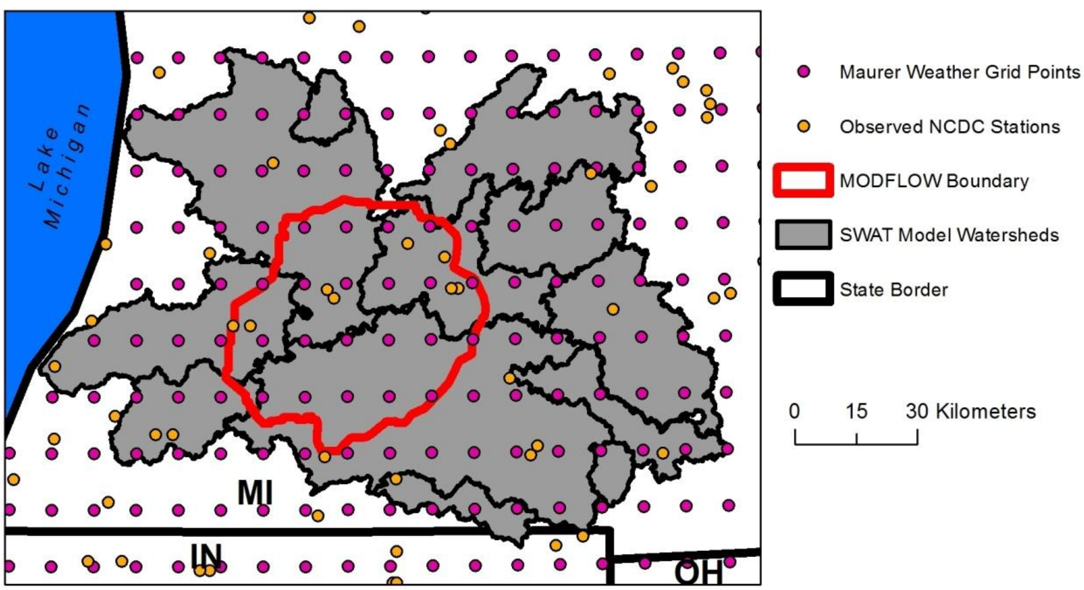

Figure 15: Maurer grid points, effectively used as climate stations in SWAT simulations.

3.3 Surface Water Modeling Outputs

SWAT generates a broad range of model outputs at different spatial and temporal resolutions. My primary SWAT model output of interest was HRU-scale estimates of annual groundwater recharge, but I also utilized other outputs to calibrate the model and make sure that its various components were functioning properly.

3.3.1 Model-wide outputs

Subbasin-scale estimates of daily streamflow and sediment loading are typically utilized to calibrate model parameters, whereas annual estimates of nutrient loading in streams are often used to map environmental risks within a watershed. I used the daily streamflow output for the subbasins that corresponded with each model's USGS gage location (*i.e.* the model outlet) to calibrate model parameters to observed baseflow conditions. I compared the baseflow fraction output to estimates reported in baseflow separation studies for the region. I used the model's evapotranspiration (ET) estimate to ensure that annual amounts were close to those reported in literature. Comparing the model's crop yield outputs to reported county-scale totals allowed me to ensure that plant growth parameters and harvest schedules were appropriately set. I also used the model's output of irrigation applications and depths to make sure that plant water stress parameter values were within a sufficient range. I will discuss my use of these outputs in greater detail in the Chapter 4: Model Calibration.

3.3.2 HRU mapping and output

In order to map SWAT's estimates of annual groundwater recharge, I had to first map each HRU. ArcSWAT gives users an option to create a GIS layer of HRUs, but in my experience it usually crashes when the number of HRUs is very high. With relatively small HRU definition thresholds of 3% each for land cover, soil type, and slope, utilizing this option was impractical. Furthermore, ArcSWAT produces the HRU output as a vector dataset, which typically results in a very large and unwieldy GIS file. The other problem with the ArcSWAT HRU layer was that unless 0% HRU definition thresholds were used, much of the GIS layer would have holes in it because those areas did not meet the criteria for inclusion as an HRU. I had to come up with a method to create an HRU layer as a more manageable raster dataset, and fill-in the holes created by the HRU definition thresholds. I developed an HRU mapping algorithm to accomplish that task, and employed it as a Python script.

The algorithm took the original HRU inputs of CDL land cover, SSURGO soil surveys, DEM-derived slope, and SWAT subbasin, then aligned them into 10-meter resolution raster datasets (to match the cell resolution of the DEM-derived slope input), and identified all of the unique combinations of those inputs on the landscape. I was then able to cross-reference each unique combination with the records in the HRU database that ArcSWAT had generated previously, and then map that HRU record ID back to the appropriate pixels in the raster. I now had a raster version of the HRU GIS layer that ArcSWAT would have likely struggled to produce.

Next, I had to account for the unique combination pixels that did not have a matching record in the HRU database, *i.e.* the areas eliminated by the HRU definition thresholds. To do this, the algorithm attempted to select an appropriate HRU ID for each orphaned pixel by iterating over a sequence of options. To illustrate how these options worked, consider the hypothetical orphaned pixel CORN -187019-1-25. This pixel had a CDL land cover value of CORN (continuous corn), overlaid the soil feature with a unique SSURGO ID (field name "MUKEY" in the SSURGO database) of 187019, belonged to slope class 1 (< 2%), and was located in SWAT subbasin 25. It may have been orphaned by the HRU definition process because soil 187019 did not account for more than 3% of the area in subbasin 25, or because area in the subbasin classified as continuous corn was less than 3% of the total. The algorithm first tried to find a matching HRU ID for this pixel in the closest subbasins. If a pixel CORN -187019-1-26 was found and had a matching record in the HRU database, then the orphan pixel was assigned that HRU ID. If no match was found, the script then looked for a nearby pixel with the same hydrologic soil group. If soil 187019 belonged to the A hydrologic soil group, the algorithm first looked for a pixel CORN -A-1-25 (within the same subbasin as the orphan), and then in nearby subbasins. If a match had still not been found, the algorithm then ignored the slope class and searched for CORN -187019-X-25 in the present and then near-by subbasins. If that search did not yield a match, the algorithm made one final effort by looking at alternative land cover classes. I developed a list of alternatives for each CDL land cover class, which the script iterated over in looking for a match. In the hypothetical example the first search would have been for CSCS-187019-1-25 (replacing continuous corn with a corn-soy four year rotation), whereas a second alternative would have been SCSC-187019-1-25 (replacing continuous corn with a soy-corn four year rotation). This final search was also extended to nearby subbasins. Finally, if no match was found, the pixel remained orphaned and would ultimately be assigned a no data value in the groundwater recharge raster. Each pixel with a matching HRU ID was assigned a groundwater recharge value in subsequent SWAT simulations.

Table 5 shows how much area was orphaned by the HRU definition process in each SWAT model that intersects the MODFLOW model boundary, and how much area was matched by the algorithm's various search options. In each model, more than 25% of watershed area was aggregated to more dominant HRU combinations during the definition process. Looking for the same combinations of land cover, SSURGO soil feature, and slope class in a neighboring subbasin resulted in the most matched area, followed by searches that looked for matching hydrologic soil groups. As a result of the searches, no model had more than 4% of its total area unaccounted for by HRUs, and therefore less than 4% of each watershed was forced to assign no data values to the groundwater recharge rasters generated by the SWAT simulations.

Table 5: Results from matching areas orphaned by the HRU definition process to existing HRU records.

SWAT Model	Initial Area % Orphaned by HRU Definition	Area % Matches Found in Neighboring Subbasins	Area % Matches Found by Hydrologic Soil Group	Area % Matches Found by Ignoring Slope	Area % Matches Found Through Alternative Land Covers	Area % Still Orphaned After Exhausting Search Options
04097500	26.3	14.8	8.1	< 0.1	1.8	1.6
04101800	30.0	13.5	10.7	< 0.1	4.8	1.0
04102500	34.0	20.8	10.1	< 0.1	1.0	2.1
04106000	35.2	16.0	14.2	< 0.1	1.1	3.9
04108660	36.7	21.4	11.4	< 0.1	1.5	2.4

Once the HRUs were effectively geo-located, I could then map the HRU-scale groundwater recharge output over the landscape at a 10-meter grid cell resolution. Figure 16 shows a map of groundwater recharge from the calibrated SWAT models' baseline condition (2001-2010), merged and then clipped to the MODFLOW boundary. The darker blue sections of the map are areas where SWAT estimated the highest average annual groundwater recharge rates, and align with areas where agricultural irrigation was most prevalent. The red, organe, and yellow areas of the map are where estimated recharge was smallest, and generally correspond with the urban areas of the cities Kalamazoo and Portage, and with open water bodies, to which SWAT does not assign recharge values. I will discuss the calibration of the SWAT model in greater detail in Chapter 4: Model Calibration.

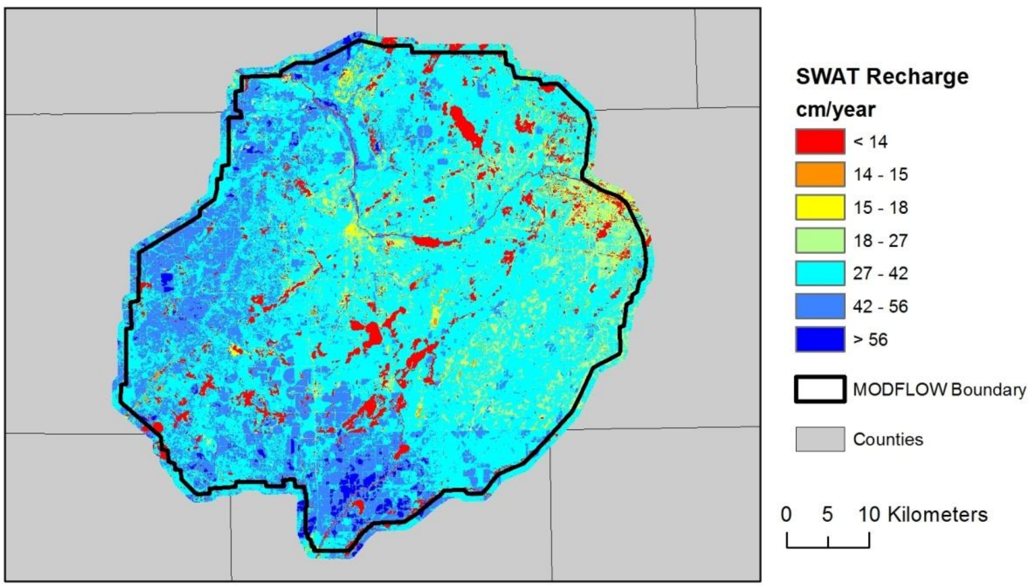

Figure 16: SWAT-modeled groundwater recharge, mapped to HRUs.

3.4 Preparing the Groundwater Model

I simulated groundwater hydraulic head with the MODFLOW model developed by Luukkonen et al. (2004), who generously shared the calibrated model's source files with me, therefore there was significantly less preparation required than with the SWAT models. While I left most of the model structure intact, there were several modifications I had to make so that it could accept inputs from the SWAT model simulations. In this section I will provide a brief overview of MODFLOW, summarize the work of Luukkonen et al. (2004), and describe how I modified their model to address my research questions.

3.4.1 MODFLOW Overview

MODFLOW (Harbaugh et al., 2000) is a 3-dimensional groundwater program developed and maintained by the USGS, and is arguably the most widely used such model in the world. It uses the Darcy groundwater flow equation to simulate hydraulic head, drawdown, and contaminant transport, among other outputs, for each grid cell in the sub-surface. MODFLOW's primary inputs are a discretized space defining dimensions of the various layers of substrata, groundwater recharge, the horizontal and vertical conductivity of the defined layers, and well pumping. The model has a modular software architecture allowing the user to turn on or off a number of optional packages that can be included in the simulation, such as pollutant transport, river leakage, sensitivity analysis, and subsidence to name a few.

3.4.2 USGS Kalamazoo MODFLOW model

Luukkonen et al. (2004) developed a groundwater model for Kalamazoo County, Michigan using MODFLOW 2000, which I refer to as the original MODFLOW model. I described the horizontal boundaries of this model in section *3.1.2 Kalamazoo MODFLOW model boundary*. The authors defined six vertical layers for the model, abstractly illustrated in Figure 17. Layers 1, 3, and 5 served primarily as productive glacial aquifers, layers 2 and 4 functioned primarily as glacial confining units, and layer 6 represented a low-permeability shale bedrock. Figure 18 through Figure 23 provide a glimpse of how the layers are actually represented within the MODFLOW model. Figure 18 shows the layers in 3D, with a view from the south to north.

Figure 19 through Figure 21 provide similar views from east to west, north to south, and west to east, respectively. Figure 22 cuts the model in half for a view of the layer depths along a horizontal transect, while Figure 23 provides a view of a vertical transect. On the model's borders it is clear that the top layer (drift aquifer) and bottom layer (shale bedrock) are thickest, whereas the transect views in Figure 22 and Figure 23 illustrate that the middle layers grow in depth towards the model's interior. In Figure 20 one can see the Marshall Sandstone feature (layer 6) in the model's northeast corner, that is only abstractly presented in Figure 17.

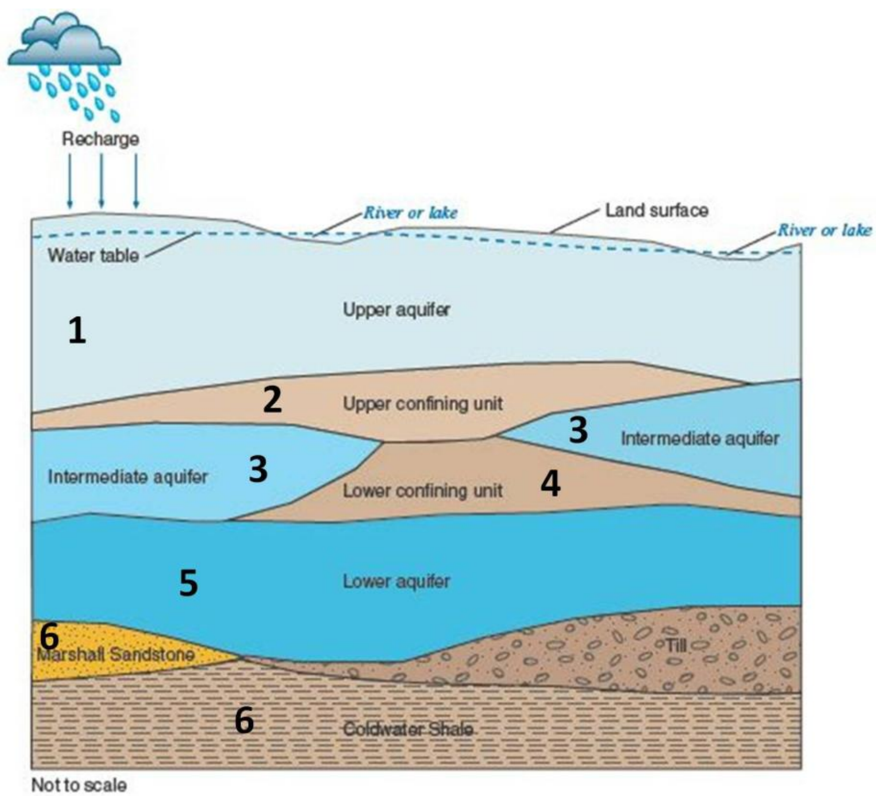

Figure 17: Borrowed from Luukkonen et al. (2004): "Figure 4. Generalized geologic section depicting hydrologic units in the Kalamazoo County area, Michigan." Modified by adding corresponding MODFLOW vertical layers.

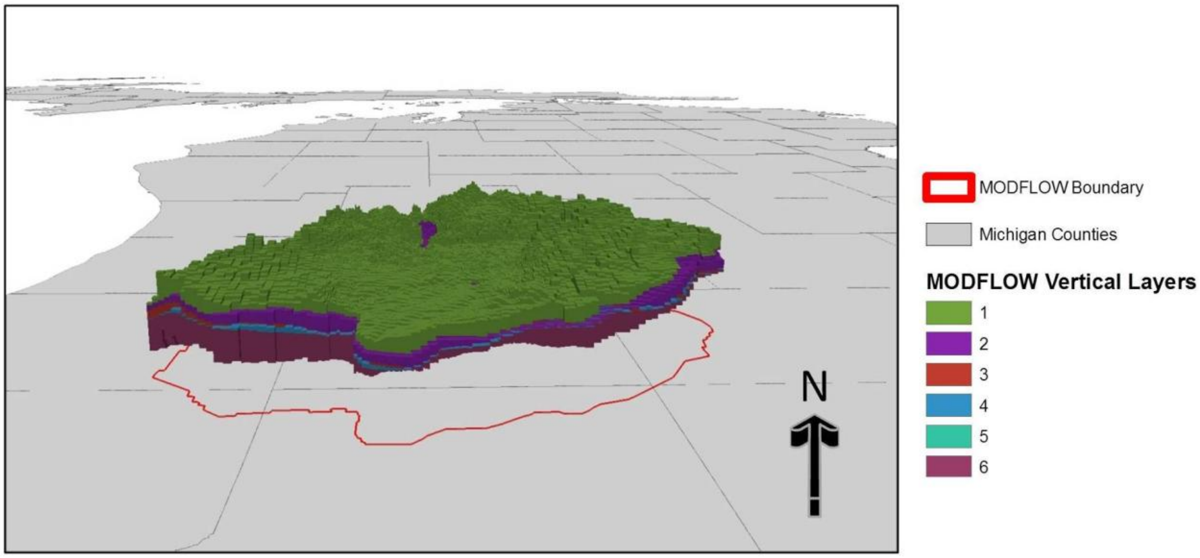

Figure 18: 3D view of MODFLOW layers, view from south to north.

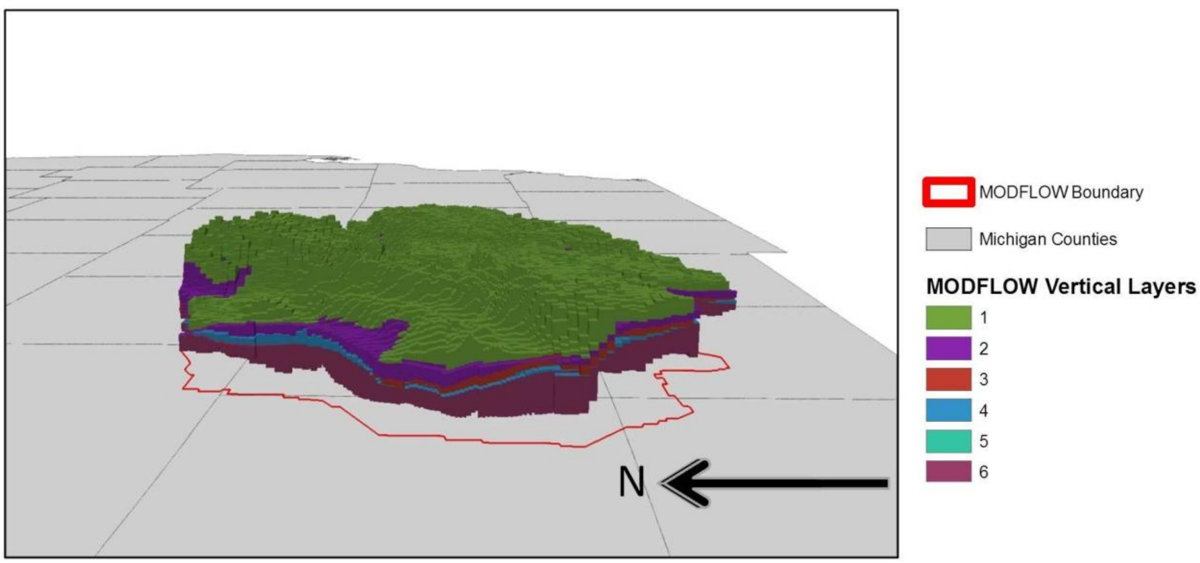

Figure 19: 3D view of MODFLOW layers, view from west to east.

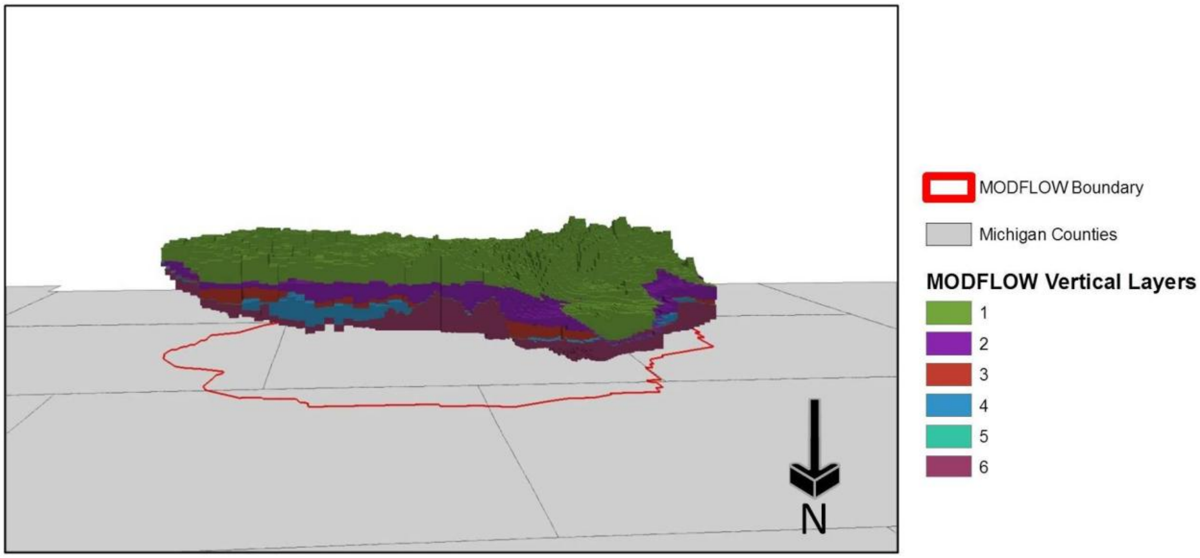

Figure 20: 3D view of MODFLOW layers, view from north to south.

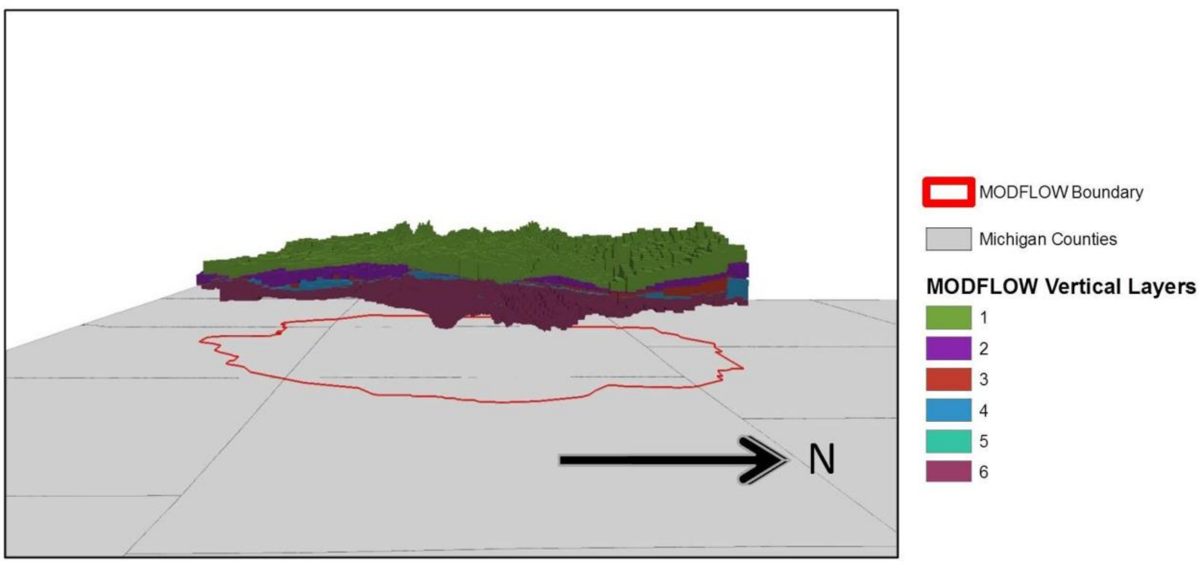

Figure 21: 3D view of MODFLOW layers, view from east to west.

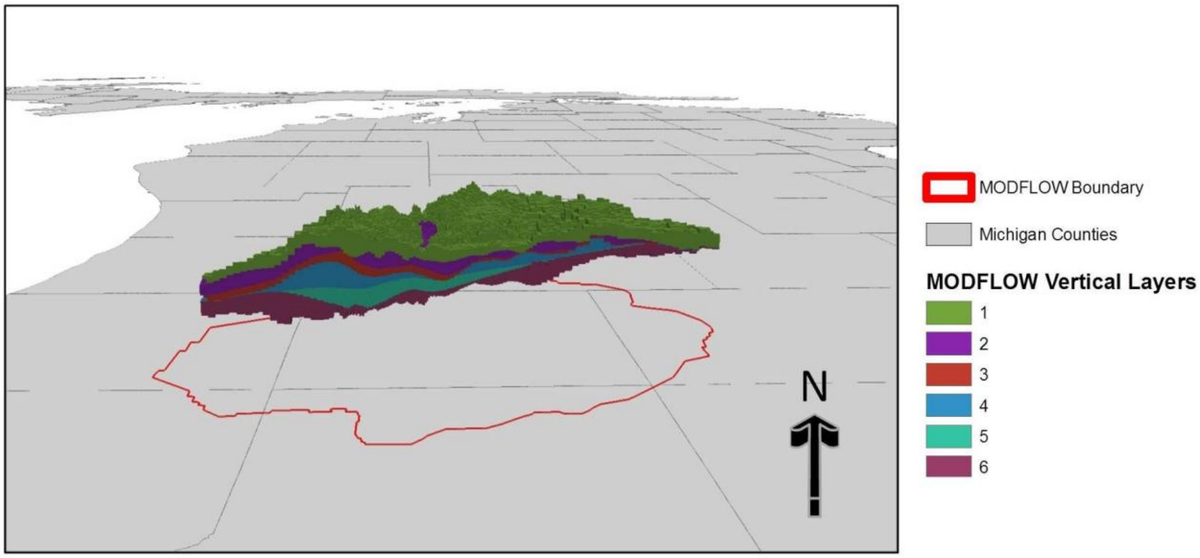

Figure 22: 3D horizontal transect of MODFLOW layers, view from south to north.

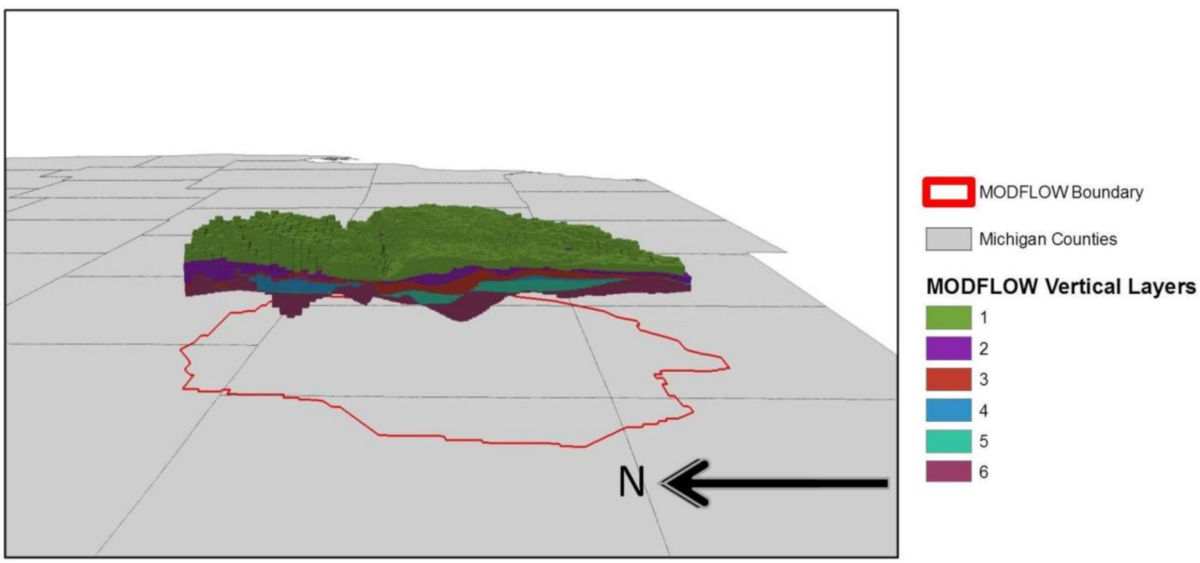

Figure 23: 3D vertical transect of MODFLOW layers, view from west to east.

The authors defined cells intersecting streams and lakes as locations of constant head, and set those head values to the observed river and lake stages (Figure 24). The primary bodies of water represented by these cells are the Kalamazoo River starting in east and exiting the model boundary in the north.

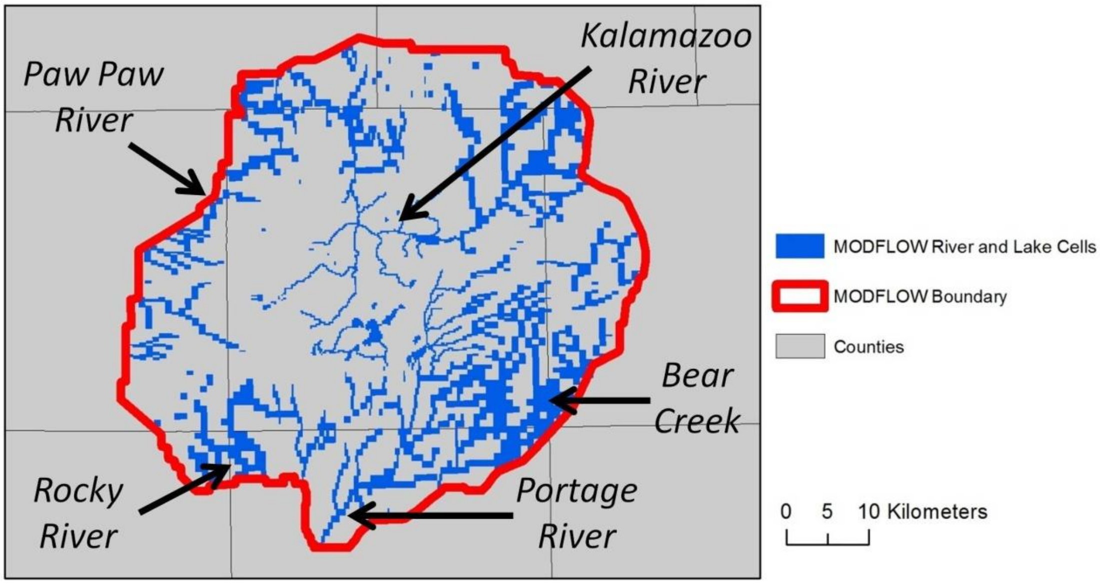

Figure 24: River and lake cells in the original MODFLOW model, represented as constant head boundaries.

The authors defined horizontal conductivities (K) for each layer from previous research. Figure 25 through Figure 30 illustrate their values. Note the maximum and minimum K values in the map legends. The maps show how K varies spatially within one layer, not how it varies from one layer to the next. As one would expect of confining geologic layers and bedrock, the maximum and range of K values in layers 2, 4, and 6 are much lower than the aquifer layers 1, 3, and 5. The authors defined vertical conductivities for each cell as 10% of corresponding horizontal conductivity values.

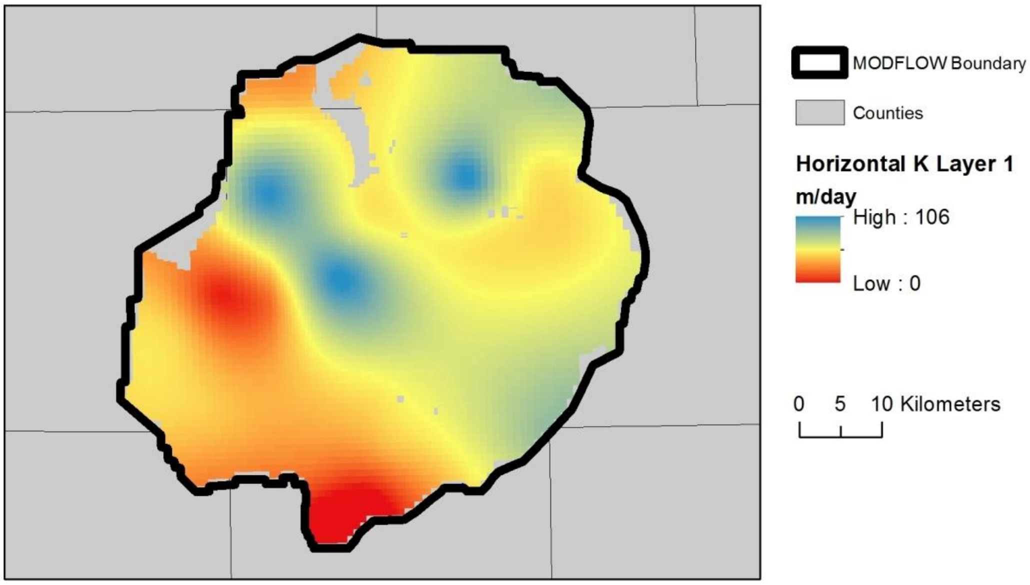

Figure 25: Horizontal conductivity in layer 1 (aquifer) of the original MODFLOW model.

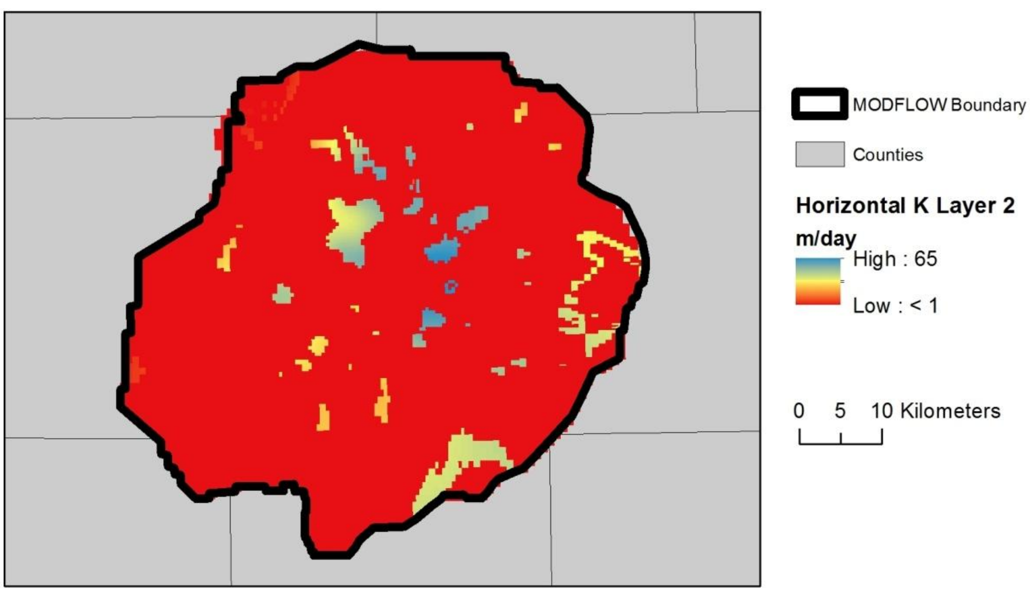

Figure 26: Horizontal conductivity in layer 2 (confining layer) of the original MODFLOW model.

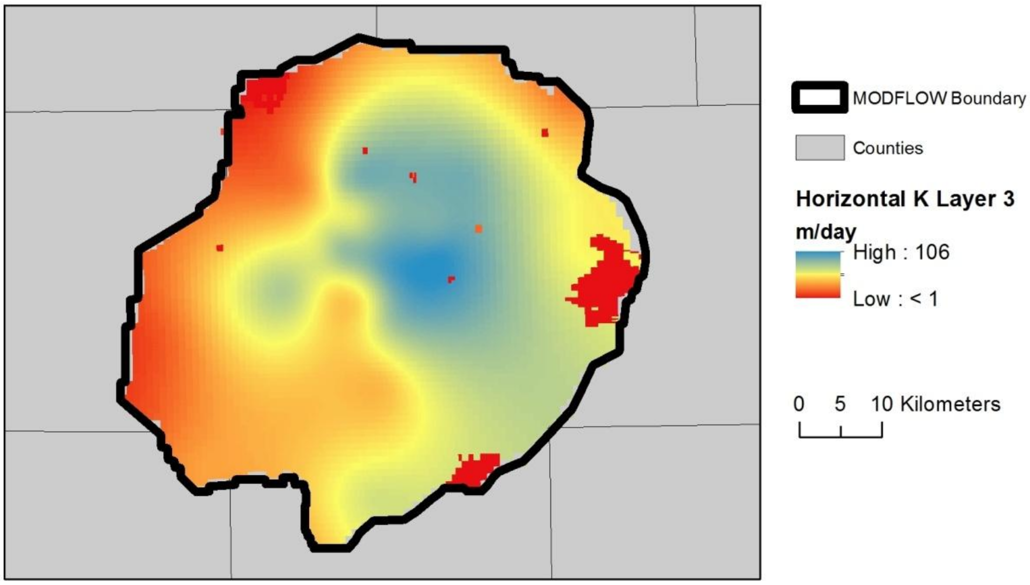

Figure 27: Horizontal conductivity in layer 3 (aquifer) of the original MODFLOW model.

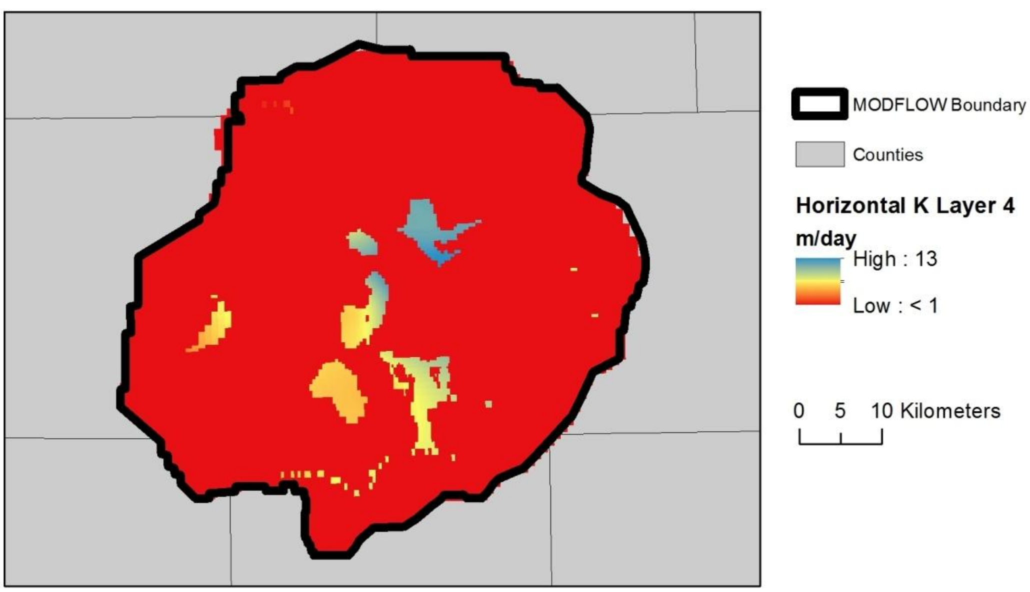

Figure 28: Horizontal conductivity in layer 4 (confining layer) of the original MODFLOW model.

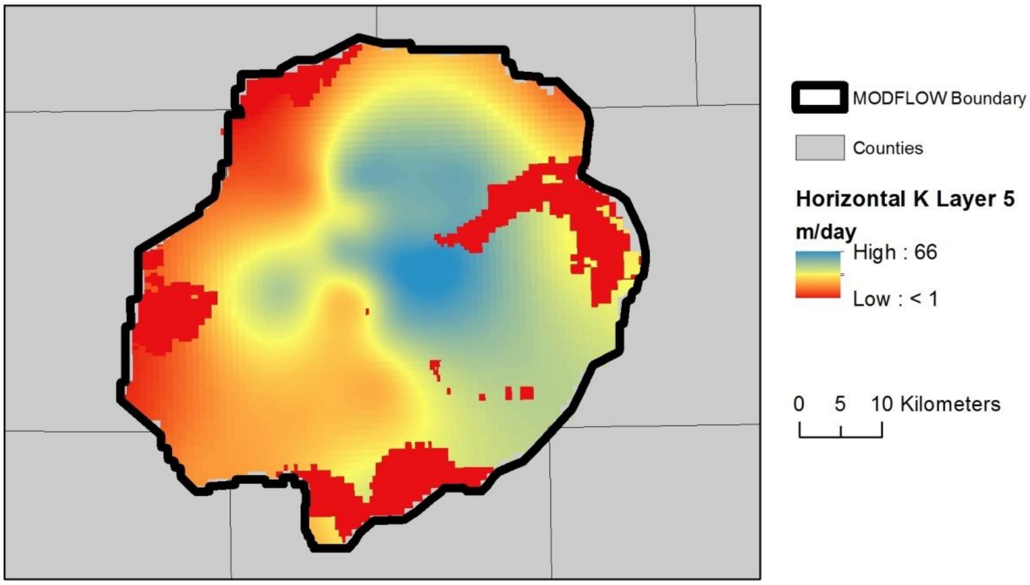

Figure 29: Horizontal conductivity in layer 5 (aquifer) of the original MODFLOW model.

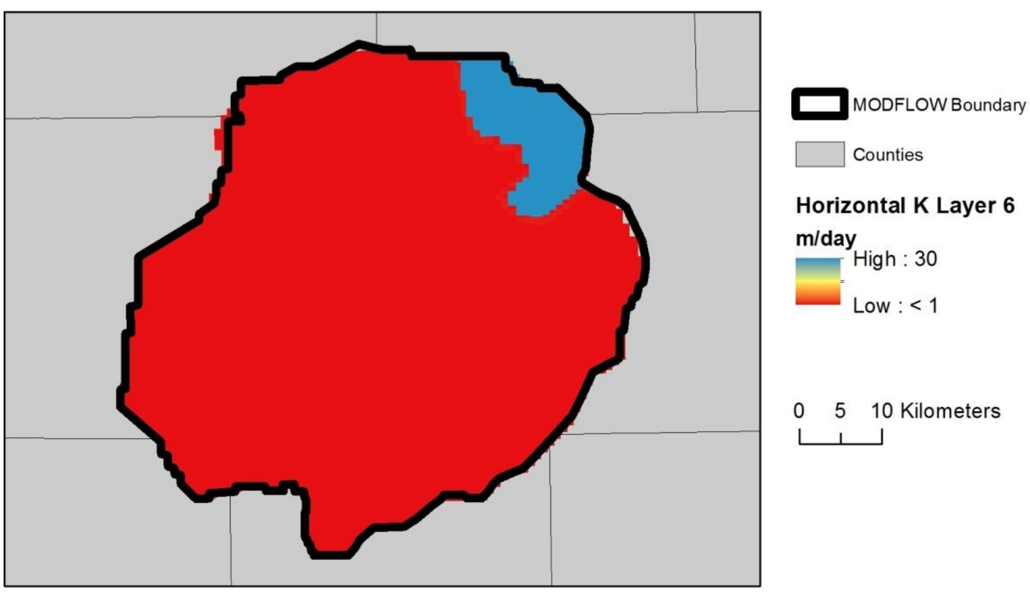

Figure 30: Horizontal conductivity in layer 6 (bedrock) of the original MODFLOW model.

The authors defined groundwater recharge in zones, and set the values for those zones from previous studies of baseflow separation (Figure 31). They subsequently modified those values during the calibration process, reducing some by 50% and increasing others by 40%. The authors utilized a MODFLOW parameter that allows recharge to only be applied to the highest active cell. For example, if there was an area in the model where confining layer 2 became an exposed outcropping (*i.e.* if the top of a layer 2 cell was above the surface elevation), the recharge was applied to those layer 2 cells in that area; so recharge did not have to be specified for every layer in the model. The large recharge values in the center of the model area corresponded to industrial discharge locations. In the original MODFLOW model, used water discharged into Austin Lake and Long Lake by Pfizer, Inc. was modeled as increased recharge.

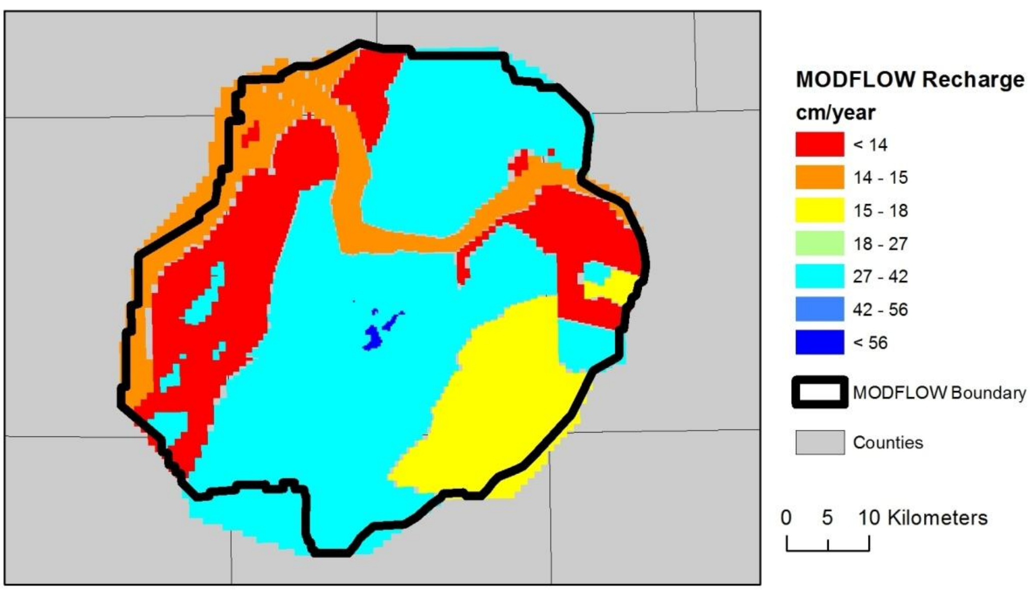

Figure 31: Recharge in the original Kalamazoo MODFLOW model.

Figure 31 can be contrasted with the baseline SWAT groundwater recharge output in Figure 16. The two maps use the same legend to facilitate the comparison, and though they were based on different time periods (the original model was calibrated against observations from various periods prior to 2004, and SWAT was calibrated against observations from 2001-2010) the climate over those periods has been relatively stable. SWAT's HRUs provided a considerably more heterogeneous landscape than recharge zones used in this original Kalamazoo MODFLOW model, and therefore allowed for a better representation of how recharge varies by land cover, soil type, and slope. It is clear that overall recharge in SWAT was greater than in MODFLOW, particularly in the western part of the study area. One potential reason for the large difference in recharge rates was that the original model's use of baseflow separation to estimate recharge. To only focus on a gaged stream's hydrograph limits the scope of analysis to precipitation that infiltrates the soil and discharges to the stream. That approach does not account for water that might percolate to the deeper aquifers that are not necessarily connected to the stream network. However, the largest source of difference between recharge rates is the fact that the original MODFLOW model does not account for the increased recharge from agricultural irrigation. Though the authors represented increased recharge from industrial discharge, it was only in a handful of locations as opposed to the large number of agricultural areas irrigated in the SWAT model. In SWAT, irrigated water has a chance to recharge the aquifer; and even though in an ideal situation an irrigation operation would be 100% efficient, inevitably some of that water returns to the system.

The original MODFLOW model included pumping at 90 grid cells (Figure 32). This number does not necessarily equal the number of active wells within the model, because pumping in MODFLOW is simply reported as a cumulative volume withdrawn from a particular cell. The withdrawals in this model were exclusively in the aquifer layers (1, 3, and 5) and appear to have primarily focused on municipal use, as indicated by the clustering around the cities of Kalamazoo and Portage.

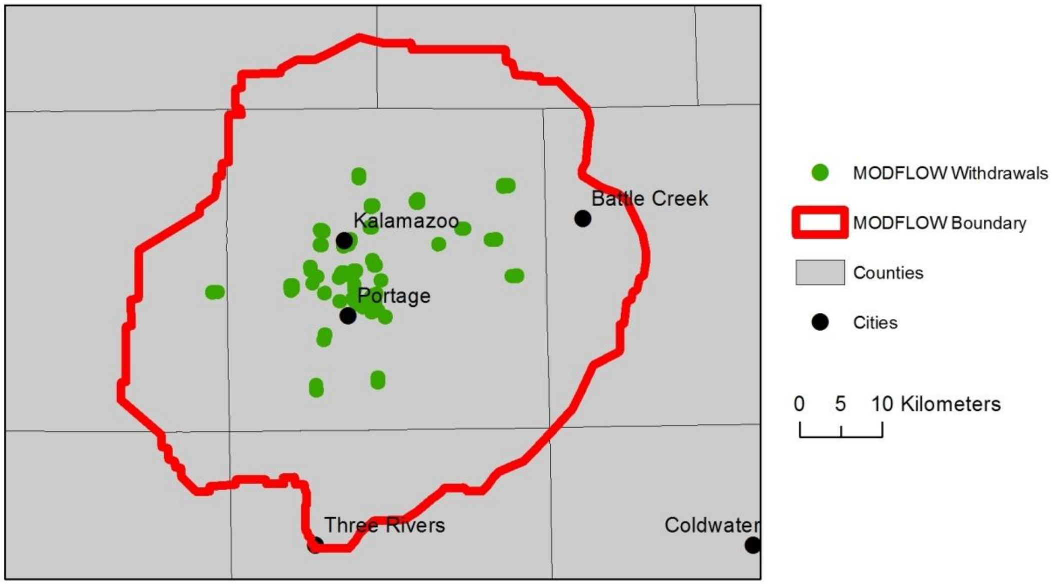

Figure 32: Cells in which withdrawals are simulated in the original MODFLOW model.

The authors produced both steady-state and transient versions of the model. The latter version allowed them to explore temporal changes within the groundwater system throughout the year. For example, with the transient model one could view water table drawdown during the agricultural pumping season, or during periods of decreased recharge and precipitation. In contrast, the steady-state model simply solves the long-term average of the model. Worded another way, if the annual daily average recharge (*i.e.* annual average recharge / 365) and pumping remained constant what would hydraulic head be in each model cell? While the transient model obviously provides more detailed analysis options, that detail comes at a cost in terms of computer processing time and storage. In order to explore the broad research questions I proposed for this project, I had to limit my analyses to outputs from the steady-state version of the original MODFLOW model.

The authors calibrated the MODFLOW model against a network of observation wells in the study area, stream discharge records, and observations of river and lake seepage. They also calibrated the model against observations during pumping periods 1966, 1987, 1994, and 2001. The authors found that the majority of estimated heads were within 3 meters of observed heads, and deemed the model's performance satisfactory.

3.4.3 Modified Inputs

In order for MODFLOW to accept a SWAT-modeled groundwater recharge input, and run simulations under forecasts of climate change, I had to customize the steady-state version of the original MODFLOW model. The two main changes were defining new recharge values for each cell and replacing the original well inputs.

I calculated average recharge values for MODFLOW based upon the intersecting cells of the baseline SWAT recharge output raster (Figure 16). I did this by utilizing ArcGIS's© Zonal Stats function, specifying the SWAT recharge raster as the value dataset and the MODFLOW cells as the zones. This process produced a single recharge value for each MODFLOW cell in a customized 2D version of a MODFLOW layer. Because the MODFLOW model boundaries vary slightly from one layer to the next, I could not simply utilize the MODFLOW cells in layer one as the zones in the Zonal Stats function. Because of the area's geology, varying surface elevation, and the depths of the model layers defined in the original MODFLOW model, the model boundaries for layer 2 are slightly larger than layer 1. Because the model used the MODFLOW parameter to apply recharge to the highest active cell (which could include cells below layer 1), I had to create a maximum boundary dataset that identified the geographic extent to which recharge could be applied (Figure 33). This maximum boundary dataset contained the cells for which I calculated average recharge, which were ultimately provided as input to MODFLOW.

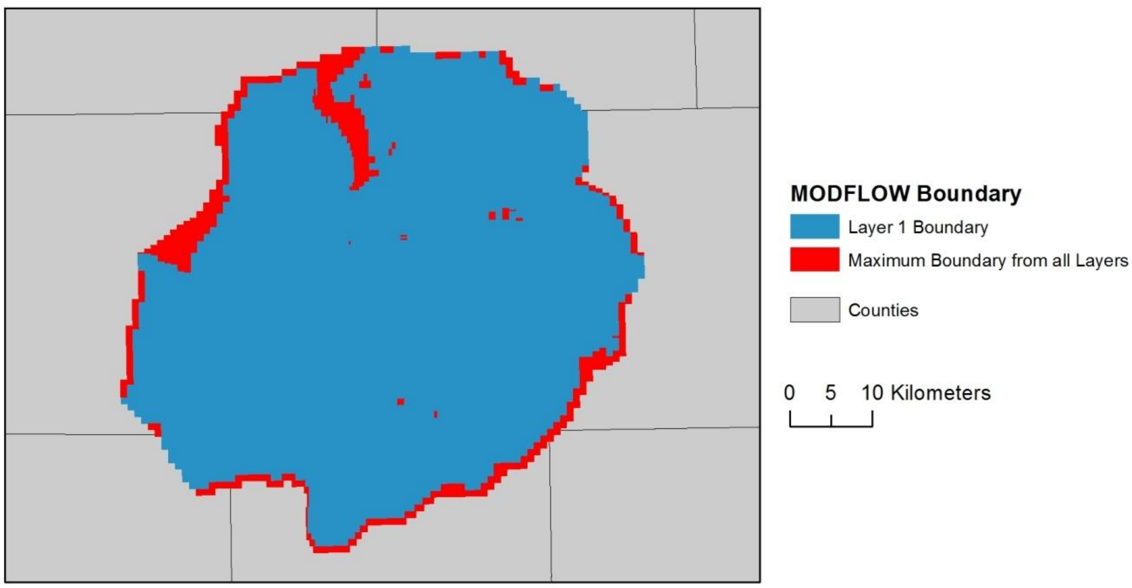

Figure 33: MODFLOW layer 1 active cells versus the maximum extent of active cells in all layers.

I did not have water use data for the agricultural and golf course irrigation wells that I included in the SWAT model (Figure 34 and Figure 35). However, SWAT did record the average annual irrigation depth applied to each irrigated HRU. I wrote a Python script that iterated over fields irrigated by SWAT HRUs, determined which well a particular irrigated field was served by, noted the respective area of each of the HRUs within each irrigated field, and calculated a total applied irrigation volume (and therefore groundwater withdrawal volume) for that location. For each well, I noted the depth of its screen in the Wellogic record and used those data to determine from which MODFLOW aquifer layer (1, 3, or 5) to withdraw the water. I summed these irrigation volumes within the MODFLOW cells to calculate total annual withdrawals for each cell in each layer.

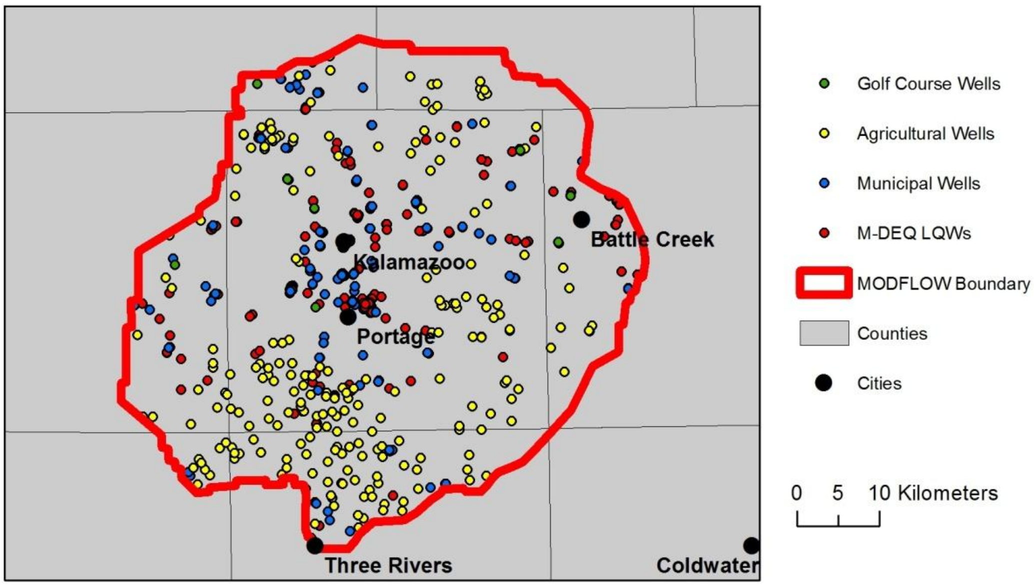

Figure 34: Well locations and type utilized to estimate groundwater withdrawals in new Kalamazoo MODFLOW model.

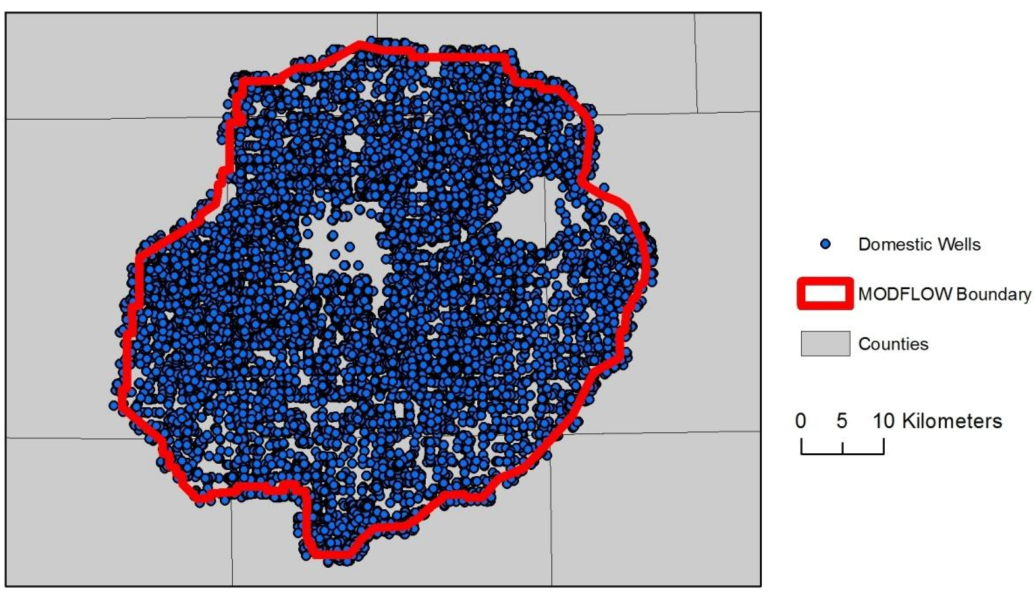

Figure 35: Domestic household wells from Wellogic.

For municipal and industrial water withdrawals, I used publicly available data from MDEQ. The department maintains databases of water use by Michigan communities and by large quantity non-agricultural withdrawals (LQW). I requested, and received, recent copies of both databases from MDEQ's Water Use Program. I calculated average annual values for community water use from 1998-2013, and for each LQW record from 2011-2013. Next, I cross-referenced the well IDs with the features in the Wellogic database so that I could map the water use (Figure 34). I also utilized the Wellogic database to include domestic withdrawals from active household wells, of which there were significantly more (25,769) than in the municipal and industrial wells (Figure 35). Based upon comparisons to USGS estimates of domestic groundwater use in Kalamazoo County for the period of 2000-2010 (Table 6), I estimated an average annual continuous pumping rate of 0.38 LPM for these wells.[8] As I did with the agricultural irrigation wells, I noted the depths of well screens to determine the MODFLOW layer from which water was likely being withdrawn, and then summed up the cumulative volume of withdrawals for each cell in which wells were located. I then used a final summation of the agricultural, community, and LQW uses for a total withdrawal from each MODFLOW cell, in each layer and wrote a new MODFLOW input well file. Contrasting Figure 34 and Figure 35 with the original model withdrawal cells in Figure 32, which did not include domestic withdrawals, makes clear that my revised model contained more withdrawals cells than the original. Table 7 compares the simulated withdrawal amounts in the original and modified

[8] I acknowledge that this is an implausible pumping rate for a well; but for a steady state model MODFLOW needs the total volume withdrawn per day, so I assumed steady and continuous pumping. A value of 0.38 LPM would translate to 545 liters per household per day, slightly below the 303-379 liters per person per day estimated by the USGS (2016). My goal however was to capture the total volume of water withdrawn by household wells, and the 0.38 LPM value brought me sufficiently close. Note that my simulated amount in Table 6 is larger than the USGS estimate, even though my study area includes small portions of the neighboring counties.

MODFLOW models. The final report by Luukkonen et al. included the community water use data specified in the model, but did not contain specific use amounts from agriculture or industry. I was able to discern the total amount withdrawn by analyzing the model's output files. In my modified model, roughly 72 million more liters per day were withdrawn from the aquifers than in the original model. This difference approximated the total amount of simulated agricultural irrigation in the modified model, which appears to be underrepresented in the original model.

Table 6: Withdrawals by sector, estimated by USGS for Kalamazoo County, versus simulated withdrawals in modified MODFLOW model.

Withdrawal Type	USGS Estimate Average (2000-2010) (MLD)	MODFLOW Baseline Estimated Withdrawals (MLD)
Community	76.5	117.7
Domestic	11.7	14.0
Industrial	98.8	104.9
Irrigation	36.0	61.7

Table 7: MODFLOW water budgets for the original model and the modified one based upon SWAT baseline outputs, water use estimates from MDEQ for community and industrial use, and domestic use from my comparison to USGS estimates.

MODFLOW Model	Community Water Use (MLD)	Domestic Water Use (MLD)	MDEQ LQW (Industry) (MLD)	Ag/Golf Irrigation (MLD)	Total Use (MLD)
Original Model	101.9	0	?	?	227.6
Modified Model	117.8	14.0	105.0	61.6	298.5
Difference	**-15.9**	**-14.0**			**70.9**

3.5 Groundwater Model Outputs

The primary output of MODFLOW is estimated steady-state hydraulic head for each grid cell in the 3D model. From this estimate the model can calculate other groundwater attributes including drawdown during a particular stress period (more applicable to transient models) and contaminant transport, neither of which I studied for this research.   Figure 36 shows the steady-state hydraulic head values for layer 3 produced by the original MODFLOW model. The head values generally followed the contours of the ground surface and the Kalamazoo River. Figure 37 shows hydraulic head for the same layer in the modified MODFLOW model, which included baseline SWAT recharge and more recent withdrawal estimates as inputs. The general spatial structure of hydraulic head in my MODFLOW model was the same as in the original model, however one can see that the higher recharge estimated by SWAT in the western portion of the study area translated to higher head there than in the original model. The other noticeable difference between Figure 36 and Figure 37 is the lower head value in the center of the original model, where the authors estimated much higher industrial water withdrawals from Pharmacia and Upjohn Company LLC than I averaged from MDEQ records between 2011 and 2013. I will analyze the hydraulic head outputs in greater detail in Chapter 4: Model Calibration.

