BIOPHYSICAL IMPACTS OF IRRIGATED AGRICULTURE ON WATER AND ENERGY CYCLES IN THE WISCONSIN CENTRAL SANDS

by

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Abstract

BIOPHYSICAL IMPACTS OF IRRIGATED AGRICULTURE ON WATER AND ENERGY CYCLES IN THE WISCONSIN CENTRAL SANDS

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Under the supervision of Professor Christopher J. Kucharik
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The Central Sands conflict over irrigated agriculture and freshwater degradation is one of the greatest environmental problems facing Wisconsin. The management of water resources in the Central Sands is and will continue to be challenging because of the diversity and number of stakeholders, scientific complexity, and political divisiveness over Wisconsin's waters. Moreover, it is likely that similar water management challenges will present themselves throughout other sandy regions in Wisconsin, Minnesota, and Michigan, where irrigated agricultural production and freshwater degradation continue to grow. Irrigated land use conversion changes the water and energy cycles at local to global scales. These changes have cascading effects on freshwater quantity and quality, local and regional climate, agricultural productivity, and human health. Though irrigation-induced impacts to water quantity and climate are relatively well-understood in arid and semi-arid regions, there is still a great opportunity to understand the biophysical impacts of irrigation on water and energy cycles in humid continental climates like Wisconsin, Minnesota, and Michigan.

My interdisciplinary work addresses four research questions related to the Wisconsin Central Sands water conflict: (1) How can conservation scientists and farmers improve communication with one another? (2) How much water do irrigated crops use?

(3) Could precision irrigation be a viable water conservation strategy? And, (4) how is irrigated agriculture altering regional climate? I collaborated with Isherwood Farms (Plover, WI), the Wisconsin Potato and Vegetable Growers Association (WPVGA) groundwater task force, 28 private landowners in the Central Sands, and the Wisconsin Department of Natural Resources (WDNR) to conduct four studies corresponding to the above research questions. My first study draws on my experiences and observations of farmers and other scientists engaged in the Central Sands conflict to identify different types of knowledge and nonknowledge exchange and generation. My second study quantifies potential recharge and evapotranspiration (ET) from six irrigated agroecosystems on Isherwood Farms using twenty-five passive capillary lysimeters and other complementary biophysical instruments between 2013-2016. The third study combines high resolution apparent electrical conductivity (EC_a) maps, ET maps, and complementary biophysical measurements to assess the intrafield variability in crop water supply and use. The fourth study uses a 60 km, W-E transect of 28 temperature and humidity stations spanning a land use conversion gradient to investigate irrigation-induced climate changes in the Central Sands.

Collectively, my dissertation improves our understanding of the impacts of irrigated agricultural production on water resources and climate in the Central Sands. This body of work also identifies several opportunities for better water management such as crop rotational strategies, precision irrigation, and boundary work amongst stakeholders. Future work could improve ET and recharge estimates at different spatial scales, test precision irrigation interventions, quantify historical climate impacts associated with irrigated agriculture, and investigate whether communication and

leadership development for scientists could improve farmer-scientist relations in the Central Sands.

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I am forever indebted to Justin, Lynn, Isaac, Angela, and Gary Isherwood for hosting my research studies on their farm and helping me install and troubleshoot equipment on a daily basis. Because of them, I have a data set rooted in real-world agronomic management with the gaps to prove it. I also learned from the Isherwoods that farmers are a lot like primary care physicians—they have got to constantly be attuned to challenges from several different disciplines. As many know, Justin Isherwood has a way with words. I would say that he also has a creative optimism towards the Central Sands water conflict that motivates me whenever I feel low. I really enjoyed Justin and Lynn's company throughout this project and am happy to count them as friends.

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Chapter 1

Introduction

1.1. Motivation

Irrigated agriculture profoundly changes the coupled water and energy cycle from field to global scales. Pumping groundwater for irrigation alters the water budget by increasing crop evapotranspiration (ET) and decreasing net groundwater recharge, resulting in groundwater depletion (Winter, 1999). Globally, 4500 km^3 of groundwater was depleted in the 20^{th} century with agricultural demand for freshwater predicted to increase during the 21^{st} century (Konikow, 2011). In addition to altering water cycles, irrigated agriculture alters energy cycles through increased latent heat flux, which consumes extra solar energy at the land surface. Additionally, irrigated agriculture may alter nighttime ground heat fluxes by maintaining soils close to field capacity and increasing the soil thermal conductivity (Kanamaru and Kanamitsu, 2008). Irrigation-induced changes to the energy budget can lead to lower daily maximum temperatures, higher daily minimum temperatures, lower evaporative demand, and changes to precipitation patterns (Bonfils and Lobell, 2007; Kueppers and Snyder, 2012).

Irrigation-induced changes to water and energy cycles change regional water supply and climate; which in turn alters freshwater quantity and quality, agricultural productivity, ecological communities, and the incidence of chronic and infectious diseases in humans, plants, and animals (Niles and Mueller, 2016; Zipper et al., 2016; Jones et al., 2017; Kim et al., 2016; Lee et al., 2016). Stakeholders in many parts of the world manage groundwater to balance freshwater and agricultural demands, but do not yet manage irrigation impacts on regional climate. Because stakeholders share groundwater as a common resource, the expansion of irrigated agriculture inevitably leads to conflicts over water rights and equity. Regional water conflicts are best described as "wicked problems," where there are no optimal or "win-win" solutions (Ritel et al., 1973). Wicked problems related to water management and conservation are best approached by developing "clumsy solutions," where stakeholders develop an uneasy base of shared knowledge, language, and spaces in which to trade policy ideas (Khan and Neis, 2010). The Wisconsin Central Sands (WCS) has had long-term wicked problems over the management of water resources and is an ideal region for characterizing changes to water quantity, climate, and stakeholder interactions arising from irrigated agricultural expansion in humid regions.

Irrigated agriculture uses over 2100 high-capacity wells in the WCS to support an agricultural and processing industry that makes Wisconsin one of the top three producers of potatoes, sweet corn, peas, and snap beans in the United States (Smail, 2016a; Keene and Mitchell, 2010) and facilitates field corn production from sandy soils. This agricultural productivity has come at the expense of streams, lakes, and wetlands, which have experienced unprecedented hydrologic stresses. Following prophetic studies predicting freshwater degradation accompanying irrigation development (Weeks et al., 1965; Weeks and Stangland, 1971), trout streams, lakes, and wetlands experienced severe hydrologic stress (Kraft and Mechenich, 2010). These stresses include the drying of the Little Plover River and the ~0.5 m loss of water levels from a score of lakes and wetlands including Huron, Pine, Fish, and Pleasant lakes during a modest dry period in 2005-2009, which collectively resulted in the loss of fisheries and wildlife habitat, property values, and tax base (Kraft and Mechenich, 2010; G. Kraft pers. comm.) Continued freshwater degradation, forest conversion, and irrigation expansion feed a water rights controversy in the Sand Counties that is acknowledged as one of the greatest environmental challenges facing Wisconsin today (Ferret, 2016).

In the WCS, crop ET constitutes 70-85% of groundwater withdrawals for irrigation, while 15-30% of pumped groundwater may be returned back into the aquifer (Weeks and Stangland, 1971; Winter, 1999). Contemporary evidence suggests that consumptive groundwater use via crop ET is not recoverable (Bradbury et al., 2017). Groundwater pumping shifts temporal recharge patterns and causes depletion in surface waters that depend on a critical zone of groundwater supplied from the first few meters of saturated aquifer thickness (Bradbury et al., 2017; Kraft et al., 2012; Condon and Maxwell, 2014). Irrigated crop ET is inferred to be of sufficient magnitude at 480-550 mm (WCS precipitation is 790-810 mm) to cause predicted and observed surface water depletion in the WCS (Weeks et al., 1965; Weeks and Stangland 1971; Tanner et al., 1974; Naber, 2011; Kraft et al., 2012; Kniffin et al., 2013; Nocco et al., 2017) and there is currently enough scientific knowledge to inform the equitable management of water resources. However, recharge and ET are extremely challenging to estimate in the field and estimates from WCS crops have not been published since C.B. Tanner’s lysimetry work in irrigated potatoes, alfalfa, and peas at Hancock Agricultural Station in the 1970s (Black et al., 1970; Tanner et al., 1974; Tanner et al., 1975). Irrigation strategies, crop cultivars, agronomic management and climate have all greatly changed in the WCS since Tanner's time. For this reason, stakeholders have several questions about the spatiotemporal distribution of ET and recharge from irrigated crops, precision irrigation, and the relationship between irrigated agriculture and climate.

1.2. Objectives

I attended several stakeholder meetings in 2011-2014 where social and physical scientists, growers, agribusiness partners, and freshwater users shared their perspectives, challenges, and different types of knowledge about the WCS water conflict. The Nelson Environment and Resources program offered me the intellectual freedom and flexibility to develop an interdisciplinary dissertation combining soil science, hydrology, crop physiology, environmental biophysics, and social science to address stakeholder questions about water use in the WCS with novelty and intrigue. I devised my dissertation research to be very much in the spirit of the Wisconsin Idea, where researchers go out into the community and collaborate with citizens to produce research that addresses real-world problems. I lived and worked in central Wisconsin for majority of my doctoral program and this presence and proximity facilitated a high degree of engagement with agricultural stakeholders that informs all chapters of my dissertation. My overarching research goals were to (1) understand and improve farmer-scientist communication and knowledge production about the WCS water conflict; (2) quantify ET and recharge from WCS irrigated agricultural systems under real-world agronomic management; (3) explore potential water conservation opportunities from precision irrigation in the WCS; and (4) identify irrigation-induced changes to regional climate in the WCS.

Over the course of my dissertation, I have collaborated with the Wisconsin Potato and Vegetable Growers Association (WPVGA) groundwater task force to exchange and create knowledge about the water and energy cycles, irrigated agriculture, and interactions between the two. I have attended bimonthly meetings with the groundwater task force from 2014-present. My full participation and identity as a researcher in WCS scientific community, hard and soft literature, and the data that I collected during a year-long participant observation period inform my findings in Chapter 2. The research goal of Chapter 2 is to create a framework for scientists wishing to improve their communication with stakeholder groups that may be perceived as wary of conservation efforts. Scientists are encouraged to build leadership skills and engage with oppositional groups (Manolis et al., 2009) and could greatly benefit from an increased understanding of how these exchanges can result in both positive and negative outcomes. In Chapter 2, I identify different types of knowledge and nonknowledge exchanges and generation that I encountered while engaging and observing other scientists engage with farmers in the WCS.

In 2012, I developed a partnership with Isherwood Farms, a sixth-generation family farm in Plover, WI that grows irrigated potatoes, sweet corn, peas, and field corn. With the collaboration of the Isherwood family, I installed twenty-five passive capillary lysimeters, 96 soil moisture and temperature probes, and three micrometeorological stations in six agroecosystems in 2013. In addition to the permanent instrumentation, I collected physiological, phenological, soils, proximally sensed, and remotely-sensed data from the six agroecosystems between 2013-2016. These data from Isherwood Farms inform Chapters 3 and 4 of my dissertation.

In Chapter 3, I quantify potential recharge and ET from six agroecosystems managed by Isherwood farms over four years (2013-2016) encompassing different crop rotations, precipitation patterns, and temperature conditions in one of the largest passive capillary wick lysimetry studies to date (Nocco et al., 2017). Chapter 3 addresses different drivers of potential recharge at the field scale including soil texture, interannual climate variability, and crop type. Additionally, Chapter 3 will inform the growing body of literature addressing the depletability of aquifers in humid regions.

WCS farmers have been experimenting with the use of apparent electrical conductivity (EC_a) maps as a proxy for soil water holding capacity to manage irrigation at the intrafield spatial scale. This precision irrigation strategy is commonly applied in arid and semi-arid regions with high soil textural heterogeneity, but has little to no research supporting its implementation in sandy, humid regions like the WCS (Daccache et al., 2015). In Chapter 4, I investigate the underlying assumptions that accompany precision irrigation implementation in the WCS. Specifically, I investigated whether traditionally irrigated crop rotations on Isherwood Farms could benefit from future precision irrigation intervention using high-resolution proximally sensed EC_a maps, remotely sensed ET maps, and complementary field observations. The goal of Chapter 4 is to quantify intrafield variability in crop water supply and use over multiple rotations.

In addition to my work on Isherwood Farms, I partnered with the Wisconsin Department of Natural Resources (WDNR), private landowners, and farmers to establish a 60-km, W-E transect consisting in the WCS. The transect spans red pine plantations, irrigated cropland, and rainfed cropland. In 2013-2014, I instrumented the transect with 28 temperature and relative humidity stations spaced 2 km apart and collected data for 31 months. In Chapter 5, I use these micrometerological measurements, WISCLAND 2.0 land cover data (WDNR, 2016), and a new irrigated lands database (Smail, 2016b) to ask, "how does irrigated agriculture impact regional climate in the WCS?" Though we have a clear understanding of irrigation-induced impacts to regional climate in arid and semi-arid climates (Leng et al., 2013; Sridhar and Anderson, 2017; Harding et al., 2015), we have little understanding of these impacts in humid continental climates like the WCS. Chapter 5 quantifies year-round changes to the diel temperature ranges and vapor pressure deficits associated with irrigated land use. The objective for Chapter 6 of my dissertation is to summarize and synthesize the body of work, discuss its limitations and outcomes, and outline opportunities for future research.

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Chapter 2

Knowledge exchange with agribusiness networks: a framework for identifying water conservation opportunities

Nocco, MA, NW Feinstein, and CJ Kucharik

In preparation for Soil and Water Conservation

Abstract

Scientists may greatly benefit from interacting with oppositional stakeholders by uncovering conservation opportunities, motives, boundary objects, and potential trading zones. However, scientists require an understanding of the way that knowledge and nonknowledge are communicated during these stakeholder interactions. We used a participant observation approach to document the physical spaces and production of knowledge and nonknowledge by scientists and farmers embedded in a community water conflict in the Wisconsin Central Sands. We found that repetitive, semiformal meetings led by farmers were an ideal setting for the coproduction of knowledge and the identification of boundary objects or common ideas. Additionally, both farmers and scientists participated in the production of knowledge and nonknowledge for advocacy-based purposes. We offer several recommendations for scientists engaging with stakeholders such as the development of coping strategies, leadership skills, and the acknowledgement of political biases. Future work could assess how coping strategies and leadership skills could improve scientist interactions with oppositional stakeholders.

2.1. Introduction

Conservation scientists generate knowledge in a wide variety of disciplines, yet differ from traditional scientists because of an additional, value-laden professional goal: to do research that informs the protection, management, and sustainable use of ecosystems and natural resources (Kareiva and Marvier, 2012). Conservation scientists link research to specific management and policy goals such as raising awareness of problems associated with the status quo, evaluating existing or past interventions, predicting future outcomes, and identifying new opportunities (Game et al., 2015). Because they evaluate past, existing, and future interventions, conservations scientists decrease the number and scope of actions that may be taken by policymakers. This reduction and repositioning of viable environmental actions is the reason why conservation scientists are also considered policy advocates and stakeholders (Pielke, 2007). In order to produce policy-relevant research, scientists benefit from nontraditional training in fields such as social science, communications, and business leadership (Green et al., 2015). Key adaptive leadership principles suggest that scientists, though, extend stakeholder networks and nurture productive conflicts by partnering with diverse interests that may be wary or oppositional to conservation measures (Manolis et al., 2009).

Partnerships with stakeholders can uncover motives and strategies, develop boundary objects or concepts that move between groups (Abson et al., 2014; Star and Griesemer, 1989), and establish "trading zones" or spaces where realistic environmental solutions can be negotiated (Kalliomäki, 2015; Feinstein, 2014; Galison, 1997). However, it is important for scientists to avoid common pitfalls associated with stakeholder engagement such as stealth advocacy (Lackey, 2007) and excessive objectivity (Sarewitz, 2004). Stealth advocacy occurs when scientists overestimate their objectivity and do not recognize that personal values are always reflected in the reduction and repositioning of environmental actions associated with conservation studies (Pielke, 2007; Lackey, 2007) . Avoiding stealth advocacy is especially important when engaging with wary stakeholder groups, as scientific knowledge and nonknowledge are often used as evidence in environmental advocacy. Scientific knowledge encompasses both “known knowns” and “known unknowns” (Böschen et al., 2010). “Known knowns” are established scientific facts and evidence, while “known unknowns” are quantifiable scientific uncertainty or knowledge that scientists are aware of but have not yet quantified (Nielsen and Sørensen, 2017). Alternatively, scientific nonknowledge encompasses “unknown knowns” and “unknown unknowns” (Nielsen and Sørensen, 2017). “Unknown unknowns” can be thought of as the unpredictable consequences of scientific and technological interventions or innovations, while “unknown knowns” involve knowledge that is either tacitly or deliberately ignored (Nielsen and Sørensen, 2017). For the context and purpose of this study, we define scientific nonknowledge as the “unknown knowns” related to knowledge production. In environmental conflicts, different stakeholders, including scientists, may inadvertently or intentionally use nonknowledge to support advocacy efforts through tactics such as denial, dismissal, diversion, or displacement of the unknown knowns (Rayner, 2012). For this reason, conservation scientists need to pay as much attention to the communication and exchange of nonknowledge as knowledge when engaging with oppositional stakeholder groups. In this work, we examine the knowledge and nonknowledge production and exchange that occurs between different types of scientists and farmers in the midst of a community conflict over freshwater quantity.

80% of freshwater in lakes, streams, wetlands, and aquifers comes from precipitation intercepted and processed by the land (USDA, 2001). In the United States, 51% of the total land area or 469 million hectares is in agricultural land use, which includes both cropland and grazing land (Nickerson et al., 2011). By interacting with and partitioning precipitation and irrigation into runoff, recharge, discharge, and evapotranspiration, agricultural land use can degrade surrounding and embedded freshwater ecosystems by diverting and polluting ground and surface waters. Freshwater degradation associated with agriculture is often watershed specific; it depends on the connectivity of surface and groundwater, other prevalent land uses, soil properties, crop types, and agronomic management practices (Peters and Meybeck, 2000). Because of the inherent tradeoffs between agricultural production and freshwater health, farmers are often resistant to conservation efforts because of unfamiliarity, potential disruption, or financial risks. Thus, partnerships between farmers and scientists are both challenging and uniquely poised to address freshwater degradation at the watershed scale.

Though there are numerous frameworks for partnering with farmers for water resources management, all approaches include the development of long-term relationships, mutual trust, respect, and equity in the process of knowledge exchange and development (Reed, 2008). The dynamics of knowledge production and exchange between scientists and farmers have been explored in great detail in cases where the educational, institutional, and communicative power of scientists greatly outweighs the power of farmers (Perkins, 2014; Tsouvalis et al., 2000; Clark and Murdoch, 1997; Wynne, 1992). This body of literature focuses on the need to hybridize local and scientific knowledge in order to avoid scientific imperialism or a one-way transfer of information, which is especially important when there is a significant power differential between scientists and farmers (Pohl et al., 2010). However, less attention has been given to the production and exchange of both knowledge and nonknowledge exchange in instances where the power differential between scientists and farmers is even or skewed towards farmers. In these cases, farmers and other agricultural stakeholders often organize formal agribusiness networks that collect, produce, and disseminate scientific information in order to drive policy, secure resource access, prevent regulatory measures, and challenge the causality of environmental problems (McGoey, 2012; Kleinman and Suryanarayanan, 2013).

We focus our inquiry on farmer-scientist interactions in the midst of the current community conflict over agricultural irrigation and degraded freshwater resources in the Central Sands region of Wisconsin. Our research goals were to (1) observe and document different types of knowledge and nonknowledge production and exchange occurring between conservation scientists and agribusiness networks; (2) understand how different communication settings enhance or deter knowledge exchange and nurture productive conflict; and (3) identify potential strategies, and pitfalls for scientists attempting to partner with agricultural stakeholders to do policy relevant conservation research.

2.2. Land use history and conflict

The Central Sands was named for its coarse glacial aquifer that supports 1000 km of headwater trout streams, >80 lakes, and numerous wetlands (Kraft et al., 2012). The sandy soils in the region hold minimal water and nutrients, making rainfed agriculture a risky venture despite the humid climate. The low-quality land was the cheapest in the state of Wisconsin and thus also the last to be cleared and developed for agriculture, in the late nineteenth century, by poor Polish, German, and Bohemian immigrants who attempted to grow potatoes, corn, rye, and marsh hay (Goc, 1990). During the Wisconsin Dust Bowl of 1933-1935, farms in the Central Sands lost approximately 1 foot or a million tons of topsoil to wind erosion, though few farms were abandoned for lack of better prospects (Bennet and Lowdermilk, 1938). An abundant supply of aluminum pipe remained following World War II and farmers began using it to extract groundwater from high-capacity wells (Isherwood, 2014).

Land-use conversion to groundwater irrigation increased potato yields from 100 to 450 bushels per acre and revolutionized the practice and demographics of agriculture in the Central Sands along with fertilizer, pesticide, and breeding advancements (French and Lynch, 1957). In the 1950s, growers with sufficient means invested heavily in center-pivot irrigation and bought out their neighbors. As the number of farmers decreased and production intensified, the number of high-capacity wells grew from 50 in 1960 to over 2700 in 2016 (Smail, 2016). High capacity wells are defined as wells that can pump over 70 gallons per minute, but most irrigation wells pump between 500-1000 gallons per minute (Wisconsn Department of Natural Resources, 2017; G. Kraft, pers. comm.).

Today, irrigation in the Central Sands contributes to making Wisconsin one of the top five producers of potatoes, sweet corn, snap beans, and peas in the United States (USDA, 2014; Keene and Mitchell 2010). Production is concentrated to 100-150 farms and the farmers participate in organization known as the Wisconsin Potato and Vegetable Grower Association (WPVGA). The association formed in 1948 and its current mission is to educate growers, fund and engage in scientific research, promote the industry, and engage in political action (WPVGA, 2017a). Potato and vegetable grower participation in the association is almost absolute and attendance at events is abundant. The WPVGA produces a monthly magazine called the Badger Common'tater that shares trade, scientific, and advocacy news geared towards an audience of farmers, distributors, and industry partners. The permanent staff of the WPVGA includes an executive director, magazine editor, director of promotion and communications, financial officer, auxiliary president, community relations coordinator, and two administrative assistants (WPVGA, 2017a). For political action and advocacy, the group retains 1-2 lobbyists specializing in environmental law and government relations from Madison, WI.

The continued expansion of irrigated agriculture in the Central Sands has been highly contested over the last sixty years (French and Lynch, 1957) and seminal, historical studies predicted severe water quantity impacts to lakes, rivers, and wetlands adjacent to high-capacity wells (Weeks and Stangland 1970, Weeks et al., 1965). These predictions came to fruition during 2005-2009 when unprecedented surface water stresses and fish kills occurred near areas of intense groundwater pumping in the Central Sands (Kraft and Mechenich, 2010; Kraft et al., 2012). The Little Plover River, an iconic class I trout stream, ran dry and suffered unprecedented fish kills, which caused an outcry amongst recreational water users and freshwater conservationists (American Rivers, 2013). Additionally, Huron, Pine, Fish, and Pleasant lakes were among several lakes to lose ~0.5 m of water levels, which unified lakefront homeowners and recreational water users against existing and continued irrigated agricultural development at the expense of losing fisheries and wildlife habitat, property values, and tax base (Kraft and Mechenich, 2010; G. Kraft pers. comm). From a scientific perspective, groundwater and surface water have been long established as a single, connected resource in the Central Sands (Bradbury et al., 2017; Weeks et al., 1965). However, from a policy perspective, they are treated as separate resources in the state of Wisconsin. Though surface waters are held in a public trust doctrine, Wisconsin has recently passed 2017 Wisconsin Act 10, which arguably privatized groundwater rights allowing the transfer, replacement, and reconstruction of wells without new permitting (Wis. Stat. § 281.34, 2017). Farmers receive permits on a first come-first serve basis to pump groundwater for irrigation as long as wells are located 1200 ft. from an outstanding or exceptional resource water or trout stream (Wisconsin Department of Natural Resources, 2017). The WPVGA has demonstrated varying degrees of wariness and opposition to regulation and management of groundwater for the past sixty years by organizing and engaging in political action to expand pumping rights (Wisconsin Senate Bill 76, 2017; Wisconsin Assembly Bills 64-68, 1959).

2.3. Historical and present farmer-scientist relations

Because of novel agricultural challenges, farmers have cultivated a century-old relationship with scientists in the agronomy, soil science, horticulture, entomology, and plant pathology departments at the University of Wisconsin-Madison (UW-Madison), a land grant research institution located 100 miles south of the Central Sands. Through organizational and state check off funds, farmers have selected and funded scientists who study various aspects of crop production, including nutrient, pest, weed, soil, and water management (Konopacki, 2016). Many scientists have benefitted from this relationship by having access to a long-term funding stream, a constant supply of relevant applied research questions, and access to conduct and share research at the Hancock Agricultural Research station, a 120-hectare experimental research farm in the Central Sands that was established in 1916 to support growers working in the droughty soils. Growers regularly sponsor annual educational and fellowship-building events in the Central Sands, which have facilitated trust between growers and agricultural scientists by creating local knowledge spaces where the production of scientific knowledge and crop yields have advanced over generations. Though scientists have conducted conservation studies at Hancock, these studies generally have had the goal of finding affordable environmental interventions that will not reduce yield or quality.

In response to the water stresses that became apparent during 2005-2009 and ensuing controversy, the WPVGA created a groundwater task force of about twenty farmers, industry representatives, and both public and private scientists to "be an advocate for responsible water use practices and informed, science-based public policy that will protect the Central Sands groundwater aquifer and its associated streams, lakes and wetlands; promote and maintain a sustainable agricultural industry; and foster vibrant rural communities" (WPVGA, 2017a). Two farmers serve as the water task force chairs and the group meets on a bimonthly basis and invites scientists, lobbyists, and other stakeholders to give presentations to the group about Central Sands water issues and research. Conservation scientists (designated here by the authors) involved in the Central Sands research community are housed in a variety institutions, including UW-Madison, the University of Wisconsin Stevens Point (UW-SP), the United States Geological Survey (USGS), the Wisconsin Geological and Natural History Survey (WGNHS), and the Wisconsin Department of Natural Resources (WDNR). Moreover, in recent years, larger Central Sands agribusinesses have hired UW-Madison faculty and graduates as industry scientists to conduct on-farm research on various aspects of water and nutrient management. Finally, the WPVGA retains 1-2 national consulting firms to critique existing scientific knowledge and generate new scientific knowledge about hydrological impacts in the Central Sands.

2.4. Participant observation approach

We collected participant observation data and conducted a review of trade publications, websites, and peer-reviewed literature to inform this study. Participant observation data were collected and recorded for one year (24 June 2015-23 June 2016) during farmer-scientist and scientist-scientist interactions within or regarding the Central Sands region of Wisconsin. We did not collect data from stakeholder groups representing freshwater interests such as trout fisherman or lakefront property owners and recognize that this is a limitation of our study and findings. During the participant observation period, we attended eight WPVGA groundwater task force meetings, the cosponsored WPVGA/University of Wisconsin Extension Grower Education Conference, the Hancock Potato Field Day, the American Water Resources Association (AWRA) Wisconsin Section Meeting, as well as several informal scientific meetings.

The quality of participant observation data is influenced by the degree of participation, biases, and cultural identity of the researchers (Dewalt and Dewalt, 2011). Our degree of participation in both the WPVGA groundwater task force and scientific community is complete and total. We regularly attended WPVGA groundwater taskforce meetings, UW-Madison Extension events (Grower Education Conference and Potato Field Day), American Water Resources Association (AWRA) Meetings, and informal scientific meetings for three years prior to commencing the study, and continued to attend meetings following the study period. Additionally, we studied biophysical and hydrological processes in the Central Sands region for three years prior to the study period and continue these studies to date. We have partnered with a sixth-generation family farm in the Central Sands to conduct long-term biophysical and hydrological field experiments prior to and following the study period. We identify as conservation scientists in that it is our goal to do policy-relevant research that supports the protection, management, and sustainable use of water resources in Wisconsin.

In order to differentiate our participant-observation from our normal participation as scientists in the community, we applied six recommended data collection techniques

(Spradley, 2016): (1) we were actively aware of our dual roles as both scientists and observers during data collection events; (2) we maintained a sense of hyper-awareness of our surroundings and processed information that we would normally ignore to avoid information overload; (3) we used a "wide-angle lens" to observe people, spaces, and interactions; (4) we attempted to engage with both scientists and farmers as an insider, while observing both ourselves and the surroundings as an outsider; (5) we employed a higher than normal degree of introspection about our behavior and observations; and (6) we kept records of data collection in the form of memorandums. We used indexing to organize data based on *a priori* interests in different types of knowledge and nonknowledge (scientific, local, vernacular), knowledge transfer and exchange (linear, bidirectional, multidirectional), and knowledge spaces (casual, semiformal, formal). Though we did not conduct any interviews, our conversations that occurred during the participant-observation period are considered analogous to interviews with the lowest possible amount of control (less control than unstructured interviews) because we still used active-listening techniques, nonintrusive verbal cues, and clarifying or naïve questions to elicit information from both farmers and scientists (Dewalt and Dewalt, 2011).

2.5. Knowledge and nonknowledge production and exchange

We present a schematic depicting the different groups of scientists and farmers, meeting spaces, and types of knowledge exchange that we observed during the course of the study (Fig. 1). Almost all scientists and farmers attended the Grower Education

Conference. UW-Madison scientists and majority of farmers attended Potato Field Day at Hancock. All scientists except agribusiness industry scientists attended the AWRA meeting and informal hydrology meetings, and a small subsection of farmers and rotating subsection of scientists attended the WPVGA groundwater task force meetings. The AWRA and Grower Education Conferences had similar formats where sessions were kept on pace by moderators, speakers gave formal presentations followed by a brief (<10 minutes) question and answer period, and informal spaces such as coffee stations, social hour/poster presentations, and meals existed for casual exchanges. Hancock Potato Field Day had a unique format where farmers visited UW-Madison field plots on movable bleachers pulled by a tractor. At each field plot, farmers listened to UW-Madison researchers give brief presentations followed by a short question and answer period. Groundwater task force meetings had an agenda consisting of different scientific and policy-oriented speakers (i.e. lobbyists). Both growers and nonpresenting scientists actively asked the presenting scientists questions and engaged in discussion both during and after scientific presentations. Because scientific presentations are interspersed with policy presentations, farmers intersperse both topics with one another and scientists are often present to witness discussion of political concerns and strategies.

All types of meetings facilitated the exchange of scientific and local knowledge, however the directionality of knowledge transfer differed based on the leadership (scientist vs. farmer) and formality of the space. Scientific knowledge was unidirectionally communicated from scientists to farmers at the UW-Madison Grower Education Conference and Hancock Potato Field Day during didactic presentations and question/answer sessions. Similarly, scientific knowledge was unidirectionally communicated from scientist to scientist at the AWRA meeting. Though they were present at scientific meetings, we did not observe hydrological consultants unidirectionally communicate knowledge in the scientific community. Bidirectional and multidirectional communication and exchange of scientific and local knowledge occurred during informal spaces and moments at the UW-Madison Grower Education Conference, Hancock Potato Field Day, and during the entirety of groundwater task force meetings. Bidirectional and multidirectional exchanges and production of scientific knowledge occurred amongst scientists studying the Central Sands conflict from different disciplines (biophysicists, hydrogeologists, soil scientists, hydrologists) during the informal spaces and moments at the AWRA meeting and the entirety of informal hydrology meetings.

2.5.1. Repetitive, semiformal meetings facilitate vernacular knowledge production and boundary object identification

Scientists and growers coproduced vernacular knowledge at the groundwater task force meetings. Vernacular knowledge governs communication between stakeholder groups and is the language through which social consensus occurs, making it equally important to traditional scientific knowledge when seeking to identify community-based water management opportunities (Simpson et al., 2015). Vernacular knowledge about farming, water, and the biophysical environment develops from images and metaphors used in everyday life, where stakeholders regularly act in response to and situated in daily tasks involving weather, water, soil, and plants (Wagner, 2007). For example, we experienced a near-ideal form of vernacular knowledge coproduction during the course of our partnership with a single Central Sands farmer to do biophysical and hydrological research over the past five years. Out of logistical necessity, curiosity, and friendliness, we interacted with each other several times a day during the field season. Our research team negotiated drainage, phenology, photosynthesis, and remote sensing measurements around his farm team's irrigation, pest management, planting, and harvest schedules. Through these everyday interactions, the farmer increased his lay knowledge about environmental biophysics and hydrology, while we increased our lay knowledge about irrigated potato and vegetable farming. Together, we coproduced vernacular knowledge about the relationship between irrigated agriculture and the water cycle in the Central Sands. Because of the similar close relationship that occurs in daily life during the field season, we observed that on-farm industry scientists also shared a coproduced vernacular knowledge base with farmers.

Though vernacular knowledge is not always a completely accurate representation of scientific facts, theories, and mechanisms, it facilitates communication about relevant ideas between and within disparate social structures. The coproduction of vernacular knowledge forces disparate stakeholders to negotiate a locally relevant common language based on mutual values, lay expertise, and traditional scientific knowledge, which should diminish power differentials and create a framework for community-based solutions (Simpson et al., 2015; Schusler et al., 2003). We suggest that, in order to coproduce vernacular knowledge, there have to be repetitive, iterative interactions between farmers and scientists over the same issues with increasing depth or “progressive engagement” (Feinstein, 2014). Though it is impractical to bring a small group of farmers and scientists together each day, a bimonthly meeting schedule over many years discussing the same topic may start to approximate interactions occurring in daily life. For example, we generated vernacular knowledge about the water budget over the course of several meetings with the groundwater task force by using a bank account analogy to describe inputs and outputs to the aquifer. Though this analogy was not perfect, it greatly facilitated discussion about our finding that net groundwater recharge could be negative or positive in a given year (Nocco et al., 2017). The semiformal nature of the meetings and existence of slides were important for returning to the same topics. However, the open discussion format during presentations facilitated longer conversations between multiple scientists and farmers about the same ideas over and over again.

In addition to the coproduction of vernacular knowledge, we were able to identify boundary objects between conservation scientists and agribusiness networks. Boundary objects are shared ideas or frameworks that bridge social worlds (Star, 1989). They have interpretive flexibility, some infrastructure, and are ill structured—meaning that each social group has its own intragroup definition and refinement of boundary objects (Star, 2010). The purpose of creating boundary objects is for disparate groups to be able to work together on the same issue without the necessity of a consensus. Through repetitive, progressive engagement at groundwater task force meetings, we identified the concepts of ‘water stewardship,’ ‘resource management,’ and ‘sustainability’ as potential boundary objects between agribusinesses and conservation scientists in the Central Sands. Both groups heavily engage with these concepts in their closed social spheres, however the concepts have different meanings to each group. The WPVGA states that farm members have been "water conservationists since our great grandparents told us to be" (WPVGA, 2017b), framing Central Sands farmers as soil and water conservationists who understand the necessity of resource protection for productive agriculture. Additionally, farmers and industry scientists on the groundwater task force repeatedly stated during meetings that Central Sands farmers grow "90-95% more potatoes on 70% of the land" as evidence for the stewardship, sustainability, and resource management of the group. However, the farmers do not consider governmental regulation or management of Central Sands water resources as necessary to apply terms such as stewardship and sustainability to their practices. Conservation scientists also used concepts such as stewardship, sustainability, and resource management, however we use these terms to support an implicit or explicit policy framework of greater government regulation of water resources in the Central Sands. Conservation scientists are less forthcoming about these viewpoints when engaging with farmers, however we observed both direct and indirect political advocacy that supports these views from all groups labeled as conservation scientists throughout the course of the study. Moreover, these viewpoints were prevalent in discussions that took place at the AWRA and informal hydrology meetings, where only scientists were present. The other key difference between farmers and conservation scientists when conceptualizing stewardship, sustainability, and resource management is the degree of tolerance for environmental harm and threshold for environmental benefits resulting from conservation interventions. During groundwater task force meetings, farmers and industry scientists often commented on how the improvements made by the industry involving increased precision, soil water monitoring, and crop rotation management were "not enough" for other stakeholders. During informal meetings among scientists, questions were often raised as to whether implementing precision agriculture or crop rotational management would "really do anything to put water back in the lakes and streams."

Because of biases towards increased governmental regulation, most conservation scientists in the Central Sands dismiss the use of concepts such as stewardship, sustainability, and resource management by the WPVGA to be examples of greenwashing rather than opportunities for boundary work. "Greenwashing" is a tactic used by industries to advertise and intentionally mislead the public about positive environmental performance, while having poor environmental performance and being aware of negative impacts (Delmas and Burbano, 2011). Though greenwashing typically occurs in environments with little government oversight such as the current water regulatory environment of the Central Sands, it is a subjective and relatively non-falsifiable diagnosis. Despite the subjectivity, it is generally acknowledged that greenwashing exists because there are no regulations or benchmark programs in place to reward corporate environmental responsibility (Parguel et al., 2011). Therefore, if conservation scientists are tempted to designate stakeholder actions or communication as greenwashing, they should rather interpret these actions as opportunities to identify boundary objects and implement environmental benchmark or ratings programs (Chelli and Gendron, 2013). These types of programs require policy-relevant science to determine what industry behaviors or actions should be rewarded, which may open significant conservation research opportunities. For example, during the course of this study, we observed WDNR scientists effectively using water stewardship as a boundary object to identify an actionable conservation opportunity and develop a water stewardship benchmarking program for farmers in the Central Sands. We further leveraged this opportunity by collaborating with WDNR scientists on a 2017 David H. Smith Conservation Fellowship project to identify specific agribusiness behaviors to reward positive water stewardship ratings. Previous environmental benchmarking programs such as the Healthy Grown Potato Label (WPVGA, 2017a) have been successful at improving and rewarding conservation-based pesticide management in the Central Sands, so we are optimistic about implementing benchmarks for water management.

2.5.2. Farmer-led semiformal spaces may be ideal trading zones

Trading zones are negotiation or exchange processes that occur between two disparate groups when both groups agree to the terms of the exchange (Galison, 1997). Trading zones have been used in a scientific context to achieve limited agreements when there is no realistic hope of a full consensus between stakeholders or groups (Kalliomäki, 2015; Feinstein, 2014). Establishing trading zones between conservation scientists and agribusiness groups may facilitate the research and development of water management solutions that are agreeable (though never ideal) for both groups. However, for trading zones to occur, disparate groups need to feel as if they are in an equitable space to bargain and negotiate (Koivunen, 2009).

The groundwater task force meetings were led by the farmers of the WPVGA. They formulated the agenda, invited guest scientist and policy speakers, and maintained the pace of the meetings. We observed that farmers appeared more socially and emotionally comfortable during scientific presentations in the farmer-led environment than the more formal presentations in scientist-led environments. For example, farmers made jokes and asked numerous questions of scientists during groundwater task force meetings. Farmers also engaged in storytelling about past experiences with water such as droughts or floods, which can be another valuable form of knowledge expression and exchange that takes place when formality is low (Krzywoszynska, 2016). Conversely, we observed that all scientists appeared less comfortable during groundwater task force meetings based on behaviors that differed from the way scientists behaved at the UW extension, AWRA, and informal hydrology meetings. For example, scientists went out of their way to state their purported objectivity in the Central Sands water conflict and either extoll or downplay their expertise in specific disciplines. We also observed differences in behaviors and power-based interactions between industry, consulting, and conservation scientists. For example, one industry scientist was protective and secretive about the policy and strategizing portion of groundwater task force meetings. When this industry scientist was present at meetings, he kindly asked us to leave when farmers started strategizing about policy, stating that the “science portion of the meeting was over.” However, in meetings that occurred in the absence of that particular industry scientist, all scientists, including conservation scientists, were including in all portions of the meetings.

We did not observe any purely equitable spaces for trading zones to exist between conservation scientists and agribusiness networks. Both the groundwater task force meetings and informal moments during the UW-Madison Grower Conference nurtured productive conflicts between conservation scientists and farmers (Manolis et al., 2009). However, the progressive engagement that occurred over the same conflicts during groundwater task force meetings allowed for a deeper exploration of different levels of conflict and their associated productivity. Additionally, the groundwater task force meetings were the only space that was tipped in favor of the farmers as opposed to the scientists in terms of power and comfort. In our opinion, the openness and comfort of farmers outweighed the relative discomfort and stress of conservation scientists during groundwater task force meetings. Thus, we recommend that conservation scientists who plan to continually engage with wary stakeholder groups develop positive coping strategies known to build professional resilience in uncomfortable or stressful spaces, such as identifying specific personal stressors, having a plan for response to stressors, mindfulness or meditation exercises, and strong supportive relationships with peers (Montero-Marin et al., 2014).

2.5.3. Agribusiness networks produced nonknowledge using dismissal and diversion tactics

In the Central Sands, agribusinesses spent a significant amount of time and resources to commodify scientific uncertainty (known unknowns) and unknown knowns as strategic nonknowledge. In community environmental conflicts, strategic nonknowledge allows organizations or actors to deny causality and responsibility, retain control of resources, and commandeer expertise (McGoey, 2012). We observed a concerted effort to create and promote nonknowledge surrounding the issue of plant water use by trees vs. irrigated crops in the Central Sands. For example, a few key farmers in leadership roles consistently asked targeted questions regarding uncertainty during all scientific presentations related to plant water use that we witnessed at both groundwater task force meetings and the Grower Education Conference. Additionally, the groundwater task force produced and aired a public relations commercial to emphasize that trees use more water than irrigated crops (WPVGA, 2017b). Finally, the groundwater task force produced an advocacy product for policy makers called the "High Capacity Well Fact Book" that contained a mixture of scientific knowledge, nonknowledge, narratives, economic impacts and demonstrative figures that collectively undermine the causal link between irrigated agriculture and freshwater degradation (WPVGA, 2017b). In the High Capacity Well Fact Book, the complexity, uncertainty, and theoretical nature of science are juxtaposed with common sense experiences that nonscientists can understand (Gieryn, 1983), which weaken scientific findings to lay audiences. For example, we observed farmers presenting bar graphs comparing the amount of rainfall across a whole county to the groundwater withdrawals made on the land fraction that is irrigated to make a lay argument that rainfall is 10-20 times the amount of withdrawn groundwater in the Central Sands. These graphs were accompanied by persuasive, common sense rhetoric such as “Now, I’m no scientist, but it looks like there is much more water going in than out.” The book contains scientific knowledge in that there are portions of specific Central Sands studies cited that support assertions that are important for policy goals—that high capacity wells may not be the sole or driving factor behind stream and lake declines and that forests use more water than irrigated cropland.

The WPVGA demonstrates the dismissal component of nonknowledge (Rayner, 2012) by the exclusion of pertinent details or graphics related to several scientific studies that demonstrate or provide evidence that high-capacity wells and irrigated agriculture may be the sole cause of freshwater degradation (Bradbury et al., 2017; Kraft et al., 2012; Kraft and Mechenich, 2010; Weeks and Stangland, 1970; Weeks et al., 1965). Dismissal differs from denial in that farmers are aware of the existence and have expressed a clear understanding of the studies that are counter to their political goals. The High Capacity Well Fact book contains the diversion component of nonknowledge (Rayner, 2012) by the inclusion of a draft review from a UW-SP chemist about the water use of forests from other parts of the world and information from the WI-DNR about methods used to calculate recharge that show that forests had lower average recharge rates than irrigated croplands in normal precipitation years, though these differences were not tested for statistical significance and a comparison of land cover types was not the purpose of the WI-DNR study. These types of nonknowledge products have been extremely effective barriers to government-regulated conservation efforts in the Central Sands and have exasperated scientists (Bergquist, 2017).

2.5.4. Scientists produced nonknowledge using dismissal and displacement tactics

We propose that scientists improve plans to quantify and communicate scientific uncertainty, while recognizing their own production of nonknowledge. We observed that conservation scientists spent considerable time in closed, scientific spaces such as AWRA or informal hydrology meetings discussing solutions to the "tree problem" mentioned above. Specifically, conservation scientists used dismissal tactics as a response to the forest water use issue by dismissing the credibility of the UW-SP scientist that participated in the High Capacity Well Fact Book or searching for methodological faults underlying the WI-DNR study such as poor satellite imagery or inappropriate spatiotemporal scales. Based on our own knowledge base and expertise, we hypothesize that the differences in water use between forests and irrigated crops in the Central Sand will be very close during most years and will be challenging to differentiate with a reasonable degree of scientific certainty using existing biophysical methods. We speculate that future studies will go back and forth about whether forests or irrigated croplands use more water and when that water use occurs. This is problematic because the majority of solutions from the conservation science community have involved increasing the amount of science about water use from different land covers in the Central Sands such as different types of trees, irrigated crops, and other rainfed systems with the intent reducing scientific uncertainty. However, it has been established that increasing the political stakes as well as the number of scientific and institutional players will also increase the scientific uncertainty associated with environmental problems

(Sarewitz, 2004). Therefore, conservation scientists engaging with agricultural stakeholder groups should focus on creating research products that quantify the socioecological dynamics of uncertainty to support decision making such as Bayesian methods or decision theory (Rissman and Carpenter, 2015; Cook et al., 2013).