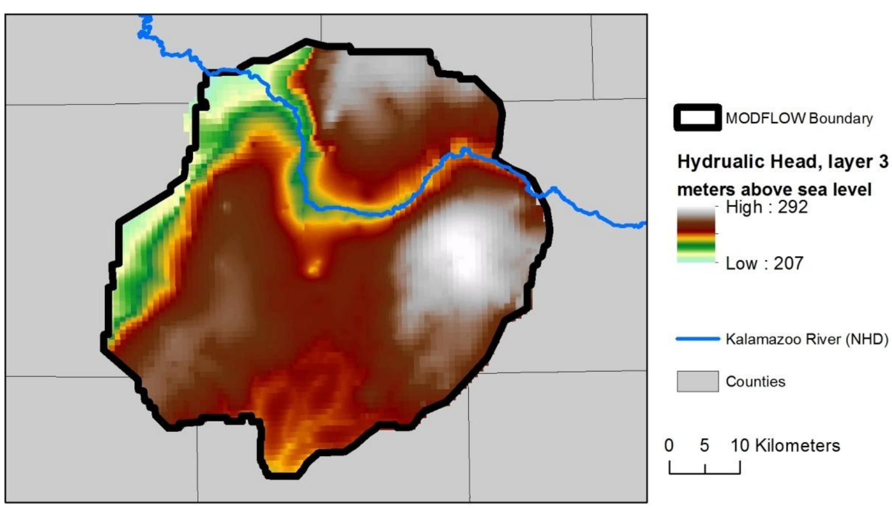

Figure 36: Simulated hydraulic head in MODFLOW layer 3 in the original MODFLOW model.

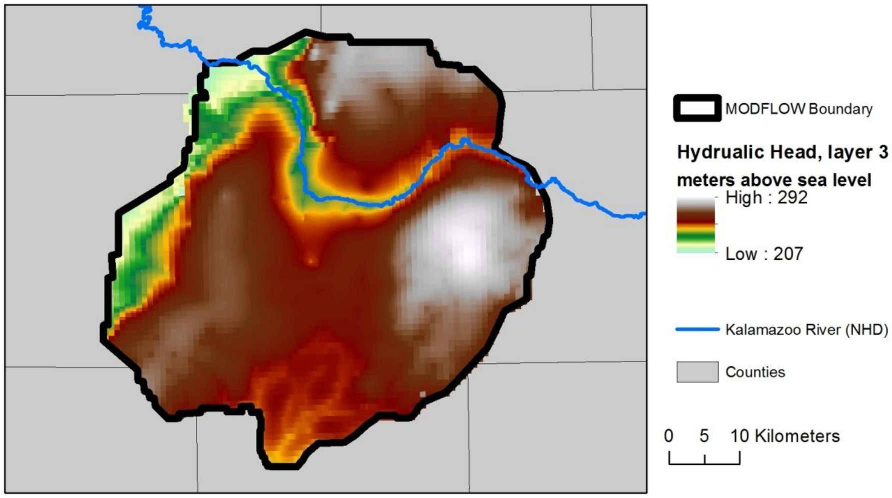

Figure 37: Simulated hydraulic head in MODFLOW layer 3 in the modified MODFLOW model using SWAT baseline recharge and water use.

The other MODFLOW output I analyzed was the model-wide water budgets produced for each simulation. Those budgets included total volumes entering and exiting the system, which for a steady-state should theoretically be equal[9]. MODFLOW breaks the budgets down further into flows through the model boundaries, total recharge, well withdrawals, and river leakage. Table 8 displays the budgets for the original MODFLOW model and the modified version. As I discussed previously, the largest difference between the two models was the higher recharge in the modified version, which the MODFLOW budget outputs quantified as 393 million liters

[9] Volume in and volume out in a steady-state model should be equal, but they typically are not. MODFLOW continuously solves Darcy flow equations until the model converges, which means that the hydraulic head values at each cell fluctuate below some threshold from one iteration to the next. I set the initial threshold at 30 centimeters, so if at one point during the model execution cell X had a hydraulic head of 250.0 meters and a head of 250.4 meters in the next iteration of calculations, the model had not converged and continued with another iteration. If the head at cell X was 250.2 in that next iteration, and all other cells met the convergence threshold, then the model converged and execution stopped. A threshold of zero would take a long time for the model to realize and would likely crash it. Those 30 centimeters of freedom means that even in a steady-state model the inputs will not necessarily equal the outputs. However, MODFLOW always reports storage as zero in a steady-state model; it states an input-output discrepancy rather than assign that volume to storage. Generally, budget discrepancies less than 5% for steady-state MODFLOW models are considered acceptable.

more recharge than in the original model. This increase affected the other budget components. The higher hydraulic head estimates resulting from the increased recharge caused less water to enter the upper aquifer through stream beds, because there was less of a head gradient in losing stream situations (where head is below the stream bed). In gaining stream situations, the overall higher head gradient caused more water to be discharged from the aquifer to the stream network. At the portions of the model boundary where head was defined as constant (which varied by model layer but generally followed the locations of surface water features), the overall higher heads created a slightly steeper gradient between the interior model cells and these constant head boundaries, which generated more flow out of the system.

Table 8: Groundwater flow budgets for the original MODFLOW model and the customized version.

	Flows into the Groundwater System (millions of liters per day)				Flows out of the Groundwater System (millions of liters per day)					
MODFLOW Model	**Boundary Flows In**	**Recharge In**	**Stream Leakage**	**Total In**	**Boundary Flows Out**	**Stream Discharge**	**Wells**	**Total Out**	**Net**	**Percent Discrepancy**
Original	22.7	2,106.6	1,151.1	**3,280.4**	228.3	2,745.2	227.5	**3,200.9**	79.5	2.4%
Modified	22.0	2,499.9	1,063.3	**3,585.2**	283.0	2,970.0	298.7	**3,552.6**	32.6	0.9%
Difference (Mod. – Orig.)	-0.7	392.5	-87.8	**304.7**	55.6	224.9	71.2	**351.7**	-46.9	-1.5%

CHAPTER 4: Model Calibration

In the previous chapter I detailed the steps I took to generate a working surface water model for the study area through SWAT, and how I modified the original Kalamazoo MODFLOW groundwater model in order to receive SWAT water use and recharge estimates. As part of that description I included results from both SWAT and the modified MODFLOW model, but I did not discuss in detail how I calibrated and validated those outputs. In this chapter I will describe the approach I took to do that, and provide the results of that effort.

4.1 Surface Water Model Calibration

The calibration of SWAT was a much more involved process than calibrating and validating the modified MODFLOW model. I had 12 SWAT models to calibrate as opposed to the single MODFLOW model. Furthermore, Luukkonen et al. (2004) had previously calibrated and validated the original MODFLOW model; I just had to revalidate it with the new inputs.

My goal for the SWAT calibrations was to sufficiently match simulated streamflow against observed baseflow conditions at the USGS gages in Figure 5 for the decade between 2001 and 2010. I selected that time period due to data availability at the 12 USGS gages, the relative time periods of the input datasets, and my plan to conduct the future scenario analyses at decadal time steps. Stream baseflow is often used as a measure of groundwater recharge (Arnold, Muttiah, Srinivasan, & Allen, 2000; Luukkonen et al., 2004; Neff et al., 2005; U.S. Geological

Survey, Michigan Water Science Center et al., 2005). In the absence of an extensive network of piezometers in the region, I determined that a model calibrated against baseflow would be the best representation of groundwater recharge. However, before focusing in on baseflow, I calibrated parameters against coarser metrics to ensure that the model's ET, crop yield, and automatic irrigation functions were working properly.

4.1.1 Evapotranspiration

Though SWAT calculates ET at the HRU-scale, there was no readily accessible observation dataset to calibrate against at that fine a scale; so I compared the model's overall basin estimate to county-scale values produced by Sanford and Selnick (2013). They employed a regression-based approach to calculate ET across the lower 48 states. They estimated an annual average of 55 to 60 cm of water in the study area returned to the atmosphere, or roughly 55-65% of annual precipitation. There are multiple options for simulating ET within SWAT, but the Penman-Monteith method yielded the best fit to the observed range. I also adjusted the HRU-scale ESCO (soil evaporation compensation factor) and EPCO (plant uptake compensation factor) parameters for each SWAT model to match the observed ET ranges. Table 9 shows the various model estimates of ET by SWAT.

Table 9: SWAT estimates of average annual evapotranspiration rates.

Gage #	SWAT Model	SWAT ET (cm/yr)	SWAT ET/Precip.
1	04096515	58.7	0.60
2	04096405	59.2	0.61
3	04097540	57.7	0.63
4	04097500	59.2	0.61
5	04103500	57.4	0.66
6	04105000	54.1	0.62
7	04106000	58.2	0.64
8	04108600	55.1	0.61
9	04108660	56.1	0.58
10	04117500	56.4	0.6
11	04101800	55.6	0.58
12	04102500	56.6	0.57

4.1.2 Crop Yields

Like ET, SWAT calculates biomass production and crop yield at the HRU-scale. However, I wrote a Python script to calculate area-weighted, model-wide averages of yield for each crop simulated in the SWAT models. I then compared those outputs to county-level totals reported by USDA NASS in the 2007 AgCensus (2007). Table 10 shows estimated corn and soy yields in the SWAT models, and the reported yields in the AgCensus for the primary intersecting county for each model. SWAT manages plant growth by tracking cumulative heat units from day to day for each HRU, and maintains a plant database that contains the necessary number of accumulated heat units for a plant to be considered mature. I modified this parameter in each model to generate a baseline crop yield that was relatively close to reported county yields in NASS. My adjustments of heat units produced better matches for corn yields than for soy, but in almost all of the models simulated soy yields were within 600 kg/ha of the reported amounts.

Table 10: Simulated crop yields in SWAT versus reported yields in NASS 2007 AgCensus.

Gage #	SWAT Model (County)	SWAT Yields (kg/ha)	County Yields (kg/ha)
1	04096515 (Hillsdale)	Corn: 8,591; Soy: 2,150	Corn: 7,086; Soy: 2,553
2	04096405 (Hillsdale)	Corn: 8,717; Soy: 2,217	Corn: 7,086; Soy: 2,553
3	04097540 (Branch)	Corn: 7,274; Soy: 2,083	Corn: 7,024; Soy: 2,688
4	04097500 (Kalamazoo)	Corn: 7,713; Soy: 2,016	Corn: 7,086; Soy: 2,688
5	04103500 (Jackson)	Corn: 8,215; Soy: 2,150	Corn: 6,396; Soy: 2,284
6	04105000 (Eaton)	Corn: 7,776; Soy: 2,016	Corn: 7,274; Soy: 2,755
7	04106000 (Calhoun)	Corn: 7,462; Soy: 1,949	Corn: 6,835; Soy: 2,688
8	04108600 (Allegan)	Corn: 7,776; Soy: 2,083	Corn: 7,024; Soy: 2,553
9	04108660 (Kalamazoo)	Corn: 7,901; Soy: 2,083	Corn: 7,086; Soy: 2,688
10	04117500 (Barry)	Corn: 8,152; Soy: 2,016	Corn: 7,274; Soy: 2,553
11	04101800 (Cass)	Corn: 7,462; Soy: 2,284	Corn: 7,588; Soy: 2,889
12	04102500 (Van Buren)	Corn: 7,042; Soy: 2,486	Corn: 7,839; Soy: 1,949

4.1.3 Irrigation Depths

SWAT decides whether to irrigate an HRU based on two criteria. First, the HRU must have been flagged as an irrigated land cover. I detailed the irrigation search algorithm I employed to identify and flag potentially irrigated areas within each SWAT model in section *3.2.5 Irrigation*. Second, the water stress of the plant on the irrigatable HRU must exceed a threshold (parameter AUTO_WSTRS in each HRU's management file). I explored several values for the threshold but ultimately found that 0.95 (out of a minimum of 0 and a maximum of 1), which translates to a 5% reduction in plant growth attributable to water stress, yielded irrigation depths that aligned best with county-level estimates from MDEQ. Table 11 compares irrigation depths for each model and county averages estimated by MDEQ (2006). Most of the SWAT simulated depths matched up well with the MDEQ estimates. The depths in models 04103500 and 04105000 did not align well, however. The counties I compared them against had significantly fewer irrigated hectares than the other counties of interest. MDEQ estimated Jackson and Eaton as having 1,592 and 573 irrigated hectares, respectively, in 2006 versus

Kalamazoo County's total of 12,067. So the potential impact of SWAT's underestimate in those models was less than if irrigation had been poorly simulated in a model that had much higher amount of irrigated hectares, such as 04097500. Additionally, the MDEQ estimates are unusually high (21 cm for Jackson and 29 cm for Eaton) when compared to the other county depths. Lastly, models 04103500 and 04105000 are only tributaries to the models of the MODFLOW study area, so any detrimental effects of poor irrigation estimates in those basins would have a minimal effect on my primary interest of groundwater recharge in and around Kalamazoo County.

Table 11: SWAT irrigation depths versus county-level estimates from MDEQ.

Gage Number	SWAT Model (County)	SWAT Irrigation (cm / year)	2006 County Irrigation (cm)
1	04096515 (Hillsdale)	13.0	13.2
2	04096405 (Hillsdale)	13.7	13.2
3	04097540 (Branch)	11.2	14.5
4	04097500 (Kalamazoo)	13.2	15.0
5	04103500 (Jackson)	11.2	20.8
6	04105000 (Eaton)	10.4	29.2
7	04106000 (Calhoun)	12.7	18.8
8	04108600 (Allegan)	15.5	15.5
9	04108660 (Kalamazoo)	17.5	15.0
10	04117500 (Barry)	8.6	17.5
11	04101800 (Cass)	17.5	9.4
12	04102500 (Van Buren)	19.1	13.2

4.1.4 Baseflow Index

Once I felt that ET, crop growth, and irrigation were within acceptable ranges of observed or expected values, I then began to focus more closely on matching baseflow conditions in each model. I started by looking at the percentage of streamflow that could be attributed to groundwater discharge, which is often referred to as a baseflow index. The USGS produced a 1-km resolution raster dataset of baseflow index values for the lower 48 states (Wolock, 2003). I calculated an average value from that dataset for each of the SWAT Models, and compared that to indexes that I calculated by running model flow outputs for the baseline period through a baseflow separation program developed by USDA-ARS (Arnold & Allen, 1999; Arnold et al., 1995).

Table 12 displays those comparisons. In almost all cases the SWAT estimates were higher than the USGS values; baseflow index estimates were equal for SWAT model 04097500. Though these results could be interpreted as demonstrating a bias in SWAT's groundwater discharge estimates, my goal for this phase of the calibration was not to precisely match the USGS estimates but to ensure that the SWAT baseflows were within a reasonable range. Furthermore, the USGS cautions that the estimates from Wolock (2003) are indicative of baseflow but may not necessarily be a true representation of it. Given that caution, I was satisfied that the indexes were generally within 10% of each other.

Table 12: SWAT baseflow indexes versus USGS estimates from baseflow separation methods.

Gage Number	SWAT Model	Baseflow Index from SWAT Streamflow	Average Baseflow Index from USGS
1	04096515	0.78	0.65
2	04096405	0.87	0.68
3	04097540	0.86	0.71
4	04097500	0.76	0.76
5	04103500	0.87	0.68
6	04105000	0.69	0.67
7	04106000	0.84	0.75
8	04108600	0.66	0.67
9	04108660	0.80	0.72
10	04117500	0.80	0.63
11	04101800	0.88	0.79
12	04102500	0.88	0.78

4.1.5 Baseflow at USGS Gages

SWAT's estimations of ET, crop yields, and irrigation depth seemed appropriate, though there was the possibility of a slight bias in baseflow index. To fine-tune the models, and put them through more formal and quantifiable calibrations, I compared their simulations of streamflow to observations at USGS gages. I downloaded the data from the USGS National Water Information System (NWIS) (USGS, n.d.-b)

As I stated previously, my goal was to calibrate the models to baseflow conditions in order to best approximate groundwater hydrology in the region. Most SWAT studies calibrate against a continuous period of streamflow. But such an approach can skew results towards large storm events, which may be important if a particular study's focus is heavily influenced by large and flashy flows. For example, if a modeler was primarily interested in simulating sediment loading, it would be critical to accurately capture those events because they often generate the majority of a stream's annual sediment load. For my study, though, I had to zero in on the baseflow signal of the hydrograph; so I had to avoid the days of the year when surface runoff dominated the river flow.

I accomplished this with the outputs from the USDA-ARS baseflow separation program described above in *4.1.4 Baseflow Index*. That program provides estimates of a daily flow value's baseflow and surface runoff fractions. As

Table 12 illustrates, the study area is dominated by baseflow, so I selected 0.75 as my cutoff for identifying days where the flow was predominantly from groundwater discharge. I considered days where surface runoff accounted for more than one quarter of a day's streamflow as too flashy for a baseflow calibration[10]. Figure 38 and Figure 39 show sample hydrographs from model 04108660, with the latter highlighting the days that met the criteria. One can see the excluded days of observed peaks in the hydrograph in Figure 39. My calibration goal was to get SWAT flows to match observed flows on those baseflow dominant days as best as it could.

[10] I explored using the daily fractions to simply pull out the daily baseflow component from the USGS gage data, but SWAT does not have a readily accessible groundwater discharge output at the stream-scale, so the comparison would have been difficult. Furthermore, the calibration program I utilized, SWAT-CUP (Abbaspour, 2015), does not have a straightforward way to utilize just observed and simulated baseflow.

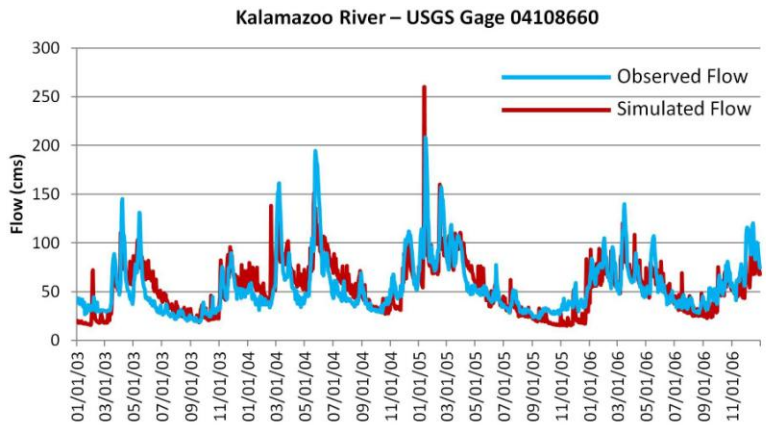

Figure 38: Full hydrograph of simulated and observed flows at gage 04108660 (Kalamazoo River outlet).

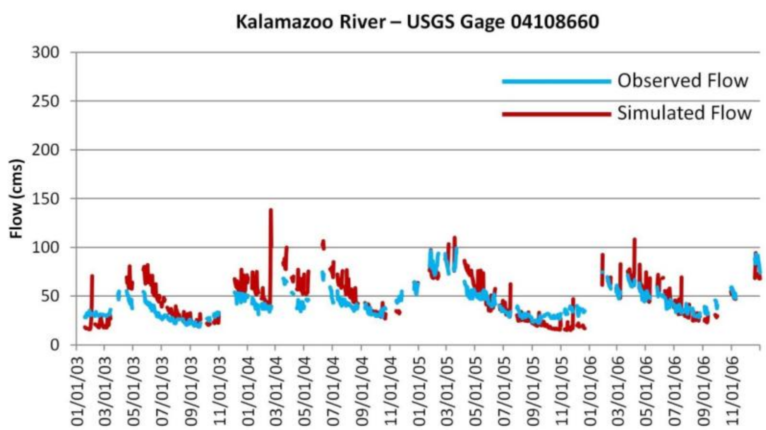

Figure 39: Hydrograph with observed flows only displayed on days where baseflow was greater than 75% of total flow.

I used the SWAT-CUP program (Abbaspour, 2015) to carry out the calibration of each model, and focused on optimizing the parameters most closely related to groundwater hydrology. Table 13 lists those parameters, along with a brief description of their functions and locations within the SWAT file architecture. SWAT-CUP ran each model up to 1,000 times, depending upon the model's size, within a range of possible parameter values to find the optimal values in terms of the Nash Sutcliffe Efficiency coefficient (NSE).

Table 13: Primary SWAT parameters modified during model calibration.

Parameter Name	Description (from SWAT documentation)	Spatial Scale	SWAT File Extension
SFTMP	Snowfall temperature.	Basin	.mgt
SMTMP	Snow melt base temperature.	Basin	.mgt
ESCO	Soil evaporation compensation factor. ESCO must be between 0.01 and 1.0. As the value of ESCO is reduced, the model is able to extract more of the evaporative demand from lower levels.	HRU	.hru
EPCO	Plant uptake compensation factor. EPCO can range from 0.01 to 1.0. As EPCO approaches 1.0, the model allows more of the water uptake demand to be met by lower layers in the soil.	HRU	.hru
CH_N2	Manning's roughness coefficient (n) for the main channel.	Stream	.rte
CH_K2	Effective hydraulic conductivity in main channel alluvium in mm/hr.	Stream	.rte
GW_DELAY	Amount of time in days that it takes for water to move through the vadose zone after percolating past the soil profile and reach the shallow aquifer.	HRU	.gw
ALPHA_BF	Baseflow alpha factor. ALPHA_BF = 2.3/BFD, where BFD is the number of days for baseflow recession to decline through one log cycle.	HRU	.gw
GW_REVAP	Groundwater revap coefficient. As GW_REVAP approaches 0, movement of water from the shallow aquifer to the root zone is restricted. As it approaches 1, the rate of transfer from the shallow aquifer to the root zone approaches the rate of potential evapotranspiration.	HRU	.gw
RECHRG_DP	Deep aquifer percolation. The fraction of percolation from the root zone which recharges the deep aquifer.	HRU	.gw
CN2	Initial SCS runoff curve number, which is a function of the soil's permeability, land use and antecedent soil water conditions.	HRU	.mgt

For each model I specified separate time periods for calibration and validation. The calibration period was for adjusting the model parameters to fit the baseflow hydrograph, while the validation period was for confirming that those calibrated parameters were sufficient. The time periods varied slightly from model to model because some of the gages started collecting daily data more recently than others. For example, gage 04108660 was missing data from 1996 through 2002, whereas gage 04106000 has a complete record back to 1931. Table 14 shows the calibration and validation periods for each of the models.

Table 14: Calibration and validation periods for SWAT models.

Gage Number	SWAT Model	Calibration Period	Validation Period
1	04096515	2002-2006	2007-2010
2	04096405	2002-2006	2007-2010
3	04097540	2002-2006	2007-2010
4	04097500	2000-2006	2007-2010
5	04103500	2002-2006	2007-2010
6	04105000	1991-2005	2006-2010
7	04106000	1993-2005	2005-2010
8	04108600	1993-2005	2006-2010
9	04108660	2003-2006	2007-2010
10	04117500	2000-2005	2006-2010
11	04101800	2002-2006	2007-2010
12	04102500	2002-2005	2006-2010

I used the NSE (1) and percent bias (PBIAS) (2) to evaluate model performance. Moriasi et al. (2007) recommended these metrics for evaluating SWAT model performance. The authors detailed a calibration and validation process by which a SWAT model is simultaneously evaluated for surface-runoff, baseflow, phosphorus loading, nitrogen loading, and sediment loading. The authors also provided a scale for NSE and PBIAS values to assess the quality of a SWAT model. Because I was not interested in sediment or nutrients, and focused solely on hydrology, I used the NSE and PBIAS scales for monthly streamflow to evaluate the SWAT models I was calibrating. Though SWAT reported daily flows, I calculated an average daily simulated flow and an average daily observed flow for each month in the calibration and validation periods. I then calculated NSE and PBIAS using those values. Table 15 details the quality scales Moriasi et al. (2007) defined for monthly flow NSE and PBIAS, color-coded to help interpret the calibration results in Table 16 and Figure 40 through Figure 43.

$$NSE = 1 - \left\{ \frac{\sum_{i=1}^{n} \left(Y_i^{obs} - Y_i^{sim} \right)^2}{\sum_{i=1}^{n} \left(Y_i^{obs} - \overline{Y^{obs}} \right)^2} \right\} \quad (1)$$

$$PBIAS = \left[\frac{\sum_{i=1}^{n} \left\{ \left(Y_i^{obs} - Y_i^{sim} \right) * 100 \right\}}{\sum_{i=1}^{n} Y_i^{obs}} \right] \quad (2)$$

Where Y_i^{obs} is the observed streamflow at a particular time unit,

and Y_i^{sim} is the simulated streamflow at that time unit.

Table 15: Calibration and validation quality scales from Moriasi et al. (2007).

	NSE	% Bias
Very Good	0.75 - 1.00	< 10%
Good	0.65 - 0.75	10 - 15%
Satisfactory	0.50 - 0.65	15 - 25%
Unsatisfactory	< 0.50	> 25%

Table 16 lists the calibration and validation results for each SWAT model, while Figure 40 through Figure 43 map those results. While most of the table is blue or green, indicating generally good model fits for baseflow, several models performed poorly. SWAT model 04096515 had very high NSE values, but simulations of baseflow were much higher than observed flow. SWAT model 04108600 had a negative calibration NSE, indicating that the overall average of flow during the calibration period was a better predictor than the simulated flows. Oddly, the model had a very good validation NSE (0.89) but a poor PBIAS (-36%). SWAT model 04103500 performed very well during the calibration period and had a good PBIAS value for validation, but the validation NSE was poor (0.37). All three of these models are in the headwater regions of the study area, and therefore have relatively small flow values, which are difficult to calibrate against, as evidenced by the dramatic swing in NSE from calibration to validation for 04108600. For example the average differences in observed and simulated monthly flows during the calibration periods for 04096515, 04103500, and 04108600 are 0.01, 0.04, and 0.02 cubic meters per second (cms), respectively. Contrast those values with the differences in the larger, better-performing models; such as 04108660 at 0.21 cms, and 04097500 at 0.22 cms.

Table 16: Calibration and validation results from the SWAT models. Negative bias values indicate that simulated baseflow was greater than observed baseflow.

Gage #	SWAT Model / Gage (River)	Calib. NSE	Calib. % Bias	Vali. NSE	Vali. % Bias
1	04096515 (St. Joseph)	0.99	-50%	0.99	-65%
2	04096405 (St. Joseph)	0.97	-6%	0.94	7%
3	04097540 (St. Joseph)	0.89	-1%	0.65	-7%
4	04097500 (St. Joseph)	0.80	-11%	0.70	1%
5	04103500 (Kalamazoo)	0.84	-1%	0.37	16%
6	04105000 (Kalamazoo)	0.58	2%	0.51	-2%
7	04106000 (Kalamazoo)	0.67	-3%	0.69	8%
8	04108600 (Kalamazoo)	-0.06	-22%	0.89	-36%
9	04108660 (Kalamazoo)	0.69	-1%	0.55	10%
10	04117500 (Thornapple)	0.64	2%	0.79	-8%
11	04101800 (Upper Dowagiac)	0.50	2%	0.50	-6%

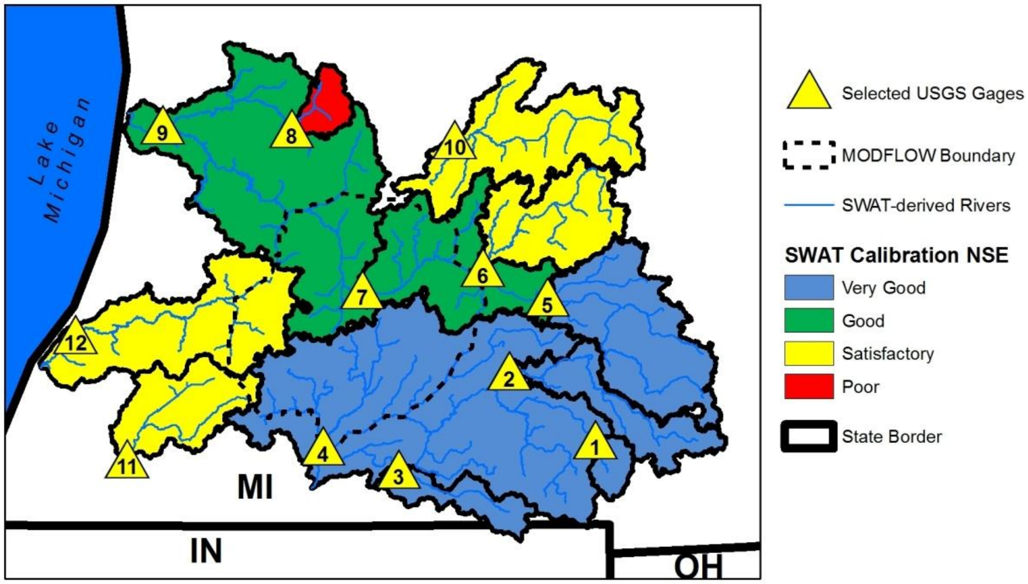

Figure 40: Nash-Sutcliffe efficiency calibration values for SWAT models.

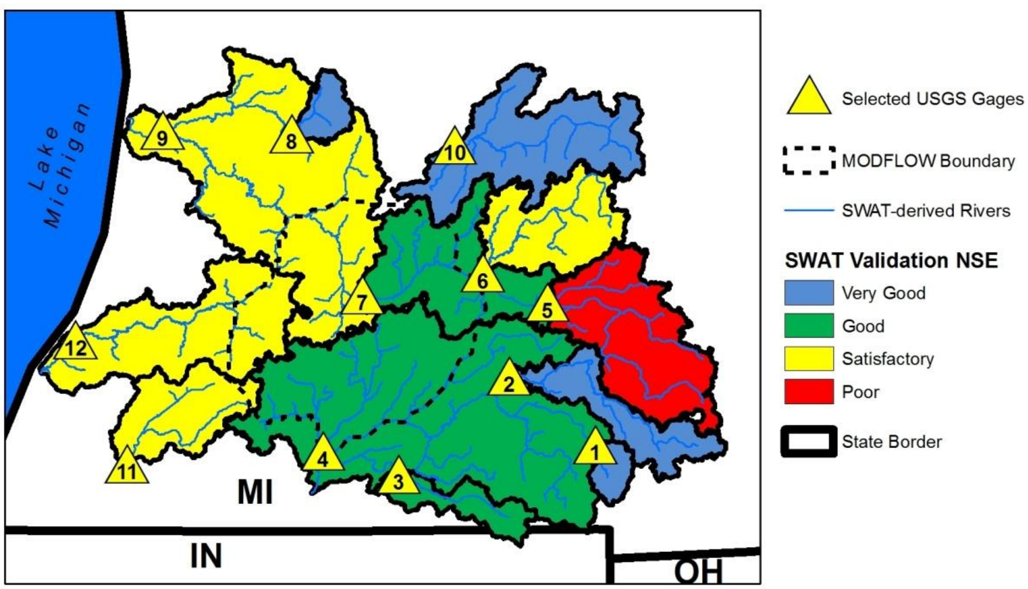

Figure 41: Nash-Sutcliffe efficiency validation values for SWAT models.

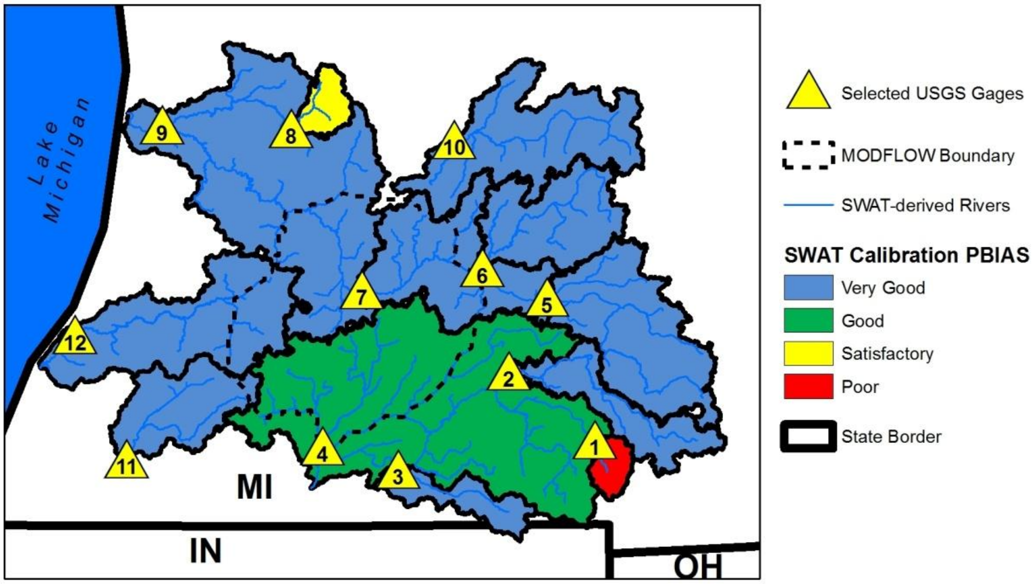

Figure 42: Percent bias calibration results for SWAT models.

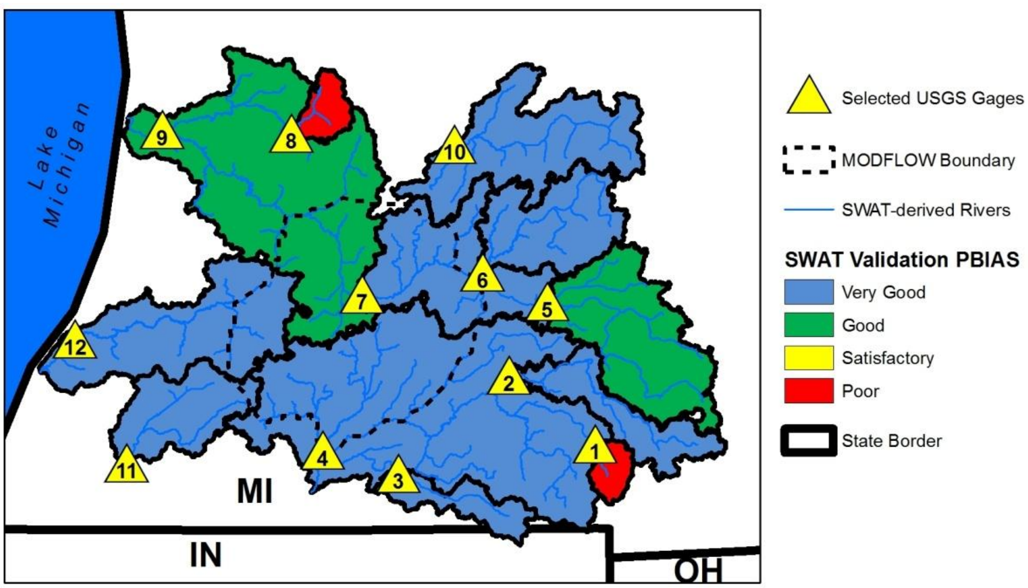

Figure 43: Percent bias validation results for SWAT models.

Though poor model fit in these tributaries affected the cumulative flows at downstream gages, their relatively small volumes contributed negligibly. Though the poor performance diminished the confidence of SWAT's groundwater recharge estimates in those basins, each of these models fell outside of the MODFLOW model boundary that defines my primary area of interest. Results from the models that intersected that area (04097500, 04106000, 04108660, 04117500, 04101800, and 04102500) were classified as satisfactory or better.

Table 17 lists the calibrated parameter values for each model and SWAT's default value for each parameter. I did not blindly accept the optimal parameter identified by SWAT-CUP, which was based on the simulation that had the highest NSE. I instead inspected SWAT-CUP's graphs for each parameter and NSE value to evaluate trends along a particular parameter range. If I did not see a clear signal in the response of NSE to incremental changes in a parameter, then I retained the model default value. For example, Figure 44 shows SWAT-CUP outputs for the RCHRG_DP parameter from the calibration of the 04106000 and 04103500 models. I observed no clear improvement in NSE by changing RCHRG_DP in 04106000, so I retained the default value of 0.05. But the changes had an obvious impact on 04103500, where I settled on a value of 0.50. It was not uncommon for one parameter to show a clear signal in one model but not in another. Figure 45 illustrates this case for the SMTMP parameter in models 04101800 and 04106000.

Table 17: Optimal model parameters identified in calibration.

Gage	SWAT Model (River)	SFTMP	SMTMP	ESCO	EPCO	CH_N2	CH_K2	GW_DELAY	ALPHA_BF	GW_REVAP	RCHRG_DP	CN2 adj.
Default SWAT Value		1.0	0.5	0.95	1	0.014	0	31	0.048	0.02	0.05	N/A
1	04096515 (St. Joseph)	-1.8	-2.0	0.75	0.40	0.080	0	1	0.025	0.09	0.20	-10%
2	04096405 (St. Joseph)	-2.0	-2.0	0.80	0.40	0.100	14	4	0.060	0.15	0.20	0%
3	04097540 (St. Joseph)	1.8	1.0	0.75	0.40	0.120	15	162	0.075	0.11	0.05	0%
4	04097500 (St. Joseph)	-2.0	-2.0	0.80	0.25	0.070	0	10	0.048	0.07	0.05	0%
5	04103500 (Kalamazoo)	1.0	0.5	0.74	0.40	0.062	0	1	0.010	0.04	0.50	-10%
6	04105000 (Kalamazoo)	1.0	0.5	0.84	0.25	0.030	0	1	0.100	0.06	0.34	-10%
7	04106000 (Kalamazoo)	-1.0	-3.0	0.85	0.25	0.014	20	1	0.010	0.02	0.05	0%
8	04108600 (Kalamazoo)	1.0	0.5	0.80	0.40	0.120	0	1	0.050	0.02	0.20	0%
9	04108660 (Kalamazoo)	-1.0	-2.5	0.85	0.35	0.014	0	1	0.029	0.02	0.35	-10%
10	04117500 (Thornapple)	1.0	0.5	0.77	0.50	0.030	3	200	0.030	0.16	0.25	0%
11	04101800 (Dowagiac)	1.0	0.5	0.95	0.33	0.150	10	250	0.059	0.05	0.05	0%
12	04102500 (Paw Paw)	-3.0	-1.5	0.85	0.40	0.030	18	250	0.090	0.10	0.15	0%

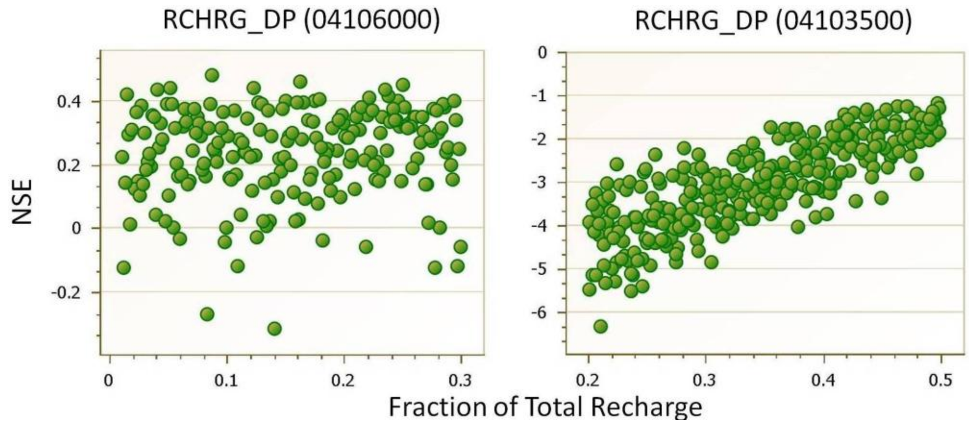

Figure 44: Changes in NSE against changes in RCHRG_DP in the calibrations of 04106000 (left) and 04103500.

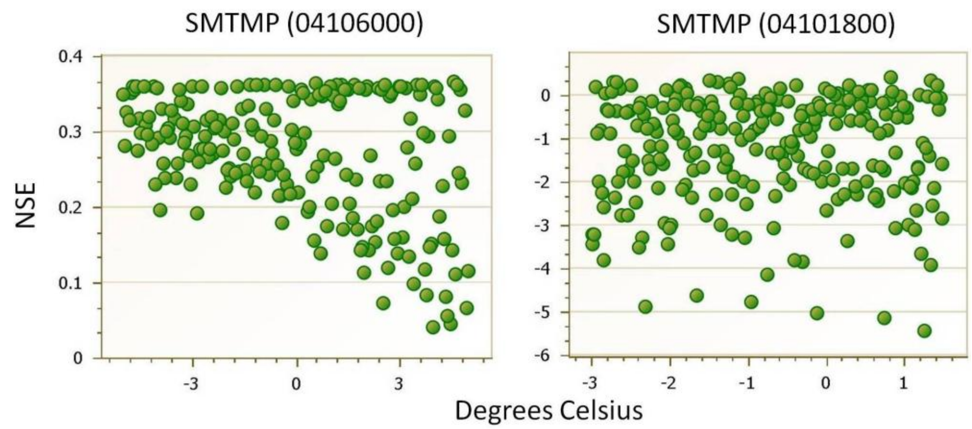

Figure 45: Changes in NSE against changes in SMTMP in the calibrations of 04106000 (left) and 04101800.

For some parameters it was relatively easy to identify the optimal value from the graph, while others required more guesswork and experimentation with manual calibration. Figure 46 shows how I was able to more easily identify the 250 GW_DELAY parameter value in calibrating 04101800 than the 0.95 value for ESCO, which required some manual re-calibration and, interestingly, happened to be the default value.

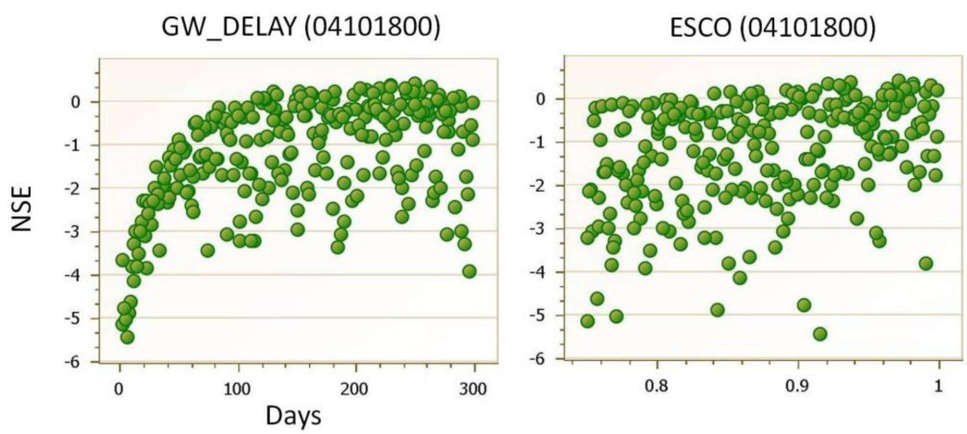

Figure 46: Changes in NSE against changes in GW_DELAY and ESCO in 04101800.

While most of the parameters in Table 17 varied only slightly from one model to the next, a few covered a broad range. The most common value for RCHRG_DP was the relatively low default of 0.05, which implies that I did not see a strong signal for that parameter when compared against NSE. But several models had values that partitioned more than 25% of infiltrated water to deep aquifer recharge. In SWAT deep aquifer recharge is lost to the system, and does not end up as baseflow in the stream network. It is possible that this hydrologic dynamic is valid within models 04103500, 04105000, 04117500, and 04108660. As

Table 12 illustrates, the baseflow indexes for these models were relatively low, implying that less streamflow was generated by groundwater discharge than in the other models. However, their surficial geologies are generally comprised of coarse till (Michigan Natural Features Inventory & Michigan Department of Natural Resources, 1998), which should facilitate infiltration and recharge. One possible cause of the high RCHRG_DP values is that drift aquifer thickness in these models is relatively thin. Figure 47 shows reported aquifer thickness in the Wellogic records, with the thinnest values occurring in the northeast section of the study area, where the high parameter values were located. In these areas, the coarse-grained drift aquifers may experience high recharge, but their relative thinness may limit their capacities to generate baseflow for the stream network, allowing more water to recharge the deeper aquifers.

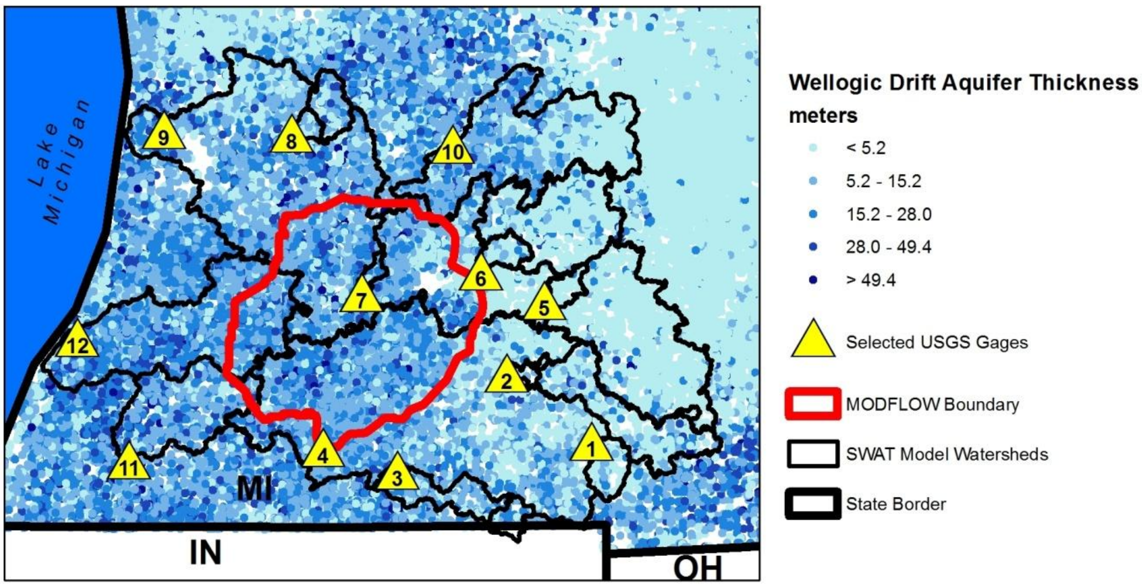

Figure 47: Drift aquifer thickness as recorded in Wellogic wells.

It is also possible that these large parameter ranges masked some aspect of the hydrologic system that I did not account for. In the case of RCHRG_DP in 04103500 it is possible that I missed an impoundment or dam on the river. Such an exclusion would have generated more flow in SWAT than observed at the USGS gage, and yielded higher NSE values for parameter changes that reduced the volume of water in the stream, which higher RCHRG_DP values would do. I cannot guarantee that the parameter values I selected for each model constituted a unique solution for groundwater flow. It is possible that other value sets could have realized similar calibration results. I was able to minimize that potential by just focusing on more than just streamflow and calibrating the model against other estimates of ET, crop yields, irrigation depths, and baseflow indexes.

4.1.6 Groundwater Recharge Sensitivity to Model Parameters

Though my calibration efforts focused on stream baseflow, I also explored how sensitive groundwater recharge was to each model parameter. I calculated these sensitivities for SWAT model 04106000 by defining a range of plausible values for each parameter, running the model over 1,000 times with randomly selected values from each range, recording the model-wide average of groundwater recharge for each simulation, and then conducting an ordinary least-squares regression with recharge as the dependent variable and the model parameters as the independent variables. In order to standardize the independent variables so that I could compare their relative weight on the dependent variable I converted each to a percentage of their respective range of values. For example, I defined a plausible range of values for ESCO of 0.6 to 1.0. For each simulation I selected a random value from a uniform distribution within that range. If the random value was 0.8 this represented 50% of the range of plausible values for ESCO [(1.0 – 0.8) / (1.0 – 0.6)]. I then used this percentage as the value for the ESCO independent variable in the regression of groundwater recharge. I treated CN2 differently because it varied by land cover and soil type, therefore I could not just select a single value to represent all HRUs in a particular SWAT model simulation. I instead calculated a relative percentage change in CN2. For example, a random value of -10 (selected from the range -20 to 10) meant that all curve numbers in a simulation were reduced by 10%. Table 18 lists the range I used for each parameter and the resulting regression coefficient.

Table 18: Groundwater recharge sensitivity analysis for SWAT model 04106000.

Model Parameter	Range	Regression Coefficient (β) and Significance
SFTMP	-5 – 5 C°	$\beta = 0.0505$, $t(1233) = 8.644$, $p < 0.001$
SMTMP	-5 – 5 C°	$\beta = 0.1920$, $t(1233) = 33.408$, $p < 0.001$
ESCO	0.60 – 1.00	$\beta = 1.1030$, $t(1233) = 192.311$, $p < 0.001$
EPCO	0.20 – 0.60	$\beta = -0.0978$, $t(1233) = -17.090$, $p < 0.001$
CH_N2	0.01 – 0.15	$\beta = 0.0044$, $t(1233) = 0.751$, $p = 0.453$
CH_K2	0 – 25mm	$\beta = -0.0083$, $t(1233) = -1.426$, $p = 0.154$
GW_DELAY	1 – 250 days	$\beta = 0.0589$, $t(1233) = 10.352$, $p < 0.001$
ALPHA_BF	0.01 – 0.20	$\beta = -0.0010$, $t(1233) = -0.173$, $p = 0.863$
GW_REVAP	0.02 – 0.14	$\beta = -0.0044$, $t(1233) = -0.760$, $p = 0.447$
RCHRG_DP	0.01 – 0.50	$\beta = 0.0100$, $t(1233) = 1.769$, $p = 0.077$
CN2	-20 – 10 %	$\beta = -0.3509$, $t(1233) = -60.607$, $p < 0.001$

When I removed the insignificant parameters the remaining independent variables explained a significant proportion of variance in groundwater recharge ($R^2 = 0.97$, $F(6, 1233) = 7087$, $p < 0.001$). The ESCO parameter had the single largest impact on recharge. A 10% increase above the minimum value of the range (0.60) resulted in an 11.03 mm increase in annual recharge. I expected this result for ESCO, because a higher value meant that less water was available for evaporation from the lower layers of the soil profile, and therefore more water was available for recharge. The other parameters that had a statistically significant impacts on recharge, in order of the relative size of the impact, were CN2, SMTMP, EPCO, GW_DELAY, and SFTMP.

Most of the signs of the regression coefficients were logical to me, but I was surprised that GW_DELAY was positive. I expected that increasing the amount of time it took for water to move through the vadose zone to the shallow aquifer would have decreased recharge, because it would have provided more opportunity for that water to be reabsorbed into the upper soil profile under dry conditions or consumed by deep-rooted plants, which the GW_REVAP parameter allowed for. In a subsequent sensitivity analysis on SWAT model 04101800 I observed the expected negative sign for the GW_DELAY coefficient. The overall effect on annual groundwater recharge was small for the parameter in both sensitivity analyses, with the maximum GW_DELAY value of 250 increasing recharge by 0.58 cm in 04106000 and decreasing it by 0.69 cm in 04101800.

I conducted the sensitivity analysis for SWAT model 04101800 to see if the relationships of particular model parameters to groundwater recharge varied spatially, and to see if the peculiar GW_DELAY coefficient sign occurred elsewhere. This model's basin was located in the southwest portion of the study area, whereas model 04106000 was more to the northeast. Like the previous model, the independent variables explained a significant proportion of variance in groundwater recharge (R^2 = 0.97, $F(6,793)$ = 4801, p < 0.001). The relative significance of the parameters between the two models was largely the same (Table 19). However, the sign on the statistically significant GW_DELAY parameter switched to negative in this model. As I described above, a negative coefficient for this parameter was more logical to me. Despite the difference in GW_DELAY, the maximum recharge increase in 04101800 that could be realized within the parameter ranges was the same as in 04106000 (14 cm), so I concluded that there was little spatial variability in parameter sensitivity.

Table 19: Groundwater recharge sensitivity analysis for SWAT model 04101800.

Model Parameter	Range	Regression Coefficient (β) and Significance
SFTMP	-5 – 5 C°	$\beta = 0.0223$, $t(788) = 2.714$, $p = 0.007$
SMTMP	-5 – 5 C°	$\beta = 0.1575$, $t(788) = 18.701$, $p < 0.001$
ESCO	0.60 – 1.00	$\beta = 1.2835$, $t(788) = 154.126$, $p < 0.001$
EPCO	0.20 – 0.60	$\beta = -0.2175$, $t(788) = -26.001$, $p < 0.001$
CH_N2	0.01 – 0.15	$\beta = 0.0066$, $t(788) = 0.785$, $p = 0.433$
CH_K2	0 – 25mm	$\beta = 0.0138$, $t(788) = 1.630$, $p = 0.103$
GW_DELAY	1 – 250 days	$\beta = -0.0684$, $t(788) = -8.298$, $p < 0.001$
ALPHA_BF	0.01 – 0.20	$\beta = -0.0071$, $t(788) = -0.857$, $p = 0.392$
GW_REVAP	0.02 – 0.14	$\beta = -0.0031$, $t(788) = -0.375$, $p = 0.708$
RCHRG_DP	0.01 – 0.50	$\beta = -0.0114$, $t(788) = -1.346$, $p = 0.179$
CN2	-20 – 10 %	$\beta = -0.4603$, $t(788) = -54.336$, $p < 0.001$

I only calculated the sensitivity of the model-wide average of annual groundwater recharge. I did not explore the sensitivities of various land covers, soil classes, or slopes. The parameter relationships might be different for the various combinations of each.

4.2 Groundwater Model Calibration

Luukkonen et al. (2004) calibrated the original MODFLOW model by comparing simulated and observed hydraulic head values at a network of observation wells in Kalamazoo County, and identifying optimal values for each recharge zone and layer's horizontal conductivity. In the modified model, I replaced the coarser recharge zones with the HRU-scale estimates from SWAT, and replaced the withdrawal data with new estimates for community, industrial, agricultural, and domestic water use. These changes did not necessarily require a recalibration of recharge and conductivity in the modified model, but they did warrant a reexamination of model outputs against observed data.

One of the benefits of studying groundwater in Kalamazoo County is that there are a relatively large number of USGS-managed observation wells for which hydraulic head values are available. I downloaded observation records for all of the wells that were active between 2001 and 2010 from the NWIS, calculated an average head value for each well for that time period, and compared those averages to the steady-state heads at the respective cells in the original and modified MODFLOW models (Figure 48) (Table 20). The simulated and observed head values were positively and strongly correlated , $r(36) = 0.95$, $p < 0.001$. At 19 of the 38 wells estimated head values from the modified model were within 1.5 meters of the observed value, which was an improvement over the original model which met that criteria at only 12 wells. However the original model had a better root mean square error (RMSE) (3) of 4.1 meters versus the modified model average error of 4.6 meters.

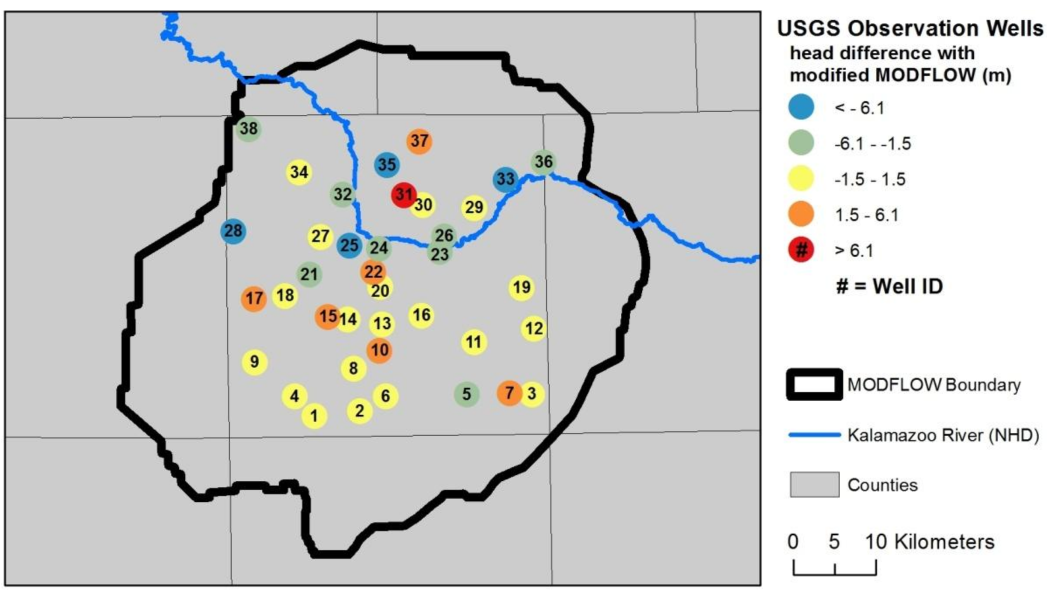

Figure 48: USGS observation wells with comparison to hydraulic head estimates in modified MODFLOW model. Well IDs correspond to the IDs in Table 18. Negative values represent higher head values in the MODFLOW model.

Table 20: USGS observation wells and their head comparisons to original and modified MODFLOW estimates. Negative difference values mean that average head was lower in the observation than the simulation.

Well ID	USGS Site #	USGS Site Name	Average USGS Head 2001-2010 (m)	Difference with Modified MODFLOW (m)	Difference with Original MODFLOW (m)
1	420533085381501	04S 11W 30BDDD01 KALAMAZOO COUNTY (K-18)	260.9	-1.0	-1.7
2	420547085342301	04S 11W 27 AAA01 KALAMAZOO COUNTY (K-23)	255.3	0.6	0.5
3	420653085190701	04S 09W 23AABB01 KALAMAZOO COUNTY (K-20)	273.5	-0.6	0.1
4	420653085395401	04S 12W 13CCCC01 KALAMAZOO COUNTY (K-17)	265.7	-1.0	-1.6
5	420657085245501	04S 10W 13 DDD01 KALAMAZOO COUNTY (K-19)	264.1	-5.1	-4.9
6	420657085320301	04S 11W 24 AAB01 KALAMAZOO COUNTY (K-24)	255.0	0.4	0.4
7	420658085210401	04S 09W 15 CCC01 KALAMAZOO COUNTY (K-21)	273.8	2.2	2.3
8	420838085344501	04S 11W 03CDDA01 KALAMAZOO CO (PRAIRIE VIEW PARK)	259.2	-0.2	-0.3
9	420858085432401	04S 12W 04BCCB01 KALAMAZOO CO (K-16)	270.9	-1.2	-0.9
10	420945085323301	03S 11W 36CAA 01 KALAMAZOO CO (K-25)	260.1	1.9	1.8
11	421016085240601	03S 09W 31ABBB01 KALAMAZOO CO (K-15)	276.2	1.5	1.5
12	421107085185301	03S 09W 26 AAA01 KALAMAZOO COUNTY (K-22)	286.0	-0.1	<0.1
13	421127085321701	03S 11W 24DBCA01 KALAMAZOO CO (RAMONA PARK)	259.0	0.5	1.6
14	421151085351601	03S 11W 22BBCD 01 KALAMAZOO CO (PORTAGE SCHOOL 4)	258.8	0.8	0.9
15	421203085370401	03S 11W 20ABBA01 KALAMAZOO CO (K-11)	263.0	2.0	1.6
16	421208085283301	03S 10W 16DCCC01 KALAMAZOO CO (K-12)	261.0	0.4	0.2
17	421312085432301	03S 12W 09ABCC01 KALAMAZOO CO (K-10)	273.4	2.0	3.7
18	421325085404801	03S 12W 11BDAD01 KALAMAZOO CO (ATWATER)	268.2	0.5	1.1
19	421358085195101	03S 09W 02DCD01 KALAMAZOO COUNTY (K-14)	288.6	0.4	-0.1
20	421358085322401	03S 11W 01DCBB01 KALAMAZOO CO (LEXINGTON GREEN)	256.0	1.1	2.4
21	421448085383601	02S 11W 31CDCB 01 KALAMAZOO CO (COLONY)	259.7	-3.4	-2.9
22	421457085325801	02S 11W 36CBCD 01 KALAMAZOO CO (EMERALD)	252.3	2.3	2.5
23	421614085270801	02S 10W 26BBCC 01 KALAMAZOO CO (MORROW)	237.9	-3.6	-3.8
24	421630085322601	02S 11W 24DCCC01 KALAMAZOO CO (K-8)	235.9	-3.1	-3.0
25	421641085350601	02S 11W 22CDBB 01 KALAMAZOO CO (STOCKBRIDGE)	230.9	-8.0	-5.3
26	421713085264601	02S 10W 23BAAB01 KALAMAZOO CO (K-7)	239.4	-5.2	-5.1
27	421716085373702	02S 11W 20BBBD 02 KALAMAZOO CO (KENDALL)	256.1	1.3	2.0
28	421742085452501	02S 12W 18CAAA01 KALAMAZOO CO (K-9)	242.2	-16.2	-10.6
29	421908085240501	02S 09W 06DBDA01 KALAMAZOO CO (K-30)	250.9	1.3	1.3
30	421918085283801	02S 10W 04DACC 01 KALAMAZOO CO (CAMPBELL)	253.8	-1.5	-1.6
31	422004085301801	01S 10W 32CDDC01 KALAMAZOO CO (K-29)	266.1	9.4	9.1
32	422006085353901	01S 11W 33DDCC01 KALAMAZOO CO (K-28)	232.6	-5.8	-4.9
33	422056085211701	01S 09W 27CCC 01 KALAMAZOO CO (K-5)	243.7	-7.1	-7.2
34	422117085393001	01S 12W 25ABCC01 KALAMAZOO CO (K-1)	255.6	0.9	4.0
35	422153085314701	01S 10W 19CBDC01 KALAMAZOO CO. (K-3)	244.6	-12.6	-12.6
36	422207085175501	01S 09W 24DAD 01 KALAMAZOO CO (K-34)	246.2	-4.1	-4.1
37	422328085285701	01S 10W 09DCD 01 KALAMAZOO CO (K-4)	274.1	2.0	1.7
38	422418085440201	01S 12W 05DDC 01 KALAMAZOO CO (K-27)	217.7	-1.6	-1.6

$$RMSE = \sqrt{\sum_{i=1}^{n}\left(Y_i^{obs} - Y_i^{sim}\right)^2} \quad (3)$$

Where $RMSE$ = root-mean square error,

Y_i^{obs} is the observed value at location *i*,

and Y_i^{sim} is the simulated value at location *i*.

I can attribute the discrepancy in the RMSE values to observation well 28. This well was the error outlier for both the original and modified models, with the original head estimate 10.6 meters higher than the average observation, and the modified model head 16.2 meters higher. Aerial imagery showed that the well was close to a golf course. I did represent the golf course in the modified model as an irrigating area, which led me to believe that I was possibly over-irrigating the area as SWAT calculated recharge. However, the original model did not include the golf course as a withdrawal, and its estimate was also too high. I believe that issue had more to do with the well's close proximity to the model boundary. The authors of the original model defined the border there for the top layer (which the observation well is within) as a no flow boundary (Figure 49). This setting created a barrier preventing flow out of the system. The head maps for layer 1 in Figure 36 and Figure 37 illustrate that the general direction of flow in that area is towards this barrier, which could cause water to accumulate within the aquifer and yield higher estimated heads. The authors defined the border in the next lowest aquifer in layer 3 as constant head (Figure 50), which facilitated flow towards the boundary and out of the system. If the boundary in layer 1 was misclassified, it could be the cause for the high errors at observation well 28. If that well is removed from the analysis, both the original and modified models have much closer RMSE values of 3.7 and 3.8 meters, respectively.

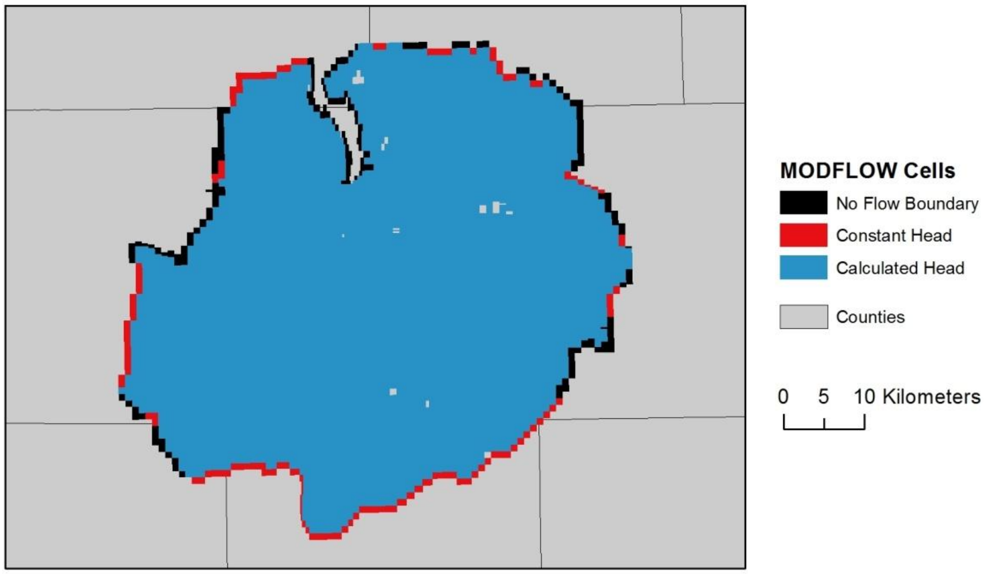

Figure 49: No flow and constant head boundaries in layer 1 of both MODFLOW models.

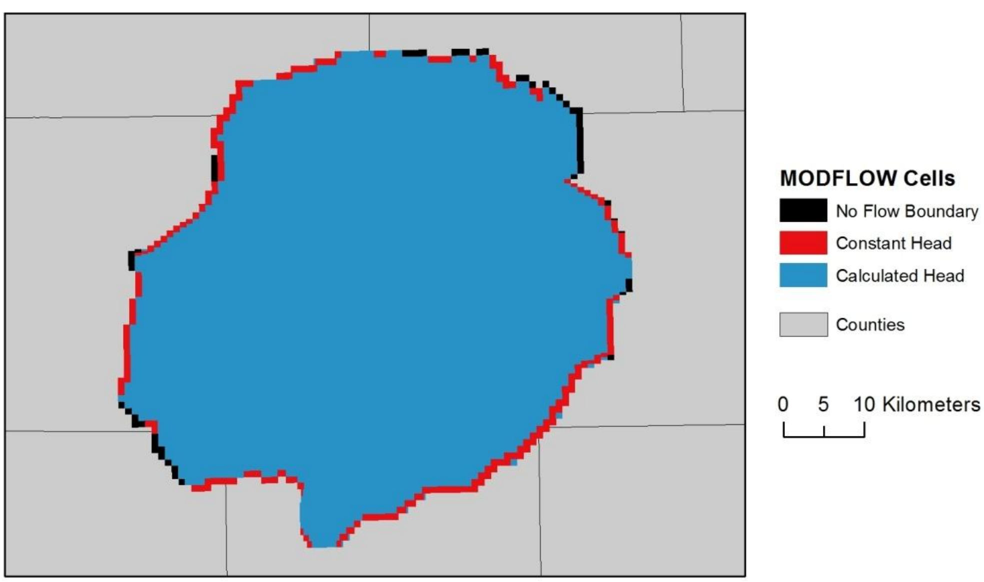

Figure 50: No flow and constant head boundaries in layer 3 of both MODFLOW models

The more likely source for the overall differences in simulated versus observed values was the starting head values in the MODFLOW models. Specifying a starting head for each cell in the model that is relatively close to the final calculated head improves MODFLOW's processing time and makes it more likely that the model will converge to a stable solution. In the original model, the authors defined the starting heads based upon observations at wells in the study area and locations where streams and lakes intersected contours on a topographic map. The authors made the valid assumption that head at a surface water feature was equal to its elevation. However, the resulting initial heads for the model varied from the observed water levels in the USGS wells to the same extent as the calculated final heads. Figure 51 shows the difference in observed and initial head between the USGS data and the modified MODFLOW model. Contrast these figures with Figure 48 and note the similarity, which implies that there was little change between initial and calculated head in the model. The average difference for the cells in which I evaluated USGS observation data was -0.5 meters (minimum of -4.8, maximum of 1.5, standard deviation of 1.2). The initial head estimate at well 28 was 11.4 meters higher than the observed water level. It is possible that that high initial value and the potential issue with flow through the model's western boundary in layer 1 combined to create a model bias in that region for higher head values.

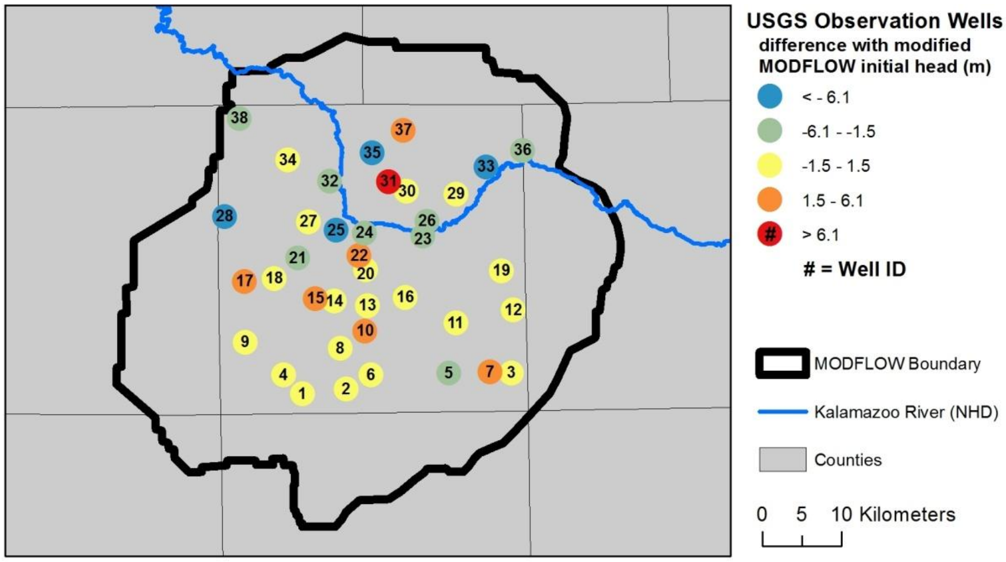

Figure 51: USGS observation wells with comparison to starting hydraulic head estimates in modified MODFLOW model. Well IDs correspond to the IDs in Table 18. Negative values represent higher head values in the MODFLOW model.

Another metric that can be used to evaluate calibrations of groundwater models is the ratio of the standard deviation of errors to the range of the observed head values (4). Ratios less than 0.1 are indicative of a good model fit (ESI, 2016). I calculated ratio values of 0.057 and 0.063 for the original and modified MODFLOW models, respectively.

$$SD\!:Range = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i^{sim} - \bar{Y}_i^{sim}\right)^2}{n-1}} \Big/ \left[\max(Y^{obs}) - \min(Y^{obs})\right] \quad (4)$$

Where $SD\!:Range$ = ratio of the standard deviation of errors to the range of observed values,

Y_i^{sim} is the observed value at location *i*,

$\bar{Y}_i^{sim}$is the average simulated value at all locations *I*,

and Y^{obs} represents all observed values.

I also compared the simulated head values in the modified MODFLOW models to static water levels in the Wellogic records. These levels are typically recorded by drillers when they install a new well. In terms of reliability, the USGS observation wells are preferable to the Wellogic static water levels for several reasons. First, the observation wells are monitored over time, and more rigorously than the static water levels, which are only single snapshots of the water table and can be decades old. Additionally, the Wellogic dataset is prone to contain errors in terms of location (wells are often geo-located by street address as opposed to coordinates) and attributes, such as some wells' static water levels being listed as an elevation while others are reported as depths. However, assuming that the majority of wells are accurate, the large number of wells can paint a distinct range of observed water table elevations and allow one to see how well simulated values approximate this range.

I selected every Wellogic well within the MODFLOW model boundary, and compared simulated head to each well's static water level. Though the two variables were highly correlated, $r(26{,}418) = 0.94$, $p < 0.001$, and though the ratio of residual standard deviation to observed head range was good (0.037) the RMSE was higher (5.9 meters) than the value calculated for the USGS observation wells (4.6 meters). Figure 52 maps the difference between MODFLOW head estimates and Wellogic water levels. There was a slight bias towards higher simulated head (Figure 53). The largest errors were found in the western and northern portions of the study area (Figure 54 and Figure 55). The blue cluster of MODFLOW over-estimates on the western border was in the same location as USGS observation well 28 from

Figure 48, supporting the idea that the constant head boundary there may be improperly defined, but also indicating that the initial head values may be too high. There was also a cluster of MODFLOW over-estimates along the Kalamazoo River as it exits the study area in the north, which was primarily the result of higher initial head values. Figure 56 shows the difference between Wellogic static water level and initial head in the MODFLOW models, reflecting the same spatial pattern of differences with calculated head.

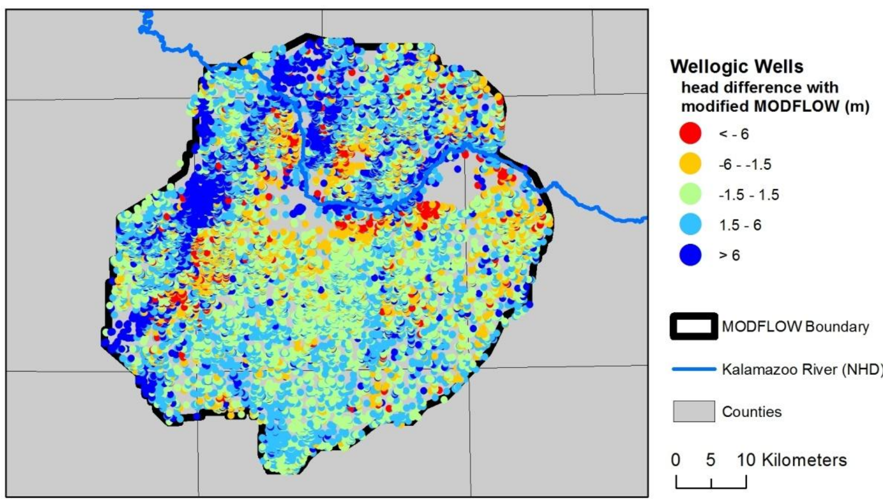

Figure 52: Wellogic wells with comparison of static water level to hydraulic head estimates in modified MODFLOW model. Negative values represent higher head values in the MODFLOW model.

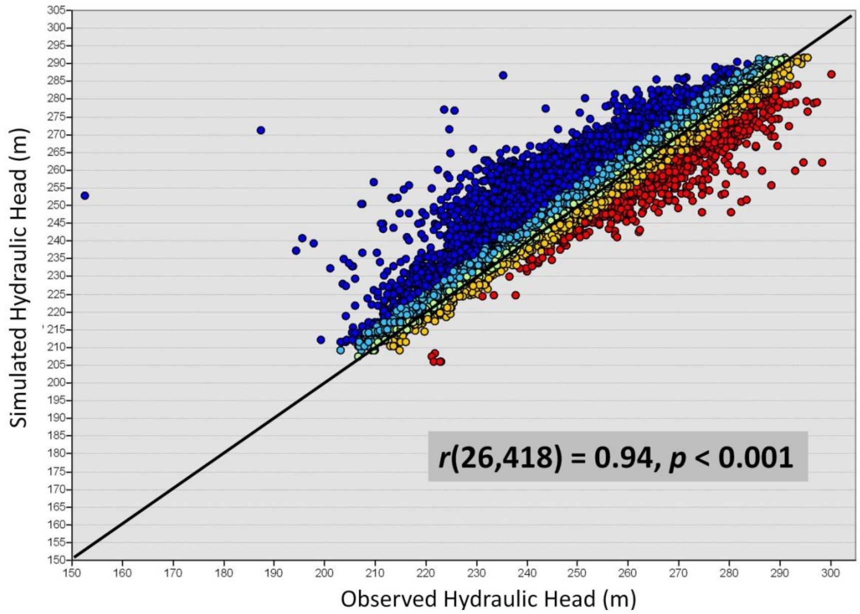

Figure 53: Simulated hydraulic head from modified MODFLOW model versus static water levels in Wellogic wells. Values are shaded in the same manner as the wells in Figure 52.

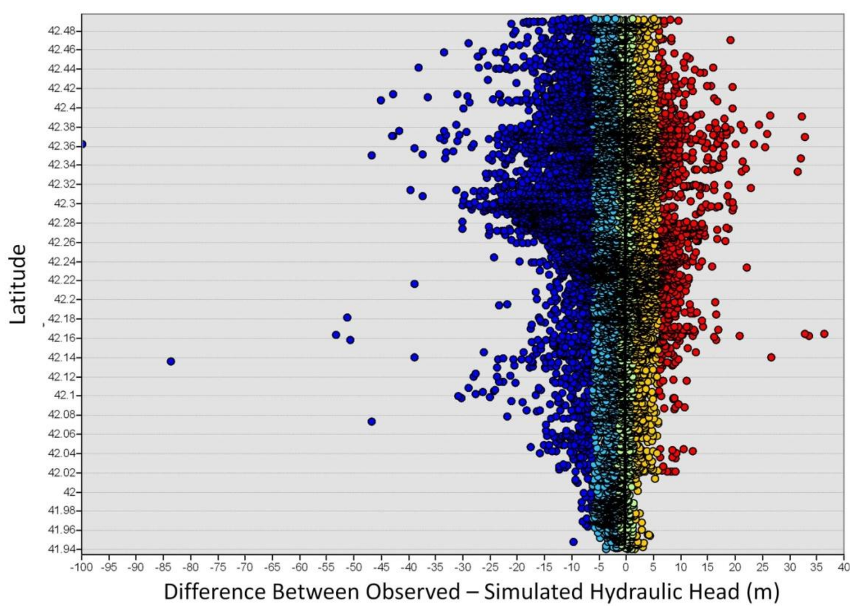

Figure 54: Simulated hydraulic head from modified MODFLOW model versus static water levels in Wellogic wells, plotted by latitude. Values are shaded in the same manner as the wells in Figure 52.

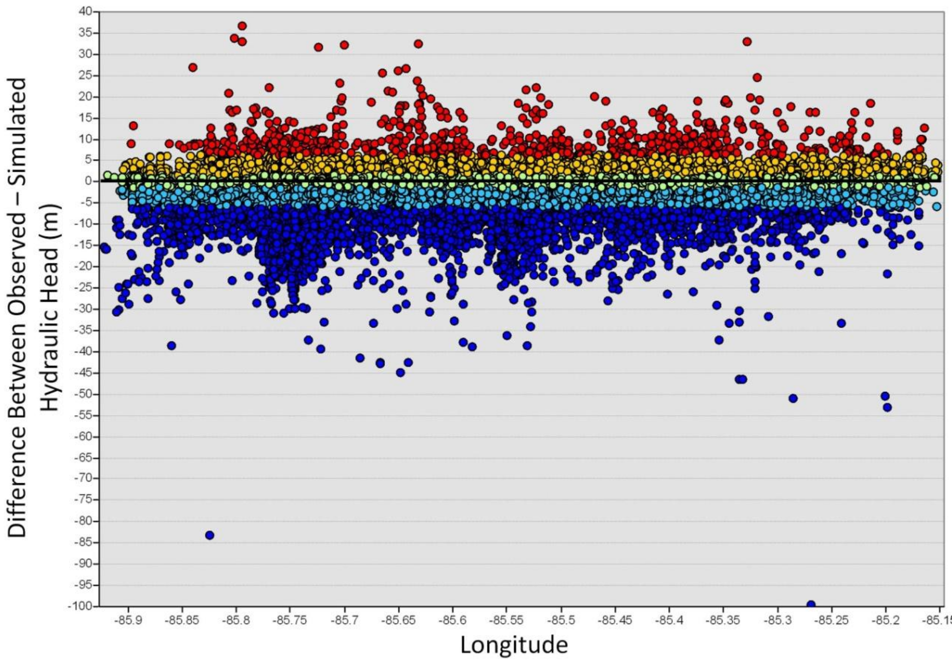

Figure 55: Simulated hydraulic head from modified MODFLOW model versus static water levels in Wellogic wells, plotted by longitude. Values are shaded in the same manner as the wells in Figure 52.

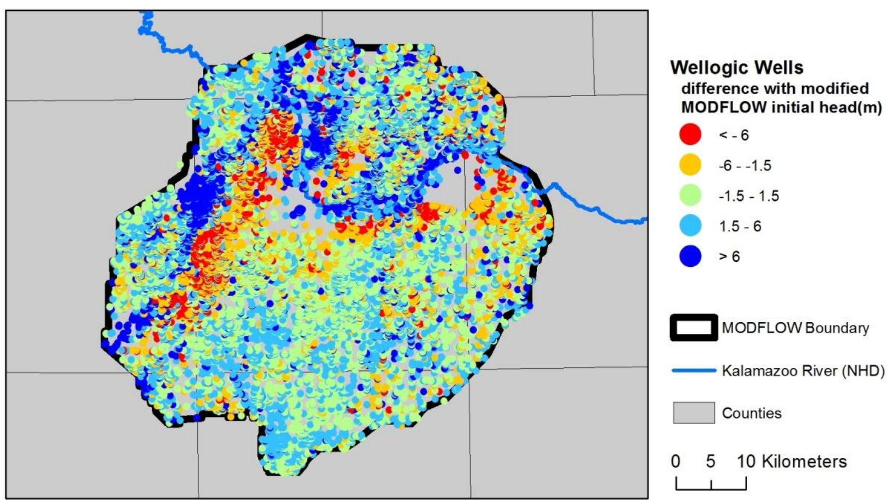

Figure 56: Wellogic wells with comparison of static water level to initial hydraulic head values in modified MODFLOW model. Negative values represent higher head values in the MODFLOW model.

I explored redefining the head boundary along the western border, but that caused the model to become unstable and it could not produce a viable solution. That instability was also likely due to the initial head values, because some cells that were classified as no flow boundaries in the original model were subsequently assigned null values of "-9999" for initial head. Converting those cells to constant head caused the model to interpret that null value as an actual initial head. The obvious solution was to then attempt to adjust the starting head values. However, adjusting those values was problematic both conceptually and technically. First, I would have to determine what the adjustments should be. I could use the USGS observation data, but that would only represent 39 cell locations, and would not be enough to adequately interpolate a surface of head values. A better solution would be to use the Wellogic static water levels, but that could propagate the aforementioned errors in the dataset into the initial head estimates. A concerted effort to reduce the noise in Wellogic by identifying errors, building a complete record that accounts for wells that were installed before the registrations were mandatory, and accounting for changes in water levels over time could have yielded an ideal representation of starting heads, but would have required significantly more time and resources than were available to me for this research. Another problem in adjusting these values is that I would be assuming that the initial heads defined by the original model's authors were not adequate. Their method of using observed water levels and elevations at surface water locations was sound. It is possible that the topographic maps they utilized to infer heads at those locations were too coarse, the interpolation method they used to estimate starting head at areas away from observed values might have introduced some degree of error, or that there was some bias in the observed water levels. But the authors did not disclose the sources of those inputs in their report, so I cannot evaluate their reliability at this time. Lastly, adjusting the starting heads proved to be a technical challenge because of the way MODFLOW stores those values. The program reads in starting heads as binary input, unlike the other inputs which are in text file formats. I experimented with adjusting the values, but was unable to re-write them in binary. I was able to produce binary outputs of ending head values, which I utilized as starting heads for subsequent decadal time steps during the future climate simulations, but I could not produce a new starting head file for the initial baseline calibration. There are commercial and freeware groundwater modeling programs that can do it, but I was unable to import the original MODFLOW model into the free applications in order to do so.

Though I would have preferred better RMSE values in the comparisons with the USGS observation well data and Wellogic static water levels, the strong correlation between those variables and the simulated head, the good ratios of residual error to observed head range, and the relatively close RMSE values between the original and modified MODFLOW models (even when outlier well 28 was included) were sufficient evidence that I did not need to recalibrate the model. However, this evaluation process provided important insight into the limitations of the model's outputs, and affected my analysis of the future simulations.

CHAPTER 5: Preparing the Future Hydrologic Model Scenarios

I sought to explore how the water table in the modified Kalamazoo MODFLOW model might fluctuate under various future scenarios of climate change and land management. In this chapter I will describe how I defined those various scenarios, and how I modified SWAT and MODFLOW to simulate them. Figure 57 illustrates the overall process that I employed.

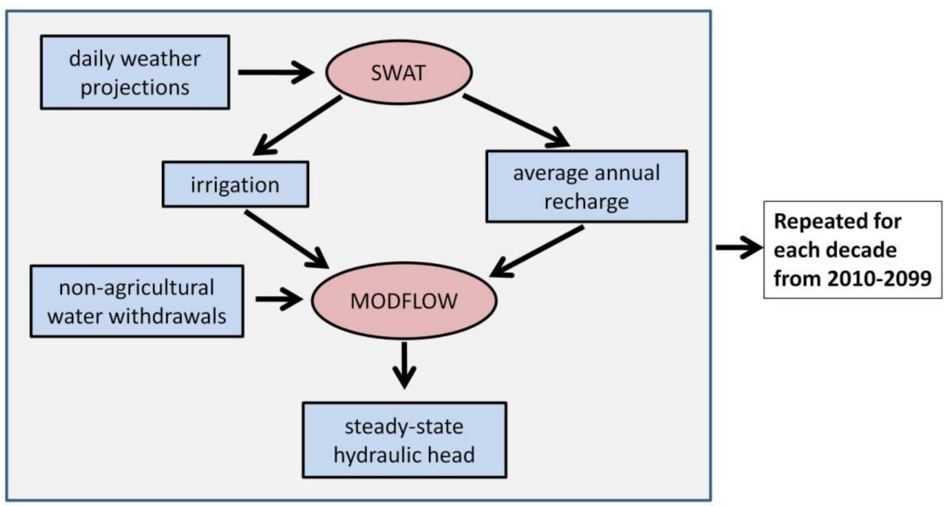

Figure 57: Process diagram for running future climate simulations through SWAT and MODFLOW.

5.1 Climate Change

5.1.1 The data source

I used projections from 11 global climate models that were statistically downscaled and organized into a standardized dataset by Hayhoe et al. (2013), which I will subsequently refer to as the Hayhoe climate dataset (HCD). In that effort, researchers processed data from 16 climate models drawn from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset (Meehl et al., 2007). The developers of the CMIP3 data ran the various climate models under multiple emission scenarios defined by the Intergovernmental Panel on Climate Change's (IPCC) Special Report on Emission Scenarios (SRES) (Nakićenović & Intergovernmental Panel on Climate Change, 2000)[11]. The IPCC distinguished those scenarios by their relative concentrations of greenhouse gases, which it selected to represent storylines of global societal development. Appendix B contains an excerpt from Nakićenović & Intergovernmental Panel on Climate Change (2000) (https://www.ipcc.ch/ipccreports/tar/wg1/029.htm) that details these different storylines. I provide a summary of the SRES scenarios I utilized in this research in Table 21, and their respective concentrations of carbon dioxide (CO_2) (Intergovernmental Panel on Climate Change, 2014) (Table 22).

Table 21: Emission scenarios used in this study.

SRES Emission Scenario	Description
A1FI	Rapid population growth in the first half of the century, which levels off mid-century. Heavy use of fossil fuels.
A1B	Rapid population growth in the first half of the century, which levels off mid-century. Balanced use of fossil fuels.
A2	Steady and continuous population growth.
B1	Rapid population growth in the first half of the century, which levels off mid-century. Wide adoption of clean and efficient resource technologies.

[11] The IPCC's Special Report on Emission Scenarios has been replaced by the Representative Concentration Pathways (RCP), which are the basis for the 5th and most current version of CMIP models. However, at the time I began this research the CMIP5 models had not been organized into a readily accessible format in the way that Hayhoe et al. (2013) had organized the CMIP3 models. Therefore my analysis does not include the most recent projections of climate change.

Table 22: IPCC carbon dioxide concentrations for each decade in 4 SRES emission scenarios.

Year	CO_2 Concentrations (ppm)			
	A1FI	**A1B**	**A2**	**B1**
2010	389	391	390	388
2020	417	420	417	412
2030	455	454	451	437
2040	504	491	490	463
2050	567	532	532	488
2060	638	572	580	509
2070	716	611	635	525
2080	799	649	698	537
2090	885	685	771	545
2100	970	717	856	549

Each of the 16 models in the HCD contained data for 2 to 4 emission scenarios, downscaled to the same 1/8 degree grid points generated by Maurer et al. (2002) (Figure 15), and stored at a daily time interval through the year 2100. Not all of the models had complete time-scales, so I selected the 11 that did to include in this research. I ultimately ran simulations for 31 different future climate projections. Table 23 lists those climate models and the emission scenarios they included.

Table 23: HCD climate models and emission scenarios included in the future climate simulations.

Climate Model Name	Originator	SRES Scenarios Included
CCSM3	National Center for Atmospheric Research, USA	A1FI, A2, B1
CGCM3-T47	Canadian Centre for Climate Modelling and Analysis, Canada	A2, A1B, B1
CGCM3-T63	Canadian Centre for Climate Modelling and Analysis, Canada	A2, A1B, B1
CNRM-CM3	Centre national de Recherches Meteorologiques, France	A2, A1B, B1
ECHAM5	Max Planck Institute for Meteorology, Germany	A2, A1B, B1
ECHO-G	National Institute of Meteorological Research / Korea Meteorological Administration	A2, A1B, B1
GFDL CM2.0	NOAA Geophysical Fluid Dynamics Laboratory, USA	A2, B1
GFDL CM2.1	NOAA Geophysical Fluid Dynamics Laboratory, USA	A1FI, A2, B1
HadCM3	UK Meteorological Office Hadley Centre	A1FI, A2, B1
HADGEM1	UK Meteorological Office Hadley Centre	A2, A1B
PCM	National Center for Atmospheric Research, USA	A1FI, A2, A1B

The general trend among all of the models was increased temperature and precipitation in the study area through the end of the century. Figure 58 shows total annual precipitation and Figure 59 shows average annual temperature for SWAT model 04108660, averaged by decade and emission scenario. For example, the last point on the A1Fi series (in red) in Figure 58 is the average annual precipitation for the period between 2090 and 2099, averaged across the four climate models that have data for that emission scenario (CCSM, GFDL CM2.1, HadCM3, and PCM). There were some differences in the amount of precipitation between SWAT models, with more rainfall in the basins closer to Lake Michigan (04108660, 04102500), but the overall trends in precipitation and temperature were the same. While the total increase in precipitation from 2010 through the end of the century is similar for the averages of all 4 emission scenarios (50 – 100mm), the increases in temperature are much less in the B1 scenario than in the others. B1's 2°C increase from 2010 to 2100 is dwarfed by the nearly 5°C increase in the A2 scenario.

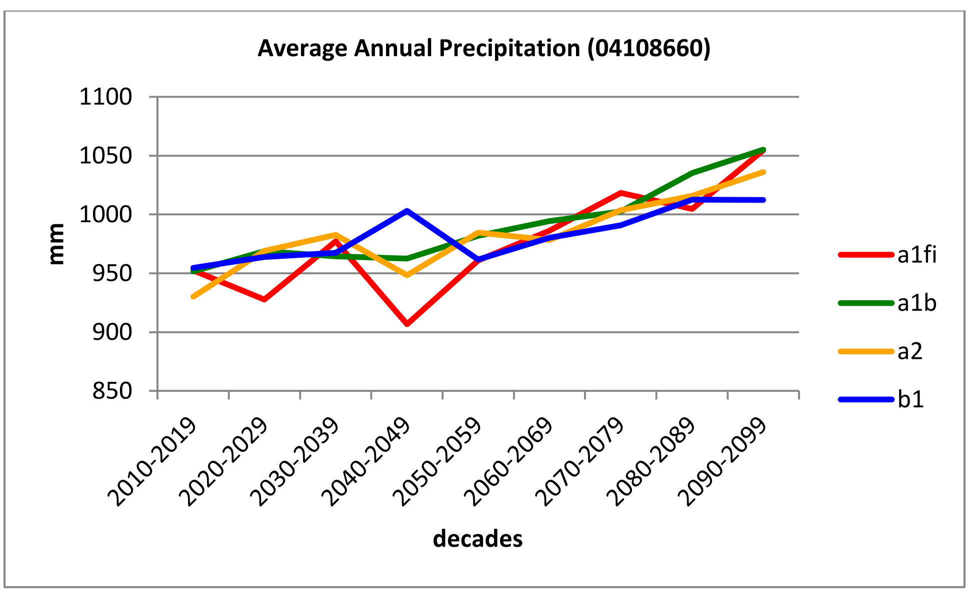

Figure 58: Annual precipitation, averaged by decade and emission scenario, for SWAT model 04108660.

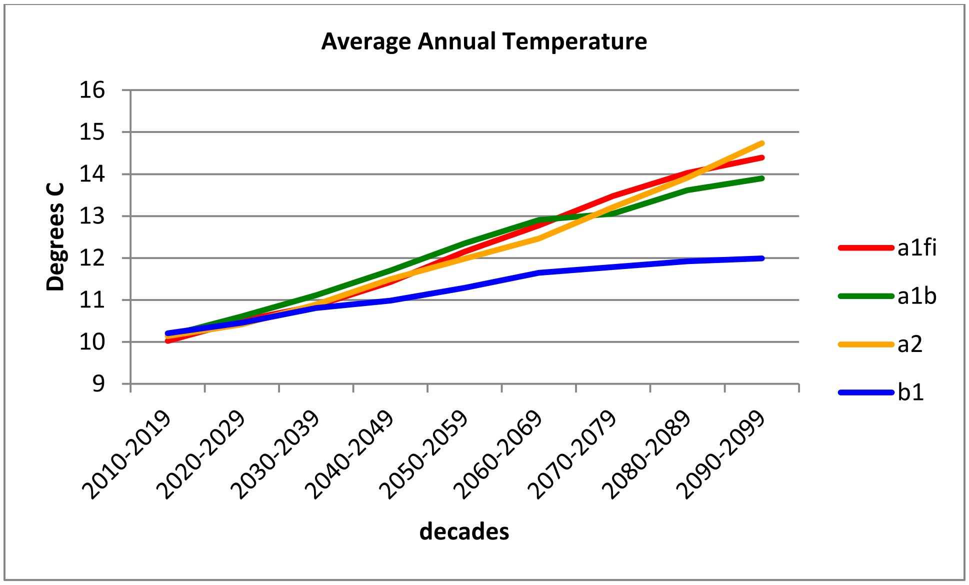

Figure 59: Average annual temperature, averaged by decade and emission scenario, for SWAT model 04108660.

Figure 60 and Figure 61 show the large amount of variability among the climate models. The dashed line in each of the graphs in the two figures represents the emission scenario lines in Figure 58 and Figure 59. Some of the more noteworthy climate model projections are the considerably drier estimates for the HADGEM1 A1B and A2 emission scenarios, the single highest precipitation projection among all models in the ECHO-G A2 scenario at the end of the century, the consistently cooler PCM climate model, and the consistently hotter ECHO-G climate model.

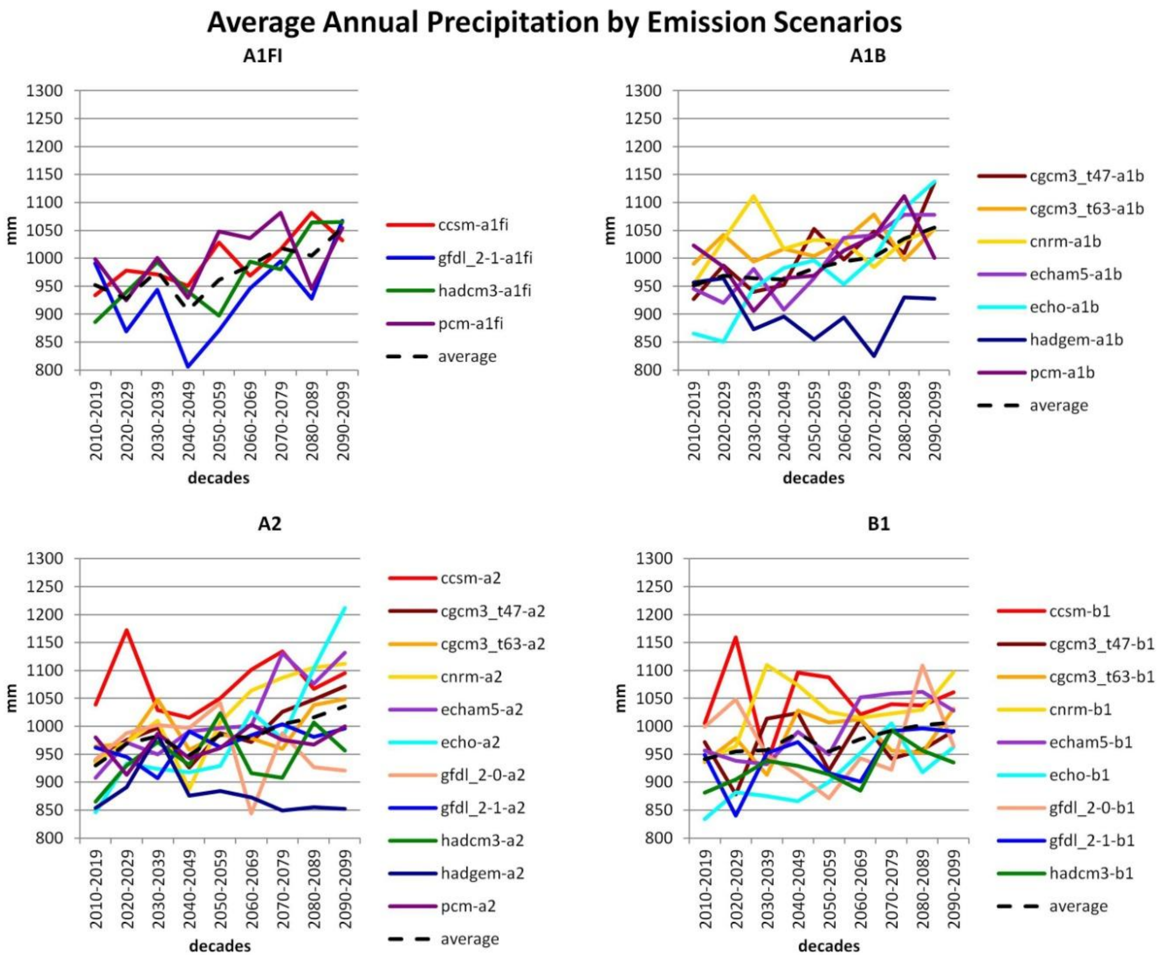

Figure 60: Average precipitation for climate models within each emission scenario for SWAT model 04108660.

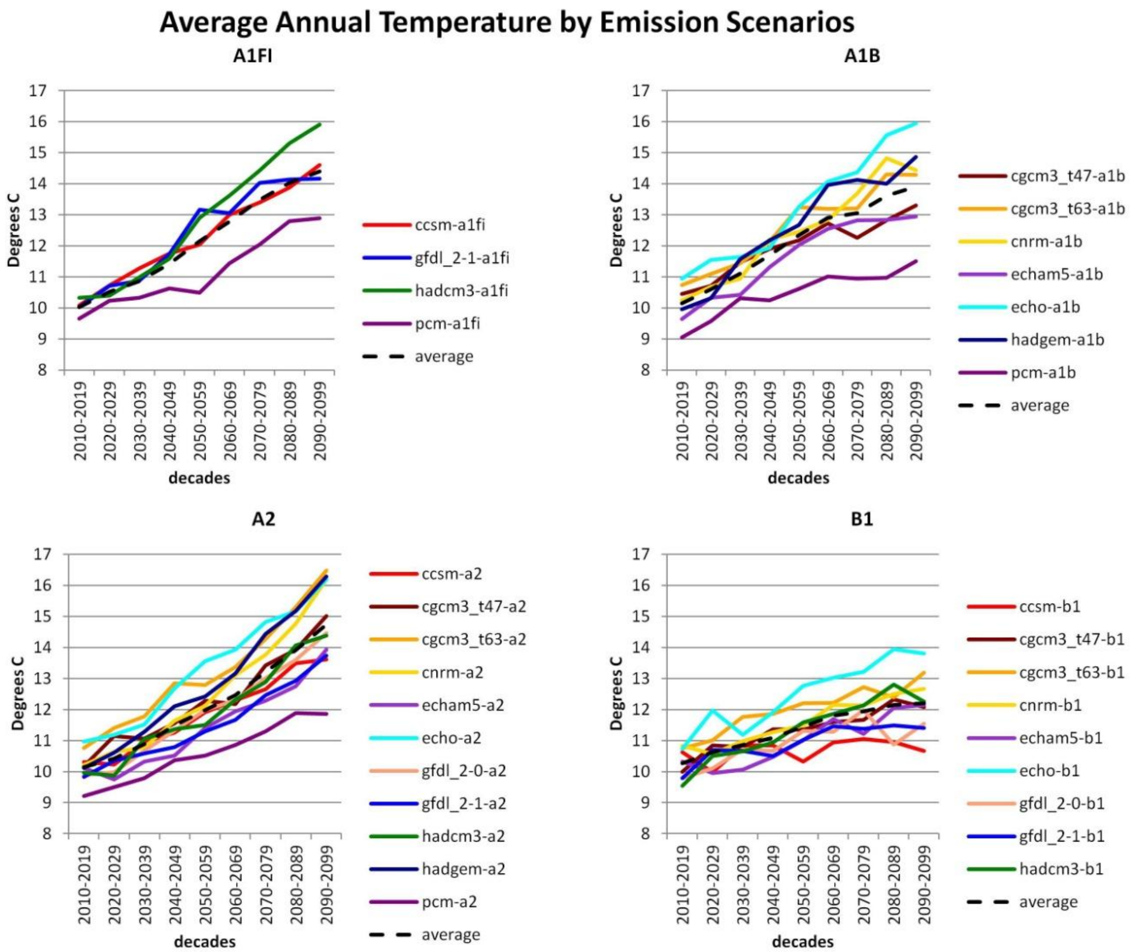

Figure 61: Average temperature for climate models within each emission scenario for SWAT model 04108660.

Figure 62 illustrates how precipitation changes by month, while Figure 63 shows the monthly changes in temperature for 04108660. For most months, decadal averages of precipitation are flat through the rest of the century. But in March, April, and May, precipitation increases; most dramatically for the A1FI emission scenario in April, which projects a 35% increase from 2010 through 2100. The A1FI scenario also projects drops in precipitation for July and August, though the rates for the other scenarios are constant. Figure 63 shows that there is little variation between the months in terms of the rate of temperature increase. Every month is projected to see its average temperature increase steadily.

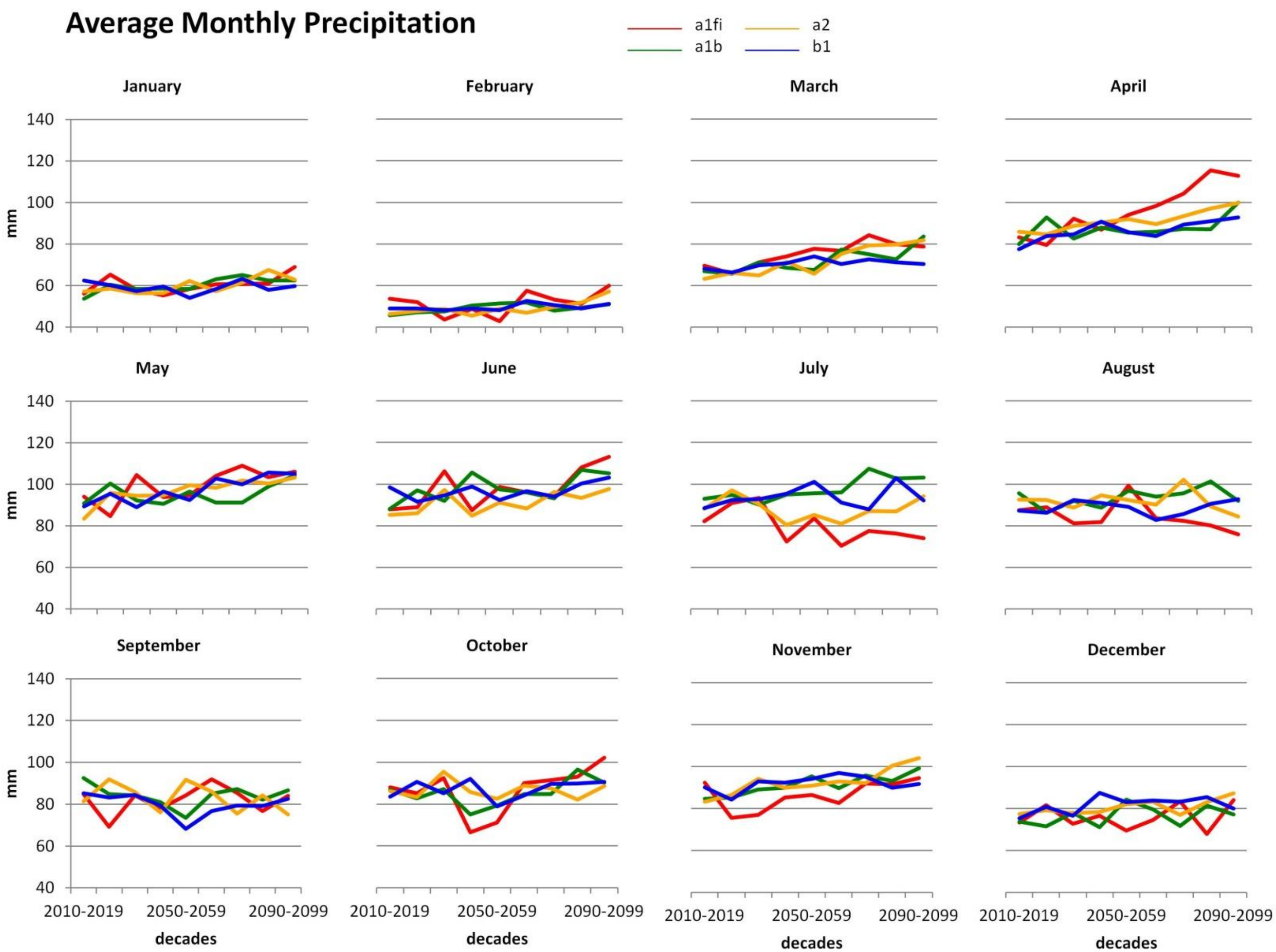

Figure 62: Average monthly precipitation, averaged by decade and emission scenario for 04108660.

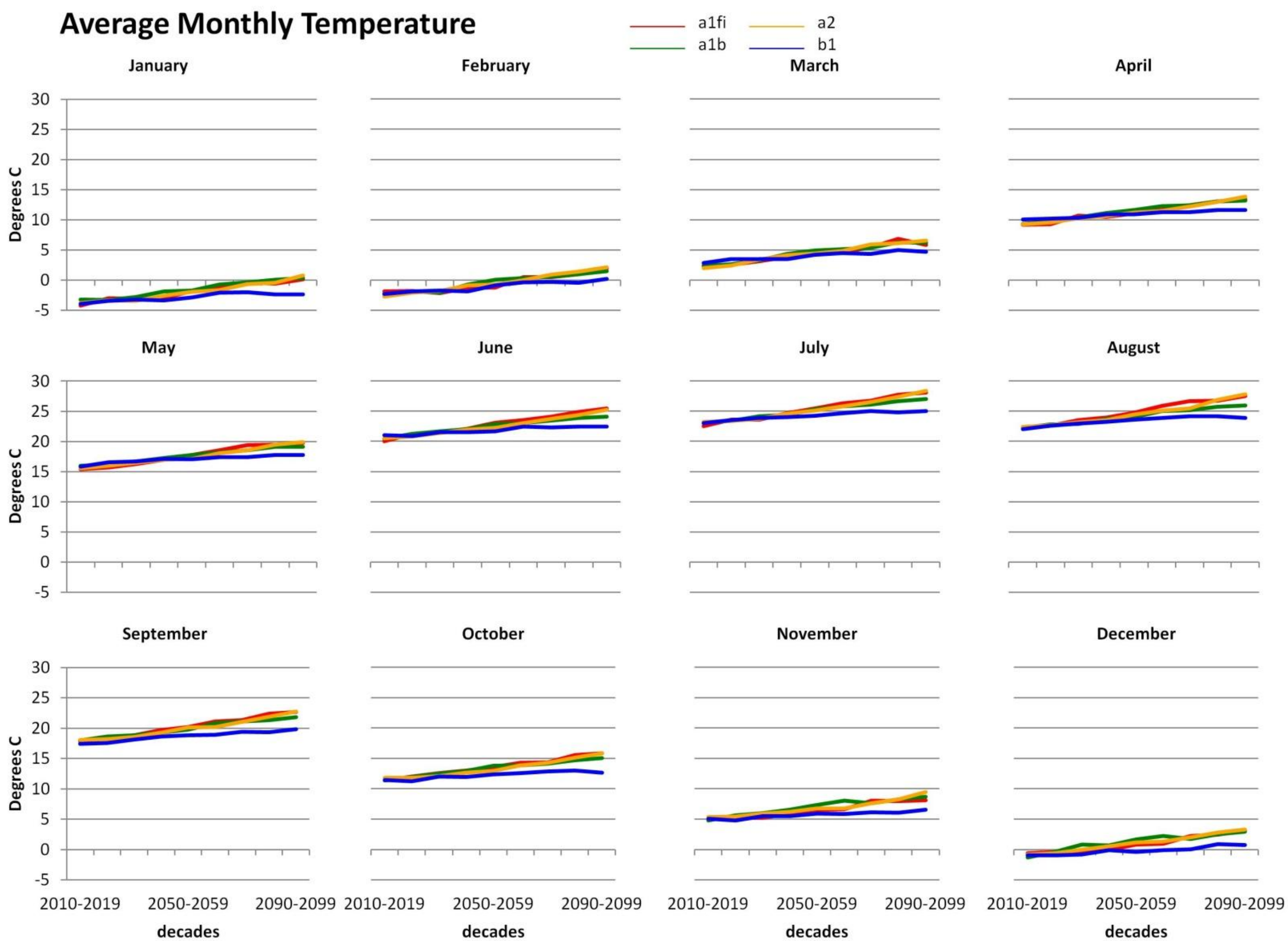

Figure 63: Average monthly temperature, averaged by decade and emission scenario for 04108660.

Figure 64 explores this precipitation decline by displaying the July averages for the 4 climate models that have A1FI emission scenarios. It is clear that the steep decline in July precipitation from climate model GFDL CM 2.1 (-67%) pulls down the overall average of the A1FI emission scenario. If that particular model is excluded from the calculation of the emission scenario average, then A1FI's July precipitation trends would be very similar to A2's. The GFDL CM2.1 example illustrates the large variability between climate models and the importance of utilizing multiple models when evaluating potential climate change impacts.

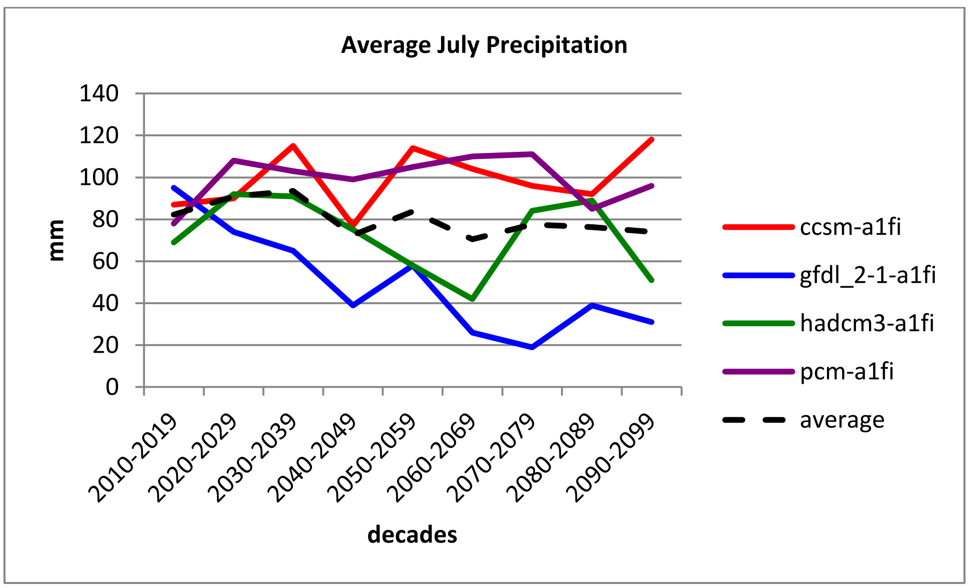

Figure 64: Average July precipitation, averaged by decade for emission scenario A1FI, for SWAT model 04108660.

5.1.2 Running future climate simulations in SWAT

As I did with the Maurer dataset during the SWAT model calibration, I treated each grid point in the HCD as a weather station to input daily precipitation and temperature through the year 2100. I ran SWAT simulations with the future climate data in decadal chunks. For example, for a single climate model simulation, such as CCSM-A1FI, I ran SWAT from 2010-2019, recorded model outputs (including HRU-scale maps of groundwater recharge), adjusted model parameters, re-ran it from 2020-2029, and repeated on through 2090-2099. There were several reasons I ran the SWAT simulations in 10-year intervals. The primary reason was to reduce uncertainty in the recharge estimates. Though the 31 future climate models produced daily outputs, they are not weather forecasts for a particular day in the future. These models are stochastic simulations that operate at daily intervals; therefore I could not assume that SWAT's calculation of recharge on a given day would be accurate. I instead viewed the climate model outputs as forecasts of long-term trends in precipitation and temperature, and calculated a 10-year average of annual recharge for each HRU. I had more confidence in this long-term average than I would have had in a single day's calculation, or a single-year's average. A second reason for the 10-year increments was because SWAT does not allow CO_2 concentration to change during a simulation. SWAT uses a default CO_2 concentration of 330 ppm as part of its plant growth sub-model, which the user can only modify prior to simulation. Stopping the model every 10 years allowed me to update this value per Table 22 prior to each decadal run. The last reason for the 10-year increments was pragmatic. It was easier to extract outputs from a full and complete SWAT model run than trying to extract a slice of data for a particular time period from the outputs.

One limitation of estimating groundwater recharge with SWAT and long-term climate projections is that the model has a tendency to overestimate the improvement in plant water efficiency in response to increased CO_2 levels. As atmospheric CO_2 increases, the stomata on plant leaves tighten, causing them to transpire less water and, subsequently, become more efficient in their use of water (Pritchard, Rogers, Prior, & Peterson, 1999; Saxe, Ellsworth, & Heath, 1998; Wand, Midgley, Jones, & Curtis, 1999; Andrew D. B. Leakey et al., 2009). This improved efficiency reduces the amount of water a plant's roots withdraw from the soil profile, reducing irrigation demand and allowing more water to recharge. The SWAT developers acknowledged this phenomenon in the model's documentation, citing a study by Morrison (1987) who found that doubling the CO_2 concentration from 330 to 660 ppm reduced leaf conductance by 40%, and that the reduction was linear. Within SWAT this effect is represented in the calculation of canopy resistance:

$$r_c = (0.5 \cdot g_{l,CO2} \cdot LAI)^{-1} \qquad (5)$$

$$g_{l,CO2} = g_l \cdot \left[1.4 - 0.4 \cdot \left(\frac{CO2}{330}\right)\right] \qquad (6)$$

Where r_c is the canopy resistance (s m^{-1}),

$g_{l,CO2}$ is leaf conductance adjusted for CO_2 concentration (m s^{-1}),

g_l is the maximum leaf conductance (m s^{-1}),

CO_2 is the atmospheric concentration of carbon dioxide (ppm),

and LAI is the leaf area index (dimensionless).

The adjustment for CO_2 was incorporated from Easterling et al. (1992).

Eckhardt and Ulbrich (2003) point out two problems with SWAT's calculation of canopy resistance in situations of elevated CO_2. First, the 40% reduction in leaf conductance is appropriate for agricultural plants, but in trees and grasses the effect is reduced (see also Ficklin, Luo, Luedeling, & Zhang, 2009). Second, SWAT's treatment of *LAI* as a static parameter fails to account for the increase in plant biomass at higher CO_2 levels (Pritchard et al., 1999; Saxe et al., 1998; Wand et al., 1999). Wu, Liu, and Abdul-Aziz (2011) made the following adjustments to $g_{l,CO2}$ and *LAI* to account for these limitations in applying SWAT to the Upper Mississippi River Basin:

$$g_{l,CO2} = g_l \cdot \left[(1+p) - p \cdot \left(\frac{CO2}{330}\right)\right] \quad (7)$$

$$LAI_{mx,CO2} = LAI_{mx} \cdot \left[(1-q) + q \cdot \left(\frac{CO2}{330}\right)\right] \quad (8)$$

Where p is a percentage decrease in leaf conductance for a vegetation class in response to elevated CO_2,

$LAI_{mx,CO2}$ is the maximum LAI for a vegetation class adjusted for CO_2 concentration,

LAI_{mx} is the maximum LAI for a vegetation class,

and q is the percentage increase in LAI for a vegetation class in response to elevated CO_2.

For the future simulations, I modified the SWAT source code to include the change in (7), and I used (8) and the CO_2 values in Table 22 to modify the maximum LAI values for each item in SWAT's plant database (plant.dat file) prior to each new decade. I selected values for p and q from Wu et al. (2011) (Table 24).

Table 24: Land cover specific percent changes in leaf conductance and LAI from elevated CO_2 levels from Wu et al. (2011).

Land Cover	Stomatal Conductance (% change from default)	Leaf Area Index (% change from default)
Cropland	-40	+37
Forest (mixed)	-16	+7
Forest (deciduous)	-24	+7
Forest (coniferous)	-8	+7
Pasture	-26	+20
Range	-21	+15

I generated test outputs with the future climate data for models 04108660 and 04102500 to confirm that the modified SWAT code was functioning properly. For each decade, the simulated average annual recharge was around 5% less and ET was about 1% greater with the modified version of SWAT than with the original version. These results confirmed that the modified SWAT code was moderating the CO_2 effect on plant water efficiency.

One aspect of climate that I left out of my future SWAT simulations was changes to solar radiation and relative humidity. The HCD did not include data for those two variables, and I did not have a basis to derive values solely from daily precipitation and temperature projections. I instead had to rely on SWAT's weather generator (Sharpley & Williams, 1990), which utilizes monthly statistics (mean, standard deviation, skewness, among others) drawn from multiple decades of observations at multiple locations to estimate solar radiation and relative humidity. I ran a few additional test scenarios where I artificially increased each monthly mean of solar radiation and relative humidity in the SWAT Weather Generator by 2% each decade to see how sensitive groundwater recharge and ET were to those variables. I ran these test simulations on SWAT model 04097540 for the CCSM3-A1FI, CCSM3-B1, HadCM3-A1FI, and HadCM3-B1 scenarios. Increasing solar radiation by 2% each decade lowered projected groundwater recharge in the last decade of the century by 4%, 6%, 3%, and 9%, and increased ET by 4%, 5%, 4%, and 3% in CCSM3-A1FI, CCSM3-B1, HadCM3-A1FI, and HadCM3-B1, respectively. Increasing relative humidity by 2% each decade increased groundwater recharge by 2%, 12%, 1%, and 12% and decreased ET by 2%, 8%, 1%, and 4% in CCSM3-A1FI, CCSM3-B1, HadCM3-A1FI, and HadCM3-B1, respectively. The large changes in recharge and ET for B1 emission scenarios were not surprising, because I essentially forced more solar radiation and moisture into scenarios that were already relatively cooler and wetter. Jha et al. (2006) found that increases in solar radiation had a relatively small effect on streamflow in the Upper Mississippi River Basin. But the signal of that effect would be more muted in an output like streamflow than in outputs like recharge and ET that are more directly affected by radiation. Nonetheless, the exclusion of these variables is a limitation of my analysis, and warrants a more thorough investigation in subsequent research.

One last limitation of running SWAT out this far into the future was that I assumed land cover to remain unchanged, which was implausible. At the very least, a growing population would likely add more impervious areas to the landscape, which could dramatically affect watershed hydrology through decreased recharge and flashier stream responses to storms. SWAT includes functionality to change the land cover on a percentage of area within specified sub-basins during a simulation. For example, a user could specify that 10% of deciduous forest area in subbasin 32 will convert to medium density urban 10 years into the simulation. However, SWAT does not allow you to specify where this change will occur; as it calculates runoff, recharge, ET, and other HRU-scale outputs for subbasin 32 it will simply assume that there is 10% less deciduous forest area and that much more area for urban medium density, and adjust outputs accordingly. Because I needed to map the groundwater recharge outputs for use in MODFLOW, this approach was not suitable. I opted to leave land cover static for the climate change simulations, and run subsequent simulations in which I modified the land cover more organically than SWAT's spatially random adjustment. I will discuss this approach later in this chapter.

5.1.3 Running future climate simulations in MODFLOW

Setting up MODFLOW to run under multiple future climate scenarios was much more straightforward than SWAT. Because I had already configured the connection between SWAT outputs and MODFLOW inputs during the calibration and validation phase, I only had to extract SWAT's HRU-scale recharge, and calculate the total water withdrawals from agricultural and golf course wells based upon SWAT's output of irrigation depths on each irrigated HRU. I then modified the input files, ran MODFLOW, and stored its outputs. One of those outputs was a map of ending head values for each cell in the model. For each decade in the future simulations (other than 2010-2019) I used the ending head map of the previous decade's MODFLOW run as the starting head input for the current run. By doing this, I improved the model's processing time and reduced the likelihood that the model would fail to converge; because the starting heads were already close to the ending heads, the model needed fewer iterations to realize the steady-state solution. For example, consider a particular cell with a starting head of 250 meters in 2010. If a climate model projected a sharp increase in recharge for 2090 that would raise the steady-state head in that cell to 265 meters, MODFLOW'S iterative calculation of head across the model domain might stabilize (*i.e.* the overall change in head across the model from one iteration to the next was less than a specified threshold and therefore stopped the iteration loop) before the calculated head in that cell reached 250 meters. However, if I instead used the starting head value from 2080, which was 247 meters, the model would be more likely to reach 250 meters for the 2090 simulation.

5.2 Expanded Urbanization

As I mentioned previously, one of the limitations of the climate change SWAT simulations was my assumption that land cover was static. I explored a scenario in which the extent of urban areas grew as a function of projected population growth. To do this, I utilized recent census data, population projections through 2040, and recent changes in land cover to identify likely areas of future urbanization in the study area. I then used those locations to generate new estimates of SWAT recharge and MODFLOW hydraulic head under both current and future climate conditions.

5.2.1 Preparing the inputs

I wanted to simulate an urbanization scenario that was not spatially random, but continued past trends of growth. Figure 65 illustrates the algorithm I developed to simulate future urbanization. I first sought to define a relationship between land cover change and population growth. I downloaded population totals for the study area from the 2001 and 2010 U.S. Census Bureau (U.S. Census Bureau, n.d.), and calculated an overall population increase for the region of 1.45% over that time period. I then calculated the various land cover changes for the region from the 2001 and 2011 National Land Cover Dataset (NLCD) products (Homer et al., 2007; Homer et al., 2015). Next, I calculated the percentage of each NLCD 2001 class that converted to a NLCD 2011 class. For example, I determined the percentage of deciduous forest area in the region that changed to medium-density residential in NLCD 2011. Next, I treated those land cover changes as a function of population growth. For example if 5% of deciduous forest pixels in NLCD 2001 changed to medium-density residential in NLCD 2011, and population growth changed by 1.45% over a similar time period[12], I then assumed that a 1% increase in population resulted in 3.4% of deciduous forest areas converting to medium density residential (5% / 1.45%). Next, I calculated an average projection of population growth for the region of 5.5% by 2040 from county-level data produced by Grimes and Fulton (2012). I then applied that 5.5% projection to the land cover change / population change function I derived earlier, assuming a direct relationship. For each land cover class I calculated the percentage of area that would change to a particular land cover by 2040 as a function of population growth. Continuing the hypothetical example from above, that function would estimate that 18.7% of deciduous forested area would convert to medium-density residential by 2040 (3.4% * 5.5%).

[12] I acknowledge that the population change period (2000-2010) and land cover change period (2001-2011) do not match. But their durations match, and it was the best available data to make such a comparison.