The second way that conservation scientists produce nonknowledge is through displacement, which is a subtle form of diversion that involves substituting a manageable nonknowledge surrogate for knowledge, such as a scientific model (Rayner, 2012). Displacement occurs when scientists use decision-support tools such as models as decision-making or pure knowledge products (Rayner, 2012). Or put in another way, our large environmental models contain both knowledge (representations of real, scientific processes and known unknowns) and nonknowledge (heroic or ridiculous assumptions that suit the task at hand that represent unknown knowns). However, we conservation scientists tend to use the known knowns and known unknowns to displace the unknown knowns. In the Central Sands, conservation scientists are careful to present models and modeling results as decision support tools capable of depicting many stakeholder-driven outcomes; or as one WPVGA farmer said about Central Sands modeling teams, “They say all the right things.” The same elderly farmer went on to warn the other farmers that the hydrological models created by conservation scientists were going to be used to “tell us how many gallons we can pump." The disconnect between what scientists say about their models and what stakeholders perceive is the result of model displacement.

When Central Sands scientists create models, they make assumptions and subjective decisions based on an understanding of the system that contains their disciplinary expertise, empirical observations, and environmental values. For example, the prevalent groundwater model of the Centrals Sands between 2012-2017 conceptualized irrigated land use as a reduction in recharge over irrigated lands that would necessitate irrigated croplands using more water than rainfed land covers such as forests (Kraft et al., 2012). During this time period, conservation scientists (we include ourselves here) communicated to other stakeholders about irrigation impacts as a reduction in recharge over irrigated lands as scientific knowledge. However, a new, more complex groundwater model conceptualized irrigated land use as both a reduction in recharge and a loss of groundwater because of pumping (Bradbury et al., 2017). After the new model was released, conservation scientists began communicating that irrigated land use was associated with both recharge and pumping impacts. One agribusiness industry scientist commented about conservation scientists, “They are all changing their story now that the new model is out.” Though modeling goals, assumptions, uncertainty, and limitations are often clearly spelled out in studies (Bradbury et al., 2017; Kraft et al., 2012, Motew and Kucharik, 2013), the way that scientists have communicated modeling results to both farmers and policy makers implied that modeled outcomes are only knowledge, rather than a combination of knowledge and nonknowledge.

Despite the issue of displacement, models are critical scientific tools for understanding regional environmental problems, especially in the realm of water conservation. Two potential solutions have been proposed to reduce displacement in scientific communication to the public. The first solution—the modeler’s solution—is to incorporate models of stakeholder behavior into ecosystem models to create hybrid socioenvironmental models that optimize different stakeholder outcomes when communicating results (Bakarji et al., 2017). This is an appropriate solution for differentiating between knowledge and nonknowledge using models in environmental conflicts that have optimal solutions where all stakeholders could potentially come away satisfied. However, most water conservation conflicts fall into the category of "wicked problems," (Rittel et al., 1973) to which there are, by definition, no optimal solutions, rather only "clumsy solutions," that are devised in trading zones with inputs from all stakeholders, though disparate stakeholders will not agree to clumsy solutions for the same reasons (Khan and Neis, 2010). For scientists attempting to avoid displacement of model outcomes as knowledge, we recommend using a quantitative storytelling approach (Saltelli and Giampietro, 2017). Quantitative storytelling involves exchanging information about the external and internal constraints of a problem as well as the desirability of different outcomes prior to doing any quantitative modeling of a "wicked problem," and presenting modeled output as *conditional* outcomes (Saltelli and Giampietro, 2017). Additionally, scientists working with models should including both alternative and typically excluded narratives and perspectives as well as sensitivity analyses that critique the most heroic of model assumptions. Or as one Central Sands grower suggested, "It seems like when you guys turn the knobs one way, you get a particular set of results. We want to see what happens when you turn the knobs the other way."

2.6. Conclusions

Because of the inherent social and community values associated with our work, conservation scientists often have to exhibit leadership skills and advocate responsibly in community environmental conflicts (Garrard et al., 2016). In order to become effective leaders, responsible advocates, and careful communicators in conservation efforts, scientists must nurture productive conflicts and forge relationships with stakeholder groups that may be wary of conservation efforts. Building vernacular knowledge, identifying boundary objects, finding trading zones, and identifying policy relevant research opportunities are all potential benefits to engaging with stakeholder groups. Conversely, inadvertently informing the social production of nonknowledge, increasing hostility between groups, misidentifying policy relevant research opportunities, and exceeding productive levels of conflict are all potential pitfalls to engaging with stakeholder groups. We used the community water conflict in the Central Sands region of Wisconsin to identify physical spaces, power dynamics, knowledge exchanges, and leadership skills that facilitated the best environment for interacting with an oppositional agribusiness stakeholder groups. Future research could use more quantitative methods to further explore how leadership and communication training and development could improve knowledge exchanges and codevelopment between scientists and oppositional stakeholder groups.

2.7. Acknowledgments

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2.9. Figures

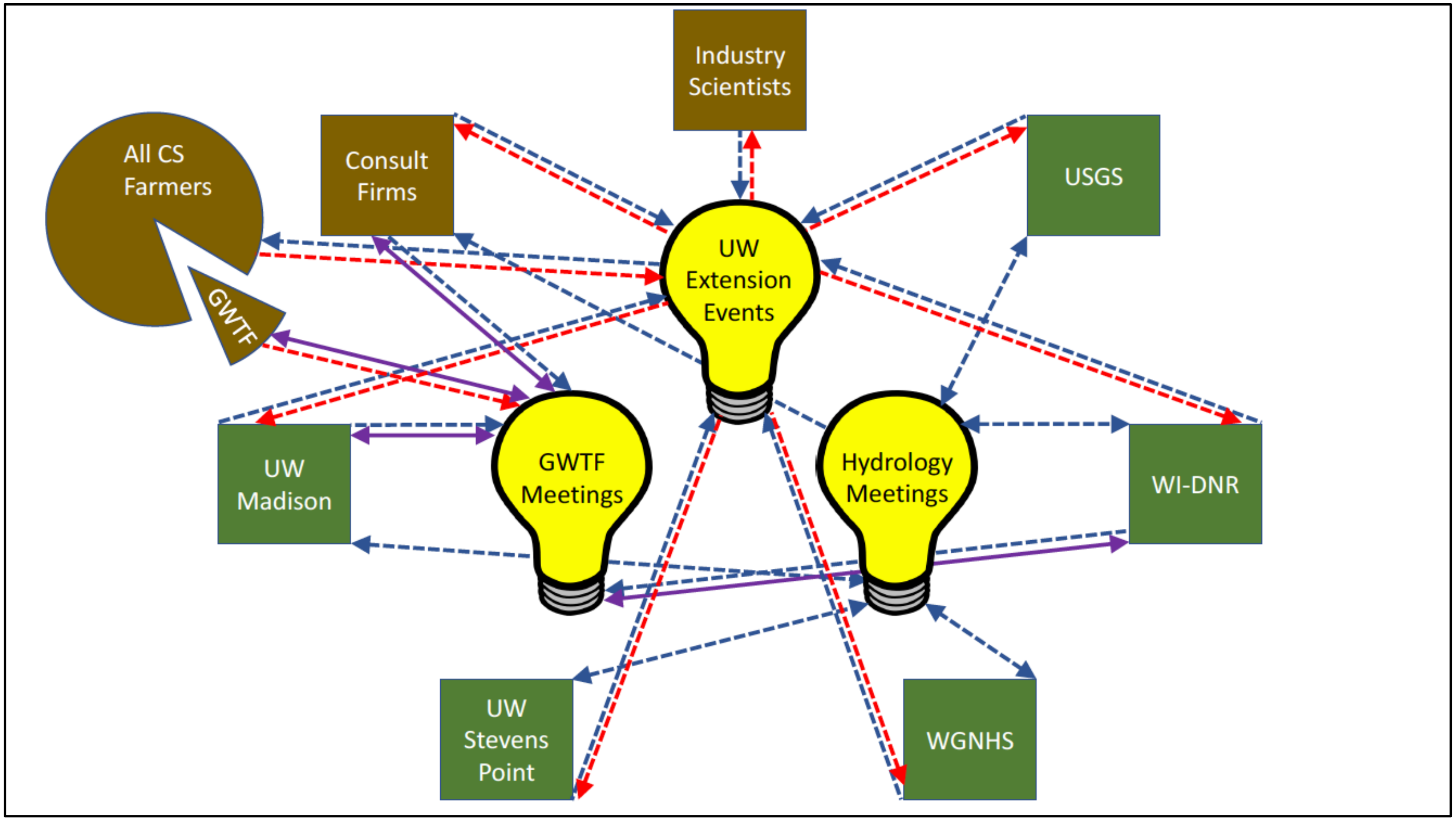

Figure 1. Communication framework the represents the types of knowledge exchanged between different stakeholder group and the spaces where knowledge was exchanged. Groups of scientists are represented by boxes where green boxes represent designated conservation scientists with a common set of values and brown boxes represent scientists that may not espouse common conservation values. The different scientist groups represented are hydrological consulting firms (Consult Firms),

Industry Scientists, United States Geological Survey hydrologists (USGS), Wisconsin Department of Natural Resources water scientists (WI-DNR), Wisconsin Geological and Natural History Survey hydrogeologists (WGNHS), University of Wisconsin-Stevens Point hydrologists and soil scientists (UW Stevens Point), University of Wisconsin-Madison environmental biophysicists, soil scientists, and hydrologists (UW-Madison). Light bulbs represent different spaces where knowledge exchange occurred such as groundwater task force meetings (GWTF Meetings), University of Wisconsin Extension Grower Education Conference and Potato Field Research Day (UW Extension Events), and scientific meetings such as the American Water Resources Association Wisconsin Section meeting and informal meetings amongst conservation scientists (Hydrology Meetings). The groundwater task force is depicted as a small portion of the entire population of Wisconsin Central Sands farmers. Blue arrows indicate scientific knowledge, red arrows indicate lay or local knowledge, and purple arrows indicate vernacular knowledge. Two-way arrows indicate a bilinear or multilinear exchange or production of knowledge, while one-way arrows indicate linear knowledge exchange or production.

Chapter 3

Drivers of potential recharge from irrigated agroecosystems in the Wisconsin Central Sands

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Abstract

The expansion of irrigated agriculture on landscapes underlain by coarse-grained, glacial aquifers in Wisconsin, Minnesota, and Michigan changes the timing and magnitude of groundwater recharge. Water managers require improved estimates of groundwater recharge to manage pumping impacts on groundwater-fed streams, lakes, and wetlands. We implemented a network of twenty-five passive capillary lysimeters to infer potential groundwater recharge and evapotranspiration (ET) from irrigated potato, sweet corn, field corn, and peas-pearl millet rotations in the Wisconsin Central Sands (WCS) from June through November in 2013-2016. We found that interannual climate variability, subtle differences in soil texture, and cropping system type drove potential recharge to varying degrees during the summer and fall seasons. Relatively finer soil texture was positively correlated to point-estimates of potential recharge. This correlation was the strongest following large precipitation events. June-November cumulative potential recharge for 2013-2016 averaged 71±235 mm across all lysimeters. Our findings suggest that aquifer depletion will be an episodic process that leaves surface waters most vulnerable to pumping and recharge impacts during and following drier

years in the WCS. Differences among cropping systems were most pronounced under average precipitation conditions, which facilitated potential groundwater losses under field corn and peas-pearl millet rotations and potential groundwater gains under potato rotations. We conclude that regional water management strategies could be effective in buffering against the interannual climate variability of recharge, while localized management strategies could increase irrigation efficiency by targeting crop and soil textural drivers.

Abbreviations: Wisconsin Central Sands (WCS); evapotranspiration (ET); soil volumetric water content (θ); change in soil moisture storage (ΔS); actual evapotranspiration (AET); reference evapotranspiration (RET); potential evapotranspiration (PET).

3.1. Introduction

Over the past sixty years, irrigated agriculture has significantly expanded in landscapes overlying the productive, coarse-grained glacial aquifers in the northern Great Lake states of Wisconsin, Minnesota, and Michigan. The same aquifers used for irrigation also supply water to streams, lakes, and wetlands, and their associated ecosystems, which are extremely sensitive to the first few meters of groundwater depletion (Watson et al., 2014). Though the humid northern Great Lake states are not usually considered water-limited for agriculture, these regions with coarse soils have limited water-holding capacity; hence productivity and profitability benefit from irrigation. Growers use supplemental groundwater irrigation to maintain agricultural soils at 75-90% of field capacity in order to grow vegetable crops with high demands for water and aeration (Curwen and Massie, 1994) as well as field corn, soybean, and forage. Pumping and distributing groundwater from high-capacity wells via center pivot irrigation systems alters the timing and magnitude of evapotranspiration (ET) and recharge in these landscapes, thereby altering groundwater supply to streams, lakes, and wetlands. In this context, we define groundwater 'recharge' as the net downward flux of water to the aquifer, which is the total downward flux minus the upward flux of groundwater extracted for irrigation; the latter expressed as volume per irrigated area. This definition of recharge as a net downward flux has been demonstrated to be a better indicator of aquifer depletion than the total downward flux as it accounts for irrigation extraction (Scanlon et al., 2012; Yang et al., 2015).

The Wisconsin Central Sands (WCS) exemplifies irrigated agriculture in the northern Great Lakes region; the WCS is a region that uses over 2100 high-capacity wells to irrigate approximately 86,500 ha of potato, maize (field and sweet), peas, and snap beans, which comprise a $550 million production industry (Smail, 2016; Keene and Mitchell, 2010). The WCS is physically delineated as the 630,000-ha region bounded by the Wisconsin River on the west and the headwater streams of the Fox and Wolf river basins on the east (Figure 1A, red box). Hydrogeologically, the WCS region is characterized by a coarse-grained, glacial drift aquifer typically >30 m thick and a water table 3 to 20 m below the surface. Though irrigation is mainly supplemental in the Great Lakes states, it has been considered economically advantageous in the WCS since it tripled yields and alleviated drought risk from the fast-draining, sandy soils in the 1950s (French and Lynch, 1957). WCS growers pump groundwater via high-capacity wells from the unconfined aquifer that also supports 1000 km of headwater trout streams, 80 lakes, and extensive wetlands (Kraft et al., 2012; Smail, 2016). Pumping effects on water levels and streamflows were already observable when there were ~700 high-capacity wells in the WCS in the late 1960s (Weeks and Stangland, 1971). However, irrigated land use conversion continued and by the mid 2000s, there were over 3000 high-capacity wells in the WCS and severe pumping impacts to streams, lakes, and wetlands were observed during a period of only modestly dry weather (Smail, 2016; Kraft et al., 2012). Among the impacts were the seasonal drying of stretches of the Little Plover River in 2005-2009, a class I trout stream that holds recreational and spiritual value for aquatic stakeholders in the WCS (Kraft and Mechenich, 2010; Kraft et al., 2012), which also was the subject of groundwater-surface water interaction studies conducted by the United States Geological Survey (USGS) in the early 1960s (Weeks et al., 1965). The groundwater declines, surface water stresses, and ongoing irrigation expansion in this region fuel a community conflict over water resources in a changing climate.

The average annual precipitation of the WCS ranges from 790-810 mm, which is typically partitioned into 60-70% ET and 30-40% recharge (Kucharik et al., 2010; Motew and Kucharik, 2013). Historical studies documenting regional climate change from 1948-2007 have shown increases in annual precipitation of 100-200 mm and June-August precipitation of 50-100 mm (Kucharik et al. 2010). Models simulating rainfed native potential vegetation over the Wisconsin Central Sands suggest that there should have been a net increase in groundwater recharge of 70-140 mm in the absence of irrigated land use (Motew and Kucharik, 2013; Kucharik et al., 2010). These findings suggest that climate change cannot account for observed groundwater declines and surface water stresses in the WCS, as groundwater recharge should have increased in the absence of conversion to irrigated land covers. A reduction in annual recharge (equivalent to net consumed irrigation) of 45 mm on irrigated lands is sufficient to explain the observed hydrological stresses and groundwater level declines of the 2000s over the WCS region (Kraft et al., 2012), and we hypothesize that a commensurate annual increase in ET from irrigated cropping systems may be responsible for the recharge reduction.

Because overland flow is negligible on the flat, sandy landscape of the WCS, recharge has been measured and modeled as the difference between precipitation and ET, where the change in soil moisture storage (ΔS) is incorporated at weekly or shorter timescales and assumed negligible at monthly or longer timescales because of limited water holding capacity (Weeks, 1965; Tanner and Gardner, 1974; Weeks and Stangland, 1971; Kraft et al., 2012; Bradbury et al., 2017). Surface runoff is also considered negligible at the field scale because of the high infiltration rates of the sandy soils (Tanner and Gardner, 1974; Weeks and Stangland, 1971; Kraft et al., 2012). ET has been modeled for different WCS vegetable crops and other land covers using crop coefficient approaches (Weeks and Stangland, 1971; Bradbury et al., 2017) and weighing lysimeters (Black, 1970; Tanner and Gardner, 1974). Because it has been assumed that precipitation does not change with crop type, differences in recharge among land covers have been measured and modeled as differences in ET (Weeks and Stangland, 1971; Tanner and Gardner, 1974; Kraft et al., 2012; Bradbury et al., 2017). Thus, current estimates of the WCS water budget at both field and regional scales assume that vegetation type and plant phenological stage are the greatest drivers of recharge and ET from irrigated agroecosystems.

In the WCS, the majority of ET occurs between May-October and ET between November-April has been estimated at less than 50 mm using large-scale weighing lysimetry techniques (Tanner and Bouma, 1975). Previous studies using hydrological models have estimated average annual ET rates of 410, 480, 490, 630 mm for prairie, deciduous forests, coniferous forests, and phreatophytes, respectively (Weeks and Stangland, 1971; Naber, 2011). Annual ET rates from irrigated cropping systems have been estimated at 530-550 mm using hydrological models and field data from large-scale weighing lysimeters in potato and snap bean agroecosystems (Black et al., 1970; Weeks and Stangland, 1971; Tanner and Gardner, 1974; Naber, 2011). However, there are no existing field estimates of ET and recharge from irrigated field corn, sweet corn, and peas in the WCS. Moreover, we have little understanding of how current cover crop and residue management impact ET and recharge from irrigated cropping systems during the fall season, which is typically modeled as bare soil (Naber, 2011; Bradbury et al., 2017). Replicated field-based estimates of ET and recharge are essential for numerical modeling and validation in the WCS, which is a critical step for adaptive management of water resources.

Groundwater regulators and stakeholders require validated numerical models to implement potential water management strategies and evaluate pumping impacts on individual streams, lakes, and wetlands. Several promising regional and local strategies could be implemented in the WCS to manage surface waters, but there is no current regional water management plan in place. Groundwater banking and managed aquifer recharge are regional strategies that buffer the impacts of interannual climate variability on aquifer supply and demand by storing groundwater surpluses during wet years

(Arshad et al., 2014; Maliva, 2014; Scanlon et al., 2016). Interfield crop rotation is a farm-scale strategy that involves the placement of low-water demand crops in sensitive areas (i.e. adjacent to streams) or phenologically staggering crops to defer peak water demand from occurring at the same time in the same vicinity (Schneekloth et al., 2009; Schneekloth et al., 1991). Precision irrigation is a local, subfield-scale strategy that focuses on reducing irrigation by mapping soil variability and installing adjustable-rate irrigation systems to target the spatially heterogeneous water demands of a single field (Sadler et al., 2005; Hedley and Yule, 2009). ET and recharge estimates are important for evaluating these water management strategies and also serve as key inputs to numerical models used to determine the short-term and cumulative impacts of irrigated agriculture on the local surface waters and the regional groundwater system.

In this study, we quantified potential recharge and ET, and evaluated key biophysical drivers from irrigated cropping systems (field corn, sweet corn, potato, peas). We made replicated, point-based estimates of potential recharge and ET using an extensive network of 96 soil moisture probes and 25 passive capillary lysimeters located below the root zone in the WCS. We define our recharge estimates as *potential* rather than *actual* recharge because drainage collection occurred 1-3 m above the water table. We also distinguish between point-based estimates of *actual* ET (AET) estimated from soil moisture and lysimetry data and meteorological indices of evaporative demand such as *reference* or *potential* ET (RET, PET) in this study. Our study objectives were to (1) quantify potential recharge and AET from irrigated cropping systems in the WCS (2) compare water use between different irrigated cropping systems, and (3) identify and evaluate the biophysical drivers of recharge in the WCS.

3.2. Materials and Methods

3.2.1. Site description

We estimated WCS potential recharge and AET in a field experiment on Isherwood Farms (Figure 1B, blue box); a 600-ha, sixth-generation family farm with 40 ha of woodland and 7 km of stream edge SE of the village of Plover, WI. Between 2013-2016, we instrumented six fields (H, G, P, L, E, W) to infer water budgets from field corn, sweet corn, potato, and pea crop rotations (Figure 2, Table 1). Typically, a post-harvest oat cover crop follows sweet corn and potato rotations, which are harvested in the beginning of September. Field corn typically senesces by the end of September and is harvested in early November after a 1-month dry-down period to reduce kernel moisture content. Crop residue is used as a post-harvest cover after field corn rotations. Forage pearl millet is a relatively novel cover crop that follows short-season peas or beans in the WCS to significantly reduce root lesion nematode populations and metam sodium application costs in potato rotations the following year (MacGuidwin et al., 2012). Four of the six fields (H, G, P, L) are the well-drained Richford series (loamy, mixed, superactive, mesic Arenic Hapludalfs), which are typically classified as loamy sand, sandy loam or sand textures (USDA-NRCS, 2008; Otter and Fiala, 1976). The other two fields (E and W) are closer to a glacial moraine with increased gravel content and are the well-drained Rosholt series (Coarse-loamy, mixed, superactive, frigid, Haplic Glossudalfs), which are also typically classified as loamy sand, sandy loam, or sand textures (USDA-NRCS, 2008; Otter and Fiala, 1976). Crop systems for the 2013-2016 experimental seasons (June-November) are specified in Table 1.

3.2.2. Drainage and soil moisture measurements

We estimated drainage below the root zone using 25 passive capillary lysimeters (Drain Gauge G3, Decagon Devices Inc., Pullman, WA) on six fields at Isherwood Farms between 2013-2015 (Figure 2, Figure 3). Ten lysimeters were installed in April 2013, an additional thirteen lysimeters were installed in October 2013, and the remaining two lysimeters were installed in April 2015. One lysimeter (W3) was destroyed during the winter of 2015-2016 and an additional lysimeter (E3) was excluded from the cropped portion of the field in 2016. Therefore, lysimeters numbered 10, 23, 25, and 23 for the 2013, 2014, 2015, and 2016 field seasons. Lysimeter installations (Figure 3) were targeted to place drainage collection at 1.4 m, which is below the homogenized root zone associated with matrix flow and above the heterogeneous interbedded structures associated with funnel flow in the WCS (Kung, 1990a; Kung, 1990b). Additional information regarding the theory, installation, and calibration of passive capillary lysimeters is available in the supplemental materials.

In order to accommodate agronomic cultivation and management, this study encompasses two experimental time periods with different drainage collection protocols each year from 2013-2016. The first three-month experimental period (hereafter referred to as ‘summer’) began after tillage and planting and ended prior to harvest (June-August). The second three-month experimental period (hereafter referred to as ‘fall’) extended from harvest through the late fall prior to soil freezing (September-November). During the summer, reservoir water levels were measured at five-minute and weekly time steps from each lysimeter. The cross-sectional surface areas of the collection reservoir and soil monolith (Figure 3) were used to calculate drainage. Five-minute drainage estimates were made using a differential pressure transducer (CTD-DG sensor, Decagon Devices Inc., Pullman, WA) located at the bottom of the collection reservoir that was connected to a data logger (EM50, Decagon Devices Inc., Pullman, WA). Additionally, drainage was manually sampled and measured on a weekly basis. Although winter and spring recharge events impact the WCS water budget, we did not include data from December-May as we were limited by our experimental configuration. We found that components of passive capillary lysimeters often froze during Wisconsin winters, which limited the consistency and reliability of drainage collection. Additionally, we found that drainage events during the spring thaw often exceeded the collection capacity (8 L) of the passive capillary wick lysimeters. These limitations would introduce unquantifiable errors to water budget estimates during the winter and spring seasons.

Between 2013-2016, we deployed a network of 96 frequency domain reflectometry probes (FDR) (5TM, Decagon Devices, Inc.) to measure soil volumetric water content (θ) and calculate weekly ΔS at each lysimetry site during the summer experiment. Forty FDR probes were deployed in 2013-2014 and an additional 56 were deployed in 2015-2016. Four FDR probes were installed, at 0.1, 0.2, 0.4, and 0.8 m depths, adjacent to each lysimeter in 2013 and 2015-2016 (Figure 3). In 2014, sets of FDR probes were installed near 1-2 lysimeters per field. Data were recorded from FDR probes using the same dataloggers used for lysimeters (EM50, Decagon Devices, Inc.). FDR probes and dataloggers were removed during the fall experiment to allow harvest and post-harvest activities to freely occur over experimental sites.

3.2.3. Meteorology, irrigation, and reference ET

We installed three weather stations ('MET', Figure 2) adjacent to fields in 2013 according to the World Meteorological Organization guide for agrometeorological observations from fixed stations (Murthy et al., 2010). A group of complementary instruments measuring precipitation, temperature, relative humidity, wind speed, and solar radiation were mounted on 2-m tripods over grass surfaces (M-TPB-KIT; Onset Computer Corp., Bourne, MA). Rain gauges employing a tipping bucket mechanism to measure rainfall at 0.25 mm resolution (S-RGA-M0002; Onset Computer Corp., Bourne, MA) were mounted at the top of the tripod bases. 12-bit temperature/relative humidity smart sensors (S-THB-M002; Onset Computer Corp., Bourne, MA) were enclosed in solar radiation shields (RS3; Onset Computer Corp., Bourne, MA) and attached to the base of the tripods on the opposite side of the rain gauges. The solar radiation sensors (silicon pyranometer, S-LIB-M003; Onset Computer Corp., Bourne, MA) measure spectral response over 300-1100 nm wavelength band and were mounted at 2 m using a south-facing light sensor bracket. Wind speed smart sensors (S-WSB-M003; Onset Computer Corp., Bourne, MA) were mounted at 2 m using a north-facing sensor bracket. Measurements were collected every 10 min and recorded using a HOBO (Onset Computer Corp., Bourne, MA) micro station data logger. Irrigation records were provided by Isherwood farms and validated for timing and magnitude using soil moisture measurements and three additional rain gauges (S-RGA-M0002; Onset Computer Corp., Bourne, MA) that received both irrigation and precipitation inputs.

Daily minimum, maximum, and average meteorological measurements were used to estimate reference ET (RET) using the ASCE standardized equations for both a uniform short grass and a relatively taller alfalfa crop (Allen et al., 1998; Walter et al., 2000) as a comparison to lysimetry-derived AET values. RET is a useful index of evaporative demand as it estimates ET from a hypothetical well-watered, uniform grass at a 0.12 m height with a constant albedo of 0.23 and surface resistance of 0.70 s m^{-1} or from a well-watered, uniform alfalfa cropping system at a 0.5 m height with a surface resistance of 45 s m^{-1} (Walter et al., 2000). Two meteorological stations malfunctioned during the 2015 field season, so all 2015 precipitation and RET values are derived from the station between fields "L" and "P". Otherwise, the station closest to each field was used to estimate the precipitation and RET. The ASCE RET equations have been primarily validated for reference surfaces in the Western and Southwestern United States under arid conditions (Evett et al., 2000; Jensen et al., 1990) and, to the best of our knowledge, have not been validated in Wisconsin, Minnesota, or Michigan. For this reason, we also estimated evaporative demand using a satellite-based model of the Priestley-Taylor potential evapotranspiration (PET) equation developed for Wisconsin and Minnesota that has been validated using irrigated crop data from the WCS (Priestley and Taylor, 1972; Jury and Tanner, 1974; Diak et al., 1998). Satellite-based Priestley-Taylor PET estimates were available for all summer experimental periods, however were only available for the entire fall experimental period in 2013 and 2016.

3.2.4. Potential Recharge, ΔS, and AET

We calculated potential net recharge (hereafter referred to as potential recharge) as the difference in drainage and irrigation over the weekly or seasonal (summer, fall) time period. We did not experimentally confirm that drainage observed from lysimeters always reached the water table. The depth to water table at Isherwood Farms ranges from 2.5-5 meters. We observed that drainage at 0.8 m did not always result in drainage at 1.4 m following precipitation events (Supplementary Materials), thus we infer that drainage at 1.4 m may not always result in downward flux occurring at the water table. Moreover, our observations reveal a lag of approximately 12-18 hours between drainage occurring at 0.8 m and drainage collected at 1.4 m following precipitation events (Supplementary Materials). At this rate, assuming no funnel flow, there could be an approximate lag of 20-108 hours between drainage occurring at 1.4 m and downward flux occurring at the water table. Therefore, we designate our measurements as potential rather than actual recharge and acknowledge this as a limitation of our study. Summer potential recharge was determined both as the difference between drainage and irrigation each week and for the entire summer period. During the fall experiment, harvest and post-harvest activities (tillage, fumigation, soil amendment application) proceeded at different rates across cropping systems, which made lysimeters inaccessible for pumping during different time periods. Irrigation only occurred during the fall experimental period in 2013. Lysimeters were pumped whenever possible and fall potential recharge results are presented on a cumulative basis.

For the summer experiment, we estimated weekly ΔS by linearly extrapolating θ values from 0.1 m to the surface, linearly interpolating θ values between 0.1-0.8 m, and using a nearest-neighbor approach to extrapolate θ values between 0.8 m and the drainage collection depth for each lysimeter. Weekly summer AET was determined for each lysimeter as the remainder of the other components of the water budget using the equation,

$$P + G - D - \Delta S = ET \quad (1)$$

where P, G, and D are precipitation, irrigation, and drainage, respectively. Because we installed the lysimeters as open systems above 0.8 m, flux convergence was possible and may constitute a source of error. The drainage to input (D:I) or storage to input (ΔS:I) ratio is a useful metric for quantifying the extent of flux convergence in passive capillary lysimeter systems, where input (I) is the sum of precipitation and irrigation (Gee et al., 2009). A D:I or ΔS:I greater than 1 is a clear indicator that flux convergence occurred during the water budget time period, as AET cannot be less than zero (Gee et al., 2009). Thus, we excluded data points from lysimeters with D:I or ΔS:I values greater than 1.0 in the calculation of crop AET. We only excluded lysimeters in weekly calculations for the weeks that they had D:I or ΔS:I values greater than 1.0. We excluded 5%, 19%, 13%, and 8% of individual weekly estimates in 2013, 2014, 2015, and 2016, respectively. We calculated weekly single crop coefficients (Allen et al., 1998) by dividing actual weekly AET estimates by weekly RET and PET estimates. Weekly AET and ΔS were not calculated during the fall experiment; instead, cumulative fall AET was determined assuming ΔS was negligible for the three-month time period. We justify our assumption of negligible storage during the fall experimental period based on observations of storage, precipitation, and RET between September 2013-May 2014 (Supplementary Materials). We observed that changes in storage are negligible until the beginning of December, when the soil freezes in the WCS and it is challenging to distinguish between soil moisture transition to ice and soil moisture losses to AET using our experimental configuration. Based on D:I values higher than 1, we excluded 0%,4%, 8%, and 0% of fall AET estimates in 2013, 2014, 2015, and 2016, respectively.

3.2.5. Crop phenology

We collected weekly measurements of leaf area index (LAI, m^2 of single sided leaf area per m^2 of ground area) during the summer experimental period using a LI-COR LAI-2200 plant canopy analyzer (LI-COR Inc., Lincoln, NE). Because passive capillary lysimeters have a relatively small collection area (507 cm^2), we did not limit LAI estimates to the area above each lysimeter. Thus, the footprint of the LAI estimates is the canopy, while the footprint of each water budget estimate is 507 cm^2. Measurements were taken under diffuse light conditions (e.g. sunrise or sunset) or clear skies. For measurements collected under clear skies, scattering effects were removed using a bidirectional model (Kobayashi et al., 2013) embedded in the post-processing software (FV2200 2.0, LI-COR Inc., Lincoln, NE).

3.2.6. Soil properties

In May 2015, we collected a total of 144 soil samples (6 per lysimeter) within a 5-m radius of lysimeters using a soil core sampler (AMS Inc., American Falls, ID). We observed that the Ap horizon generally extended to 0.3-0.4 m below the surface at all sites. Our goal was to quantify topsoil and subsoil properties at each lysimeter and we collected three soil samples at a 0-0.30 m depth (hereafter referred to as 'topsoil') and three soil samples at a 0.45-0.60 m depth (hereafter referred to as 'subsoil'). Samples were dried at 105°C and sieved through 2 mm diameter mesh to quantify gravel content by weight. Soil organic matter content by weight was determined using the loss on ignition method (Heiri et al., 2001). Soil samples were analyzed for particle size distribution by laser light diffraction (Coulter LS230, Beckman Coulter, Inc., Brea, California) using the optical model and parameterization of Arriaga et al., (2006). We used the complete particle size distribution to quantify percent sand/silt/clay and classify mean topsoil and subsoil texture per lysimeter according to the USDA textural soil classification system.

3.2.7. Data analyses

In order to understand the effects of crop phenology, soil properties, and interannual climate variability on the water budget, we developed statistical models for the weekly (summer only) and cumulative experimental periods. We considered each lysimeter and soil moisture site to be a single experimental unit with crop type and year as categorical independent variables, topsoil and subsoil properties as continuous independent variables (sand/silt/clay, organic matter content, elevation), and potential recharge and AET as continuous dependent variables. Because there were not enough replicates to develop covariate models of crop type, year, and soil properties, we statistically isolated crop vs. year vs. soil effects and interpret our model results in a covariate framework. We examined the effect of crop type and year on potential recharge using repeated measures ANOVA models for unbalanced data and Tukey honest significant difference (HSD) post hoc tests (alpha level 0.05). Linear regressions were used to investigate the effect of elevation, soil texture, and organic matter content on potential recharge.

Because precipitation events in the WCS are likely to increase in magnitude and intensity in a future changing climate (Vavrus and Behnke, 2014), we sought to better understand the relationship between precipitation and drainage on an event basis. We examined the relationships between crop type, θ, soil texture, and drainage during five summer rain events (out of 16 total), in 2015, that supplied 60% of the total rainfall and occurred on 15 June, 6 July, 13 July, 7 August, and 18 August. For this analysis, we defined antecedent water content (θ_i) as the θ value logged an hour prior to the rain events. We operationally defined field capacity (θ_{fc}) for each event as the θ value at the approximate inflection point that exists between the steep negative slope associated with gravitational drainage and the shallow negative slope associated with root water uptake and AET from each soil layer. The effects of crop type on θ_i and drainage were tested for the five events using repeated measures ANOVA models for unbalanced data and Tukey honest significant difference (HSD) post hoc tests (alpha level 0.05). Linear regression models were used to understand the relationships between R, θ_i, θ_{fc}, and soil texture. All statistical analyses were performed using the MATLAB Statistical Toolbox (MATLAB, 2015). A USDA soil texture classification map was created using the R soil texture wizard package (Moeys, 2015).

3.3. Results

3.3.1. Summer Crop Water Budgets

All cropping systems had typical yields in 2013-2016 and no significant limitations to growth were present from diseases, pests, or nutrient deficiencies. Summer precipitation (June-August) was 194±2, 397±11, 297±4, and 278±11 mm for 2013, 2014, 2015, and 2016, respectively. These values represent a wide range of conditions in Central Wisconsin, where the 100-year average for summer precipitation is 292 mm

(Wisconsin State Climatology Office, 2016). Average summer temperatures were 19.9, 19.9, 19.5, and 20.8°C for 2013, 2014, 2015, and 2016. All summer temperatures represent relatively normal conditions, as the 100-year average summer temperature is 19.7°C in Central Wisconsin (Wisconsin State Climatology Office, 2016).

Summer grass RET estimates were 331±10, 322±15, 297±1, and 336±4 mm for the 2013, 2014, 2015, and 2016 experiments. Summer alfalfa RET values were expectedly higher at 372±25, 360±30, 331±1, and 372±10 mm for the 2013, 2014, 2015, and 2016 experiments, respectively. Priestley-Taylor PET had the highest estimate of evaporative demand with values of 443, 428, 397, and 429 mm for the 2013, 2014, 2015, and 2016 growing seasons. Summer AET values averaged across all cropping systems reflected differences in evaporative demand, precipitation, and irrigation and were 414±34, 402±43, 356±50, and 346±36 mm for the 2013, 2014, 2015, and 2016 experiments. Potato and sweet corn had comparable AET values of 391±23 and 394±29 mm during the 2013 summer experiment (Table 2). Potatoes began the summer of 2013 with higher LAI and AET than sweet corn, though there were almost no differences in potential recharge (Figures 4-6). There were statistically significant differences in weekly AET and potential recharge during the second half of 2013, when the potato canopy began senescing and required less water (Figures 4-6).

During the summer of 2014, potatoes had the highest AET of 455±37 mm, followed by peas-pearl millet, field corn, and sweet corn, which had AET values of 434±16, 431±40, and 405±43 (Table 2). There were three weeks with statistically significant differences in AET between cropping systems in 2014; however, only one week had statistically significant differences in potential recharge (Figures 4-5). During the last two weeks of high precipitation in the summer of 2014, AET greatly exceeded RET and PET (Figure 5). Potatoes had the maximum peak LAI in 2014 followed by peas, while peas had the maximum peak LAI in 2015 followed by potatoes (Figures 5-6). Field corn and sweet corn ranked third and fourth in peak LAI, respectively, during both the 2014 and 2015 summer experiments (Figure 6). Field corn had the highest peak LAI in 2016, followed by sweet corn and potatoes, respectively (Figure 6). The summer of 2015 demonstrated the largest differences in AET between cropping systems where peas-pearl millet had the highest AET of 417±33 mm, followed by field corn, potato, and sweet corn, which had AET values of 385±31, 331±34, and 303±28 mm, respectively (Table 2). In both 2015 and 2016, five weeks had statistically significant differences in AET between cropping systems. In 2015, four weeks had statistically significant differences in potential recharge between cropping systems (Figures 4-5). However, only the last week of the summer of 2015 had both statistically significant differences in potential recharge and AET between cropping systems (Figures 4-5). In 2016, there were only two weeks with statistically significant differences in potential recharge between cropping systems and they both also had statistically significant differences in AET. Field corn, sweet corn, and potato ranked from highest to lowest in summer ET for 2016 with values of 373±39, 342±34, and 322±36 mm, respectively.

Using short-grass RET and lysimetry-derived AET measurements, summer weekly crop coefficients averaged 1.2±0.7, 1.2±0.5, 1.3±0.6, and 1.5±0.9 across all four years for potatoes, sweet corn, field corn, and peas-pearl millet, respectively. Summer crop coefficients calculated using alfalfa RET averaged 1.07±0.64, 1.05±0.47, 1.18±0.59, and 1.32±0.82 across all four years for potatoes, sweet corn, field corn, and peas-pearl millet, respectively. Summer crop coefficients calculated using Priestley-Taylor PET were the lowest and averaged 0.91±46, 0.87±0.35, 0.96±0.42, and 1.06±0.57 across all four years for potatoes, field corn, and peas-pearl millet, respectively. There were no statistically significant relationships between LAI estimates and lysimetry-derived crop coefficients for individual crops or across all cropping systems (Figure 7).

There were statistically significant differences ($F = 5.039$, $p = 0.0031$) in summer potential recharge averaged across all cropping systems between 2013, 2014, 2015, and 2016, which were -163±72, 147±266, 68±166 mm, and 9±157, respectively. 2013 had significantly lower potential recharge than 2014-2016, reflecting its low precipitation. Though there were no statistically significant differences in summer potential recharge between cropping systems in 2013-2016, there were observable differences that fell just short of statistical significance ($F = 2.7217$, $p = 0.0702$) in 2015 when precipitation and temperature conditions were close to the 100-year average (Table 2). The variability of summer potential recharge within cropping systems differed during the 2013-2016 experiments and coincided with the variability of soil texture within a cropping system. For example, in 2014, sweet corn and field corn had the highest coefficients of variation in silt content of 31 and 18%. Likewise, in 2014, sweet corn and field corn also had the highest coefficients of variation in potential recharge of 213% and 134%. The same trend was present in 2015, where sweet corn and potato cropping systems had the highest coefficients of variation in silt content of 29 and 21% and also the highest coefficients of variation in potential recharge of 139 and 170%, respectively. Potato cropping systems had high variability in summer potential recharge in the absence of soil textural variability, demonstrated by the coefficient of variation in potential recharge of 487% in 2014 when the coefficient of variation in silt content was only 7%.

3.3.2. Fall Crop Water Budgets

Cumulative precipitation for the fall experiment (September-November) was 150±8, 165±2, 247±0, and 262±5 mm for 2013, 2014, 2015, and 2016, respectively. The 100-year average is 207 mm of precipitation during this time period, which indicates that 2013 and 2014 were drier than average fall seasons, while 2015 and 2016 were wetter than average (Wisconsin State Climatology Office, 2016). Average fall temperatures were 8.3, 7.8, and 11.1, and 11.5°C for 2013, 2014, 2015, and 2016. The 100-year average temperature during this time period is 7.9°C, which makes 2013 and 2014 relatively average fall seasons (Wisconsin State Climatology Office, 2016). 2016 and 2015 were the first and third warmest fall seasons in the 100-year record for Central Wisconsin, respectively (Wisconsin State Climatology Office, 2016).

Fall RET estimates for a short-grass reference were 118±10, 93±5, 131±7, and 123±6 mm for the 2013, 2014, 2015, and 2016 experiments. Expectedly, RET values for an alfalfa reference were higher at 148±22, 109±12, 162±13, and 152±6 mm for the 2013, 2014, 2015, and 2016 experiments, respectively. Though estimates were unavailable for fall 2014 and 2015 experiments, Priestley-Taylor PET estimates were 105 and 134 mm for the 2013 and 2016 experiments, respectively. Fall AET values were 120±54, 125±35, 174±69, and 217±32 mm for 2013, 2014, 2015, and 2016 experiments, reflecting the increased temperature and precipitation in 2015 and 2016. Potato and sweet corn cropping systems had comparable fall AET in 2013 (Table 3). In the 2014 fall experiment, peas-pearl millet had the highest AET of 144±14 mm, followed by field corn, potato, and sweet corn, which had AET values of 135±23, 134±12, and 102±46 mm (Table 3). Though their ranking reversed, field corn and peas-pearl millet again had the first and second highest fall AET of 224±32 and 207±33 mm in 2015 (Table 3). Unlike the fall of 2014, sweet corn had a larger AET value of 188±39 mm in 2015 compared to potato cropping systems, which had the lowest AET of 89±71 mm (Table 3). In 2016, sweet corn had the largest AET value of 236±9 mm followed by field corn and potato, which had AET values of 221±17 and 204±41 mm, respectively.

There were statistically significant differences ($F = 3.2506$, $p = 0.0263$) in fall potential recharge values between 2013, 2014, 2015, and 2016, which were 30±51, 49±54, 96±110, and 46±30 mm, respectively. 2015 had significantly higher fall recharge than 2013, 2014, and 2016. There were statistically significant differences ($F = 8.088$, $p = 0.0009$) between cropping systems for the 2015 fall experiment, resulting from the high potential recharge observed from potato cropping systems. Potato cropping systems planted with oat cover crops potentially recharged 210±129 mm or 85% of incoming precipitation in 2015, while field corn, peas-pearl millet, and sweet corn cropping systems had average potential recharge values of 23±32, 40±33, and 58±39 mm, which only accounted for 9, 17, and 23% of fall precipitation (Table 3).

3.3.3. Cumulative Crop Water Budgets

Cumulative AET values were 535±63, 531±51, 536±57, and 566±45 mm for 2013, 2014, 2015, and 2016, respectively. Cumulative potential recharge averaged for 2013-2016 across all four cropping systems was 71±235 mm. There were statistically significant differences ($F = 4.1288$, $p = 0.0090$) in cumulative potential recharge values averaged across all cropping systems between 2013, 2014, 2015, and 2016, which were -133±111, 196±333, 164±311, and 55±183 mm, respectively. 2013 had both a dry summer and fall, which resulted in a cumulative potential recharge reduction that was statistically lower than 2014 and 2015. 2014 had a wet summer and a drier fall, which resulted in an average of 36±61% of incoming June-November precipitation potentially recharged by cropping systems. The high variability of potential recharge values in the field corn and sweet corn cropping systems also coincided with the high variability of soil texture in these systems for the cumulative 2014 experiment, as observed in the summer experiment (Table 4). There were statistically significant differences ($F = 3.617$, $p = 0.0301$) in potential recharge between cropping systems for the 2015 cumulative experimental time period, where there was an average summer followed by a wet, hot fall. Field corn and peas-pearl millet cropping systems had cumulative potential groundwater losses of -58±61 mm and -47±59 mm, respectively (Table 4). Conversely, potatoes and sweet corn had cumulative potential recharge values of 376±406 and 199±226 mm, which accounted for 69±74 and 37±42% of precipitation, respectively. Though potential recharge was not as high from potato cropping systems in 2016 as it was in 2015, potatoes had the highest cumulative potential recharge of 114 ±253 mm in 2016, followed by field corn and sweet corn, which potentially recharged 6±30 and -8±70 mm, respectively. 2016 was comparable to 2015 in the magnitude of precipitation, however there was a lower number of large precipitation events (>25 mm), which may explain its lower potential recharge and applied irrigation compared to 2015.

3.3.4. Soil and topographic drivers of potential recharge

All of the topsoil in this study was classified as either sandy loam or loamy sand, while all of the subsoil fell into either loamy sand or sand USDA textural categories (Figure 8). However, there was only a weak, significant correlation (R^2=0.1888, F = 5.3520, p-value=0.0300) between topsoil and subsoil texture, and we observed that relatively finer-textured topsoil often overlaid relatively coarser-textured subsoil. We found statistically significant relationships between potential recharge and soil texture during the summer experiments in 2014, 2015, and 2016. For simplicity, we present linear relationships in terms of silt content (%) as a proxy for all three soil textural categories in Figures 9 and 10; however, statistical results for sand, silt, and clay are contained in the supplementary materials. Silt and clay content (%) had a significant positive correlation to summer potential recharge, while sand content (%) had a significant negative correlation to summer potential recharge for both soil depths in 2014 and topsoil in 2015 and 2016 (Figure 9, Supplementary Materials). These correlations were not significant between soil texture and fall recharge in 2014 and 2015, but were significant between subsoil texture and fall recharge in 2013 and 2016 (Figure 10, Supplementary Materials). We found no statistically significant relationships between organic matter content, elevation, and potential recharge.

3.3.5. Event-based analyses of drainage and θ

We further analyzed the relationship between topsoil texture (% silt), θ_i, θ_{fc}, and drainage during five major rain events in the summer of 2015. Though the rate and magnitude of precipitation, drainage, and θ differed for each rain event (Figure 11), we found statistically significant relationships between topsoil texture, θ_i, θ_{fc}, and drainage across all five events (Figure 12). All significant θ relationships occurred at a depth of 0.1 m ($\theta_{i,0.1}$ or $\theta_{fc,0.1}$). Despite observed differences in AET and phenology, there were no statistically significant differences in drainage, θ_i, or θ_{fc} between cropping systems for individual rain events. We found a statistically significant ($p < 0.05$) positive linear relationship between $\theta_{i,0.1}$ and topsoil silt content with R^2 values of 0.189, 0.482, 0.374, 0.291, and 0.402 for the 15 Jun, 6 Jul, 13 Jul, 7 Aug, and 18 Aug events. However, there were no significant correlations between $\theta_{i,0.1}$ and drainage for any of these events. We also found statistically significant positive linear relationships ($p < 0.01$) between $\theta_{fc,0.1}$ and topsoil silt content for all events except the 19-mm event that occurred on 15 June (Figure 12). Subsequently, there were also statistically significant ($p < 0.05$) positive correlations between $\theta_{fc,0.1}$ and drainage for all events except the 38-mm event that occurred on 13 July. The statistically significant positive relationship ($p < 0.05$) between drainage and topsoil silt content was also present for the 15 June, 6 July, and 18 August events. The correlative relationships between $\theta_{fc,0.1}$, topsoil silt content, and drainage were the strongest during the largest rain event, which was the 58-mm event that occurred on 18 August. These relationships were the weakest during the 38-mm event on the 13 July, where there were no significant explanatory variables for drainage. There were no statistically significant relationships between crop type and drainage for the five major rain events in 2015.

3.4. Discussion

3.4.1. Though cropping systems exhibited distinctive hydrological patterns, interannual climate variability was the greatest driver of potential recharge

Interannual climate variability was the most consistent driver of the differences in potential recharge observed in this study. Because irrigated crops transpire at maximum rates regardless of precipitation, dry summers such as 2013 have similar AET to wet or average summers such as 2014-2016 in the WCS. During dry summers, groundwater withdrawals compensate for limited precipitation and expose locally sensitive surface waters to the dual stresses of increased pumping and reduced recharge (Mossbarger et al., 1989). Because only 20% of September-November precipitation was potentially recharged to the aquifer, we speculate that any recharge losses at the end of dry growing seasons such as 2013 will not likely be recovered until the following spring snowmelt under cropping systems in the WCS. This study also demonstrates that for irrigated landscapes in the humid Great Lakes region, wet growing seasons such as 2014 may buffer impacts to locally sensitive surface waters via increased potential recharge, while growing seasons with average precipitation distributed as a few, large precipitation events such as 2015 facilitated the largest differences in potential recharge between cropping systems. If the four drought-free years of this study are considered representative of the long-term average, cumulative potential recharge remains positive from irrigated agroecosystems in the WCS. Consequently, groundwater levels will not decrease further than those predicted by a steady-state groundwater flow model with zero recharge. These findings suggest that groundwater depletion in irrigated humid and semi-humid regions is on a very different trajectory than irrigated arid regions such as the High Plains that experience net recharge losses nearly every growing season (Scanlon et al., 2012). Though the potential recharge values observed in this study demonstrate that irrigated agriculture in the WCS may have severe consequences for lakes, streams, and wetlands relying on the top few meters of the aquifer, they also demonstrate that irrigated agriculture could continue functioning indefinitely in the WCS and similar humid regions in a stable, degraded state.

Groundwater depletion in irrigated humid regions like the WCS may also be localized and episodic (Kraft et al., 2012; Mubako et al., 2013; Yang et al., 2015); meaning that certain surface waters near pumps or pumping clusters could show more depletion than a steady-state, regional solution would indicate in a given year, depending on the combination of nearby crop rotations and the magnitude and distribution of precipitation. From a sustainability perspective, ours and similar findings (Kraft et al., 2012) suggest that groundwater resources in the WCS should be managed based on regional or local valuation of aquatic ecosystem services rather than overall aquifer depletability. Localized water management strategies such as precision irrigation and interfield crop rotation may be most effective during growing seasons such as 2015, when differences in potential recharge patterns between cropping systems will be most pronounced and subject to spatiotemporal intervention. The episodic nature of depletion in the WCS may also support groundwater banking or managed aquifer recharge strategies as regional steps to balance seasonal variation in groundwater supply and demand, while protecting the region against climate extremes and uncertainty (Arshad et al., 2014; Maliva, 2014; Scanlon et al., 2016).

This is the first field study to evaluate potential recharge and AET under irrigated field corn cropping systems in the WCS. Irrigated field corn in this study had an average June-November AET of 581 mm, which is credible compared to 539-639 mm yr^{-1} measured with eddy covariance methods from rainfed field corn in southwest Michigan, where the combination of greater evaporative demand and water limitations would favor comparable AET rates (Abraha et al., 2015). June-November AET in this study was significantly less than the 699-709 mm yr^{-1} reported for irrigated field corn in Nebraska using eddy covariance methods (Suyker and Verma, 2008), which is to be expected given the increased evaporative demand from aridity and removal of water limitations via irrigation. June-November AET values were 19-91 mm greater than previously modeled annual AET rates for irrigated field corn in the WCS (Weeks and Stangland, 1971; Naber, 2011), and we suggest that the most likely reason for this discrepancy is that previous modeling attempts did not account for field corn residue as a fall cover and assumed bare soil following harvest. Using equilibrium tension lysimeters in a study 140 km south of the WCS on silt loam soils, Brye et al. (2000) found that no-till field corn systems covered in fall residue decreased drainage by an average of 112 mm yr^{-1} compared to chisel plow systems (Brye et al., 2000). In this study, we suggest that presence of residue created a surface soil moisture storage layer that may have intercepted, stored, and evaporated fall precipitation; therefore inhibiting fall recharge. Because we did not explicitly measure weekly changes in fall soil and residue moisture storage, we cannot distinguish whether fall precipitation was intercepted and stored by residue until tillage the following spring or whether precipitation was intercepted and evaporated by residue during the months of September-November. Though the residue effect was the most pronounced in field corn, it was also present in peas-pearl millet and sweet corn cropping systems, warranting future investigation.

Though they are varietals of the same species, sweet corn and field corn have different hydrological patterns in the WCS, where sweet corn comprised 18% of irrigated agricultural land use in 2015 (USDA-NASS, 2015). Sweet corn has a shorter growing season, receives less irrigation, and typically maintains a lower LAI than field corn. During three large rain events in July and August of 2015, very little water penetrated below field corn's root zone, while sweet corn systems had significant drainage, which also suggests differences in rooting depth between field and sweet corn that have been found in other studies (Sanford and Panuska, 2015; Weaver, 1926). These are the first field estimates of AET and potential recharge from irrigated sweet corn in the Midwestern United States, and our average growing season AET estimate of 360 mm is expectedly lower than estimates from warmer, more arid regions such as 436 mm in North Carolina (Van Bavel, 1961) and 487 mm in California (Phene et al., 1991).

Peas made up 4% of WCS irrigated crops in 2015 (USDA-NASS, 2015) and exhibited low recharge in a wet summer and a net loss of groundwater in an average summer. These hydrological patterns likely occur because of high leaf area index and water demands. Water budgets in this study are the first field estimates of AET and potential recharge for irrigated peas in the Midwestern United States. The closest geographical pea AET rates measured were 170-420 mm under a variety of biophysical conditions across Alberta, Canada (Mckenzie et al., 2004). Our study had an average AET of 241 mm for peas, which falls near the median of previously measured values in Alberta. Using pearl millet as a biofumigant cover crop is still a novel practice for WCS, where snap beans, soybeans, or winter wheat cover crops usually follow peas (Delahaut and Thiede, 1999). Therefore, it is inappropriate to extrapolate August-November water budgets from this study to all pea cropping systems in the WCS region.

Potatoes made up 20% of the irrigated landscape in 2015 (USDA-NASS, 2015) and exhibited higher variability in AET and recharge patterns than other cropping systems in this study. Potatoes fields differ from other cropping systems by containing hills and furrows, which increase the spatial variability of drainage as observed here and in previous lysimetry studies (Gee et al., 2009; Herath et al., 2014). Our summer 2016 AET value of 322 mm for irrigated potato can be compared to the summer 1972 AET values of 270-285 mm measured by Tanner and Gardner (1974), who used large-scale weighing lysimeters to assess water-saving irrigation methods under somewhat similar conditions in the WCS. Though precipitation was nearly the same for both summers, 1972 had 1°C lower monthly temperatures and the water-saving irrigation methods exposed potatoes in the 1972 experiment to water stress in late June that was not present in 2016, which supports the higher AET values observed in this study (Tanner, 1974). Additionally, the Priestley-Taylor-derived crop coefficient for irrigated potatoes was 0.91 in this study, which is nearly the same as that which was previously observed in the WCS by Jury and Tanner (1975) using large-scale weighing lysimeters (Jury and Tanner, 1975). Though we demonstrated here that potato production may pose a lower risk to groundwater quantity concerns than field corn and peas, we cannot dismiss a potential tradeoff between groundwater quantity and quality. Because the majority of potato roots proliferate in the top 0.25 m, precipitation events >25 mm carry applied nitrogen out of the root zone and into the aquifer (Saffigna et al., 1976), which has led to nitrate-N levels

2-4 times greater than the US MCS standard for drinking water of 10 ppm in the WCS (Stites and Kraft, 2001). Future work must continue to investigate cost-effective solutions such as surfactants (Cooley et al., 2009, Arriaga et al., 2009) for keeping nitrogen in the root zone, while maintaining high levels of recharge from potatoes in the WCS.

3.4.2. Soil texture was a significant driver of potential recharge

In this study, soil texture was a significant driver of recharge during the fall of 2013 and 2016 and the summers of 2014-2016. In sandy loams and loamy sands located within a 2-km radius of one another, finer-textured soils increased drainage and potential recharge at the field scale. Additionally, positive correlative relationships existed between finer topsoil texture, $\theta_{fc,0.1}$, and drainage for five large rain events in 2015. If we only consider the textbook differences in hydraulic conductivity associated with soil texture (Campbell and Norman, 1998), this is a counterintuitive finding. However, because irrigated, sandy agroecosystems are maintained at or near field capacity, hydraulic conductivity should not be limiting to drainage through relatively siltier soils. Moreover, when understanding the spatial variability of drainage, preferential flow is the rule rather than the exception (Flury et al., 1994). Preferential flow in this experiment may have been caused by macropore formation (Hendrickx et al., 2001; Jarvis, 2007), hydrophobicity (Doer et al., 2000), or a combination of these processes. Relatively finer-textured soil could have facilitated macropore formation via cracks (Beven and German, 1982), which we occasionally observed at the soil surface in these locations. Large rain events increase preferential flow (Jarvis, 2007) and the strength of the positive correlations between topsoil texture, $\theta_{fc,0.1}$, and drainage for the 58-mm rain event in 2015 supports a macropore hypothesis (Perillo et al., 1999). We also observed statistically significant positive correlations between $\theta_{i,0.1}$ and topsoil texture for all five large precipitation events in 2015. Because soils in the WCS are maintained near field capacity, higher antecedent soil moisture in relatively siltier soils may also pose an explanation for the observed relationship between topsoil texture and drainage either in conjunction with or in the absence of macropore flow. The lack of correlation between $\theta_{i,0.1}$ and event-based drainage is inconsistent with both the antecedent soil moisture and macropore hypotheses, however macropore flow has been documented across a variety of soil types in the absence of this relationship (Flury et al., 1994).

The relationships between soil texture and recharge observed in this study could also be indicative of soil hydrophobicity in relatively sandier parts of the field. Soil hydrophobicity occurs when aromatic plant materials complex with soil mineral particles to form a transient, repellent layer on the topsoil, and has been previously demonstrated in the WCS (Cooley et al., 2007). Hydrophobicity is positively correlated to sand content and sandy soils can wet up and return to a water repellent state upon drying during the growing season (Doerr et al., 2000). Hydrophobic soils have a higher water entry potential than their hydrophilic counterparts (Bauters et al., 2000) and this could explain why higher silt content was positively correlated to potential recharge in this study. Lysimeters with higher silt content may have had lower water entry potentials than their sandier counterparts, which consequently increased infiltration and drainage during precipitation events. Further, targeted field and modeling experiments in the absence of confounding crop effects will be required to isolate mechanisms and understand the correlative relationships observed in this study.

3.4.3. Crop phenology may be an inconsistent predictor of point-based potential recharge estimates

Prior to this study, there have been three large, replicated passive capillary lysimetry studies in cropping systems where "collection efficiency" was assessed as the ratio of measured to modeled drainage using canopy-scale estimates of AET to predict point-based drainage (Brandi-Dohrn et al., 1996; Louie et al., 2000; Gee et al., 2009). In these previous studies, measured, point-based drainage was highly variable, with collection efficiencies ranging from 25-300%, and the authors identified intrafield variability in AET, infiltration, and runoff as possible sources of error (Brandi-Dohrn et al., 1996; Louie et al., 2000; Gee et al., 2009). This is the first large, replicated lysimetry study to quantify subtle differences in soil texture as an underlying explanation for intrinsic variability in drainage over short distances. For this reason, we contend that semi-empirical AET estimates generated for the canopy scale may be misleading when used to predict and evaluate point-based measurements of drainage made using passive capillary lysimeters.

In the same manner, caution must be exercised when attempting to use point-based measurements of AET to predict and evaluate AET at the canopy scale (Allen et al., 2011). Small-area lysimeters such as those used in this study do not necessarily capture the canopy-level effects of LAI from their surroundings (Dugas and Bland, 1989). Crop coefficients represent canopy-level changes in plant phenology and are correlated to LAI (Ding et al., 2013, Allen et al., 1998). The lack of correlation between canopy-level estimates of LAI and crop coefficients derived from point-based AET estimates in this study demonstrates the limitations of small-scale lysimetry. In order to develop a comprehensive framework for crop water management at the regional scale in the WCS, it is imperative that small-scale lysimetry is combined with larger scale methods for estimating AET such as eddy covariance, aerial remote sensing, and crop simulation modeling (Allen et al., 2011; Evett et al., 2016).

Finer-textured soils were positively correlated to increased consumptive groundwater use in this study, which has critical implications for precision irrigation and nutrient management in the WCS. Precision agricultural models predict AET, storage, and drainage at subfield scales based on assumption of uniform rather than preferential flow (Moiling et al., 2005; Nelson et al., 2013; Plauborg et al., 2015). Because precision irrigation operates at the subfield scale where preferential flow processes dominate, realistic assessments of groundwater and nutrient savings may require subfield-based validation of AET, storage, and drainage using lysimetry or other methods. For recharge estimates required at areal scales, accounting for preferential flow processes based on macropores and soil repellency becomes impractical and models of groundwater recharge using validated estimates of crop AET are still the preferred method (Hendrickx and Flury, 2001). However, with increasing computational power, recharge estimates are now possible at an intermediary scale between 30-100 m, where it is possible and often desirable to address site-specific water management goals with hydrological models (Allen et al., 2005; Githui et al., 2012). Future work is required to clarify whether representation of preferential flow processes is important and feasible for these intermediary scales.

3.5. Conclusions

Over 14% of the WCS landscape is currently irrigated cropland and land use conversion to irrigated agriculture continues to grow throughout the northern Great Lakes region (Smail, 2016). We have demonstrated that interannual climate variability, cropping system, and soil texture all drive groundwater recharge to varying degrees in the WCS. In a relatively average growing season, irrigated sweet corn and potato rotations recharged the underlying aquifer, while irrigated field corn and peas-pearl millet rotations depleted groundwater. Removing field or sweet corn residue after harvest to increase recharge may not be a viable option for the WCS, as soils are prone to erosion and cover crop establishment may be difficult in mid-October, when field corn is typically harvested. In the case of peas, if water quantity is a greater concern than biofumigation, it may be possible to replace pearl millet with a cover crop that uses less water. Though potato cropping systems recharged the aquifer in an average year, the potential for a reduction in groundwater quality cannot be ignored in water management planning. Because of crop rotation and differences in precipitation, the impact of WCS irrigated agriculture on freshwater resources will be different each year. Understanding cumulative impacts within this hydrological patchwork will require explicit prediction and representation of crop rotations in process-based models. The WCS and regions like it would greatly benefit from interdisciplinary research to better understand and predict drivers of crop rotations, such as markets, pest and disease management, and climate.

The potential preferential flow patterns observed in this study were at a scale that is important for precision agricultural applications, but may not be important for the regional scale at which communities manage water. Replicated passive capillary lysimetry paired with soil moisture sensors was a useful method for characterizing the spatiotemporal variability of water budgets and statistically assessing differences between cropping systems. One possible limitation to water budgets quantified in sandy soils using passive capillary lysimetry may be the tendency to overestimate drainage. As the surrounding soil drains between 0 to -11 kPa, flux convergence could be occurring towards the lysimeter. Because managing water resources in the WCS requires a high level of certainty, it would be prudent to compare the water budgets presented here to other methods in the future, such as equilibrium tension lysimetry, aerial remote sensing, or eddy covariance.

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3.8. Tables

Table 1. Cropping Systems

Site/year	Crop	Planting Date	Harvest Date	Post-harvest cover
H				
2013	sweet corn	25 May	5 Sep	oats and sweet corn residue
2014	peas	22 May	27 Jul	pearl millet
2015	potato	1 May	16 Sep (*vine kill 13 Aug*)	oats
2016	field corn	15 May	11 Nov	field corn residue
G				
2014	potato	9 May	10 Sep *(vine kill 22 Aug)*	oats
2015	field corn	10 May	28 Oct	field corn residue
2016	sweet corn	2 Jun	31 Aug	oats and sweet corn residue
P				
2013	potato	15 May	16 Sep *(vine kill 23 Aug)*	oats
2014	field corn	12 May	3 Nov	field corn residue
2015	sweet corn	30 May	1 Sep	oats and sweet corn residue
2016	potato	6 May	2 Oct *(vine kill 19 Aug)*	oats
L				
2013	potato	15 May	16 Sep *(vine kill 23 Aug)*	oats
2014	sweet corn	24 May	25 Aug	oats and sweet corn residue
2015	sweet corn	30 May	1 Sep	oats and sweet corn residue
2016	potato	7 May	5 Oct *(vine kill 19 Aug)*	oats
E				
2013	sweet corn	25 May	5 Sep	oats and sweet corn residue
2014	sweet corn	24 May	25 Aug	oats and sweet corn residue
2015	potato	3 May	21 Sep *(vine kill 20 Aug)*	oats
2016	field corn	16 May	11 Nov	field corn residue
W				
2013	potato	15 May	19 Sep *(vine kill 26*	oats

			Aug)	
2014	field corn	15 May	3 Nov	field corn residue
2015	peas	30 May	23 Jul	pearl millet
2016	potato	4 May	28 Sep *(vine kill 19 Aug)*	oats

Table 2. Summer water budgets

Cropping System (# Lysimeters)	Sand-Silt-Clay (%, topsoil)	Precipitation (mm)	Irrigation (mm)	Drainage (mm)	Drainage:Input	ET (mm)	Net Potential Recharge (mm)
1 Jun-3 Sep 2013							
Potato (6)	72-20-8 (6-5-2)	194 (3)	214 (23)	62 (80)	0.15 (0.19)	391 (23)	-152 (74)
Sweet corn (4)	76-17-7 (4-3-1)	193 (2)	223 (28)	56 (47)	0.14 (0.12)	394 (29)	-167 (69)
1 Jun-3 Sep 2014							
Field corn (8)	69-22-9 (6-4-2)	404 (3)	160 (10)	374 (283)	0.66 (0.51)	431 (40)	214 (287)
Peas-Pearl millet (4)	75-18-7 (4-3-1)	381 (0)	119 (0)	142 (65)	0.28 (0.13)	434 (16)	23 (65)
Potato (3)	78-15-7 (1-1-1)	381 (0)	195 (0)	218 (112)	0.38 (0.19)	455 (37)	23 (112)
Sweet corn (8)	71-22-8 (9-7-1)	404 (3)	168 (27)	357 (410)	0.62 (69)	405 (43)	189 (403)
10 Jun-1 Sep 2015							
Field corn (5)	78-15-7 (1-1-1)	294 (0)	102 (33)	22 (7)	0.05 (0.02)	385 (31)	-81 (33)
Peas-Pearl millet (4)	74-18-8 (2-2-1)	302 (0)	155 (0)	69 (42)	0.15 (0.09)	417 (33)	-87 (42)
Potato (8)	74-19-7 (5-4-1)	298 (5)	162 (28)	327 (291)	0.70 (0.60)	331 (34)	166 (283)
Sweet corn (8)	67-24-9 (8-7-2)	294 (0)	91 (16)	231 (202)	0.60 (0.51)	303 (28)	140 (195)
1 Jun-30 Aug 2016							
Field corn (7)	75-18-7 (3-2-1)	282 (14)	73 (1)	35 (22)	0.10 (0.06)	373 (39)	-38 (22)
Potato (11)	68-23-9 (7-6-2)	280 (11)	101 (39)	162 (200)	0.45 (0.61)	322 (36)	61 (216)
Sweet corn (5)	78-15-7 (1-1-1)	271 (0)	89 (0)	49 (62)	0.14 (0.17)	342 (34)	-40 (62)

†Standard deviation reported in parentheses.
‡Drainage:Input is the ratio of drainage divided by the sum of precipitation and irrigation (total inputs).
§Net potential recharge is the difference between drainage and irrigation.

Table 3. Fall water budgets

Cropping System (# Lysimeters)	Sand-Silt-Clay (%, topsoil)	Precipitation (mm)	Irrigation (mm)	Drainage (mm)	Drainage:Input	ET (mm)	Net Potential Recharge (mm)
4 Sep-2 Dec 2013							
Potato (6)	72-20-8 (6-5-2)	155 (6)	3 (4)	44 (58)	0.29 (0.39)	113 (65)	41 (59)
Sweet corn (4)	76-17-7 (4-3-1)	142 (4)	14 (12)	29 (42)	0.18 (0.26)	127 (38)	15 (37)
4 Sep-1 Dec 2014							
Field corn (8)	69-22-9 (6-4-2)	166 (2)	0	56 (77)	0.34 (0.46)	135 (23)	56 (77)
Peas-Pearl millet (4)	75-18-7 (4-3-1)	164 (0)	0	20 (14)	0.12 (0.08)	144 (14)	20 (14)
Potato (3)	78-15-7 (1-1-1)	164 (0)	0	30 (12)	0.18 (0.07)	134 (12)	30 (12)
Sweet corn (8)	71-22-8 (9-7-1)	166 (2)	0	64 (46)	0.39 (0.28)	102 (46)	64 (46)
2 Sep-2 Dec 2015							
Field corn (5)	78-15-7 (1-1-1)	247 (0)	0	23 (32)	0.09 (0.13)	224 (32)	23*** (32)
Peas-Pearl millet (4)	74-18-8 (2-2-1)	247 (0)	0	40 (33)	0.16 (0.13)	207 (33)	40*** (33)
Potato (8)	74-19-7 (5-4-1)	247 (0)	0	210 (129)	0.85 (0.52)	89 (71)	210*** (129)
Sweet corn (8)	67-24-9 (8-7-2)	247 (0)	0	58 (39)	0.24 (0.16)	188 (39)	58*** (39)
31 Aug-29 Nov 2016							
Field corn (7)	75-18-7 (3-2-1)	265 (3)	0	44 (16)	0.17 (0.06)	221 (17)	44 (16)
Potato (11)	68-23-9 (7-6-2)	258 (3)	0	53 (40)	0.21 (0.16)	204 (41)	53 (40)
Sweet corn (5)	78-15-7 (1-1-1)	268 (0)	0	32 (9)	0.12 (0.03)	236 (9)	32 (9)

†Standard deviation reported in parentheses.
‡Drainage:Input is the ratio of drainage divided by the sum of precipitation and irrigation (total inputs).
§Net potential recharge is the difference between drainage and irrigation.
***Statistical significance at the 0.001 level.

Table 4. Cumulative water budgets

Cropping System (# Lysimeters)	Sand-Silt-Clay (%, topsoil)	Precipitation (mm)	Irrigation (mm)	Drainage (mm)	Drainage:Input	ET (mm)	Net Potential Recharge (mm)
1 Jun-2 Dec 2013							
Potato (6)	72-20-8 (6-5-2)	349 (9)	217 (26)	106 (127)	0.19 (0.23)	531 (73)	-111 (122)
Sweet corn (4)	76-17-7 (4-3-1)	336 (2)	237 (16)	86 (88)	0.15 (0.16)	539 (51)	-151 (99)
1 Jun-1 Dec 2014							
Field corn (8)	69-22-9 (6-4-2)	570 (5)	160 (10)	430 (348)	0.59 (0.48)	525 (56)	270 (352)
Peas-Pearl millet (4)	75-18-7 (4-3-1)	545 (0)	119 (0)	162 (64)	0.24 (0.09)	571 (32)	43 (64)
Potato (3)	78-15-7 (1-1-1)	545 (0)	195 (0)	249 (112)	0.34 (0.15)	553 (41)	54 (112)
Sweet corn (8)	71-22-8 (9-7-1)	570 (5)	168 (27)	421 (440)	0.57 (0.58)	477 (68)	254 (434)
10 Jun-2 Dec 2015							
Field corn (5)	78-15-7 (1-1-1)	542 (0)	102 (33)	45 (35)	0.07 (0.06)	624 (52)	-57* (61)
Peas-Pearl millet (4)	74-18-8 (2-2-1)	550 (0)	155 (0)	108 (59)	0.15 (0.08)	620 (81)	-47* (59)
Potato (8)	74-19-7 (5-4-1)	546 (6)	162 (28)	538 (415)	0.75 (0.56)	419 (82)	376* (406)
Sweet corn (8)	67-24-9 (8-7-2)	542 (0)	91 (16)	290 (232)	0.45 (0.36)	479 (57)	199* (226)
1 Jun-29 Nov 2016							
Field corn (7)	75-18-7 (3-2-1)	547 (10)	73 (1)	79 (30)	0.12 (0.05)	594 (42)	6 (30)
Potato (11)	68-23-9 (7-6-2)	538 (13)	101 (39)	215 (236)	0.35 (0.40)	528 (54)	114 (253)
Sweet corn (5)	78-15-7 (1-1-1)	539 (0)	89 (0)	82 (70)	0.13 (0.11)	578 (36)	-7 (70)

†Standard deviation reported in parentheses.
‡Drainage:Input is the ratio of drainage divided by the sum of precipitation and irrigation (total inputs).
§Net potential recharge is the difference between drainage and irrigation.
*Statistical significance at the 0.05 level.

3.9. Figures

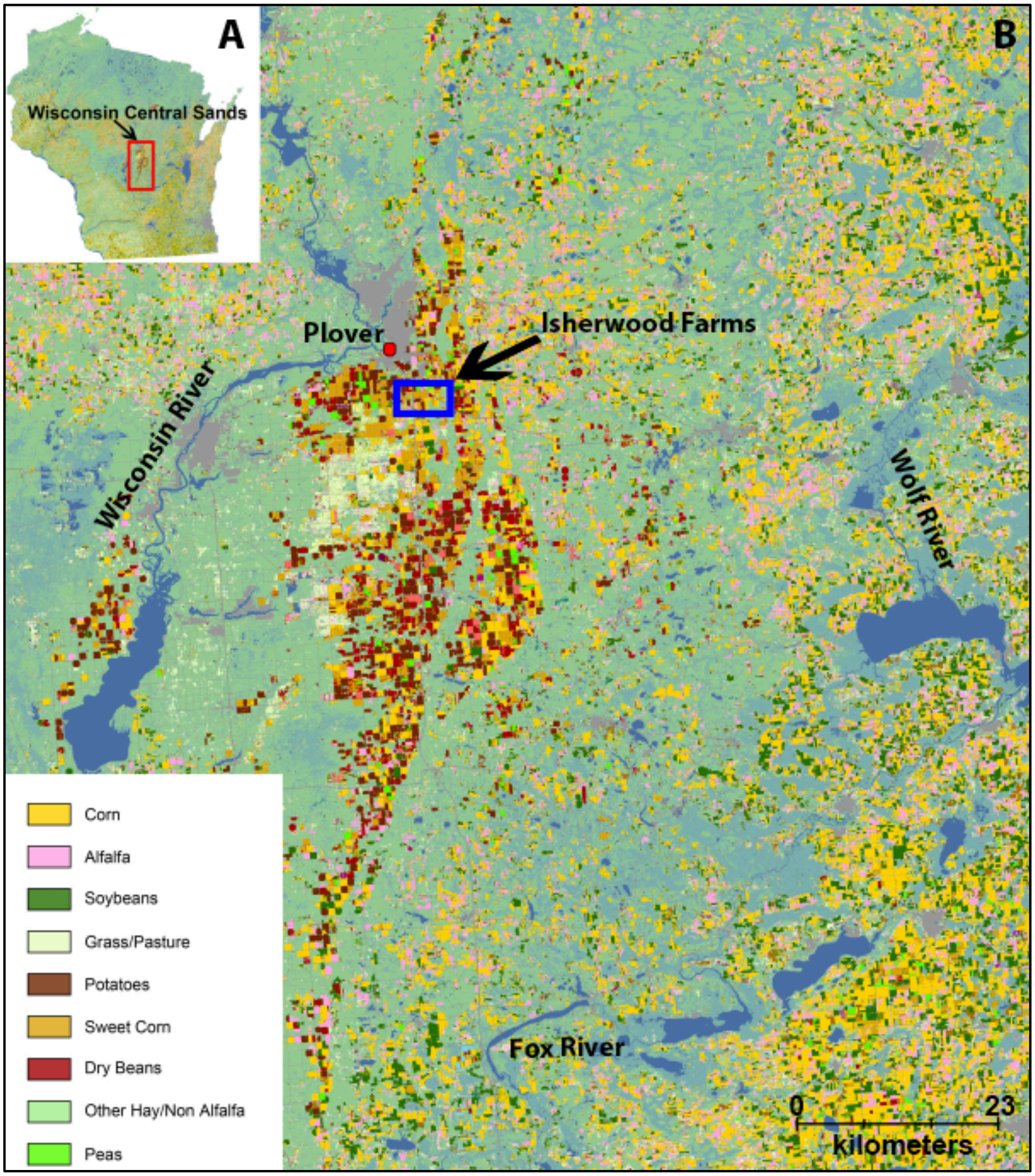

Figure 1. (A) Location of Central Sands region in the state of Wisconsin outlined by red box. (B) Dominant cropping systems in the Wisconsin Central Sands depicted using USDA National Agricultural Statistics Survey 2015 Cropland Data Layer. Isherwood Farms field site outlined by blue box.

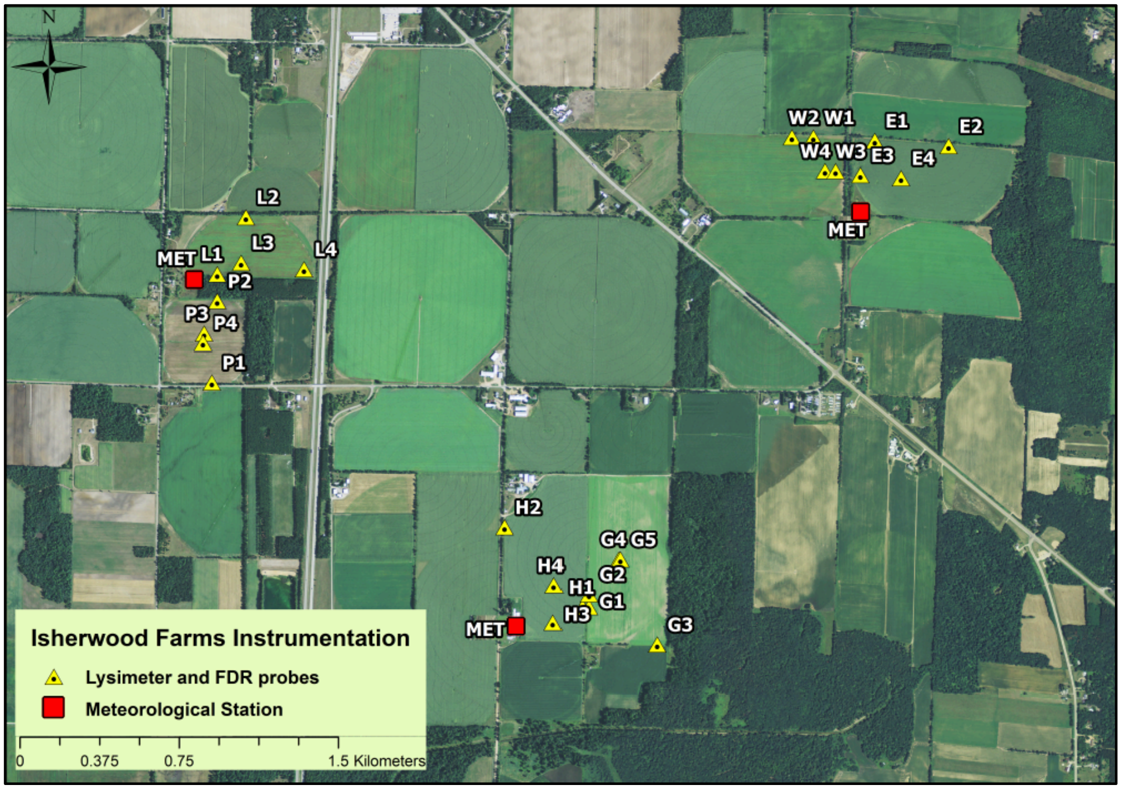

Figure 2. Isherwood Farms field instrumentation sites surveyed using RTK GPS system (0.03 m accuracy). Georeferencing conducted using 2013 National Agriculture Imagery Program data for Portage County, WI.

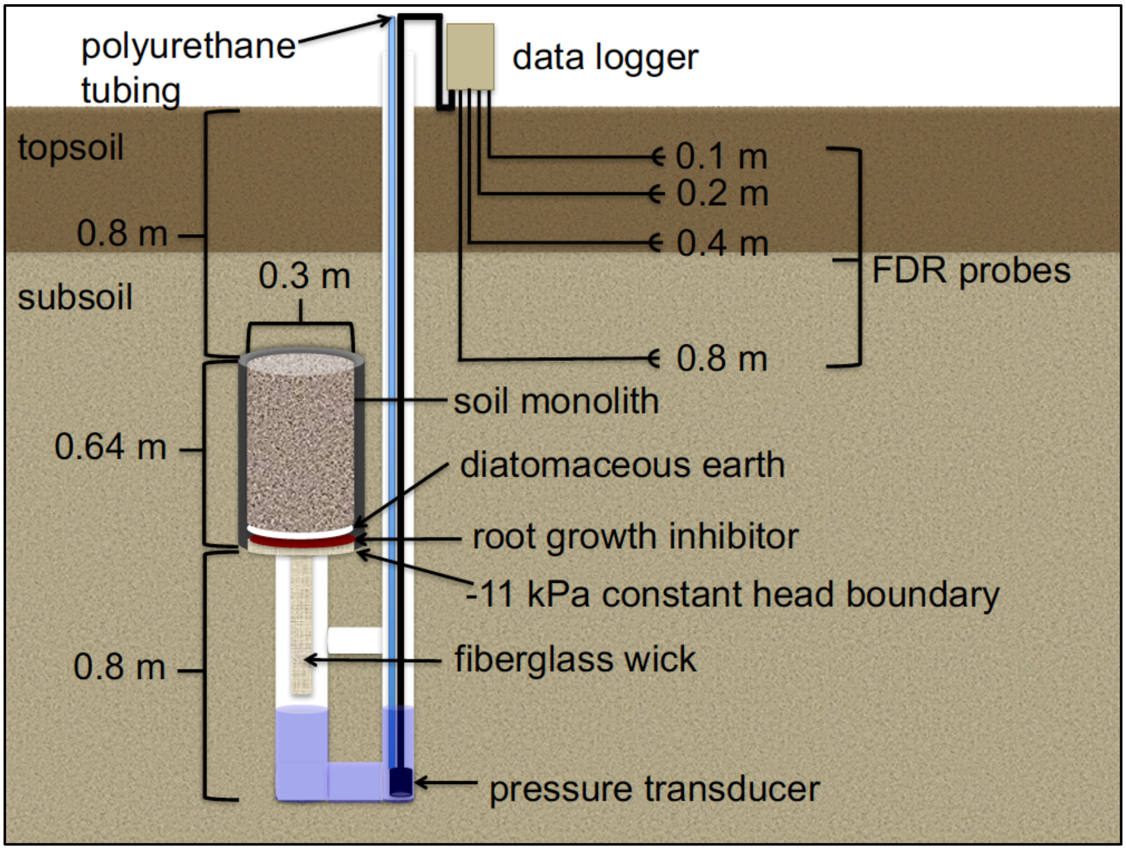

Figure 3. Lysimeter and frequency domain reflectometry (FDR) probe configuration schematic (not to scale).

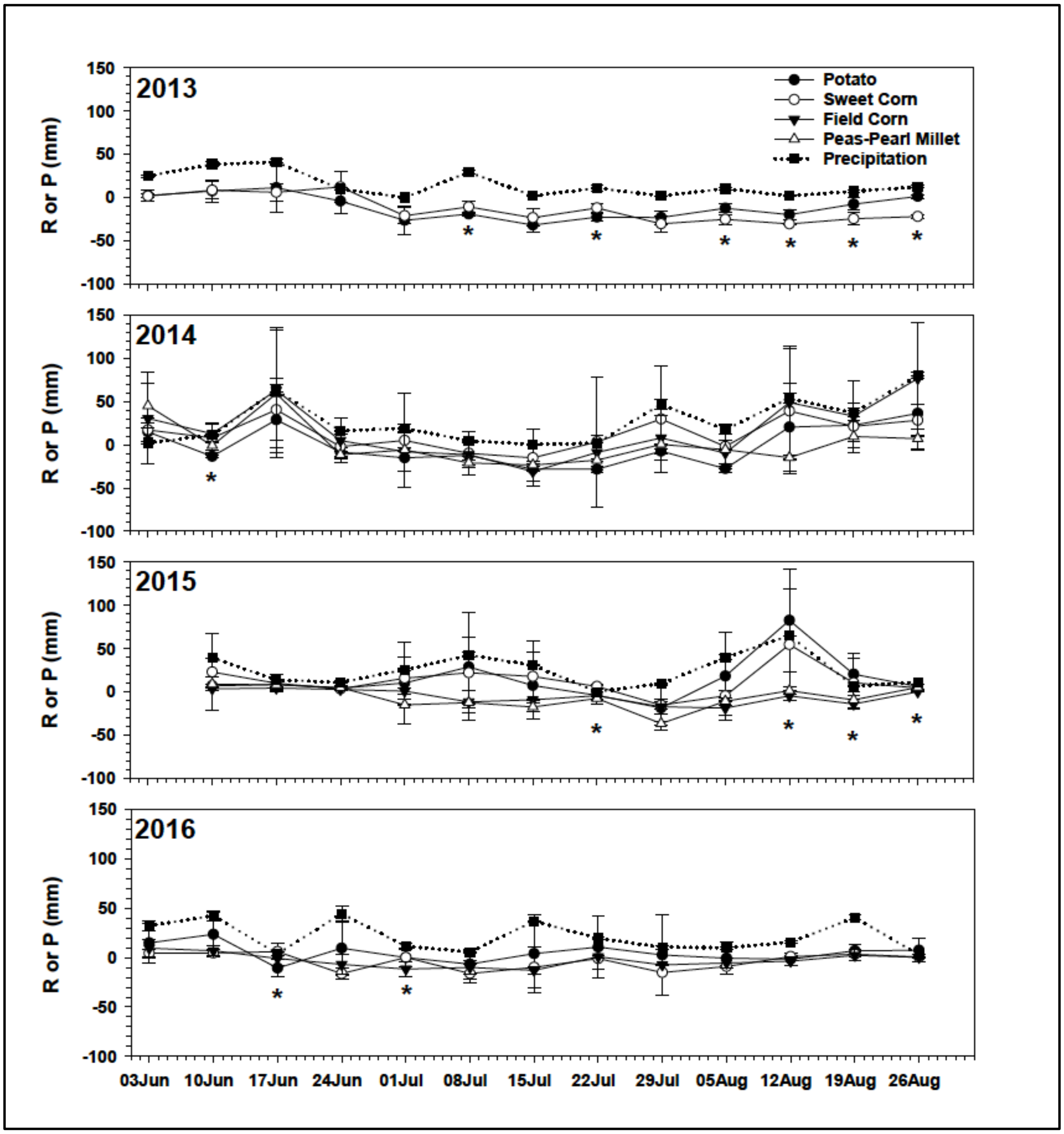

Figure 4. Weekly average potential recharge (R, mm) or precipitation (P, mm) over the summer experimental period in 2013-2016. Starred weeks indicate significant differences between cropping systems ($p < 0.05$) evaluated by weekly repeated-measures ANOVA models for unbalanced data.