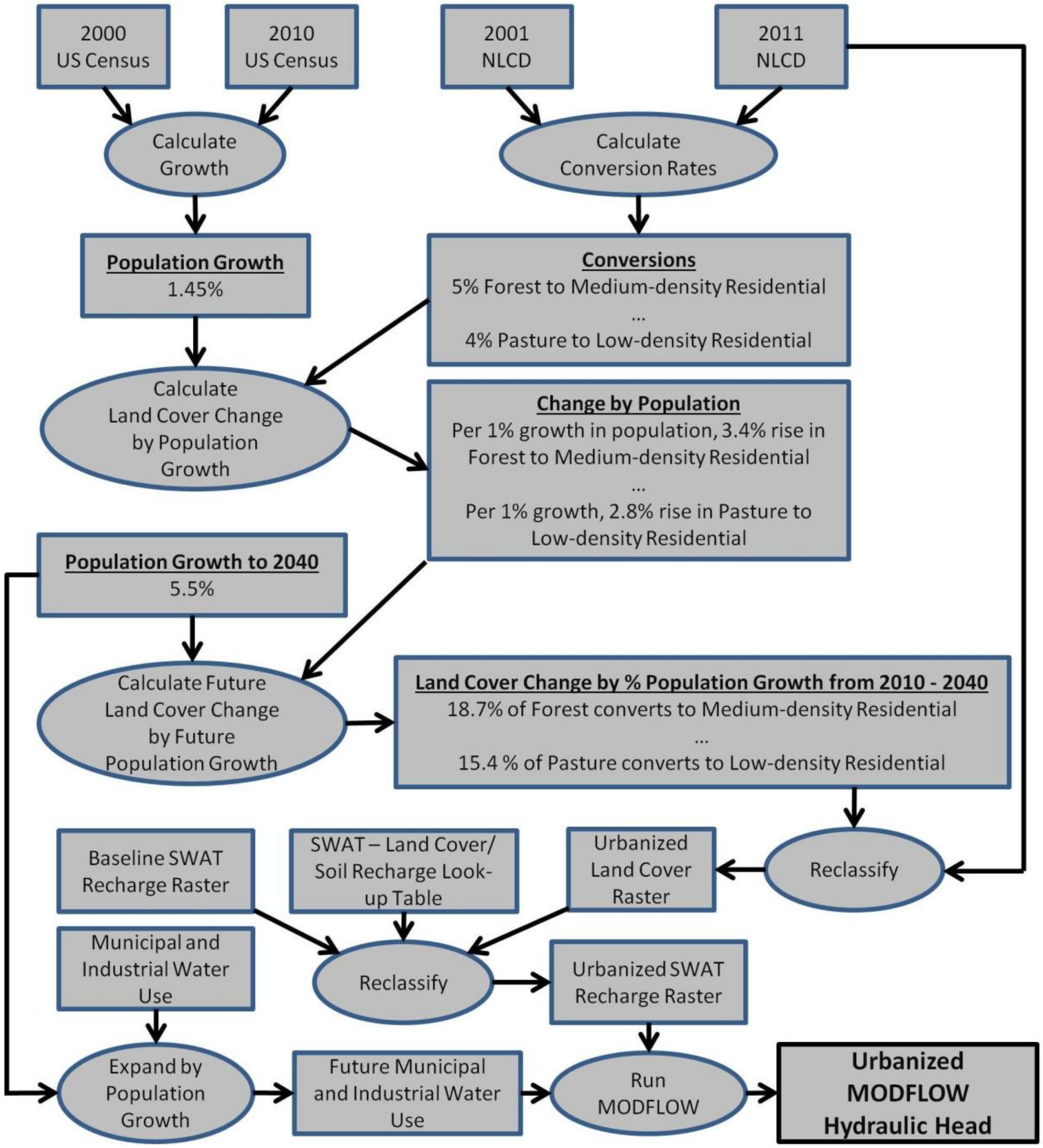

Figure 65: Flow chart for urbanization algorithm. Rectangles represent data, ovals represent functions. The land cover change rates used in the chart are hypothetical, and are solely for demonstration.

The next step in creating the urbanized scenario was to apply those projections to a map of land cover. I developed an algorithm that sought to reclassify pixels in the NLCD 2011 using the land cover change percentages I derived from the 2040 projected population. That algorithm's basic premise was that land cover will tend to urbanize closer to already urbanized areas, and will do so at a rate consistent with estimates of population-driven change from 2001-2011. Continuing with the previous example, the algorithm identified all of the deciduous forest pixels in NLCD 2011 and then sought to convert 18.7% of them to medium-density residential. However, it did not randomly change those pixels; it prioritized them by the degree to which each was adjacent to other urban pixels. For example, if a particular deciduous forest pixel was surrounded by urban pixels, then it was given the highest conversion priority. If the pixel's neighborhood was a majority of urban pixels (5 or more out of the 8 neighbors) it was given the next highest priority. A plurality of urban pixels received the next highest priority; and having at least one urban pixel neighbor received the lowest. The algorithm would not convert a deciduous forest pixel if it did not have urban neighbors. The algorithm iterated randomly over all of the deciduous forest pixels until 18.7% had been converted to medium-density residential, or until there were no more deciduous forest pixels with adjacent urban ones. The algorithm then moved on to the next land cover change relationship, deciduous forest to high-intensity residential, for example. Because the goal of this process was to create a hypothetical urbanization scenario, the algorithm did not convert pixels to non-urban classes, such as deciduous forest to pasture, nor did it convert urban pixels to classes of lesser imperviousness, such as high-intensity residential to low-intensity residential, or to open grass land. The algorithm's output was a raster dataset of urbanized areas in 2040. Figure 66 shows examples of land cover before and after the urbanization algorithm was utilized.

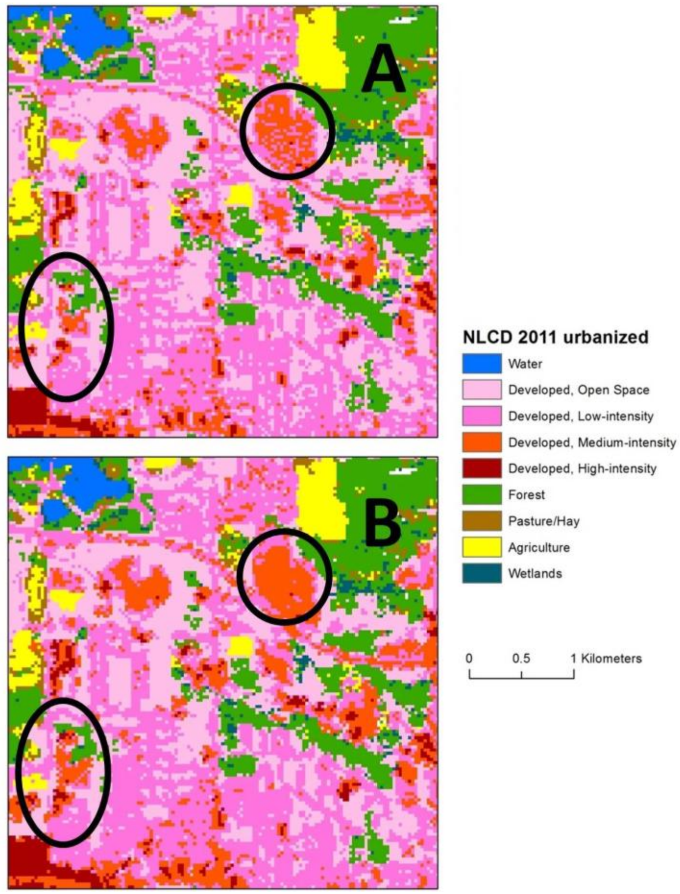

Figure 66: Results from urbanization algorithm. A) Sample from NLCD 2011 raster for SWAT model 04108660. B) Same area after running urbanization algorithm. Circled areas highlight areas of notable change.

5.2.2 Running future urbanization scenarios in SWAT

I then sought to generate new SWAT outputs with the urbanized land cover dataset. I first converted the dataset from urban NLCD codes to the standard land covers SWAT keeps in its database (Table 25). At first I attempted to use this urbanized land cover dataset to create a new set of HRUs, but quickly realized that the HRU definition process would aggregate most of these urbanized areas up to larger land cover classes, thereby defeating the point of the exercise. I instead used a look-up table of recharge values that I had generated as an output of each SWAT simulation to manually assign a recharge value to a particular cell. The look-up table contained annual recharge estimates for each HRU (*i.e.* for each unique land cover, soil type, slope, and subbasin combination) for a particular simulation (*e.g.* CCSM CM3 – A1FI). For example, as I discussed in *3.3.2 HRU Mapping and Outputs*, I generated an annual recharge raster dataset from each SWAT simulation, which I then used as an input to MODFLOW. If the urbanization algorithm projected a particular land cover pixel to convert to SWAT's urban high-density class (URHD), I changed the value in the original recharge raster for just that pixel to an appropriate URHD value stored in the look-up table[13]. The non-urbanizing pixels retained their original recharge values. The end result was a recharge raster which reflected updated values (always less than the original recharge estimate) for urbanizing pixels. I generated such a raster for every SWAT simulation, including all of the climate scenarios.

Table 25: NLCD 2011 urban class conversions to SWAT urban classes.

NLCD 2011 Land Cover Class	NLCD 2011 Code	SWAT Land Cover Class	SWAT Land Cover Code
Developed, Open Space	21	Residential-Low Density	URLD
Developed, Low Intensity	22	Residential-Medium/Low Density	URML
Developed, Medium Intensity	23	Residential-Medium Density	URMD
Developed, High Intensity	24	Residential-High Density	URHD

There were limitations to this approach. Ideally I would have utilized data that projected population growth to 2100, so that the landscape could urbanize over time as opposed to using what amounts to a single snapshot of an urbanized future; but that dataset does not exist.

[13] I did not just pick a random recharge value, though. I utilized a prioritization scheme similar to the approach I used to assign IDs to HRUs orphaned by the HRU definition process (see *3.2.6 HRU Definition*). This scheme sought to find a recharge value that matched the slope and soil type of the urbanizing pixel, and started looking in the pixel's sub-basin, then in the next closest subbasin, and so on.

Another limitation of my approach was that I assumed that the relationship between land cover and population growth was valid and linear. There are multiple drivers of urbanization, including regional economic health, government fiscal policy, transportation infrastructure, and demographic shifts, but past and projected population growth was readily accessible and served as an adequate indicator of increasing imperviousness in the region. Lastly, there are feedbacks in any long-term projection, especially for processes as complex as urbanization; my simple approach here likely failed to account for some of those. My goal in this study was to provide an initial assessment of the role of land cover change on recharge and hydraulic head, which this relatively simple approach allowed me to do. As I more fully explore those relationships in subsequent research, I will employ more sophisticated and computationally intensive urban growth models such as SLEUTH (Silva & Clarke, 2002; UCSB, n.d.).

5.2.3 Running future urbanization scenarios in MODFLOW

Running the urbanized scenarios through MODFLOW required little additional preparation. I had already established the connection between SWAT and MODFLOW during the calibration and validation; so I only had to provide the SWAT recharge from the urbanized scenarios to MODFLOW. The one additional modification I made was to assume a one to one relationship between population growth and water use and increase municipal and industrial water withdrawals to reflect the projected 5.5% population increase reported in Grimes and Fulton (2012). I acknowledge that a linear relationship for water use with both population growth and economic activity are tenuous assumptions. Though an increase in the population necessarily adds more straws to the region’s figurative glass of water, a linear relationship with consumption does not account for future improvements in water use efficiency or conservation (which are hard to project). While industrial water use is likely more directly linked with economic growth than population growth, I did not have data on long-term projections of economic growth. However, I anticipate that an expansion in urbanization will entail some increase in industrial activity, and therefore felt it important to simulate such an increase, even if it required a relatively crude assumption.

5.3 Expanded Agriculture

I generated hypothetical examples of expanded agricultural areas in much the same manner as I generated the urban scenarios. I calculated rates of land cover change to row-crop agriculture[14] from the NLCD 2001 to NLCD 2011, and then used those rates to identify the most likely pixels to convert to row-crop agriculture in the future. Whereas in the urbanization scenario I used a projected population increase of 5.5% to drive the future land cover change, in this agricultural expansion scenario I picked an arbitrary target of converting 5% of the landscape. I initially explored using changes in agricultural hectares from the 2002 and 2012 NASS Ag Censuses, but those numbers declined in the study region over that time period. However, one of the tenets of this research is that a growing global population will require more food production from water-abundant regions. Therefore I sought to explore the

[14] I focused the agricultural expansion on row-crop agriculture, and did not include pasture land. The vast majority of agricultural hectares (79%), farms (81%), and agricultural market value (83%) for Kalamazoo County are from cropland (NASS - U.S. Department of Agriculture, 2012), therefore I assumed that a future increase in agricultural production would also be dominated by cropland as opposed to pasture land for livestock. Furthermore, because I did not model livestock production in the initial, calibrated SWAT models (see *3.2.3 Land Cover*) I could not expand its presence in the future SWAT simulations.

potential impacts of expanding agriculture in such a region, even if recent trends indicate that farmland may be decreasing. Figure 67 illustrates the approach I developed.

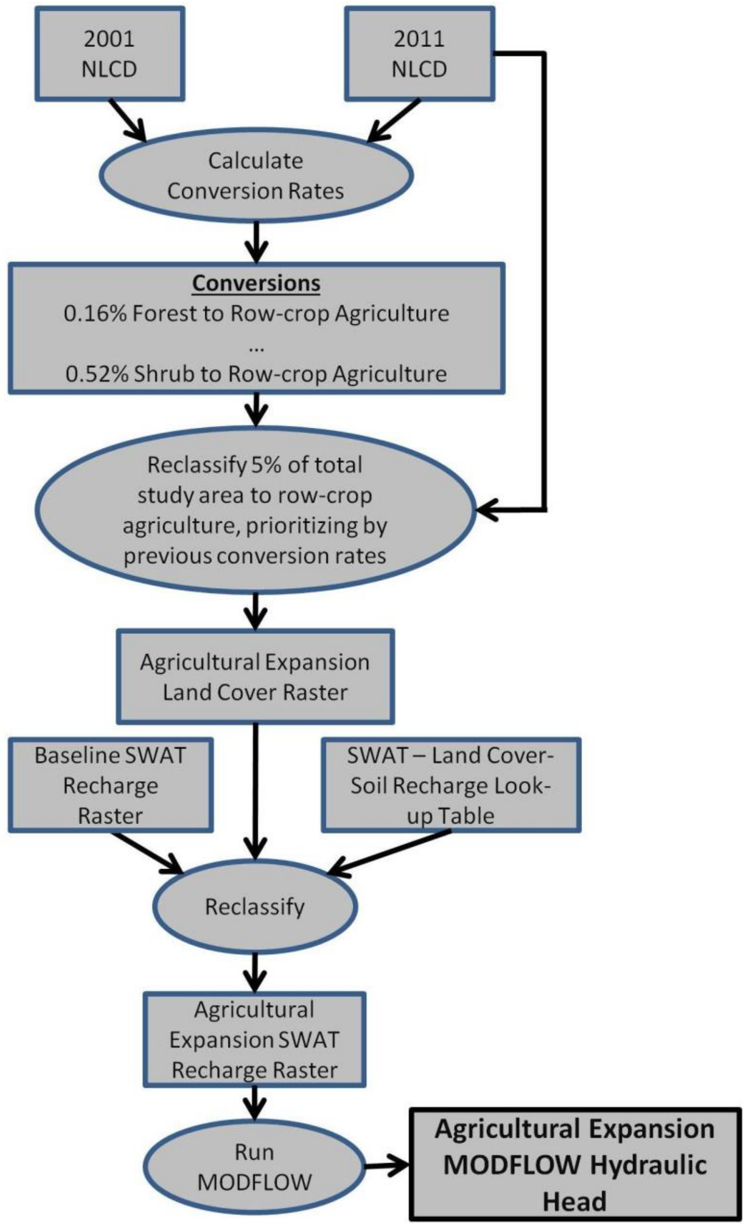

Figure 67: Flow chart for agricultural expansion algorithm. Rectangles represent data, ovals represent functions.

5.3.1 Preparing the inputs

I calculated the percentage of each NLCD 2001 class that changed to row-crop agriculture in NLCD 2011. The most likely land covers to do so were barren land (NLCD code 31, 4.05% of NLCD 2001 pixels converted to agriculture), shrub (NLCD code 52, 0.78%), pasture (NLCD code 81, 0.24%), and deciduous forest (NLCD code 41, 0.16%). I developed a search algorithm to convert these pixels that functioned the same way as the urbanization algorithm. It iterated over the land covers above, in the order they were listed, and then randomly iterated over the land cover's pixels, analyzing each pixel's neighborhood to evaluate how likely it would convert. For example, barren land pixels surrounded by agriculture were highly likely to convert. If the algorithm selected a particular pixel to change, it decided the agricultural class to assign it to by identifying the most dominant SWAT class in the neighborhood (*e.g.* CSCS - corn-soy-corn-soy rotation, SOYB – continuous soybean, CORD – deep-aquifer irrigated continuous corn). Once the algorithm had iterated over all of the barren land pixels, it then randomly searched through shrub pixels, and so on. If at any point 5% of the total landscape had been converted the search stopped. Figure 68 shows examples of land cover before and after the agricultural expansion algorithm was utilized.

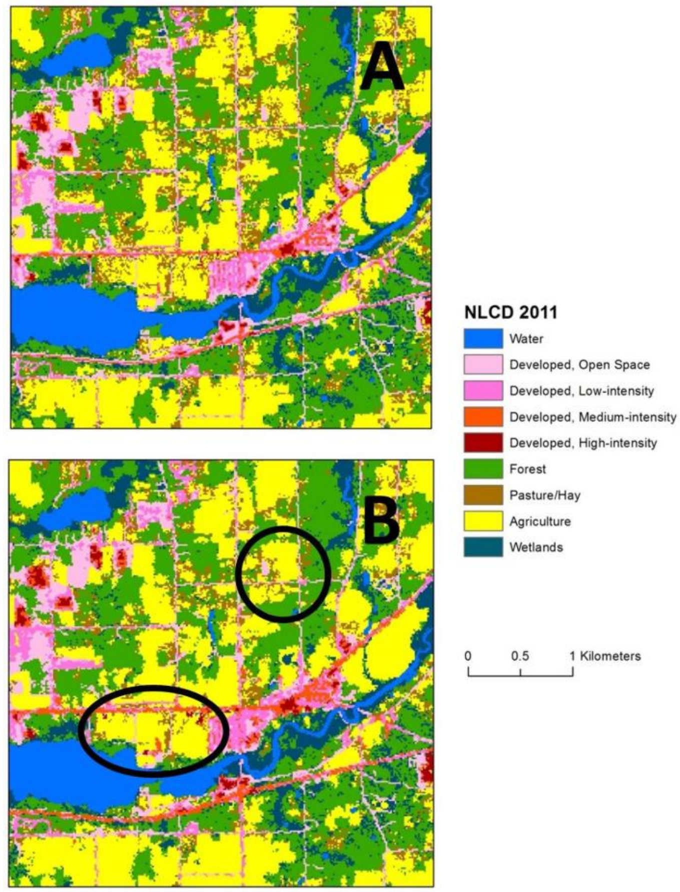

Figure 68: Results from agricultural expansion algorithm. A) Sample from NLCD 2011 raster for SWAT model 04106000. B) Same area after running agricultural expansion algorithm. Circled areas highlight notable changes.

5.3.2 Running future agricultural expansion scenarios in SWAT

As I did in the urbanization expansion scenario, I generated new recharge rasters based upon the agricultural expansion using the HRU look-up table. This approach was much faster and more efficient then trying to create completely new HRUs and re-running SWAT for every climate scenario, and avoided the issue of losing all of the changed pixels during the HRU definition process. In expanding the agricultural areas I made no assumptions about changes in irrigation. If the neighborhood of a changing pixel happened to be dominated by an irrigated land cover class then the conversion would result in an increase in total irrigation, but only because of the land cover change; I did not turn on irrigation on any previous un-irrigated agricultural pixels.

5.3.3 Running future agricultural expansion scenarios in MODFLOW

To generate new MODFLOW outputs for the agricultural expansion scenario I simply provided the new SWAT recharge rasters as inputs. I still calculated agricultural withdrawals from the SWAT irrigation estimates, but those amounts likely changed little. As I described in the previous section, additional irrigation was only added if a particular changing pixel's neighborhood was dominated by an irrigated land cover. The maximum increase in irrigated area would have been 5% of the total study area, but this was never the case. In SWAT model 04106000 less than 1% of the landscape changed to an irrigated land cover.

5.4 Combined Scenarios

Lastly, I combined the urbanization and agricultural expansion algorithm outputs into a combined scenario in which imperviousness increased for a fraction of the landscape while another fraction was moved into agricultural production from barren land, shrub, pasture, and forest. Like the previous scenarios, this combined scenario was ultimately run through MODFLOW to yield hydraulic head estimates for all of the climate models.

CHAPTER 6: Hydrologic Model Results and Analysis

6.1 SWAT Outputs

SWAT produced estimates on a range of outputs, and at various spatial scales for each simulation. These outputs included basin-wide averages of groundwater recharge, evapotranspiration, and streamflow, and HRU-scale outputs of recharge, irrigation totals, and crop yields. In this section I will present these outputs for the various climate change scenarios. Because I did not run SWAT for the urbanization and agricultural expansion scenarios (I simply modified the values of the groundwater recharge rasters for selected pixels), I do not have basin-scale outputs to display for them.

6.1.1 Basin-scale ET

I will show the results of ET first because they will inform the presentation of the groundwater recharge results.

ET exhibited varying results, both between emission scenarios and between the SWAT models that intersected the MODFLOW model boundary (Figure 69)[15]. While ET was relatively flat in the A1B and B1 scenarios, it dropped off dramatically in the A2 and A1FI scenarios, in spite of their significantly higher temperatures at the end of the century. These differences are a direct result of the improved plant water efficiency at elevated CO_2 levels, (*see section 5.1.2 Running Future Climate Simulations in SWAT*). A1FI and A2 have the highest concentrations of

[15] Though I generated outputs for all 12 of the SWAT models that I calibrated, to conserve space on the page I chose to focus on the results for just those models that intersect, the MODFLOW model boundary.

CO_2 (Table 22). I ran a test climate change simulation on SWAT model 04097540 in which I held CO_2 constant (Figure 70 and Figure 71) through the century. ET increased in all simulations, with the higher temperatures driving the largest ET rates in the A1FI and A2 emission scenarios.

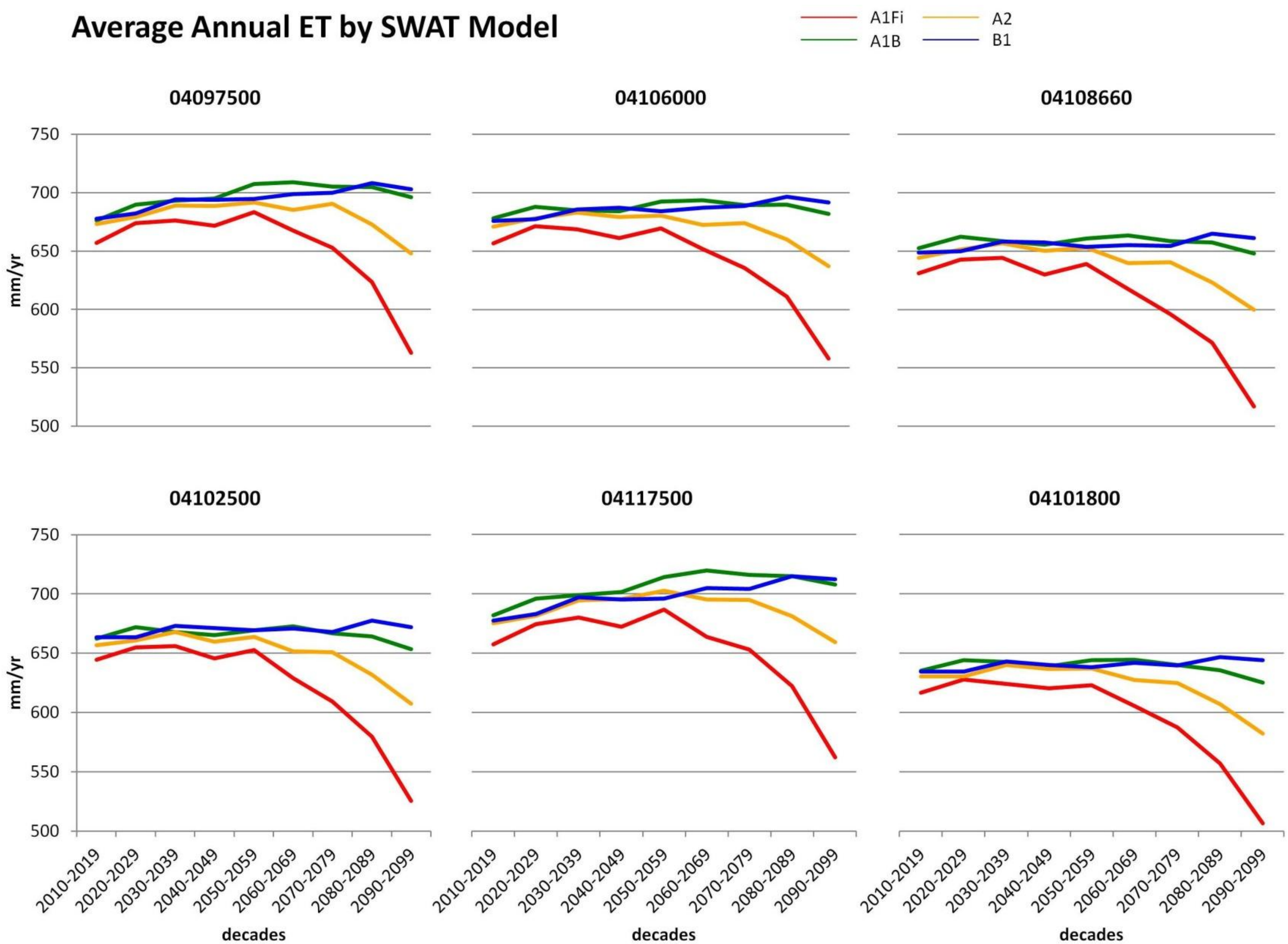

Figure 69: Average annual ET rates by emission scenario, across the 6 SWAT models that intersect the MODFLOW model boundary.

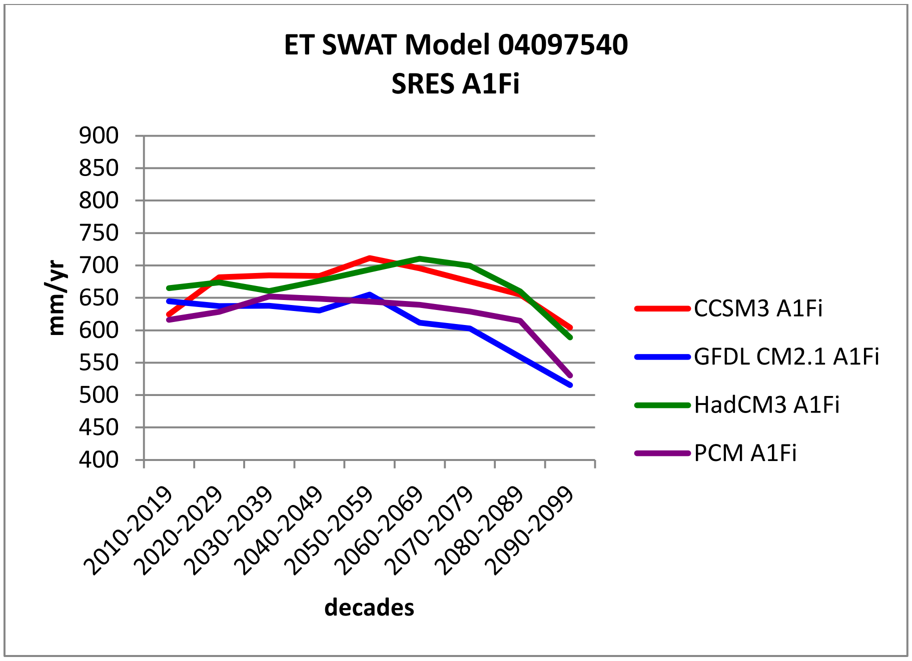

Figure 70: ET for SWAT model 04097540, under 4 climate models from emission scenario A1FI.

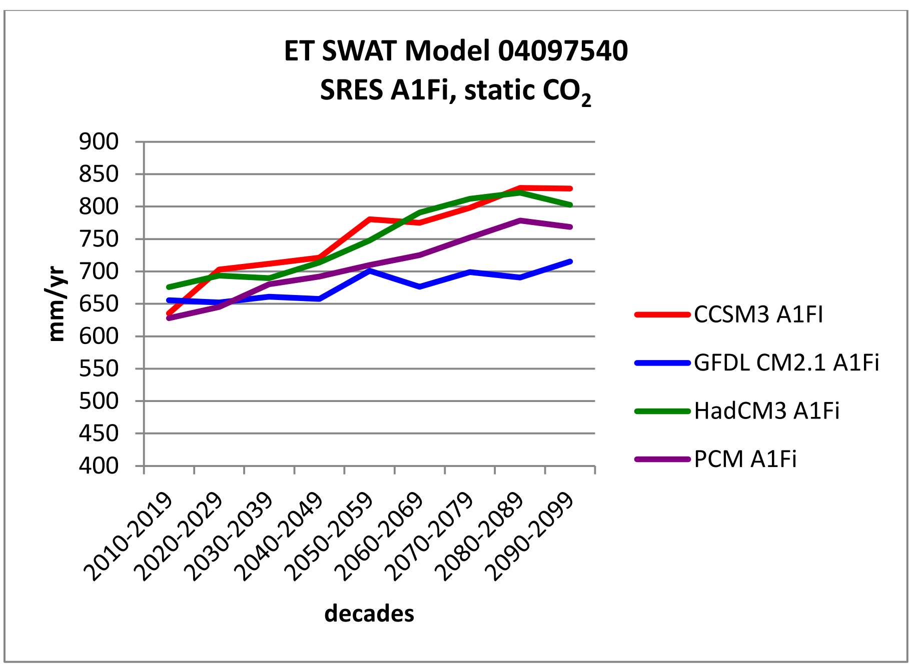

Figure 71: ET for SWAT model 04097540, under 4 climate models from emission scenario A1FI, but with CO_2 levels held constant at SWAT's default value of 330 ppm.

The difference in ET rates between the SWAT models was mainly due to their varying soil types. Model 04117500 had a much higher concentration of soils in the C and D hydrologic groups (Table 26). C and D soils are characterized by higher percentages of clay than the A or B groups, giving them a much higher water retention capacity. The soils in 04117500 were better able to retain infiltrated water than in the other SWAT models, thereby providing more opportunity for that water to be used by plants or to evaporate directly from the soil profile. Even though the models closer to Lake Michigan (04108660, 04101800, and 04102500), received more precipitation, 04117500's clay-rich soils yielded higher rates of ET.

Table 26: Hydrologic soil groups (HSG) in selected SWAT models.

SWAT Model	% of soils in HSG A	% of soils in HSG B	% of soils in HSG C	% of soils in HSG D
04097500	14	78	3	5
04106000	20	66	8	6
04108660	38	48	10	4
04102500	46	42	9	3
04117500	9	68	21	2
04101800	36	58	0	6

Figure 72 shows average ET rates for each month (*e.g.* the average January ET from 2030 through 2039) for SWAT model 04108660. ET rates for the A1B and B1 emission scenarios rates are relatively flat through 2100, while A1FI and A2 trend downward. A1FI in particular drops off at the end of the century for every month, with the summer months experiencing the sharpest decline. This large summer decline was expected because that is when the now water-efficient plants would otherwise be at their peak stages of photosynthesis and transpiration. Despite these differences, the relative volumes of monthly ET did not change across the various emission scenarios or decades. For each scenario and decade, ET was lowest in January, steadily rose to June and July, and then began to decline.

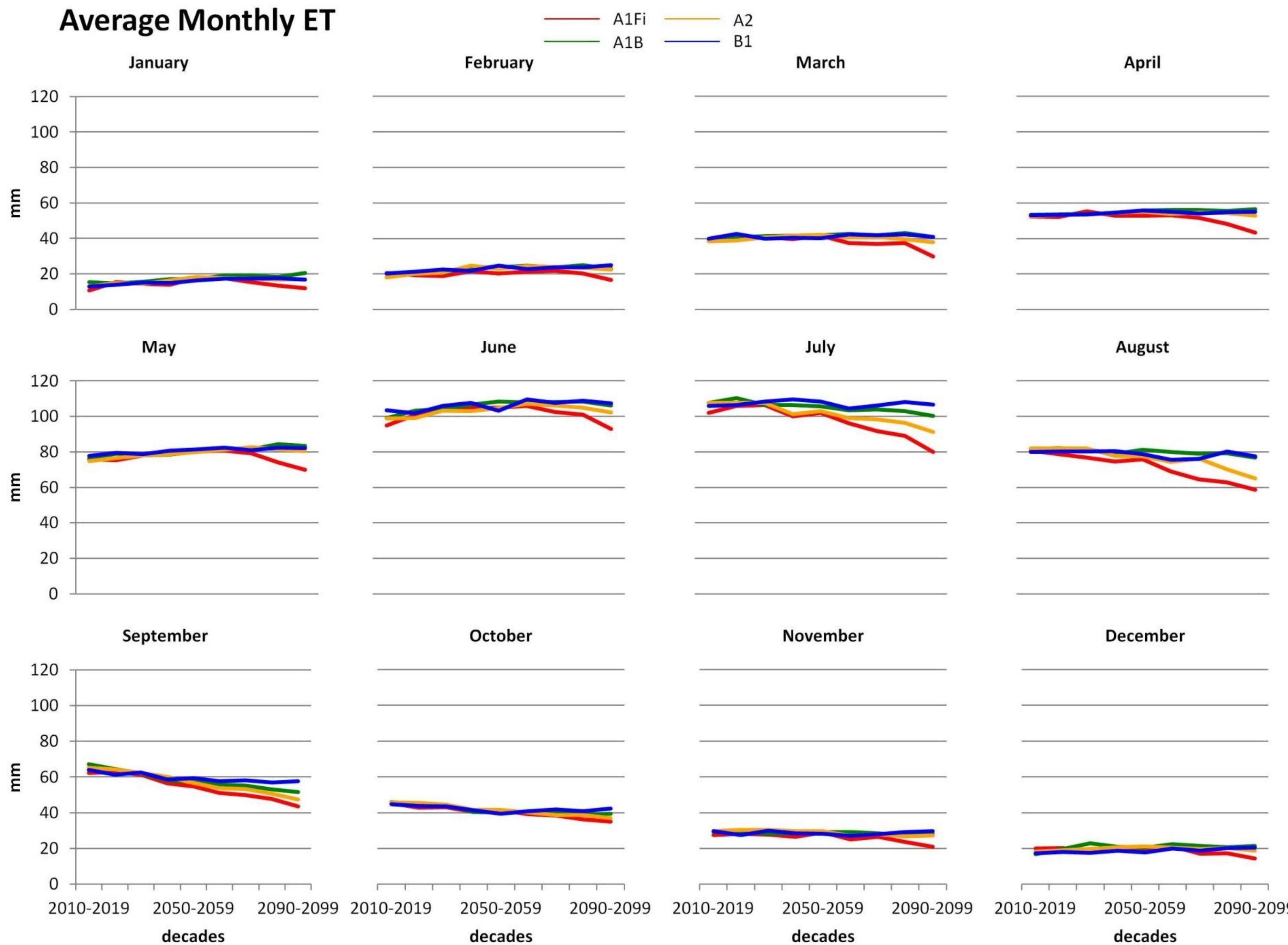

Figure 72: Average monthly ET rates by emission scenario, in SWAT model 04108660.

6.1.2 Basin-scale Groundwater Recharge

When averaged by emission scenario, groundwater recharge increased throughout the century in the 5 SWAT models that intersected the MODFLOW model boundary, with A1FI projecting the largest increase and B1 projecting the smallest (Figure 73). The variability in recharge between emission scenarios was primarily because of changes in ET. Though the projections of average annual precipitation showed slight differences between the emission scenarios (Figure 58), those differences alone did not account for the projected changes in recharge. Using SWAT model 04097500 as an example, the A1Fi emission scenario projected average annual recharge at the end of the century to be 452 mm, and 257 mm in the B1 emission scenario, a difference of 195 mm. A1Fi projected average annual precipitation for 04097500 at the end of century to be 1049 mm under emission scenario A1FI, and 988 mm under B1; a difference of 61 mm. A1Fi projected average annual ET for 04097500 to be 563 mm under A1FI, and 703 mm under B1; a difference of 140 mm. In this case, 72% (140mm/195mm * 100) of the increase in recharge between the two emission scenarios was the result of decreased ET.

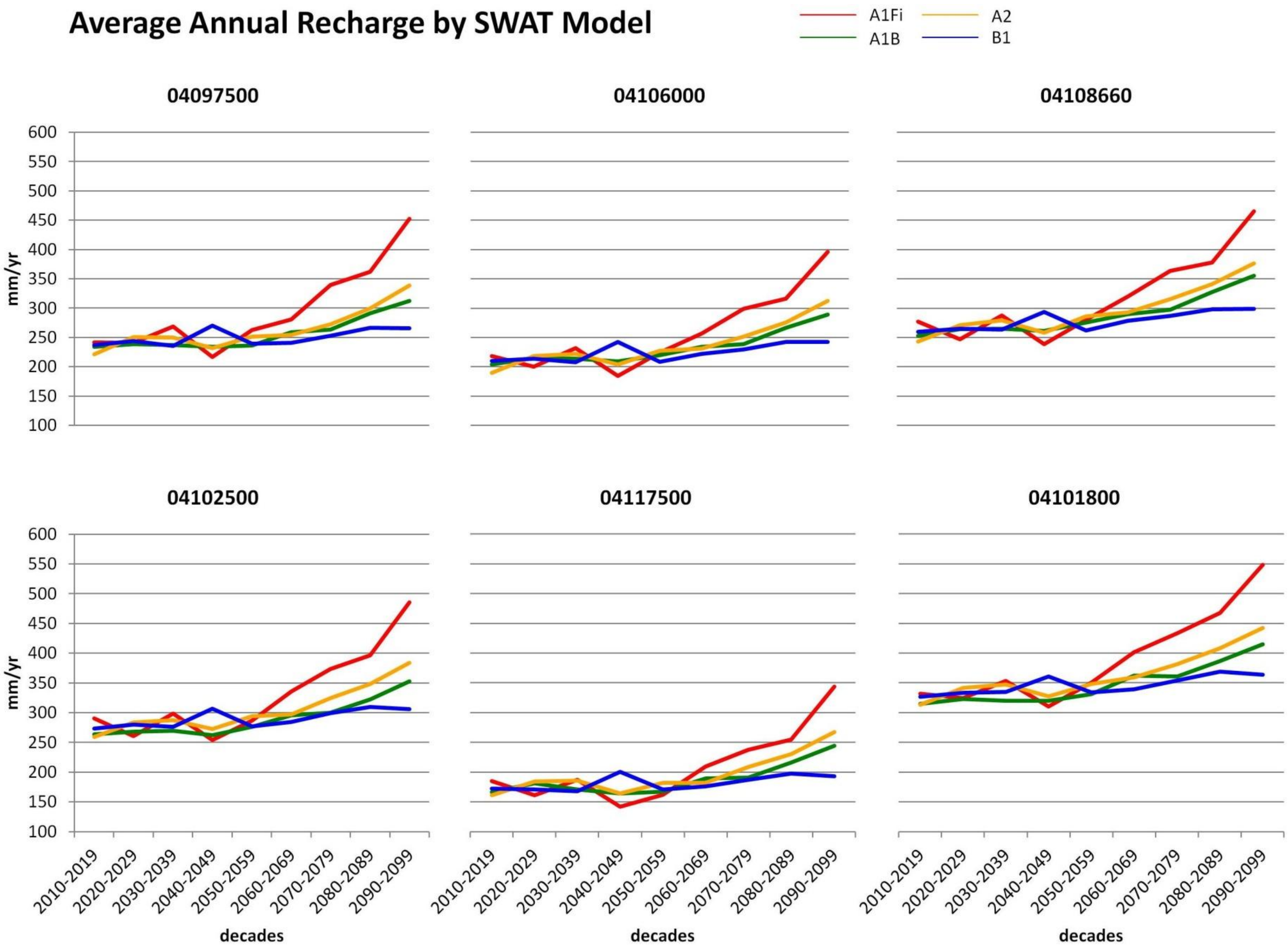

Figure 73: Average annual recharge rates by emission scenario, across the 6 SWAT models that intersect the MODFLOW model boundary.

The variability between the SWAT models was partially attributable to differences in precipitation and soil type. The models closer to Lake Michigan (04108660, 04101800, and 04102500), and therefore more prone to lake effect snow, tended to have higher recharge totals. Model 04101800 had the highest overall recharge totals because of its proximity to the lake, but also because it had the highest concentration of soils belonging to the well-drained A and B hydrologic soil groups (Table 26).

Figure 74 and Figure 75 illustrate recharge in SWAT model 04108660. Figure 74 shows average recharge rates for each month (*e.g.*, the average January recharge from 2030 through 2039). The results showed a general trend of increasing recharge for each month, particularly for the A1FI and A2 scenarios, with a few exceptions. Recharge dipped slightly in March for the B1 scenario, and was relatively flat for all of the scenarios in July and August. When compared to Figure 62, it might seem odd that recharge was flat in those months for the A1FI scenarios, because of the projected decline in precipitation. However, as seen in Figure 72, the reduction in ET for A1FI was most dramatic during those two months, offsetting the additional volume brought by the higher precipitation. The most dramatic increase in monthly recharge was in April for the A1FI scenario, which corresponded with a sharp increase in precipitation (Figure 62) and the time of year in which ET began to drop off more substantially (Figure 72). Figure 75 shows recharge among the eleven climate models that had data for emission scenario A2, and illustrates the large variability among them. With data from climate model HadGEM-A2, SWAT projected an average July recharge of 0.4 mm, whereas climate model ECHO projected 56.5 mm.

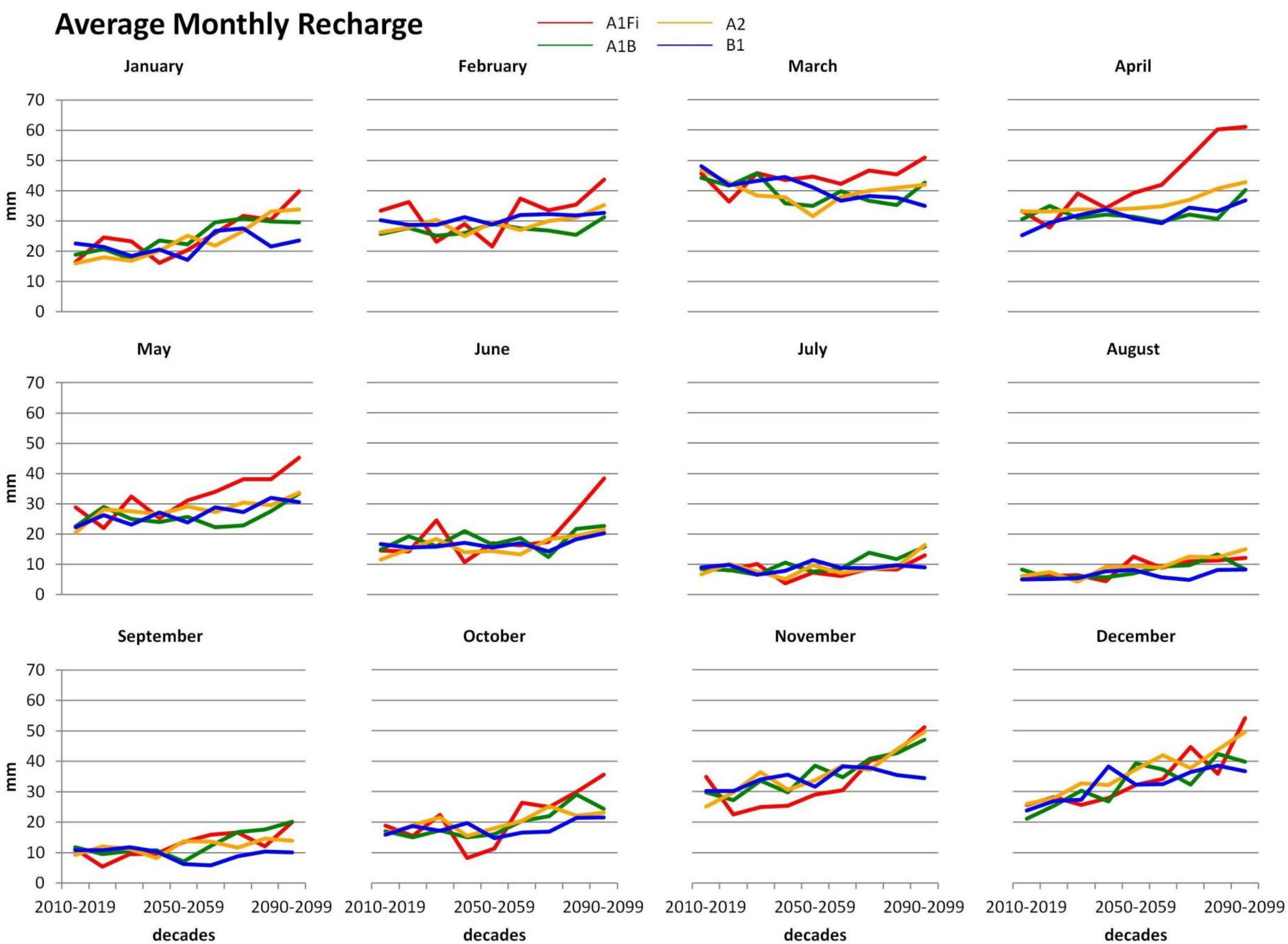

Figure 74: Average monthly recharge rates by emission scenario, in SWAT model 04108660.

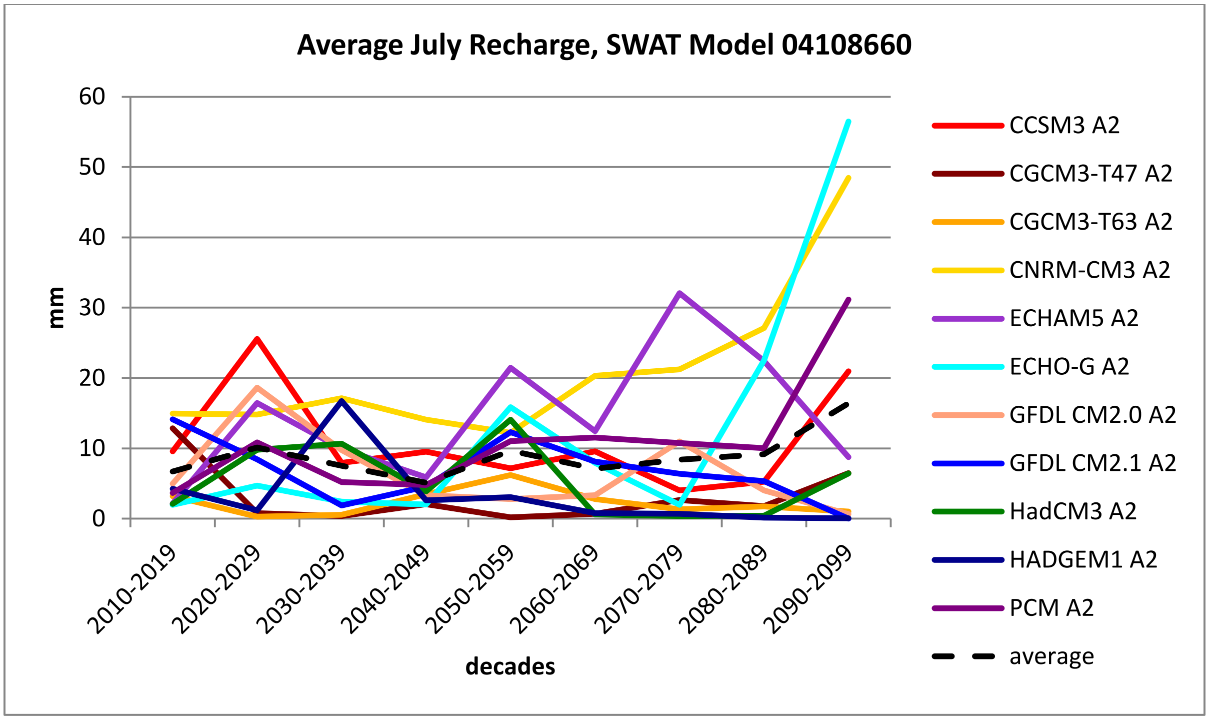

Figure 75: Average recharge in July for SWAT model 04108660, for the climate models with data for SRES A2.

6.1.3 Irrigation

Though SWAT calculates and reports irrigation at the HRU spatial scale, I calculated basin-wide averages in order to observe trends over time and compare separate models. Whereas with ET and recharge SWAT projected that the outputs would increase in some climate models and decrease in others, SWAT projected reductions in irrigation for almost all of the climate models. Irrigation only increased in the GFDL CM2.0 climate model's A2 and B1 emission scenarios, and the HADGEM1 A1B climate model. The trend was clear in the emission scenario averages for each SWAT model (Figure 76), and in the graphs for each of the climate models simulated in SWAT model 04108660 (Figure 77). As with the previous outputs, the differences between the emission scenarios were primarily a function of CO_2 concentration. SWAT's irrigation routine is based on the daily water demand for each plant; as plants become more water efficient at the elevated CO_2 levels, they require less irrigation. The reduction in irrigation was also a function of the overall increase in precipitation. Even though ET increased for the A1B and B1 emission scenarios in SWAT model 04097500, which would imply that there was less water in the soil profile and therefore a greater demand for it, irrigation declined. Model 04097500 was projected to see the same overall increase in precipitation, in all emission scenarios, as in model 04108660 (Figure 58).

6.1.4 Streamflow

The effect of CO_2 on ET had a corollary effect on streamflow. More water retained in the soil profile meant that more water was available to be discharged as baseflow into streams. Figure 78 shows the changes in groundwater discharge, averaged by emission scenario, for SWAT model 04108660. The trend in Figure 78 was the same for the other SWAT models, though their varying precipitation amounts caused the total volumes of groundwater discharge to differ. Figure 79 indicates that the surface runoff component of streamflow was relatively flat through the end of the century and for all emission scenarios. As the century progressed and CO_2 levels increased, more streamflow came from groundwater. Using the streamflow projections from 04108660, the baseflow index increased from 87% in the 2010-2019 time period to 92% at the end of the century under the A1FI emission scenario, but only from 87% to 88% under the B1 scenario.

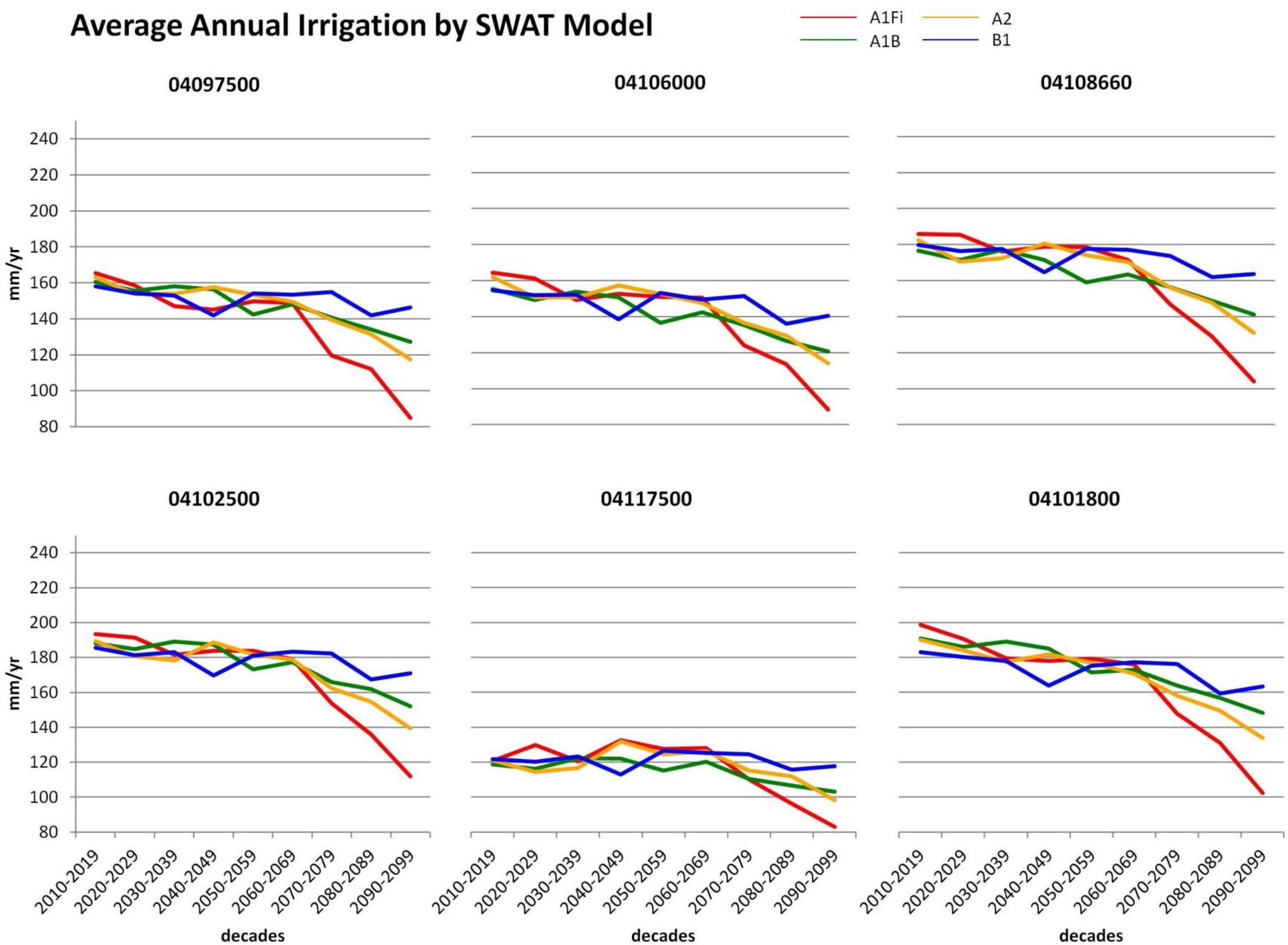

Figure 76: Average annual irrigation rates by emission scenario, across the 6 SWAT models that intersect the MODFLOW model boundary. Note that these are average depths applied to irrigated land covers; they do not represent the overall volume of irrigation in a particular SWAT model.

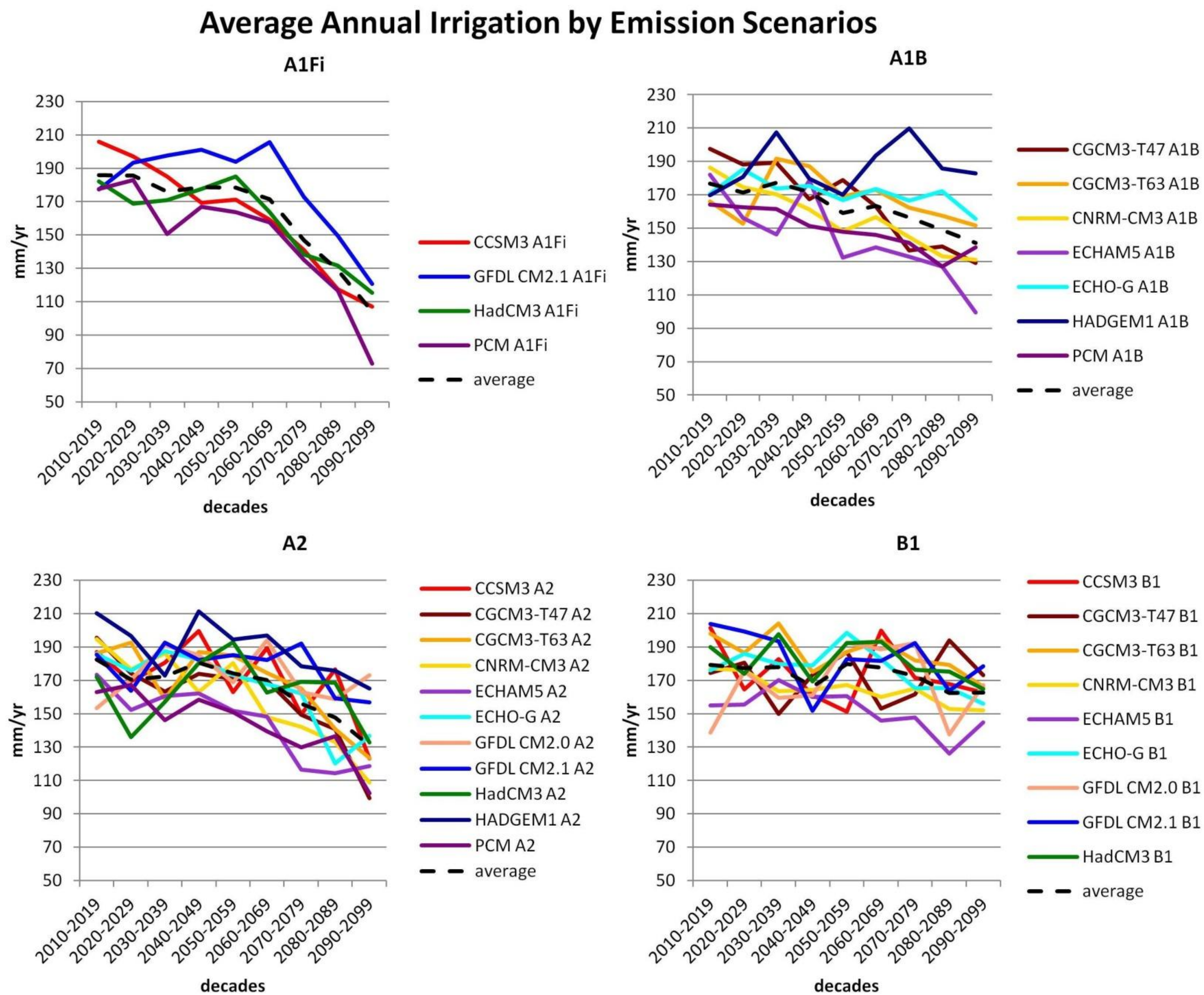

Figure 77: Average annual irrigation by emission scenario, for SWAT model 04108660.

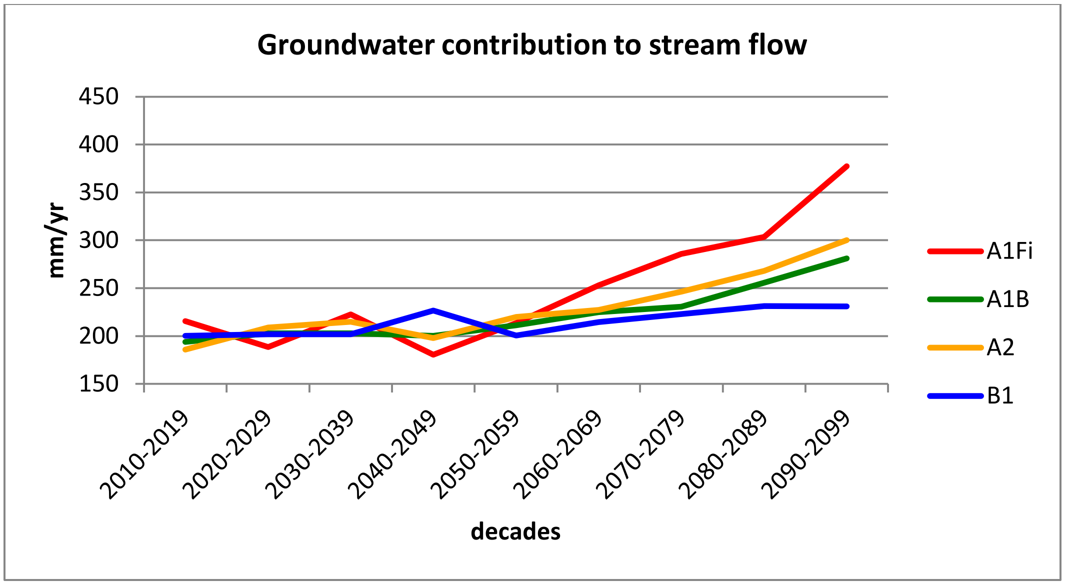

Figure 78: Groundwater discharge to streams in 04108660, averaged by emission scenario.

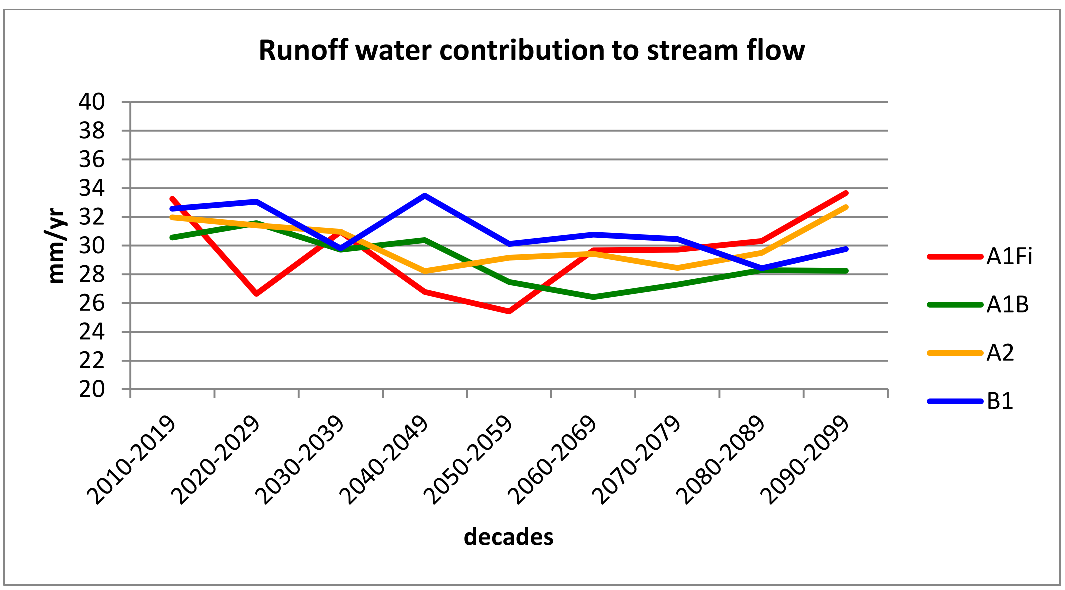

Figure 79: Surface water runoff to streams in 04108660, averaged by emission scenario.

Figure 80 shows average daily flow by month, averaged by emission scenario, for SWAT model 04108660. All the months reflected the annual trend of increasing flow throughout the century, with March in the B1 emission scenario being the only exception. The most striking result in those graphs was the dramatic increase in the A1FI scenario, with an average increase in monthly flow of 75% from the 2010-2019 period through the end of the century, including a 95% increase for August. Less obvious were the subtle changes in the timing of the year's flows. There was a slight shift among the emission scenarios for more of the overall flow volume to occur in the later spring and early summer at the end of the century than in the beginning. For example, in the B1 scenario, March had the highest average daily flow for the 2010-2019 time period, but only the 4th highest by the end of the century. By the 2090-2099 time period the highest flows for B1 occurred in April, which was also the month of highest flow for the three other emission scenarios. The other scenarios all had at least one spring or summer month move up in the relative rankings of flows, at the expense of a winter month.