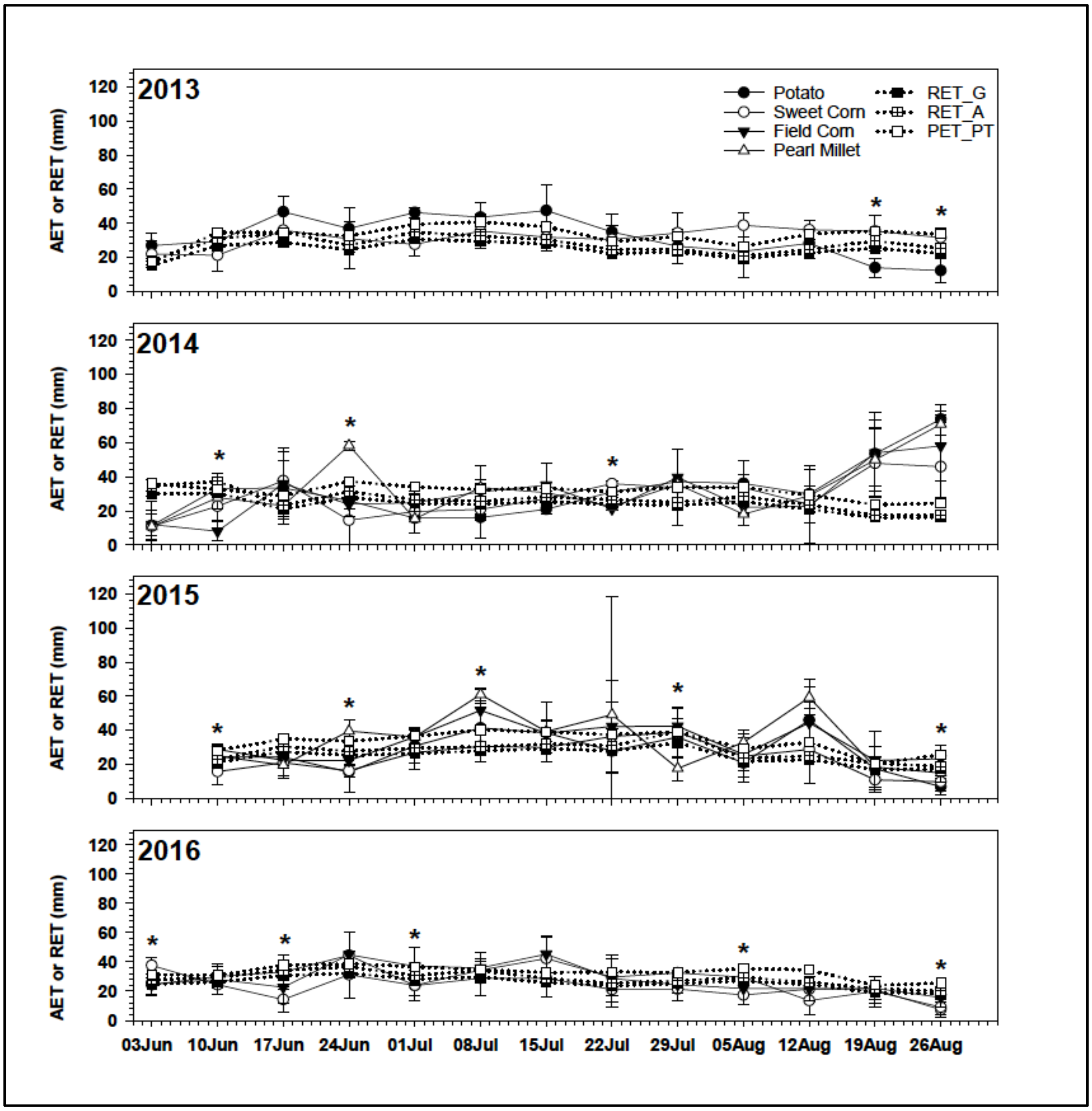

Figure 5. Weekly average grass reference (RET_G, mm), alfalfa reference (RET_A, mm), potential (PET_PT, mm), or actual crop evapotranspiration (mm) over the summer experimental period in 2013-2016. Starred weeks indicate significant differences between cropping systems ($p < 0.05$) evaluated by weekly repeated-measures ANOVA models for unbalanced data.

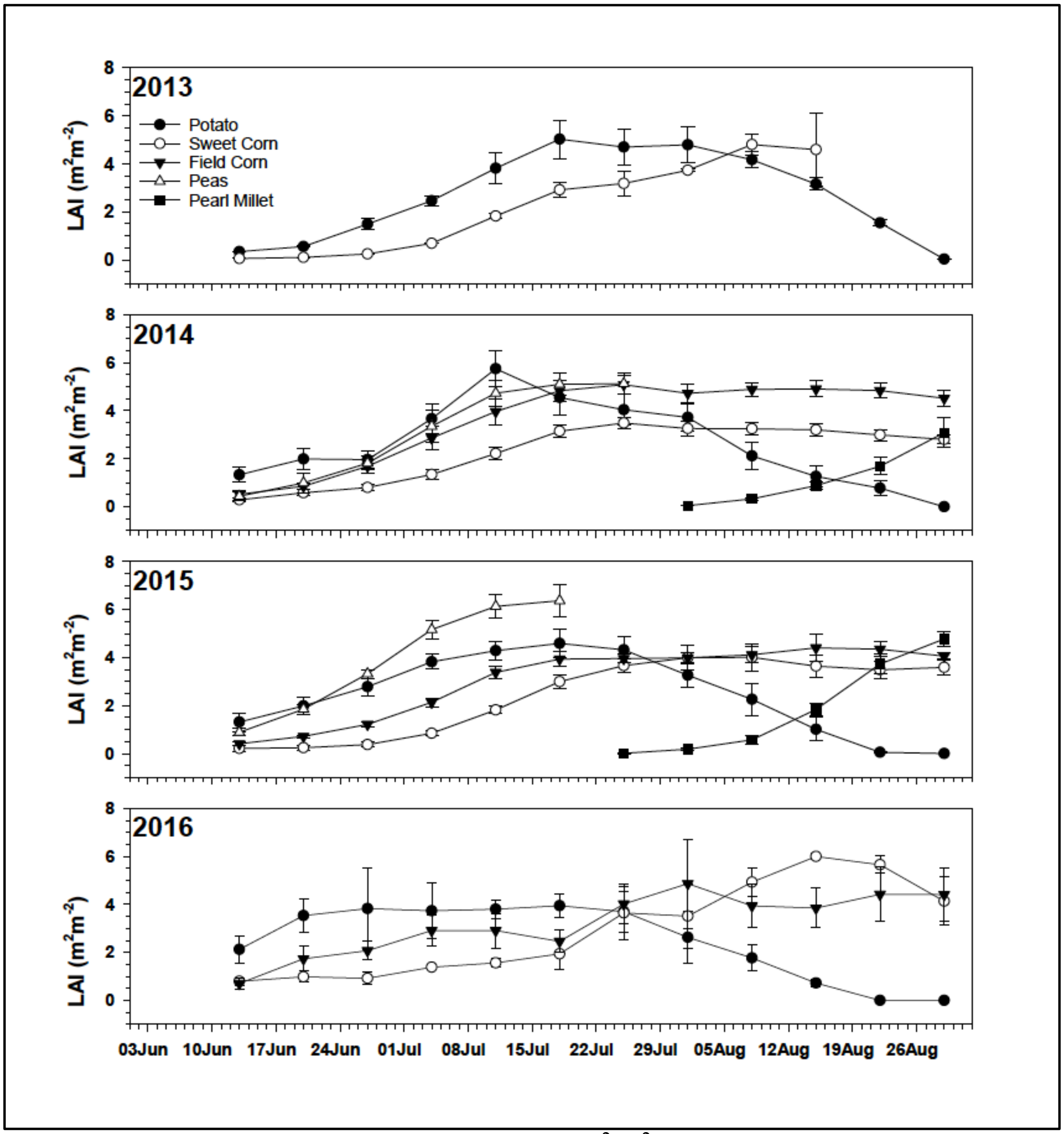

Figure 6. Weekly average leaf area index (LAI, m^2m^{-2}) for each cropping system in 2013-2016. The transition from peas to pearl millet is differentiated as separate time series in 2014 and 2015.

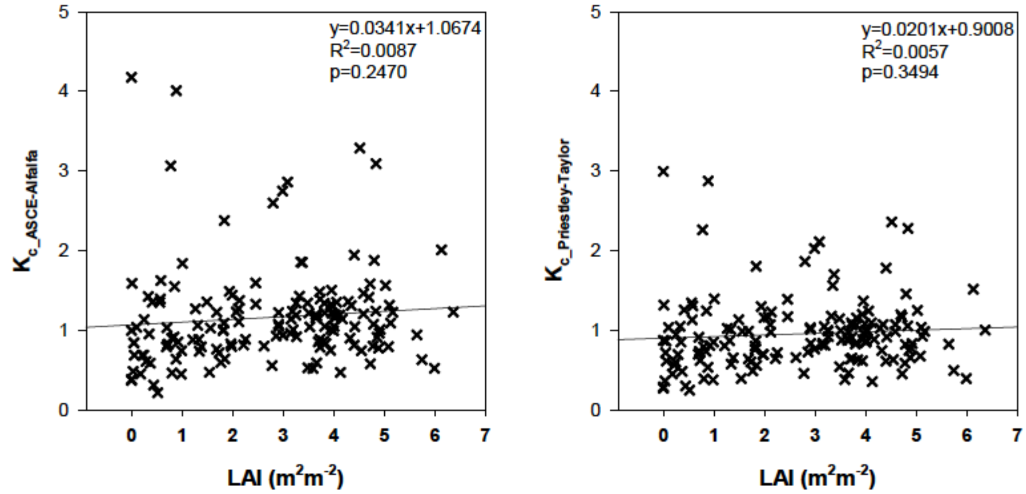

Figure 7. Fitted linear regressions between single crop coefficients ($K_{c\_ASCE\text{-}alfalfa}$ and $K_{c\_Priestley\text{-}Taylor}$) and leaf area index (LAI, m^2m^{-2}) across all cropping systems and all years (2013-2016). Crop coefficients were derived by dividing weekly, point-based lysimetry estimates of actual evapotranspiration (ET) by ASCE alfalfa reference ET or Priestley-Taylor potential ET. Best fit is delineated by solid line.

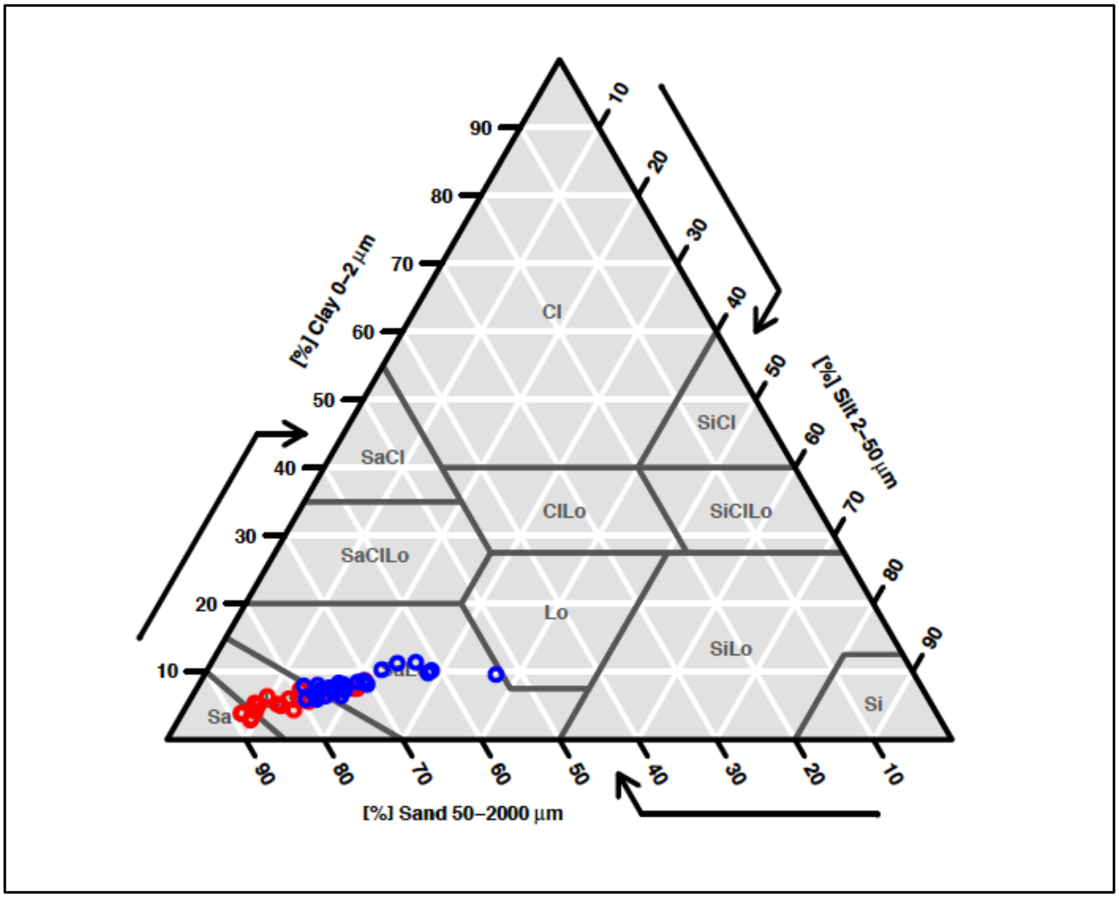

Figure 8. USDA soil textural classification of topsoil (0-0.3 m depth, blue circles) and subsoil (0.45-0.60 m depth, red circles) at each instrumented site.

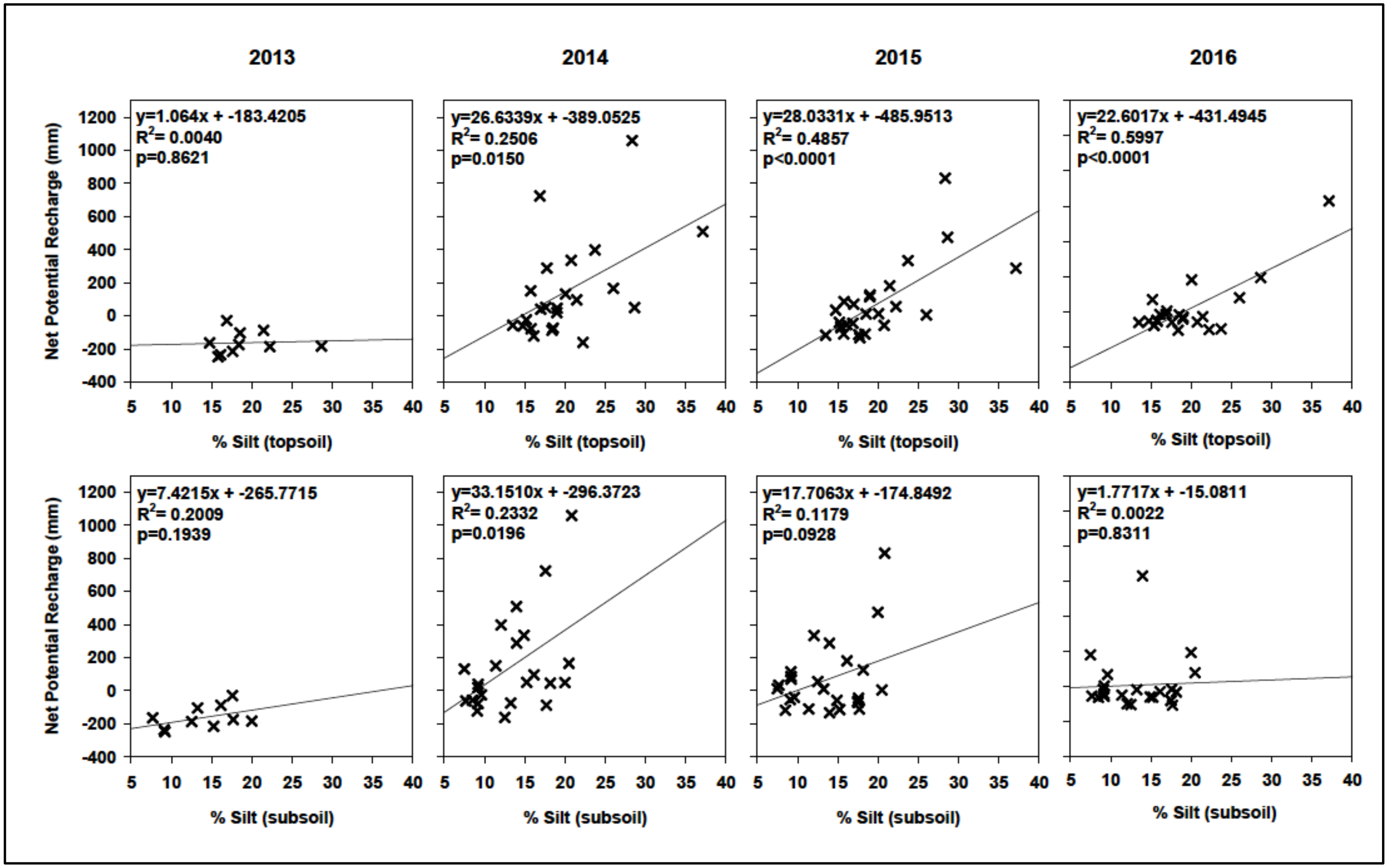

Figure 9. Fitted linear regressions between potential recharge and silt content (0-0.3 m depth, 0.45-0.60 m depths) for summer experimental period. Best fits are delineated by solid lines.

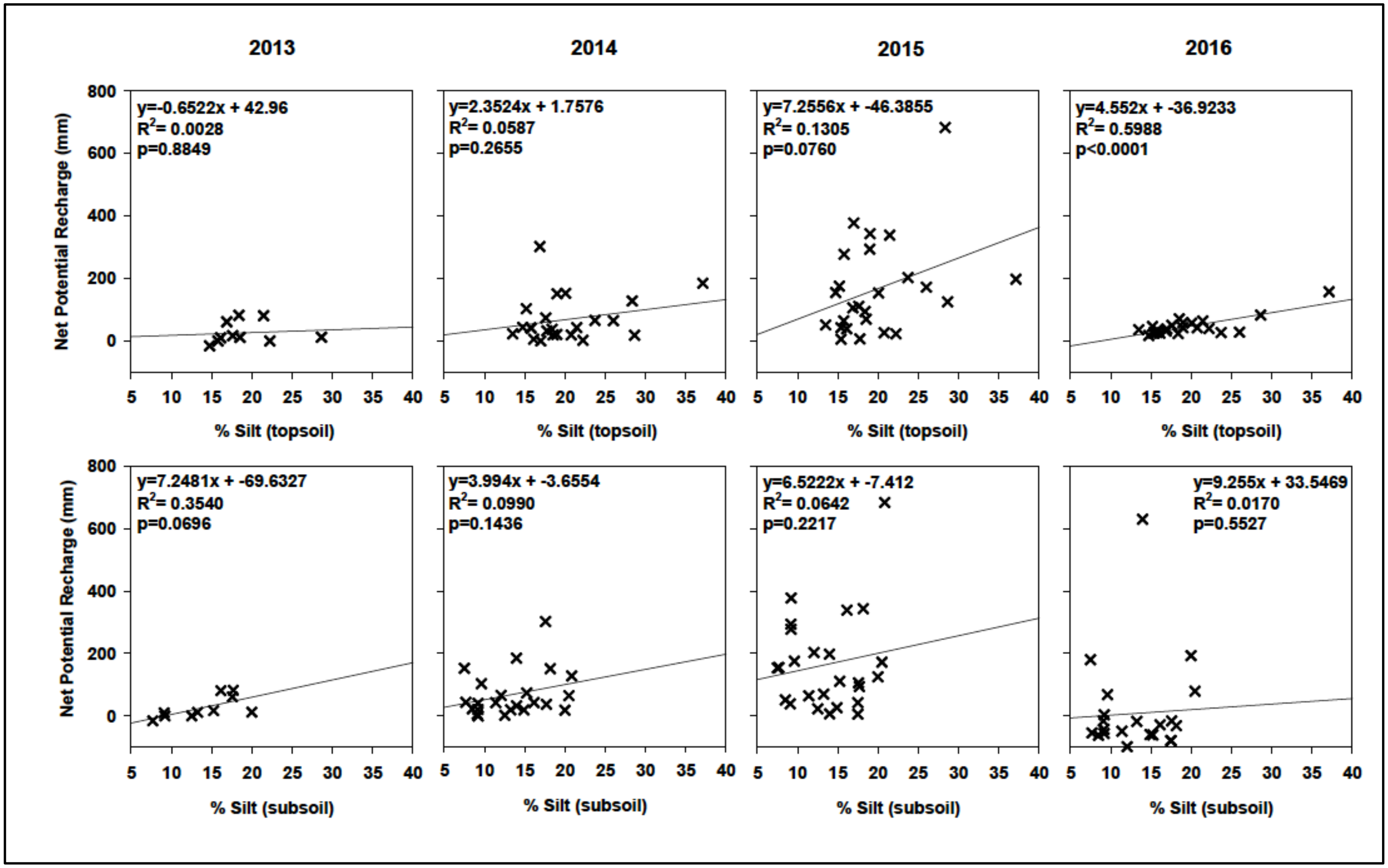

Figure 10. Fitted linear regressions between potential recharge and silt content (0-0.3 m depth, 0.45-0.60 m depths) for fall experimental period. Best fits are delineated by solid lines.

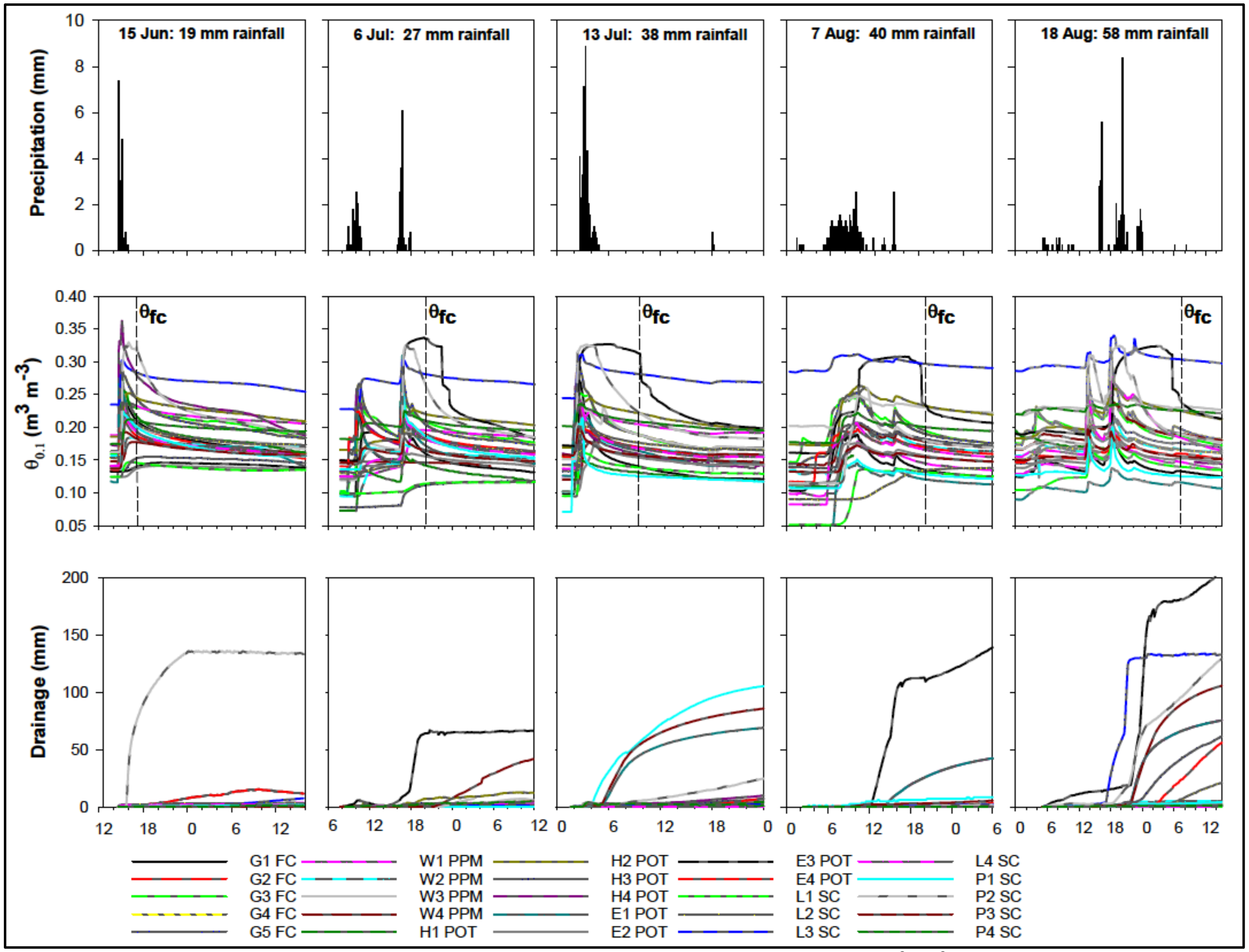

Figure 11. Precipitation (top, mm), soil moisture at 0.1 m (middle, $\theta_{0.1}$, m^3m^{-3}), and drainage (bottom, mm) time series for 5 events between 10 June-2 September 2015 that represented 60% of total summer precipitation. Operational definition of field capacity demarcated by dashed line in $\theta_{0.1}$ time series.

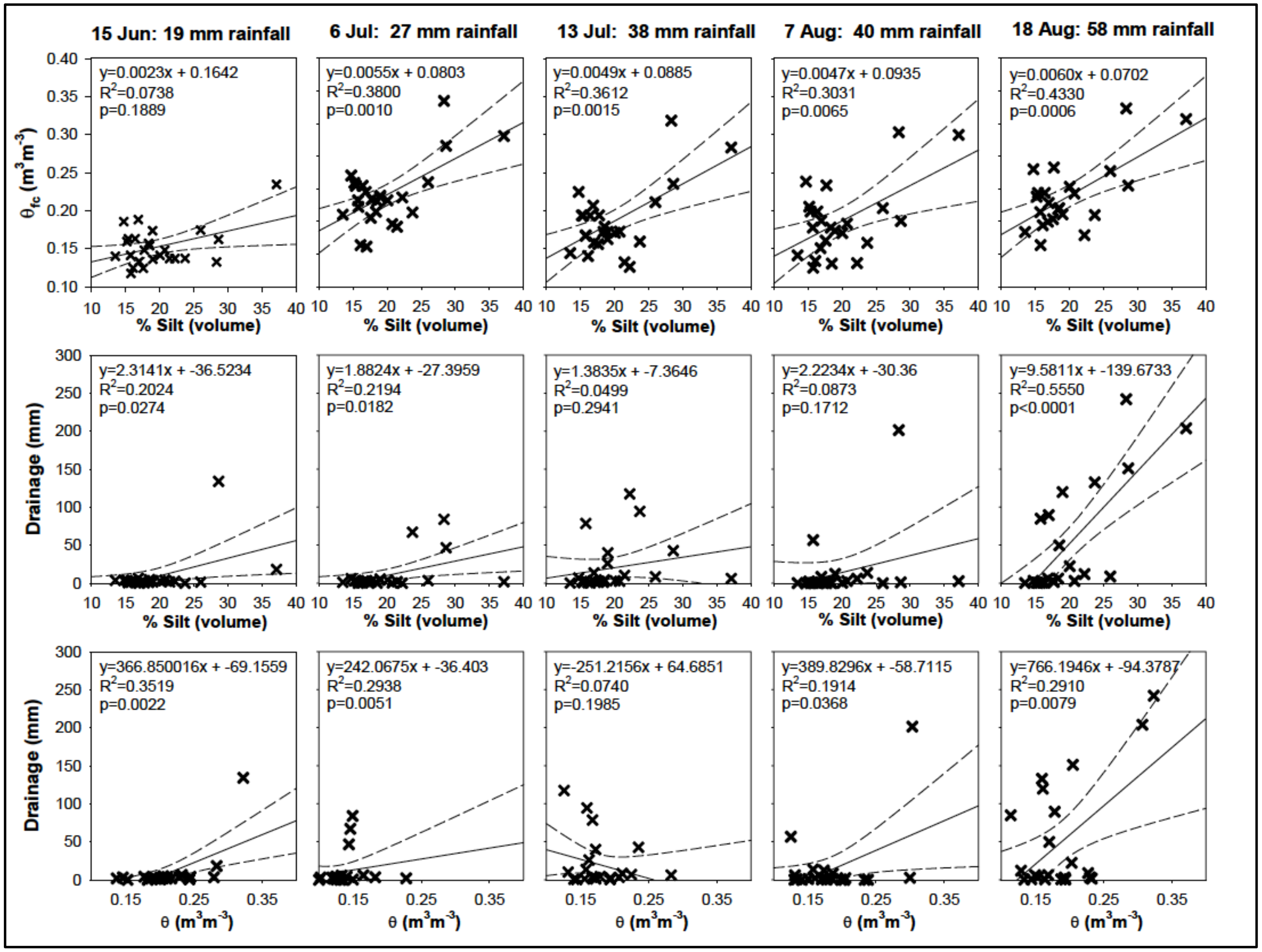

Figure 12. Fitted linear regressions between field capacity at 0.1 m (θ_{fc}, m^3m^{-3}), topsoil silt content (0-0.3 m depth, % volume), and drainage (mm) for 5 events between 10 June-2 September 2015 that represented 60% of total summer precipitation. Best fits are delineated by solid lines.

3.10. Supplementary Information

3.10.1. Lysimetry Theory

Vadose zone lysimetry has been the benchmark that validates all other assessments of recharge because the drainage exiting the root zone can be physically captured by lysimeters (Farahani et al., 2007). The change in soil moisture storage (ΔS) can also be quantified by interpolating soil moisture measurements taken above lysimeters, which consequently allows point-based inference of evapotranspiration (ET) as the remainder of the water budget at each lysimetry site with known precipitation, irrigation (if applicable) and runoff (if applicable). Lysimeters disrupt the soil water potential at the drainage collection depth with an artificially imposed boundary condition and collection reservoir.

Typically, lysimeters are categorized as zero-tension, equilibrium tension, or passive capillary according to their imposed boundary condition. Zero-tension or pan lysimeters only collect drainage when soil water potential is greater than 0 kPa and as a result, tend to underestimate drainage because of flux divergence (Brandi-Dohrn et al., 1996). Equilibrium tension lysimeters have a transient boundary condition that can be automated to match measured adjacent soil water potential, which likely makes them the most accurate lysimeter available to measure drainage in medium to finer-textured soils (Brye et al., 1999; Brye et al., 2000; Masarik et al., 2004). However, tension control using equilibrium tension lysimeters poses challenges at low soil suction, which typically occurs in coarse-textured, irrigated soils (Morari, 2006). Additionally, replication of equilibrium tension lysimeters is often cost-prohibitive and these lysimeters require regular in-field maintenance, which relegates them to agricultural field edges and experimental plots (Brye et al., 1999; Brye et al., 2000; Masarik et al., 2004). Passive capillary lysimeters are typically composed of a soil monolith connected to a fiberglass wick that mimics soil suction by forming a hanging water column and imposing a constant boundary condition at the collection depth (Gee et al., 2002; Gee et al., 2003).

The constant boundary condition associated with passive capillary lysimeters can cause flux convergence or divergence if surrounding soil has significantly higher or lower water potential than the lysimeter and drainage flux is very low. However, at modeled drainage fluxes between 1-10,000 mm, passive capillary lysimeters have 100% collection efficiency in sand-textured soils (Gee et al., 2009). Additionally, a 2.5-year comparison between passive capillary and large-scale weighing lysimeters in sandy soils in Germany found cumulative drainage to have less than 5% variability between lysimeter types with drainage timing and flux rate also being comparable (Gee et al., 2009). These considerations as well as their sturdiness make passive capillary lysimeters ideally suited for collecting drainage from real-world, irrigated cropping systems in the Wisconsin Central Sands, where agricultural water management constrains soil water potential between saturation (0 kPa) and field capacity (-3 to -12 kPa) (Mcguire and Lowery, 1992; Wietersen et al., 1993; Black et al., 1970).

High replicate variability is a known challenge to collecting point-based estimates of drainage using vadose zone lysimetry (Brye et al., 2000). Subtle, intrafield differences in crop growth, soil texture, organic matter content, and elevation all contribute to the variability of ET, soil moisture, infiltration, and runoff; which mechanistically contribute to the variability in drainage at different points on an agricultural field (Moiling et al., 2005; Norman, 2013). In order to better understand these mechanisms, we directly quantified ET for each lysimetry site as the balance of measured precipitation, irrigation, drainage, and ΔS. To our knowledge, this is the first lysimetry study to directly address the spatial variability of drainage in agricultural fields by identifying key biophysical drivers.

Our goal for this study was to collect drainage at or just below the zero-flux plane, which occurs past the effective rooting depth where the vertical hydraulic gradient is zero and all drainage is partitioned to recharge rather than ET (Scanlon et al., 2002; Healy et al., 2010). The effective rooting depths for crops growing in the Wisconsin Central Sands are 0.5 m for potato, 0.6 m sweet corn and peas, and 1.2 m for field corn (Curwen and Massie, 1994), though surface irrigation and root system plasticity often lead to the maximum effective rooting depth for field corn in irrigated systems to be less than 0.8 m (Coelho and Or, 1999; Phene et al., 1991). Above the zero-flux plane, external homogenizing forces such as crop roots, tillage, microbial activity, freezing, and thawing make the assumption of relatively uniform, columnar water flow through a sandy soil matrix reasonable (Kung, 1990a) and a lysimeter may be used to estimate vertical drainage from its corresponding surface area. However, assumptions of uniform vertical flow to lysimeters below the depth of 1.5 m are inappropriate for the Wisconsin Central Sands, as relatively undisturbed genetic interbedded structures have been demonstrated to promote funnel flow in these soils, which laterally transports drainage through exponentially smaller portions of the soil matrix with depth (Kung, 1990a; Kung, 1990b). Therefore, the optimal depth for drainage collection in our experiment is 1.0-1.5 meters below the soil surface, which is where we established our lysimetry network.

3.10.2. Lysimetry Installation

During installation, we used a 0.5 m diameter auger to create 2.2 m deep holes for lysimeters. Stainless steel cores were filled with monoliths collected from the soil at a 0.8-1.4 m depth, at a 6-8 m distance from the installation hole. A thin layer of diatomaceous earth was added to the bottom of the monoliths to facilitate hydraulic connectivity between the fiberglass wick and overlying soil. We took undisturbed soil monoliths using a sledgehammer method for 17 lysimeters where soil structure was strong enough to remain intact during monolith excavation. The remaining 8 soil monoliths on gravelly fields E and W lost 20-100% of their monoliths upon excavation and were repacked with adjacent soil. Soil horizons were separated and backfilled on top of lysimeters to the approximate observed bulk density of surrounding soils.

We allowed the soil around lysimetry systems to settle under cultivation with heavy machinery before collecting experimental drainage measurements. Though it is possible for heavy machinery to operate above lysimeters, all wiring, tubing, and electronics required burial or removal during planting, tillage, and harvest. We used an RTK GPS system (GSR2700ISX, Sokkia Ltd., Tokyo, Japan) to survey the latitude, longitude, and elevation (0.01 m accuracy) of each lysimeter in order to employ the greatest precision and least disturbance when burying, relocating, and excavating equipment around cultivation.

3.10.3. Lysimetry Calibration

Because of known measurement error with submerged differential pressure transducers (Carpenter et al., 2004), we used the manually sampled drainage values to implement a post-hoc calibration on the pressure transducer time series via the calibration equation:

$$t_{cal} = \left[\left(\frac{t_{raw} - t_i}{t_f - t_i}\right) * (p_f - \mathrm{p}_i)\right] + p_i \qquad (1)$$

where t_i, t_f and p_i, p_f are the pressure transducer (*t)* and pumped values (*p)* of the initial (*i*) and final (*f*) points of the calibration time period, respectively; t_{raw} is the uncorrected transducer value between t_i and t_f, and t_{cal} is the resulting calibrated transducer value. We found that calibration was the most necessary for very wet time periods, where lysimeters accurately captured the timing of drainage events, but tended to over or underestimate the magnitude of drainage events.

3.10.4. References

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3.10.5. Supplementary Tables

Supplemental Table 1. Lysimeter Characteristics

Lysimeter	Installation Date	Elevation (m)	Collection depth (m)	Topsoil texture (% sand-silt-clay)	Subsoil texture (% sand-silt-clay)	Topsoil OM (% by weight)	Subsoil OM (% by weight)
H1	Jan 2013	330.41	1.63	70-21-8	77-16-7	2.8	0.7
H2	Apr 2013	330.95	1.65	79-15-6	88-8-4	1.6	1.6
H3	Oct 2013	329.93	1.40	77-17-6	87-9-4	2.4	0.8
H4	Oct 2013	330.31	1.27	75-19-6	88-9-3	2.4	0.8
G1	Oct 2013	330.59	1.14	79-13-8	86-9-5	1.9	0.6
G2	Oct 2013	330.48	1.27	78-16-7	83-11-5	2.1	0.6
G3	Oct 2013	329.46	1.33	77-15-8	84-10-6	2.0	0.8
G4	Apr 2015	330.53	1.57	78-15-7	75-18-8	1.7	0.7
G5	Apr 2015	330.52	1.45	78-15-7	75-18-8	1.7	0.7
P1	Apr 2013	329.20	1.73	67-22-10	2-13-6	1.4	0.8
P2	Apr 2013	328.96	1.37	61-29-10	73-20-8	2.1	0.9
P3	Oct 2013	329.72	1.30	65-24-11	83-12-5	1.5	0.6
P4	Oct 2013	329.64	1.45	63-26-11	72-21-8	2.2	1.0
L1	Apr 2013	330.00	1.65	78-16-6	86-9-5	2.8	1.0
L2	Apr 2013	330.00	1.52	73-19-8	79-13-7	2.7	1.5
L3	Oct 2013	328.87	1.32	53-37-10	82-14-4	8.4	2.0
L4	Oct 2013	329.42	1.35	71-20-8	89-8-4	2.5	0.8
E1	Apr 2013	334.77	1.41	77-16-7	88-9-3	1.2	0.8
E2	Apr 2013	335.60	1.45	75-18-7	79-15-6	1.2	0.4
E3	Oct 2013	334.97	1.42	62-28-10	71-21-9	1.7	0.6
E4	Oct 2013	335.45	1.45	73-19-7	75-18-7	0.9	0.7
W1	Apr 2013	334.71	1.55	76-17-8	76-18-7	1.1	0.5
W2	Apr 2013	334.52	1.45	74-18-7	75-18-8	1.5	1.5
W3	Oct 2013	334.81	1.47	74-18-8	80-14-6	1.4	0.4
W4	Oct 2013	334.83	1.52	71-21-9	79-15-6	1.4	0.5

Supplementary Table 2. Weekly statistical results for summer experiments

Potential Recharge 2013	3 Jun	10 Jun	17 Jun	24 Jun	1 Jul	8 Jul	15 Jul	22 Jul	29 Jul	5 Aug	12 Aug	19 Aug	26 Aug
F-ratio	0.06	0.02	0.13	2.37	0.31	6.99	2.01	13.75	1.75	12.87	15.35	13.88	290.63
p-value	0.8144	0.8893	0.7280	0.1621	0.5903	0.0295*	0.1940	0.0060**	0.2221	0.0071**	0.0044**	0.0058**	<0.001***
Potato	3 (2)	8 (5)	11 (9)	-4 (7)	-26 (6)	-19b (2)	-32 (4)	-22b (2)	-23 (3)	-12a (2)	-20a (2)	-7a (3)	1a (1)
Sweet Corn	2 (2)	9 (6)	6 (11)	12 (8)	-21 (7)	-11a (2)	-23 (5)	-12a (2)	-30 (4)	-25b (3)	-30b (2)	-24b (4)	-22b (1)
Potential Recharge 2014													
F-ratio	0.71	3.69	0.37	0.88	0.30	0.37	0.78	0.39	0.86	1.49	1.05	0.59	2.81
p-value	0.5579	0.0302*	0.7746	0.4672	0.8240	0.7729	0.5173	0.7602	0.4771	0.2480	0.3942	0.6267	0.0673
Field corn	30 (12)	13a (4)	63 (21)	5 (6)	-8 (13)	-11 (6)	-31 (8)	-9 (17)	8 (14)	-10 (6)	49 (22)	33 (10)	77 (15)
Peas-Pearl Millet	45 (17)	-1ab (6)	59 (29)	-11 (9)	-6 (18)	-21 (9)	-23 (11)	-18 (24)	0 (20)	-6 (9)	-15 (31)	10 (15)	7 (22)
Potato	15 (20)	-13b (7)	29 (34)	-8 (10)	-15 (21)	-12 (10)	-28 (12)	-28 (27)	-7 (24)	-27 (10)	20 (35)	23 (17)	36 (25)
Sweet Corn	17 (12)	8a (4)	40 (21)	-2 (6)	5 (13)	-10 (6)	-15 (8)	3 (17)	30 (14)	-2 (6)	39 (22)	21 (10)	28 (15)
Potential Recharge 2015													
F-ratio	-	3.7594	0.7591	16.1293	0.2860	1.8075	1.4234	9.3942	1.0804	4.4103	4.1815	3.8503	11.1323
p-value	-	0.0661	0.5296	<0.001***	0.8349	0.1767	0.2640	<0.001***	0.3789	0.0148*	0.0181*	0.0243*	<0.001***
Field corn	-	3 (12)	4 (3)	1a (2)	-11 (13)	-8 (20)	-4 (15)	-18a (4)	-18 (7)	-5b (14)	-13b (22)	0b (10)	-8c (2)
Peas-Pearl Millet	-	9 (13)	8 (3)	-14b (2)	-13 (15)	-19 (22)	-4 (17)	-38b (4)	-13 (7)	-3ab (15)	-11ab (25)	11ab (11)	5ab (2)
Potato	-	7 (9)	9 (2)	-7b (2)	0 (11)	33 (16)	12 (12)	-22a (3)	-20 (5)	46a (11)	72a (18)	38a (8)	6a (2)
Sweet Corn	-	23 (9)	10 (2)	3a (2)	-1 (11)	26 (16)	31 (12)	-12a (3)	-8 (5)	0b (11)	40ab (18)	31ab (8)	0b (2)

Potential Recharge 2016													
F-ratio	0.8646	3.4473	7.4473	3.0520	4.0245	1.0366	0.8239	0.6398	0.7191	0.9538	1.1228	1.5205	2.0271
p-value	0.4364	0.0517	0.0038**	0.0697	0.0340*	0.3729	0.4531	0.5379	0.4994	0.4021	0.3450	0.2428	0.1579
Field corn	9 (6)	7 (6)	-1ab (3)	-7 (8)	-12b (3)	-10 (5)	-12 (11)	1 (9)	-7 (11)	-6 (4)	-4 (2)	2 (2)	0 (3)
Potato	15 (5)	23 (5)	-11b (3)	9 (6)	0a (3)	-7 (4)	4 (9)	11 (7)	3 (9)	-1 (4)	-2 (2)	7 (2)	7 (3)
Sweet Corn													
AET 2013													
F-ratio	1.0543	2.1786	0.0227	0.9038	2.4109	1.9829	3.4235	0.4956	1.1210	3.3389	2.5148	21.5357	17.5904
p-value	0.3346	0.1835	0.8844	0.3785	0.1591	0.1967	0.1014	0.5014	0.3249	0.1051	0.1514	0.0017**	0.0057**
Potato	26 (3)	30 (4)	38 (8)	33 (6)	40 (5)	44 (4)	48 (5)	35 (4)	27 (5)	24 (5)	28 (3)	14b (3)	12b (3)
Sweet Corn	22 (4)	21 (4)	36 (9)	23 (8)	28 (6)	35 (4)	32 (7)	31 (5)	34 (6)	39 (6)	36 (4)	35a (4)	32a (3)
AET 2014													
F-ratio	0.0211	10.0507	0.4250	16.5525	1.5560	1.5880	2.3662	77.1094	0.1387	2.7901	0.2189	0.1208	2.6920
p-value	0.9956	<0.001***	0.7389	<0.001***	0.2366	0.2271	0.1049	<0.001***	0.9351	0.0742	0.8812	0.9466	0.0862
Field corn	12 (3)	8b (3)	36 (7)	24b (4)	25 (3)	31 (5)	35 (3)	21c (1)	40 (6)	22 (4)	23 (6)	54 (8)	58 (8)
Peas-Pearl Millet	11 (6)	28a (3)	23 (11)	58a (5)	15 (4)	34 (7)	31 (4)	23c (1)	36 (8)	18 (6)	29 (7)	50 (10)	71 (8)
Potato	11 (5)	33a (4)	33 (11)	26b (5)	16 (5)	16 (8)	21 (5)	31b (1)	37 (9)	36 (6)	30 (10)	54 (12)	74 (12)
Sweet Corn	11 (3)	23a (3)	38 (7)	18b (4)	20 (3)	21 (5)	27 (3)	36a (1)	34 (8)	34 (4)	24 (7)	48 (7)	46 (6)
AET 2015													
F-ratio	-	5.1855	0.5829	10.2414	1.5645	7.1710	1.3064	0.5182	3.7608	0.6858	2.8568	0.8778	9.9870
p-value	-	0.0082**	0.6328	0.0003**	0.2326	0.0003**	0.3030	0.6750	0.0295*	0.5730	0.0815	0.4761	0.0003**
Field corn	-	29a (3)	22 (3)	22b (4)	36 (4)	52a (5)	38 (4)	42 (11)	42a (5)	26 (5)	44 (7)	22 (5)	23a (2)
Peas-Pearl Millet	-	25ab (3)	20 (3)	40a (4)	36 (4)	61a (5)	39 (5)	49 (18)	18b (6)	33 (7)	60 (8)	18 (6)	15ab (3)
Potato	-	24ab (2)	24 (2)	15b (3)	31 (3)	43ab (4)	39 (3)	28 (10)	36ab (5)	21 (5)	46 (11)	18 (7)	7b (2)
Sweet Corn	-	16b (2)	21 (2)	16b (3)	27 (3)	31b (4)	30 (4)	36 (9)	39a (5)	25 (4)	29 (7)	11 (5)	10b (2)

AET 2016													
F-ratio	6.5614	0.7589	4.7748	1.3944	4.3271	1.0651	2.9057	0.9688	3.4065	4.1371	1.6516	0.0801	4.0628
p-value	0.0068**	0.4843	0.0209*	0.2749	0.0274*	0.3644	0.0880	0.3975	0.0556	0.0322*	0.2168	0.9233	0.0361*
Field corn	25b (3)	28 (3)	23ab (4)	45 (6)	37a (4)	36 (4)	45 (6)	29 (5)	24 (2)	22ab (3)	22 (3)	22 (3)	16a (2)
Potato	24b (2)	30 (3)	33a (3)	45 (6)	24b (3)	29 (3)	29 (5)	21 (4)	24 (2)	17b (2)	21 (3)	21 (3)	7b (2)
Sweet Corn	38a (3)	24 (3)	14b (6)	31 (7)	24ab (4)	34 (5)	42 (7)	30 (6)	32 (3)	29a (3)	14 (4)	20 (4)	9ab (2)

†Standard error reported in parentheses.
‡Net potential recharge is the difference between drainage and irrigation.
§AET refers to actual evapotranspiration.
¶The letters ‘abc’ following weekly means indicate significant differences between crops where crops with different letters were significantly different according to Tukey’s HSD ($p < 0.05$).

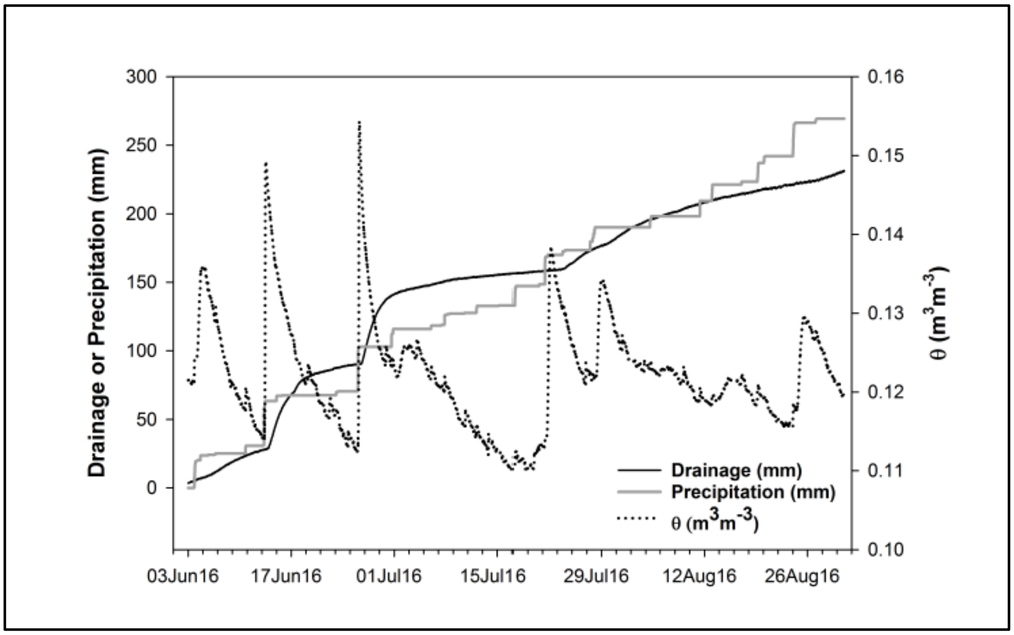
Supplementary Table 3. Linear regression results for summer and fall experiments

Experiment	F-ratio	p-value	R^2	Slope	y-intercept
Summer					
2013 recharge x topsoil sand	0.0638	0.8070	0.0079	-1	-81
2013 recharge x topsoil silt	0.0322	0.8621	0.0040	1	-183
2013 recharge x topsoil clay	0.1872	0.6767	0.0229	7	-218
2013 recharge x subsoil sand	2.6069	0.1451	0.2458	-6	324
2013 recharge x subsoil silt	2.0112	0.1939	0.2009	7	-266
2013 recharge x subsoil clay	3.6375	0.0929	0.3126	23	-304
2014 recharge x topsoil sand	7.0016	0.0151**	0.2500	-22	1709
2014 recharge x topsoil silt	7.0240	0.0150**	0.2506	27	-389
2014 recharge x topsoil clay	3.6162	0.0710	0.1469	71	-433
2014 recharge x subsoil sand	5.3728	0.0306*	0.2037	-23	2039
2014 recharge x subsoil silt	6.3848	0.0196**	0.2332	33	-296
2014 recharge x subsoil clay	2.2380	0.1495	0.0963	58	-186
2015 recharge x topsoil sand	20.5613	<0.001***	0.4720	-23	1695
2015 recharge x topsoil silt	21.7194	<0.001***	0.4857	28	-486
2015 recharge x topsoil clay	7.8752	0.0100*	0.2551	70	-500
2015 recharge x subsoil sand	2.4638	0.1302	0.0968	-12	1034
2015 recharge x subsoil silt	3.0753	0.0928	0.1179	18	-175
2015 recharge x subsoil clay	0.8598	0.3634	0.0360	26	-86
2016 recharge x topsoil sand	21.3985	<0.001***	0.5047	-17	1231
2016 recharge x topsoil silt	31.4563	<0.001***	0.5997	23	-431
2016 recharge x topsoil clay	2.6703	0.1171	0.1128	33	-254
2016 recharge x subsoil sand	0.0030	0.9570	0.0001	0	-19
2016 recharge x subsoil silt	0.0466	0.8311	0.0022	2	-15
2016 recharge x subsoil clay	0.6091	0.4439	0.0282	107	-17
Fall					
2013 recharge x topsoil sand	0.0122	0.9148	0.0015	0	4
2013 recharge x topsoil silt	0.0223	0.8849	0.0028	-1	43
2013 recharge x topsoil clay	0.0001	0.9943	0.0000	0	30
2013 recharge x subsoil sand	4.3771	0.0698	0.3536	-5	461
2013 recharge x subsoil silt	4.3845	0.0696	0.3540	7	-70
2013 recharge x subsoil clay	3.0534	0.1187	0.2762	16	-67
2014 recharge x topsoil sand	1.2182	0.2822	0.0548	-2	183
2014 recharge x topsoil silt	1.3087	0.2655	0.0587	2	2
2014 recharge x topsoil clay	0.4997	0.4874	0.0232	5	7
2014 recharge x subsoil sand	1.8154	0.1922	0.0796	-3	265
2014 recharge x subsoil silt	2.3077	0.1436	0.0990	4	-4
2014 recharge x subsoil clay	0.5451	0.4685	0.0253	5	18
2015 recharge x topsoil sand	2.6380	0.1180	0.1029	-5	476
2015 recharge x topsoil silt	3.4533	0.0760	0.1305	7	-46
2015 recharge x topsoil clay	0.2878	0.5968	0.0124	8	35
2015 recharge x subsoil sand	1.1662	0.2914	0.0483	-4	438

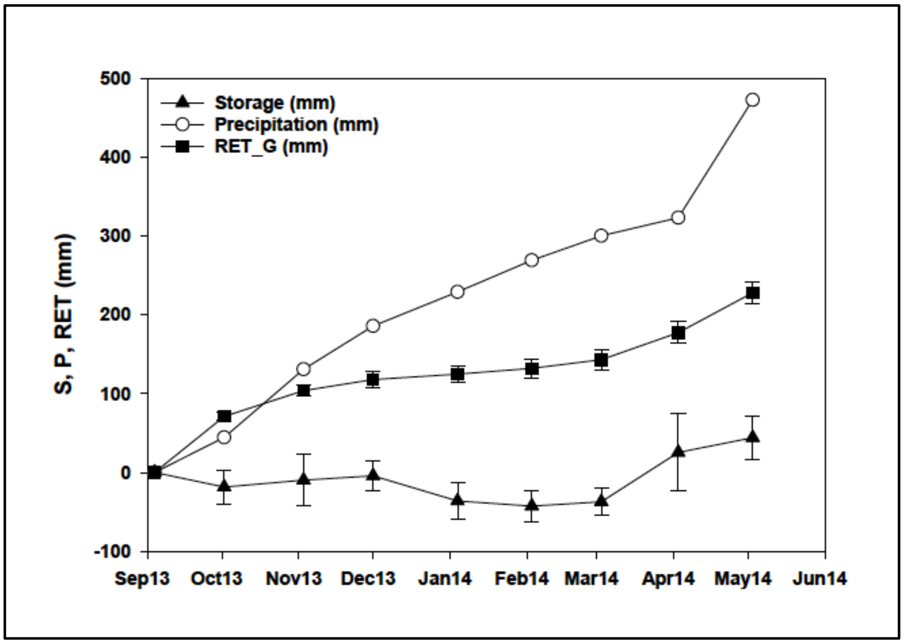
2015 recharge x subsoil silt	1.5781	0.2217	0.0642	7	8
2015 recharge x subsoil clay	0.2575	0.6166	0.0111	7	54
2016 recharge x topsoil sand	21.1068	<0.001***	0.5013	-3	276
2016 recharge x topsoil silt	31.3465	<0.001***	0.5988	4	-37
2016 recharge x topsoil clay	2.5260	0.1269	0.1074	6	-2
2016 recharge x subsoil sand	0.1380	0.7140	0.0065	0	81
2016 recharge x subsoil silt	0.3641	0.5527	0.0170	1	34
2016 recharge x subsoil clay	0.0824	0.7769	0.0039	-1	53

† ‘Recharge’ refers to net potential recharge, calculated as the difference between drainage and irrigation.
‡ ‘Topsoil’ refers to 0-30 cm depth, ‘subsoil’ refers to 45-60 cm depth.

3.10.6. Supplementary Figures



Supplemental Figure 1. Drainage at 1.4 m (mm), precipitation (mm), and volumetric water content at 0.8 m (θ, m^3m^{-3}) for lysimeter L4 during the 2016 growing season.



Supplemental Figure 2. Cumulative soil moisture storage (S, mm), reference evapotranspiration for a grass surface (RET_G, mm), and precipitation (P, mm) averaged for six lysimeters between September 2013 and May 2014.

Chapter 4

Combining high-resolution proximal and remote sensing of soil properties and evapotranspiration to assess the need for precision irrigation interventions

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Abstract

The growth of irrigated agriculture and decline of surface waters in sandy regions throughout the northern Great Lake states of Wisconsin, Minnesota, and Michigan has led to groundwater management and policy challenges. The Wisconsin Central Sands (WCS) is region in the northern Great Lakes where increasing irrigation has severely stressed headwater streams, lakes, and wetlands. We investigated whether WCS agroecosystems could benefit from future precision intervention by comparing high-resolution maps of apparent electrical conductivity (EC_a) and evapotranspiration (ET), and complementary ground observations to assess intrafield variability in crop water availability and use. Our research goals were to (1) assess the relationships between EC_a and soil properties in the WCS; (2) use aerial imagery, ground observations, and the High-Resolution Mapping of EvapoTranspiration (HRMET) model to create high-resolution ET maps for WCS crop rotations; and (3) identify persistent differences in ET, EC_a, and soil properties that would support precision irrigation interventions across different crop rotations. Our findings suggest that proximal sensing of EC_a is a promising

approach for identifying intrafield soil variability throughout the WCS, despite extremely narrow observed EC_a ranges (0-11 mS m^{-1}). We also demonstrated the synergy of a combined high-resolution EC_a and ET mapping approach for quantifying variability in soil properties and water use over different crop rotations. By quantifying intrafield relationships between EC_a, soil properties, and ET, we found that all crop rotations in the WCS may not respond to greater spatiotemporal control of irrigation. Moreover, we found that current intuitive irrigation practices can amplify or diminish variability in crop water use, despite observable differences in intrafield soil variability. We recommend that future research consider intrafield soil variability, crop rotations, and current intuitive irrigation practices when quantifying water savings and yield potential from precision irrigation in the WCS and similar agroecosystems.

4.1 Introduction

The northern Great Lakes states of Wisconsin, Michigan, and Minnesota are known for having a humid climate and relatively abundant groundwater supply. Coarse-grained, glacial aquifers throughout these states support coldwater trout streams, lakes, wetlands, and rapidly expanding irrigated agriculture (Kraft et al., 2012; Watson et al., 2014). The Wisconsin Central Sands (WCS, Fig. 1a) is an example of a relatively small (6400 km^2) ecological region in the northern Great Lakes where the sandy soils and groundwater supply have facilitated intense agricultural productivity that helps make Wisconsin the fourth leading producer of fresh market and processing vegetables (e.g. potatoes, sweet corn, peas) behind California, Idaho, and Washington (United States

Department of Agriculture, 2014). Groundwater is strongly connected to the 1000 km of headwater streams, 80 lakes, and abundant wetlands in the WCS, where freshwater conservation, surface water health, and agricultural sustainability are priorities for ecological, agricultural, and regulatory stakeholders (Wisconsin Department of Natural Resources, 2015). Recent optimization modeling in the WCS has demonstrated that reducing both the frequency and magnitude of pumping could diminish adverse impacts on adjacent surface waters (Bradbury et al., 2017). Precision irrigation is a precision agricultural practice that applies different depths of water to different zones within a field in order to optimize the spatiotemporal application of water, and has been recommended as a strategy for the conservation of groundwater quantity and quality (Sadler et al., 2005; Delgado et al., 2005). However, to address fundamentally different conservation challenges in humid, sandy regions, precision irrigation strategies must quickly adapt to unpredictable precipitation patterns, limit nitrogen leaching, and reduce the magnitude and frequency of groundwater pumped for irrigation (Daccache et al., 2015).

To be most effective, precision irrigation operators need information about spatial heterogeneity in soil water retention properties and plant water use. Current precision irrigation strategies use some combination of proximal and remotely sensed measurements to create subfield-scale maps of soil texture, soil hydrologic properties such as total plant available water content (θ_{awc}), phenology, and evapotranspiration (ET) (Mulla, 2013). Growers use maps, meteorological data, and ground observations for decision support in scheduling and applying irrigation at the subfield scale (~100 m^2) (Liakos et al., 2015). High-resolution (<30 m) maps of soil properties can be created using georeferenced apparent electrical conductivity (EC_a) data from electromagnetic surveys, guided soil sampling, and geostatistical interpolation (Hedley et al., 2013; Padhi and Misra, 2011).

Previous work has shown that proximally sensed, high-resolution maps of EC_a strongly correlate to particle size distribution and soil properties at the subfield scale and this technique is widely used for precision irrigation applications (Rezaei et al., 2016; Haghverdi et al., 2015; Sudduth et al., 2005; Hedley and Yule, 2009a; Hedley and Yule 2009b; Gooley et al., 2014). Though many studies have assessed relationships between EC_a and soil properties, these relationships are site-specific and local calibration is required to build accurate maps of soil properties using EC_a (Misra and Padhi, 2014). For example, the relationships between EC_a and different soil hydrologic properties have been characterized as linear (Hedley and Yule, 2009a; Gooley et al., 2014) or nonlinear (Daccache et al., 2015; Misra and Padhi, 2014) in different agroecosystems. Though growers in the WCS are experimenting with high-resolution EC_a mapping as a surrogate for soil properties, there have been no studies to date validating the relationships between EC_a and soil properties in the irrigated, sandy agroecosystems of the northern Great Lake states, where there is usually minimal intrafield variability in soil texture. Moreover, to the best of our knowledge, there have been no studies in agroecosystems that compare EC_a–derived maps of soil properties to high-resolution maps of ET derived from aerial imagery.

Remotely sensed, high-resolution maps of ET can be created using satellite or aircraft imagery from multiple wavelength bands to estimate canopy surface temperature and reflectance-based vegetation indices (Zipper and Loheide, 2014; Semmens et al., 2016; Kustas et al., 2016). Canopy surface temperature, aerodynamic temperature, and remotely sensed vegetation indices form the basis for several energy balance models that either explicitly represent vegetation and soil as two sources within a pixel (Norman et al., 1995; Kustas and Norman, 2000; Yang and Shang, 2013) or combine vegetation and soil together as a single source within a pixel (Bastiaanssen et al., 1998; Feng and Wang, 2013). The majority of these remotely sensed ET models require the designation of 'hot/dry' vs. 'cold/wet' pixels to indicate the minimum and maximum limits of ET within an image and facilitate contextual scaling of ET values between these limits (Norman et al., 1995; Bastiaanssen et al., 1998; Allen et al., 2007; Timmermans et al., 2015). Though the contextual scaling approach requires less input data and processing (Kustas et al., 2016) and can reduce uncertainty in ET estimates arising from meteorological inputs (Davis et al., 2007), it has unique drawbacks for precision agricultural applications where fields are relatively homogenous and endmember pixels are challenging to identify (Zipper and Loheide, 2014). Moreover, in irrigated, high-value cropping systems such as the WCS, agricultural fields are maintained to minimize water stress; which makes it especially challenging to identify 'hot/dry' pixels in the relatively small image domain (<1 km^2) needed to capture high-resolution data. To meet the unique challenges of mapping ET for the irrigated agroecosystems in this study, we use and further validate the High-Resolution Mapping of EvapoTranspiration (HRMET) model (Zipper and Loheide, 2014) to estimate ET using high-resolution (< 3 m) airborne imagery and local meteorological forcing.

The comparison of high-resolution maps of ET, a dynamic indicator of crop water use, and relatively static soil properties such as θ_{awc} may expose potential benefits and drawbacks to implementing precision irrigation in sandy, rotational agroecosystems. Transpiration is a physiological indicator of crop growth and yield, as it is links the carbon and water cycles (Campbell and Norman, 1998). Additionally, differences in transpiration drive the spatial variability of water availability within a cropping system, generating “hot spots” or opportunities for precision irrigation intervention (Zipper and Loheide, 2014; Semmens et al., 2016). Crops that are consistently under or over irrigated may exhibit low transpiration, which can be a physiological indicator of water or oxygen limitations (Feddes et al., 2001). Persistent differences in the magnitude and variability of ET within a cropping system can indicate differences in soil texture that are likely to coincide with EC_a-based maps of soil properties and potentially impact agricultural productivity (Zipper and Loheide, 2014; Zipper et al., 2015). However, the relationships between soil properties and ET may change with different crop rotations because of differences in canopy structure, root distributions, and physiology. As such, there may be differences in the amount of “precision” required to optimize water use in potato, sweet corn, field corn, and pea cropping systems in the WCS.

This study investigates whether traditionally irrigated crop rotations could benefit from future precision irrigation intervention by comparing high-resolution proximally sensed EC_a maps, remotely sensed ET maps, and complementary edaphic, phenological, and physiological observations to assess intrafield variability in crop water availability and use. Our research goals were to (1) assess the relationships between EC_a and soil properties describing particle size and hydrologic properties in the WCS; (2) Use aerial imagery, onsite meteorological data, ground observations, and the HRMET model to create high-resolution maps of ET for key WCS crop rotations (potatoes, sweet corn, field corn, peas); and (3) Identify persistent intrafield differences in the magnitude and variability of ET, EC_a, and soil properties that would indicate the need for precision irrigation intervention within and across different crop rotations.

4.2. Approach

4.2.1. Site description

We mapped EC_a and ET, and collected complementary ground observations from six commercial vegetable fields (H, G, P, L, E, W) in the WCS that each had an average planted area of 23 ha for the 2014-2016 growing seasons. We partnered with Isherwood Farms, a 600-ha, sixth-generation family farm growing irrigated potatoes, sweet corn, field corn, and peas in the WCS (Fig. 1). Isherwood Farms, like the majority of farms in the WCS, schedules irrigation events intuitively based on weather monitoring, soil conditions, and crop observations. In these agroecosystems, irrigation typically commences at the end of June and supplements rainfall in 6-15 mm events every 2-3 days. All six fields are relatively flat and well drained, with sand, loamy sand, and sandy loam textures classified as either the Richford (loamy, mixed, superactive, mesic Arenic Hapludalfs) or Rosholt (coarse-loamy, mixed, superactive, frigid, Haplic Glossudalfs) series (Otter and Fiala, 1976). Agronomic information for each crop, field, and growing season are presented in Table 1.

4.2.2 EC_a surveys and soil analyses

In order to investigate emerging local EC_a survey practices, we worked with a WCS-based precision agricultural consulting firm to conduct EC_a surveys (Precision Waterworks LLC, Plainfield, WI, USA). We collected shallow (EC_{a_sh}, integrated over 0-0.3 m) and deep (EC_{a_dp}, integrated over 0-0.9 m) EC_a measurements using the Veris Soil EC 3100 (Veris Technologies, Salina, KS, USA) in 18-m wide transects covering each of the six fields. EC_a surveys were collected prior to cultivation when soil moisture was at or near field capacity in April 2015 for fields P, L, E, and W and in April 2016 for fields H and G. EC_a data were collected in conjunction with a Real Time Kinematic Global Positioning System (RTK-GPS) operating at submeter accuracy (Trimble Geoexplorer 6000, Trimble Inc., Sunnyvale, CA, USA). We interpolated EC_a point data to a 2-m grid using an ordinary kriging method and spherical variogram models (Daccache et al., 2015; Hedley and Yule, 2013) in ArcMap 10 (ESRI, 2010).

We used a zone-based soil sampling approach based on 3-4 EC_a classes per field (Peralta et al., 2013). Zones were designated using the EC_{a_dp} data and the standard deviations classification method that is being widely used in the WCS, where EC_a classes were created with equal value ranges occurring at intervals of one standard deviation from the mean (Precision Cropping Technologies Ltd., Narrabri, Australia). We used the EC_{a_dp} data for zone delineation, as it has been demonstrated to remain relatively stable over time compared to EC_{a_sh} data (Sudduth et al., 2003). We collected and analyzed three soil cores at 0-0.30 (topsoil) and 0.45-0.60 m (subsoil) depths at three sites per zone (EC_a subzones, Fig. 2). EC_a subzones were chosen to maximize topographic variability within a zone. Topsoil depth differed both within and between fields, and the two soil sampling depths were chosen to ensure that the topsoil sample would be in the A horizon and the subsoil sample would be in the B horizon across all six fields. Samples were dried at 105°C, sieved through 2 mm diameter mesh, and soil organic matter (SOM) content by % weight was determined using the loss on ignition method (Heiri et al., 2001). We used laser light diffraction (Coulter LS230, Beckman Coulter, Inc., Brea, California, USA) and the optical model of Arriaga et al., (2006) to determine particle size distributions and classified mean sand/silt/clay content (% volume) using the United States Department of Agriculture (USDA) particle size classification system. Sand content (% volume), clay content (% volume), and SOM (% weight) were used as inputs to the hydrologic pedotransfer functions of Saxton and Rawls (2006) to determine field capacity at -33 kPa (θ_{fc}), permanent wilting point at -1500 kPa (θ_{pwp}), and θ_{awc} (θ_{fc} -θ_{pwp}). Additionally, θ_{fc} and θ_{pwp} estimates were operationally validated using soil moisture observations in a companion study (Nocco et al., 2017).

We examined the strength and direction of intrafield relationships between EC_{a_sh}, EC_{a_dp}, soil textural and hydrologic properties, and ET using Kendall's tau correlation coefficient matrices (22-23 variables per matrix per field). Soil properties (%sand/silt/clay, θ_{fc}, θ_{pwp}, θ_{awc}, and SOM with the subscript 'top' or 'sub' for topsoil or subsoil) as well as "relative ET" estimates (see section 2.6) were extracted for each of the three samples taken at each EC_a subzone within a field (n=36-42 per field). The Kendall's tau coefficient is a nonparametric measure of correlation for ordinal, continuous data assuming a monotonic relationship. Tau values range from -1 to 1, where -1 is a perfect negative relationship, 0 indicates no relationship, and 1 is a perfect positive relationship. Statistical significance was assessed at an alpha level of 0.05 for all correlations. We assumed that the relationship between ET and soil properties would be monotonic in sandy soils, where ET limitation due to anoxic conditions is rare. We used linear regression models to spatially predict θ_{awc_top} in ArcMap 10 (ESRI, 2010). In order to assess intrafield variability in θ_{awc}, we created normalized maps of relative θ_{awc_top} (θ_{awc-R}). To calculate θ_{awc-R}, we linearly normalized mean θ_{awc} rates to the 5th and 95th percentile for each θ_{awc_top} map using the Percent Clip stretch type in ArcMap 10 (ESRI, 2010).

4.2.3. Airborne missions and data processing

Twelve airborne missions were conducted during the core of the growing season in 2014-2016 (4 per June-August) to capture high-resolution remotely sensed data during different crop rotations, phenological stages, and meteorological conditions. We acquired thermal and multispectral imagery over six fields from equipment mounted on the underside of a single engine 3-passenger Cessna aircraft. Though all attempts were made to have airborne missions coincide with cloud-free days, some images were discarded or cut off because of cloud interference. The thermal imagery was captured using a FLIR A320 thermal infrared imaging camera at a pixel size of 1-2 m (FLIR Systems, Wilsonville, OR, USA). We performed atmospheric corrections using ThermaCAM Researcher Pro 2.7 software (FLIR systems, 2003), georeferenced the data to NAIP imagery (National Agricultural Imaging Program, 2013), and mosaicked images using

ArcMap 10 (ESRI, 2010). We estimated the mean and standard deviation of surface temperature data using a 25-pixel moving window approach (Zipper and Loheide, 2014).

We collected multispectral images using a 6-sensor Tetracam Multi Camera Array (MCA) system (Tetracam Inc., Chatsworth, CA, USA) at a pixel size of 0.6-0.8 m with multiband sensors centered at 450, 570, 620, 650, 670, and 860 nm. Multispectral images were coregistered using Pixelwrench (Tetracam, 2001) and georeferenced to Portage County NAIP imagery (National Agricultural Imaging Program, 2013). We converted digital numbers captured by the MCA system to surface reflectance values using the control points method described by Kang et al., (2016). In brief, we chose 3-5 stable control points (e.g. healthy green grass, concrete parking area) present in each image and collected ten spectral reflectance measurements at 1 nm resolution from each point using an ASD handheld spectrometer (Analytical Spectral Devices, Inc., Boulder, CO, USA). We averaged spectral reflectance measurements at 10 nm intervals matching each MCA band in order to build linear relationships between digital numbers and surface reflectance values at each control point, which we used to convert digital numbers to surface reflectance values. All digital number-surface reflectance fits had R^2 values >0.71. We computed the Enhanced Vegetation Index (EVI; Huete et al., 1999; Boegh et al., 2002) for each image using surface reflectance data and spatially aggregated images to 5 m resolution to ensure that both plants and soil would be present in each pixel to represent the canopy scale of phenological indices (Kustas et al., 2016). Overpass time, image collection height, and meteorological conditions for each airborne mission are detailed in Table 2 and Fig. 3.

4.2.4. Crop phenology

We collected weekly measurements of leaf area index (LAI, m^2 m^{-2}) during the growing seasons of 2014-2016 using a LI-COR LAI-2200 plant canopy analyzer (LI-COR Inc., Lincoln, NE, USA). LAI measurements were collected under diffuse light conditions (e.g. sunrise or sunset) or clear skies. Scattering effects were removed for clear sky measurements using a bidirectional model (Kobayashi et al., 2013) embedded in post-processing software (FV2200 2.0, LI-COR Inc., Lincoln, NE). During the 2014 growing season, LAI measurements were collected along a random transect of 10 locations (10 measurements/location) across each field. During 2015-2016, weekly LAI measurements were collected within a 5-m radius of each EC_a subzone (10 sampling points per subzone) demarcated in Fig. 2. Canopy height (*h)* measurements were taken on a weekly basis along a random transect of 10 points for each field in 2014. In 2015 and 2016, *h* was measured within 3-4 days of each airborne mission at each EC_a subzone. Thus, LAI and height measurements in 2014 were average estimates for each field, while 2015-2016 measurements were spatially explicit by EC_a subzone. We used smoothing splines in the Matlab Curve Fitting Toolbox (Matlab, 2015b) to interpolate LAI and *h* values to the date of each airborne mission.

Vegetation indices such as EVI have often been used to predict LAI and *h* for energy balance modeling using empirical relationships developed from ground-based measurements of phenology (Baret et al., 1991; Anderson et al., 2004). The relationships between EVI, LAI, and *h* in cropping systems are often best represented by different simple functional forms including linear, power, and exponential fits with two or three coefficients (Kang et al., 2016). We compiled all 2015-2016 spatially explicit LAI, *h*, and EVI values for each EC_a subzone to generate models to predict LAI and *h* from EVI for field corn, sweet corn, potato, peas, and pearl millet (mid-season cover crop following peas, Table 1). The data were fit using a nonlinear least squares regression approach with six possible functional forms (linear, power, and exponential with two or three coefficients). We chose the best functional form for each crop model of LAI or *h* based on minimizing RMSE values. We used the permutation-based approach of Zipper and Loheide (2014) to estimate uncertainty in crop models of LAI and *h* for each remotely sensed image. We executed 50 permutations of LAI or h models for each crop data set, each time eliminating 5 random data points, fitting the remaining data, and using the eliminated points to determine the model fit; thereby generating 50 fitted LAI and *h* models for each crop. We then used the 50 different sets of model coefficients to fit LAI and *h* at each EVI pixel, generating mean and standard deviations of LAI and *h* for each image.

4.2.5. Micrometeorology

Three micrometeorological weather stations were installed (MET, Fig. 1) adjacent to fields in 2013 according to the World Meteorological Organization guide for agrometeorological observations from fixed stations (Murthy et al., 2010). Instruments measuring precipitation (S-RGA-M0002; Onset Computer Corp., Bourne, MA, USA), temperature and relative humidity (S-THB-M002; Onset Computer Corp., Bourne, MA, USA), wind speed (S-WSB-M003; Onset Computer Corp., Bourne, MA, USA), and solar radiation (silicon pyranometer, S-LIB-M003; Onset Computer Corp., Bourne, MA, USA) were mounted on 2-m tripods over grass surfaces (M-TPB-KIT; Onset Computer Corp., Bourne, MA, USA). Measurements were collected every 10 min and recorded using a HOBO (Onset Computer Corp., Bourne, MA, USA) micro station data logger. Isherwood Farms provided irrigation records, which were validated using soil moisture measurements (Nocco et al., 2017) and three additional rain gauges. Two meteorological stations malfunctioned during the 2015 field season, so all 2015 values are derived from the station between fields 'L' and 'P'. For airborne missions where the field or sweet corn canopy height exceeded 2 m, we used meteorological data from a 7.6 m high NWS station 4 km from the field site to run HRMET over the fields with crops > 2 m. Wind speed measurements must be taken above canopy height when using HRMET, as sensible heat flux is calculated based on the gradient between surface canopy temperature and the air temperature above the canopy. The heights of wind speed measurements are standardized and adjusted using logarithmic profiles in the calculation of the friction velocity and aerodynamic resistance.

We estimated uncertainty in meteorological inputs using data collected from all stations 30 minutes before and after the mean image collection time (6-7 data points/station) for each airborne mission. We estimated reference ET (RET) at the hourly scale for each airborne mission using micrometeorological data and ASCE standardized equations for a uniform grass crop (Allen et al., 1998; Walter et al., 2000). RET is an index of evaporative demand that incorporates key biophysical drivers to estimate ET from a hypothetical well-watered, uniform grass at a 0.12 m height with a surface resistance of 70 s m^{-1} (Walter et al., 2000).

4.2.6. HRMET model overview, inputs, and uncertainty analyses

HRMET is a one-dimensional (vertical), process-based energy balance model that uses vegetation structure, land surface temperature, and meteorological data to estimate latent heat flux as the residual of the energy balance, which can then be converted to ET (Zipper and Loheide, 2014). HRMET uses a two-source algorithm to estimate available energy for vegetation and soil and a single-source iterative calculation of sensible heat flux at a pixel, which eliminates the need for contextual scaling using 'hot/dry' or 'cold/wet' pixels and makes HRMET well suited for precision agricultural applications. For more information about the theory and structure of HRMET, please refer to Zipper and Loheide (2014). HRMET is an open-source model and code is available at https://github.com/szipper/HRMET.git.

Here, we apply HRMET in a gridded manner over our domain using local meteorological data (section 2.5) and remotely sensed maps of LAI and *h* (section 2.4) and canopy surface temperature (section 2.4) as inputs. We use a spatial resolution of 2 m in order to match the resolution of the canopy surface temperature data. The micrometeorological inputs (derived from micrometeorological stations) required for HRMET include air temperature (°C), wind speed (m s^{-1}), air vapor pressure (kPa), and atmospheric pressure (kPa). Finally, HRMET requires emissivity and albedo values for both vegetation and soil to calculate the energy balance. We used emissivity values of 0.94 and 0.95 for vegetation and soil; assuming a standard deviation of 0.01 because there is a small range in emissivity for these surfaces (Campbell and Norman, 1998). We used albedo values of 0.20 and 0.11 for vegetation and sandy soils; assuming a standard deviation of 0.05 (Campbell and Norman, 1998).

We assessed the influence of error from all model inputs on ET estimates using a Monte Carlo uncertainty approach (Serbin et al., 2014; Zipper and Loheide, 2014). The mean and standard deviation of all spatial, meteorological, and empirical inputs were used to create an ensemble of input data based on the standard normal distribution. We then solved HRMET 300 times at each pixel with a randomly selected group of inputs for each permutation of HRMET. We conducted a power analysis with field 'P' (the smallest field with the shortest model run time) to determine that 300 permutations were required to ensure stability. The 300 ET estimates were used to calculate the final mean and standard deviation of ET for each pixel. Because it is currently unfeasible to collect and process daily, high-resolution maps of ET in the near real-time frame required for irrigation decision support (Anderson et al., 2012), we use the relative ET index (ET_R; Zipper and Loheide, 2014) to examine intrafield variability in ET over different growing seasons and crop rotations. To calculate ET_R, we linearly normalized final mean ET rates to the 5th and 95th percentile for each mosaicked set of images for a single field on a given measurement date. Thus, an ET_R value of 1 indicates the maximum ET rates within an image, while an ET_R value of 0 indicates minimum ET rates within an image. We assessed intrafield relationships between ET and soil properties by extracting estimates of ET_R for each EC_a subzone (Fig. 2). In order to identify persistent patterns between ET_R and soil properties, ET_R values were averaged across all missions, by crop rotation, and by month, and included in coefficient correlation analyses (section 2.2).

4.2.7. Shuttleworth-Wallace validation

We validated HRMET estimates of instantaneous ET for potato, sweet corn, and peas-pearl millet cropping systems with the Shuttleworth-Wallace model, which uses a dual-source approach that is ideal for both sparse and full canopy conditions (Shuttleworth and Wallace, 1985). HRMET does not require calibration and has already been validated in field corn using the Shuttleworth-Wallace approach (Zipper and Loheide, 2014), so we did not perform validation in field corn. In addition to the phenological and meteorological inputs also required for HRMET, the Shuttleworth-Wallace model requires soil and canopy surface resistance inputs to estimate instantaneous ET (mm hr^{-1}). We collected phenological, physiological, and meteorological inputs during or immediately after airborne missions in 2015-2016. We started surface resistance input data collection an hour before each mission and ended an hour afterwards. We collected 7-10 measurements of stomatal conductance (SC-1 Leaf Porometer, Decagon Devices, Inc., Pullman, WA, USA) and 20 measurements of surface soil moisture (Thetaprobe ML2x, Delta-T Devices, Cambridge, UK) at 2-5 EC_a subzones in potato, sweet corn, or peas-pearl millet agroecosystems to use as surface resistance inputs to the Shuttleworth-Wallace model. These measurements provided us with 2-5 validation points for each of the 8 airborne missions in 2015-2016. Any Shuttleworth-Wallace points that did not have a complementary HRMET estimate (due to clouds) were eliminated from the validation, leaving 26 total validation points.

4.3. Results

4.3.1. EC_a, particle size, and soil hydrologic properties

All six fields had statistically significant ($p < 0.05$) correlations between EC_{a_sh} and all topsoil properties including %$sand_{\_top}$/$silt_{\_top}$/$clay_{\_top}$, $SOM_{\_top}$, θ_{fc_top}, θ_{pwp_top}, and θ_{awc_top} (Figs. 4-9). Though the strength of topsoil associations differed across fields, the direction of these associations was the same, where EC_{a_sh} was positively associated with $silt_{\_top}$, $clay_{\_top}$, $SOM_{\_top}$, θ_{fc_top}, θ_{pwp_top}, and θ_{awc_top}, and negatively associated with $sand_{\_top}$. All six fields also had a significant ($p < 0.001$) positive correlation between EC_{a_sh} and EC_{a_dp}, however only field H had significant ($p < 0.05$) positive correlations between all complementary topsoil and subsoil properties—$sand_{\_top}$ vs. $sand_{\_sub}$, $silt_{\_top}$ vs. $silt_{\_sub}$, etc. (Figs. 4-9). Consequently, the relationships between EC_{a_dp} and soil properties differed across the six fields. On field H (Fig. 4), EC_{a_dp} was not correlated to subsoil properties, but was weakly correlated ($p < 0.05$) to all topsoil properties except $clay_{\_top}$. On field G (Fig. 5), EC_{a_dp} was not correlated to subsoil properties, but was strongly correlated ($p < 0.001$) to topsoil properties except $clay_{\_top}$. Field P (Fig. 6) had similar correlations ($p < 0.05$) between EC_{a_dp}, subsoil, and topsoil properties. On field L (Fig. 7), EC_{a_dp} had no significant correlation to subsoil properties, but was significantly correlated ($p < 0.01$) to topsoil properties. Field E (Fig. 8) had weak or insignificant relationships between EC_{a_dp} and subsoil properties and strong correlations ($p < 0.01$) between EC_{a_dp} and topsoil properties. On field W (Fig. 9), EC_{a_dp} was correlated ($p < 0.01$) to all subsoil properties except $SOM_{\_sub}$ and weakly correlated ($p < 0.05$) to $SOM_{\_top}$, θ_{fc_top}, and θ_{pwp_top}.

Fields with greater spatial variability in θ_{awc_top} (Figure 10) tend to have stronger intrafield correlations between θ_{awc_top} and EC_{a_sh}. Fields G, E, and L had the most intrafield variability in θ_{awc_top} and consequently, had the strongest correlation between θ_{awc_top} and EC_{a_sh} (tau=0.69, 0.68, and 0.61, respectively). Fields P and H have moderate intrafield variability in θ_{awc_top} and have tau values between θ_{awc} and EC_{a_sh} of 0.61 and 0.41, respectively. Field W appears to have almost no intrafield variability and has the lowest tau value between θ_{awc_top} and EC_{a_sh} of 0.32. Maps of $\theta_{awc\text{-}R}$ (Fig. 11) indicate that the fields with the most intrafield variability in θ_{awc_top} and strongest relationships between θ_{awc_top} and EC_{a_sh} (fields G, E, L, P) have large, distinctive patches of relatively higher and lower θ_{awc_top}, while fields with limited intrafield variability (H, W) have many small patches of relatively higher and lower θ_{awc_top}.

4.3.2. Crop phenology

LAI and *h* relationships with EVI for field corn, sweet corn, potatoes, peas, and pearl millet were best represented by simple functional forms including linear, power, and exponential fits with two or three coefficients. Goodness of fit information is presented for each chosen LAI or *h* model in Table 3. For LAI, peas had the strongest fit with an R^2 value of 0.974, followed by sweet corn, field corn, potatoes, and pearl millet with R^2 values of 0.788, 0.464, 0.431, and 0.393, respectively. RMSE values for LAI-EVI fits were 0.327, 0.783, 1.127, 1.140, and 0.401 m^2 m^{-2} for peas, sweet corn, field corn, potatoes, and pearl millet, respectively. Peas also had the strongest fit for *h* with an R^2 value of 0.952, followed by sweet corn, field corn, pearl millet, and potatoes with R^2 values of 0.762, 0.632, 0.516, and 0.416. RMSE values for *h*-EVI fits were 0.053, 0.391, 0.498, 0.028, and 0.090 m for peas, sweet corn, field corn, pearl millet, and potatoes, respectively.

LAI for each field for each airborne mission is depicted in Fig. 12. Potato fields had relatively higher LAI compared to field and sweet corn during June missions, reflecting their early planting dates (Fig. 12, Table 1). Pea fields had the highest LAI overall, approaching nearly 6 m^2 m^{-2} during the missions on 16 July 2014, 23 July 2014, and 2 July 2015. The pearl millet cover crop following peas did not reach canopy closure during 2014 and 2015 airborne missions. Field corn is planted earlier than sweet corn (Table 1) and had a higher LAI during the June missions in 2014 and 2016 (no imagery available in June 2015) and the early July missions in 2015 and 2016 (Fig. 12). However, field corn and sweet corn had comparable LAI during mid-July and August airborne missions in 2014-2016 (Fig. 12).

4.3.3. HRMET validation

HRMET performed comparably to the Shuttleworth-Wallace ET model in irrigated vegetable crops (Fig. 13). The slope of the linear relationship between the

Shuttleworth-Wallace and HRMET models was 1.032, the RMSE was 0.074 mm hr^{-1}, and the R^2 value was 0.814 across all points (n=26). Comparing across only potato validation points (n=10), the slope of the linear relationship between the Shuttleworth-Wallace and HRMET models was 1.087, the RMSE was 0.038 mm hr^{-1}, and the R^2 value was 0.943. Comparing across only sweet corn validation points (n=11), the slope of the linear relationship between the Shuttleworth-Wallace and HRMET models was 1.079, the RMSE was 0.102 mm hr^{-1}, and the R^2 value was 0.700. There are not enough validation points to separately compare pea (n=3) and pearl millet (n=2) crop validations. HRMET performed well in both sparse and full canopy conditions. The validation included sparse canopy conditions during the June flights for sweet corn, potato, and peas as well as the August 2015 flight for pearl millet. Full canopy conditions were validated via the July flights for sweet corn, potato, and peas. Sparse canopy conditions during senescence were also validated for potato during the August 2015 and 2016 flights.

4.3.4 ET magnitude and uncertainty

The per pixel mean and standard deviation of ET resulting from Monte Carlo uncertainty analyses are mapped in Figs. 14 and 15, respectively. Images in Figs. 14 and 15 are mapped using an identical color scale that covers the average minimum and maximum values observed across all airborne missions for the mean and standard deviation of ET. There is little to no interfield or intrafield spatial variability in the standard deviation of ET per pixel across all twelve airborne missions (Fig. 15), indicating that the uncertainty of ET estimates is derived from the variability of meteorological data. The four airborne missions occurring on 6 June 2014, 18 August 2016, 11 August 2015, and 16 July 2014 had the highest uncertainty in per pixel ET estimates with coefficients of variation (CVs) of 69, 66, 64, and 34% averaged across all pixels for all fields. These four dates also had the highest standard deviations in solar radiation (253-300 W m^{-2}) observed across all twelve airborne missions (Table 2). Observationally, these were four missions where cloud conditions were rapidly changing and it was challenging to capture thermal and multiband imagery around clouds. The uncertainty in per pixel ET estimates of the other eight missions was low and CVs averaged across all pixels and all fields were 7-15%, reflecting more stable solar radiation values with standard deviations of 21-80 W m^{-2}.

Mean ET ranged from 40-120% of hourly reference ET (RET) estimates (Table 2) for airborne missions occurring in June and 95-180% of hourly RET estimates for airborne missions occurring in July and August. Interfield differences in ET within each airborne mission are less than or equal to intrafield differences in ET with some exceptions resulting from differences in phenology or possible water limitation. Table 4 contains the mean and standard deviation of ET estimates for each field, where standard deviations are indicative of intrafield variability in ET as opposed to uncertainty of ET within a pixel.