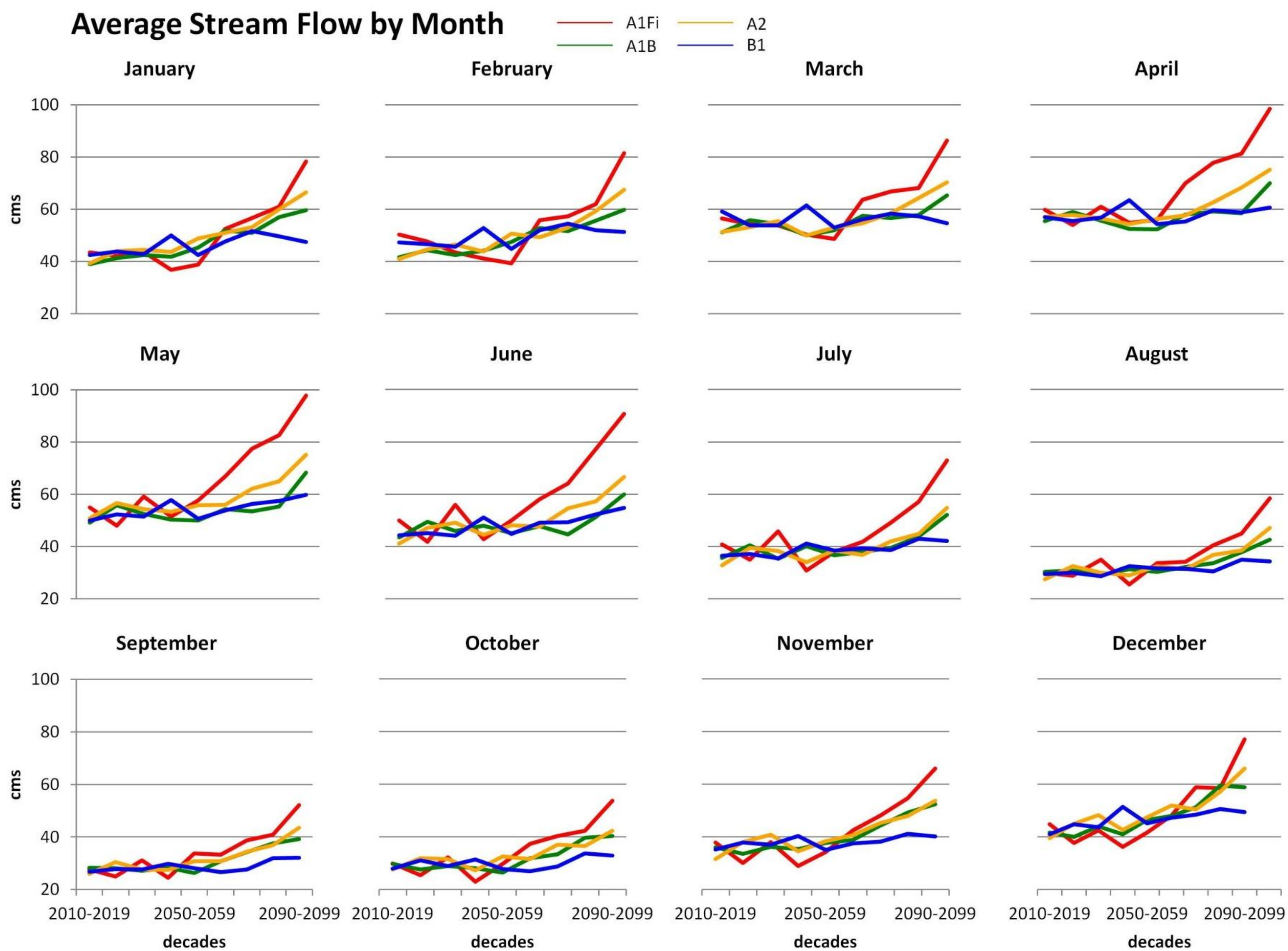

Figure 80: Average daily streamflow by month, averaged by emission scenario, for SWAT model 04108660.

6.1.5 Crop Yields, Planting Dates, and Harvest Dates

Similar to irrigation, SWAT reports crop outputs at the HRU scale; but I also calculated basin-wide averages from the HRU outputs. Projected corn and soybean yields were relatively flat through the end of the century when averaged by emission scenario, with slight increases for the A1FI and A1B scenarios. That trend held for each of the SWAT models. Figure 81 illustrates changes in corn yields for SWAT model 04108660. It is important to point out the lines in Figure 81 represent average yields among climate models for each emission scenario; corn yield was sensitive to variation among the climate models (Figure 82). Yields were another output that demonstrated the importance of considering multiple future climate models.

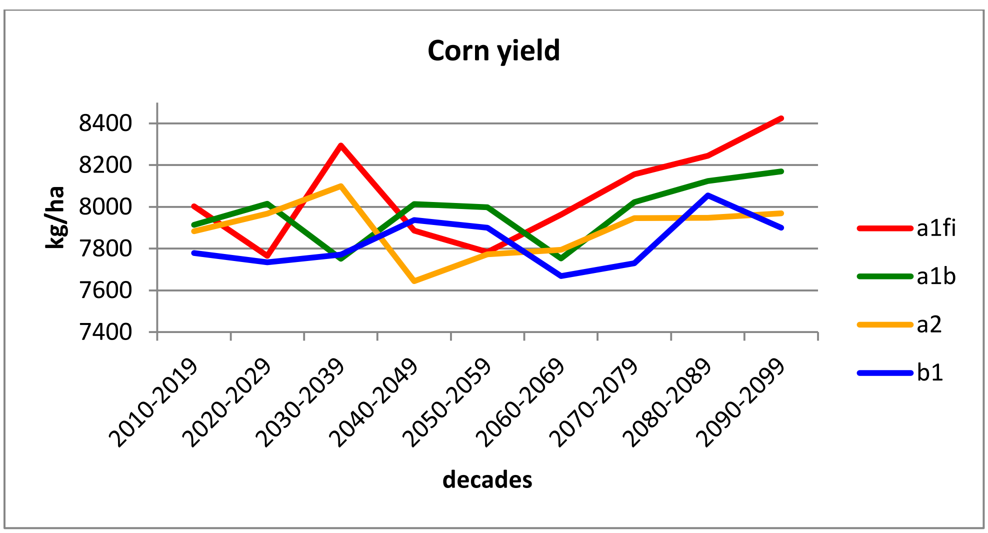

Figure 81: Annual corn yield, averaged by emission scenario, for SWAT model 04108660.

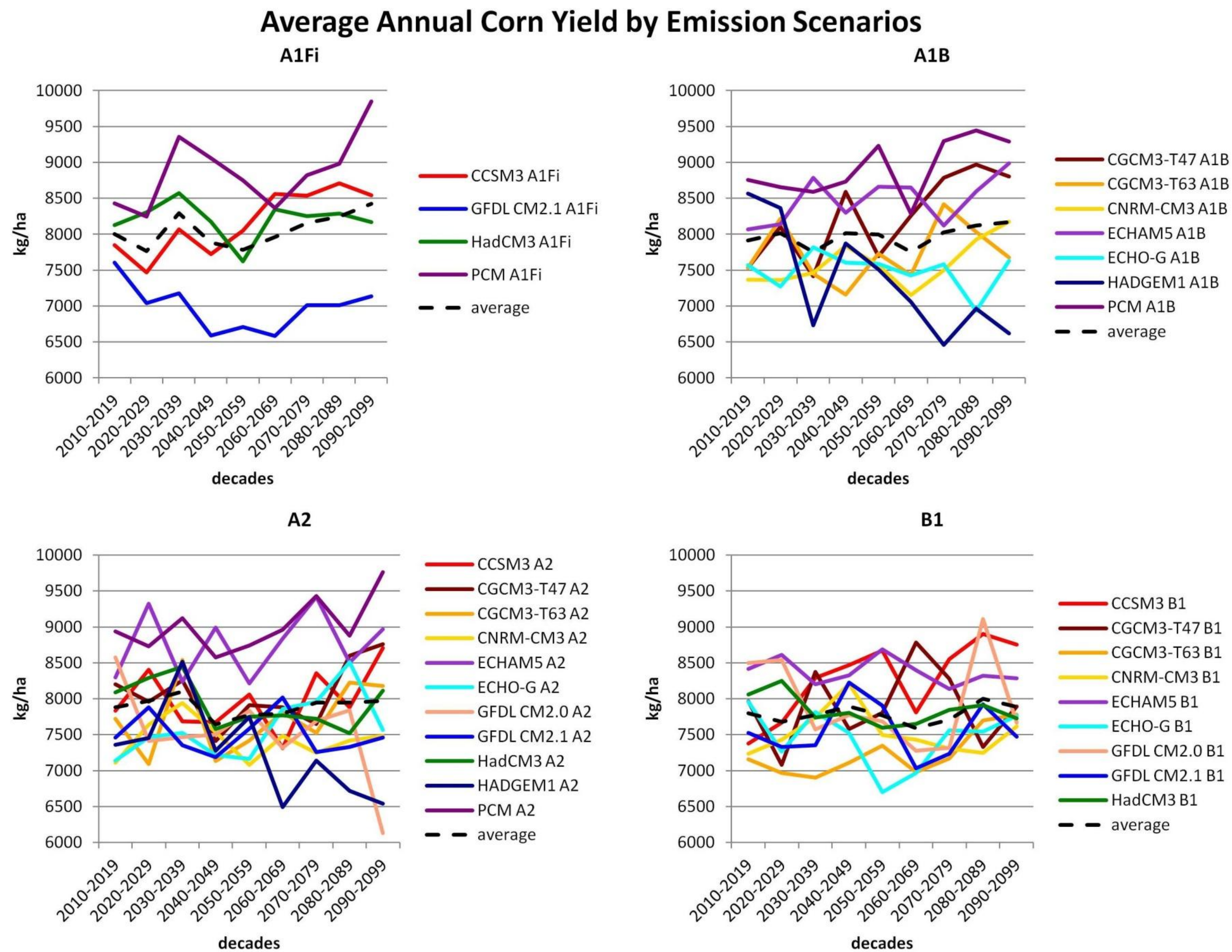

Figure 82: Annual corn yields by emission scenario, for SWAT model 04108660.

There is a rich literature exploring potential changes in crop yields under climate change, with a number of studies projecting increases that are at least partly due to the improved plant water efficiency and higher biomass caused by elevated CO_2 (Erda et al., 2005; Leakey, Bernacchi, Dohleman, Ort, & Long, 2004; Wall et al., 2001). However, some studies point out that the effect may be overestimated (Deryng, Conway, Ramankutty, Price, & Warren, 2014; Andrew D. B. Leakey et al., 2009; Long, Ainsworth, Leakey, Nösberger, & Ort, 2006; Marshall, Aillery, Malcolm, & Williams, 2015; Ruiz-Vera et al., 2013). In Figure 81, the A1FI scenario projected an increase in yields, from which one could infer that the higher CO_2 levels in that scenario caused the higher increase in yields relative to the other emission scenarios; but the overall increase was muted, particularly when compared to the CO_2 effect on recharge. One reason why the yields were not higher was the projected change in growing season. SWAT bases a plant's growth cycle on accumulated heat units throughout the year. When certain thresholds are met particular land management activities are triggered (planting, fertilization, harvest, etc.). SWAT also allows users to define specific calendar dates for these activities; but knowing that the models I simulated had to be flexible to adapt to higher temperatures, I used the heat unit scheduling approach. In the hotter A1FI emission scenario, plants accumulated heat units much faster than in the other scenarios, which caused the harvest threshold to be met earlier in the year. This shortened growing season limited the amount of biomass a crop could generate in a given year. The only way to lengthen the season while still utilizing the heat unit scheduling approach would have required redefining each plant's threshold values. I did not have a sound basis for specifying new values for a future scenario, so I left them at the calibrated values. Figure 83 and Figure 84 show average harvest and planting dates for corn in

SWAT model 04108660. The increase in temperature through 2100 caused corn to be planted on average about 8 days earlier at the end of century, but harvested a full month earlier in the A1FI and A2 scenarios, shortening the growing season by 3 weeks.

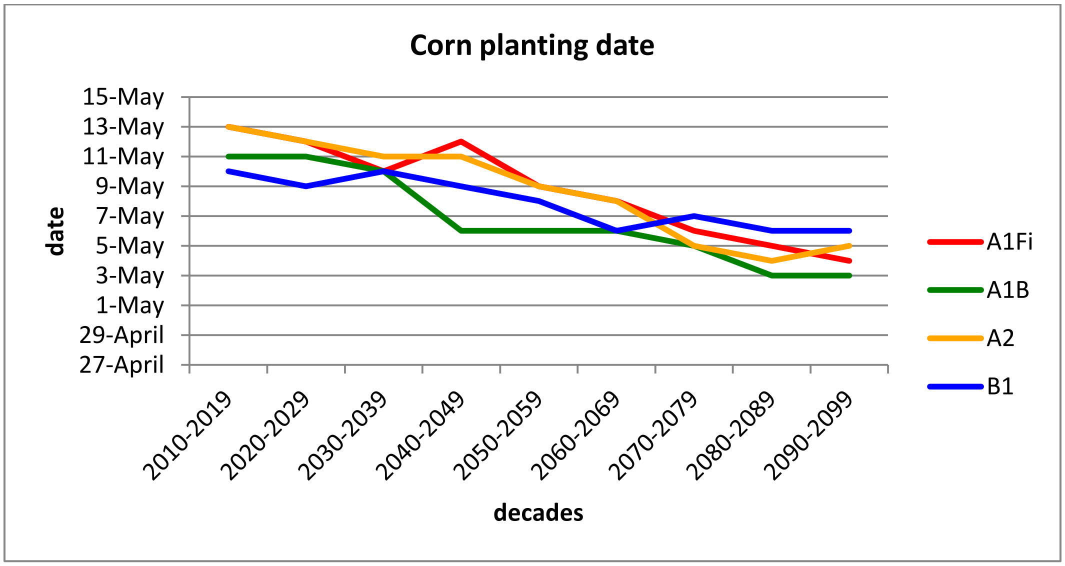

Figure 83: Planting date for corn, averaged by emission scenario, for SWAT model 04108660.

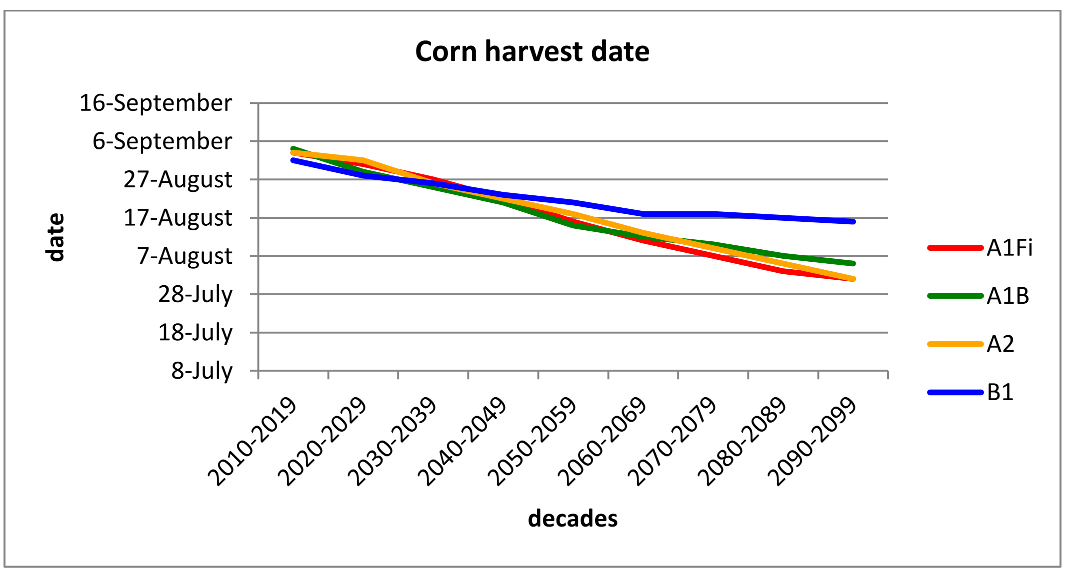

Figure 84: Harvest date for corn, averaged by emission scenario, for SWAT model 04108660.

Figure 84 reveals the peculiarity that the SWAT timing of corn harvest for the most recent decade of the simulation (2010-2019) was more than a full month earlier (around September 3rd) than is typical. The period for corn harvesting in Michigan can begin September 5th, but is most active between October 10th and November 25th(NASS - U.S. Department of Agriculture, 2010). As I discussed in *4.1.2 Crop Yields*, I evaluated crop yield simulations from SWAT against reported county-level totals in the Ag Census series from USDA-NASS. During that process, I noticed that a number of crop HRUs were not reaching their heat unit harvest thresholds, skewing the overall yield numbers lower. I tried to find a balance by adjusting each crop's heat unit maturity levels so that yields approximated Ag Census data, and all crops reached maturity. A consequence of this balance was that crops tended to be harvested earlier than usual, as was the case corn in 04108660. I felt it more important to ensure that the amount of annual crop biomass was more accurately represented than its timing, though I acknowledge the importance that such timing can have hydrologically. Using a specific calendar date to schedule harvest would avoid this problem, but as I stated earlier, that strategy would not work for a long-term climate change study.

There are potential hydrological consequences for an early simulated harvest in SWAT, including an early termination to plant transpiration for a given year. SWAT's outputs include only ET, it does not separately report evaporation and transpiration; therefore, it is difficult to estimate how much less water is transpired after a crop is "harvested". I explored this problem for a single HRU in the 04108660 SWAT model. The HRU was represented by a continuous corn land cover, a soil of the B hydrological soil group, and a 0-2% slope. I tracked daily outputs for 2010 and noted the following hydrologically pertinent outputs: harvest date, precipitation, ET, recharge, and surface runoff. SWAT's heat scheduling simulated the crop's planting on May 7^{th}, reaching maturity on August 5^{th}, and "harvest" on August 22^{nd}, for a reasonable growing season length of 91 days. Crops in SWAT cease to transpire once they reach maturity, as shown in Figure 85 in which the daily rate of ET dropped immediately after August 5^{th}. Though there were still days in 2010 of relatively high ET, those values were entirely comprised of evaporation. One might expect that this early cessation of transpiration would trigger a shift in the proportion of precipitation that ends up as recharge as opposed to ET or surface runoff; however, Figure 86 shows that any such change was muted for this particular HRU. Figure 86 illustrates how the respective proportions of cumulative daily precipitation change throughout the year among ET, recharge, and surface runoff. After corn transpiration ceased on August 5^{th} (as represented by the black, dashed vertical line), recharge's proportion of cumulative daily rainfall continued a steady decrease that began back in March, ending with a final share of roughly 38% of the year's precipitation, while ET accounted for 59%, and surface runoff 3%. I ran an additional SWAT simulation in which I did not let heat units dictate the agricultural calendar, but instead specified planting and harvest dates manually, and increased the heat units needed for corn to reach maturity. These changes resulted in a more plausible corn schedule of planting on May 7^{th}, and harvesting on October 29^{th}; however, to ensure a date of maturity in early September, I had to increase corn's accumulated heat unit maturity threshold from 1,205 to an unlikely value of 1,600. Figure 87 reflects the change in ET under this alternative approach. Note the overall increase in ET in August under this approach as opposed to the same time period in the scenario that utilized heat unit scheduling (in which an early maturity caused transpiration to cease). Figure 88 illustrates that the share of annual precipitation among ET, recharge, and surface runoff was only slightly different when the more plausible agricultural calendar was implemented. ET's portion increased by 2% (11 mm), recharge's decreased by 4% (39 mm), and surface runoff's increased by 2% (23 mm).

Though the overall effect of the early harvest on recharge is relatively small (39 mm), it does indicate that the recharge estimates likely have a positive bias. Because all of the simulations for calibration and for future projections utilized heat-unit scheduling, the bias is endemic. However, as the goal of this project is to explore potential future trends in recharge and groundwater, the bias does not limit my ability to draw conclusions about how recharge rates and water table depths might change in general. Furthermore, as I described earlier, the heat-unit scheduling approach was the most viable means to simulate crop growth far into the future. Regardless, subsequent research should strive to more accurately represent a typical agricultural calendar during calibration.

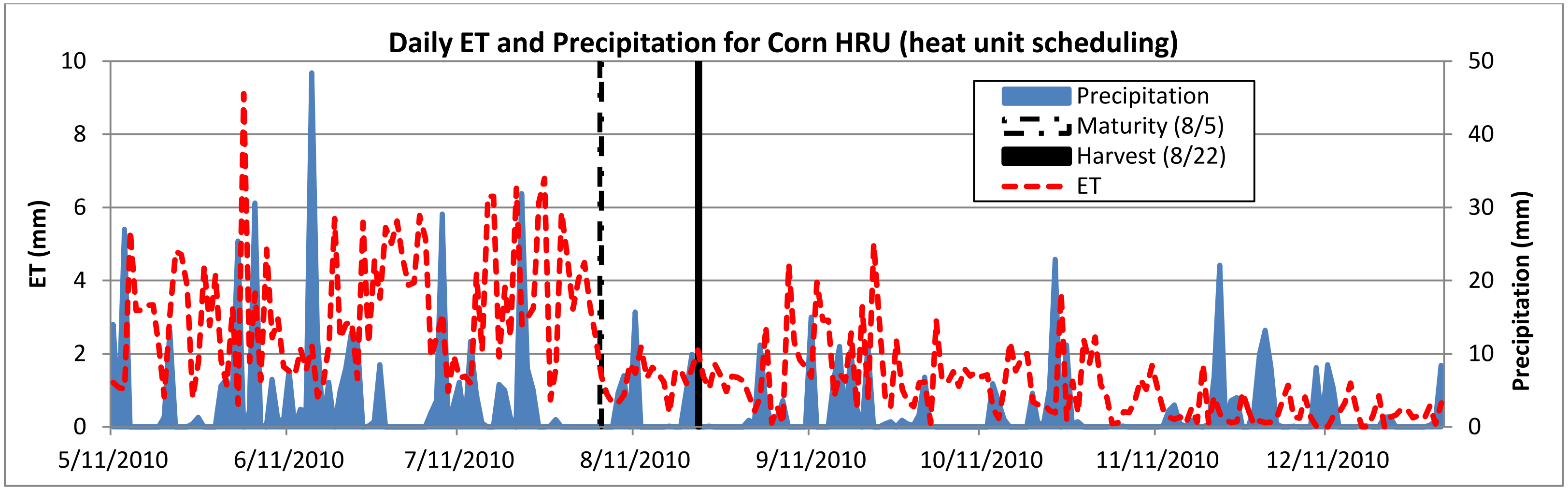

Figure 85: Daily ET for a corn HRU when using heat units to schedule planting and harvest.

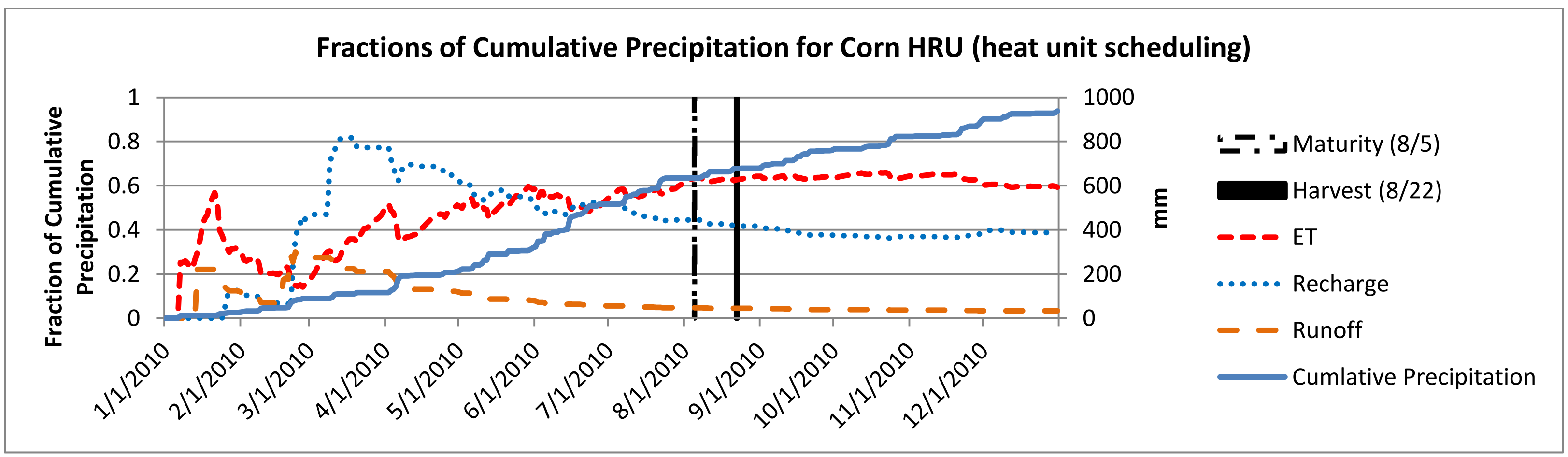

Figure 86: Fraction of cumulative precipitation accounted for by ET recharge and runoff for a corn HRU in SWAT model 04108660, when using heat units to schedule planting and harvest.

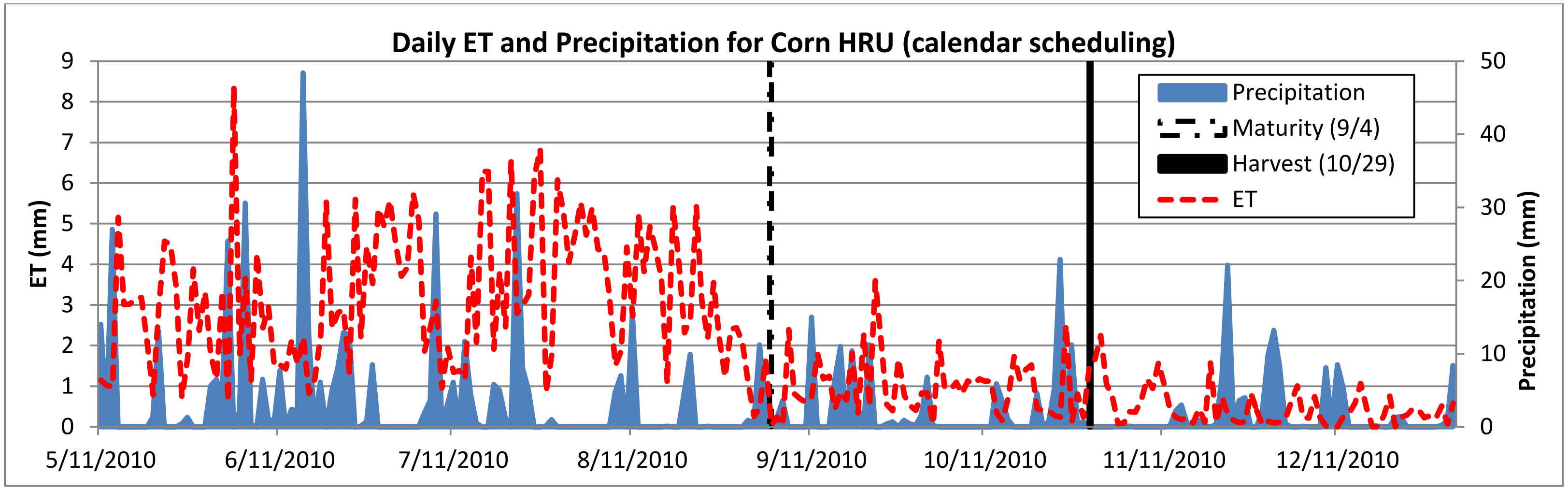

Figure 87: Daily ET for a corn HRU when manually specifying planting and harvest dates.

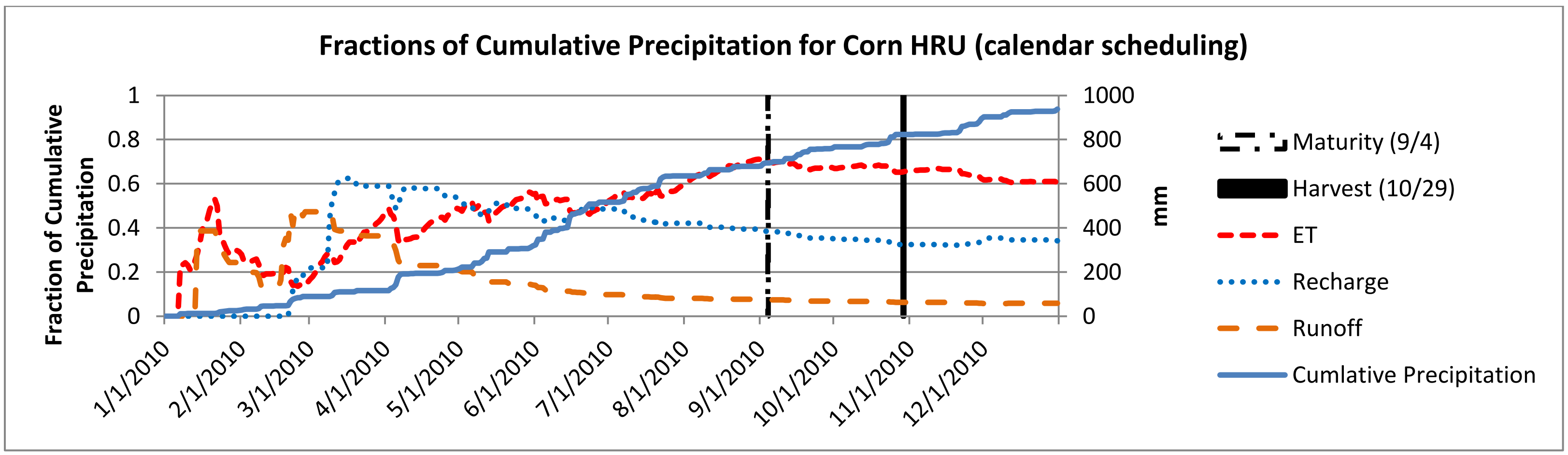

Figure 88: Fraction of cumulative precipitation accounted for by ET recharge and runoff for a corn HRU in SWAT model 04108660, when manually specifying planting and harvest dates.

6.1.6 SWAT HRU-scale Recharge

The basin-scale SWAT outputs were informative because they clearly illuminated the potential impacts of climate change on surface water hydrology, but the primary SWAT output of interest for this project was groundwater recharge at the HRU scale. MODFLOW can accept a spatially explicit representation of recharge, which the basin-scale estimates could not provide. I generated recharge rasters for every climate scenario and land management scenario (urban expansion, agricultural expansion, combined urban and agricultural expansion). I ultimately stitched these SWAT basin-sized rasters into ones that covered the MODFLOW study area, like the one illustrated in Figure 16.

These rasters reflected the trend of increasing recharge throughout the century, particularly for the A1Fi and A2 emission scenarios, but also highlighted how recharge varied spatially within the study area. The highest recharge areas were in the south and western portions of the study area, partly because of higher precipitation rates closer to Lake Michigan, partly because of the coarser soil texture, partly because of fewer impervious surfaces there than in the more urbanized areas in the central and eastern portions of the study area, and partly because those areas were heavily irrigated[16]. Figure 89 shows a closer view of the baseline recharge in the southern portion of the study area. It is clear how the higher recharge values followed the delineation of irrigated fields identified by the search algorithm discussed in *3.2.5 Irrigation*, and how the more urbanized areas exhibited less recharge. The basic geographic

[16] An optimal irrigation system would apply just enough water to bring a crop to maturity, and yield no additional recharge. However, average efficiencies range from 65% - 95% for various irrigation systems (Howell, 2003). I used SWAT's efficiency parameter (IRR_EFF in .mgt files) default value of 90% for irrigated HRUs. Therefore, every irrigated field received additional soil moisture at a time (May through August) when recharge is typically low (Figure 74), resulting in higher annual recharge values for these fields as opposed to non-irrigated fields, which has been observed in other research (Willis & Black, 1996).

structural pattern of recharge did not change from the various climate change simulations. Figure 90 shows recharge maps averaged by emission scenario, assuming static land cover[17] at the end of the century for SWAT model 04108660. As the basin-scale graphs illustrated, recharge was highest for the A1FI scenario at the end of the century, followed by A2, A1B, and B1.

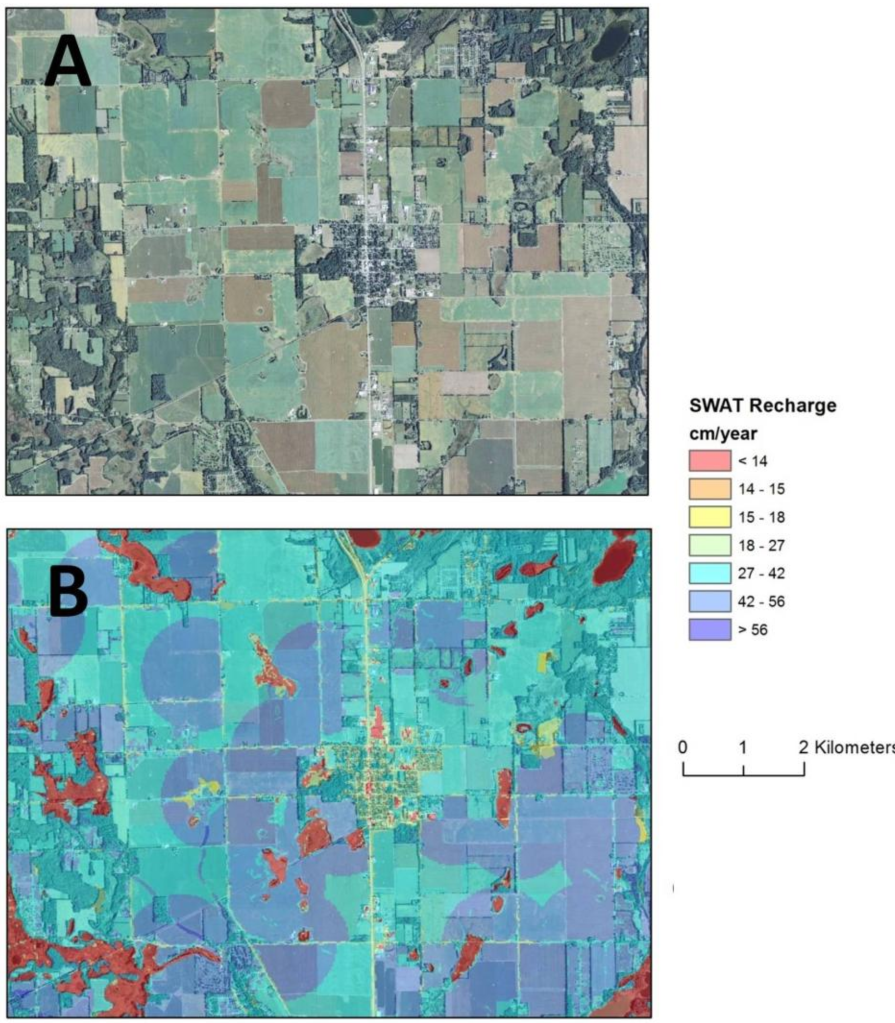

Figure 89: A) Aerial photograph of Schoolcraft, MI. B) SWAT baseline recharge raster output for the same area in A. Aerial photo from USDA-FSA (2014).

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[17] At this spatial scale there was little visual change in the recharge maps for the three other land management scenarios.

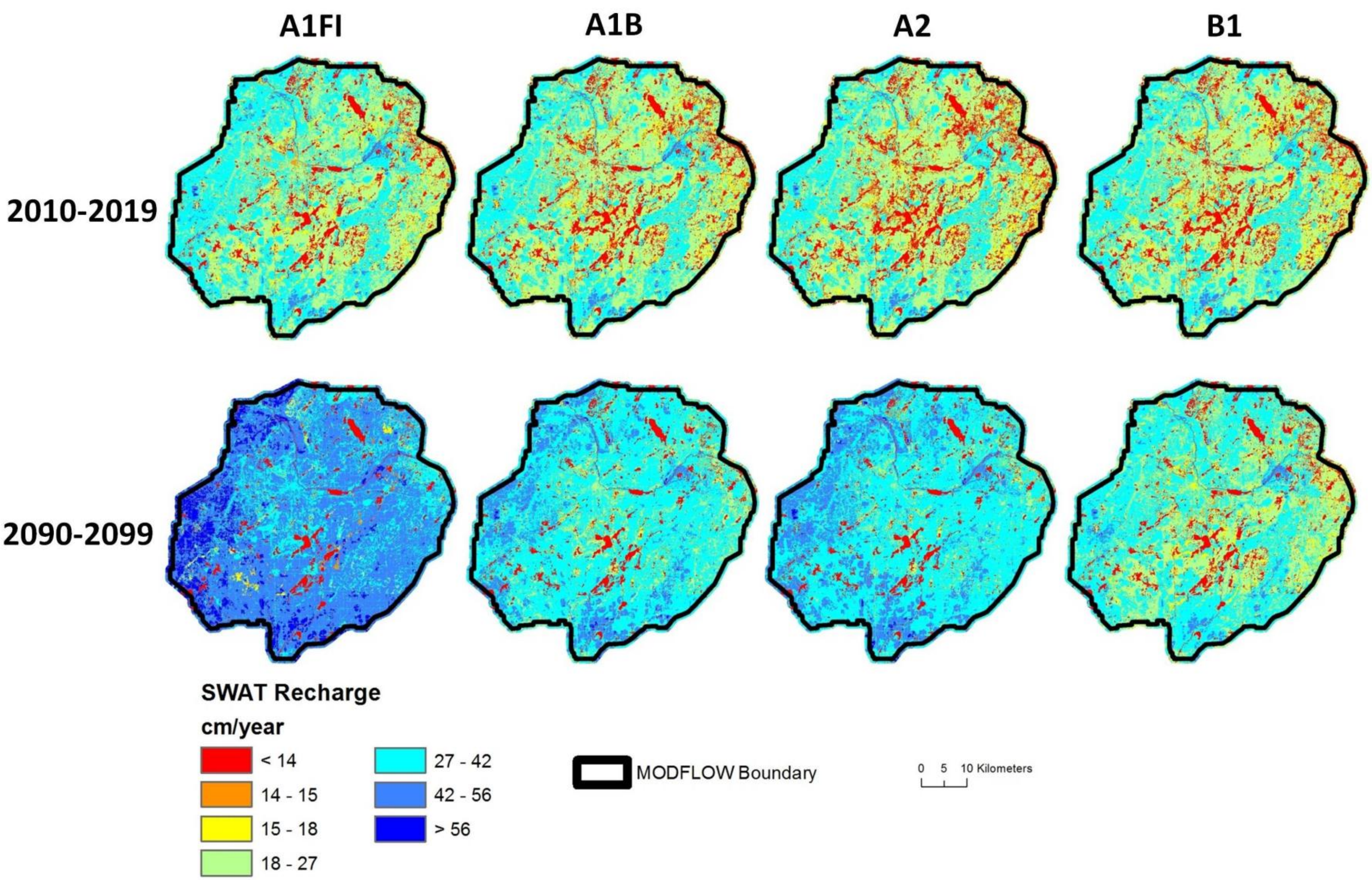

Figure 90: Raster maps of SWAT recharge, averaged by emission scenario and assuming no land cover change, for the 2010-2019 and 2090-2099 decades.

6.1.7 Geographic Means of Recharge

Though there was little visible change in the relative spatial structure of the recharge maps, I sought to quantify the extent to which the spatial distribution of recharge changed between climate model scenarios, and between land management scenarios. To do this, I calculated a geographic mean of each recharge raster with the Mean Center tool in the ArcGIS© spatial statistics toolkit, and compared its distance and direction to a reference center point. The tool calculates the geographic mean as a function of the x and y coordinates, and the recharge estimate of each cell (9). Though it is theoretically possible that the geographic mean center could yield a coordinate of no change when recharge changed dramatically at both ends of an axis through the center (*e.g.*, equal increases in recharge were observed at the eastern and western edges of the study area), such an outcome is unlikely given the irregular shape of the study area and the heterogeneous spatial distribution of recharge.

$$\bar{X}_w = \frac{\sum_{i=1}^{n}(w_i x_i)}{\sum_{i}^{n} w_i}\ ,\ \bar{Y}_w = \frac{\sum_{i=1}^{n}(w_i y_i)}{\sum_{i}^{n} w_i} \quad (9)$$

Where $\bar{X}_w$ is the x coordinate of the recharge-weighted mean center,

$\bar{Y}_w$ is the y coordinate of the recharge-weighted mean center,

n is the total number of active MODFLOW cells,

x_i is the x coordinate MODFLOW cell i,

y_i is the y coordinate MODFLOW cell i,

w_i is the recharge of MODFLOW cell i.

From the ArcGIS© help files.

Figure 91 shows the geographic mean center for recharge in climate model CCSM-A1Fi for the decade 2010-2019. The white cross represents the geographic mean center for recharge, while the black dot represents the geographic mean center (un-weighted) of the top layer of the MODFLOW model. At that scale, the difference was relatively small, but provided a visual reference for the center of the study area and illustrated the tendency for higher recharge values in the western portion of the study area. If there was no spatial tendency for recharge, the white cross would fit perfectly within the circle. Figure 92 shows a zoomed in view of this center region to illustrate the differences in geographic mean center by emission scenario. Each dot in Figure 92 represents the geographic mean of recharge averaged by emission scenario across the 31 climate models, for a particular decade between 2010 and 2100, and for the static land cover scenario (*i.e.* no urbanization or agricultural expansion). Note the scale of Figure 92; the furthest point from the geographic mean of the study area (represented by the black dot) was 1.5 kilometers to the west. That particular point was the geographic mean for the recharge in the HADGEM1-A1B climate scenario for 2070-2079, indicating that this simulation yielded a greater concentration of recharge in the west than any of the other climate models and decades.

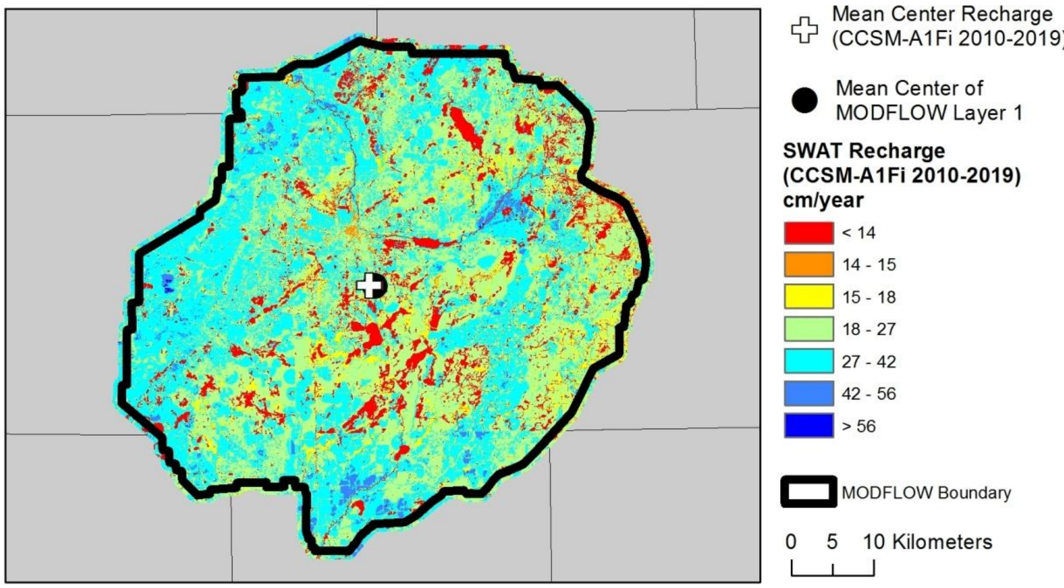

Figure 91: Geographic mean center for recharge in climate model CCSM-A1Fi for the decade 2010-2019.

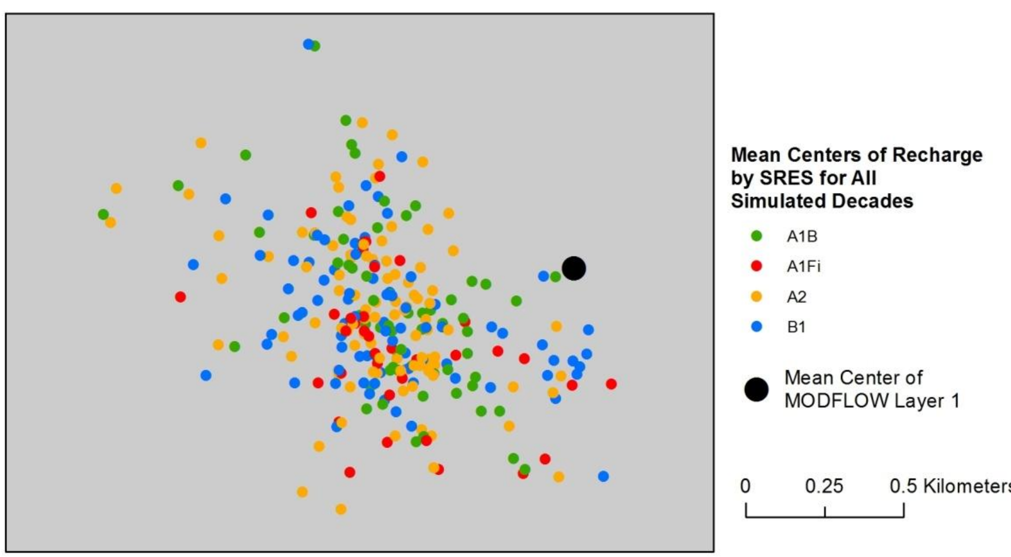

Figure 92: Geographic mean centers of recharge. Each dot represents an average value for a particular climate model and decade.

Though 1.5 kilometers is a relatively small distance when compared against a study area that is 61 kilometers wide at the widest points of both the east-west and north-south transects, the geographic mean allows for a comparison of how the distribution of recharge varies which would otherwise be difficult to discern solely from visual inspection. Figure 93 through Figure 97 explore these distributions to illustrate differences in recharge by time, land cover scenario, climate model, and emission scenario. Figure 93 shows how that distribution changed over time for the CCSM3 climate model. The large circles with black dots in them represent the geographic means for the 2010-2019 decade for each of the three emission scenarios CCSM3 simulated, and are useful for comparing how recharge varied over time within an emission scenario. There was greater spatial variability in recharge in the A1FI scenario over time than in the A2 scenario.

While the concentration of recharge for A1Fi and A2 climate models generally moved along a northwest to southeast transect, it moved along a southwest-northeast transect for the B1 scenario. All of the A1FI geographic means were to the southeast of the 2010-2019 geographic mean, but A2 had two in the southwest (2060-2069 and 2080-2089) and B1 had one to the northwest (2030). These trends were not common from climate model to climate model. Figure 94 shows the same emission scenarios for climate model HADCM3, which were quite different than the distributions for CCSM3. This lack of uniformity suggests that the differences in geographic mean recharge between climate models are likely due to differences in the geographic distribution of precipitation among the projections. In the case of Figure 93 and Figure 94, the only differences between models CCSM3 and HADCM3 were their precipitation and temperature projections, which yielded distinct trends of geographic mean recharge.

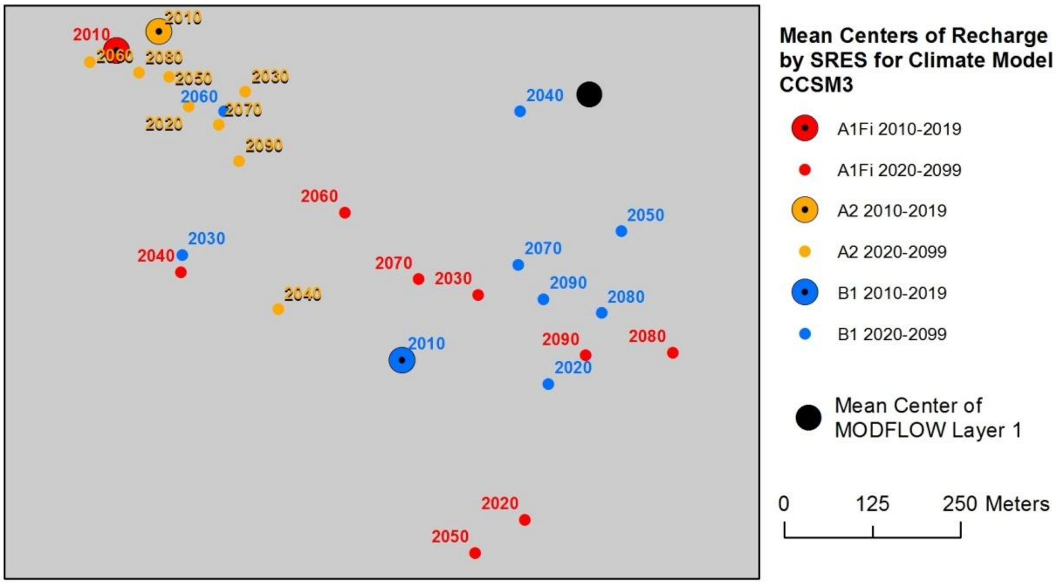

Figure 93: Geographic mean centers of recharge for climate model CCSM3.

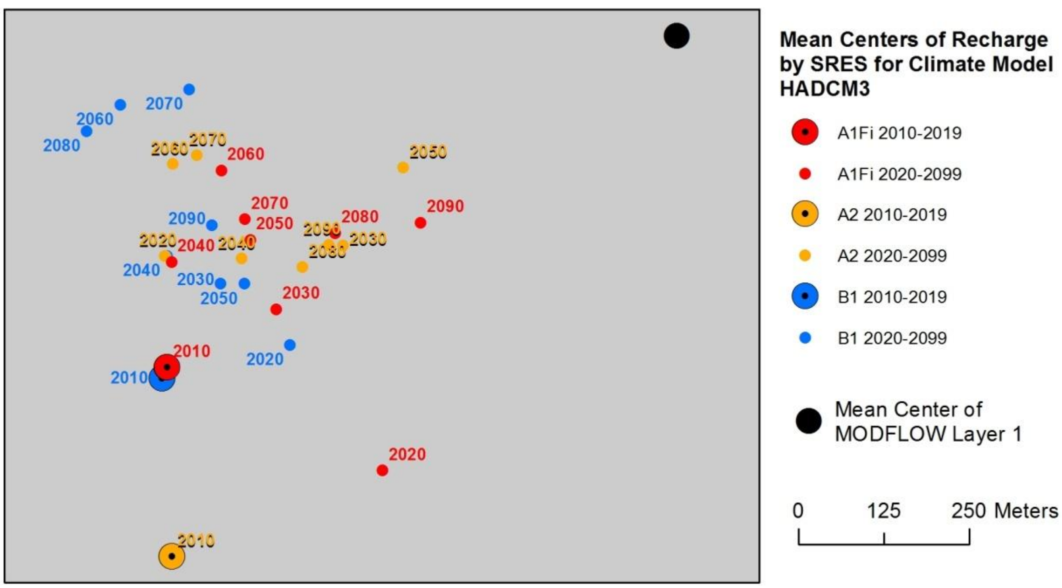

Figure 94: Geographic mean centers of recharge for climate model HADCM3.

Though there was clear variability in the inter-model recharge spatial distributions, there was general consensus among models and emission scenarios regarding the effect of the different land cover scenarios. Figure 95 shows how the geographic mean recharge points varied among the scenarios of agricultural expansion, urbanization, combined agricultural and urban expansion, and static land cover for the CCSM climate scenario. In all the scenarios and for all of the decades[18] the same general pattern of a southeastern progression of geographic means from static land cover, to agricultural expansion, to urban expansion, to the combined urban and agricultural expansion scenario was visible. Though the distance between each land cover scenario's geographic mean centers was very small, the trend was clear and consistent. Because the agricultural expansion scenario focused on growing out areas where agriculture was already present, most of the expansion occurred in the southern part of the study area, where agriculture was more highly concentrated. Recharge was generally higher on agriculture than other land cover classes because of its higher permeability and likelihood of being irrigated. Therefore the geographic recharge mean for that scenario being drawn to the south is not surprising. The urban expansion scenario had a similar effect, but as a push instead of a pull. The cities of Kalamazoo and Portage, where most of the urban expansion was concentrated, is in the north portion of the study area. The higher imperviousness in that scenario pushed the recharge geographic means towards the southeast (Kalamazoo was just to the west of the center point). The combined scenario captured both the pull of agricultural expansion and push of urbanization to move the geographic mean further southeast.

[18] Each singled-color cluster in Figure 92 represents a particular decade for an emission scenario. I left the decade labels out of Figure 92 so as not to clutter the map.

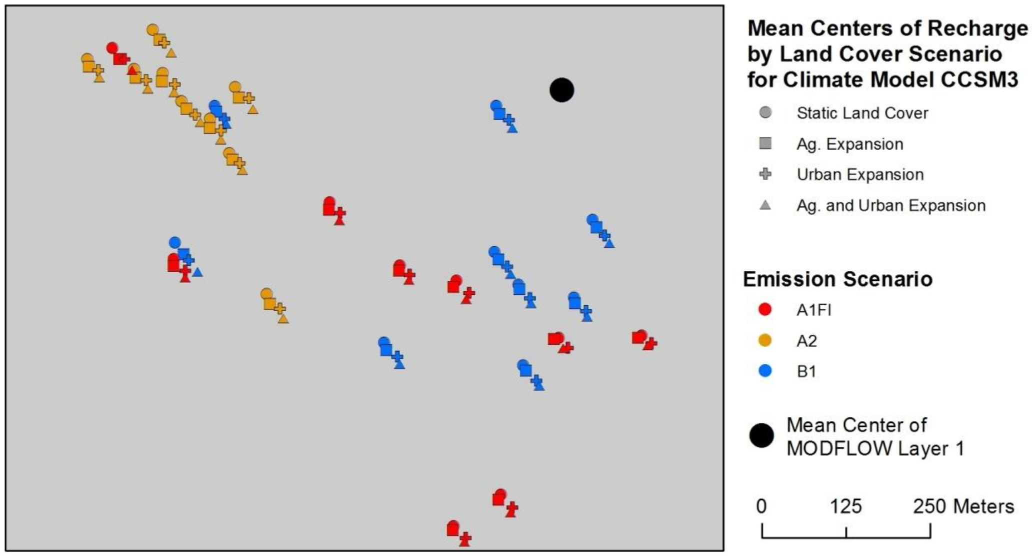

Figure 95: Geographic mean centers of recharge by emission and land cover scenarios for climate model CCSM3.

Table 27 lists the top ten comparisons of geographic mean recharge points that yielded the greatest divergence within a particular model[19]. For example, the distance between the geographic mean recharge for the 2010-2019 decade in climate model ECHAM5 under emission scenario A1B was 1,062 meters. This particular value represented the largest single change in the distribution of recharge from a reference decade (2010-2019) to a change decade (2070-2079). Figure 96 identifies these two geographic means within the map of all static land scenario geographic means, originally presented in Figure 92. The difference indicates an increase in recharge in the northern portion of the study area that is greater than an increase in the south, or that there was a recharge decrease in the south. It is interesting that several of the largest changes in the distribution of recharge were over the course of a single decade; 2040-2049 to 2050-2059 for the ECHO-G-B1 climate model, for example, was the third largest

[19] Note that these differences are only for the static land cover scenario (*i.e.* no change over time). Because of the relative similarity of geographic means of the different land cover scenarios options within a particular decade, as illustrated in Figure 95, I did not want to clutter Table 27 with duplicate records of the same climate model in the same decade, but under different land cover scenarios.

overall difference (Table 27). These relatively fast changes in the distribution of recharge can indicate shifts in weather patterns for a climate model, or more subtle shifts in hydrologic dynamics.

Table 27: The top differences in geographic mean recharge from a referenced decade to a change decade. These distances are for the static land cover scenarios.

Climate Scenario	Starting Decade	Ending Decade	Geographic Mean Recharge Difference/Distance (m)	Direction of Difference
ECHAM5-A1B	2010-2019	2070-2079	1,062	North
HADGEM1-A1B	2010-2019	2070-2079	1,030	Northwest
ECHO-G-B1	2040-2049	2050-2059	933	Southwest
CCSM3-A1Fi	2010-2019	2080-2089	901	Southeast
CCSM3-A1Fi	2010-2019	2020-2029	885	Southeast
HADGEM1-A1B	2010-2019	2050-2059	869	Northwest
CCSM-A1Fi	2010-2019	2050-2059	869	Southeast
ECHAM5-A2	2010-2019	2070-2079	853	North
GFDL CM2.0-A2	2010-2019	2090-2099	837	North
ECHO-A2	2050-2059	2060-2069	821	East

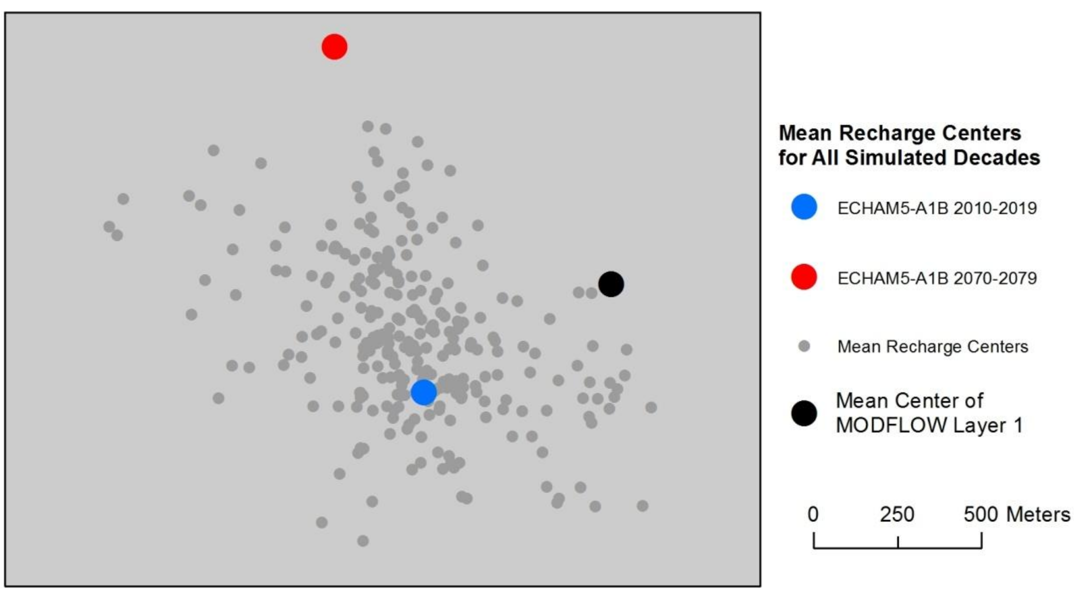

Figure 96: Geographic mean recharge center difference between the decades 2010-2019 and 2070-2079 within the ECHAM5-A1B climate model.

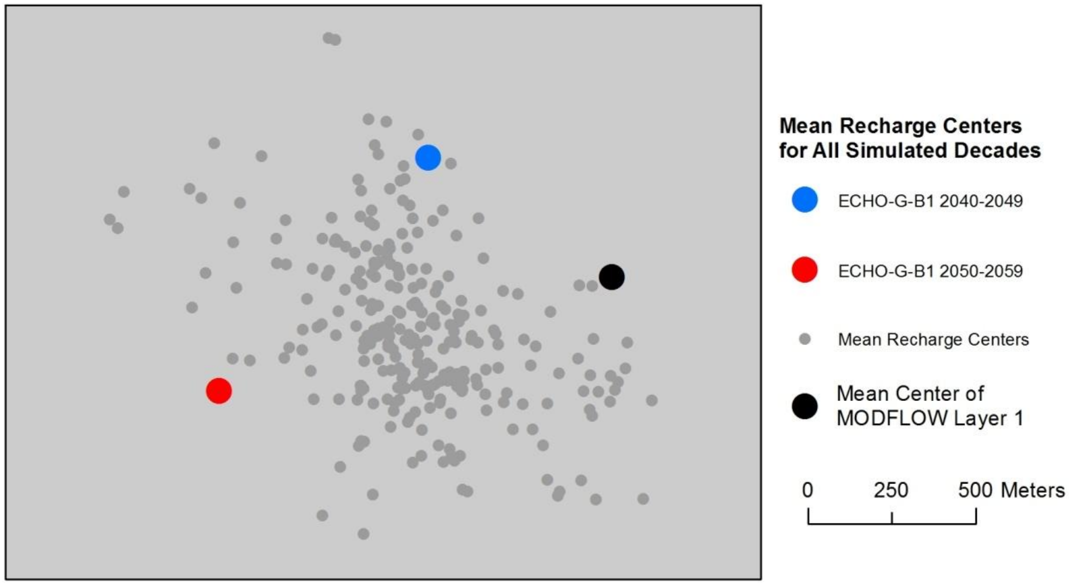

Figure 97: Geographic mean recharge center difference between the decades 2040-2049 and 2050-2059 within the ECHO-G1-B1 climate model.

There are multiple potential causes for varied spatial distributions, including different precipitation patterns from decade to decade, changes in irrigation demand and timing resulting from differences in temperature, and different responses from plants to CO_2 effects on water use efficiency. For example, in the higher CO^2 scenarios, the reduction in ET would be more acute in areas dominated by agriculture as opposed to forest, affecting the spatial distribution of recharge from one scenario to the next. Each of these variables would be different from scenario to scenario, model to model, and decade to decade, producing a wide range of potential distributions. Mapping them, like in Figure 92, (1) helps clarify the broader trends in the data, such as recharge's westward tendency, (2) validates the expected trends in recharge among the different land cover scenarios, and (3) helps identify models and points in time when recharge change may be greatest. It also provides further evidence of the variability among the different climate models and emission scenarios, supporting the need for employing multiple models in climate change studies like this.

6.2 MODFLOW Outputs

As I did for SWAT, I generated MODFLOW outputs at various spatial scales. I calculated how model-wide averages of estimated hydraulic head changed from one scenario to the next, which allowed me to identify the combinations of climate and land cover management that had the largest impact on the water table for a particular future decade. I also explored how the spatial distribution of hydraulic head changed among the various scenarios, employing the geographic mean center approach I used for recharge.

6.2.1 Overall head change

As could be expected given the previously modeled changes in recharge under the various climate scenarios, hydraulic head exhibited similar behavior through the century. Figure 98 shows the average change in hydraulic head (calculated from all of the cells in the MODFLOW model's top layer), averaged by emission scenario, from a base decade of 2010-2019. Figure 99 overlays average annual recharge by emission scenario for SWAT model 04108660 on top of the average head changes, illustrating the direct relationship between recharge and hydraulic head trends. In the emission scenarios in which recharge increased (A1Fi, A1B, A2) average hydraulic head increased as well, while it changed little under emission scenario B1[20]. These figures

[20] It is worth pointing out that these values represent trends for average change over time. A 122 centimeter increase in hydraulic head is well below the 457 centimeter RMSE I calculated by comparing the MODFLOW model

represent the static land cover management scenario (*i.e.* it assumes no change over time). One might wonder why an 20.3 cm increase in recharge from 2010-2019 through 2090-2099 for the A1Fi scenario translated to a 122 centimeter increase in head over that same time period. This result was a function of the reductions in ET from improved plant water use efficiency discussed earlier, and soil porosity. The sharp reduction in ET at the end of the century for emission scenario A1FI (Figure 69) left more water in the soil profile, and subsequently reduced demand for irrigation. Combining a reduction in agricultural water withdrawals with increased recharge caused a greater increase in hydraulic head than from recharge alone. Furthermore, the fact that the water volume was dispersed over the air space within the soil profile meant that the height of the hydraulic head increased more than the depth of the water itself[21].

estimates to USGS observations, and further below the 579 centimeter RMSE when compared to Wellogic static water levels; but average change is not the same as the average error. The RMSE indicates the extent to which a simulated value may differ from an observed value. On average, the MODFLOW model heads differed with the observed heads by 457 centimeters. But the average changes in head I am reporting here represent how much it will increase or decrease for a particular cell, regardless of whether the simulated baseline head value was close to the observed value. A 122 centimeter increase in head by the end of the century for a cell in which the error of the baseline simulated head was 457 centimeters does not mean that the projected increase is invalid. The simulated head value for that cell at the end of the century would probably still be 457 centimeters above where the actual head value would be, but I would expect the actual head value to be 122 centimeters higher than the original observation.