Observable differences in LAI (Fig. 12) aligned with interfield differences in ET during the 7 August 2014, 16 June 2015, 2 July 2015, 11 Aug 2015, 1 July 2016, and 18 August 2016 missions. Sweet corn was planted the latest in all three years and, consequently, had low LAI and ET in June and early July images. Senescing potato crops and pearl millet cover crops with partial canopy cover limited ET in August images. In the absence of observable differences in phenology, water limitations may have caused interfield differences in ET on 6 June 2014 and 2 July 2015. During the 6 June 2014 mission, fields P and W had very similar LAI values (Fig. 12) for field corn, but field P had a mean ET of 0.18 mm hr^{-1}, while field W had a mean ET of 0.31 mm hr^{-1} (Table 4). Water limitation on field P may have resulted from an absence of rain in the four days preceding the 6 June 2014 mission, which took place prior to irrigation initiation. Similarly, during the 2 July 2015 mission, fields L and P had very similar LAI values for sweet corn (Fig. 12), but field L had a mean ET of 0.12 mm hr^{-1}, while field P had a mean ET value of 0.47 mm hr^{-1} (Table 4). Water limitation on field L may have resulted from an absence of rain and irrigation in the four days preceding the 2 July 2015 mission, as field L was irrigated on 2 July 2015 after the mission, while field P had been irrigated by total of 21 mm in the four days prior to the flight.

4.3.5. Persistent patterns in ET

Relative ET (ET_R) maps facilitate the comparison of intrafield variability in ET across airborne missions and are presented in Fig. 16. Qualitatively, several of the ET_R maps exhibit similar patterns to the $\theta_{awc\text{-}R}$ maps for each field (Fig. 11), especially for June and early July missions. Quantitatively, there were also significant correlations ($p < 0.05$) between June and July ET_R and several soil properties on fields H, G, L, E, and W, corroborating observed similarities between ET_R and $\theta_{awc\text{-}R}$ maps (Figs. 4-5, 7-9, 11, 16).

Only fields H, E, and G had several significant correlations ($p < 0.05$) between August ET_R and several soil properties (Figs. 4-5, 8).

There was a statistically significant correlation ($p < 0.05$) between average ET_R, EC_{a_sh}, and θ_{awc_top} on fields H, G, L, E, and W (Figs.4-5, 7-9). The strength of correlations between ET_R and individual soil properties differed for each field. Field H had tau values of 0.28, -0.56, 0.49, 0.50, 0.39, and 0.43 that denoted the strength and direction of the significant correlations ($p < 0.05$) between average ET_R and EC_{a_sh}, $sand_{\_top}$, $silt_{\_top}$, $clay_{\_top}$, θ_{pwp_top}, θ_{fc_top}, and θ_{awc_top}, respectively (Fig. 4). There were also significant correlations ($p < 0.05$) on field H between average ET_R and EC_{a_dp}, $sand_{\_sub}$, $silt_{\_sub}$, $clay_{\_sub}$, θ_{pwp_sub}, θ_{fc_sub}, and θ_{awc_sub}, with tau values of 0.28, -0.40, 0.41, 0.28, 0.30, 0.32, and 0.40, respectively (Fig. 4). There were no significant correlations ($p < 0.05$) between average ET_R and either $SOM_{\_top}$ or $SOM_{\_sub}$ on field H (Fig. 4). Field G had tau values of 0.42, -0.48, 0.50, 0.32, 0.47, 0.29, 0.36, which denoted the strength and direction of the significant correlations ($p < 0.05$) between average ET_R and EC_{a_sh}, $sand_{\_top}$, $silt_{\_top}$, $SOM_{\_top}$, θ_{pwp_top}, θ_{fc_top}, and θ_{awc_top}, respectively (Fig. 5). Though there was a significant correlation ($p < 0.05$) between average ET_R and EC_{a_dp} with a tau value of 0.39, there were no significant correlations between average ET_R and other subsoil properties on field G (Fig. 5). There were no significant correlations between average ET_R and any topsoil or subsoil properties on field P (Fig. 6). Field L had significant correlations ($p < 0.001$) between ET_R and EC_{a_sh}, $sand_{\_top}$, $silt_{\_top}$, $SOM_{\_top}$, θ_{pwp_top}, θ_{fc_top}, and θ_{awc_top} with tau values of 0.68, -0.44, 0.48, 0.45, 0.53, 0.54, and 0.52, respectively (Fig. 7). Like field G, there was a significant correlation ($p < 0.001$) between average

ET_R and EC_{a_dp} with a tau value of 0.42 on field L, but there were no significant correlations between average ET_R and other subsoil properties (Fig. 7). Field E had significant correlations ($p < 0.001$) between average ET_R and EC_{a_sh}, $sand_{\_top}$, $silt_{\_top}$, $clay_{\_top}$, θ_{pwp_top}, θ_{fc_top}, and θ_{awc_top} with tau values of 0.46, -0.62, 0.55, 0.57, 0.58, 0.57, and 0.60, respectively (Fig. 8). There were also significant correlations ($p < 0.01$) on field E between average ET_R and EC_{a_dp}, $sand_{\_sub}$, $silt_{\_sub}$, $clay_{\_sub}$, θ_{pwp_sub}, θ_{fc_sub}, and θ_{awc_sub} with tau values of 0.53, -0.54, 0.55, 0.43, 0.37, 0.50, and 0.55, respectively (Fig. 8). Similar to field H, there were no significant correlations ($p < 0.05$) between average ET_R and either $SOM_{\_top}$ or $SOM_{\_sub}$ on field E (Fig. 8). Field W had significant correlations ($p < 0.01$) between average ET_R and EC_{a_sh}, $sand_{\_top}$, $silt_{\_top}$, $clay_{\_top}$, $SOM_{\_top}$, θ_{pwp_top}, θ_{fc_top}, and θ_{awc_top} with tau values of 0.59, -0.42, 0.36, 0.40, 0.31, 0.43, 0.42, and 0.40, respectively (Fig. 9). Additionally, there were significant correlations ($p < 0.05$) on Field W between average ET_R and EC_{a_dp}, $sand_{\_sub}$, $silt_{\_sub}$, $clay_{\_sub}$, $SOM_{\_sub}$, θ_{pwp_sub}, θ_{fc_sub}, and θ_{awc_sub} with tau values of 0.49, -0.32, 0.30, 0.44, 0.23, 0.42, 0.31, and 0.30, respectively (Fig. 9).

Only three (H, E, W) out of the five fields with field corn rotations had significant correlations ($p < 0.05$) between field corn ET_R and soil properties. Fields H and E had significant correlations ($p < 0.05$) between field corn ET_R and several topsoil and subsoil properties, while majority of the significant correlations ($p < 0.05$) on field W were between field corn ET_R and subsoil properties. Of the four fields with sweet corn rotations (G, P, L, E), fields G, L, and E had significant correlations ($p < 0.05$) between sweet corn ET_R and several different topsoil properties, while field P only had one significant correlation ($p < 0.05$) between sweet corn ET_R and EC_{a_sh} (Figs. 5-8). Only field E had significant correlations ($p < 0.05$) between sweet corn ET_R and subsoil properties (Fig. 8). There were significant correlations ($p < 0.05$) between ET_R and several topsoil properties for potato rotations on all six fields (Figs. 4-9). Similar to sweet corn, only field E had significant correlations ($p < 0.05$) between potato ET_R and EC_{a_dp}, $sand_{\_sub}$, $silt_{\_sub}$, $clay_{\_sub}$, θ_{pwp_sub}, θ_{fc_sub}, and θ_{awc_sub} (Fig. 8). Of the two fields (H,W) with peas-pearl millet rotations, field W had significant correlations ($p < 0.05$) between peas-pearl millet ET_R and EC_{a_sh}, $sand_{\_top}$, $silt_{\_top}$, $clay_{\_top}$, $SOM_{\_top}$, θ_{pwp}, θ_{fc}, and θ_{awc}, while field H had no significant correlations between peas-pearl millet ET_R and any soil properties.

4.4. Discussion

4.4.1. Shallow EC_a surveys may best inform precision irrigation in the WCS

In this study, crop water use primarily correlated to topsoil properties and EC_{a_sh}, which suggests that it may be most practical for precision irrigation managers to rely on shallow EC_a surveys as surrogates for θ_{awc}. The intrafield EC_a values (0-11 mS m^{-1}) from the six cropping systems in this study are the lowest reported range that has been demonstrated to predict intrafield differences in soil properties. EC_a predicted soil particle size, SOM, hydrologic properties, and ET for different crop rotations in the coarse, irrigated agroecosystems of the WCS. Thus, we extend the lower EC_a limit of previous findings from irrigated, sandy systems (Farahani et al., 2005) and demonstrate that EC_a maps may serve as a surrogate for θ_{awc} and other soil properties in soils that may have previously been considered too homogenous for effective use of proximal sensing techniques.

We observed distinctive topsoil and subsoil layers in all six fields in this study; evidenced by weak or nonexistent correlations between intrafield topsoil and subsoil properties. Yet, on all fields except W, deep EC_a measurements had stronger relationships with topsoil properties (0-0.3 m) than subsoil properties (0.4-0.6 m). Though peak responses should theoretically occur at 0.1-0.2 and 0.5-0.6 m for shallow and deep EC_a measurements (Sudduth et al., 2005), respectively, site-specific differences in soil layering can alter peak signals and depth-wise variation (Sudduth et al., 2013). For example, two out of the six fields in this study, P and E, had an almost perfect positive correlation between shallow and deep EC_a measurements, which can indicate either that differences between soil layers down to 0.9 m are negligible (Sudduth et al., 2005) or that extremely conductive topsoil is reducing the response depth of proximal sensors (Barker, 1989). In this case, field P has thick, dark-colored topsoil in the northern portion of the field that may have obscured differences between soil layers across the whole field. Alternatively, the soils on field E have progressively more gravel with depth and the topsoil is much more conductive than the subsoil, which may have decreased the response depth of the deep EC_a measurement. Further investigation including more stratified soil coring to greater depths, EC_a-penetrometry measurements, and inversion approaches could inform the development of comprehensive soil layer models using EC_a surveys (von Hebel et al., 2014; Sudduth et al., 2013). However, our results suggest that these additional measures may not be necessary to implement precision irrigation for relatively shallow-rooted crops like potatoes and sweet corn in coarse, irrigated agroecosystems.

Though we did not measure the actual reduction in applied irrigation that could result from precision irrigation interventions, the observed intrafield relationships between EC_a, $\theta_{awc,}$ and ET demonstrate that significant water savings using precision irrigation may be possible in the WCS. Studies on relatively coarse fields with θ_{awc} ranging from 0.11-0.23 m^3m^{-3} have found 15-26% mean annual water savings from precision irrigation intervention (Hedly and Yule, 2009b; Daccache et al., 2015). Though these previous studies have had higher values than the θ_{awc} range of 0.03-0.15 m^3 m^{-3} observed here, they still provide some context as to what could be accomplished in the WCS with precision irrigation. Fields with large, homogenous patches of θ_{awc}, such as G, P, L, and E, may be better suited to precision irrigation guided by EC_a mapping, as these fields may be the most straightforward to divide into 2-4 zones using geostatistical techniques for implementing variable rate irrigation (Moral et al., 2010; Peralta et al., 2013).

We found that EC_a had the most consistent, strongest relationships with sand, silt, and θ_{awc} across all six fields; indicating that these may be the most reliable surrogate soil properties to derive from EC_a maps in the WCS. Previous research has identified clay or cation exchange capacity as having the strongest relationships with mapped EC_a in the Midwestern United States (Sudduth et al., 2003); however, our findings supplement increasing evidence that mapped EC_a reflects a combination of different soil properties that are site specific (Daccache et al., 2015). Agroecosystems in this study exhibited either strong EC_a relationships with clay (field E) or SOM (fields G, L), but there were no agroecosystems that had strong EC_a relationships with both clay and SOM. This dichotomy may be indicative of agricultural soils in the WCS, which either tend to be upland gravelly soils closer to glacial moraines interspersed with reddish-brown clay deposits or windblown sands interspersed with organic, marshland soils that were drained for agriculture in the early 1900s (Kniffin et al., 2014; Butler, 1978; Faustini, 1985).

4.4.2. Precision irrigation benefits may be both rotation specific and field specific

Precision irrigation guided by EC_a mapping may be more likely to reduce the irrigation applied to sweet corn and potato rotations than field corn in the WCS and similar agroecosystems. In this study, sweet corn and potatoes rotations had the strongest intrafield relationships between ET_R, shallow EC_a, and topsoil properties. These intrafield relationships in potatoes and sweet corn rotations were most apparent in June and early July, while field corn rotations had either no significant intrafield relationships between ET_R, EC_a, and soil properties or ET_R relationships that extended to deep EC_a and subsoil properties. Field corn, even when irrigated, has much deeper roots than sweet corn and potatoes (Sanford and Panuska, 2015) and has also been genetically engineered over the past 50 years to have high water-use efficiency (Reyes et al., 2015). The idea of rotation-specific precision irrigation should be applicable to other agroecosystems where relatively shallow-rooted, high water-demand crops that could benefit from precision irrigation are rotated with deep-rooted, water-efficient crops that may not be worth the time and effort required for precision irrigation interventions.

We also propose that precision irrigation benefits will be field specific because of both intrafield soil variability *and* current intuitive irrigation practices, which could be amplifying or diminishing observed intrafield variability in ET. All fields in this study had relationships between EC_a, soil properties, and ET_R except field P. This was a perplexing result as field P had strong intrafield relationships between EC_a and soil properties and also large, distinctive patches of different soil properties that are ideally suited for irrigation zone management. A possible explanation for the lack of intrafield variability in ET_R may be found by comparing irrigation on field P to field L, which had the strongest intrafield relationships between EC_a, soil properties, and ET_R. Field P and L have very similar soil types, are separated by only ~100 m, and were both planted with sweet corn in 2015 and potatoes in 2016. However, field P received 28 and 78 mm yr^{-1} more irrigation than field L in 2015 and 2016, respectively. We suggest that the increased irrigation on field P may have irrigated the relatively finer-textured portions of the field at higher rates than necessary and washed out intrafield differences in ET_R. Alternatively, decreased irrigation on field L may have under-irrigated the relatively coarser-textured portions of the field and amplified intrafield differences in ET_R. Both fields may be candidates for precision irrigation based on their soil heterogeneity, however specific interventions would differ based on current intuitive irrigation practices.

4.4.3. Utility of HRMET for precision irrigation

Using aerial imagery, onsite meteorological data, and ground observations to drive HRMET was an effective approach for developing high-resolution maps of ET in the irrigated, rotational agroecosystems of the WCS in both partial and full canopy conditions. When converted to the ET_R index, these high-resolution maps were a valuable tool for quantifying intrafield ET variability within and across crop rotations in different fields. HRMET estimates of ET were 0.1 mm hr^{-1} closer to Shuttleworth-Wallace estimates in irrigated potatoes, sweet corn, and peas-pearl millet systems in the WCS than rainfed field corn in southern Wisconsin during a droughty year (Zipper and Loheide, 2014). We suggest that the improved agreement between HRMET and Shuttleworth-Wallace in the WCS results from the removal of water limitations in WCS systems as the Shuttleworth-Wallace model is intended to estimate ET from well-watered canopies (Brisson et al., 1998; Shuttleworth and Wallace, 1985).

A long-term goal of water managers in the WCS is to have high-resolution, satellite-derived estimates of ET available for growers to use in real-time irrigation management. However, acquiring frequent cloud-free imagery of cropping systems has been a long-term challenge in the midwestern United States (Zhu et al., 2017) and has been especially challenging for acquiring frequent imagery in the WCS. The high standard deviation of solar radiation inputs during missions with shifting cloud cover increased uncertainty in ET estimates by 4-fold per pixel. Though it is possible to capture thermal images by avoiding clouds with the aid of a deft pilot, it may not be worth the effort if the magnitude of ET derived from these images does not have enough certainty to be useful in satellite-based model validation. Analyses are underway to implement an integrated data fusion approach and create high-resolution (30-m) daily maps of ET by fusing Landsat, MODIS, and GOES satellite imagery data (Cammaleri et al., 2014).

HRMET estimates of ET in the WCS and other regions could be especially useful for validating satellite-based daily ET estimates that are gap-filled using the "self-preservation" ratio of actual to reference ET (i.e. crop coefficients) during cloudy periods (Semmens et al., 2016; Anderson et al., 2012).

Crop coefficients observed for HRMET estimates in this study were high with an average of 1.3 and ranging from 0.95-1.80 under full canopy conditions. Higher than expected crop coefficients have also been observed from lysimetry-derived estimates of ET in WCS cropping systems (Nocco et al., 2017) and free-drainage lysimeters planted with irrigated prairies, shrubs, and turfgrass in Dane County, Wisconsin (Nocco et al., 2016). FAO RET estimates have never been validated using large-scale weighing lysimeters or eddy-covariance systems planted with irrigated grass in the northern Great Lake states and future validation experiments may be useful, given the pervasiveness and utility of RET models (Pereirra et al., 2015). RET models are often parameterized with satellite-derived estimates of phenology (Campos et al., 2017). Though they met the needs of this study, we do not recommend applying our pearl millet LAI and *h* models to future studies as the ground observations used did not span multiple phenological stages. However, our EVI models of field corn, sweet corn, potato, and pea LAI and *h* may useful in future studies with an understanding of their strengths and limitations.

In this study, the relationships between EVI, LAI, and *h* were weaker in potatoes and field corn than sweet corn and peas. Hysteresis in the relationship between reflectance and canopy chlorophyll content from growth to senescence has been demonstrated to alter EVI values at different phenological stages (Peng et al., 2017). We speculate that the relatively weaker relationships between EVI, LAI, and *h* in potato results from the inclusion of LAI and *h* values for both growing and senescing canopies in EVI fits. We also propose that dramatic differences in soil background noise levels on the specific fields used to fit EVI, LAI, and *h* in field corn (G, E, and H) caused relatively weaker fits compared to sweet corn. Though EVI is considered resistant to soil background noise (Huete et al., 1997), it still is affected by soil background noise when differences in soil color are dramatic (Viña et al., 2011). Field G has a prevalent dark patch that caused a higher level of background noise prior to canopy closure, while fields E and H are relatively homogenous in color with little to no background noise. Comparatively, the fields used to fit EVI, LAI, and *h* in sweet corn (P, L, G) all had the same types of variability in soil color and, presumably, similar levels of soil background noise. Future work quantifying soil background noise and intrafield albedo differences in these systems may be useful for improving modeled relationships between EVI, LAI, and *h*.

4.5. Conclusions

The WCS and similar agricultural regions in the northern Great Lake states have an increasing burden to produce high-value vegetables with decreased pressure on groundwater resources. Precision irrigation is gaining traction as a water conservation strategy for the WCS that could maximize vegetable production and water-use efficiency while minimizing environmental impacts. EC_a-derived θ_{awc} maps, especially when paired with soil sampling or soil moisture monitoring, can help growers identify intrafield management zones for precision irrigation. Intrafield maps of crop ET and the ET_R index can help growers assess the sensitivity of different crop rotations to intrafield management zones and potential return on investment in precision irrigation technology. We demonstrated that proximal surveys of EC_a were a useful surrogate for assessing intrafield variability in soil properties such as θ_{awc}, despite reporting the lowest range of observed EC_a values (0-11 mS m^{-1}) for this purpose. Moreover, we found that in rotational systems like the WCS, shallow EC_a surveys may be most useful for informing precision irrigation, as shallow-rooted crops like potatoes and sweet corn are most likely to benefit from precision interventions based on their patterns of intrafield crop water use. We also validated HRMET in potatoes, sweet corn, peas, and pearl millet, and demonstrated its utility for assessing intrafield patterns in crop water use in sandy, irrigated agroecosystems at the spatiotemporal scale necessary for validating future satellite-based efforts.

Combining high-resolution EC_a and ET mapping could critically inform precision irrigation in sandy, rotational agroecosystems located in humid climates like the WCS. Intrafield maps of crop ET and the ET_R index can help growers assess the sensitivity of different crop rotations to drought, develop intrafield management zones, and maximize return on investment in precision irrigation technology. In this study, we demonstrated that intrafield relationships between EC_a, soil properties, and ET_R can be specific to (1) different fields in the WCS, depending on intrafield soil variability and current intuitive irrigation practices (2) different crop rotations grown on the same field, where shallow-rooted crops exhibit greater intrafield variability in water use, and (3) different months in the June-August growing season. However, further studies are needed to assess long-term water savings, water use efficiency, and the yield potential of precision irrigation interventions in the WCS.

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4.8. Tables

Table 1. Cropping Systems

Site/year	Planted Area (ha)	Crop	Planting Date	Harvest Date
H				
2014	26	peas	22 May	27 Jul *(pearl millet cover crop)*
2015	26	potato	1 May	16 Sep (*vine kill 13 Aug*)
2016	26	field corn	15 May	11 Nov
G				
2014	30	potato	9 May	10 Sep *(vine kill 22 Aug)*
2015	30	field corn	10 May	28 Oct
2016	30	sweet corn	2 Jun	31 Aug
P				
2014	14	field corn	12 May	3 Nov
2015	14	sweet corn	30 May	1 Sep
2016	14	potato	6 May	2 Oct *(vine kill 19 Aug)*
L				
2014	16	sweet corn	24 May	25 Aug
2015	16	sweet corn	30 May	1 Sep
2016	16	potato	7 May	5 Oct *(vine kill 19 Aug)*
E				
2014	25	sweet corn	24 May	25 Aug
2015	25	potato	3 May	21 Sep *(vine kill 20 Aug)*
2016	25	field corn	16 May	11 Nov
W				
2014	28	field corn	15 May	3 Nov
2015	28	peas	30 May	23 Jul *(pearl millet cover crop)*
2016	28	potato	4 May	28 Sep *(vine kill 19 Aug)*

Table 2. Airborne Missions

Airborne Missions	Date (DOY)	Flight time (UTC)	Air temperature (°C)	Wind speed (m s^{-1})	Solar radiation (W m^{-2})	Vapor pressure (kPa)	Reference ET (mm hr^{-1})
1	06 Jun 14 (157)	16:12-16:28	24.8 (0.5)	1.1 (0.7)	690 (277)	1.7 (0.1)	0.45
2	16 Jul 14 (197)	15:50-16:17	20.1 (0.8)	1.3 (0.5)	791 (253)	1.3 (0.1)	0.42
3	23 Jul 14 (204)	15:07-15:24	21.6 (0.7)	1.2 (0.3)	650 (21)	1.7 (0.0)	0.40
4	07 Aug 14 (219)	15:38-15:54	24.1 (0.3)	1.3 (0.7)	664 (28)	1.8 (0.1)	0.42
5	16 Jun 15 (167)	17:15-17:45	21.4 (0.5)	0.8 (0.3)	1058 (80)	1.4 (0.0)	0.64
6	02 Jul 15 (183)	16:21-16:36	20.3 (0.4)	0.8 (0.4)	785 (26)	1.3 (0.0)	0.49
7	27 Jul 15 (208)	16:02-16:19	27.6 (0.5)	1.1 (0.4)	730 (75)	2.4 (0.0)	0.55
8	11 Aug 15 (223)	15:37-15:58	23.5 (0.5)	1.2 (0.1)	500 (296)	1.8 (0.0)	0.39
9	17 Jun 16 (169)	15:40-16:13	25.6 (0.4)	0.9 (0.6)	727 (67)	1.9 (0.1)	0.51
10	01 Jul 16 (183)	15:42-16:19	18.3 (0.7)	2.1 (0.4)	813 (44)	1.4 (0.1)	0.45
11	01 Aug 16 (214)	15:34-16:05	25.7 (0.6)	0.7 (0.3)	691 (33)	2.2 (0.1)	0.50
12	18 Aug 16 (231)	16:15-16:38	27.4 (1.1)	1.6 (1.0)	543 (300)	2.4 (0.1)	0.32

Table 3. LAI-EVI and height-EVI fits

Crop type	Phenological variable	n	Prediction Model	Coefficients (Confidence Intervals) a	b	c	$RMSE$	R^2
Field corn	LAI (m^2 m^{-2})	122	ax^b	3.986 (3.581, 4.391)	1.308 (0.935, 1.681)	-	1.127	0.464
	h (m)	96	$ax^b + c$	2.486 (1.951, 3.022)	1.471 (0.555, 2.387)	0.115 (-0.526, 0.755)	0.498	0.632
Sweet corn	LAI (m^2 m^{-2})	124	ax^b	4.848 (4.496, 5.199)	1.323 (1.115, 1.531)	-	0.783	0.788
	h (m)	123	$ax + b$	2.369 (2.130, 2.609)	-0.1758 (-0.321, -0.031)	-	0.391	0.762
Potato	LAI (m^2 m^{-2})	209	ax^b	4.675 (4.379, 4.971)	0.6257 (0.504, 0.748)	-	1.140	0.431
	h (m)	213	ab^x	0.252 (0.2294 0.275)	0.7435 (0.620, 0.867)	-	0.090	0.412
Peas	LAI (m^2 m^{-2})	29	$ax + b$	5.386 (5.036, 5.737)	-0.1658 (-0.412, 0.080)	-	0.327	0.974
	h (m)	29	$ax + b$	0.593 (0.561, 0.625)	1.266 (1.048, 1.483)	-	0.053	0.952
Pearl Millet	LAI (m^2 m^{-2})	13	ax^b	1.739 (0.526, 2.952)	0.393 (-0.148, 0.934)	-	0.401	0.393
	h (m)	12	$ax^b + c$	3.633 (-11.680, 18.940)	4.743 (-0.969, 10.460)	0.111 (0.077, 0.145)	0.028	0.516

Table 4. Field ET estimates

Airborne Mission	Date (DOY)	H (mm hr^{-1})	G (mm hr^{-1})	P (mm hr^{-1})	L (mm hr^{-1})	E (mm hr^{-1})	W (mm hr^{-1})
1	06 Jun 14 (157)	0.36 (0.02)	0.35 (0.04)	0.18 (0.04)	0.35 (0.02)	0.34 (0.04)	0.31 (0.04)
2	16 Jul 14 (197)	0.76 (0.02)	0.73 (0.02)	0.78 (0.02)	0.77 (0.02)	0.68 (0.02)	na
3	23 Jul 14 (204)	0.67 (0.01)	0.66 (0.01)	0.65 (0.01)	0.65 (0.01)	0.63 (0.01)	0.64 (0.01)
4	07 Aug 14 (219)	0.50 (0.02)	0.66 (0.01)	0.75 (0.01)	0.74 (0.01)	0.74 (0.01)	0.74 (0.01)
5	16 Jun 15 (167)	na	na	0.59 (0.04)	0.48 (0.06)	0.79 (0.01)	0.72 (0.02)
6	02 Jul 15 (183)	0.73 (0.01)	0.55 (0.05)	0.47 (0.01)	0.12 (0.05)	0.71 (0.03)	0.75 (0.01)
7	27 Jul 15 (208)	0.73 (0.02)	0.78 (0.02)	0.78 (0.01)	0.79 (0.01)	0.75 (0.02)	na
8	11 Aug 15 (223)	na	0.52 (0.02)	0.45 (0.02)	na	0.44 (0.03)	0.37 (0.02)
9	17 Jun 16 (169)	0.55 (0.03)	0.36 (0.05)	0.54 (0.03)	0.50 (0.05)	0.69 (0.02)	0.45 (0.04)
10	01 Jul 16 (183)	0.73 (0.02)	0.53 (0.01)	0.74 (0.02)	0.71 (0.02)	0.71 (0.04)	0.74 (0.02)
11	01 Aug 16 (214)	0.74 (0.01)	0.73 (0.01)	0.68 (0.01)	0.70 (0.01)	0.73 (0.01)	0.70 (0.02)
12	18 Aug 16 (231)	na	0.59 (0.02)	0.31 (0.03)	0.22 (0.04)	0.61 (0.03)	0.37 (0.05)

4.9. Figures

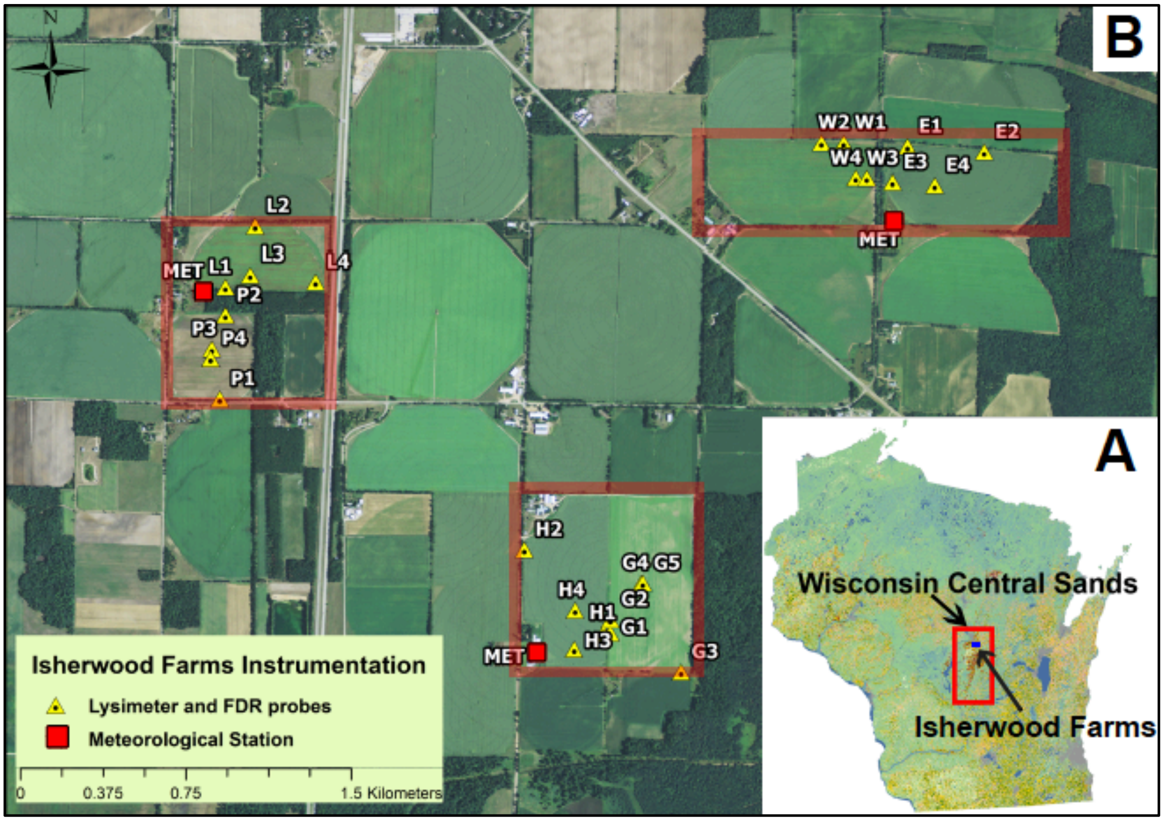

Figure 1. (A) Location of Central Sands region in the state of Wisconsin outlined by red box and location of Isherwood Farms field site demarcated by blue box. (B) Isherwood Farms field instrumentation sites surveyed using RTK GPS system (0.03 m accuracy). Letters 'H', 'G', 'P', 'L', 'E', and 'W' denote different agroecosystems. Red boxes outline aerial mission domains. Georeferencing conducted using 2013 National Agriculture Imagery Program data for Portage County, WI.

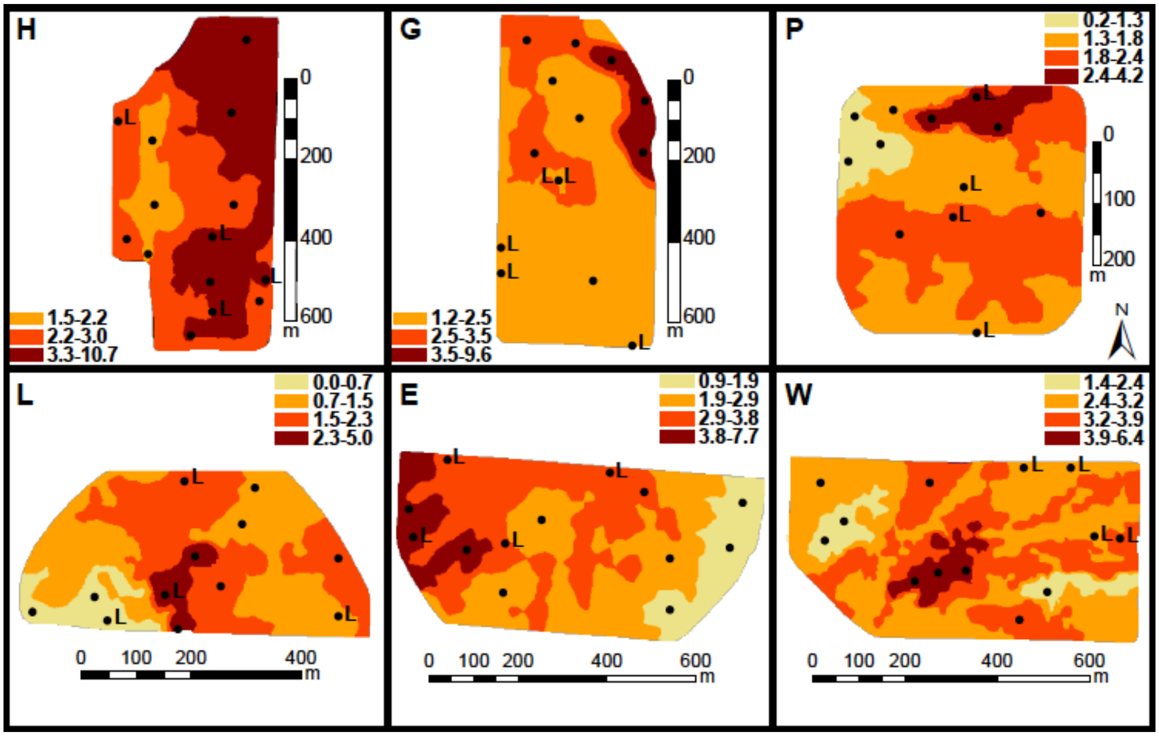

Figure 2. Apparent electrical conductivity (EC_a) classes for each of the six experimental agroecosystems (H, G, P, L, E, W) on Isherwood Farms. EC_a values for each intrafield class are reported in mS m^{-1}. Intrafield EC_a subzones used to collect soil cores, LAI, and height observations are demarcated by black dots. Black dots labeled 'L' represent lysimeter and frequency domain reflectometry (FDR) probe configuration sites.

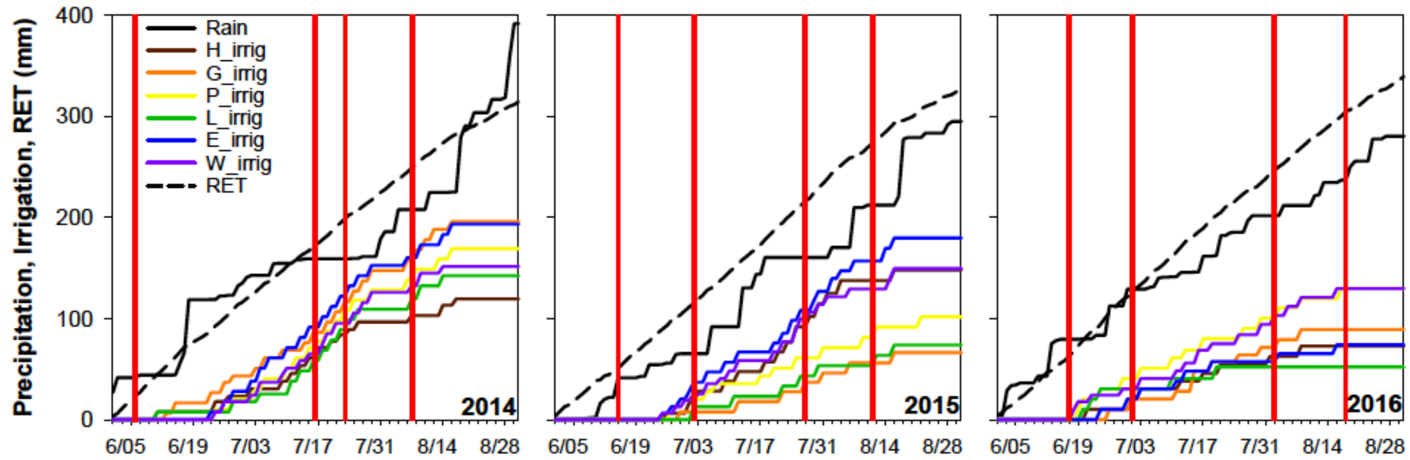

Figure 3. Cumulative precipitation (mm, 'Rain'), irrigation (mm), and reference evapotranspiration (mm, 'RET') data for 1 June-31 August for 2014-2016 growing seasons on Isherwood Farms. Irrigation time series for fields H, G, P, L, E, W are labelled as H_irrig, G_irrig, P_irrig, L_irrig, E_irrig, and W_irrig, respectively. Airborne missions are demarcated by red vertical lines.

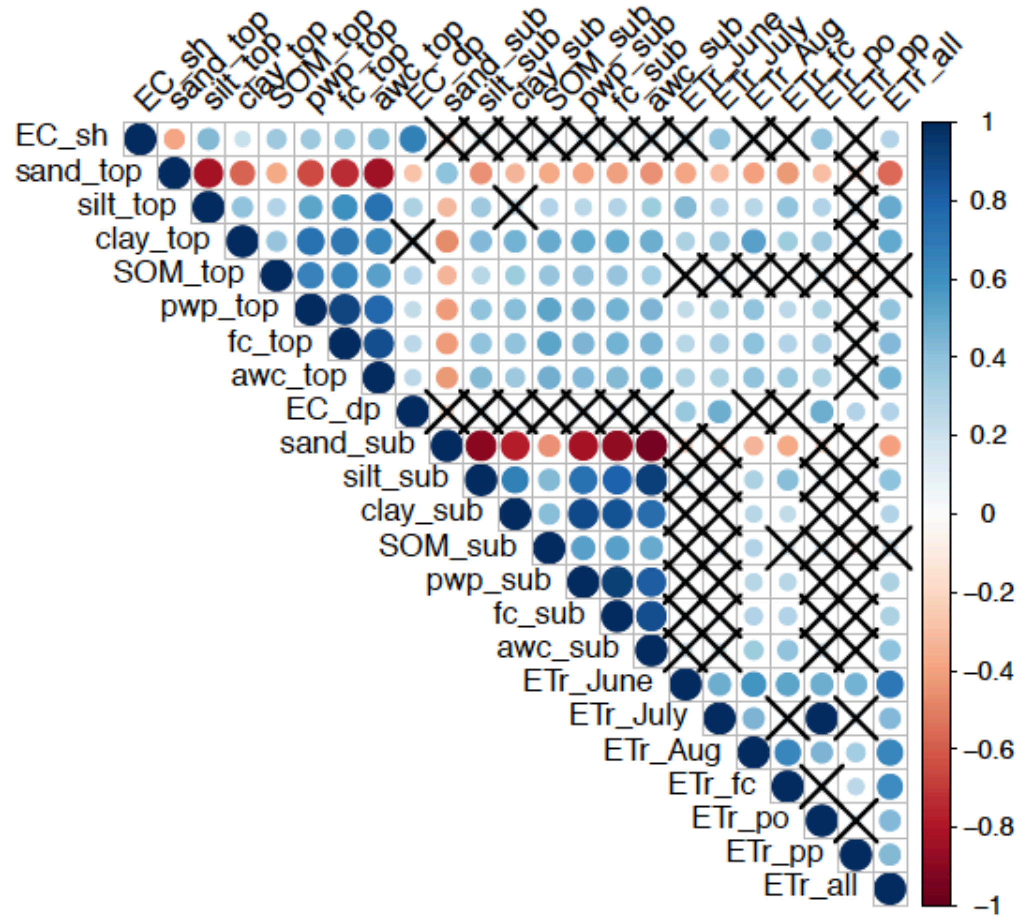

Figure 4. Kendall's tau correlation coefficient matrix for field H. Circle color indicates the direction of the relationship (blue=positive correlation, red=negative correlation) and circle size indicates the strength of the relationship with the largest circles representing 1 or -1. Correlations are all statistically significant at an alpha level of 0.05 unless they are crossed out with "X" symbols. 'EC_sh' and 'EC_dp' are apparent electrical conductivity for shallow and deep measurements, respectively. 'SOM', 'pwp', 'fc', 'awc', and 'ETr' are abbreviations for soil organic matter, permanent wilting point, field capacity, available water content, and relative evapotranspiration, respectively. The underscores 'top', 'sub', 'fc', 'po', and 'pp' are abbreviations for topsoil, subsoil, field corn, potatoes, and peas-pearl millet.

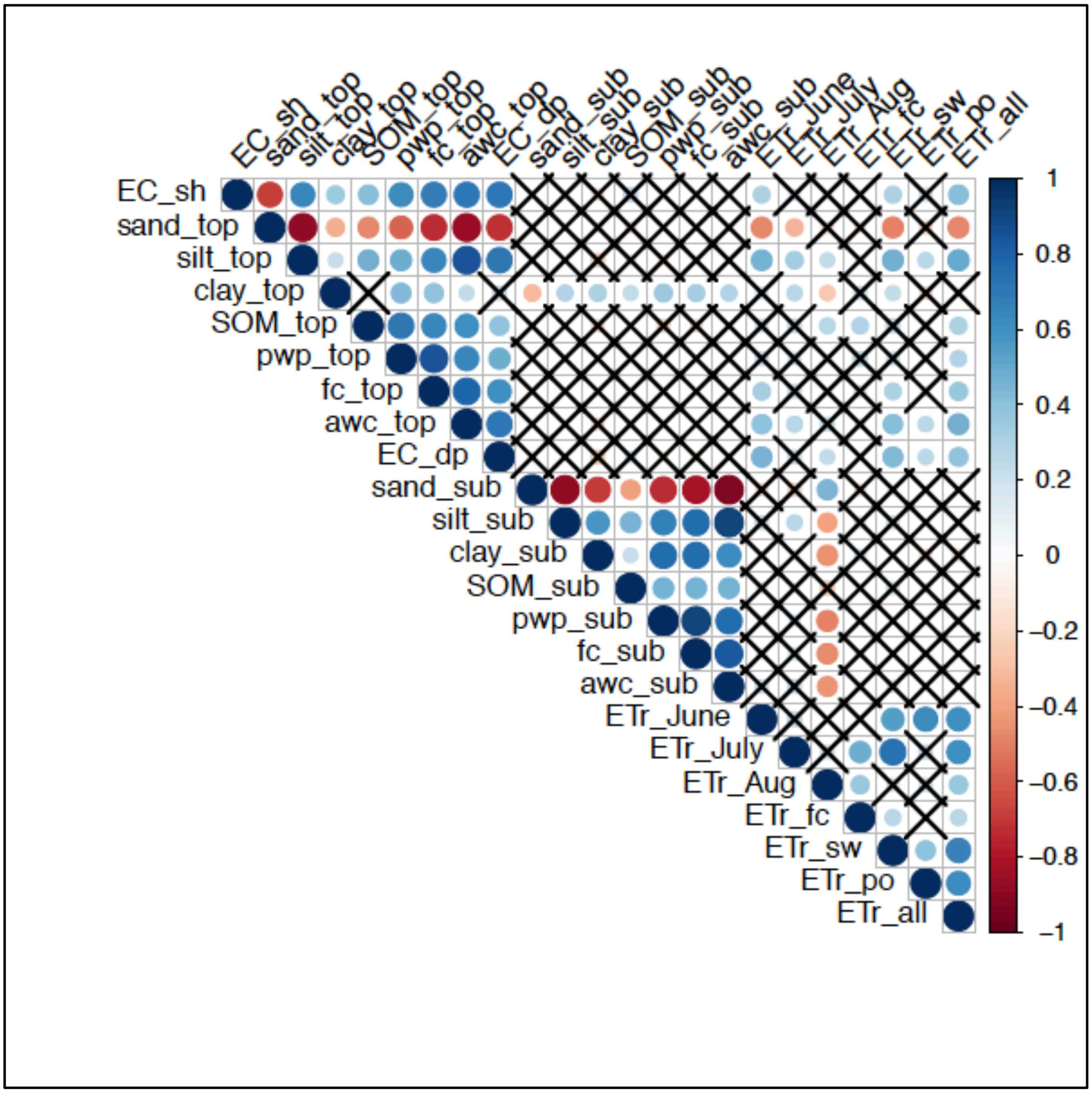

Figure 5. Kendall's tau correlation coefficient matrix for field G. Circle color indicates the direction of the relationship (blue=positive correlation, red=negative correlation) and circle size indicates the strength of the relationship with the largest circles representing 1 or -1. Correlations are all statistically significant at an alpha level of 0.05 unless they are crossed out with "X" symbols. 'EC_sh' and 'EC_dp' are apparent electrical conductivity for shallow and deep measurements, respectively. 'SOM', 'pwp', 'fc', 'awc', and 'ETr' are abbreviations for soil organic matter, permanent wilting point, field capacity, available water content, and relative evapotranspiration, respectively. The underscores 'top', 'sub', 'fc', 'sw', and 'po' are abbreviations for topsoil, subsoil, field corn, sweet corn, and potatoes.

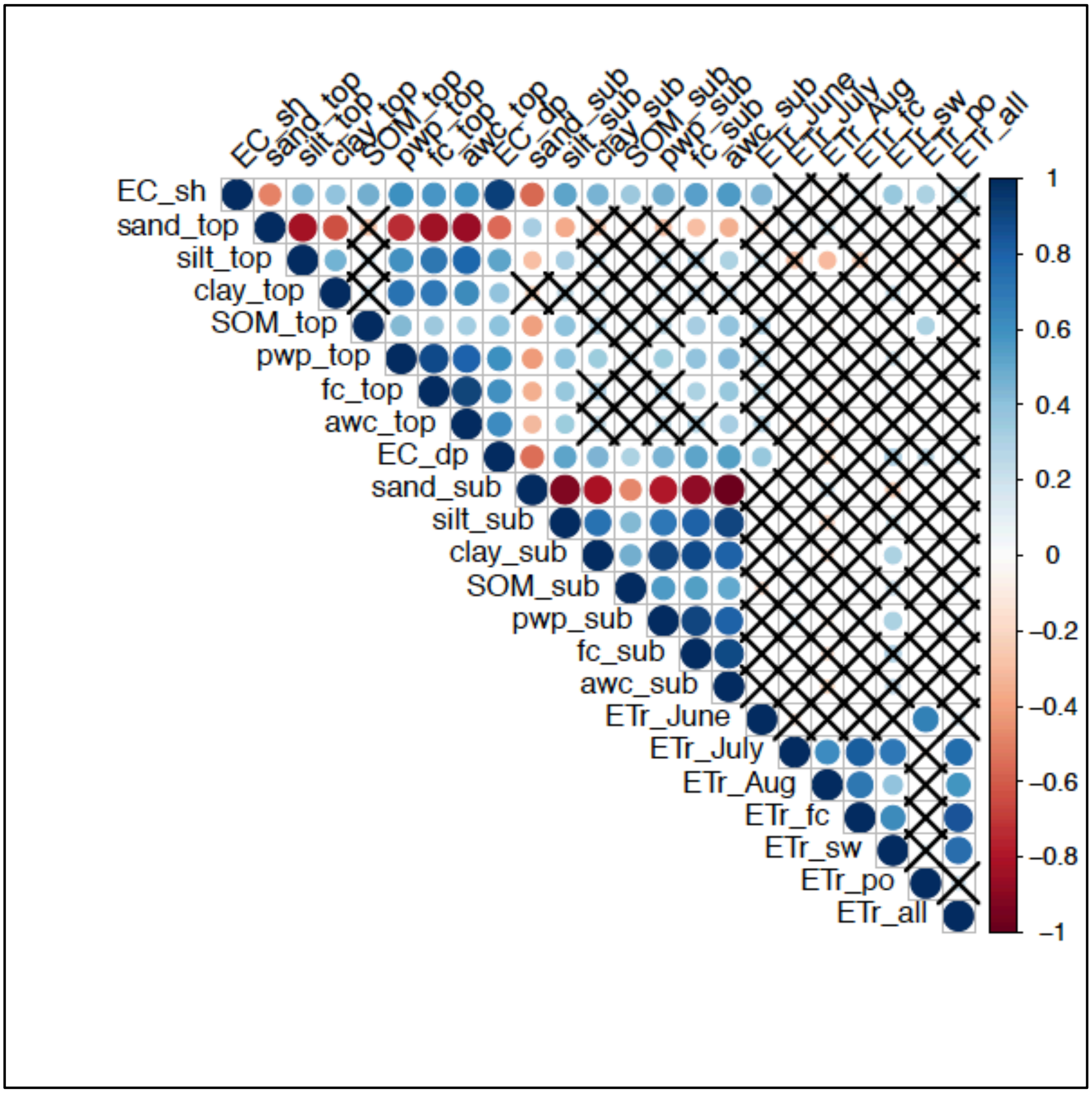

Figure 6. Kendall's tau correlation coefficient matrix for field P. Circle color indicates the direction of the relationship (blue=positive correlation, red=negative correlation) and circle size indicates the strength of the relationship with the largest circles representing 1 or -1. Correlations are all statistically significant at an alpha level of 0.05 unless they are crossed out with "X" symbols. 'EC_sh' and 'EC_dp' are apparent electrical conductivity for shallow and deep measurements, respectively. 'SOM', 'pwp', 'fc', 'awc', and 'ETr' are abbreviations for soil organic matter, permanent wilting point, field capacity, available water content, and relative evapotranspiration, respectively. The underscores 'top', 'sub', 'fc', 'sw', and 'po' are abbreviations for topsoil, subsoil, field corn, sweet corn, and potatoes.

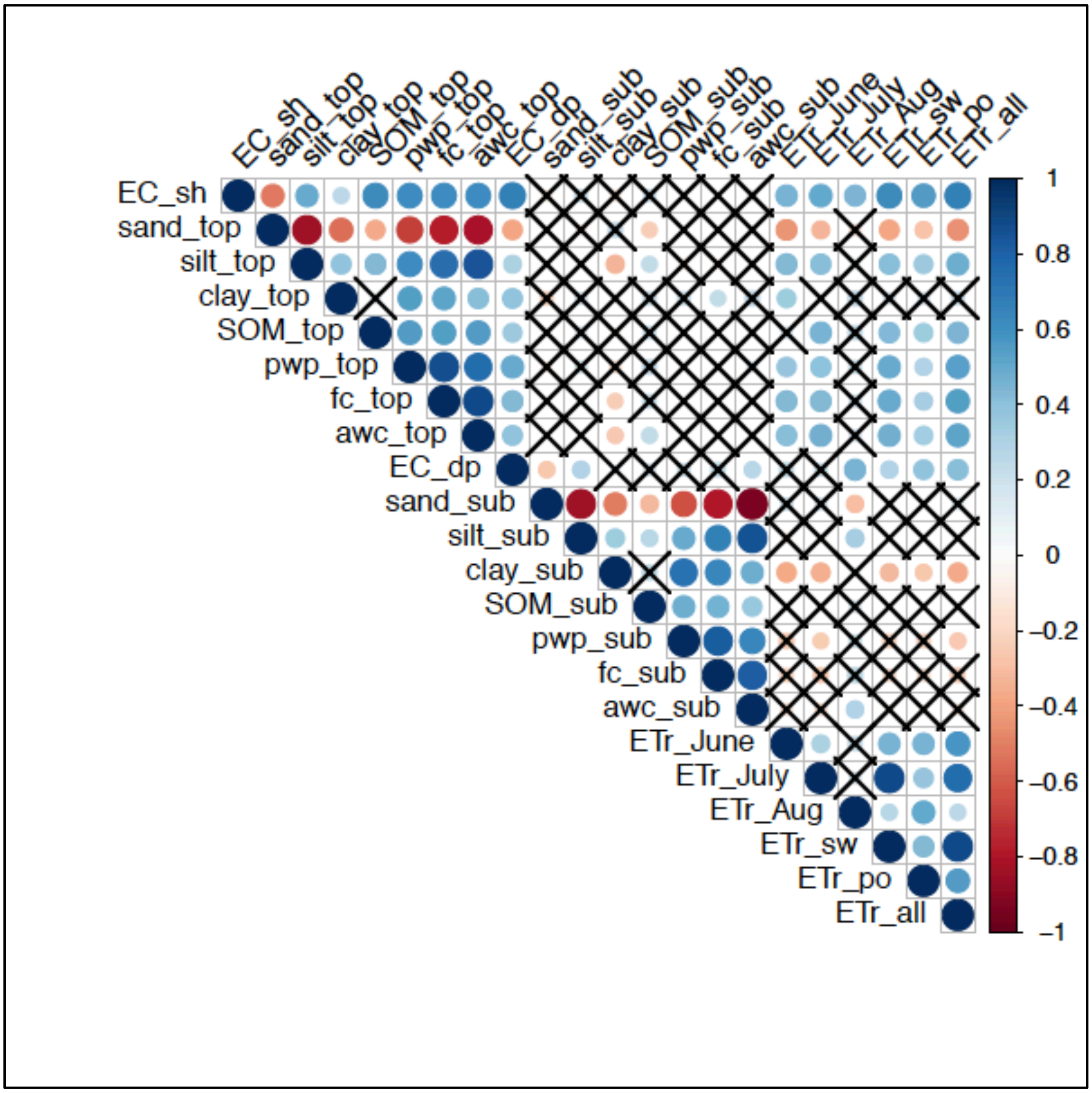

Figure 7. Kendall’s tau correlation coefficient matrix for field L. Circle color indicates the direction of the relationship (blue=positive correlation, red=negative correlation) and circle size indicates the strength of the relationship with the largest circles representing 1 or -1. Correlations are all statistically significant at an alpha level of 0.05 unless they are crossed out with “X” symbols. ‘EC_sh’ and ‘EC_dp’ are apparent electrical conductivity for shallow and deep measurements, respectively. ‘SOM’, ‘pwp’, ‘fc’, ‘awc’, and ‘ETr’ are abbreviations for soil organic matter, permanent wilting point, field capacity, available water content, and relative evapotranspiration, respectively. The underscores ‘top’, ‘sub’, ‘sw’, and ‘po’ are abbreviations for topsoil, subsoil, sweet corn, and potatoes.

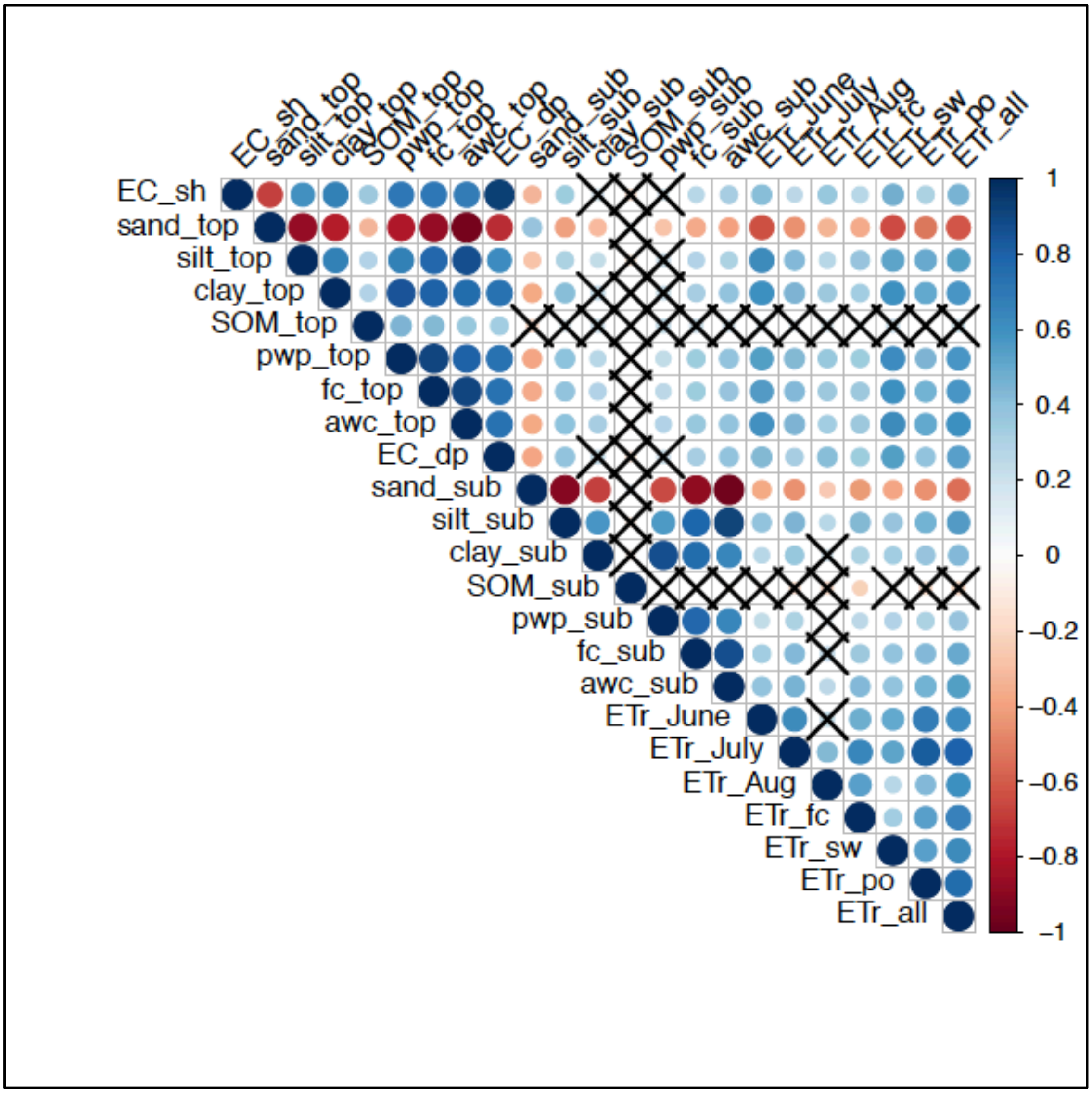

Figure 8. Kendall's tau correlation coefficient matrix for field E. Circle color indicates the direction of the relationship (blue=positive correlation, red=negative correlation) and circle size indicates the strength of the relationship with the largest circles representing 1 or -1. Correlations are all statistically significant at an alpha level of 0.05 unless they are crossed out with "X" symbols. 'EC_sh' and 'EC_dp' are apparent electrical conductivity for shallow and deep measurements, respectively. 'SOM', 'pwp', 'fc', 'awc', and 'ETr' are abbreviations for soil organic matter, permanent wilting point, field capacity, available water content, and relative evapotranspiration, respectively. The underscores 'top', 'sub', 'fc', 'sw', and 'po' are abbreviations for topsoil, subsoil, field corn, sweet corn, and potatoes.

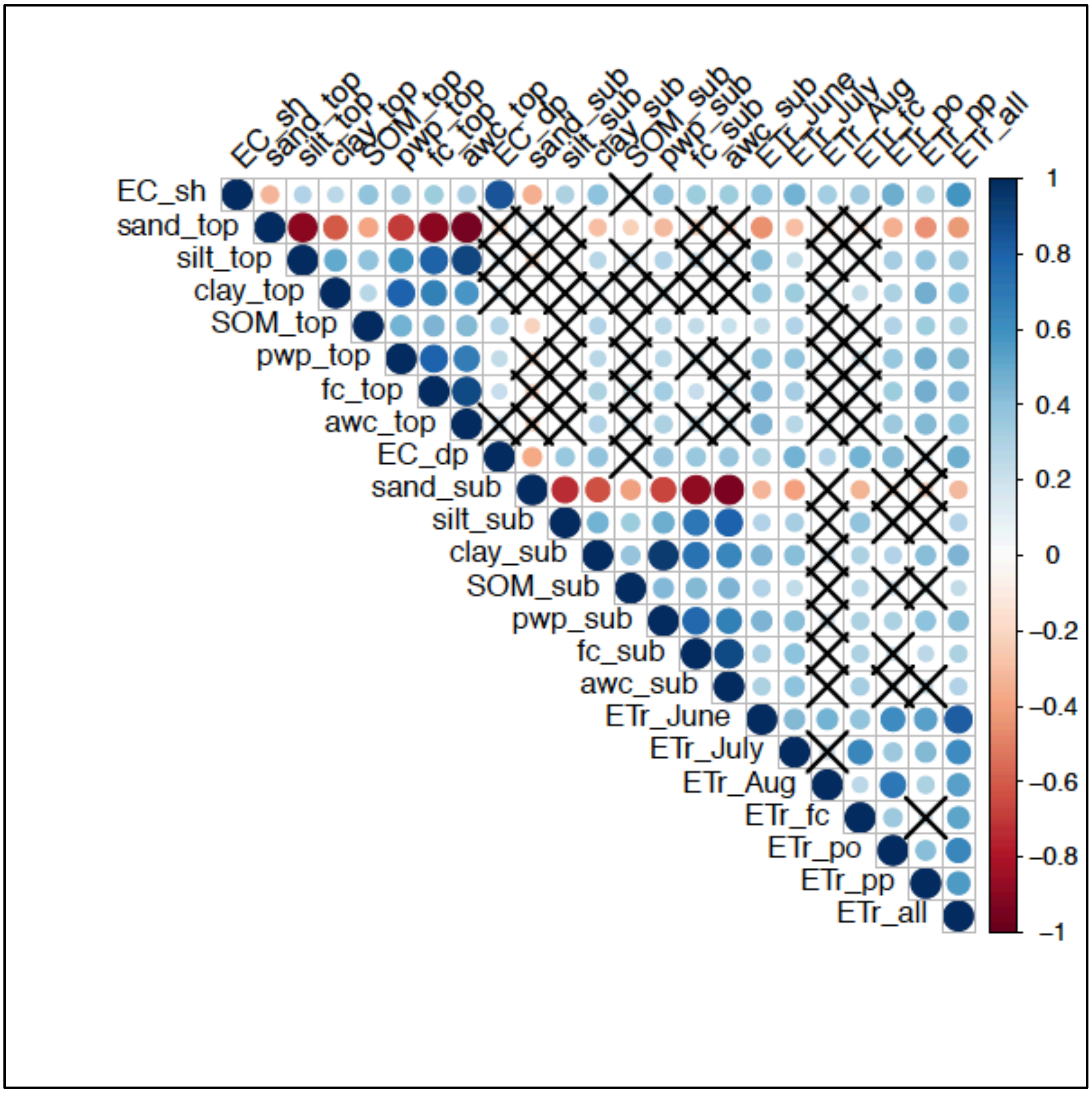

Figure 9. Kendall's tau correlation coefficient matrix for field W. Circle color indicates the direction of the relationship (blue=positive correlation, red=negative correlation) and circle size indicates the strength of the relationship with the largest circles representing 1 or -1. Correlations are all statistically significant at an alpha level of 0.05 unless they are crossed out with "X" symbols. 'EC_sh' and 'EC_dp' are apparent electrical conductivity for shallow and deep measurements, respectively. 'SOM', 'pwp', 'fc', 'awc', and 'ETr' are abbreviations for soil organic matter, permanent wilting point, field capacity, available water content, and relative evapotranspiration, respectively. The subscripts 'top', 'sub', 'fc', 'po', and 'pp' are abbreviations for topsoil, subsoil, field corn, potatoes, and peas-pearl millet.

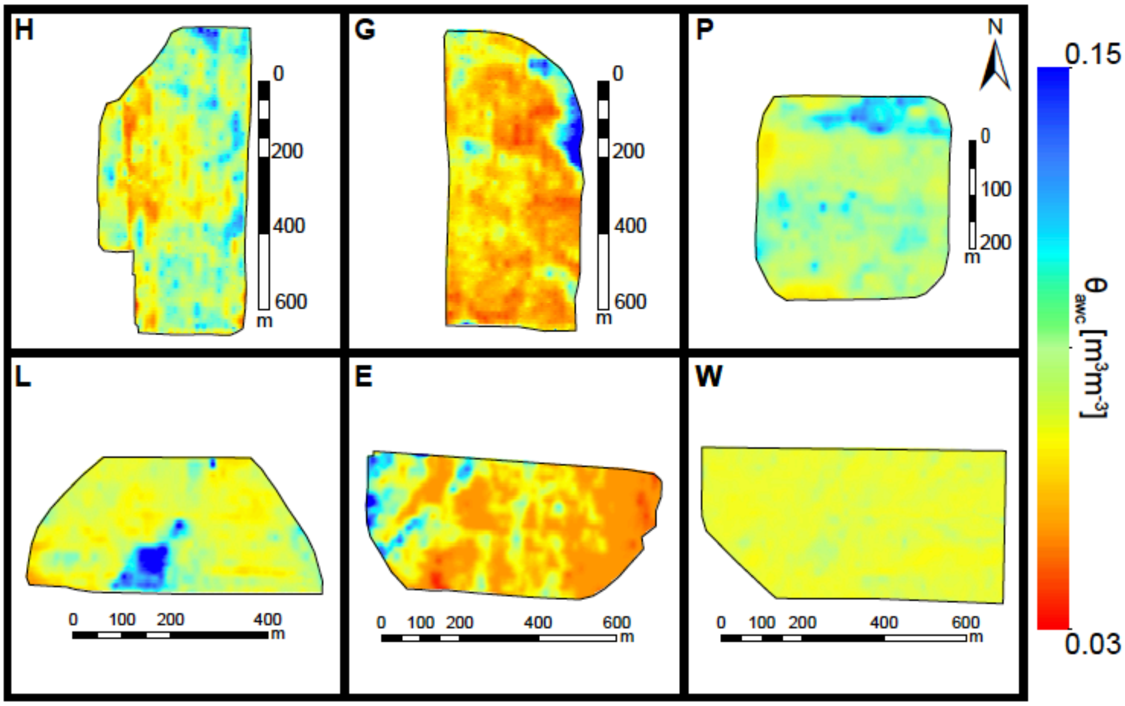

Figure 10. Maps of topsoil plant available water content (θ_{awc_top}, $m^3\ m^{-3}$) for fields H, G, P, L, E, and W derived from apparent electrical conductivity surveys. All maps are scaled to the same color bar.

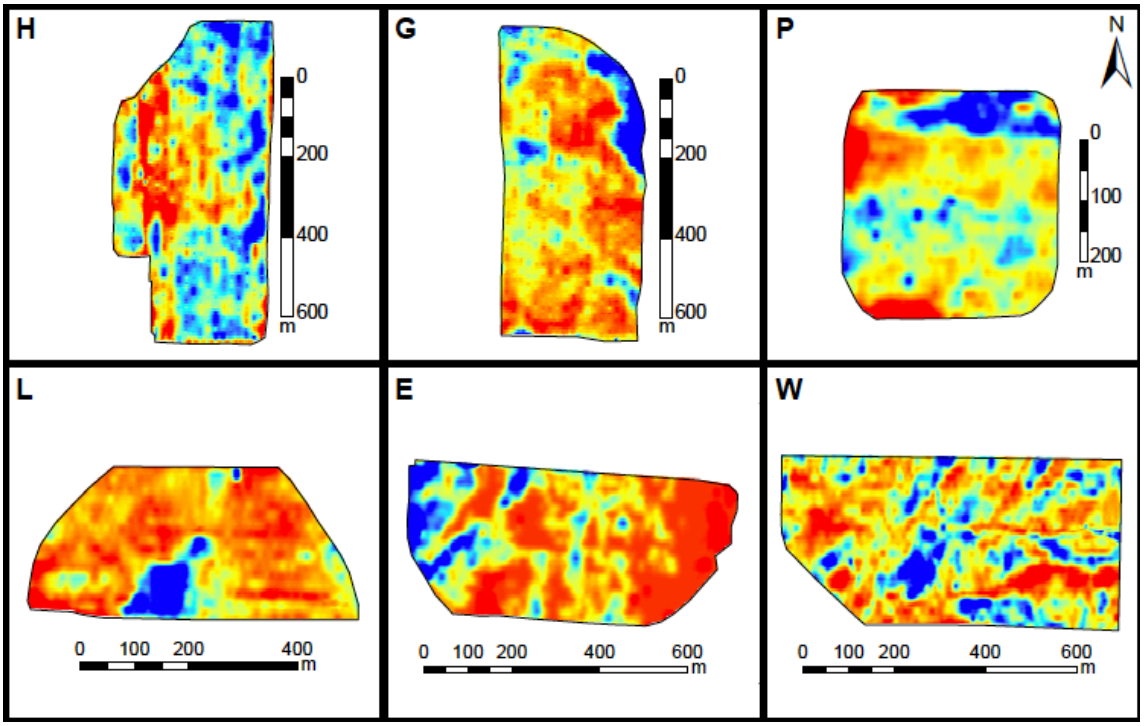

Figure 11. Maps of relative topsoil plant available water content (θ_{awc_top}, m^3m^{-3}) for fields H, G, P, L, E, and W derived from apparent electrical conductivity surveys. Color bars represent linearly normalized mean θ_{awc} rates to the 5th (red) and 95th (blue) percentile for each field.

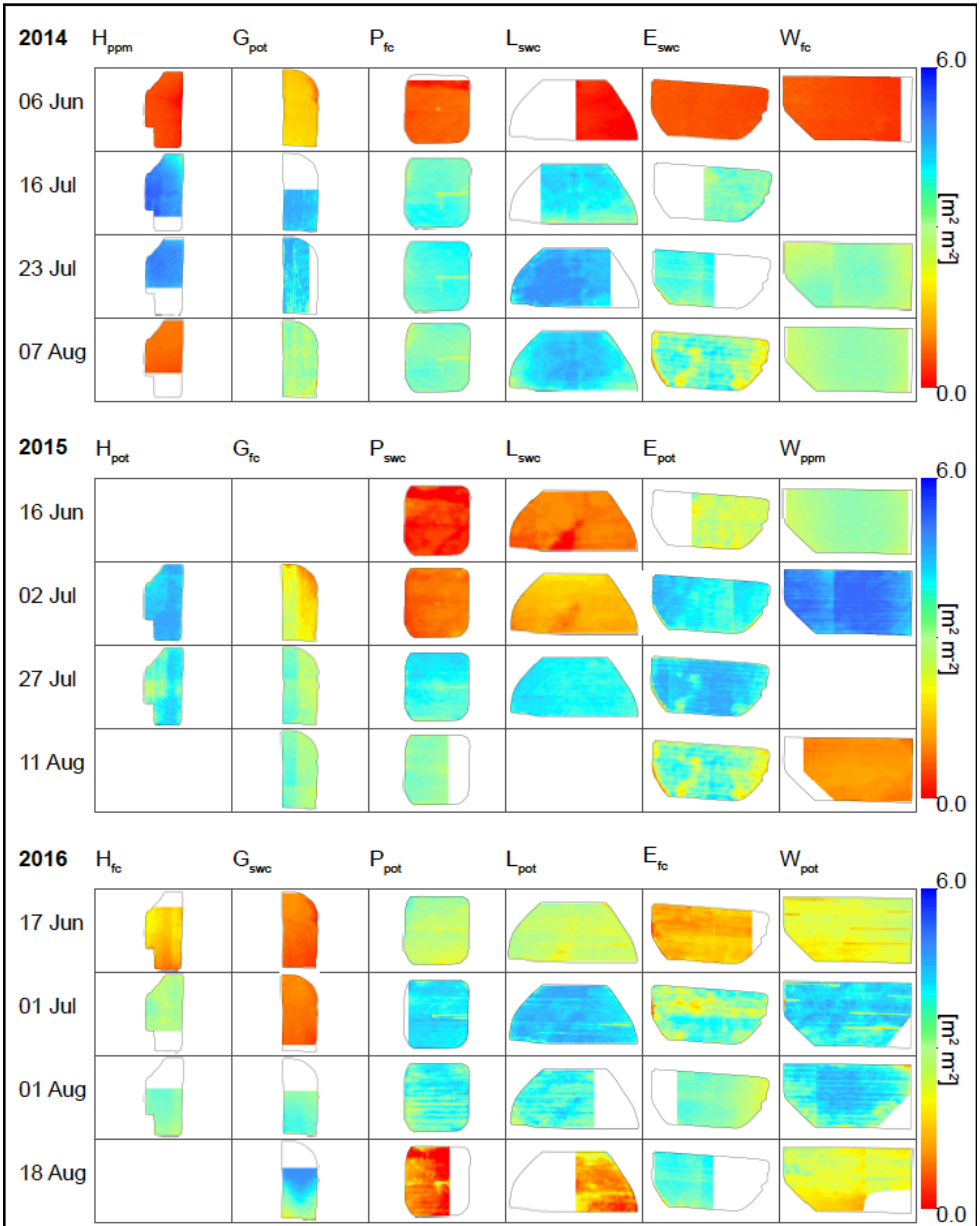

Figure 12. Leaf area index (m^2m^{-2}) for fields H, G, P, L, E, and W for twelve airborne missions in 2014-2016. Subscripts 'ppm', 'pot', 'fc', and 'swc' represent peas-pearl millet, potatoes, field corn, and sweet corn, respectively. All maps are linearly scaled to the same color bar. Blank spaces indicate missing imagery because of cloud interference during missions.

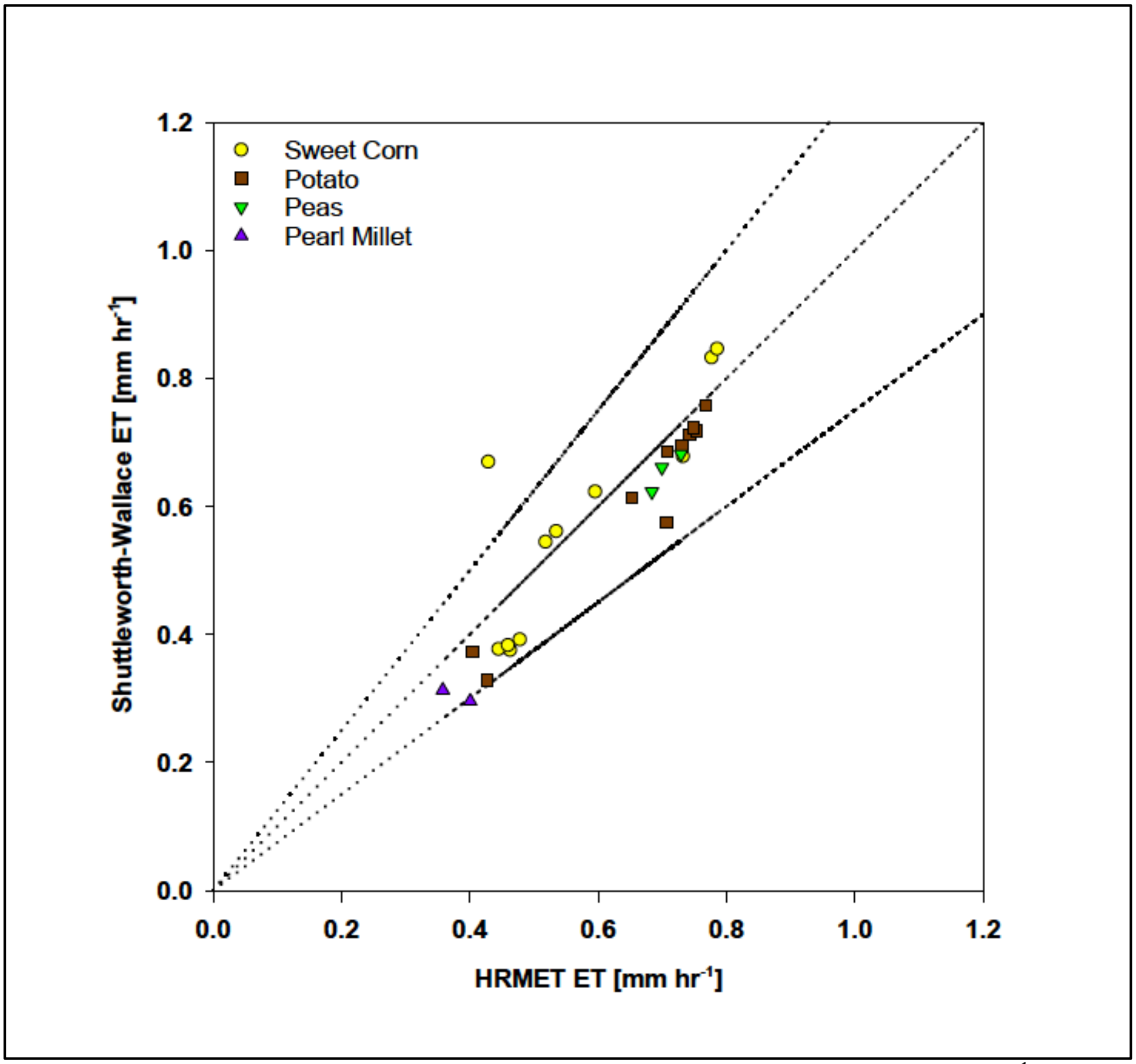

Figure 13. Comparison of HRMET and Shuttleworth-Wallace ET rates (mm hr^{-1}) for irrigated sweet corn, potatoes, peas, and pearl millet cropping systems. The dashed lines represent a 1:1 fit ±25% error.

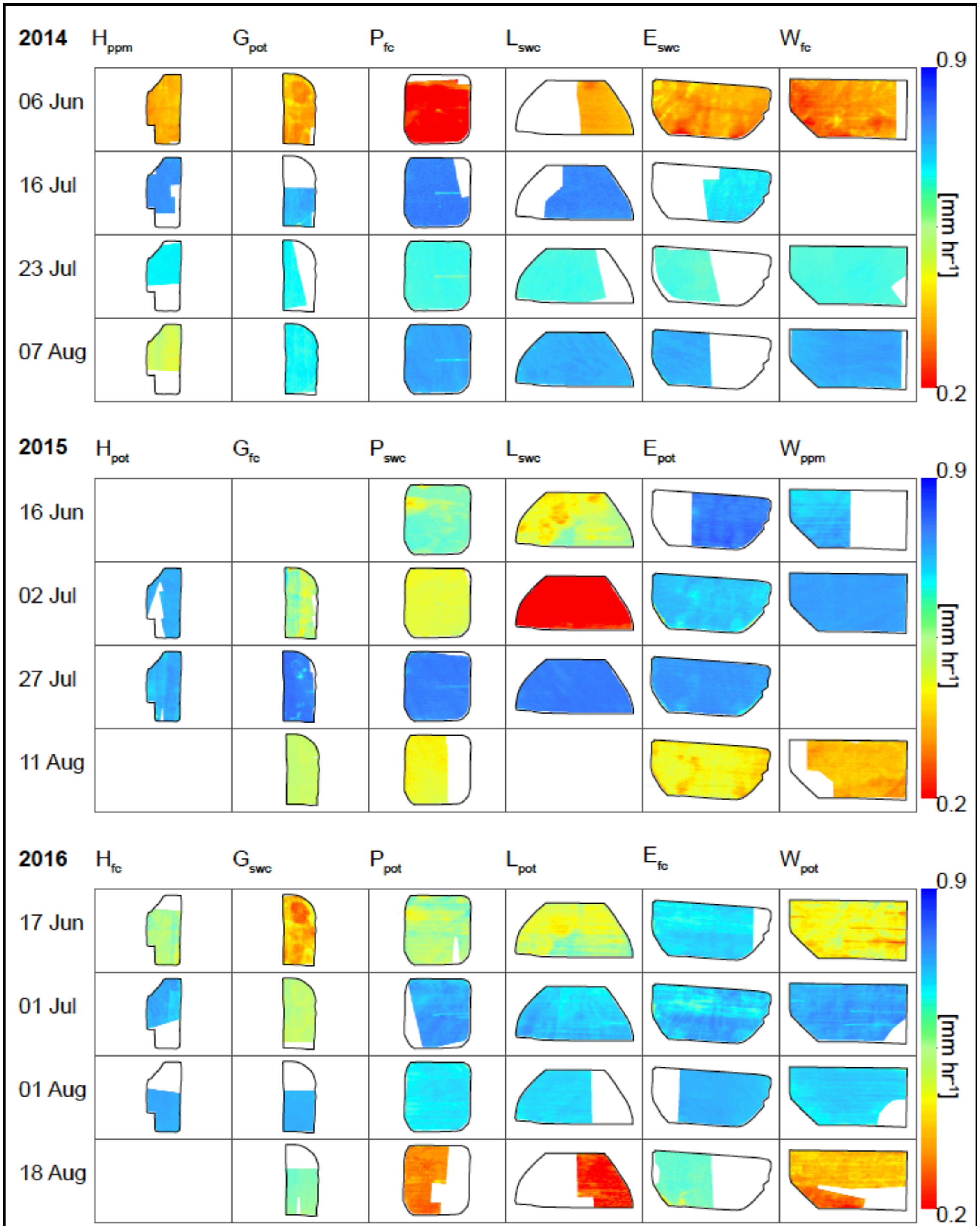

Figure 14. HRMET-calculated mean ET rates (mm hr[-1]) for fields H, G, P, L, E, and W for twelve airborne missions in 2014-2016. Subscripts ‘ppm’, ‘pot’, ‘fc’, and ‘swc’ represent peas-pearl millet, potatoes, field corn, and sweet corn, respectively. All maps are linearly scaled to the same color bar. Blank spaces indicate missing imagery because of cloud interference during missions.

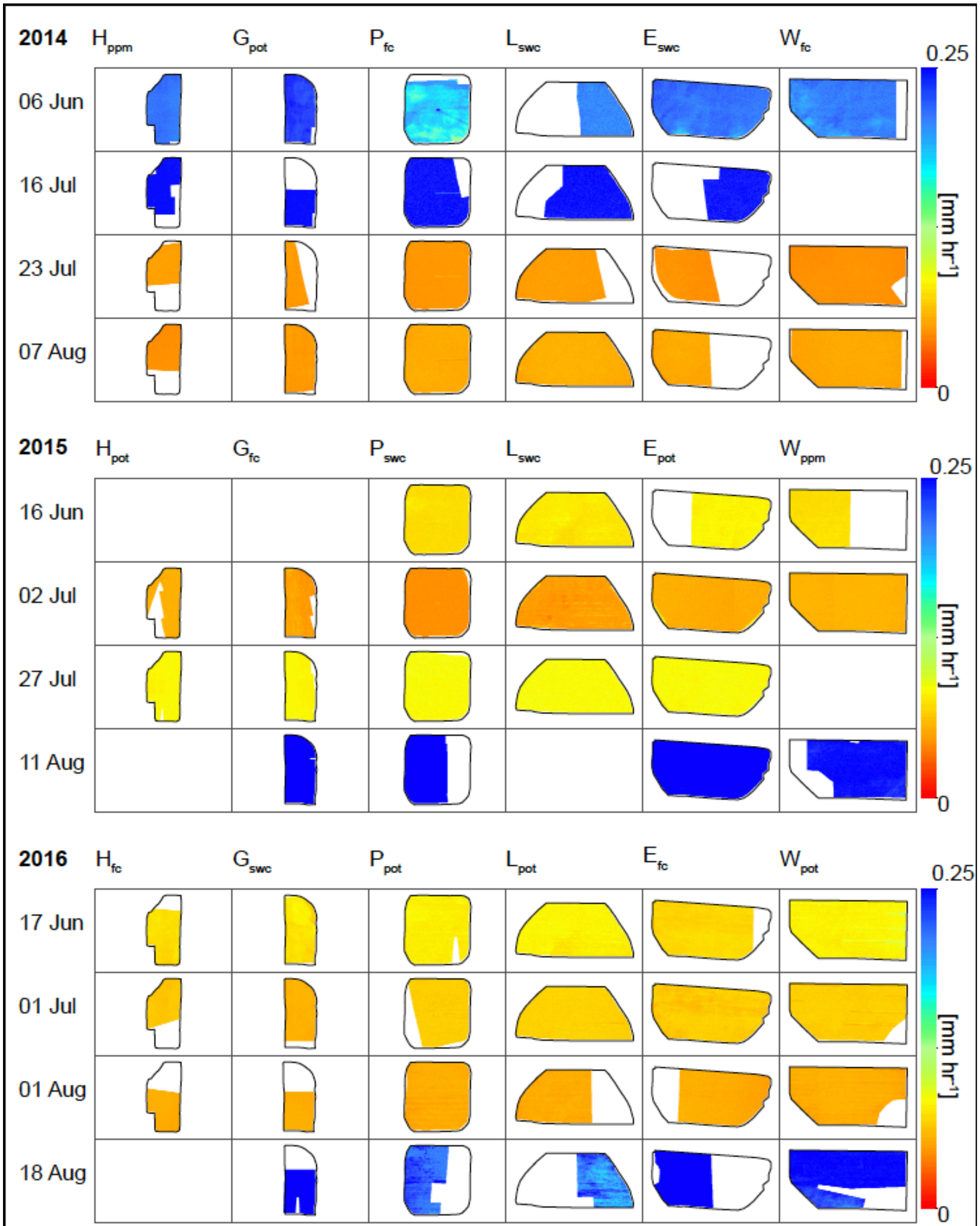

Figure 15. Standard deviation of HRMET-calculated ET rates (mm hr^{-1}) for fields H, G, P, L, E, and W for twelve airborne missions in 2014-2016. Subscripts 'ppm', 'pot', 'fc', and 'swc' represent peas-pearl millet, potatoes, field corn, and sweet corn, respectively. All maps are linearly scaled to the same color bar. Blank spaces indicate missing imagery because of cloud interference during missions.

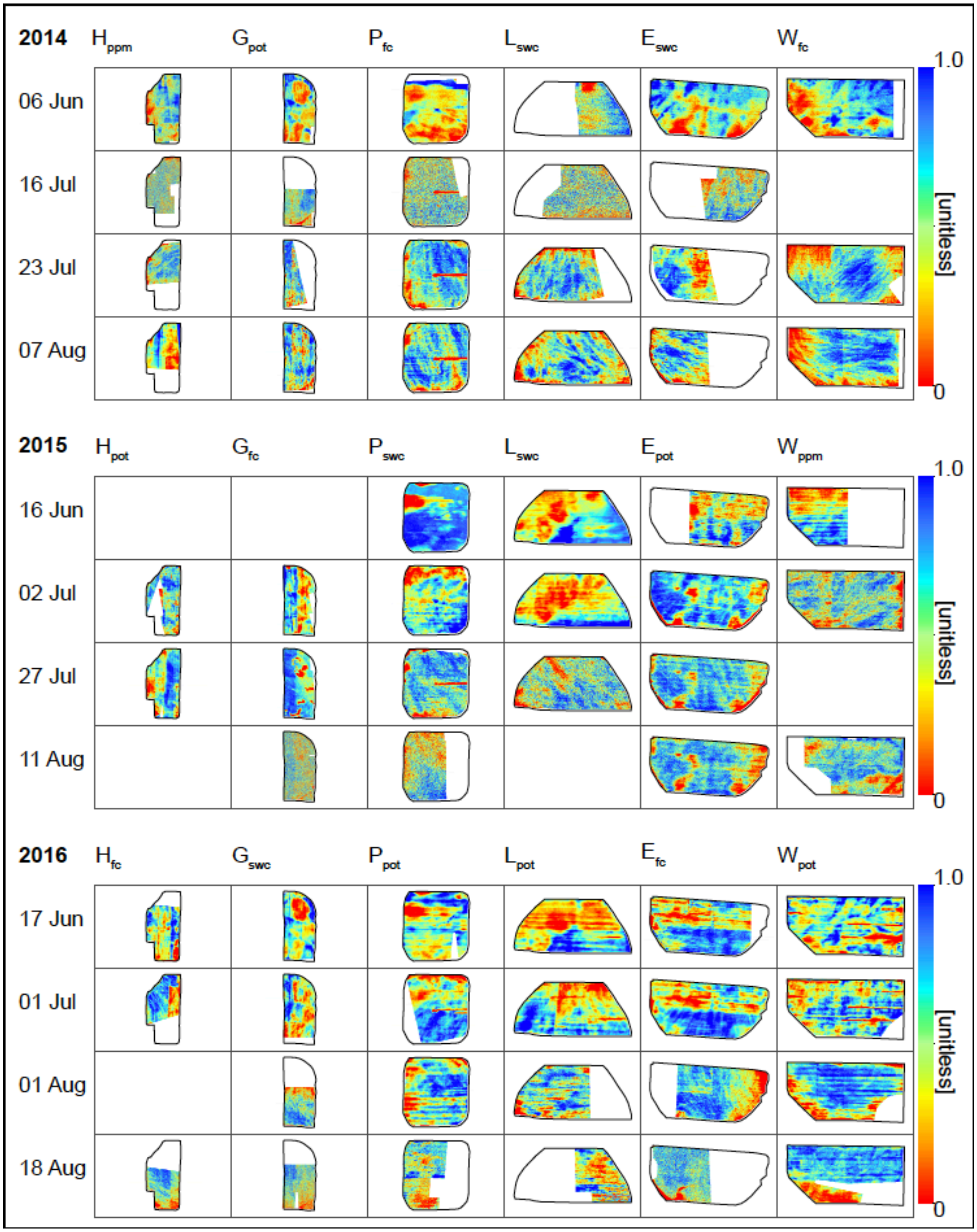

Figure 16. Maps of relative evapotranspiration (ET_R, unitless) for fields H, G, P, L, E, and W for twelve airborne missions in 2014-2016. Subscripts 'ppm', 'pot', 'fc', and 'swc' represent peas-pearl millet, potatoes, field corn, and sweet corn, respectively. Color bars represent linearly normalized mean θ_{awc} rates to the 5^{th} (red) and 95^{th} (blue) percentile for each field. Blank spaces indicate missing imagery because of cloud interference during missions.