[21] If you were to pour a full 250 mL glass of water into a 500 mL glass filled with dry sand that has a porosity of 0.5 (*i.e.* 50% of the total volume in the glass would be air), the water table within the sand would rise to the brim of the 500 mL ounce glass; 20 cm of water would have caused a 40 cm rise in the water table.

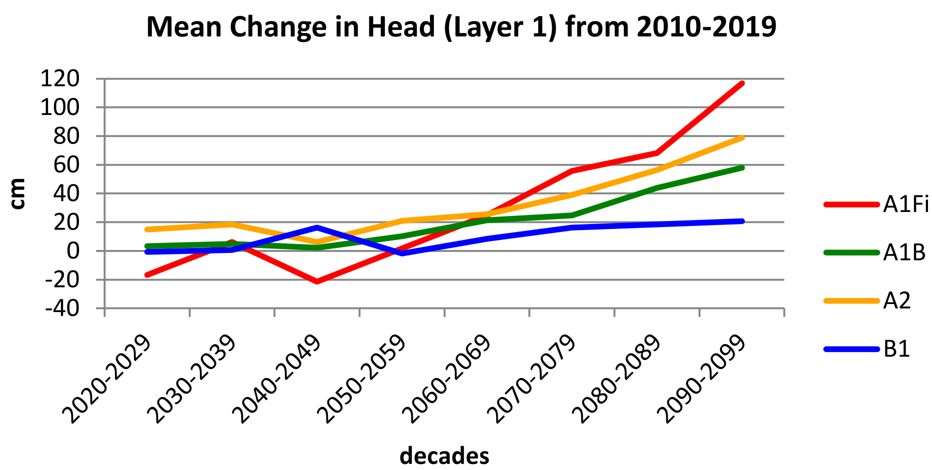

Figure 98: Average change in hydraulic head for all of the cells in MODFLOW model layer 1, averaged by emission scenario.

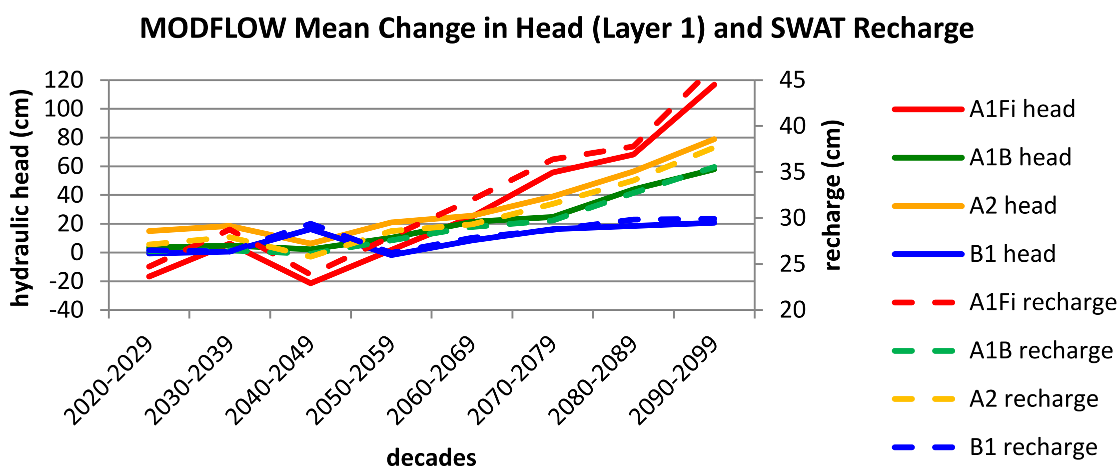

Figure 99: Average change in hydraulic head for all of the cells in MODFLOW model layer 1, averaged by emission scenario, along with the average recharge by emission scenario.

The values in Figure 98 and Figure 99 were averaged from the average change in head by the climate models that had simulations for those scenarios. Figure 100 shows how the average change in head varied among the models within the emission scenarios. The dashed black line in each graph of Figure 100 corresponds to the emission scenario line in the Figure 98 and Figure 99. As was the case for recharge, there was a fair amount of variability in head change between the various climate models of a particular emission scenario, especially for A1B and A2. Under the A1B emission scenario, climate model CGCM3-T47 projected a mean change of 128 centimeters by the end of the century, whereas HADGEM1 projected a drop of 5 centimeters. For the 2030-2039 decade climate model CNRM-CM3 projected a 69 centimeter average increase in head, whereas the PCM climate model projected the exact opposite, a 69 centimeter average reduction in head. Though among the climate models that simulated A2 emission scenarios there was general consensus of an increase in average head by the end of the century, the ECHO-G climate model projected a 156 centimeter increase in head (the highest among any simulation) while the PCM model only projected a 40 centimeter increase. Overall, changes in head were relatively flat within the B1 emission scenario climate models, but there were still some large differences for certain decades. In the 2020-2029 decade, CCSM3 projected a 79 centimeter increase in average head, whereas the GLFDL CM2.1 projected a decrease of 66 centimeters. This variability is further proof of the need to evaluate multiple climate model simulations in such a study.

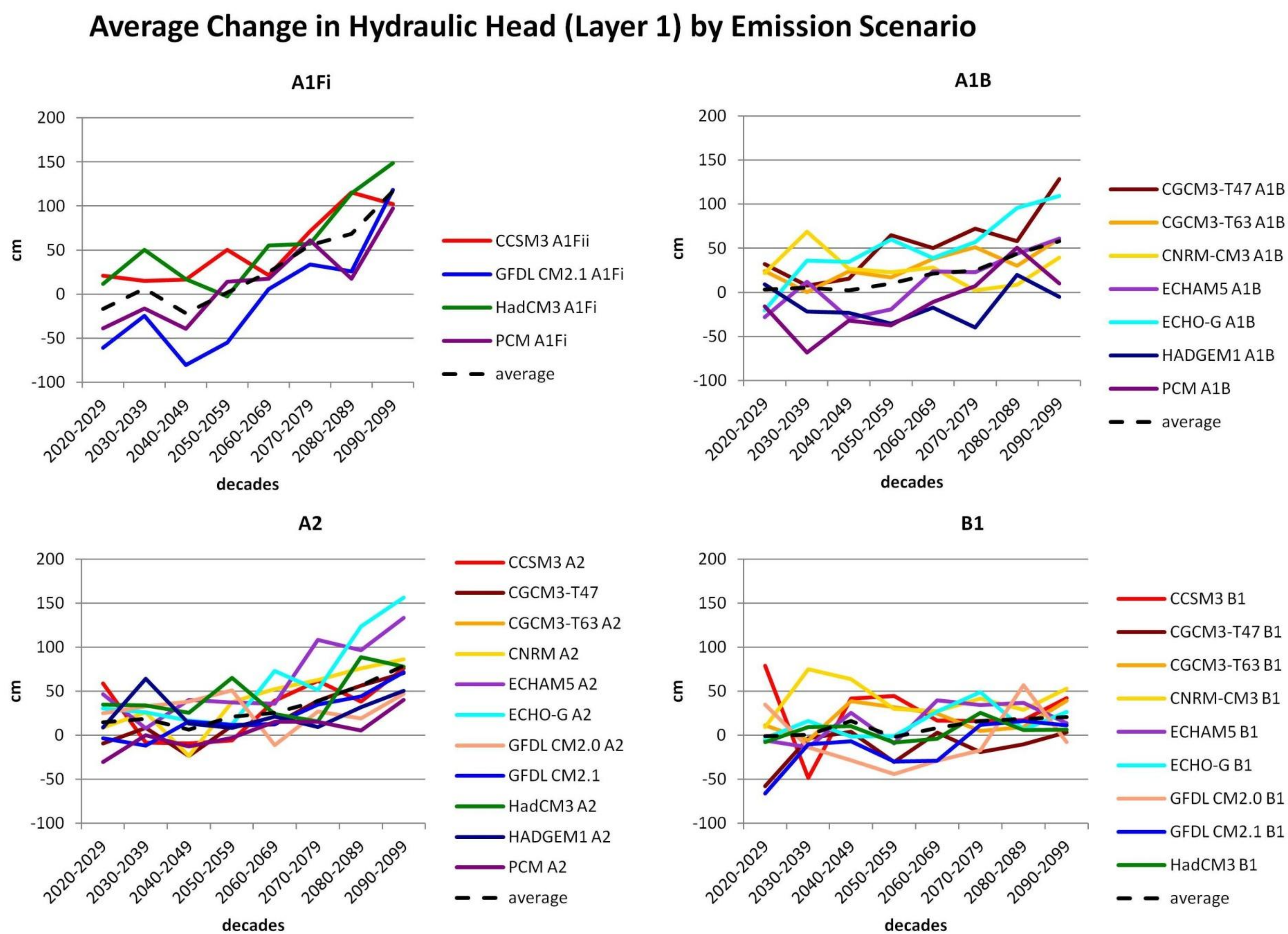

Figure 100: Average change in hydraulic head for the top MODFLOW layer among the various climate models of the four emission scenarios.

I also calculated mean hydraulic head change for the 5 lower MODFLOW layers, but there was little visible change; the graphs above were virtually identical to the graphs for each other layer. Additional calculations for the three other land cover management scenarios also yielded nearly identical graphs to the static scenario. The lack of a clear difference in this output was not surprising, though, because I only modified, at most, 10% of the landscape, which would have had a more localized effect on hydraulic head than a model-wide estimate like average change. Table 28 lists the average head change, across all of the climate simulations and decades, by MODFLOW layer in numeric format. There was slightly less change simulated in the lower layers of the model, which was not surprising because the changes in recharge most directly impacted the upper model layers and because, based upon well depths listed in Wellogic, most of the water withdrawals occur in the upper layers. Table 29 lists the average change in head when comparing static land cover scenarios to one of the three land cover change scenarios. For example, on average when urban areas were expanded, average hydraulic head dropped by 1.8 centimeters. This drop was mainly due to increased imperviousness causing less recharge and because of higher water use by an assumed larger population. An increase in agricultural area resulted in a slight average increase in hydraulic head, driven mainly by a tendency for agricultural land covers to recharge at higher rates than pasture or forest, which were the primary land covers that were converted in that scenario[22]. An increase in urban areas over that same time period resulted in average decrease in hydraulic

[22] The agricultural expansion scenario did not necessarily increase the amount of irrigation. Converted pixels assumed the dominant agricultural land cover around them, which may or may not have been an irrigated land cover class in SWAT. I did not explicitly increase the amount of withdrawal for irrigation within MODFLOW under this land cover scenario.

head. As one would expect, the average change for combined land cover scenario fell between the agricultural and urban expansion changes.

Table 28: Average change in hydraulic head by MODFLOW layer number.

MODFLOW Layer Number	Average Hydraulic Head Change Across all Simulations (cm)
1	7.54
2	7.40
3	7.32
4	7.17
5	7.02
6	7.03

Table 29: Average change in hydraulic head by land management scenario.

Land Cover Management Scenario Change	Average Hydraulic Head Change Across all Simulations (cm)
Static to agricultural expansion	0.06
Static to urban expansion	-1.80
Static to combined agricultural and urban expansion	-1.74

Table 30 and Figure 101 explore a selection of hydraulic head change scenarios of particular interest[23]. The first 3 records in Table 30 are the simulations that projected the largest average increase in hydraulic head from the starting period. Each of these three scenarios projected increases greater than 122 centimeters by the end of the century. One interesting aspect of the

[23] The selected scenarios are all for the static land cover scenario. The differences in head between the static land cover scenario and any of the other three for a particular decade was relatively small. The purpose of Table 29 is to distinguish the climate models that project the largest changes in head among the simulations. If I included all of the land cover change scenarios in the pool from which I selected the records in Table 30, the first four records would have been for the four different land scenarios of ECHO-A2. Therefore, to allow for a better comparison of the various climate model differences, I focused only on the static land cover scenario for this particular analysis.

ECHO-A2 estimate is that head increased despite an increase in ET over that time period. The increase in recharge was primarily the result of a 45% increase in precipitation from 2010-2019 through 2090-2099. Though two of the three simulations were from the A2 emission scenario, this was not an indication that that scenario was the most likely to increase hydraulic head. The A1Fi scenario estimated the highest CO_2 concentrations, which translated to the lowest ET levels and highest recharge rates. The HadCM3 climate model also had an A2 scenario, which projected a smaller increase in hydraulic head (78 centimeters) than its A1Fi counterpart. Had there been an ECHO-A1Fi scenario, it likely would have projected the largest overall increase in hydraulic head.

Table 30: Selected hydraulic head change scenarios of interest.

	Climate Scenario	Time Period	Average Change in Hydraulic Head (cm)
1	ECHO-A2	2010-2019 to 2090-2099	156
2	HADCM3-A1Fi	2010-2019 to 2090-2099	148
3	ECHAM5-A2	2010-2019 to 2090-2099	133
4	GFDL CM2.1 – A1Fi	2080-2089 to 2090-2099	92
5	CCSM-B1	2030-2039 to 2040-2049	90
7	PCM-A1B	2010-2019 to 2030-2039	-68
8	GFDL CM2.1 – A1Fi	2010-2019 to 2040-2049	-80
9	CCSM-B1	2020-2029 to 2030-2039	-127

Average Change in Hydraulic Head (Layer 1) for Selected Scenarios, with SWAT Recharge, SWAT ET, and Projected Precipitation

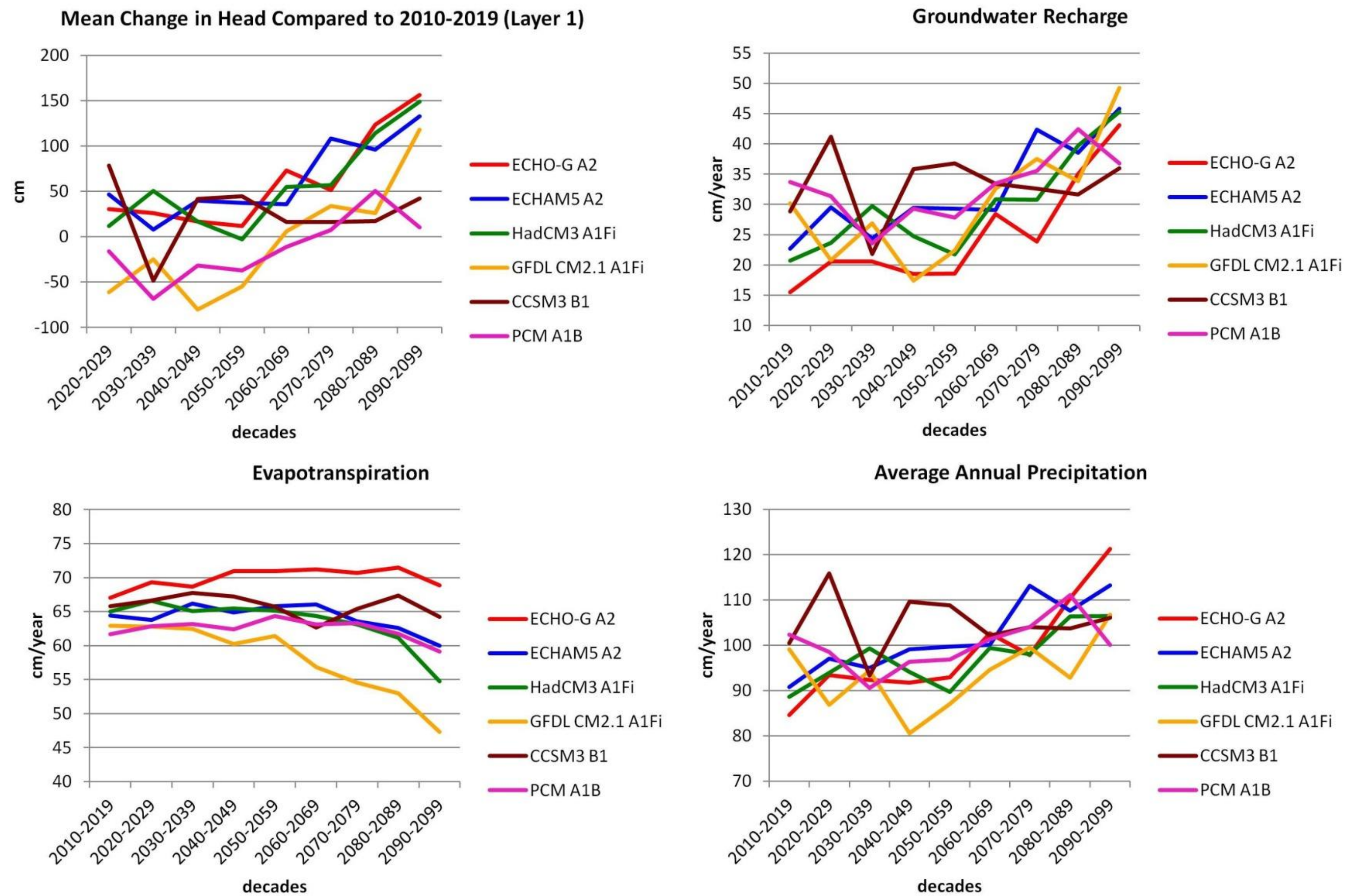

Figure 101: Average change in hydraulic head from 2010-2019 for selected climate scenarios, compared to SWAT recharge, SWAT ET, and precipitation

Rows 4 and 5 in Table 30 represent the two largest single changes in hydraulic head from one decade to another. Both the GFDL CM2.1-A1Fi and CCSM-B1 climate scenarios projected relatively quick increases in hydraulic head over the course of a decade, though for different reason. Figure 101 shows that GFDL CM2.1-A1Fi estimated a sharp reduction in ET and similarly sharp increase in precipitation from the 2080-2089 decade to 2090-2099, which combined caused an even sharper increase in recharge. The CCSM-B1 climate scenario projected a similarly sharp increase in recharge for the 2030-2039 decade to 2040-2049; however, this change was driven almost exclusively by increased precipitation, as ET was relatively flat over that period. Most of the head comparisons from which I selected the scenarios in Table 30 (67%) projected increases over time; however, several climate scenarios indicate relatively large decreases. The last three records in Table 30 represent the largest declines in hydraulic head among all of the simulations. The main causes of these declines were drops in precipitation. The 127 centimeter decrease in head from 2020-2029 to 2030-2039 for climate model CCSM-B1 was the result of a 20% drop in precipitation over that time period, which then markedly increased over the next decade. Though I conducted this study at decadal intervals, Table 30 and Figure 101 illustrate that the climate models can project dramatic changes over relatively short time periods, as evidenced by climate model CCSM-B1.

6.2.3 Spatial distribution of head change

The analysis above focused on overall changes in hydraulic head among the various simulations, and averaged across the entire model. As I did with SWAT's recharge projections, I also explored how the changes in hydraulic head varied spatially.

Figure 102 maps the change in head from 2010-2019 to 2090-2099, averaged by emission scenario. The maps reflect the trends in Figure 98; change was highest for A1Fi (up to 7.16 meters), and least for B1. The clearest spatial trend within the distribution of head change was that the largest changes occurred at the areas furthest away from the model's river network. The locations of the river cells, originally shown in Figure 24, are obvious in the A1Fi map of Figure 102. MODFLOW treats river cells as areas of constant head; therefore they do not change during a model simulation. Those fixed heads constrain the extent to which head can increase in nearby cells, particularly in a steady-state simulation. The cells furthest from those fixed heads have more freedom to fluctuate. For all four of the emission scenarios, that freedom led to the largest increases in head change as a response to increased recharge. High changes were also located along the edges of the model, near no-flow boundaries; these included the hot-spots in the southwest corner and northwestern portion of the study area identified in Figure 49. These spatial trends were similar to results in the original MODFLOW model's report, in which the authors simulated a recharge reduction scenario and reported the greatest changes in head in the southwestern and north central portions of the study area (Luukkonen et al., 2004).

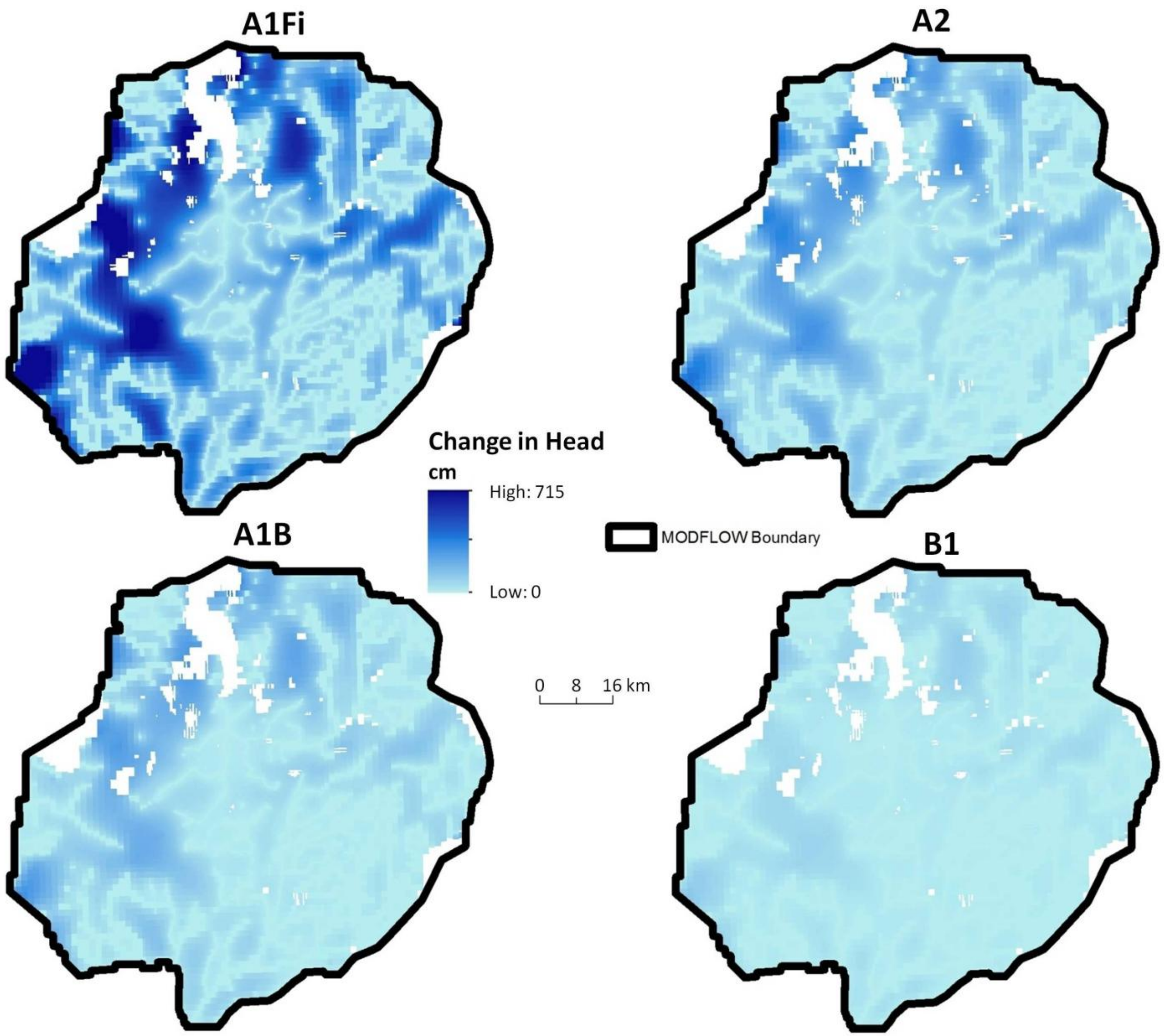

Figure 102: Change in Hydraulic head from 2010-2019 to 2090-2099, averaged by emission scenario.

As I did for recharge, I calculated geographic mean centers of hydraulic head to better quantify how its spatial distribution changed from one scenario to the next. Unlike the previous analysis of MODFLOW outputs, this exploration of the changes in hydraulic head focuses on the projected head values, not the values of change over time. Figure 103 shows the geographic mean center of hydraulic head in the top layer of the MODFLOW model, for climate scenario CCSM-A1Fi during the 2010-2019 time period. When compared to the un-weighted geographic mean center of the MODFLOW cells, the head mean center is pulled slightly to the east by the higher values along the model's eastern boundary. Figure 104 displays the geographic means of hydraulic head for all of the simulations; each dot represents the geographic mean of a particular climate model, decade, and MODFLOW layer number.

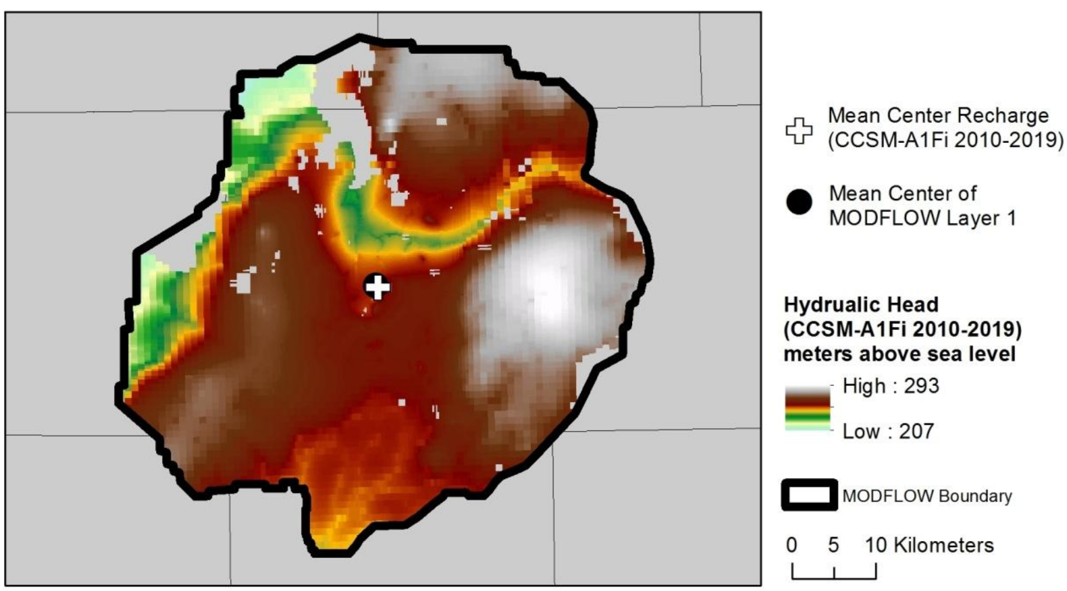

Figure 103: Geographic mean center for recharge in climate model CCSM-A1Fi for the decade 2010-2019.

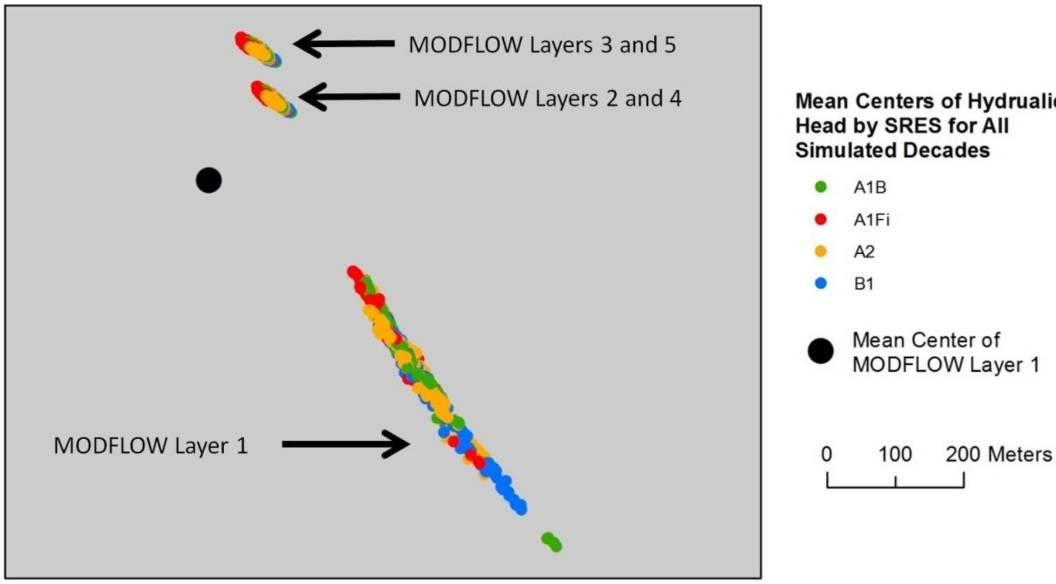

Figure 104: Geographic mean centers of hydraulic head. Each dot represents an average value for a particular climate model, MODFLOW layer, and decade.

This distribution of geographic means is much more uniform than the more widely dispersed recharge means in Figure 92, indicating that there was less spatial variability among the changes in hydraulic head under the various simulations than there was among the changes in recharge. This likely was driven by the relationship of each particular cell to its neighbors. For recharge, there was a greater likelihood that neighboring cell values could be significantly different than for hydraulic head. It is possible that a particular cell might be dominated by urban land covers (with low overall recharge) but be next to a cell dominated by open space (higher recharge); or a cell dominated by sandy soils is next to a cell with more clay in it. These types of scenarios are a by-product of mapping geographic data with nominal classes. In such cases there are clear boundaries between neighboring features (*e.g.* corn next to forest, soil A vs. soil B). Because recharge is driven largely by land cover and soil, its distribution is going to reflect those boundaries to a certain degree, as shown in Figure 91. In contrast, hydraulic head represents continuous data and is not as prone to the relatively sudden changes in value over space as is nominal data. Furthermore, hydraulic head values are heavily dependent upon the neighboring values. MODFLOW iteratively solves its groundwater flow equations by comparing estimated head values to its neighbors until the changes between iterations stabilize and a relatively smooth distribution of the water table is realized. Ultimately, the continuous and neighbor-dependent nature of the hydraulic head gives its geographic mean less freedom to vary than that for recharge, which was at least partially derived from nominal spatial data.

There were three distinct clusters of the geographic means of hydraulic head in Figure 104. The most northern cluster was comprised of head estimates for the third and fifth vertical layers of the MODFLOW model. The cluster below that represented the second and fourth layers, while the southernmost and longest cluster represented the top layer. The second and fourth layers were modeled as confining layers (Figure 17); they share similar attributes of hydraulic conductivity, therefore projections of hydraulic head in those layers were also similar. The other three layers were defined as aquifers with similar conductivities. However, the top layer differed from the other two in several regards that caused its distribution of geographic means to be distinct. First, its spatial extent was slightly smaller because of the way layer heights were defined in the original model. The top layer was effectively thinned out at the northwest corner where the Kalamazoo River exited the study area, which subsequently skewed the layer's geographic means towards the southeast. Second, the top layer, unlike the other aquifer layers, was allowed to have cells go dry if hydraulic head fell below its bottom elevation, which caused the distribution of head to vary further. Lastly, as shown in Table 28, the top layer exhibited a tendency for greater fluctuation in hydraulic head than the other layers, mainly due to its direct interaction with groundwater recharge.

I took a closer look at the distribution of geographic mean hydraulic head for the CCSM3 climate scenario to explore how these means changed over time (Figure 105). Like those for recharge (Figure 93) the hydraulic head means for each decade fluctuated around the reference means for the 2010-2019 time period. For example, there was no consistent direction of change among the hydraulic head geographic means for CCSM3-B1. The 2020-2029 geographic mean for CCSM3-B1 indicated a shift in hydraulic head towards the northwest, whereas the 2030-2039 geographic mean projected a shift to the southeast. Figure 105 helps explain why some of the means differed from the 2010-2019 reference means. CCSM3-B1 2020-2029 experienced a large increase in precipitation (Figure 101), which resulted in head increases in the no flow boundaries along the southwest and western borders, and in the north where there was a relatively large gap between river cells of constant head; all of which combined to pull the geographic mean north and west. In contrast, the CCSM3-B1 2030-2039 scenario saw a significant drop in precipitation, which most affected the areas furthest from river constant head cells. In these areas head dropped in comparison to 2010-2019 levels, and pushed the geographic mean southwest. Similar to the CCSM3-B1 2020-2029 result, the CCSM3-A1Fi 2080-2089 geographic mean was pulled northwest in response to an increase in precipitation, but also because of the sharp drop in ET (and subsequent increase in recharge) from the higher CO_2 levels. For the 2040-2049 simulation of CCSM-A2 the drop in precipitation caused an overall drop in head in the northwest portion of the study area, pushing the geographic mean southeast.

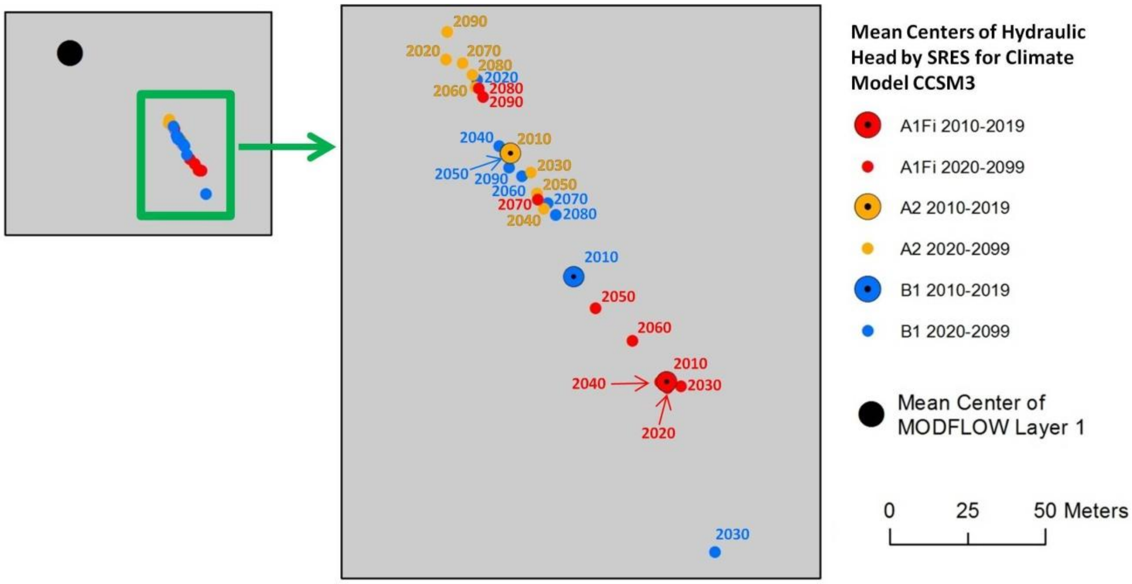

Figure 105: Geographic mean centers of hydraulic head for climate model CCSM3.

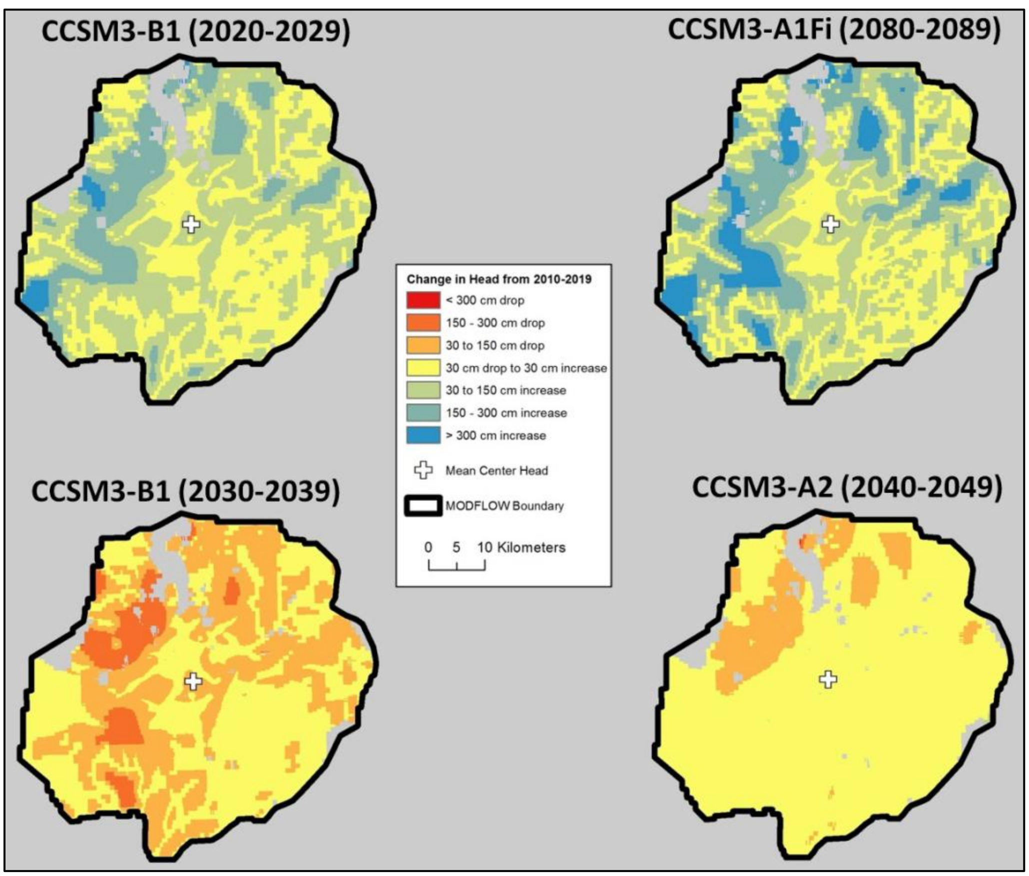

Figure 106: Change in hydraulic head from the 2010-2019 simulation of the respective climate scenario.

I also explored how the distribution of hydraulic head geographic means changed by the land cover management scenarios. Figure 107 shows how those means varied for a sub-set of decadal simulations under the CCSM3 climate model. The land cover management scenario geographic means did not cluster together by decade, like they did for recharge (Figure 95), so I drew polygons around them to mark the decadal groupings. Though not as clear as it was among the recharge geographic means, there was a general pattern of difference for head change among the four land cover scenarios. Most of the urbanizing areas were in the city of Kalamazoo, to the northwest of the static land cover geographic mean, creating a push effect as a result of the lower recharge rates. This general trend occurred in the examples from CCSM3 in Figure 107. There was a tendency for the agricultural expansion scenario geographic mean to stay close to that of the static land cover scenario in the CCSM3 climate model, which was not the case among other models. That geographic mean exhibited varying degrees of distance and direction from the reference static land cover mean. Because the combined land cover change scenario included the agricultural expansion, it also did not reflect a clear and consistent trend. One potential cause for this spatial variability when compared to the urbanization scenario is that the areas which were urbanized were more concentrated in a single area (the City of Kalamazoo) than the more geographically dispersed conversions to agriculture. This geographic focus of the urban conversions created a stronger center from which a pushing force might be evident in a measure of dispersion like the geographic mean center.

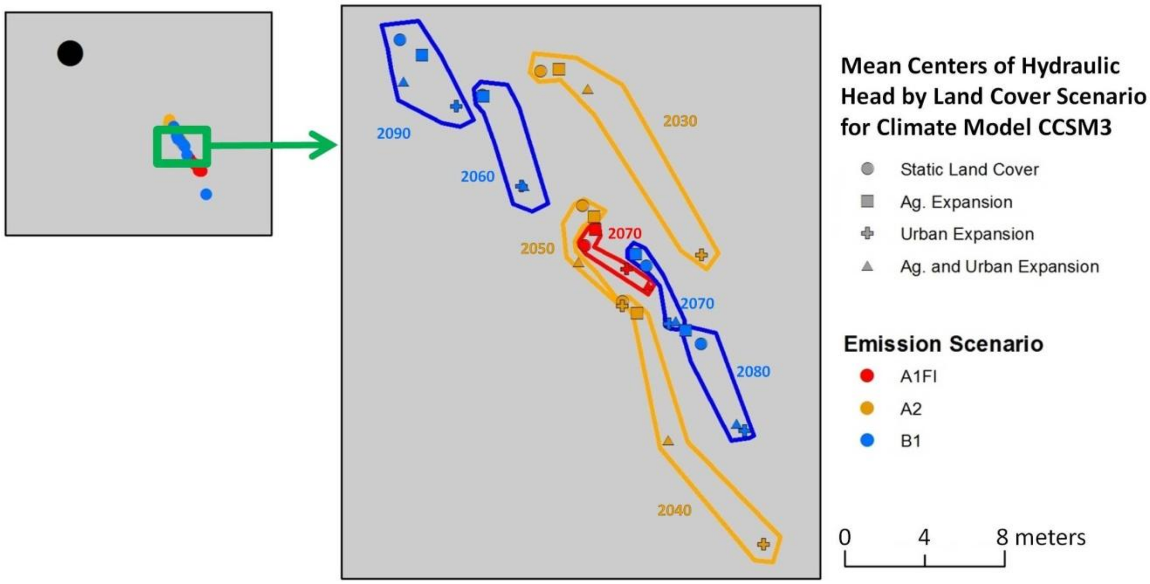

Figure 107: Geographic mean center of hydraulic head by land cover scenario, for climate model CCSM3.

6.3 Hypothesis Evaluation

In section *1.3 Hypotheses*, I stated my expectations regarding how hydraulic head would change under the following four general scenarios: 1) a changing climate, 2) urban expansion, 3) agricultural expansion, 4) a combination of the previous 3. I ran too many simulations to state separate hypotheses for each combination of climate model, emission scenario, land cover scenario, and decade. But I did calculate difference of means paired t-tests between each scenario and a reference scenario. I employed the paired version of the t-test because I was able to calculate change for each individual MODFLOW cell from the reference scenario to the change scenario. For example, to estimate if a changing climate had a statistically significant impact on hydraulic head, I compared each head value in the MODFLOW cells of a particular climate scenario, decade from 2020-2099, and MODFLOW layer number to the corresponding head values from the equivalent 2010-2019 scenario (*e.g.* average head for CCSM3-B1 2050-2059 in MODFLOW layer 3 and the static land cover scenario versus the average head for CCSM3-B1 2010-2019 in MODFLOW layer 3 and the static land cover scenario). To estimate if urban expansion had a statistically significant impact on hydraulic head, I compared each head value in a particular urban expansion land cover scenario to the matching cells in the equivalent static land cover scenario (*e.g.* average head for CCSM-B1 2050-2059 in MODFLOW layer 3 and urban expansion scenario versus the average head for CCSM-B1 2050-2059 in MODFLOW layer 3 and the urban expansion scenario). In the first example the decade changed, in the latter the land cover scenario was the difference.

All these various comparisons for the 4 hypotheses translated into 6,510 difference of means t-tests. Traditionally t-test results are reported with a statement of the t-test statistic, the degrees of freedom utilized, and the probability that the two scenarios are not significantly different. I could not list all of those here, so I instead state the percentage of relevant simulations that indicated that the difference in head between the reference and change scenarios was statistically significant, and the average difference across those simulations.

Here are the hypotheses and the results of the paired t-tests.

For a water-abundant and agriculturally productive region:

1. The water table will rise under a future scenario of a higher temperatures and more precipitation.

H_O: $WTE_{\text{current}} \geq WTE_{\text{CC}}$

H_A: $WTE_{\text{current}} < WTE_{\text{CC}}$

where:

WTE_{current} = average water table elevation under the current climate conditions

WTE_{CC} = average water table elevation under the climate change scenario

Results:

$WTE_{\text{CC}} - WTE_{\text{current}} =$ 22.3 cm

Percentage of scenarios in which hydraulic heads in $WTE_{current}$ were higher than WTE_{CC} and the differences were statistically significant: 73%

Null Hypothesis Result: **Reject H_O**

Analysis: In the vast majority of model simulations (73%) in which climate change was compared to current climate conditions, hydraulic head was higher and the difference was statistically significant. This result was skewed lower by the fact that it included comparisons from earlier simulations (*i.e.* 2020-2029, 2030-2039, etc.) in addition to scenarios that reflect the projected change at the end of the century. If this comparison was limited to the change in head across scenarios for the 2090-2099 decade, the average difference would have been 60.6 centimeters, with 94% of those scenarios statistically significant.

2. The water table will drop under a future scenario of increased urbanization due to greater municipal water use and reduced groundwater recharge from and expansion of impervious surfaces.

H_O: $WTE_{\text{current}} \leq WTE_{\text{URB}}$

H_A: $WTE_{\text{current}} > WTE_{\text{URB}}$

where:

WTE_{current} = average water table elevation under a scenario of no land cover change

WTE_{URB} = average water table elevation under a scenario expanded urbanization

Results:

$WTE_{\text{URB}} - WTE_{\text{current}} = -1.8$ centimeters

Percentage of scenarios in which hydraulic heads in $WTE_{current}$ were higher than WTE_{URB} and the differences were statistically significant: 86%

Null Hypothesis Result: **Reject H_O**

Analysis: In the vast majority of model simulations (86%) in which an expansion of urban areas was modeled, hydraulic head was lower and the difference was statistically significant. Even though the average difference was less than two centimeters, it still proved to be statistically significant.

3. The water table will drop under a future scenario of agricultural expansion due to increased water withdrawals for irrigation.

H_O: $WTE_{\text{current}} \leq WTE_{\text{AG}}$

H_A: $WTE_{\text{current}} > WTE_{\text{AG}}$

where:

WTE_{current} = average water table elevation under a scenario of no land cover change

WTE_{AG} = average water table elevation under a scenario of expanded agriculture

Results:

$WTE_{\text{AG}} - WTE_{\text{current}}$ = 0.1 centimeters

Percentage of scenarios in which hydraulic heads in $WTE_{current}$ were higher than WTE_{AG} and the differences were statistically significant: 43%

Null Hypothesis Result: **Fail to reject H_O**

Analysis: The change in head when agricultural expansion was simulated was quite small, and the sign of the average was not what I expected. I had anticipated observing a drop in the water table caused by additional withdrawals for irrigation, but it rose slightly instead. I failed to anticipate the dramatic drop in ET, and subsequent drop in irrigation demand, resulting from the improved plant water use efficiency at the elevated CO_2 scenarios. If I limited the comparison to the moderate CO_2 emission scenarios (B1), the water table drops slightly (0.3 centimeters), but for most of those scenarios the differences were not statistically significant.

<u>4. The water table will rise under a scenario of future climate change, increased urbanization, and increased agricultural production because increasing precipitation will have a greater impact on the water table than expanded urbanization.</u>

H_O: $WTE_{\text{current}} \geq WTE_{\text{COM}}$

H_A: $WTE_{\text{current}} < WTE_{\text{COM}}$

where:

WTE_{current} = average water table elevation under a scenario of no land cover change

WTE_{COM} = average water table elevation under the combined scenarios

Results:

$WTE_{\text{COM}} - WTE_{\text{current}} =$ 20.5 centimeters

Percentage of scenarios in which hydraulic heads in $WTE_{current}$ were lower than WTE_{COM} and the differences were statistically significant: 73%

Null Hypothesis Result: **Reject H_O**

Analysis: In the majority of model simulations (73%) in which climate change, and expansions of both urban and agricultural areas was modeled, hydraulic head was higher and the difference was statistically significant. It is clear given the results in the previous hypotheses that the effects of climate change were much greater than either of the land cover change scenarios.

CHAPTER 7: Social Indicators of Groundwater Sustainability

I sought to explore the broader societal context for the hydrologic questions I was addressing. More specifically, I wanted to engage the largest users of water and assess their awareness of threats to groundwater sustainability, assess their attitudes towards conservation practices, and identify the constraints that might limit their ability to employ those practices. These metrics are collectively referred to as social indicators of water health, and are typically used in the context of reducing non-point source pollution in surface waters. I used them to evaluate groundwater sustainability, and gathered the data to construct them by administering an online survey to large-quantity water users in Michigan.

The social indicators approach has been used previously to measure a local watershed population's awareness of threats to surface water quality, attitudes towards conservation practices that would reduce pollutant loading to streams, and the constraints in adopting those practices (Prokopy et al., 2009). To my knowledge, no one has administered a social indicator survey exclusively for groundwater.

The geographic scope of this analysis differed from that of the hydrologic modeling. I administered the survey to large-quantity water users throughout Michigan, as opposed to the hydrologic modeling focus on Kalamazoo County. In a more tightly coupled study, the survey would have sampled from all of the large-quantity water-users in Kalamazoo County, and painted a more detailed picture of the societal context of the hydrologic model results.

However, I could not guarantee and effective sample size of that population, considering that the state-wide population of large-quantity water users was only 2,882. Furthermore, partnering with the State of Michigan's Water Use Program was the most cost-effective means of engaging the large-quantity water user population, which opened up my sample to the entire state. A targeted survey within Kalamazoo County would have necessitated paper surveys by mail, and in-person interviews, for which I did not have sufficient resources. Conversely, a state-wide groundwater model would have been similarly cost-prohibitive.

7.1 Survey Methods

As mandated in Public Act 148 of 2003, the State of Michigan requires large-quantity water users, defined as those with the ability to withdraw more than 378,541 LPD (265 LPM), to report their use annually (MDARD, 2015). Users in the agricultural industry must report to the Michigan Department of Agriculture and Rural Development (MDARD), while all others must report to the Michigan Department of Environmental Quality (MDEQ). In 2012 the State offered an online reporting option in addition to the traditional paper mailings. In 2013 Michigan mandated online submission. I received permission from the respective water-use program administrators in each department to provide users with an opportunity to voluntarily take the survey upon completion of their online 2013 water report. With support from the graduate school at Michigan State University, I was able to offer the users an opportunity to enter a drawing for one of twenty $50 gift cards. The survey was only available online. I did not interview anyone, or mail out paper versions of the survey. Because the survey was anonymous and did not ask for sensitive information, MSU's Internal Review Board deemed the project exempt from additional external review (Appendix C).

7.1.1 Survey Construction

I developed two versions of the survey, one tailored for respondents in the agricultural sector and another for respondents outside of agriculture. Most of the individuals in this latter group identified their sector of work as manufacturing, turf-grass, sanitation, and school management. I will refer to the two versions as the agricultural survey and the non-agricultural survey. Those who reported their 2013 water use to MDARD were offered the agricultural survey, whereas those who reported to MDEQ were offered the non-agricultural survey. The agricultural version contained 70 questions; the non-agricultural version contained 54. Both took between 10 to 15 minutes to complete. Full copies of both surveys, along with their respective responses frequencies, can be found in Appendix D.

I structured the survey in the same manner as that used by the Social Indicators Data Management and Analysis System (SIDMA), an online tool designed for US EPA by researchers and state governments in the Great Lakes region to facilitate the construction, administration, and analysis of social indicator surveys (Great Lakes Regional Water Program, 2011). SIDMA is designed to assess social indicators of surface water quality, with a greater focus on pollutant loading and habitat health, and is used by local and state governments, academics, and non-profit environmental groups across the country. MDEQ requires groups receiving watershed management plan funds to gather social indicator data through SIDMA. The tool organizes the indicators into several groups: awareness, attitudes, and behavior. I developed companion indicators for groundwater. Table 31 lists those indicators alongside their original versions in SIDMA[24].

Table 31: Original social indicators in SIDMA, and their modified names for the groundwater survey.

Indicator ID in SIDMA (Modified ID #)	Original Indicator	Modified for Groundwater Survey
1.1 (1.1)	Awareness of consequences of pollutants to water quality	Awareness of consequences of excessive groundwater use
1.3 (1.2)	Awareness of sources of pollutants impairing waterways	Awareness of threats to future groundwater availability
1.4 (1.3)	Awareness of appropriate practices to improve water quality	Awareness of appropriate practices to conserve groundwater
2.1 (2.1)	General water-quality-related attitudes	General groundwater-related attitudes
2.2 (2.2)	Willingness to take action to improve water quality	Willingness to take action to conserve groundwater resources
3.1 (3.1)	Constraints to behavior change	Constraints to behavior change towards water conservation
3.2 (3.2)	Constraints to adopting key practices	Constraints to adopting key water conservation practices

SIDMA calculates a score for each indicator by recoding and averaging responses to certain groups of questions. I organized both the agricultural and non-agricultural surveys into 9 categories, similar to those used within SIDMA.

1. *Your Opinions on Groundwater Conservation* – assesses the degree to which respondents believe that groundwater conservation is important.

[24] Not all of the indicators within SIDMA lent themselves to being modified for groundwater. For example, original indicator 1.2 measures awareness of types of pollutants impairing waterways. But I was primarily interested in issues of groundwater supply, not contamination; so I left this indicator out of my survey.

2. *Threats to Future Groundwater Availability* – assesses the degree to which respondents believe that certain threats (such as increased irrigation) to groundwater availability are or will be a problem in their area.

3. *Impacts of Excessive Groundwater Use* – assesses the degree to which certain impacts of excessive groundwater use (such as dry wells) are or will be a problem in their area.

4. *Groundwater Conservation Practices* – assesses respondents' familiarity of certain groundwater conservation practices (such as drip irrigation).

5. *Specific Constraints of Practices* – assesses the degree to which certain factors (such as cost) limit the respondents' ability to implement a specific groundwater conservation practice. For the agricultural survey this practice was irrigation scheduling. For the non-agricultural survey this practice was water system auditing.

6. *Making Decisions for Your Property* – assesses the degree to which factors limit the respondents' ability to implement a broad range of groundwater conservation practices.

7. *About Your Water Use* – gathers details about the type, water source, and total water use of respondents' operations.

8. *About You* – gathers demographic information about the respondents.

9. *Information Sources* – gathers information on the sources respondents rely on for water news and information, and the extent to which they trust those sources.

For example, Category 1, *Your Opinions on Groundwater Conservation*, asks respondents to state the degree to which they agree or disagree with several statements. One of those is, "It is important to conserve groundwater, even if it slows economic development." An individual's response to this question and the others in Category 1 are averaged to calculate that individual's score for Indicator 2.1, *General Groundwater Related Attitudes*.

The question formats on the groundwater surveys ranged from multiple-choice, to Likert-scale, and open-ended. The surveys were anonymous, and all questions were voluntary. The only potentially sensitive question on either survey asked the respondents to report their total annual water use for 2013; but given the respondents' anonymity, Internal Review Board at Michigan State University was satisfied that no harm could be done with that information. Prior to taking the survey the online form asked respondents to voluntarily identify their Michigan county and township, to facilitate geographic comparisons in the subsequent analysis.

7.1.2 Survey Administration

I collaborated on SIDMA's development as a programmer for the Institute of Water Research at Michigan State University, where the system is hosted. As SIDMA's primary web-programmer I was able to create a temporary clone of the system in order to gather the survey responses for my study. By storing the responses within a SIDMA clone, which I will refer to as SIDMA-GW (SIDMA for groundwater), I was able to utilize the system's analytical functions to evaluate the data. These functions included the visualization of response frequencies to individual questions, the calculation of indicator scores, and statistical tests of significance between groups of respondents.

I created the surveys in SIDMA-GW and established public web-links for the agricultural and non-agricultural versions. The links first directed respondents to an informed consent page, and then to the appropriate survey. I also placed a password on each version so that if someone (or some software) happened upon the link, they could not unwittingly or maliciously submit false responses. I then coordinated with the water-use administrators at MDARD and MDEQ to have the public links presented to the users upon submitting their online 2013 reports. MDARD allows individuals to start reporting their year's water use in December of that year, so my goal was to have the survey links in place well before then. MDEQ typically opens the reporting period in January or February of the following year.

Because Michigan's Department of Information Technology (M-DIT) is responsible for hosting all of the State's websites, including the water-use reporting system, I had to coordinate the logistics of adding the survey links to the MDARD and MDEQ reports with M-DIT. Despite making a formal request for the links to be added months in advance, and despite the support and authorization of the MDARD and MDEQ water-use program administrators, M-DIT did not add the links until February of 2014. M-DIT's initial concern was that a link to an external website was a security risk that the State could not accept. Unfortunately, I was not notified of this concern until December 2013, and only after months of unanswered phone calls and ignored emails. With added support from the MDARD and MDEQ water use program administrators, M-DIT finally added the links in February 2014.

M-DIT's delay meant that I had missed a large portion of agricultural water users who submitted early. MDARD estimated that I missed upwards of 50% of the submissions, whereas MDEQ estimated that I missed 10%. Out of a total of 1,402 total water-use reports submitted to MDARD, only 76 took the survey. The response rate for the non-agricultural survey, 200 out 1,482, was slightly better. I was hoping to receive a total of 350 respondents, which would have produced a ± 5% margin of error on the responses to certain questions. The MDEQ response rate instead yielded a ± 6.5% margin of error, whereas the MDARD rate yielded a ± 11% rate, both at the 95% confidence interval. The MDARD rate severely limited my analysis of the survey results, particularly in comparing results between agricultural and non-agricultural respondents, and in comparing results between sub-groups, such as males and females, and geographic regions. Furthermore, the delay meant that I likely oversampled late-reporting individuals, which could be a distinctly different group in terms of age, gender, income, awareness of groundwater threats, willingness to adopt conservation, among others, than early reporters.

7.2 Survey Results

I analyzed the survey results from several perspectives. First, I looked at the response frequencies for individual questions on the agricultural and non-agricultural surveys. For example, using the sample question from above, I evaluated the percentages of agricultural respondents that felt that conserving groundwater was more important than economic development. Given the margin of error from the sample size, I assessed whether there was a clear signal in the collective response to that question. I then compared those frequencies between the two surveys, to see if there were any clear differences between the agricultural and non-agricultural respondents. Next, I analyzed the social indicator scores for the two surveys, and then evaluated their differences for statistical significance. Lastly, I sub-divided the agricultural and non-agricultural respondents into sub-groups by age, education level, income, and total water use, and then compared social indicator scores between those groups. Detailed response frequencies and indicator scores on the agricultural and non-agricultural surveys are available in Appendix E.

7.2.1 Response Frequencies for Agriculture Respondents

Because of the ±11% margin of error on the agricultural survey, I looked for questions in which the difference in response frequencies among a particular question's answer options was greater than 22%. For example, if a question had five answer options on a Likert scale ranging from "Strongly Disagree" to "Strongly Agree", and each option was selected by 20% of the respondents, then I would be unable to conclude that no consensus opinion existed among the population of large-quantity water users. It would be possible that 31% would have selected "Strongly Agree" while 9% would have selected "Strongly Disagree." However, if 62% of the sample had selected "Strongly Agree" and 38% had selected "Strongly Disagree," then I could be confident that a majority of large-quantity water users strongly agreed, because the minimum value for that option within the margin of error would have been 51%.

For the *Your Opinions on Groundwater Conservation* category, there was general consensus among agricultural respondents that groundwater conservation was important. 93% of respondents felt that conserving groundwater was a personal responsibility, and 63% were willing to change their current practices to do so. There was less support for conservation at the expense of economic development, but a majority (60%) still agreed that conservation was more important.

The *Threats to Future Groundwater Availability* category presented this statement and question to respondents:

> "The following items may threaten the availability of groundwater resources in the future. In your opinion, how much of a threat are the following items in your area?"

It is important to note the last part of the question. A respondent may have deemed an item a threat, but perhaps not in her region. For example, she may feel that climate change is a threat to groundwater in the southwestern U.S., but not in Cass County, Michigan. The question focused on the respondent's area to avoid that potential spatial ambiguity. Among agricultural respondents, the strongest consensus was that household water use was a small threat; 72% selected "Not a Threat" or "Slight Threat", versus 28% that selected "Moderate Threat" or "Severe Threat." The next strongest consensus was that increased irrigation was a small threat (68% versus 30%), followed by increasing demand for agricultural goods as a small threat (64% versus 35%), and climate change as a small threat (59.2% to 36.9% - just above the 22% margin of error difference threshold). Responses to the other proposed threats did not reflect a clear signal beyond the 22% margin of error difference threshold.

The *Impacts of Excessive Groundwater Use* category was similar in structure to the previous one, but focused specifically on impacts as opposed to threats. The category asked respondents, “In your opinion, how much of a problem are the following issues in your area?” Note that like the previous category, this one asked respondents to focus on their area, not evaluate whether the listed impacts were problems nationally or globally. There was general consensus that none of the impacts were problems. In order by the size of the consensus, most felt that neighbor conflict was not a problem or only a slight problem (80% versus 16%), followed by groundwater contamination (75% versus 13%), land subsidence (72% versus 11%), degraded aquatic habitat (78% versus 17%), and wells running dry (77% versus 19%).

Because the previous two categories asked respondents to focus on their respective areas, it is possible that stratifying the respondents spatially might reveal different trends. With salt-water intrusion becoming more of a problem in the western part of the state (Schindler, 2012), one might expect to see more respondents from that region categorize groundwater contamination as a severe problem. However, given the small size of the state-wide sample, I could not sort respondents into regional classes of sizes large enough to meaningfully evaluate them.

The *Groundwater Conservation Practices* category asked respondents to describe their level of experience among a list of practices. I based the list on MDARD’s Generally Accepted Agricultural and Management Practices (GAAMPs) for Irrigation Water Use (MDARD, 2012). The strongest signals were for irrigation system inspection (85% currently use it), minimizing irrigation application drift (79%), conservation tillage (75%), and scheduling irrigation with respect to crop needs and soil moisture (71%). Furrow diking and drip irrigation were generally deemed not relevant to a respondent’s property (63% and 27%, respectively).

The *Making Decisions for my Property* category sought to identify the constraints that prevented respondents from adopting groundwater conservation practices by asking the following question:

> "In general, how much does each issue limit your ability to change your management practices?"

All but two of the issues were deemed to have little to no effect among the majority of respondents. The first of those two issues was personal out of pocket expense, which 74% of respondents rated as limiting their ability to change practices "Somewhat" or "A lot." The other issue was a lack of government funds for cost sharing a practice, for which no clear signal was present. The two least limiting issues were not owning the property on which a practice could be implemented (80% of respondents categorized as "Not at all" limiting, implying that most of the respondents were property owners), and neighbor approval (74% categorized as "Not at all" limiting).

The *Information Sources* category measured the degree to which respondents trusted certain sources of information about water quality and quantity. Unsurprisingly, groups that work more closely with farmers, and therefore are more likely to have established personal relationships with them, were deemed more trustworthy than groups charged with regulating them or promoting changes to their operations. 96% of respondents rated Michigan State University Extension as "Moderately" to "Very" trustworthy (70% selected "Very"). The other most trusted sources were county soil and water conservation districts (85% respondents rated as "Moderately" to "Very" trustworthy), NRCS (79%), MDARD (77%), and crop consultants (77%). Respondents deemed US EPA and MDEQ less trustworthy (58% and 47%, respectively), but not to the degree from which I could infer a consensus, given the margin of error. The one source for which there was a consensus of untrustworthiness among respondents was environmental groups. 49% of respondents trusted them “Not at all,” and 37% only trusted them “Slightly.”

The other portions of the survey were not structured in a table format as the previous categories were, and sought to gain a clearer picture of the demographics of the sample. 96% of respondents were male, ruling out any comparison between sub-groups by gender. The average age was 51, and ranged from 19 to 73. Most had completed at least some level of college, and had total household incomes above $50,000. Most identified their particular sectors within agriculture as row-crop or vegetable/specialty; and most groundwater users knew whether their water came from bedrock or glacial aquifers. If they wanted to learn more about water conservation, they were most likely to seek information at workshops and meetings (80%), through trade publications (72%), in newsletters (71%), on the internet (69%), or in conversations with others (59%). They were least likely to seek out information on the radio (5%).

7.2.2 Social indicator scores for agricultural respondents

SIDMA-GW used the same approach designed by SIDMA’s authors to convert the response frequencies above into social indicator scores for each of the indicators in Table 31. It did this by assigning a score to each response option (following the same convention the original SIDMA used for surface water quality indicators), calculating an average score for each respondent from the questions that pertained to a particular indicator, and then averaging scores amongst the respondents. Consider *Indicator 1.1: Awareness of consequences of excessive groundwater use*. The score for this indicator could range from 1 (representing less awareness) to 2 (more awareness). SIDMA-GW calculated the score from responses to the questions in the survey's *Impacts of Excessive Groundwater Use* category. Table 32 illustrates how SIDMA-GW assigned indicator scores to the response options in that category. Overall, agricultural respondents trended toward less awareness of groundwater consequences as defined by the survey (*M* = 1.30, *SD* = 0.34), though the large standard deviation amongst indicator scores relative to their narrow range of possible scores (1.0 – 2.0) indicates that this tendency was not particularly strong.

Table 32: Response scores for the Indicator *1.1: Awareness of consequences of excessive groundwater use*.

Question: Excessive use of groundwater (use at a rate faster than the groundwater system can replenish itself) can lead to a variety of consequences for communities. In your opinion, how much of a problem are the following issues in your area?					
Options:	**Not a Problem**	**Slight Problem**	**Moderate Problem**	**Severe Problem**	**Don't Know**
Indicator scores:	1	1.5	2	2	0

SIDMA-GW calculated *Indicator 1.2: Awareness of threats to future groundwater availability*, from responses to the questions in the *Threats to Future Groundwater Availability* category. SIDMA-GW calculated this indicator in a similar fashion to *Indicator 1.1* above, as shown in Table 33. Scores ranged from 1 (not a threat) to 2 (severe or moderate threat). The average score leaned slightly towards viewing the items as a threat (*M* = 1.56, *SD* = 0.40); but the standard deviation of those scores made this another weak tendency. In my earlier analysis of the response frequencies for this category, I concluded that most respondents deemed these items as not being small threats, because clear majorities selected either the "Not a Threat" or

“Slight Threat” options. However, SIDMA-GW classifies “Slight Threat” as the middle value of the *Indicator 1.2* range, and a large number of respondents selected that option when evaluating the threat level of the items.

Table 33: Response scores for the Indicator 1.2: Awareness of threats to future groundwater availability.

Question: The following items may threaten the availability of groundwater resources in the future. In your opinion, how much of a threat are the following items in your area?					
Options:	**Not a Threat**	**Slight Threat**	**Moderate Threat**	**Severe Threat**	**Don’t Know**
Indicator scores:	1	1.5	2	2	0

SIDMA-GW calculated *Indicator 1.3: Awareness of appropriate practices to conserve groundwater*, from a combination of responses to the questions in the *Groundwater Conservation Practices* and *Specific Constraints of Practices* categories. For this indicator SIDMA-GW, and the original SIDMA, expects the survey author to identify a key practice to evaluate. This practice might be one of particular importance, perhaps because it has been shown to be the most effective as improving water quality or, in this case, conserving groundwater within agriculture. I discussed this with the MDARD water-use program administrator, and selected irrigation scheduling as the key practice, which involves irrigating based upon current soil moisture conditions, soil infiltration rates, crop water needs, and rainfall measurements for each field. SIDMA-GW calculated this indicator by combining scores from the *Groundwater Conservation Practices* category with the score for the similarly worded question, focused on irrigation scheduling, in the *Specific Constraints of Practices* category. Scores to the latter question were weighted more heavily than the scores to the other category, and ranged from 1 (less awareness) to 2 (more awareness) (Table 34). Overall, agricultural respondents exhibited strong awareness of the practices listed on the survey (M = 1.84, SD =

0.29), driven mainly by the large percentage of respondents currently using irrigation scheduling (71%).

Table 34: Response scores for Indicator 1.3: Awareness of appropriate practices to conserve groundwater. The final indicator score is calculated by taking the sum of the weighted scores calculated for the two categories.

Instruction: Please indicate which statement most accurately describes your level of experience with each practice listed below.					
Options:	**Not relevant for my property**	**Never heard of it**	**Somewhat familiar with it**	**Know how to use it; not using it**	**Currently using it**
Indicator scores from *Groundwater Conservation Practices* category	0	1	1.5	2.0	2.0
Indicator scores for Irrigation Scheduling in *Specific Constraints of Practices* category	0	1	1.5	2.0	2.0
Final indicator score for 1.3	Calculated by weighting the average indicator score for the first row (*Groundwater Conservation Practices*) by 0.4, and the score for the second row (*Irrigation Scheduling*) by 0.6.				

SIDMA-GW calculated *Indicator 2.1: General groundwater related attitudes* from the survey's *Your Opinions on Groundwater Conservation* category (Table 35). Scores ranged from 1 (less positive) to 5 (more positive). The overall score among agricultural respondents was positive (*M* = 3.97, *SD* = 0.69), with majorities selecting "Agree" or "Strongly Agree" for each of the listed statements.

Table 35: Response scores for the Indicator 2.1: General groundwater related attitudes.

Instruction: Please indicate your level of agreement or disagreement with the statements below.					
Options:	**Strongly Disagree**	**Disagree**	**Neither Agree or Disagree**	**Agree**	**Strongly Agree**
Indicator scores:	1	2	3	4	5

SIDMA-GW calculated *Indicator 2.2: Willingness to take action to conserve groundwater resources* from a single question in the survey's *Specific Constraints on Practices* category, and therefore focused solely on irrigation scheduling (Table 36). The question asked respondents if they were willing to try this practice. Scores ranged from 1 (less willing) to 2 (more willing). The overall score among agricultural respondents was very high (M = 1.91, SD = 0.19). 83% indicated that they were willing to try irrigation scheduling or already employed the practice, and none of the respondents said that they would not try it.

Table 36: Response scores for the Indicator 2.2: Willingness to take action to conserve groundwater resources.

Instruction: Please indicate your level of agreement or disagreement with the statements below.			
Options:	**Yes or Already Do**	**Maybe**	**No**
Indicator scores:	2	1.5	1

Indicators *3.1: Constraints to behavior change* and *3.2: Constraints to adopting key practices* measured the degree to which certain factors limit respondents from employing groundwater conservation practices, with the latter focused exclusively on irrigation scheduling. SIDMA-GW calculated both indicators in the same manner (Table 37). Scores ranged from 1 (more constraint) to 4 (less constraint). For both indicators, respondents reported generally little limitation in their ability to adopt groundwater conservation practices (M = 3.08, SD = 0.54, and M = 3.27, SD = 0.73, respectively).

Table 37: Response scores for the Indicators 3.1 and 3.2: Constraints to behavior change

Question: In general, how much does each issue limit your ability to change your management practices?					
Options:	**Not at All**	**A Little**	**Some**	**A lot**	**Don't Know**
Indicator scores:	4	3	2	1	0

7.2.3 Response frequencies for non-agricultural respondents

I analyzed the response frequencies for the non-agricultural survey in the same manner I did the agricultural survey, by looking for questions in which a clear signal was evident in spite of the margin of error, which was slightly better (±6.5%) than the other survey.

Similar to the agricultural survey, there was general consensus among non-agricultural respondents to the questions in the *Your Opinions on Groundwater Conservation* category. Most agreed that groundwater conservation was a personal responsibility and were willing to change their behavior to do so. Also like the agricultural survey results, there was less, but still general agreement, that groundwater conservation was more important than economic growth.

For the *Threats to Future Groundwater Availability* category, most respondents felt that growing water use by industry and increasing imperviousness were "Moderate" to "Severe" threats in their respective areas (61% and 57%, respectively). Like the agricultural survey, most respondents felt that increasing water use by households was only a "Slight" threat or "Not at all" (57%). It was noteworthy that climate change responses were mixed; 18% deemed it "Not a threat," whereas 21% felt it was a "Severe threat".

Non-agricultural responses to the *Impacts of Excessive Groundwater Use* category were generally similar to those on the agricultural survey, with general consensus that none of the listed impacts were problems. However, that agreement was slightly weaker among the non-agricultural respondents. Specifically, a smaller percentage of non-agricultural respondents felt that wells running dry was not a problem (35% versus 57%) and that degraded aquatic habitat was not a problem (29% versus 49%).

The *Groundwater Conservation Practices* category asked respondents to describe their level of experience on different list of practices than the ones listed on the agricultural survey. The practices for the non-agricultural survey were geared more towards industrial and commercial applications of water. The strongest signals were for using flow-meters (50% currently use it) and keeping records of system maintenance (57% currently use it).

There were some clear differences between the agricultural and non-agricultural respondents in the *Making Decisions for my Property* category. Agricultural respondents were more likely to consider personal out of pocket expense as a limiting factor for adopting conservation practices; 36% said that it was “Not at all” a factor versus only 7% selecting that option on the agricultural survey. The two groups also differed with regards to property ownership as a limiting factor. 29% of non-agricultural respondents rated not owning the property as limiting them “A lot,” versus only 1% of agricultural respondents. These two questions may help paint a clearer picture of who the nonagricultural respondents were. A large number of them may have been property, facility, or utility managers of companies that use large amounts of water. Such a position would not expose them to the risk of personal out-of-pocket expense that a farmer may face when evaluating the implementation of a practice. Furthermore, they would not likely be property owners in the way a farmer would likely own his or her land.

One of the biggest differences between the agricultural and non-agricultural respondent groups was in their rating of water information sources. There was much more trust of US EPA, MDEQ, and local health departments among the non-agricultural respondents (43%, 62%, and 50%, respectively, trusted them "Very much"), versus the ratings of the same groups among the agricultural respondents (13%, 17%, and 17%, respectively, trusted them "Very much"). There were some similarities, though; non-agricultural respondents also held Michigan State University Extension in high regard (58% trusted them "Very much").

There were some similarities and slight differences in the demographics of the two respondent groups. The vast majority of non-agricultural respondents were male (82%), and few sought water information or news from the radio (5.2%). But the non-agricultural respondents tended to have more education (63% had completed 4 years of college or more) than agricultural respondents (44%), and were less likely to seek water information from trade publications or magazines (46% versus 72%).

7.2.4 Social indicator scores for non-agricultural respondents

SIDMA-GW converted the response frequencies from the non-agricultural respondents to indicator scores using the same survey categories and score conversions described in *7.2.2 Social Indicator Scores for Agricultural Respondents*. For *Indicator 1.1: Awareness of consequences of excessive groundwater use*, there was a slight tendency for non-agricultural respondents to not view the listed consequences as problems in their area (M = 1.46, SD = 0.37). However, similar to the agricultural respondents' average score for this indicator, the large standard deviation relative to the narrow range of possible scores (1.0 – 2.0) indicated that this tendency was not strong.

Scores for *Indicator 1.2: Awareness of threats to future groundwater availability* revealed a tendency to view the listed items as threats (*M* = 1.69, *SD* = 0.29), which was driven by relatively large numbers of respondents deeming increasing water use by industry and the growth of impervious areas as “Moderate” to “Severe” threats to future groundwater availability in their respective regions.

Whereas for the agricultural survey SIDMA-GW weighted scores for *Indicator 1.3: Awareness of appropriate practices to conserve groundwater* by the familiarity of respondents with irrigation scheduling, for the non-agricultural survey SIDMA-GW weighted scores by familiarity with water system auditing. This practice entails conducting thorough evaluations of an operation’s water use to identify and correct areas of inefficiency, and was recommended as a key practice to evaluate by the MDEQ water use program administrator. Overall, respondents exhibited a general awareness of the practices listed on the survey (*M* = 1.66, *SD* = 0.27). But that awareness was driven less by respondents’ familiarity with water system auditing than the other practices. Of all of the practices presented to the respondents, water system auditing had the highest percentage selecting “Never heard of it” (22%), and the fewest selecting “Currently use it” (20%).

As was reported for the agricultural survey, scores for *Indicator 2.1: General groundwater related attitudes* were positive (*M* = 3.92, *SD* = 0.65), with majorities selecting “Agree” or “Strongly Agree” for each of the listed statements.

The average score amongst non-agricultural respondents for *Indicator 2.2: Willingness to take action to conserve groundwater resources* showed a general openness to adopting water system auditing as part of their operation (*M* = 1.66, *SD* = 0.30). Though *Indicator 1.3* revealed a general unfamiliarity with the practice, 39% indicated that they were willing to try water system auditing, while 55% said that they might be willing to try it.

For the constraints indicators, respondents implied that the listed items were more likely to limit their ability to adopt groundwater conservation practices. This tendency applied to conservation practices in general, as measured by *Indicator 3.1: Constraints to behavior change* (*M* = 2.63, *SD* = 0.81), and to water system auditing, as measured by *Indicator 3.2: Constraints to adopting key practices* (*M* = 2.75, *SD* = 0.66). For *Indicator 3.1*, equipment access appears to have been the main source of constraint, with 54% categorizing it as limiting them "Some" or "A lot." For *Indicator 3.2*, cost was the main source of constraint in adopting water system auditing; 60% categorized it as limiting them "Some" or "A lot." This last item was interesting, because when rating conservation practices in general (in the *Making Decisions for my Property* category), only 47% non-agricultural respondents defined "Personal out-of-pocket expense" as limiting them "Some" or "A lot." The difference in the cost effect could be because respondents believed that adopting water system auditing would be more expensive than a generic conservation practice; but it could also be the result of the question's wording. When rating water system auditing constraints, respondents were specifically asked about "Cost," whereas when considering conservation practices in general they were asked about "personal" expense. It is possible that the term "cost" used above could apply to a business expense, which, depending on the respondent and their relation to their operation's water use (*i.e.* a facility manager versus a business owner), could mean something much different, and be less limiting, than a personal expense.

7.3 Indicator Score Comparisons Between Groups

I tested the differences in indicator scores between various groups for statistical significance, which is a function that SIDMA (and therefore, SIDMA-GW) provides. I first compared agricultural respondents to non-agricultural respondents. I then subdivided the agricultural and non-agricultural samples into sub-groups by age, education level, income, and total water use. For each sub-group I defined a cutoff value that marked the dividing line between younger and older, less educated and more educated, lower income and higher income, and smaller water users and larger water users. I then conducted further tests for statistical significance of the differences between the paired groups. I intended to also look at differences by gender and geographic region, but did not have sufficient sub-sample sizes, and therefore left them out of the analysis. I conducted independent difference of means t-tests to evaluate the significance of the differences between groups.

7.3.1 Indicator differences among agricultural vs. non-agricultural respondents

For my first set of comparisons, I looked at the differences in indicator scores between the agricultural and non-agricultural respondents. I must point out that there is inherent uncertainty in this comparison because the groups did not receive identical surveys. The agricultural group was asked to assess their familiarity with conservation practices more applicable to farming, whereas the non-agricultural group's practices dealt more with building management. Some of the constraints to practice adoption also varied between the surveys. For example agricultural respondents were asked to rate the degree to which concerns over reduced crop yields might prevent them from adopting groundwater conservation practices. Nonetheless, I felt that there were enough identical and similar questions to justify a comparison.

I formulated hypotheses for how the two groups' indicators scores would differ (Table 38), and based my alternative hypotheses upon previous studies related to social indicators, which I discussed in *Section 1.3 Hypotheses*. My specific hypotheses for the agricultural and non-agricultural differences were also informed by my experience working with county-level conservation districts, helping them target and promote soil and water conservation practices to farmers. Through that experience I realized how farmers viewed soil and water as critical capital within their operations. Therefore I believed that farmers would tend to view potential threats to groundwater as being more severe than water users in a non-agricultural setting. I also observed that farmers are generally well aware of existing options for conservation, and open to adopting them provided there was sufficient cost sharing from the government. However, my interaction with farmers was primarily through the county conservation district offices, which attracts farmers who are likely pre-disposed to supporting conservation. Nonetheless, I expected the agricultural respondents to exhibit more sensitivity to groundwater threats and consequences, more awareness of conservation practices, and generally more positive attitudes towards groundwater conservation. I had no basis to expect a difference in the constraints that agricultural and non-agricultural respondents faced in adopting conservation practices.

Table 38: Hypotheses for differences between agricultural and non-agricultural social indicator scores.

Indicator	Null Hypotheses	Alternative Hypotheses
Indicator 1.1: Awareness of consequences of excessive groundwater use	$Awareness\_1.1_A = Awareness\_1.1_N$	$Awareness\_1.1_A > Awareness1.1_N$
Indicator 1.2: Awareness of threats to future groundwater availability	$Awareness\_1.2_A = Awareness\_1.2_N$	$Awareness\_1.2_A > Awareness\_1.2_N$
Indicator 1.3: Awareness of appropriate practices to conserve groundwater	$Awareness\_1.3_A = Awareness\_1.3_N$	$Awareness\_1.3_A > Awareness\_1.3_N$
Indicator 2.1: General groundwater related attitudes	$Attitudes\_2.1_A = Attitudes\_2.1_N$	$Attitudes\_2.1_A > Attitudes\_2.1_N$
Indicator 2.2: Willingness to take action to conserve groundwater resources	$Attitudes\_2.2_A = Attitudes\_2.2_N$	$Attitudes\_2.2_A > Attitudes\_2.2_N$
Indicator 3.1: Constraints to behavior change	$Constraints\_3.1_A \neq Constraints\_3.1_N$	$Constraints\_3.1_A = Constraints\_3.1_N$
Indicator 3.2: Constraints to adopting key practices	$Constraints\_3.2_A \neq Constraints\_3.2_N$	$Constraints\_3.2_A = Constraints\_3.2_N$

Table 39 lists the results of difference of means independent t-tests for each indicator. At least among these samples of large quantity water users, I could not support my assumption that the agricultural respondents would exhibit more awareness of groundwater threats or impacts of excessive groundwater use. To the contrary, the awareness of the non-agricultural respondents was significantly higher. I was able to reject the null hypothesis that agricultural respondents would have the same level of awareness of conservation practices as non-agricultural respondents, with agricultural respondents exhibiting more awareness. There was not a significant difference between the two groups regarding their general attitudes towards groundwater conservation, forcing me to retain the null hypothesis that their attitudes were equal. But agricultural respondents did exhibit greater willingness to adopting conservation practices, allowing me to reject the null hypothesis that the two groups were equally willing. I expected both groups to report similar levels of constraint in adopting conservation, but the non-agricultural respondents indicated significantly more limitations, causing me to retain the null hypothesis.

Table 39: Difference of means t-test results for comparison of agricultural and non-agricultural social indicators.

Ind. ID	Average Agricultural Score	Average Non-agricultural Score	Difference	Statistically Significant	Null Hypothesis Result
1.1	$Awareness\_1.1_A$ = (M=**1.30,** SD=0.34)	$Awareness1.1_N$ = (M=**1.46,** SD=0.37)	**-0.16**	**Yes** $t(268) = 3.14$, $p = 0.002$	**Fail to reject**
1.2	$Awareness\_1.2_A$ = (M=**1.56,** SD=0.29)	$Awareness\_1.2_N$ = (M=**1.69,** SD=0.29)	**-0.13**	**Yes** $t(268) = 3.28$, $p = 0.001$	**Fail to reject**
1.3	$Awareness\_1.3_A$ = (M=**1.85,** SD=0.18)	$Awareness\_1.3_N$ = (M=**1.66,** SD=0.27)	**0.19**	**Yes** $t(200) = 6.56$, $p < 0.001$	**Reject**
2.1	$Attitudes\_2.1_A$ = (M=**3.97,** SD=0.69)	$Attitudes\_2.1_N$ = (M=**3.92,** SD=0.65)	**0.05**	**No** $t(272) = 0.60$, $p = 0.548$	**Fail to reject**
2.2	$Attitudes\_2.2_A$ = (M=**1.91,** SD=0.19)	$Attitudes\_2.2_N$ = (M=**1.66,** SD=0.30)	**0.25**	**Yes** $t(208) = 8.21$, $p < 0.001$	**Reject**
3.1	$Constraints\_3.1_A$ = (M=**3.08,** SD=0.54)	$Constraints\_3.1_N$ = (M=**2.63,** SD=0.81)	**0.45**	**Yes** $t(194) = 5.24$, $p < 0.001$	**Fail to reject**
3.2	$Constraints\_3.2_A$ = (M=**3.27,** SD=0.73)	$Constraints\_3.2_N$ = (M=**2.75,** SD=0.66)	**0.52**	**Yes** $t(254) = 5.40$, $p < 0.001$	**Fail to reject**

These results clearly forced me to reconsider some of the assumptions I made at the beginning of this research. A logical next step would be to try and gather a more robust sample size to see if these relationships hold. I would also explore removing the "… in your area" aspect of the awareness indicators, to avoid the ambiguity of respondents feeling that a particular item is a threat to groundwater sustainability, but not in their immediate area. This re-wording might better measure a respondent's general sense of the threats to groundwater and awareness of impacts from excessive use.

7.3.2 Indicator Differences by Age, Education, Income, and Water-use

My approach to evaluating the differences in indicators among the other groupings varied slightly from the one I described above. For the agricultural and non-agricultural comparison I had two separate surveys, which effectively stratified the large quantity water user population for me. However, for the other groupings, I had to conduct parallel analyses between sub-groups on both the agricultural and non-agricultural surveys. For example, to evaluate differences by age, I compared indicator scores among younger agricultural respondents and older agricultural respondents, and separately, compared indicator scores among younger non-agricultural respondents and older non-agricultural respondents. I explored combining all of the responses into a single unified survey, and then stratifying by age, but that approach would have been problematic. I would have embedded the significant differences between the agriculture and non-agricultural samples into an analysis on age, clouding any conclusions I might make. I therefore decided to keep the surveys separate, but conduct parallel comparisons for each indicator.

Table 40 lists the break points that I used to divide the agricultural and non-agricultural respondents into separate groups by age, income, education, and water use. In the case of age and water use I used the median values among agricultural respondents as the break points, so as to create more balanced sub-sample sizes.

Table 40: Sub-sample sizes and break points.

Grouping	High Break	Low Break	Agricultural High N	Agricultural Low N	Non-agricultural High N	Non-agricultural Low N
Age	>= 55	< 55	35	39	68	121
Education	>= Associate’s Degree	< Associate’s Degree	31	44	158	37
Income (household)	>= $75,000	< $75,000	40	33	130	52
Water Use	>= 15 MG/yr.	< 15 MG/yr.	31	31	75	91

Because I conducted separate comparisons for agricultural and non-agricultural respondents, I present the hypotheses (Table 41) and results (Table 42) in combined and less formal formats rather than numerous tables of t-test results for each individual comparison. My hypotheses applied to both the agricultural and non-agricultural cases. For example, my expectation that younger respondents would be more willing to adopt conservation practices applied to both the agricultural and non-agricultural comparisons. I generated my expectations for the differences between the sub-groups from the same sources I drew from for my agricultural versus non-agricultural hypotheses. I expected older respondents to be more inclined than younger respondents to think that threats to groundwater sustainability and the impacts of excessive use were problems in their respective areas because those individuals likely had more experience with those items in the past and therefore inclined to think they could happen again. For example an older farmer may have experienced more years of drought, and therefore would be more inclined to view wells running dry as a problem. I also expected that the additional experience would have given older populations more opportunity to become familiar with groundwater conservation practices, but perhaps less likely to change behavior as routines and opinions became entrenched. I expected older respondents to also be slightly wealthier than younger respondents, and therefore less likely to be constrained by cost in adopting conservation practices. My expectation for education differences was rather straightforward. I expected education beyond high school to yield more overall knowledge, including with regards to groundwater threats and impacts, and to correlate with higher incomes which would limit constraints and lower the potential relative opportunity costs of adopting practices. I applied that same reasoning to my expectations for income and water use, though I did not have expectations for how either of those variables would affect awareness.

Table 41: Expectations for sub-group indicator comparisons. Blank cells indicate that I had no expectation.

Indicator	Age	Education	Income	Water Use
Indicator 1.1: Awareness of consequences of excessive groundwater use	H > L	H > L		
Indicator 1.2: Awareness of threats to future groundwater availability	H > L	H > L		
Indicator 1.3: Awareness of appropriate practices to conserve groundwater	H > L	H > L		
Indicator 2.1: General groundwater related attitudes	H < L	H > L	H > L	
Indicator 2.2: Willingness to take action to conserve groundwater resources	H < L	H > L	H > L	H > L
Indicator 3.1: Constraints to behavior change	H < L	H < L	H < L	H < L
Indicator 3.2: Constraints to adopting key practices	H < L	H < L	H < L	H < L

Table 42: Indicator score differences among sub-groups. Differences were calculated as high-group (H) score minus low-group (L) score. Bold differences are statistically significant.

Ind. ID	Age (Ag.) H-L	Age (Non-ag.) H-L	Ed. (Ag) H-L	Ed (Non-ag.) H-L	Income (Ag.) H-L	Income (Non-ag.) H-L	Use (Ag.) H-L	Use (Non-ag.) H-L	Expectations Met
1.1	-0.02	-0.10	-0.12	0.07	-0.05	-0.07	-0.04	-0.06	
1.2	-0.02	-0.07	0.04	0.08	-0.02	-0.08	0.00	-0.04	
1.3	0.02	0.03	**0.13**	**0.11**	0.07	**0.13**	0.00	**0.10**	Ed. (both) Inc. (Non-ag.)
2.1	0.04	-0.03	0.16	0.20	0.12	-0.04	-0.03	0.13	
2.2	0.06	-0.05	0.02	**0.11**	0.04	0.05	-0.02	0.04	Ed. (Non-ag.)
3.1	0.11	0.01	0.15	0.11	0.12	0.11	-0.20	**0.40**	Use (Non-ag.)
3.2	0.07	0.01	0.22	**0.26**	0.03	0.14	-0.29	**0.35**	Ed (Non-ag.) Use(Non-ag.)

Most of my expectations were not met. There was no difference in indicator scores between the different age groups, for both the agricultural and non-agricultural respondents. With regards to education level, those having earned an associate's degree or higher were more familiar with groundwater conservation practices (*Indicator 1.3*); but that was the only indicator in which the differences were statistically significant for both the agricultural and non-agricultural respondents. Furthermore, the difference in *Indicator 1.3* among the education sub-group was the only one that was statistically significant for both the agricultural and non-agricultural pairings. Non-agricultural respondents in the higher income and higher water-use sub-groups were also more likely to be aware of groundwater conservation practices. Higher-educated non-agricultural respondents were also more willing to adopt conservation practices than their lower-educated counterparts (*Indicator 2.2*), and had fewer constraints to adopting water system auditing (*Indicator 3.2*). Both of these results met my expectation, but it is interesting that there was not a significant difference in overall constraints for adopting conservation practices (*Indicator 3.1*). My first thought was that this result may have captured an economic difference in that the lower-educated group viewed water system auditing as more cost-prohibitive than other practices; but there was not a significant difference for this indicator between the high and low income groups. Non-agricultural respondents that used more than 56.7 million liters of water in 2013 reported less constraint in adopting water system auditing (*Indicator 3.2*) and conservation practices in general (*Indicator 3.1*), as expected.

The lack of significant difference results among the agricultural respondents may be an accurate representation of homogeneity in groundwater awareness, attitudes, and constraints within that sector, but it may also be a function of the low sample size. In order to have sub-groups of sufficient size, I set my age break point at a relatively high level of 55 years. It is possible that the delay in the agricultural survey's distribution may have caused me to miss some of the younger members of the agricultural sector, who might have been less daunted by having to report water use online than older and less tech-savvy members, and were therefore more likely to report their use early. 2013 was the first year that the State of Michigan made online water use reporting mandatory. The older population, which had more experience with submitting paper forms, perhaps delayed having to switch over to an online submission until they absolutely had to. Ultimately, I may not have adequately captured the younger and older populations.

7.4 Summary

Though most of my expectations on how social indicators scores would differ between groups were not met, the exercise still provided insight into how the largest users of groundwater viewed its conservation. There was not a clear consensus among respondents that consequences of excessive groundwater use was a problem in Michigan, but there was greater tendency for non-agricultural water users to hold that view than agricultural water users. Non-agricultural water users were also more likely to view issues like increasing irrigation and climate change as threats to groundwater sustainability in the state. Both groups were already quite familiar with groundwater conservation practices, and generally willing to adopt them. Agricultural water users already employed many of the practices listed on the survey, such as irrigation scheduling, and system maintenance. Cost was the main factor limiting each group's ability to adopt conservation practices, with non-agricultural respondents also citing a lack of property ownership as a limiting factor. Both groups viewed groundwater as an important resource and tended to view its conservation as a personal responsibility, and were generally willing to take action to do so. Efforts to compare the indicators by age, education level, income, and total water use yielded mixed results. Higher educated respondents were more willing to adopt conservation practices, but no other indicator had a similar consensus across the different groups. A larger sample size might have lead to clearer distinctions amongst the groups.

CHAPTER 8: Discussion

There are a broad range of implications that can be drawn from the results of the hydrologic modeling, on such topics as groundwater availability, irrigation demand, the agricultural calendar, the impacts of urbanization, aquatic habitat, and flood risk, to name a few. However, the 31 different projections of future climate I utilized in this study were not monolithic, and, therefore, neither were the hydrologic modeling outputs. Different models projected increases in ET while others resulted in decreases. On average, the water table rose in certain decades for some emission scenarios, but declined in others. Some models saw dramatic swings in precipitation and streamflow from one decade to the next, while others remained relatively flat. To pull meaning from such results one must not only analyze the trends in the data, but also fully consider and evaluate the limitations and uncertainties therein. In this section I discuss the key takeaways from the modeling outputs, explore the implications of my conclusions, and explain how the results of the social indicator surveys can inform policy efforts to adapt to the projected changes in groundwater resources.

8.1 Hydrological Modeling Limitations / Sources of Uncertainty

In a project of this scale, using models as complex as SWAT and MODFLOW, I had to make assumptions in both the conceptual modeling framework and in the accuracy of the various model inputs. These assumptions introduced uncertainty into the model outputs and limited the conclusions that could be drawn from them. I reviewed the assumptions I made in developing the SWAT and MODFLOW models in Chapters 3, 4, and 5, but discuss some of the most critical ones here.

8.1.1 Plant water use efficiency under elevated CO_2

The single most important assumption in this study was the improvement in plant water use efficiency in response to elevated CO_2 as defined in Section *5.1.2 Running future climate simulations in SWAT*. To summarize, studies have shown that plant stomata narrow in response to higher concentrations of CO_2, which causes them to transpire less water. Ultimately, this reduction in ET leaves more water in the soil profile available for groundwater recharge and stream baseflow, and decreases irrigation demand.

SWAT accounts for this effect in its calculation of leaf conductance, but published studies have found that SWAT likely overestimates the ET reduction because it applies it uniformly to all land cover classes and fails to account for the potential increase in plant biomass resulting from elevated CO_2 (Eckhardt & Ulbrich, 2003; Wu et al., 2011). I followed the recommendations from those studies and modified SWAT's source code to account for varying rates of change in leaf conductance and LAI for agriculture, forest, pasture, and range land covers. Despite those modifications, SWAT projected sharp declines in ET, and, therefore, sharp increases in recharge at the end of the century for the climate projections under the high CO_2 emission scenarios (A1Fi and A2). The increase was less in the moderate A1B scenario, while the B1 scenario, which assumes that CO_2 concentration levels off mid-century, projected slight increases in ET by 2100. While a portion of the increases in recharge under the various climate models was the result of higher projected rates of precipitation, the CO_2-induced drop in ET sparked the sharp rise in recharge.

If SWAT's estimation of decreased leaf conductance was overstated, then so were my projections of recharge increase, a higher water table, greater baseflow, and declining irrigation demand. There is consensus within the literature that the effect of decreased leaf conductance under higher CO_2 is real (Leakey et al., 2004; Leakey et al., 2009; Leakey, Uribelarrea, Ainsworth, Naidu, & al, 2006; Wall et al., 2001), but disagreement as to the effect's extent (Foti, Ramirez, & Brown, 2012; Kergoat et al., 2002). The initial studies that informed SWAT's formulation of decreased plant conductance considered the effects of CO_2 levels up to 660 ppm (Morrison, 1987). The A1Fi emission scenarios anticipated a concentration level of almost 1,000 ppm by 2100, so there is some uncertainty as to whether SWAT can still accurately simulate the effect at that level. Ainsworth et al. (2002) reviewed 111 studies of soybean response to CO_2 levels ranging from 450 to 1,250 ppm and found that at levels above 850 ppm conductance dropped by 51%. Ficklin et al. (2009) simulated ET with SWAT in an agricultural watershed in CA at 970 ppm and estimated a 37% reduction. I did not produce ET estimates specifically for soybean, but on average the corn-soy-corn-soy 4-year rotation projected a 20% drop in ET from the 2010-2019 time period for the A1Fi scenario through the end of the century. Compared to that study and the results from Ainsworth et al. (2002) my estimates were conservative.

A number of studies identified the response of ET to increasing CO_2 as a significant source of uncertainty and an important topic for future research (Deryng et al., 2014; Elliott et al., 2014; Ficklin et al., 2010, 2009; Foti et al., 2012; Jha et al., 2006; Marshall et al., 2015). I stand behind the results from this project, and argue that its projections are relatively conservative when compared to similar studies. However, I acknowledge the uncertainty in this particular aspect of the hydrologic model, and remain open to reevaluating these results as the community formulates a better understanding of the relationship between CO_2 and ET.

8.1.2 Irrigation locations

In section *3.2.5 Irrigation* I described how I identified potential locations of agricultural and golf-course irrigation. The basis for the areas I selected relied on proximity to an active irrigation well in the Wellogic database, contiguous agricultural land cover pixels on A or B hydrologic soil groups, and aerial photography for golf course digitizing. As I discussed earlier Wellogic suffers from errors of commission and omission, so it is possible that some of the fields that were irrigated by SWAT should not have been, and vice versa. Additionally, though the algorithm I developed attempted to delineate farm field boundaries, in some circumstances only portions of fields were irrigated, which is unlikely in practice. Overall, my estimates of total irrigated hectares and volumes were relatively close to reported totals by MDEQ and estimates from the USDA Ag-Census; the precise locations of those hectares, however, are more likely in error. Irrigated fields tended to yield the highest recharge estimates, so this spatial error is important when evaluating projections of recharge or hydraulic head change at individual field scales.

8.1.3 Tile drainage

I did not simulate tile drainage in SWAT or MODFLOW. My primary reason for excluding it from the study was because of SWAT's relatively coarse treatment of its effect on recharge. SWAT simulates tile drainage by requiring the specification of an impervious layer below the tile, which facilitates a water table rise that can then reach it. This impervious layer effectively sets recharge to zero for tiled fields, which is implausible. Another reason I left tile drainage out of the simulations was because this part of Michigan is dominated by well-draining A and B hydrologic soils, making tiles much less common than in the areas of the state dominated by C hydrologic soils, like the Saginaw Bay Basin. A third reason for the exclusion was because there is no readily accessible dataset that maps tile drainage locations. I could have assumed that agricultural lands on C soils with slopes less than 2% were likely to be tiled, and parameterized those HRUs accordingly in SWAT. However, that would have still rendered an implausible situation of no recharge occurring on those locations, and there were relatively few of them in the study area. Lastly, the original MODFLOW model did not include a tile drainage representation, so I left it out of my revised groundwater model as well.

8.1.4 Water withdrawals

I attempted to represent all of the various withdrawals from the study area's groundwater system, including agricultural and golf course irrigation, domestic water wells, municipal water supply, and industrial use. The irrigation withdrawals were driven by SWAT's simulation of plant water demand, which relied on the location of irrigated fields within SWAT. Like those fields, the other withdrawals also based their locations on Wellogic records. Any spatial errors in those records could have created withdrawals from the aquifer where none actually occur. The volumes for the non-irrigation withdrawals were based on reported use to MDEQ. Any errors or biases in MDEQ's reports would have affected the simulated rates of withdrawal from the aquifers. Table 8 illustrates that withdrawals accounted for 8% of all flows out of the groundwater system in the modified MODFLOW model (79 MGD out of 939 MGD). A positive bias of 50% in estimated withdrawals, for example, would not have a substantial effect on model-wide average head, but could have a larger impact on the drawdown around individual well locations. If a more detailed analysis of a particular location within Kalamazoo County is needed, such as the farms around an area of intense irrigation or the area near the City of Kalamazoo's primary pumping center, a greater effort should be made to account for the uncertainty in water withdrawals.

8.1.5 Land cover change

The geographic and temporal scope of this project limited my ability to account for land cover change in SWAT's projections of recharge and, therefore, MODFLOW's projection of hydraulic head. SWAT has a function for updating land use over time, but it does so for individual HRUs, which effectively makes the change aspatial. I felt that it was necessary to more faithfully simulate changes in land cover by allowing them to be governed by neighboring classes. I developed an urban expansion scenario that focused the changes in areas that had previously shown a tendency to urbanize in earlier land cover datasets, and was driven by a projection of regional population growth to 2040 by Grimes and Fulton(2012). I similarly developed an agricultural expansion scenario, but selected and arbitrary growth of 5%, and programmed it so that land cover changes reflected the specific crop types around them. I also created a combined scenario in which the land cover changes for each of the preceding scenarios were included in one realization. Each of these scenarios represented single future representations of land cover. They were snapshots, and did not represent continuous change over time. To do this in SWAT would have required re-defining the HRU structure for each scenario. Because I was utilizing 12 different SWAT models at very fine spatial resolutions, such an approach would have severely limited model processing time and storage space on the hard drive.

I ran 3,348 SWAT simulations (12 SWAT models * 9 decades * 31 climate models) with a static land cover representation (*i.e.* no change), which yielded the same number of recharge rasters for input into MODFLOW. I then derived a look-up table of recharge values, based on SWAT sub-basin, land cover, soil type, and slope class, for each simulation. I used this look-up table to re-define recharge values at the locations identified as urbanizing or converting to agriculture in the land cover change scenarios. This approach ultimately produced 13,392 recharge rasters, one for each simulation and each land cover scenario (static, urbanization, agricultural expansion, and combined).

I acknowledge that assuming that a trend of urbanization based upon population projections to 2040, and that an arbitrary 5% growth in agriculture would be representative of land cover conditions in 2090 is almost as unlikely as assuming that there will be no land cover change. However, given the computational limits imposed by the size of the area I modeled, the century-long time scale, and the number of climate models simulated, this approach was the most feasible way to explore the potential impacts of land cover change on recharge and hydraulic head. If anything, the urban results that I presented here should be considered conservative. It is more likely that by 2100 the population will be significantly greater than what was projected for 2040, and that the extent of imperviousness in the region will have grown considerably, leading to a much greater reduction in recharge and hydraulic head for urban areas than I report here. I am less confident in projecting a similar increase in agriculture though the end of the century, because I cannot assume that a growth in local population will necessarily translate to a growth in agriculture.

8.1.6 Farm management adaptation to changing climates

It is likely that as temperature rises through 2100 that farmers can plant earlier (Figure 83), allowing for growing higher yield versions of crops that are better suited to the longer growing season or for planting more than one crop within the calendar year. I did not attempt to simulate either of these scenarios, and instead let SWAT schedule the harvest dates based upon each crop's accumulated heat units. This decision resulted in harvests occurring about a month earlier (Figure 84), limiting the number of days in which ET could occur, which likely inflated recharge estimates for September and October. In *6.1.5 Crop Yields, Planting Dates, and Harvest Dates* I explored this problem in greater detail for a single corn HRU in SWAT model 04108660, and estimated a positive annual recharge bias of 39 mm when utilizing heat units to schedule planting and harvest. A full-season crop or two-harvest scenario would likely increase ET and decrease recharge.

8.1.7 Solar radiation and relative humidity

The climate models I utilized had daily projections of precipitation and temperature, but not for solar radiation or relative humidity. I illustrated in section *5.1.2 Running future climate simulations in SWAT* that increases in each attribute could have a large impact on ET and groundwater recharge, particularly relative humidity. The literature on potential changes in future humidity is relatively thin, with mixed results. Seager et al. (2007) projected decreases in relative humidity for regions that are already arid, but slight increases in areas expected to be wetter, such as the Great Lakes. Sherwood et al. (2010) projected slight decreases in relative humidity for the Great Lakes latitudes. Given these conflicting results for relative humidity and the relatively small impact that simulated solar radiation increases had on recharge, I left the values for each input at the monthly averages specified in the SWAT Weather Generator. However, as future research provides more insight into how these attributes might vary in response to climate change, it will be worth exploring their potential impacts on hydrology in greater detail.

8.1.8 Steady-state vs. transient groundwater modeling

The estimations of hydraulic head in the study were all drawn from steady-state simulations of the groundwater system. These simulations calculated the long-term average of hydraulic head for each cell in the model. Each value represented where head would be if recharge, withdrawal rates, and constant head boundaries (such as river and lake stages) were held constant over time. The steady state simulation provides a baseline from which simulations that do reflect changes in those inputs over time, and include groundwater storage, can be evaluated. Such simulations are called transient groundwater models. Their temporal variability allows for an exploration of how hydraulic head may fluctuate under periods of high stress, such as summer pumping during periods of low recharge, or how aquifer storage may change throughout the year. This finer detail of transient modeling comes at a cost in terms of computer processing time and hard drive storage, both of which are substantially greater than in steady-state simulations. The scope of this project limited my analysis to calculations of steady-state head.

I explored how hydraulic head fluctuated at four USGS observation wells (numbers 3, 4, 23, and 30 in Table 20 and Figure 48) in the study area from 2000 through 2014 (Figure 108 through Figure 111). Daily records of water levels were available for Wells 23 and 30, which are located in the central portion of the study area where land use is mixed between agriculture and forests. Only intermittent records were available for Wells 3 and 4, which were located in the southern portion of study area where agriculture and irrigation are most prevalent. Though the fluctuations over that time period are relatively small (Well 23's head values had a range difference of 2.7 meters, while the others were all below 2 meters), when compared with some of the decadal steady-state projections of hydraulic head from various climate models (Table 30) they imply that seasonal ponding is will be more frequent. For example, the ECHO-A2 climate model projects an increase in steady-state head of 1.56 m by the end of the century. If we assume that the temporal variability of hydraulic head observed for 2000-2014 remained constant into the future, such an increase would be enough to raise the head above the surface elevation at well 23 during early spring, and for significant portions of the year at Wells 30 and 4. Well 3 would evidently not be subject to such ponding. However, the 1.56 m increase in ECHO-A2 was the largest simulated change in head into the future. Most climate scenarios projected smaller increases, but the temporal variability of hydraulic head observed at Well 4, and the current shallowness of the water table around it, implies that seasonal ponding would be likely in many of the future simulations.

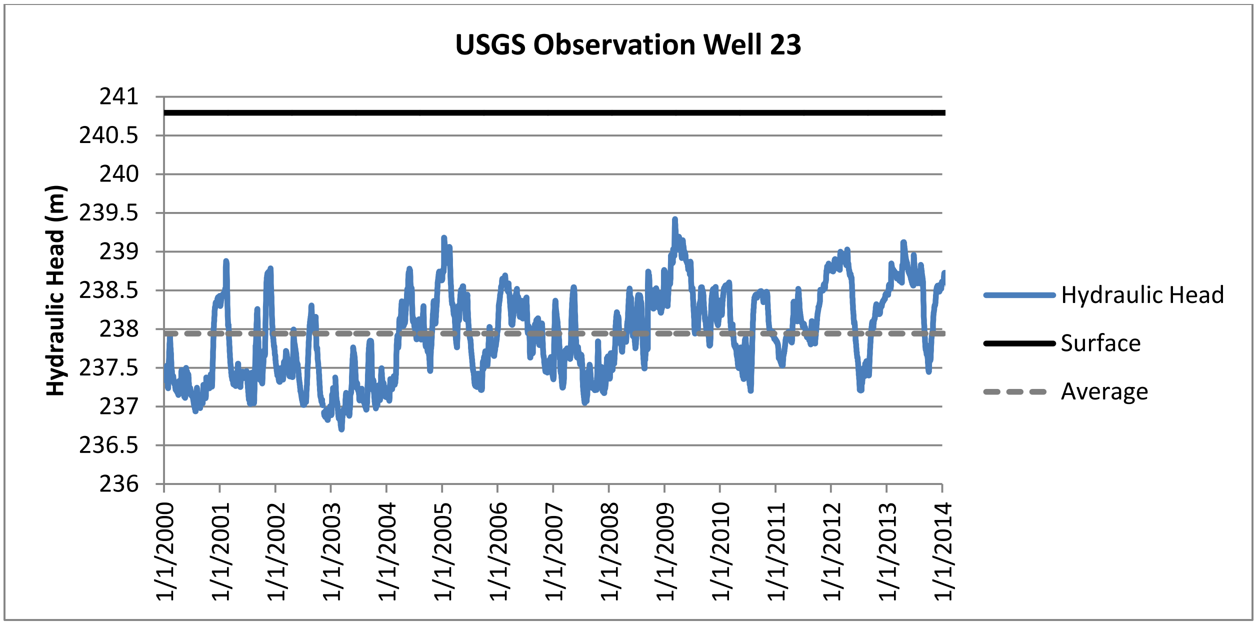

Figure 108: Daily fluctuation of hydraulic head at USGS observation well 23.

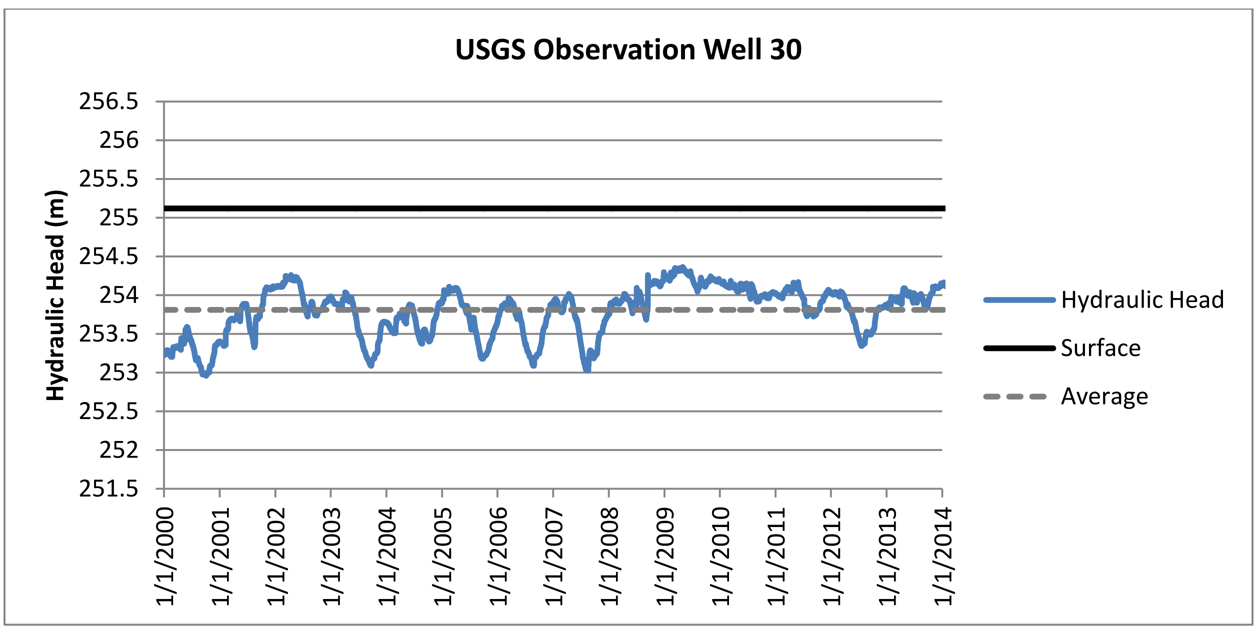

Figure 109: Daily fluctuation of hydraulic head at USGS observation well 30.

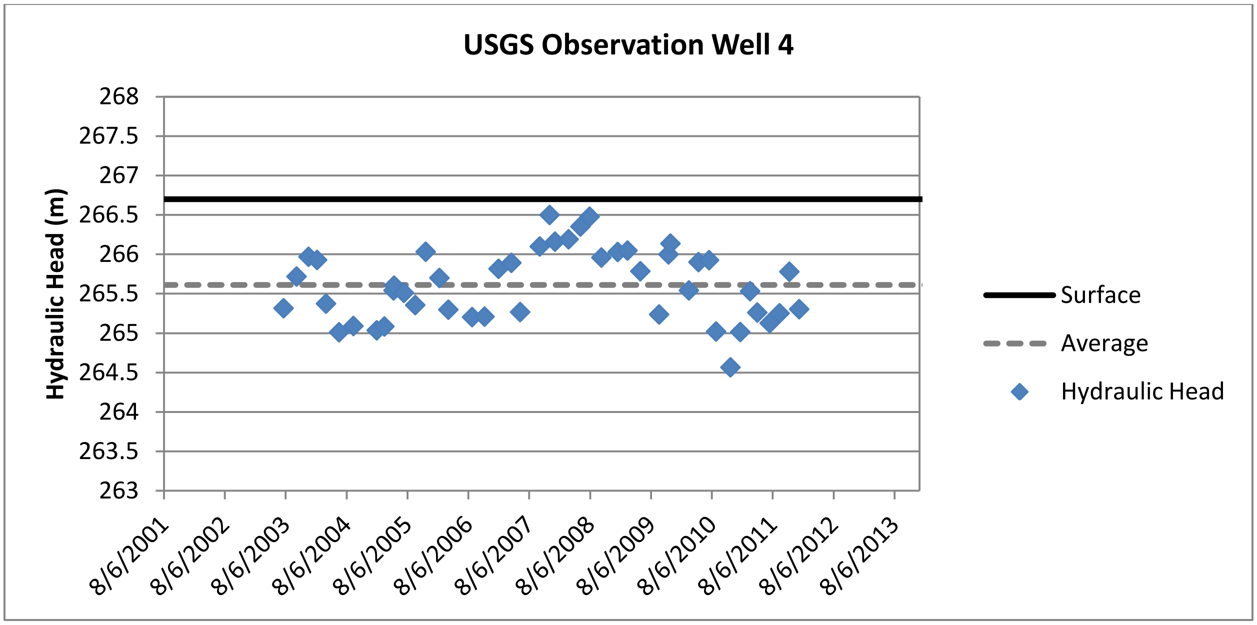

Figure 110: Daily fluctuation of hydraulic head at USGS observation well 4.

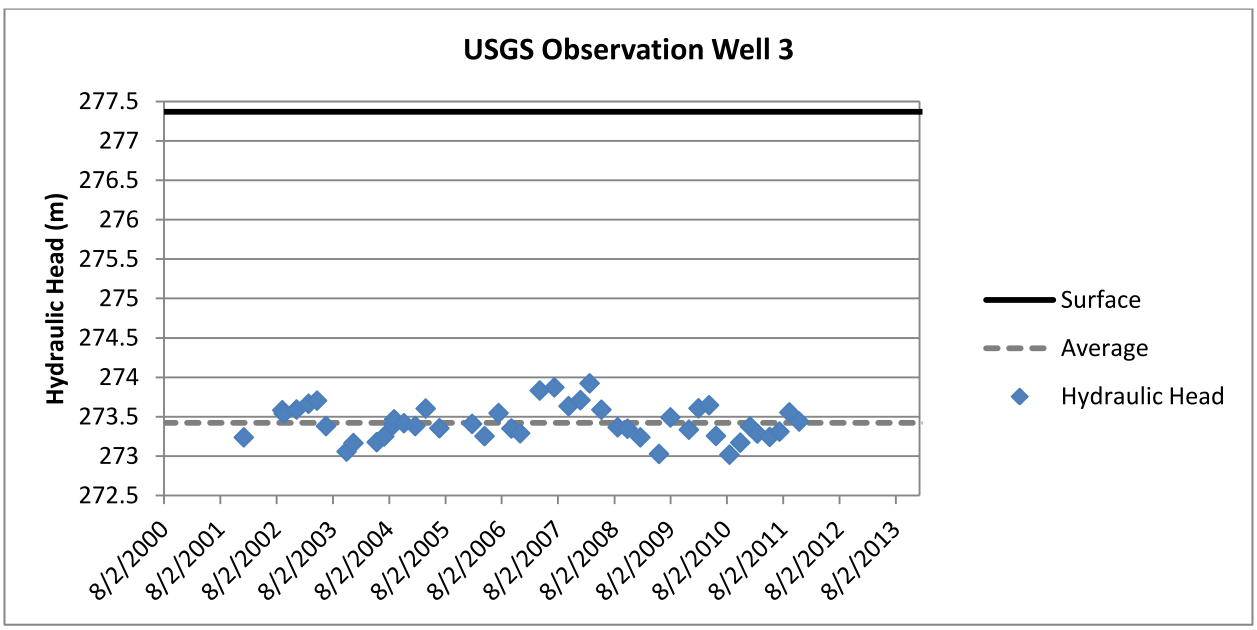

Figure 111: Daily fluctuation of hydraulic head at USGS observation well 3.

It is possible that the temporal variability of hydraulic head may change in the future, perhaps reflecting more dramatic swings from season to season. In such a case, ponding may not be more or less frequent, but may be more severe. Subsequent research on specific climate models or time periods of interest should explore transient simulations in order to better analyze the temporal variability in future hydraulic head changes, and more precisely evaluate the ponding risks that a changing climate may pose.

8.1.9 Groundwater starting hydraulic heads and boundary conditions

By comparing original and modified MODFLOW models to groundwater observations at USGS wells and to static water levels in the Wellogic database, I noticed a slight bias in the simulated hydraulic head values (Figure 51 through Figure 53). I attributed some of this error to potentially misidentified no-flow boundaries in the western portion of the original model's top layer, and to starting head values that may have been set too low in the original model. The bias did not affect my analysis of fluctuations in hydraulic head under climate change because I focused on projected change from the model baseline, not on the estimated head values themselves. If a more precise estimate of the actual head value for a given point in the future is needed, then the starting heads should be re-evaluated and corrected for any bias. This could be done by filtering out noise and bad data in Wellogic in order to interpolate a more realistic starting head layer from static water levels in the well records. This effort would also require a re-evaluation of river and lake stages to ensure that the values specified at these constant head locations were accurate and up to date.

The constant head at rivers was another limitation of this study. Though several of the SWAT simulations predicted large increases in streamflow at the end of the century (Figure 80), I did not update the constant head definitions within MODFLOW to account for the likely increase in river stage under the more extreme projections. One reason for not doing this was because I did not have output from SWAT for each river cell in the MODFLOW model, and therefore could not provide new stage values to those cells. Furthermore, I would have needed the channel dimensions for each stream segment in order to convert SWAT flow volumes to river stages, which I did not have. The consequence of this limitation was that even under those extreme projections of increased flow, heads at the river and lake cells remained low, which forced greater changes in head to occur at the areas furthest from the stream network (Figure 102).

Subsequent studies that need greater detail of head changes under one of the high-flow scenarios should explore defining a new stream network that could be tied more directly to SWAT projections of flow volumes, and that may have channel dimension data available to convert flows to stages. Alternatively, if a sufficient relationship between flow and stage could be established for each stream segment, then updated constant head values could be calculated for the corresponding MODFLOW river cells.

8.1.10 RMSE

I compared estimated head values in the baseline version of the modified MODFLOW model to observations at USGS wells and static water levels in Wellogic records. Overall the simulated head values were highly correlated with the observed heads (r=0.95) and Wellogic levels (r=0.94), and exhibited good ratios of residual error to observation range (0.063 for observation wells, 0.037 for Wellogic). However, the RMSE values (4.6 meters for observation wells, 5.9 meters for Wellogic) were probably too high to use simulated head values for applications that demand more precision within the groundwater system, such as contaminant tracking or pumping drawdown at certain locations.

The high RMSE did not limit my analysis of head changes over time, for the same reason that the slight bias in simulated head did not. My evaluation of head change was from a simulated future value to a simulated reference value (for the 2010-2019 time period). I expect that the overall changes between simulated values would be realized in observed values, when such data was finally observable at a future date.

8.1.11 Decadal intervals

I projected data at decadal intervals for two reasons. The primary reason was to avoid giving readers of these results the impression that projections for a particular day necessarily meant that those projections would come to pass. Though the climate models that were input to SWAT and MODFLOW provided estimates of precipitation and temperature at daily intervals, they were not weather forecasts. Those models were climate forecasts that indicate what long-term trends in weather might look like. For example, the CCSM3-A1Fi climate scenario does not predict with high confidence that 5 centimeters of rain will fall on May 15th, 2093 along with a high temperature of 95°. However, the model predicts with greater confidence that that particular forecast would be indicative of the climate for that region at that time of year. I similarly did not want to give a false impression about daily estimates of recharge or streamflow. Therefore, I concluded that decadal intervals would be sufficiently temporally coarse to avoid such confusion. The other reason for choosing these intervals was that it significantly reduced the amount of disk storage that would have been needed to store SWAT and MODFLOW outputs at daily, monthly, or even annual intervals.

It is important to remember that the projections represent long-term averages. For the static land cover scenario and the HadCM3-A2 climate scenario, average annual groundwater recharge during the 2080-2089 time period was projected to be 33.3 cm. It is likely that some of the years during that simulation were above that amount, and some were below that amount. The relatively high annual average does not rule out the possibility that droughts might occur towards the end of the century, but could support an argument that they would be less likely if that climate scenario proved prescient. The same can be said for projections of low flows not ruling out flood events, or high increases in hydraulic head not ruling out some wells running dry during summer months.

8.1.12 Scalability and Transferability

This study focused on a single county in southwest Michigan. Are the results and analysis that I presented for Kalamazoo County scalable to the entire state of Michigan, the Great Lakes Region, or the globe? Or, even if one holds the scale at the county-level, would the trends in recharge, ET, streamflow, irrigation, and hydraulic head be transferable to Waupaca County, WI, Tulare County, CA, or Yuanyang County, China? The answers to those questions largely depend on the physical characteristics of those areas/regions and how similar they are to the study area.

Kalamazoo County's land cover is predominantly agriculture (40%), forest (21%), or urban (20%) on top of well draining soils (23% and 69% in the A and B hydrologic soil groups, respectively). In addition to climate, these characteristics were the primary drivers of the region's surface water hydrology, and to a lesser degree its sub-surface hydrology. The distribution of hydraulic head and available water was dependent on rates of recharge, especially in the top aquifer. But those attributes were also affected by the layering of glacial sediments and aquitards. I regard this study's projections of hydrological outputs as representative of areas or regions with similar land cover concentrations, soil composition, climate projections, and sub-surface stratigraphy. Therefore, I would expect to observe similar trends in recharge, ET, streamflow, irrigation demand, and hydraulic head for the other counties of southwest Michigan, such as Cass, Calhoun, and St. Joseph counties.

With regards to transferability, the more dissimilar the characteristics of a proposed area, the less confident I would be in observing the same hydrologic trends as I simulated in Kalamazoo. For example, Ottawa County, MI shares many physical characteristics with this project's study area, including land cover and climate; therefore I would expect to see trends in recharge and ET similar to those projected for Kalamazoo County. However, its groundwater hydrology is heavily influenced by its western border with Lake Michigan, which might alter the trends in hydraulic head relative to those projected in this study. I would expect somewhat different results for Huron County, MI in northeastern Lower Peninsula (the thumb-tip). That part of the state is also dominated by agriculture; but the soils have a much higher clay content, which limits recharge because the clays have a higher holding capacity and are more likely to be tile drained. The clay soils also cause groundwater withdrawals to extend deeper into the sub-surface, where transmissivity is higher. Huron County's climate projections are similar to those for Kalamazoo County, so I do expect to see similar trends of increasing recharge and streamflow in the A1Fi and A2 emission scenarios, but theorize that the soil composition and tile drainage would mute them considerably.

With regards to scalability, I would have more confidence in the applicability of the SWAT outputs to a broader geographic region than in the MODFLOW projections of hydraulic head. Provided that the proposed region was relatively similar to Kalamazoo County in terms of land cover, soil, and projected climate, then I would expect to see similar trends in recharge, ET, and streamflow. Significant variations on any of those characteristics would lessen my confidence in those expectations. Other studies have projected spatially variable responses in recharge and ET under various future climate models (Ficklin et al., 2010; Leipprand & Gerten, 2006; Luo, Ficklin, Liu, & Zhang, 2013). Hydraulic head, on the other hand, is largely dependent on the local stratigraphy. Though there are other parts of Michigan where the substrata is similar to Kalamazoo's, the phenomena is highly spatially variable, and makes it difficult to expect very similar hydraulic head trends for the state as a whole, or for even broader regions. However, this study could serve as a baseline for the development of a coarser, broader model of hydraulic head. I strove to account for as many hydrological input variables, at the finest spatial resolutions, as possible. It would be difficult and cost-prohibitive to replicate that effort at a regional or state-wide scale. But by re-evaluating this study with coarser inputs, such as less detailed crop-rotation maps, ignoring point source discharge, and larger spatial resolutions for MODFLOW cells, one could start to measure the marginal benefit of modeling to such a detail. This re-evaluation process could inform efforts to similarly model larger areas, as researchers weigh the tradeoffs of detailed inputs versus useful and meaningful outputs.

8.2 Implications of Hydrologic Modeling Results

Conceding the limitations and uncertainties discussed above, the trends I observed in the model outputs yielded several key implications.

8.2.1 Rise in the water table

The average trend for all four emission scenarios was an increase in hydraulic head through the end of the century. In only 2 of the 31 climate scenarios (HADGEM1-A1B and GFDL CM2.0-B1) was head lower in 2090-2099 than the scenario's starting point of 2010-2019, and in both cases the drop was less than 7.6 cm. Though many of the models indicated a drop in head at various decadal intervals, the overall trend was still upward. The effect of CO_2 on ET caused the rise to be greatest in the A1FI and A2 emission scenarios, with average increases of 116 and 79 centimeters, respectively. The highest single projection was from the ECHO-G-A2 scenario (155 centimeters). The fact that these results represent decadal averages of steady-state simulations makes the projections conservative. If the ECHO-G-A2 scenario accurately represents the future climate, then water tables will likely rise much higher than 155 centimeters at various points in time from 2090-2099, such as during the periods of snow-melt or during the rainy spring season.

Though a steady rise in the water table implies that fresh water supplies for Kalamazoo County will be more abundant in the future, it also poses risks. Flooding will be more likely as the water tables approach the surface. Crops will be at greater risk from ponding water, which could necessitate the installation of tile drainage in areas that have not previously needed it. Additional tile drainage could add to the flashiness of streams during large storm events, adding to their erosive forces and putting more stream banks at risk. The added drainage could also contribute more pollutant loading from fertilizers and manure (Sims, Simard, & Joern, 1998).

8.2.2 Land cover change did not have a large impact on the water table

Assuming a very conservative population growth of 5.5% through the end of the century, water tables dropped by an average of only 1.8 cm among the scenarios in which urban areas expanded. An expansion of agriculture raised the water table by an average of only 0.064 cm. That these were steady-state averages implies that the fluctuation may be greater during various points in time. These results also indicate that climate change had a larger impact on water resources than land cover change, similar to projections for surface runoff and recharge in other studies (Barlage et al., 2002; Sun & Cornish, 2005). While the relatively small drop in the urban scenarios does not pose a significant risk to the supply of water for urban areas, it is indicative of potential threats to water quality in the region. As less precipitation recharges the aquifers, more will be lost to surface runoff; which increases pollutant loading to the stream network, and creates flashier flows that threaten stream bank stability. The urban areas themselves will be at slightly greater risk for flash flooding. All of this could overwhelm municipal sanitation systems, and increase the likelihood of combined sewer overflows polluting the stream network and Lake Michigan.

8.2.3 Less demand for irrigation

Another corollary for the improvement in plant water use efficiency at the higher CO_2 levels is that there will be less demand for irrigation. In almost all of the scenarios irrigation steadily decreased through the century (Figure 76), reflecting similar projections in other studies (Ficklin et al., 2010; Konzmann, Gerten, & Heinke, 2013; Thomson, Rosenberg, Izaurralde, & al, 2005). Though some of the drop in demand can be attributed to a projected increase in precipitation, most of that increase occurs during the spring months when irrigation is not typically needed. Additionally, the average drop in demand was greatest in the A1Fi emission scenario, which projected average decreases in precipitation for July and August. A drop in irrigation demand could be a boon for farmers. Those that are able to switch to exclusively rain-fed agriculture can save on the costs of managing and maintaining an irrigation system. The farmers' savings would mean a loss of the irrigation industry, however.

8.2.4 More streamflow

Higher water tables, greater imperviousness, less irrigation, and, perhaps, more tile drainage will translate to more streamflow. All of the emission scenarios projected steady increases in streamflow through the century, with the A1Fi scenario estimating a striking 75% increase by 2100. These results differ with the findings of Reeves (2010), which projected decreases in baseflow for a relatively small subbasin in southwest Michigan under a single A1Fi climate model, but did not account for the improvement in plant water use efficiency. Other studies have also projected increases in flows from climate change (Betts et al., 2007; Chaplot, 2007; Ficklin et al., 2009; Jha et al., 2006). Much of this increase was attributable to the higher projected rates of precipitation; but the more extreme flow estimates (like the models in the A1Fi scenario) were affected by the reduction in ET at the higher CO_2 levels, which translated to an increase in groundwater recharge.

As with the higher water tables, the higher flow volumes will put the region at greater risk for flooding. Less precipitation will be needed to cause streams to overflow their banks. The larger flows will also likely add to the overall turbidity of the stream water, which may negatively affect some of the more sensitive fish species in those waters. Even though more water will come from groundwater discharge as opposed to flashier and more erosive surface runoff, the large volumes moving through the channel will threaten streambank stability, potentially impacting the structural integrity of homes along the river and further degrading the overall quality of the stream water.

8.2.5 The growing season will start earlier, and last longer

Another potential boon for farmers will be the longer growing season. I let SWAT manage the scheduling of planting and harvesting dates through accumulated heat units. In all of the emission scenarios average planting and harvest dates moved up steadily in the calendar year, similar to findings in other studies (Eckhardt & Ulbrich, 2003). For the A1Fi and A2 emission scenarios planting dates moved up 1 week by 2100, while harvest dates moved up 3 weeks; however the climate would have supported extending harvest to the normal dates, thereby adding a month to the present day growing season. That extra month could allow farmers to plant higher yield varieties of corn and soybean that would benefit from the longer season. It could also allow for multiple harvests within a calendar year. Double-cropping would likely increase ET as crops would have more opportunity to extract and transpire water from the soil profile, subsequently decreasing the amount eligible to become recharge. Planting two crops could also require double the fertilizer and pesticide, and therefore increase agricultural pollutant loading streams.

8.3 Limitations of Social Indicator Survey Results

My survey to measure social indicators of groundwater sustainability among large quantity water users in Michigan provided some insight on the degree to which certain threats to groundwater are deemed severe in Michigan, the familiarity of users with conservation practices, and their willingness to adopt conservation. My analysis did suffer from several key limitations, though.

8.3.1 Focus on large quantity water users

I only offered the survey to the largest water users in Michigan. This limitation was primarily a consequence of convenience. I did not have the resources to conduct a thorough sample of the Kalamazoo region's population, which would have required mailings and interviews. I was able to secure permission from administrators at MDARD and MDEQ to offer an online survey to water users that had just submitted their mandatory 2013 reports to the State of Michigan. Only individuals or organizations that user more than an average of 378,541 LPD are required to report their use to the State. In addition to the convenience of administering an online survey, this approach allowed me to draw a state-wide sample, which opened up the possibility of exploring regional differences in social indicators. It also allowed me to engage those individuals whose awareness of and attitude towards groundwater conservation is arguably most important. Any effort to improve groundwater sustainability through conservation would likely realize a higher return on investment by focusing on this group. But by limiting my population to only the largest water users, I was unable to measure the social indicators of the broader public, whose results might have been more politically relevant in the eyes of the policy makers who could most effectively implement and fund groundwater conservation programs.

8.3.2 Sample size and composition

Due to technical issues with having the M-DIT add a link to my survey to the Michigan Water Use Reporting Program, some of the early reporters did not have a chance to take it. As a result, I only received 76 responses to the agricultural version of the survey out of a total of 1,402 individuals that submitted water use reports to MDARD, and 200 responses to the non-agricultural survey out of 1,482 that submitted water use reports to MDEQ. The small samples forced me to evaluate the response frequencies to each survey question within a ±11% margin of error among the agricultural respondents, and a ±6.5% margin of error among the non-agricultural respondents.

The low response rate also likely skewed the composition of the sample. It is possible that by failing to engage those who submitted their water use reports early, I failed to represent the more conscientious water users who might have been predisposed to favoring groundwater conservation. The delay may have also skewed the sample by age; the median age among agricultural respondents was 55 years old. 2013 was the first year that the State of Michigan required large quantity users to report online, which may have been daunting for the older generation, causing them to delay their report submissions until the last minute.

8.3.3 Awareness focused on local threats and impacts

Two sections of the survey were designed to measure the awareness of the respondents to threats to groundwater and to the consequences of excessive groundwater user. The questions in those sections asked respondents to rate the degree to which various items were threats in their area, and the degree to which various consequences were a problem in their area. Many agricultural respondents deemed climate change as "not at all" a threat to groundwater, which could represent two different opinions. It could imply that users do not deem climate change a threat in any capacity, or it could mean that they deem it a threat but not in their respective areas. The same uncertainty could have occurred in the questions about consequences of excessive use. Most agricultural respondents felt that degraded aquatic habitat was "not at all" a problem in their area, but perhaps some of them viewed it as a problem in the abstract, which would have been a valuable piece of information to gather.

8.4 Implications of Social Indicator Survey Results

The relatively small sample size of survey respondents, and subsequent high margin of error, forced me to focus on questions on the survey for which there was clear consensus. In my comparison of responses between groups, such as agricultural and non-agricultural, and educated and highly-educated, I had to look at response frequency differences greater than the combined margins of error on individual questions, and skip comparisons for which bin sizes were too small, such as regional comparisons (north vs. south, east vs. west). Given those constraints, here are the key implications I identified among the responses.

8.4.1 Generally positive attitudes towards groundwater

The vast majority of respondents acknowledged the importance of groundwater as a resource, and viewed ensuring its long-term sustainability as a personal responsibility. Efforts to promote groundwater conservation or to inform the broader public about threats to groundwater resources should focus on the feeling of personal responsibility as a shared value upon which broad-scale support for protecting those resources could be built.

8.4.2 Less awareness of water conservation practices among non-agricultural users

While the agricultural respondents were generally already familiar with many of the farming-related conservation practices listed on the survey (such as drip irrigation and irrigation scheduling), there was less familiarity among the non-agricultural respondents of their respective practices (such as water system auditing). These results imply that more can be done to promote water conservation outside of agriculture. Considering that on average 84% of withdrawals in Kalamazoo County are from non-agricultural sectors (Table 6), a targeted effort could have a substantial impact.

8.4.3 Conservation practice adoption will need sufficient cost-sharing

Both agricultural and non-agricultural respondents identified the cost of adoption as a significant constraint limiting their ability to implement water conservation practices. Interestingly, most agricultural respondents felt that a lack of sufficient government cost share was not a constraint, but that personal out-of-pocket expense was. These results indicate that despite a strong sense of personal responsibility for protecting groundwater in both agricultural and non-agricultural groups, monetary incentives will be needed to facilitate changes in the adoption of conservation.

8.4.4 The source of conservation promotion is important

Agricultural and non-agricultural groups both rated Michigan State University Extension and county conservation districts as highly trusted sources for water news and information. Agricultural respondents generally viewed crop consultants, MDARD, NRCS, and Farm Bureau as trustworthy, and USEPA less so. They were highly skeptical of environmental groups. The non-agricultural respondents tended to view USEPA and MDEQ more favorably. How well a message of water conservation or a discussion of threats to groundwater sustainability will be received depends on the audience and the messenger. These results do not mean that environmental groups do not have an important role to play in protecting groundwater resources and informing the public, but they imply that such groups would be more successful if they coordinated their message and activities with more trusted groups, such as Michigan State University Extension.

8.5 Policy Recommendations

The implications of the hydrological modeling and social indicator survey results lead me to recommend several courses of action for policy makers at the federal, state, and local levels of government. It bears repeating that the survey only sampled large quantity water users in Michigan, therefore my recommendations are primarily directed at state and local government agencies there. While I expect that the general trends of the social indicator survey results would also apply to large quantity water users in other Great Lakes states, each state has a distinct history of government regulation that might affect an agency's ability to effectively promote or carry out a particular policy. The recent crisis of lead levels in Flint drinking water likely diminished the current level of trust MDEQ among the general public, for example.

Several steps should be taken to adapt to and mitigate an increase in flood likelihood. First, local governments should evaluate current flood-plain regulations and consider prohibiting new development within the 500-year boundary, or mandating that new structures meet strict specifications to withstand frequent flooding. State and local governments should support the enhancement of early warning systems for flooding, and encourage residents to develop emergency response plans (International Joint Commission, 2003). The early warning systems should have reliable sources of funding to support their continued evolution as communication technologies change over time. In addition, governments and non-governmental organizations (NGOs) should raise awareness about the existence of these early warning systems, and the importance of developing emergency response plans. That promotion should engage the broader population, but target populations within identified flood zones. US EPA, MDEQ, and local governments should provide funding for and promote investments in green infrastructure, such as permeable pavement, green roof technology, rain gardens, and water harvesting through rain barrels and cisterns (US EPA, 2015). Efforts should also be taken to preserve existing wetlands and, where practical, restore historical ones lost to development. By facilitating greater infiltration of precipitation, these practices can help mitigate the overall magnitude of a flood event, while also lessening the amount of pollutants that might be swept up by surface runoff.

Rising water tables may force more farmers to install tile drainage, which could degrade water quality in ditches and streams (Sims et al., 1998). USDA and MDARD should provide additional support for practices that can mitigate this threat, such as manure incorporation into the soil, filter strips, grassed waterways, water table control structures, and installing end-of-tile filters (Cornell University Cooperative Extension, 2011; Lemke et al., 2011). The higher flood-risk can also threaten yields, which is why more farmers should be encouraged to consider flood insurance for their crops (Theobald, 2014). If enough farmers participate it could reduce premiums and minimize the chance of a catastrophic flood rendering the insurance program insolvent.

Efforts should also be made to minimize the potential threats to water quality that could arise from a longer growing season or double-cropping. USDA and MDARD should provide support for organic farming to reduce potentially higher pesticide concentrations in surface waters, and for other practices that could help keep nutrients on the land, such as filter strips, manure management, and conservation tillage.

The results of the social indicators survey demonstrated that more should be done to raise awareness of water conservation practices outside of agriculture. US EPA and MDEQ should develop a strategy to more effectively communicate the benefits of water conservation programs like water system auditing and water recycling among large quantity water users. The agencies should also offer cost sharing options to reduce the constraints these users might face in adopting such practices.

In all of the recommendations above that entail the promotion of a particular strategy or raising awareness about an issue, care should be taken in identifying the target audiences, determining which agency or NGO the audience will be most receptive to, and crafting a message that will effectively convey the necessary information. For the efforts primarily directed at the agricultural community, federal and state agencies should look to partner with local soil and water conservation districts, university extensions offices, and crop consultants. While NGOs may play a critical role in identifying priority areas or coordinating overall program strategies, the survey results indicated that engagement of the individual farmer by one of the aforementioned groups will yield a greater chance of conservation adoption. University extensions offices, in addition to MDEQ, should also be utilized to engage the non-agricultural community of large quantity water users.

CHAPTER 9: Conclusion

9.1 The Problem

I sought to explore the potential impacts of climate change on the hydrology in the Great Lakes Region. Though the threat of higher temperatures and changing precipitation patterns warrant evaluations of potential impacts on water-stressed regions like the western United States, Sub-Saharan Africa, and the Middle East, it is also important to gage what those impacts might be for water-rich areas. Projections of more severe and prolonged droughts in the water-stressed parts of the world will place greater demand for food production in the agricultural areas of water-rich regions, like Kalamazoo County, MI. Ensuring the agricultural viability of those areas, and therefore the viability of their water resources, will be critical to meeting the needs of a growing global population.

Previous studies of climate change in the Great Lakes Region tended to focus on either surface or groundwater hydrology, were conducted at relatively coarse geographic scales, and employed a small number of climate models (Croley & Luukkonen, 2003; Lofgren et al., 2002; Luukkonen et al., 2004; Reeves, 2010). In this study I simulated changes in both surface and groundwater hydrology, modeled each at relatively fine spatial resolutions for Kalamazoo County, utilized 31 different projections of daily climate through the year 2100, and integrated scenarios of land cover change. This approach allowed me to explore a broad range of potential climate scenarios, and identify the most consistent trends among them in terms of water table elevations, groundwater recharge, evapotranspiration, streamflow, and irrigation demand, among others.

In addition to exploring the potential hydrological impacts of climate change, I also sought to better understand how individuals valued groundwater resources, the degree to which they felt those resources were at risk from climate change and other potential threats, and their familiarity with and willingness to adopt water conservation practices. These traits are collectively referred to as social indicators, and have typically been used as an alternative means of measuring water quality. My goal here was to not only lay out a potential future for hydrology in an agriculturally important area of water-rich region, but to also discuss how social indicators of groundwater sustainability can inform the development of strategies to adapt to that future.

9.2 Methods

9.2.1 Hydrologic modeling

To simulate the hydrological impacts of climate change I employed SWAT to model surface water and recharge, and an existing USGS MODFLOW model for Kalamazoo County produced by Luukkonen et al. (2004) to model groundwater. I constructed 12 different SWAT watershed models for the study area, and calibrated each to observed baseflow conditions from 2000-2010 in order to produce reliable estimates of field-scale groundwater recharge. I then used the averaged annual recharge estimates from SWAT as spatially-explicit inputs into a steady-state version of the USGS Kalamazoo County MODFLOW model. I then compared MODFLOW outputs of hydraulic head to observed water levels in 38 USGS observation wells in Kalamazoo County, and to static water levels in over 26,000 well records in the State of Michigan's Wellogic database. Based upon those comparisons, I concluded that the groundwater model did not need further recalibration. Next, I ran the SWAT models up to the year 2100 with daily projections of precipitation and temperature from 31 different climate scenarios, which had been downscaled and organized into a standardized dataset by Hayhoe et al. (2013). I then used average annual recharge values from SWAT to generate steady-state hydraulic head MODFLOW models for each decade from 2010-2100 in the 31 climate models. I also calculated additional scenarios of land cover change for each climate simulation. In one scenario urban areas expanded as a function of a projected 5.5% growth in population growth to 2040, in another agricultural areas expanded by 5%, and in another both urban and agricultural areas expanded.

9.2.1 Social indicators survey

To measure social indicators of groundwater sustainability I administered an online survey to large-quantity water users in Michigan. The voluntary survey was offered to individuals and organizations that had just completed their required 2013 water use online report submission to the State of Michigan. I offered two versions of the survey, one tailored for agricultural groundwater conservation, for those required to report their use to MDARD, and another tailored for commercial and industrial groundwater conservation, for those required to report to MDEQ.

9.3 Key Findings

9.3.1 Hydrologic modeling

The hydrologic outputs from SWAT and MODFLOW generally reflected the overall trend amongst the climate models of increasing in precipitation through the rest of the century. SWAT estimates of annual groundwater recharge were higher at the end of the century than at the beginning in all but one of the 31 climate models, and hydraulic head was higher in all but two. There was inter-model variability for the various decades, with some projecting sharp increases in recharge and head in one decade while others projected decreases, but the overall trend was up. These trends were more pronounced in the climate scenarios in which CO_2 concentrations were highest (A1Fi and A2). At these higher levels plants became more efficient in their water use, causing them to transpire less and leave more water in the soil that became recharge (Andrew D. B. Leakey et al., 2009; Pritchard et al., 1999; Saxe et al., 1998; Wand et al., 1999). Among climate scenarios that assumed the A1Fi emission scenario, in which CO_2 concentrations climbed to 970ppm by 2100, recharge increased an average of 68% from the 2010-2019 time period to the end of the century, while ET dropped 18%. For the climate models that adopted the B1 emission scenario, in which CO_2 levels off at 549ppm by 2100, there was a 13% increase in recharge and a 2% increase in ET. In the A1Fi model, hydraulic head increased by an average 116 centimeters by the end of the century, compared to 21 centimeter average increase in the B1 models. The trends in recharge and ET had corollary effects on other SWAT outputs. Daily streamflow increased by an average of 63%, 51%, 38%, and 13%, and irrigation dropped by 43%, 28%, 20%, and 9% in the climate models for A1Fi, A2, A1B, and B1 emission scenarios, respectively. The steady rise in temperature also extended the growing season by 3 weeks in the B1 climate models, and by 5 weeks in the others. These extensions included about a one week earlier start to the growing season.

The results above assumed that the land cover in the region did not change. When I allowed the extent of urban areas to grow by 5.5%, thereby adding more imperviousness to the study area, hydraulic head dropped by an average of only 1.80 cm. Alternatively, when I allowed the extent of agricultural areas to expand by 5%, head increased by an average of only 0.06 cm. When the models accommodated both land cover scenarios head dropped by 1.74 cm, implying that urbanization will have a slightly larger impact on the region's water table than will growth in agriculture. These results indicate that climate change will have a much larger impact on hydraulic head than a relatively moderate change in land cover.

There were also consistent patterns in the spatial distributions of recharge and hydraulic head among the various climate scenarios. Urbanization tended to push the geographic mean centers of each output further south in the study area, away from the urban centers of Portage and the City of Kalamazoo. Fluctuations in head were greatest at points furthest from the stream network, which was defined as a constant head boundary in MODFLOW. The largest of these changing head locations was in the southwest portion of the study area, between tributaries of the Paw Paw and Portage Rivers.

9.3.2 Social indicators of groundwater sustainability

The relatively small sample sizes of the survey respondents limited the analysis of the results to questions for which there was clear consensus, and ruled out stratifying sub-samples by gender and geographic region. The majority of respondents considered groundwater a critical resource and felt a personal responsibility for its conservation. There was not a clear consensus as to whether respondents deemed climate change a threat to groundwater sustainability. Most respondents were already familiar with a variety of water conservation practices. Agricultural respondents tended to be more familiar with and more willing to adopt such practices than their non-agricultural counterparts, which I expected. The agricultural respondents also indicated fewer constraints in adopting conservation practices than the non-agricultural respondents, which ran counter to my expectation. However, both groups identified cost as one of the most important factors affecting their ability to change their current conservation practices. Efforts to identify key differences among all respondents by age, education, income, and total water use were generally unsuccessful. The only consistent and statistically significant difference was that respondents with an associate's degree or greater tended to be more familiar with water conservation practices. Both agricultural and non-agricultural respondents regarded the Michigan State University Extension service as very trustworthy source for information regarding water, and were less trusting of environmental groups. However, they differed with regards to regulatory agencies, with the non-agricultural respondents rating US EPA and MDEQ more highly than their agricultural counterparts.

9.4 Implications

While the projected increases in groundwater recharge and hydraulic head for Kalamazoo County through the end of the century can be interpreted as indicators of abundant water supplies, they do not guarantee the region a consistent and sufficient supply of freshwater, and elevate risks for flooding and water quality degradation. The projections I presented here represent decadal averages, and therefore imply that recharge, ET, irrigation, hydraulic head, and the other outputs will sometimes be higher and other times lower. The expected rise in the water table implies that drought will be less likely in the future, but does not mean that it will not occur, which is why these results should not be taken as a reason to abandon conservation efforts, or loosen present-day regulations on water withdrawals. A projected bumper crop of freshwater in 50 years does not give us license to spend the windfall today. The sensitive fish species in the coldwater streams of southwest Michigan will still rely on today's baseflow conditions, regardless of what these models project for the future. The higher water tables and larger streamflows will put the area at a greater risk for floods, particularly if, there is an increase in the number of extreme precipitation events (International Joint Commission, 2003; IPCC, 2014). These flash floods will be exacerbated by expanded imperviousness around urban areas, and increase the amount of pollutant loading to streams through surface runoff. The erosive force of water in the stream channels will increase, eroding stream banks and further degrading the quality of the water for habitat.

The agricultural community may benefit financially from reduced costs of irrigation maintenance and the prospect of an extended growing season, but the higher water tables may necessitate expanding tile drainage in the region, and flood risks will threaten yields in addition to the region's population. Furthermore, a longer growing season would expose the stream network to additional pollutant loading from agriculture, especially if farmers try to fit two harvests into a single year.

To what extent are these results indicative of future hydrological trends outside of Kalamazoo County? While each location is unique, Kalamazoo County's heterogeneous landscape facilitates a comparison of these results to other areas in the Great Lakes Region. The county's high concentration of agricultural in its southern portion make the results germane to other areas in the region where farming is prevalent and long term climate projections are similar, such as eastern Wisconsin, northern Indiana, Michigan's Lower Peninsula, and northern Ohio. The growing cities of Kalamazoo and Portage make the results relevant to other urban centers in the region, particularly the implications of increasing imperviousness. Kalamazoo's soils may be sandier than other parts of the region, and its aquifer structure unique, but I expect that models of other parts of the Great Lakes Region with similar climate projections would yield similar overall trends to the ones produced for Kalamazoo County.

9.5 Future Research

This study provided a comprehensive review of surface and groundwater hydrology under a broad range of climate models and emission scenarios at a very fine spatial resolution, but very coarse temporal resolution. Models should be generated for specific decades and climate models of interest to produce a better picture of inter-annual variability in the recharge and hydraulic head trends. More precisely, monthly outputs should be generated with a transient groundwater model to explore potential climate impacts on aquifer storage and the change in head during pumping periods throughout the year. This more temporally detailed model should also more tightly couple simulations of streamflow with constant head values in MODFLOW's river cells. In the model's current configuration river cells retain their present day heads through the rest of the century, despite SWAT projections of increased streamflow.

Future research along this path should explore better simulations of land cover change and water withdrawals. While my representation of urbanization and agricultural expansion was more spatially honest than other attempts that simply increased recharge in broad geographic swaths, it did not account for other relevant factors like transportation networks or current land uses (it focused exclusively on land cover). Urbanization models like SLEUTH (Silva & Clarke, 2002) might provide better representations of future imperviousness. The algorithm I developed to identify irrigated areas adequately represented the overall volume of withdrawn water and irrigation rates, when compared to reported values, but tended to miss portions of irrigated fields. If a record of digitized irrigated fields exists, or if farm field boundaries in datasets like the USDA's Common Land Unit could be connected to irrigation records, then the spatial accuracy of SWAT's recharge estimates, which are much higher for irrigated areas, could be greatly improved.

Though I expect the results of this study to be generally transferrable to other areas in the Great Lakes Region, additional models should be developed at similar scales but in different locations. These models could confirm the degree to which the Kalamazoo model is generalizable, or reveal the particular landscape, land management, or stratigraphic attributes that distinguish the hydrologic output projections from one another.

The climate models I downloaded and processed from the HCD were the best available at that time. These models were based on data from phase 3 of the Coupled Model Intercomparison Project (CMIP3), and utilized four of the scenarios defined in the IPCC's Special Report on Emissions (SRES) from 2007. CMIP3 has since been replaced by CMIP5, and the SRES has been replaced by various scenarios of Representative Concentration Pathways (RCPs) which are based upon different levels of radiative forcing. Future studies of climate change impacts on hydrology should explore employing these more recent climate models and emission scenarios.

Lastly, this study was the first to utilize SIDMA in the evaluation of social indicators of groundwater sustainability. While the results provided insights into the overall awareness among respondents to threats to sustainability, their willingness to implement water conservation practices, and the constraints that limit their ability to adopt those practices, my analysis was limited by a small sample size and a focus on large quantity water users. A future survey with a larger sample could provide additional insight into indicator differences by gender, income, region, and other demographic variables. Furthermore, surveying the general public could help delineate differences between large scale (agriculture and industry) and domestic users, and inform conservation strategies that could engage much larger populations.

APPENDICES

APPENDIX A

SWAT Land Cover Classes Utilized in this Study

Table 43: SWAT land cover classes utilized in this study, sorted from most common to least common.

SWAT Land Cover Code	Description	% Area of All 12 SWAT Models
FRSD	Forest-Deciduous	19.17
WETF	Wetlands-Forested	11.80
CSCS	Corn-soy rotation	11.27
SCSC	Soy-corn rotation	8.48
PAST	Pasture	7.36
APAP	Alfalfa-pasture rotation	5.74
URLD	Residential-Low Density	5.41
CORN	Continuous Corn	4.54
URML	Residential-Med/Low Density	3.67
WATR	Water	3.20
ALFA	Continuous Alfalfa	1.74
CSWC	Corn-soy-wheat rotation	1.53
SCWS	Soy-corn-wheat rotation	1.50
CSCH	Corn-soy rotation (shallow-aquifer irrigated)	1.18
PAST	Pasture	1.15
URMD	Residential-Medium Density	0.84
CORH	Continuous Corn (shallow-aquifer irrigated)	0.74
SOYB	Soybean	0.71
CSCD	Corn-soy rotation (deep-aquifer irrigated)	0.63
RNGE	Range-Grasses	0.61
CSCU	Corn-soy rotation (surface-water irrigated)	0.61
SCSH	Soy-corn rotation (shallow-aquifer irrigated)	0.60
HAY	Hay	0.54
ACAC	Alfalfa-corn rotation	0.52
SCSD	Soy-corn rotation (deep-aquifer irrigated)	0.37
URHD	Residential-High Density	0.37
CCWC	Corn 3 yr wheat 1 yr rotation	0.37
SCSU	Soy-corn rotation (surface-water irrigated)	0.37
WCWS	Wheat-corn-soy rotation	0.34
WWHT	Winter Wheat	0.32
CORD	Continuous Corn (deep-aquifer irrigated)	0.31
FRSE	Forest-Evergreen	0.30
CACA	Corn-alfalfa rotation	0.30
CORU	Continuous Corn (surface-water irrigated)	0.29
BLUG	Kentucky Bluegrass	0.28
SSWS	Soy 3 yr wheat 1 yr rotation	0.25
WSWS	Wheat-soy rotation	0.22

SWAT Land Cover Code	Description	% Area of All 12 SWAT Models
APAH	Alfalfa-past rotation (shallow-aquifer irrigated)	0.16
APAU	Alfalfa-past rotation (surface-water irrigated)	0.15
FRST	Forest-Mixed	0.15
GRAP	Vineyard	0.14
WCWC	Wheat-corn rotation	0.09
BARR	Barren	0.08
ALFH	Continuous Alfalfa (shallow-aquifer irrigated)	0.08
APAD	Continuous Alfalfa-past rotation (deep-aquifer irrigated)	0.07
ALFU	Continuous Alfalfa (surface-water irrigated)	0.07
FRST	Forest-Mixed	0.07
CSWU	Corn-soy-wheat rotation (surface-water irrigated)	0.06
CSWD	Corn-soy-wheat rotation (deep-aquifer irrigated)	0.06
WETN	Wetlands-Non-Forested	0.06
CSWH	Corn-soy-wheat rotation (shallow-aquifer irrigated)	0.06
PAST	Pasture	0.05
AGRR	Agricultural Land-Row Crops	0.05
GOCH	Bermuda grass (shallow-aquifer irrigated)	0.04
SASA	Soy-alfalfa rotation	0.04
ALFD	Continuous Alfalfa (deep-aquifer irrigated)	0.04
CUCM	Cucumber	0.04
SCWU	Soy-corn-wheat rotation (surface-water irrigated)	0.04
GOCP	Bermuda grass (pond irrigated)	0.04
ACAH	Alfalfa-corn rotation (shallow-aquifer irrigated)	0.04
POTA	Potato	0.04
SCWH	Soy-corn-wheat rotation (shallow-aquifer irrigated)	0.03
FRST	Forest-Mixed	0.03
CACH	Corn-alfalfa rotation (shallow-aquifer irrigated)	0.03
PTBN	Pinto Beans	0.03
CCWD	Corn 3 yr wheat 1 yr rotation (deep-aquifer irrigated)	0.03
SCWD	Soy-corn-wheat rotation (deep-aquifer irrigated)	0.03
SOYU	Soybean (surface-water irrigated)	0.03
SOYH	Soybean (shallow-aquifer irrigated)	0.03
GOCT	Bermuda grass (stream irrigated)	0.03

Table 43 (cont'd)

SWAT Land Cover Code	Description	% Area of All 12 SWAT Models
ASAS	Alfalfa-soy rotation	0.02
CCWH	Corn 3 yr wheat 1 yr rotation (shallow-aquifer irrigated)	0.02
ACAU	Alfalfa-corn rotation (surface-water irrigated)	0.02
ASPR	Asparagus	0.02
CCWU	Corn 3 yr wheat 1 yr rotation (surf irri)	0.02
GOCD	Bermuda grass (deep-aquifer irrigated)	0.02
AGRR	Agricultural Land-Row Crops	0.01
SOYD	Continuous Soybean (deep-aquifer irrigated)	0.01
WCSH	Wheat-corn-soy rotation (shallow-aquifer irrigated)	0.01
OATS	Oats	0.01
ACAD	Alfalfa-corn rotation (deep-aquifer irrigated)	0.01
CACD	Corn-alfalfa rotation (deep-aquifer irrigated)	0.01
CELR	Celery	0.01
WSWH	Wheat-Soy rotation (shallow-aquifer irrigated)	0.01
WWHU	Winter Wheat (surface-water irrigated)	0.01
CACU	Corn-alfalfa rotation (surface-water irrigated)	0.01
RYE	Rye	0.01
HAYU	Hay (surface-water irrigated)	0.01
ONIO	Onion	0.01
WWHH	Winter Wheat (shallow-aquifer irrigated)	0.01
PEPP	Peppers	0.01
WCSU	Wheat-corn-soy rotation (surface-water irrigated)	0.01
SSWU	Soy 3 yr wheat 1 yr rotation (surf irrigated)	0.01
HAYD	Hay (deep-aquifer irrigated)	0.01
SSWH	Soy 3 yr wheat 1 yr rotation (shallow-aquifer irrigated)	0.01
WCSD	Wheat-corn-soy rotation (deep-aquifer irrigated)	0.01
WCWH	Wheat-corn rotation (shallow-aquifer irrigated)	0.01
WCWD	Wheat-corn rotation (deep-aquifer irrigated)	0.01
HAYH	Hay (shallow-aquifer irrigated)	0.01
RNGB	Range-Brush	< 0.01
SCRN	Sweet Corn	< 0.01
FRST	Forest-Mixed	< 0.01

SWAT Land Cover Code	Description	% Area of All 12 SWAT Models
WMEL	Watermelon	< 0.01
WWHD	Winter Wheat (deep-aquifer irrigated)	< 0.01
WSWD	Wheat-Soy rotation (deep-aquifer irrigated)	< 0.01
TOMA	Tomato	< 0.01
WSWU	Wheat-Soy rotation (surface-water irrigated)	< 0.01
SSWD	Soy 3 yr wheat 1 yr rotation (deep-aquifer irrigated)	< 0.01
WCWU	Wheat-corn rotation (surface-water irrigated)	< 0.01
SASU	Soy-alfalfa rotation (surface-water irrigated)	< 0.01
SASH	Soy-alfalfa rotation (shallow-aquifer irrigated)	< 0.01
AGRR	Agricultural Land-Row Crops	< 0.01
CLVR	Red Clover	< 0.01
AGRR	Agricultural Land-Row Crops	< 0.01
FRST	Forest-Mixed	< 0.01
GRSG	Grain Sorghum	< 0.01
SASD	Soy-alfalfa rotation (deep-aquifer irrigated)	< 0.01
ASAU	Alfalfa-soy rotation (surface-water irrigated)	< 0.01
ASAH	Alfalfa-soy rotation (shallow-aquifer irrigated)	< 0.01
ASAD	Alfalfa-soy rotation (deep-aquifer irrigated)	< 0.01
AGRL	Agricultural Land-Generic	< 0.01
AGRR	Agricultural Land-Row Crops	< 0.01
STRW	Strawberry	< 0.01
AGRR	Agricultural Land-Row Crops	< 0.01
WBAR	Winter Barley	< 0.01
AGRR	Agricultural Land-Row Crops	< 0.01
PEAS	Garden or Canning Peas	< 0.01
PNUT	Peanut	< 0.01
CRRT	Carrot	< 0.01
FRSE	Forest-Evergreen	< 0.01
AGRR	Agricultural Land-Row Crops	< 0.01
SUNF	Sunflower	< 0.01
SWCH	Alamo Switchgrass	< 0.01
SGBT	Sugarbeet	< 0.01
AGRL	Agricultural Land-Generic	< 0.01
CABG	Cabbage	< 0.01

APPENDIX B

Emission Scenario Storyline Summaries

Emission Scenario Storyline Summaries

The following is an excerpt from "Box SPM-1: The Main Characteristics of the Four SRES Storylines and Scenario Families," from the IPCC's Special Report on Emission Scenarios (Nakićenović & Intergovernmental Panel on Climate Change, 2000)

- The A1 storyline and scenario family describes a future world of very rapid economic growth, global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies. Major underlying themes are convergence among regions, capacity building, and increased cultural and social interactions, with a substantial reduction in regional differences in per capita income. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. The three A1 groups are distinguished by their technological emphasis: fossil intensive (A1FI), non-fossil energy sources (A1T), or a balance across all sources (A1B)[25].

- The A2 storyline and scenario family describes a very heterogeneous world. The underlying theme is self-reliance and preservation of local identities. Fertility patterns across regions converge very slowly, which results in continuously increasing global population. Economic development is primarily regionally oriented and per capita economic growth and technological change are more fragmented and slower than in other storylines.

- The B1 storyline and scenario family describes a convergent world with the same global population that peaks in mid-century and declines thereafter, as in the A1 storyline, but with rapid changes in economic structures toward a service and information economy, with reductions in material intensity, and the introduction of clean and resource-efficient technologies. The emphasis is on global solutions to economic, social, and environmental sustainability, including improved equity, but without additional climate initiatives.

[25] Balanced is defined as not relying too heavily on one particular energy source, on the assumption that similar improvement rates apply to all energy supply and end use technologies.

APPENDIX C

MSU IRB Exemption Letter

MICHIGAN STATE
UNIVERSITY

Initial IRB Application Determination *Exempt*

October 4, 2013

To: Glenn O'Neil
Suite 101A
1405 South Harrison Road
East Lansing, MI 48823

Re: **IRB# x13-963e** Category: Exempt 2
Approval Date: October 4, 2013

Title: Social Indicators of Ground Water Sustainability Among Large-quantity Water Users in Michigan

The Institutional Review Board has completed their review of your project. I am pleased to advise you that **your project has been deemed as exempt** in accordance with federal regulations.

The IRB has found that your research project meets the criteria for exempt status and the criteria for the protection of human subjects in exempt research. **Under our exempt policy the Principal Investigator assumes the responsibilities for the protection of human subjects** in this project as outlined in the assurance letter and exempt educational material. The IRB office has received your signed assurance for exempt research. A copy of this signed agreement is appended for your information and records.

Renewals: Exempt protocols do not need to be renewed. If the project is completed, please submit an *Application for Permanent Closure*.

Revisions: Exempt protocols do not require revisions. However, if changes are made to a protocol that may no longer meet the exempt criteria, a new initial application will be required.

Problems: If issues should arise during the conduct of the research, such as unanticipated problems, adverse events, or any problem that may increase the risk to the human subjects and change the category of review, notify the IRB office promptly. Any complaints from participants regarding the risk and benefits of the project must be reported to the IRB.

Follow-up: If your exempt project is not completed and closed after three years, the IRB office will contact you regarding the status of the project and to verify that no changes have occurred that may affect exempt status.

Please use the IRB number listed above on any forms submitted which relate to this project, or on any correspondence with the IRB office.

Good luck in your research. If we can be of further assistance, please contact us at 517-355-2180 or via email at IRB@msu.edu. Thank you for your cooperation.

Sincerely,

H. McGee

Harry McGee, MPH
SIRB Chair

Office of Regulatory Affairs
Human Research Protection Programs

Biomedical & Health Institutional Review Board (BIRB)

Community Research Institutional Review Board (CRIRB)

Social Science Behavioral/Education Institutional Review Board (SIRB)

Olds Hall
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East Lansing, MI 48824
(517) 355-2180
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Email: irb@msu.edu
www.humanresearch.msu.edu

APPENDIX D

Response Frequencies to Social Indicator Surveys

Survey Response Frequencies

Tabular results can be sorted by clicking on the appropriate arrow. Chart results can be viewed for each question by clicking on its text. The numeric values used in calculating mean and stadard deviations are presented in parentheses. 'Total Responses' refers to the number of users that provided an answer to a particular question. 'Valid Responses' refers to the number of users that provided a answer that was not "Don't Know" or "Not Relevant."

Ag survey

Your Opinions on Ground Water Conservation

Please indicate your level of agreement or disagreement with the statements below.

Question # ↓↑	Strongly Disagree (1) ↓↑	Disagree (2) ↓↑	Neither Agree nor Disagree (3) ↓↑	Agree (4) ↓↑	Strongly Agree (5) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
1. Using recommended water management practices effectively conserves ground water.	2.6	1.3	5.3	56.6	34.2	4.18 (0.81)	76 / 76
2. It is my personal responsibility to help conserve ground water resources.	1.3	0	5.3	50.7	42.7	4.33 (0.7)	75 / 75
3. It is important to conserve ground water, even if it slows economic development.	2.7	9.3	28	42.7	17.3	3.63 (0.97)	75 / 75
4. I would be willing to change my management practices to conserve ground water resources.	1.3	3.9	31.6	46.1	17.1	3.74 (0.84)	76 / 76

Impacts of Excessive Ground Water Use

Excessive use of ground water (use at a rate faster than the ground water system can replenish itself) can lead to a variety of consequences for communities. In your opinion, how much of a problem are the following issues in your area?

Question # ↓↑	Not a Problem (1) ↓↑	Slight Problem (2) ↓↑	Moderate Problem (3) ↓↑	Severe Problem (4) ↓↑	Don't Know (9) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
1. Degraded aquatic habitat in nearby streams, rivers, wetlands, lakes, and/or ponds due to excessive ground water use	48.7	28.9	10.5	6.6	5.3	1.74 (0.92)	72 / 76
2. Wells running dry	57.3	20	5.3	13.3	4	1.74 (1.07)	72 / 75
3. Land subsidence	48.6	23	5.4	5.4	17.6	1.61 (0.88)	61 / 74
4. Neighbor conflict over ground water availability	56.6	23.7	9.2	6.6	3.9	1.64 (0.92)	73 / 76
5. Ground water contamination (e.g. salt water intrusion) due to excessive ground water use	53.3	22.7	4	9.3	10.7	1.66 (0.98)	67 / 75

Ground Water Conservation Practices

Please indicate which statement most accurately describes your level of experience with each practice listed below.

Question # ↓↑	**Not relevant for my property (9)** ↓↑	**Never heard of it (1)** ↓↑	**Somewhat familiar with it (2)** ↓↑	**Know how to use it; not using it (3)** ↓↑	**Currently use it (4)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ **/ Total Responses** ↓↑
1. Drip irrigation	26.7	1.3	14.7	24	33.3	3.22 (0.83)	55 / 75
2. Regular irrigation system inspection and calibration	2.7	0	8	4	85.3	3.79 (0.58)	73 / 75
3. Minimizing drift and off-target application of water (e.g. applying in low-wind conditions, increasing droplet size)	10.7	0	4	6.7	78.7	3.84 (0.48)	67 / 75
4. Furrow diking	63.2	10.5	13.2	11.8	1.3	2.11 (0.88)	28 / 76
5. Conservation tillage	11.8	0	7.9	5.3	75	3.76 (0.61)	67 / 76
6. Low-elevation spray application (LESA)	20	25.3	12	20	22.7	2.5 (1.21)	60 / 75
7. Low-energy precision application (LEPA)	18.7	33.3	18.7	16	13.3	2.11 (1.13)	61 / 75
8. Irrigation auditing	5.3	14.7	33.3	16	30.7	2.66 (1.09)	71 / 75

Specific Constraints of Practices

Irrigation Scheduling*: Irrigation scheduling involves the coordination of water application with current soil moisture conditions, soil infiltration rates, crop water needs, and rainfall measurements for each field.*

1. How familiar are you with this practice? **(Responses: 76)**

1.3% Not relevant

2.6% Never heard of it

18.4% Somewhat familiar with it

6.6% Know how to use it; not using it

71.1% Currently use it

2. If the practice is not relevant, please explain why.

3. Are you willing to try this practice? **(Responses: 75)**

82.7% Yes or already do

17.3% Maybe

0% No

How much do the following factors limit your ability to implement this practice?

Question # ↓↑	Not at all (4) ↓↑	A little (3) ↓↑	Some (2) ↓↑	A lot (1) ↓↑	Don't Know (9) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
4. Don't know how to do it	65.2	15.9	13	5.8	0	3.41 (0.93)	69 / 69
5. Time required	42.9	20	25.7	11.4	0	2.94 (1.08)	70 / 70
6. Cost	51.5	10.6	21.2	9.1	7.6	3.13 (1.09)	61 / 66
7. The features of my property make it difficult	58	18.8	17.4	2.9	2.9	3.36 (0.88)	67 / 69
8. Insufficient proof of water conservation benefit	69.6	11.6	10.1	2.9	5.8	3.57 (0.81)	65 / 69
9. Desire to keep things the way they are	66.7	15.9	11.6	5.8	0	3.43 (0.92)	69 / 69
10. Hard to use with my farming system	60	18.6	15.7	4.3	1.4	3.36 (0.91)	69 / 70
11. Lack of equipment	50	22.9	14.3	12.9	0	3.1 (1.08)	70 / 70

Making Decisions for my Property

In general, how much does each issue limit your ability to change your management practices?

Question # ↓↑	Not at all (4) ↓↑	A little (3) ↓↑	Some (2) ↓↑	A lot (1) ↓↑	Don't Know (9) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
1. Personal out-of-pocket expense	6.8	18.9	48.6	25.7	0	2.07 (0.85)	74 / 74
2. Lack of government funds for cost share	30.1	19.2	30.1	15.1	5.5	2.68 (1.09)	69 / 73
3. My own physical abilities	61.6	15.1	20.5	2.7	0	3.36 (0.9)	73 / 73
4. Not having access to the equipment that I need	38.4	30.1	17.8	13.7	0	2.93 (1.06)	73 / 73
5. Lack of available information about a practice	36.1	34.7	19.4	9.7	0	2.97 (0.98)	72 / 72
6. No one else I know is implementing the practice	50.7	20.5	8.2	9.6	11	3.26 (1.02)	65 / 73
7. Concerns about reduced yields	34.2	34.2	19.2	12.3	0	2.9 (1.02)	73 / 73
8. Approval of my neighbors	74	13.7	11	0	1.4	3.64 (0.68)	72 / 73
9. Don't want to participate in government programs	58.9	13.7	16.4	11	0	3.21 (1.08)	73 / 73
10. I do not own the property	79.5	12.3	6.8	1.4	0	3.7 (0.66)	73 / 73
11. The need to learn new skills or techniques	43.8	32.9	17.8	2.7	2.7	3.21 (0.84)	71 / 73

About Your Water Use

1. Which best describes your operation? **(Responses: 76)**

55.3% row-crops

19.7% orchards

19.7% livestock

30.3% vegetable / specialty

11.8% nursery

10.5% other

2. If you answered "other" to question 1 above, please briefly describe your operation.

3. Where does your ground-water come from? **(Responses: 72)**

37.5% Glacial aquifer

23.6% Bedrock aquifer

5.6% Other

18.1% Does not apply (I primarily use surface water)

15.3% Do not know

4. Approximately how many gallons of water did your operation use in 2013? (please only write the number of gallons, do not include the word "gallons") (Mean=69913819.82; SD = 124916733.11; Min = 0; Max = 522032072; Range = 522032072; n = 62)

About You

1. What is your gender? **(Responses: 75)**

96% Male

4% Female

2. What is your age? (please only write the number of years, do not include the words "years" or "years old") (Mean=50.7; SD = 11.97; Min = 19; Max = 73; Range = 54; n = 74)

3. What is the highest grade in school you have completed? **(Responses: 75)**

1.3% Some formal schooling

14.7% High school diploma/GED

25.3% Some college

14.7% 2 year college degree

37.3% 4 year college degree

6.7% Post-graduate degree

4. What was your total household income last year? **(Responses: 73)**

6.8% Less than $24,999

17.8% $25,000 to $49,999

20.5% $50,000 to $74,999

15.1% $75,000 to $99,999

39.7% $100,000 or more

5. Where are you likely to seek information about soil and water conservation issues? (Check all that apply) **(Responses: 75)**

70.7% Newsletters/brochure/factsheet

69.3% Internet

5.3% Radio

80% Workshops/demonstrations/meetings

58.7% Conversations with others

72% Trade publications/magazines

2.7% None of the above

Information Sources

People get information about water quality and quantity from a number of different sources. To what extent do you trust those listed below as a source of information about water?

Question # ↓↑	**Not at all (1)** ↓↑	**Slightly (2)** ↓↑	**Moderately (3)** ↓↑	**Very much (4)** ↓↑	**Am not familiar (9)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ / **Total Responses** ↓↑
1. Soil and Water Conservation District	5.3	6.7	28	57.3	2.7	3.41 (0.85)	73 / 75
2. Local government (e.g. county health department)	20	26.7	34.7	17.3	1.3	2.5 (1.01)	74 / 75
3. Natural Resources Conservation Service	6.8	13.7	31.5	47.9	0	3.21 (0.93)	73 / 73
4. U.S. Environmental Protection Agency	27.8	30.6	27.8	12.5	1.4	2.25 (1.01)	71 / 72
5. Michigan State University Extension	2.7	1.3	26.7	69.3	0	3.63 (0.65)	75 / 75
6. Michigan Department of Agriculture and Rural Development (M-DARD)	6.8	13.5	35.1	41.9	2.7	3.15 (0.91)	72 / 74
7. Michigan Department of Environmental Quality (M-DEQ)	14.7	32	34.7	17.3	1.3	2.55 (0.95)	74 / 75
8. Environmental groups	48.6	36.5	10.8	2.7	1.4	1.67 (0.78)	73 / 74
9. Michigan Farm Bureau	4	20	29.3	46.7	0	3.19 (0.9)	75 / 75
10. Crop consultants / agribusiness	5.5	16.4	34.2	42.5	1.4	3.15 (0.9)	72 / 73
11. Neighbors / friends	8	38.7	33.3	18.7	1.3	2.64 (0.88)	74 / 75
12. Farm Service Agency	18.9	23	35.1	21.6	1.4	2.6 (1.04)	73 / 74

Survey Response Frequencies

Tabular results can be sorted by clicking on the appropriate arrow. Chart results can be viewed for each question by clicking on its text. The numeric values used in calculating mean and stadard deviations are presented in parentheses. 'Total Responses' refers to the number of users that provided an answer to a particular question. 'Valid Responses' refers to the number of users that provided a answer that was not "Don't Know" or "Not Relevant."

NonAg survey

Your Opinions on Ground Water Conservation

Please indicate your level of agreement or disagreement with the statements below.

Question # ↓↑	Strongly Disagree (1) ↓↑	Disagree (2) ↓↑	Neither Agree nor Disagree (3) ↓↑	Agree (4) ↓↑	Strongly Agree (5) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
1. Using recommended water management practices effectively conserves ground water.	2	1	11.6	59.6	25.8	4.06 (0.77)	198 / 198
2. It is my personal responsibility to help conserve ground water resources.	2	1	8.6	56.1	32.3	4.16 (0.78)	198 / 198
3. It is important to conserve ground water, even if it slows economic development.	1.5	8.6	29.8	46.5	13.6	3.62 (0.88)	198 / 198
4. I would be willing to change my management practices to conserve ground water resources.	2	2.5	21.2	59.6	14.6	3.82 (0.78)	198 / 198

Threats to Future Ground Water Availability

The following items may threaten the availability of ground water resources in the future. In your opinion, how much of a threat are the following items in your area?

Question # ↓↑	**Not a Threat (1)** ↓↑	**Slight Threat (2)** ↓↑	**Moderate Threat (3)** ↓↑	**Severe Threat (4)** ↓↑	**Don't Know (9)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ / **Total Responses** ↓↑
1. Increasing irrigation	12.8	36.7	29.6	15.3	5.6	2.5 (0.92)	185 / 196
2. Climate change	17.9	24.6	29.2	21	7.2	2.57 (1.04)	181 / 195
3. Increasing water use by households	19.8	37.6	32	8.6	2	2.3 (0.89)	193 / 197
4. Increasing water use by municipalities	14.2	27.9	39.1	15.2	3.6	2.57 (0.93)	190 / 197
5. Increasing water use by industry (non-ag)	12.2	23.9	34	26.9	3	2.78 (0.99)	191 / 197
6. Increasing water use by power utilities	17.9	23.1	32.3	19.5	7.2	2.57 (1.03)	181 / 195
7. Increasing demand for agricultural goods	13.6	29.8	33.8	15.7	7.1	2.55 (0.94)	184 / 198
8. Increasing acres of impervious surfaces that reduce infiltration (e.g. pavement)	12.6	22.7	32.3	24.2	8.1	2.74 (1)	182 / 198

Impacts of Excessive Ground Water Use

Excessive use of ground water (use at a rate faster than the ground water system can replenish itself) can lead to a variety of consequences for communities. In your opinion, how much of a problem are the following issues in your area?

Question # ↓↑	**Not a Problem (1)** ↓↑	**Slight Problem (2)** ↓↑	**Moderate Problem (3)** ↓↑	**Severe Problem (4)** ↓↑	**Don't Know (9)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ / **Total Responses** ↓↑
1. Degraded aquatic habitat in nearby streams, rivers, wetlands, lakes, and/or ponds due to excessive ground water use	29.1	26.6	24.1	13.1	7	2.23 (1.04)	185 / 199
2. Wells running dry	34.8	28.8	15.7	13.6	7.1	2.09 (1.06)	184 / 198
3. Land subsidence	35.7	26	19.4	3.6	15.3	1.89 (0.9)	166 / 196
4. Neighbor conflict over ground water availability	50.8	21	16.9	4.1	7.2	1.72 (0.91)	181 / 195
5. Ground water contamination (e.g. salt water intrusion) due to excessive ground water use	39.9	19.7	19.7	12.1	8.6	2.04 (1.09)	181 / 198

Ground Water Conservation Practices

Please indicate which statement most accurately describes your level of experience with each practice listed below.

Question # ↓↑	**Not relevant for my property (9)** ↓↑	**Never heard of it (1)** ↓↑	**Somewhat familiar with it (2)** ↓↑	**Know how to use it; not using it (3)** ↓↑	**Currently use it (4)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ / **Total Responses** ↓↑
1. Use of flow-meters	9.1	2	23.7	15.2	50	3.24 (0.92)	180 / 198
2. Regular water system inspection and calibration	9.6	3.6	28.9	9.6	48.2	3.13 (1)	178 / 197
3. Keeping records of water system maintenance	8.3	0.5	23.8	10.9	56.5	3.34 (0.89)	177 / 193
4. Water re-use and recycling (including rain water)	11.2	0.5	32.7	32.1	23.5	2.89 (0.8)	174 / 196
5. Water efficient fixtures and appliances	6.1	0	24.9	22.8	46.2	3.23 (0.84)	185 / 197

Specific Constraints of Practices

Water System Auditing*: Thorough evaluations of system performance helps identify and correct areas of inefficiency.*

1. How familiar are you with this practice? **(Responses: 198)**

3% Not relevant

22.2% Never heard of it

43.4% Somewhat familiar with it

11.6% Know how to use it; not using it

19.7% Currently use it

2. If the practice is not relevant, please explain why.

3. Are you willing to try this practice? **(Responses: 194)**

38.7% Yes or already do

54.6% Maybe

6.7% No

How much do the following factors limit your ability to implement this practice?

Question # ↓↑	**Not at all (4)** ↓↑	**A little (3)** ↓↑	**Some (2)** ↓↑	**A lot (1)** ↓↑	**Don't Know (9)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ / **Total Responses** ↓↑
4. Don't know how to do it	32.1	17.1	24.4	15.5	10.9	2.74 (1.13)	172 / 193
5. Time required	12.3	15.9	33.3	24.6	13.8	2.18 (1.01)	168 / 195
6. Cost	7.2	15.4	25.1	34.9	17.4	1.94 (0.98)	161 / 195
7. The features of my property make it difficult	26.5	16.3	24	11.7	21.4	2.73 (1.08)	154 / 196
8. Insufficient proof of water conservation benefit	40.5	13.3	20	8.7	17.4	3.04 (1.08)	161 / 195
9. Desire to keep things the way they are	43.4	21.7	19.7	5.1	10.1	3.15 (0.95)	178 / 198
10. Physical or health limitations	76.8	4.5	4	1.5	13.1	3.8 (0.6)	172 / 198

Making Decisions for my Property

In general, how much does each issue limit your ability to change your management practices?

Question # ↓↑	Not at all (4) ↓↑	A little (3) ↓↑	Some (2) ↓↑	A lot (1) ↓↑	Don't Know (9) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
1. Personal out-of-pocket expense	35.5	12.2	17.3	29.4	5.6	2.57 (1.28)	186 / 197
2. Not having access to the equipment that I need	17.8	16.8	33	20.8	11.7	2.36 (1.05)	174 / 197
3. Lack of available information about a practice	23.9	22.8	24.9	21.8	6.6	2.52 (1.11)	184 / 197
4. No one else I know is implementing the practice	37.9	13.3	19	15.4	14.4	2.86 (1.17)	167 / 195
5. I do not own the property	50.5	6.6	9.2	28.6	5.1	2.83 (1.35)	186 / 196
6. The need to learn new skills or techniques	36.6	19.6	24.2	12.9	6.7	2.86 (1.09)	181 / 194

About Your Water Use

1. Which best describes the industry for which you use water? **(Responses: 196)**

3.6% Mining
5.1% Power utility
30.1% Turf-grass
0.5% Beverage
26.5% Manufacturing
15.8% Potable or sanitary
18.4% Other

2. If you answered "other" to question 1 above, please briefly describe your operation.

3. Where does your ground-water come from? **(Responses: 193)**

8.8% Glacial aquifer
21.2% Bedrock aquifer
41.5% Do not know the aquifer type
25.9% Does not apply, I primarily use surface water
2.6% Other

4. Approximately how many gallons of water did your operation use in 2013? (please only write the number of gallons, do not include the word "gallons") (Mean=5230088298.1; SD = 56916429728.35; Min = 0; Max = 731124000000; Range = 731124000000; n = 166)

About You

1. What is your gender? **(Responses: 192)**

81.8% Male
18.2% Female

2. What is your age? (please only write the number of years, do not include the words "years" or "years old") (Mean=28580.64; SD = 390724.21; Min = 25; Max = 5400000; Range = 5399975; n = 191)

3. What is the highest grade in school you have completed? **(Responses: 195)**

0% Some formal schooling
6.2% High school diploma/GED
12.8% Some college
16.9% 2 year college degree
43.1% 4 year college degree
21% Post-graduate degree

4. What was your total household income last year? **(Responses: 182)**

1.1% Less than $24,999
6% $25,000 to $49,999
21.4% $50,000 to $74,999
36.8% $75,000 to $99,999
34.6% $100,000 or more

5. Where are you likely to seek information about soil and water conservation issues? (Check all that apply) **(Responses: 194)**

57.2% Newsletters/brochure/factsheet
77.3% Internet
5.2% Radio
55.2% Workshops/demonstrations/meetings
40.2% Conversations with others
45.9% Trade publications/magazines
2.1% None of the above

Information Sources

People get information about water quality and quantity from a number of different sources. To what extent do you trust those listed below as a source of information about water?

Question # ↓↑	**Not at all (1)** ↓↑	**Slightly (2)** ↓↑	**Moderately (3)** ↓↑	**Very much (4)** ↓↑	**Am not familiar (9)** ↓↑	**Mean** ↓↑ **(SD)** ↓↑	**Valid Responses** ↓↑ / **Total Responses** ↓↑
1. Local government (e.g. county health department)	2.6	14	32.1	49.7	1.6	3.31 (0.81)	190 / 193
2. U.S. Environmental Protection Agency	7.2	17	31.4	43.3	1	3.12 (0.94)	192 / 194
3. Michigan State University Extension	2.6	7.8	25	57.8	6.8	3.48 (0.77)	179 / 192
4. Michigan Department of Agriculture and Rural Development (M-DARD)	2.6	9.8	30.4	39.7	17.5	3.3 (0.8)	160 / 194
5. Michigan Department of Environmental Quality (M-DEQ)	1.5	7.7	27.3	61.9	1.5	3.52 (0.71)	191 / 194
6. Environmental groups	26.9	30.6	34.7	4.7	3.1	2.18 (0.9)	187 / 193
7. Neighbors / friends	22.7	44.8	25.3	5.2	2.1	2.13 (0.83)	190 / 194

Threats to Future Ground Water Availability

The following items may threaten the availability of ground water resources in the future. In your opinion, how much of a threat are the following items in your area?

Question # ↓↑	Not a Threat (1) ↓↑	Slight Threat (2) ↓↑	Moderate Threat (3) ↓↑	Severe Threat (4) ↓↑	Don't Know (9) ↓↑	Mean ↓↑ (SD) ↓↑	Valid Responses ↓↑ / Total Responses ↓↑
1. Increasing irrigation	25	43.4	26.3	3.9	1.3	2.09 (0.82)	75 / 76
2. Climate change	31.6	27.6	30.3	6.6	3.9	2.12 (0.96)	73 / 76
3. Increasing water use by households	37.3	34.7	22.7	5.3	0	1.96 (0.91)	75 / 75
4. Increasing water use by municipalities	22.7	37.3	26.7	12	1.3	2.28 (0.96)	74 / 75
5. Increasing water use by industry (non-ag)	16	36	36	10.7	1.3	2.42 (0.89)	74 / 75
6. Increasing water use by power utilities	22.4	27.6	35.5	9.2	5.3	2.33 (0.95)	72 / 76
7. Increasing demand for agricultural goods	25.3	38.7	32	2.7	1.3	2.12 (0.83)	74 / 75
8. Increasing acres of impervious surfaces that reduce infiltration (e.g. pavement)	19.7	34.2	19.7	21.1	5.3	2.44 (1.06)	72 / 76

APPENDIX E

Indicator Scores on Social Indicator Surveys

Indicator Score Differences

The results below represent the scores (Mean) for the particular survey on various social indicators.

Click on the indicator name to see how that particular indicator is calculated.

"N/A" values are displayed when an indicator could not be calculated, either due to the survey lacking the questions that contribute to that indicator or because no responses are present for those questions.

Note: the Awareness indicators are only calculated only calculated on questions that have been identified as "Key Questions" by the user here.

Ag survey

AWARENESS			
Ind. #	**Indicator**	**Mean**	**SD**
1.1	Awareness of consequences of excessive ground water use (value range 1-2, less aware - more aware)	1.30 (n=75)	0.34
1.2	Awareness of threats to future ground water availability (value range 1-2, less aware - more aware)	1.56 (n=76)	0.29
1.3	Awareness of appropriate practices to conserve ground water (value range 1-2, less aware - more aware)	1.85 (n=76)	0.18

ATTITUDES			
Ind. #	**Indicator**	**Mean**	**SD**
2.1	General ground water-related attitudes (value range 1-5, less positive - more positive)	3.97 (n=76)	0.69
2.2	Willingness to take action to conserve ground water resources (value range 1-2, less positive - more positive)	1.91 (n=75)	0.19

CONSTRAINTS			
Ind. #	**Indicator**	**Mean**	**SD**
3.1	Constraints to behavior change (value range 1-4, more constraint - less constraint)	3.08 (n=74)	0.54
3.2	Constraints to adopting key practices (value range 1-4, more constraint - less constraint)	3.27 (n=70)	0.73

Indicator Score Differences

The results below represent the scores (Mean) for the particular survey on various social indicators.

Click on the indicator name to see how that particular indicator is calculated.

"N/A" values are displayed when an indicator could not be calculated, either due to the survey lacking the questions that contribute to that indicator or because no responses are present for those questions.

Note: the Awareness indicators are only calculated only calculated on questions that have been identified as "Key Questions" by the user here.

NonAg survey

AWARENESS			
Ind. #	**Indicator**	**Mean**	**SD**
1.1	Awareness of consequences of excessive ground water use (value range 1-2, less aware - more aware)	1.46 (n=195)	0.37
1.2	Awareness of threats to future ground water availability (value range 1-2, less aware - more aware)	1.69 (n=194)	0.29
1.3	Awareness of appropriate practices to conserve ground water (value range 1-2, less aware - more aware)	1.66 (n=198)	0.27

ATTITUDES			
Ind. #	**Indicator**	**Mean**	**SD**
2.1	General ground water-related attitudes (value range 1-5, less positive - more positive)	3.92 (n=198)	0.65
2.2	Willingness to take action to conserve ground water resources (value range 1-2, less positive - more positive)	1.66 (n=194)	0.3

CONSTRAINTS			
Ind. #	**Indicator**	**Mean**	**SD**
3.1	Constraints to behavior change (value range 1-4, more constraint - less constraint)	2.63 (n=196)	0.81
3.2	Constraints to adopting key practices (value range 1-4, more constraint - less constraint)	2.75 (n=186)	0.66

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