Chapter 5

Regional climate impacts of irrigated land use conversion in the Wisconsin Central Sands

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Abstract

Irrigation-induced impacts to climate are primarily associated with arid and semi-arid regions, where there are dramatic differences in evapotranspiration between irrigated and rainfed landscapes. However, very little is known about irrigation-induced impacts to climate in humid regions where irrigated land use is significantly expanding. For example, irrigated land use is increasing in sandy regions underlain by coarse, glacial aquifers throughout the Northern Great Lakes of Minnesota, Wisconsin, and Michigan. The coarse aquifers in these regions provide groundwater to support the intense production of crops such as potatoes, field corn, sweet corn, beans, and peas. This study examined whether irrigated land use conversion from rainfed cropland and forests to irrigated potato and vegetable systems could lead to changes in temperature and humidity in the Wisconsin Central Sands (WCS), a small ecological region that has undergone and continues to undergo significant land use conversion from rainfed cropland and pine plantations to irrigated potato and vegetable production. We established a 60-km, longitudinal transect consisting of 28 stations across varying land uses in the WCS and monitored surface air temperature and relative humidity for 31 months. We quantified

irrigated-land use in both time and space by using fractional cover of irrigated croplands, surrounding forest cover, and a novel irrigated lands database that contains monthly estimates of pumped groundwater by parcel for the state of Wisconsin. We found that irrigated land cover decreased the diel temperature range (DTR) by an average of 3°C and the vapor pressure deficit (VPD) by an average of 0.10 kPa, compared to surrounding pine plantations and rainfed agriculture. Differences in VPD across the land use gradient were seasonal, while differences in DTR were comparable year-round. Interannual variability in temperature had greater impacts on changes to DTR and VPD across the irrigated land use gradient than interannual variability in precipitation, though there were no droughts during the study period. Future work could examine the entire Northern Great Lakes region using historical climate records and process-based modeling to better characterize irrigation-induced changes to regional climate at longer temporal scales.

5.1. Introduction

The northern Great Lake states of Minnesota, Wisconsin, and Michigan converted 150,000 hectares of forests, wetlands, and rainfed cropland to irrigated land use between 1997 and 2012 (USDA, 2014; Lark et al., 2015). Though these states have continental climates, farmers grow potatoes, field corn, and other vegetable crops on sandy soils that require supplemental groundwater irrigation from underlying coarse, glacial aquifers. A growing body of literature has documented and predicted ground and surface water quality and quantity outcomes from irrigated land use in the northern Great Lake states (Nocco et al., 2017; Bradbury et al., 2017; Vashisht et al., 2015; Kraft et al., 2012; Kraft and Stites, 2003; Weeks and Stangland, 1971). However, very little is known about irrigation-induced impacts in continental regional climates, despite a robust body of literature documenting effects in arid and semi-arid regions (Yang et al., 2017; Kueppers and Snyder, 2012; Lobell and Bonfils, 2008; Kueppers et al., 2007). Quantifying irrigation-induced differences to climate in humid, temperate regions is critical to informing stakeholder expectations and water management planning (Niles and Mueller, 2016), estimating growing season length and crop phenology phase (Zipper et al., 2016), forecasting crop disease and pest risks (Jones et al., 2017), and predicting chronic and infectious human disease risks (Kim et al., 2016; Lee et al., 2016). In this study, we use the Wisconsin Central Sands as a representative region to quantify irrigation-induced changes to temperature and humidity in the northern Great Lake states and similar regions with continental climates where irrigated agriculture is expanding.

Observational and modeling studies from arid and semi-arid regions provide an understanding of how irrigated agriculture alters water and energy cycles that could be applicable to the northern Great Lake states. Irrigated agriculture alters the partitioning of the energy budget relative to surrounding landscapes by increasing the latent heat flux, decreasing sensible heat flux, and accordingly altering surface air temperatures (Leng et al., 2013), humidity (Sridhar and Anderson, 2017), potential evapotranspiration (Han et al., 2014), and precipitation patterns (Harding et al., 2015, Yang et al., 2017). Though irrigated-induced impacts to regional climate are often referred to as the "irrigation cooling effect," (Kueppers et al., 2007), nighttime warming or the increasing of daily minimum temperatures has also been observed in some cases because of high thermal conductivity and heat capacity in wet soils (Mahmood et al., 2006; Christy and Norris, 2006) in addition to the reduction of daily maximum temperatures because of increased evapotranspiration (ET) (Huber et al., 2014; Bonfils and Lobell, 2007). This reduction in daily maximum temperatures and increase in daily minimum temperatures associated with irrigated land use is referred to as an overall reduction in the diel temperature range (DTR), which is the difference between daily maximum and minimum temperatures (Kukal and Irmak, 2016).

In the northern Great Lake states, we hypothesize that biophysical characteristics, spatial intensity, and increased ET from irrigated agroecosystems impact regional climate relative to surrounding rainfed forests, wetlands, and cropland. The conversion of forests to rainfed agriculture decreases the diel temperature range by 0.5-1°C in the Midwestern United States by increasing albedo and evapotranspiration (Oleson et al., 2004; Bonan, 2001). It has also been demonstrated that the spatial intensity of irrigated agricultural land use drives irrigation-induced changes to regional climate (Haddeland et al., 2006; Kueppers et al., 2007; Bonfils and Lobell 2007; Lobell and Bonfils 2008; Qian et al., 2013). Additionally, increased spatial intensification of rainfed cropland via higher planting densities and leaf area indices has cooled summer maximum temperatures in the Midwestern United States (Mueller et al., 2015). Irrigated systems in the northern Great Lake states may be even more intensely cropped than rainfed cropland because irrigated vegetables such as peas, beans, and sweet corn are regularly double cropped (Delahaut and Thiede, 1999). Small, irrigated regions in the Midwestern United States have not yet been shown to contribute to differences in latent heat flux and surface temperature resulting from irrigated land use at the national scale (Ozdogan et al., 2010; Leng et al., 2014). However, Lu et al., (2017) recently modeled irrigated Midwestern agricultural lands using a precision irrigation approach and found that irrigated Midwestern regions had increased soil moisture and decreased precipitation, which reduced the sensitivity of latent heat flux to soil moisture. These findings indicate that irrigation may an important driver of regional water and energy cycles in humid continental climates. Though modeling studies have been and will continue to be extremely useful for understanding mechanisms driving water and energy cycles, observational studies are foundational for detecting the existence of irrigation-induced impacts to regional climate and validating modeling attempts.

In this study, we focus on quantifying irrigation-induced changes to near surface (2-m) air temperature and humidity using a transect with a dense number of observations that spans different land covers in the northern Great Lake states—irrigated agroecosystems, red pine plantations, mixed forests, and rainfed agroecosystems. Previous observational studies have quantified irrigation-induced impacts by making pairwise comparisons between irrigated and rainfed lands using governmental records and *a priori* rules for land use designation (Han and Yang, 2013; Zhu et al., 2012; Lee et al., 2009; Lobell and Bonfils, 2008; Bonfils and Lobell, 2007). However, designating irrigated land use in this manner is problematic, as irrigation is a time-varying forcing that changes for a particular parcel based on evaporative demand, rainfall, and differences in crop rotation (Lobell and Bonfils, 2008). Previous studies in arid and semi-arid climates have assumed that irrigation only occurs during the growing season and does not have significant interannual or seasonal variability as a driver (Zhu et al., 2012; Bonfils and Lobell, 2007; Lobell and Bonfils, 2008). These assumptions may not hold for the northern Great Lake states, where supplemental irrigation may vary greatly within and across years based on the magnitude and frequency of rainfall and the shifting water demands of different high-value vegetable crop rotations.

Our study directly quantifies irrigated land use as a continuous, time-varying forcing by using a unique database on irrigated lands coverage developed, validated, and maintained by the Wisconsin Department of Natural Resources (WDNR), which is based on monthly reporting of groundwater withdrawals georeferenced to specific irrigated parcels (Smail, 2016a). We also quantified the effects of irrigated and other relevant land covers as continuous drivers of temperature and humidity using the Wiscland 2.0 dataset (WDNR, 2016). To the best of our knowledge, no previous observational studies have used both spatially explicit groundwater withdrawals and fractional land cover classification to quantify irrigation-induced impacts to regional temperature and humidity. Our overall study objectives were to (1) detect any irrigation-induced changes to temperature and humidity, and (2) quantify specific time-varying and land cover drivers of irrigation-induced changes to climate in the northern Great Lake states.

5.2. Methods

5.2.1. Study area

The Wisconsin Central Sands (WCS, Fig. 1A) is a relatively small (6300 km^2), agricultural region with over 2100 high-capacity wells used to irrigate potato, field corn, and vegetable crops with groundwater from a coarse, sandy aquifer (Smail, 2016a). Nearly all crops grown in the Wisconsin Central Sands are irrigated (Fig. 1B). Irrigated agricultural production is the most concentrated in the center of the region and expands radially into adjacent rainfed cropland and forests (Fig. 1B). The WCS has a moist continental climate (Köppen classification: Dfa) and the 1981-2010 mean annual precipitation is 832 mm, mean January temperature is -9.4°C, and mean July temperature is 21.2°C (National Oceanic and Atmospheric Administration, 2017). Average annual potential evapotranspiration ranges from 470-570 mm (Motew and Kucharik, 2013) and average annual applied irrigation is 212 mm, but varies greatly ranging from 94-376 mm depending on interannual variability and irrigated crop type (Smail, 2013). There is a small temperature dependence on longitude in the WCS that varies with time of year; average monthly temperatures may vary up to 0.4°C from west (warmer) to east (cooler) across the WCS (Moran and Hopkins, 2002).

5.2.2. Temperature and Relative Humidity Data

In cooperation with private landowners, we installed 28 HOBO U23 Pro v2 temperature and relative humidity (RH) sensors in solar radiation shields (Onset Computer Corp; Bourne, MA, U.S.A.) on 3.2 m fence posts across a 60-km longitudinal transect with varying concentrations of irrigated land use in the WCS (Fig. 1B). Two distinct regions of sandy loam or loamy sand are present in the center of the transect, where irrigated lands are heaviest (Fig. 1C). Irrigated potatoes and vegetable cropping systems are most concentrated in the center of the transect (Fig. 1D). The western portion of the transect is largely covered by red pine plantations with some oak cover (Fig. 1E-F). The eastern transect edge is a mix of rainfed agriculture, pine, and oak cover (Fig. 1E-F; WDNR, 2016). Sensors were mounted at a 2-m height and spaced approximately 2 km apart from one another in flat, open areas; typically, in pivot corners of agricultural fields or unshaded openings in residential or wooded areas (Murthy, 2010). Sensors have an operational temperature range of -40 to 70°C, ±0.21°C accuracy from 0 to 50°C, and a resolution of 0.02°C at 25°C (Onset Computer Corp, 2017). Additionally, sensors have an operational RH range of 0-100%, ±2.5% accuracy from 10-90%, and a resolution of 0.05% RH (Onset Computer Corp, 2017). Sensor response time for both temperature and RH is 40 minutes in air moving at 1 m s^{-1}. We recorded instantaneous measurements every 15 minutes from 1 January 2014 to 8 September 2016, with a gap in data occurring during May 2014, which was left out of monthly analyses. We also estimated daily reference evapotranspiration (RET) for each sensor using ASCE equations for a short grass (Walter et al., 2000). For RET data inputs, we used temperature and relative humidity data from each sensor and solar radiation and wind speed data from a micrometeorological station installed 14 km north of the center of the transect (Nocco et al., 2017).

In addition to sensor data from the transect, we compared monthly average regional temperature and precipitation to 1981-2010 normals for the entire WCS region in order to identify months with abnormally low or high temperature or precipitation during the study period that would impact the entire transect. We used data from twelve cooperative stations in the WCS, which are surrounded by rainfed agriculture, irrigated agriculture, forests, and urban land use, and are representative of a regional average rather than particular land uses (Wisconsin State Climatology Office, 2017).

5.2.3. Wisconsin Irrigated Lands Coverage

We extracted monthly applied irrigation values (ML) at a 2-km radius from each temperature and RH sensor for all months with reported withdrawals between 1 January 2014 and 31 August 2016 from the Wisconsin Irrigated Lands Coverage database (Smail, 2016b). Months with reported withdrawals across the transect were April-October 2014, May-September 2015, and June-October 2016. The database combines the United States Department of Agriculture (USDA) Cropland Datalayer (USDA, 2016), statewide tax parcel data, and statewide water withdrawal locations and volumes to (1) identify agricultural lands, (2) identify agricultural tax parcels, (3), use buffered WDNR irrigation withdrawal locations to identify irrigated tax parcels, and, (4) cross-reference tax parcel ownership with withdrawal records to estimate monthly applied irrigation from agricultural parcels. Where cross-referencing did not match, irrigated parcels were validated on-the-ground and withdrawals were manually applied to parcels (Smail, 2016b).

5.2.4. Land Cover and Soil Data

We obtained coverage data (%) for all level 3 land cover classes within a 2-km radius of each temperature and RH sensor from the Wisconsin Initiative for Statewide Cooperation on Landscape Analysis and Data (WISCLAND 2.0, WDNR, 2016). We only considered land cover classes with significant representation in the transect domain for statistical analyses. These classes included dairy rotation, potato/vegetable rotation, warm-season grass, pine, and oak. We also obtained coverage data (%) for each of the four USDA hydrologic soil groups (HSG, A-D) within a 2-km radius of each temperature and RH sensor from the gridded Soil Survey Geographic (gSSURGO) database for the state of Wisconsin (Soil Survey Staff, 2016).

5.2.5. Statistical analyses and modeling

Ordinary least squares (OLS) regressions were used (ArcMap 10, ESRI, 2011) to identify multiple drivers of temperature, vapor pressure deficit (VPD), and RET patterns across the WCS. We considered groundwater withdrawals, land cover classes, and HSG as potential explanatory variables. Monthly averages of daily surface air temperature (T_{ave}, °C), maximum temperature (T_{max}, °C), minimum temperature (T_{min}, °C), diel temperature range (DTR, °C), and vapor pressure deficit (VPD, kPa), as well as total monthly and growing season RET (June-August, mm) were considered as response variables. Because July 2015 had the greatest magnitude of supplemental irrigation observed, we used it as a representative growing season month to identify significant relationships between explanatory and response variables. We used January 2015 as a representative winter month to identify any significant relationships between explanatory and response variables when groundwater withdrawals are not taking place. Additionally, we tested for spatial autocorrelation using the global Moran's I index test on OLS residuals (Arcmap 10, ESRI, 2010). Because spatial autocorrelation was often present, we used geostatistical methods to model relationships between explanatory and response variables.

We used Empirical Bayesian Kriging (EBK) Regression Prediction (ArcGIS Pro 1.2, ESRI, 2016) to visualize monthly average DTR and VPD on 60 km x 4 km resolution grids for 31 months between January 2014-August 2016. EBK Regression Prediction is a form of regression kriging that is useful for small spatial datasets when encountering collinearity amongst explanatory variables. We chose five explanatory variables that had linear relationships with response variables: HSG B cover (Fig. 1C), potato/vegetable cover (Fig. 1D), pine cover (Fig. 1E), oak cover (Fig. 1F), and monthly applied irrigation when present. These variables were transformed into 3-5 principle components and used to fit a regression model to point data. Model residuals were interpolated using the EBK method (Pilz and Spöck, 2008), which creates a distribution of semivariogram models using several simulations in order to account for uncertainty associated with choosing a single semivariogram model (Krivoruchko, 2012).

5.3. Results

5.3.1. Drivers

During the growing season in July 2015, HSG B (sandy loams or loamy sands with 50-90% sand content by volume), potato/vegetable cover, pine cover, oak cover, and monthly groundwater withdrawals all were significantly ($p < 0.05$) and linearly related to T_{max}, T_{min}, DTR, and VPD (Fig. 2-3, Supplemental Figs. 1-2). Surprisingly, though HSG A (sands with >90% sand and gravel content by volume) had high coverage throughout the transect, it had no significant linear relationships with any of the response variables. Significant ($p < 0.05$) spatial autocorrelation was present for July 2015 relationships where pine cover, monthly groundwater withdrawals, and HSG B were explanatory variables. In January 2015, HSG B, potato/vegetable cover, pine cover, and oak cover all had significant relationships with T_{max}, DTR, and VPD (Fig. 4-5, Supplemental Fig. 3). Significant ($p < 0.05$) spatial autocorrelation was present for January 2015 relationships where pine cover was an explanatory variable. Though the strength of relationships differed between explanatory and response variables during July and January 2015 (Figs. 2-5), the direction of linear relationships remained the same and supported a shrinking DTR and smaller VPD with different indicators of irrigated land use in the WCS. Specifically, DTR and VPD decreased with increasing HSG B, potato/vegetable cover, and monthly groundwater withdrawals; and increased with pine and oak cover. We did not detect significant ($p < 0.05$) relationships between any of the explanatory variables and T_{ave} or RET. Average June-August RET across the entire transect was 310, 320, and 333 mm for 2014, 2015, and 2016, respectively.

In order to compare daily temperature patterns in predominantly pine vs. potato/vegetable, we present time series for a warm week during January and July 2015 for three temperature/RH sensors with 67-69% pine cover and three temperature/RH sensors with 76-80% potato/vegetable cover within a 2 km radius (Fig. 6). In January, both predominantly pine and potato/vegetable areas generally started the day with similar pre-dawn, minimum temperatures (Fig. 6A). However, the predominantly pine area recorded higher maximum temperatures than the potato/vegetable areas, which occurred during the middle of the day. There were no significant differences in minimum temperatures between pine and potato/vegetable areas in January. Contrastingly, in July, the pine area regularly reached both a higher T_{max} and returned to a lower T_{min} than the potato/vegetable area; indicating a shrinking DTR from both extremes in the potato/vegetable area during the growing season (Fig. 6B). Though we did not see significant relationships between explanatory variables and RET, the predominantly pine area had an average of 6, 3, and 4 mm higher June-August RET than the potato/vegetable area for 2014, 2015, and 2016, respectively.

If we assume that potato/vegetable cover is the sole explanatory variable, a conversion to 100% potato/vegetable cover in the WCS would result in a 0.7 to 4.2°C reduction of monthly DTR and with an average reduction of 2.7°C across all 31 months based on OLS regression results (Fig. 7). Similarly, a conversion from surrounding land covers to 100% potato/vegetable cover in the WCS would result in a 0.03 to 0.18 kPa reduction in VPD with an average reduction of -0.06 kPa across all 31 months (Fig. 7). A conversion to 80% potato/vegetable cover, which is the densest irrigated cover represented in our study, would have an average DTR reduction of 2.2°C and VPD reduction of 0.05 kPa from surrounding unirrigated land uses. Both DTR and VPD reduction from potato/vegetable conversion exhibit some seasonality, where relatively smaller reductions occur during winter months.

5.3.2. Monthly Trends

Monthly temperatures were 2-6°C below the 1981-2010 normals from January-April 2014 and 2-8°C higher than 1981-2010 normals for Central Wisconsin between September and December 2015. Additionally, 2014 was a markedly wet year, with April, June, and August receiving 73, 44, 54 mm greater than the 1981-2010 average precipitation for the region. July 2014, July 2015, and April 2016 were the driest months during the study period, receiving 53, 34, and 37 mm lower than normal precipitation. There were no sustained (>2 months) periods of abnormally low or high precipitation during the study period.

EBK regression kriging models of monthly average DTR and VPD values are presented for 31 months between January 2014-August 2016 in Figs. 8 and 9, respectively. Differences in DTR ranged from 0.8-4.5°C across the land-use gradient and there was an average difference of 3°C across all 31 months between the western portion of the transect, which was heavily covered with red pine plantations, and the central portion of the transect, which was heavily covered with irrigated potato and vegetable crops (Fig. 8). The geostatistical model including five explanatory variables shows a 0.8°C greater average reduction in DTR at 80% potato/vegetable coverage than the OLS model using potato/vegetable cover as the sole explanatory variable. Differences in VPD ranged from 0.03-0.24 kPa across the land use gradient with an average difference of 0.10 kPa between the pine plantations in the west and irrigated potato/vegetable crops in the middle (Fig. 9). Like DTR, the geostatistical model including five explanatory variables shows a 0.05 kPa greater average reduction in VPD at 80% potato/vegetable coverage than the OLS model with a single explanatory variable.

Root mean square error (RMSE) values are relatively high for both modeled DTR (2.3-2.5°C) and VPD (0.02-0.11 kPa) during the colder than average temperature period between January-April 2014 and DTR and VPD appeared to be driven by a W-E gradient more than land cover. Other than this cold time period, spatial patterns followed a land cover gradient and RMSE values were low, ranging from 0.2-0.7°C for monthly DTR models and < 0.04 kPa for monthly VPD models. Differences in VPD had greater seasonality than differences in DTR with winter months decreasing VPD across land covers. Spatial trends also differed between DTR and VPD. There was generally more uniformity in the reduction of DTR across irrigated lands compared to red pine plantations (Fig. 1, Fig. 8), while the greatest VPD reduction was usually concentrated at the eastern side of the irrigated lands, where there is also a patch of high HSG B cover (Fig. 1, Fig. 8). We observed no reversals in spatial trends across the land use gradient. Though low vs. high DTR and VPD areas expanded and contracted, the western forested area generally maintained a higher DTR and VPD than the central irrigated area, with the eastern edge of the transect falling in between the two regions.

5.4. Discussion

5.4.1. Irrigated land cover reduces DTR and VPD during the growing season in a continental climate

We observed up to a 4.5°C reduction in DTR across an irrigated land-use gradient in the WCS, which is comparable to observed and modeled reductions of DTR in irrigated arid and semi-arid climates (Huber et al., 2014; Lobell and Bonfils, 2008). In contrast, we observed up to a 0.24 kPa reduction in VPD from rainfed to irrigated land uses in the WCS, which is less than the 1-2 kPa reduction in VPD observed from irrigated land-use impacts in arid climates (Burman et al., 1975). The discrepancy between observing a similar magnitude of DTR reduction and much lower magnitude of VPD reduction across an irrigated land use gradient in humid, temperate climates may be the result of observed increases in T_{min}. Though there are some observed instances of regional T_{min} increasing with irrigation (Mahmood et al., 2006; Christy and Norris, 2006), the majority of observational and modeling studies from arid and semi-arid systems report reductions in DTR that stem solely from T_{max} reductions with T_{min} either having no significant changes or reductions lower than T_{max} (Kukal and Irmak, 2016; Xu et al., 2016). We speculate that the reason for increased T_{min} in irrigated areas is because sandy soils maintained at or near field capacity have higher soil thermal conductivity and heat capacity, which increases ground heat flux and causes nighttime warming of near surface air temperatures (Kanamaru and Kanamitsu, 2008).

We did not detect a significant reduction in monthly or seasonal RET, which was surprising given the reduction in T_{max} and VPD observed in heavily irrigated areas. Based on the Bouchet-Morton complementary hypothesis and previous studies of irrigation-induced changes to evaporative demand (Han et al., 2014), we anticipated that increased actual ET from irrigated lands would decrease evaporative demand (indicated by RET), assuming that energy inputs for ET remained the same across the transect (Bouchet, 1963; Morton, 1965; Ozdogan et al., 2006). The lack of significant differences in daily RET across the irrigated land use gradient in the WCS may have occurred because of two limitations of this study: 1) RET does not account for known differences in albedo between forests and croplands (Campbell and Norman, 1998) that could cause differences in available energy for ET across the transect; and 2) despite supplemental irrigation, actual daily ET from irrigated potato and vegetable crops was not high enough compared to forests and rainfed agriculture to significantly lower average daily inputs to RET such as temperature and vapor pressure deficit during the 31-month study period, which had average or below average growing season temperatures. Thus, our lack of detection of RET differences does not necessarily mean that differences in evaporative demand between irrigated and surrounding land uses are not present in continental climates—future work should use different methods such as long-term climate records or satellite observations to detect differences.

5.4.2. Irrigated land cover reduces DTR and VPD in the absence of active irrigation

We observed significant decreases in DTR and VPD across irrigated lands in the absence of active groundwater withdrawals and active irrigation between September-May. These observations indicate that increased ET from supplemental irrigation cannot be the sole driver of DTR and VPD differences between rainfed and irrigated land uses in the WCS. We suggest that biophysical differences between forests and agricultural systems (irrigated *or* rainfed) are responsible for these differences. The central part of the transect, where there was the highest coverage of irrigated cropland, was also the area with highest coverage of cropland in general (WDNR, 2016). During winter months, increased snow cover over croplands results in a higher surface albedo compared to forests (Bonan, 2008), which could explain the reductions in T_{max} and DTR observed in this study.

In order to study impacts, irrigated land use has to be quantified in relation to surrounding land use—whether it is urban, forested, or rainfed cropland. Surrounding rainfed lands may be associated with other regional climate forcings such as urbanization, which is known to confound the detection of irrigation-induced climate effects (Zhu et al., 2012; Lobell and Bonfils, 2008). In the sandy aquifers of the northern Great Lake states, forests surrounding irrigated agricultural lands may confuse our understanding of irrigation-induced cooling impacts if they are not also considered as additional explanatory variables. In this study, including pine and oak as explanatory variables associated with irrigated and surrounding land covers created more comprehensive models of DTR and VPD than using irrigated potato/vegetable cover as the sole explanatory variable. If we had not included pine cover in EBK regression kriging models, we may not have observed that the conversion from pine to potato/vegetable cover may cause greater reductions in DTR and VPD than the conversion from rainfed croplands to potato/vegetable cover.

5.4.3. Irrigation-induced climate impacts may depend on interannual climate variability

Differences in DTR and VPD across the irrigated land use gradient were contingent on interannual temperature variability. These differences were not present during the abnormally cold time period between January-April 2014. During those cold months, differences in DTR and VPD followed the larger W-E gradient in temperatures (warmer to cooler) observed over the state of WI (Moran and Hopkins, 2002). We did not observe amplified differences in DTR and VPD between rainfed and irrigated lands during the warm fall of September-December 2015 either, which may be because no groundwater withdrawals were occurring during this time period. We speculate that we might have observed amplified differences in DTR and VPD during a sustained period of above average temperatures during the growing season, which did not occur during the study period. Our findings suggest that temperature may be a greater modulator of irrigation-induced climate impacts in the northern Great Lake states than precipitation. Differences in DTR and VPD did not have a strong dependence on precipitation in this study. Wetter than average months with relative normal temperatures such as June and August 2014 did not have diminished differences in DTR and VPD across the irrigated land use gradient. Our findings are generalizable to other sandy areas in the northern Great Lake states to a certain extent, in that we would expect to see year-round reductions in DTR and VPD with conversion from pine, oak, or rainfed land uses with the highest reductions occurring under pine to potato/vegetable conversion. However, the lack of drought conditions, short study period, and relatively small spatial coverage of our transect may limit extrapolation of our specific ranges in DTR (0.8-4.5°C) and VPD (0.03-0.24 kPa) reductions. Future work should use a larger study area and longer observational records to develop and validate statistical or process-based models that can be used across the Northern Great Lake states to predict historical and future climate impacts associated with irrigated land use conversion.

5.5. Conclusions

The northern Great Lake states of Wisconsin, Minnesota, and Michigan are experiencing heavy conversion from forests, wetlands, and rainfed cropland to irrigated cropland. We observed significant reduction in DTR and VPD associated with irrigated agriculture across a land use gradient in the WCS encompassing red pine plantations, rainfed croplands, and irrigated potato/vegetable crops. Future modeling experiments may be useful to isolate DTR and VPD trends that occur because of irrigation-enhanced ET from DTR and VPD trends that result from biophysical differences between forests and croplands.

Changes in DTR and VPD associated with irrigated land use expansion may have significant implications for land use policy in the northern Great Lake states, given the accompanying social, agriculture, human health, and ecological impacts. For example, irrigation-induced impacts to temperature can influence farmer perceptions about climate change vulnerability and risk. Farmers in heavily irrigated regions may be less inclined to engage in adaptive management efforts because irrigated land-use buffers extreme high and low temperatures in their immediate surroundings (Niles and Mueller, 2016). These reductions in DTR can decrease heat and frost stress, alter growing degree days and crop development, enhance or moderate pest populations, and fundamentally affect crop yields. For example, decreased DTR has been associated with an increase in potato yields (Zhao et al., 2016) that may also be accompanied by increases in potato nematode populations (Jones et al., 2017). Changes in crop pest population dynamics and crop growth associated with DTR reductions can also apply to plants and insect populations as a whole. As such, changes to DTR can favor or limit species growth leading to differences in species richness and diversity (Peng et al., 2013; Vasseur et al., 2014). Moreover, reductions in DTR and VPD can impact human health; specifically impacting vulnerable populations such as children and the elderly. For example, reductions in DTR can alleviate human respiratory and circulatory disease symptoms in children (Xie et al., 2017), reduce mortality in elderly populations (Kim et al., 2016;), while increasing infectious and vector-borne disease risks in the general population (Lee et al., 2016). Thus, reductions in regional DTR and VPD could have far-reaching socioecological impacts. These types of complex outcomes must be considered by policy makers when making future decisions about expansion of irrigated land use, and support further study of irrigation-induced changes to climate in the northern Great Lake states.

5.6. Acknowledgments

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5.8. Figures

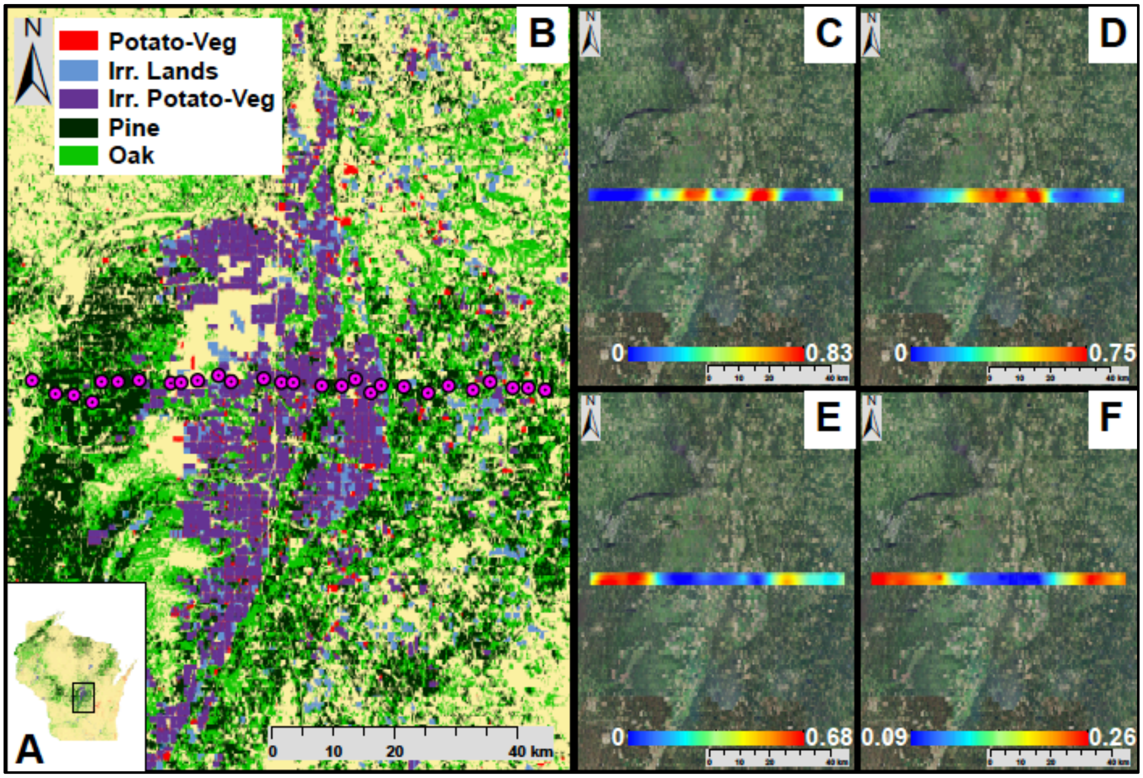


Figure 1. 2015 National Agriculture Imagery Program data depicting (A) Irrigated lands (blue and purple parcels) in the state of Wisconsin with the Wisconsin Central Sands region outlined by the black rectangle, (B) Potato and vegetable cover, irrigated lands, irrigated potato-vegetable cover, pine cover, and oak cover in Wisconsin Central Sand region, with locations of the 28 temperature/relative humidity sensors across a 60-km longitudinal transect designated by pink circular markers, (C) USDA hydrologic soil category B (50-90% sands classified as loamy sands or sandy loams) coverage (fraction) across transect, (D) Potato and vegetable land cover (fraction) across transect, (E) Pine cover (fraction) across transect, and (F) Oak cover (fraction) across transect.

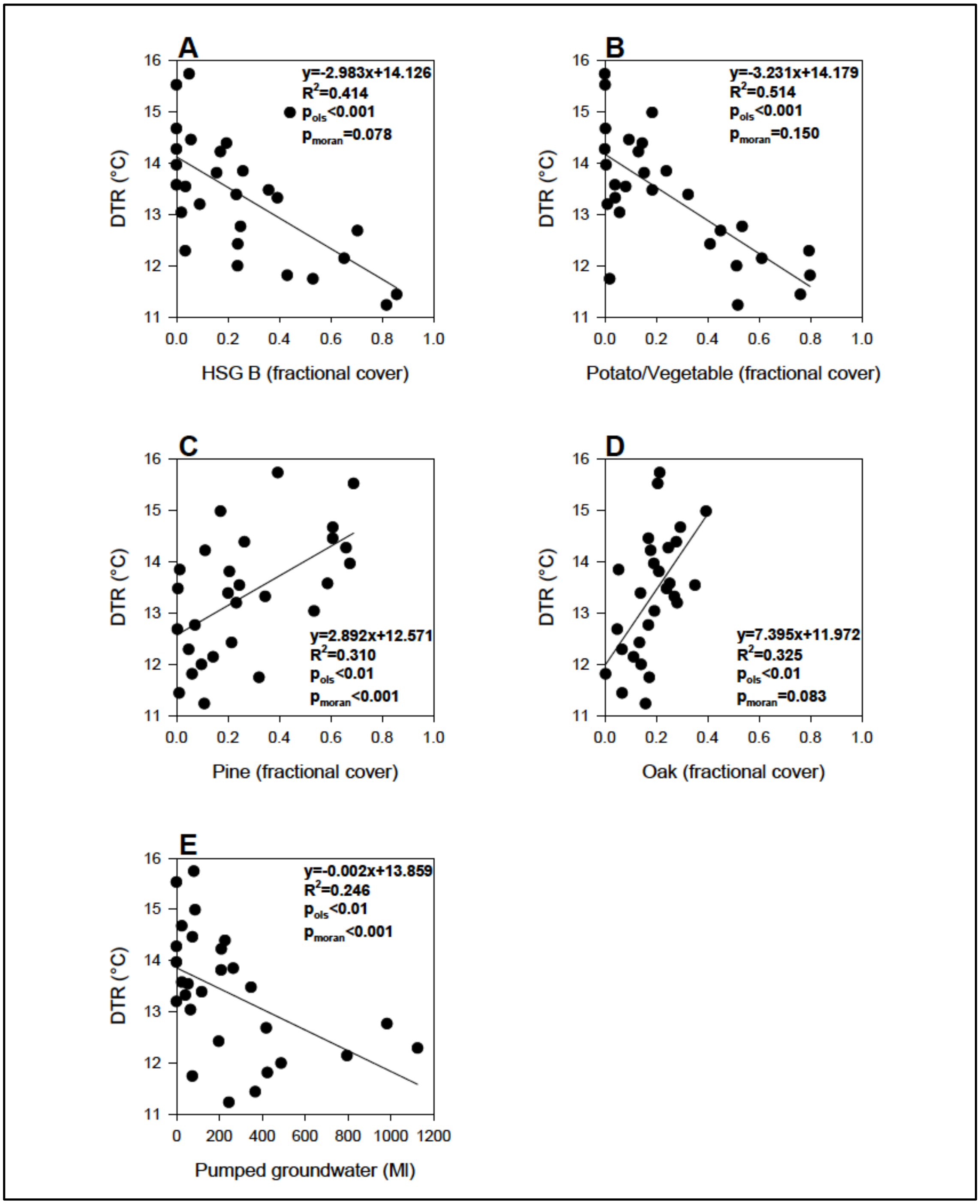


Figure 2. July 2015 Ordinary Least Squares regression results for (A) diel temperature range (DTR, °C) vs. USDA hydrologic soil category B (fractional cover), (B) DTR vs. potato/vegetable (fractional cover), (C) DTR vs. pine (fractional cover), (D) DTR vs. oak (fractional cover), and (E) DTR vs. pumped groundwater (Ml).

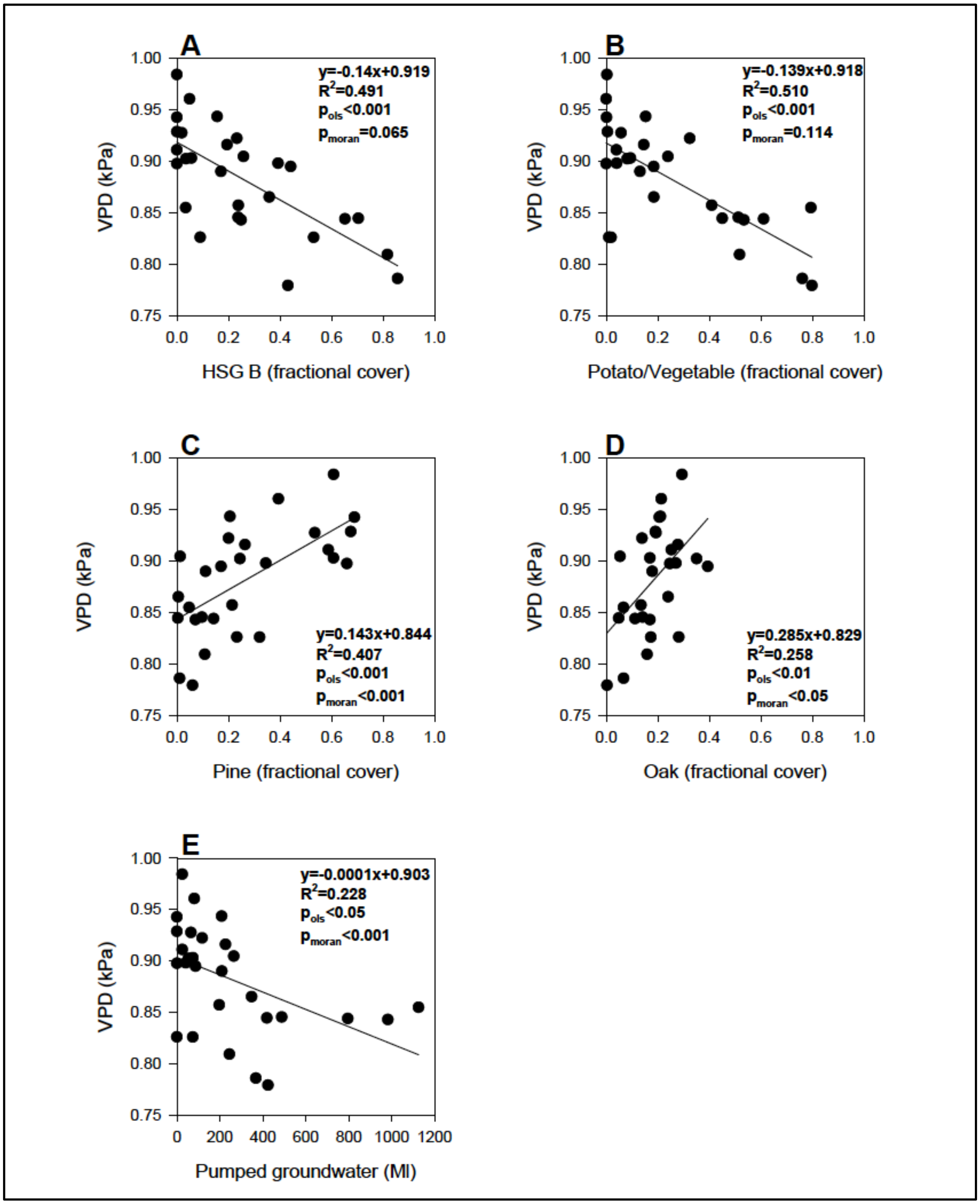


Figure 3. July 2015 Ordinary Least Squares regression results for (A) vapor pressure deficit (VPD, kPa) vs. USDA hydrologic soil category B (fractional cover), (B) VPD vs. potato/vegetable (fractional cover), (C) VPD vs. pine (fractional cover), (D) VPD vs. oak (fractional cover), and (E) VPD vs. pumped groundwater (Ml).

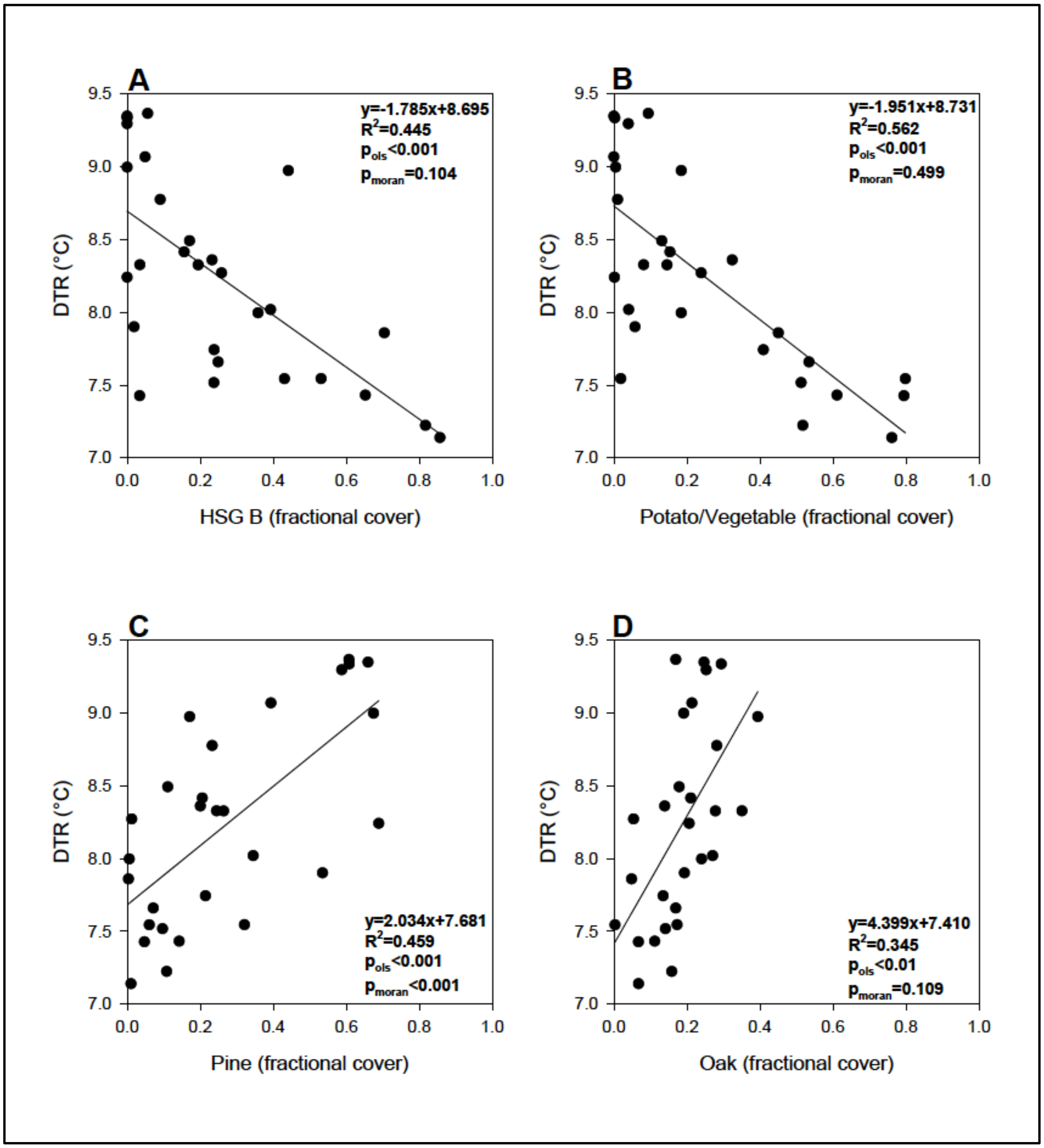


Figure 4. January 2015 Ordinary Least Squares regression results for (A) diel temperature range (DTR, °C) vs. USDA hydrologic soil category B (fractional cover), (B) DTR vs. potato/vegetable (fractional cover), (C) DTR vs. pine (fractional cover), and (D) DTR vs. oak (fractional cover).

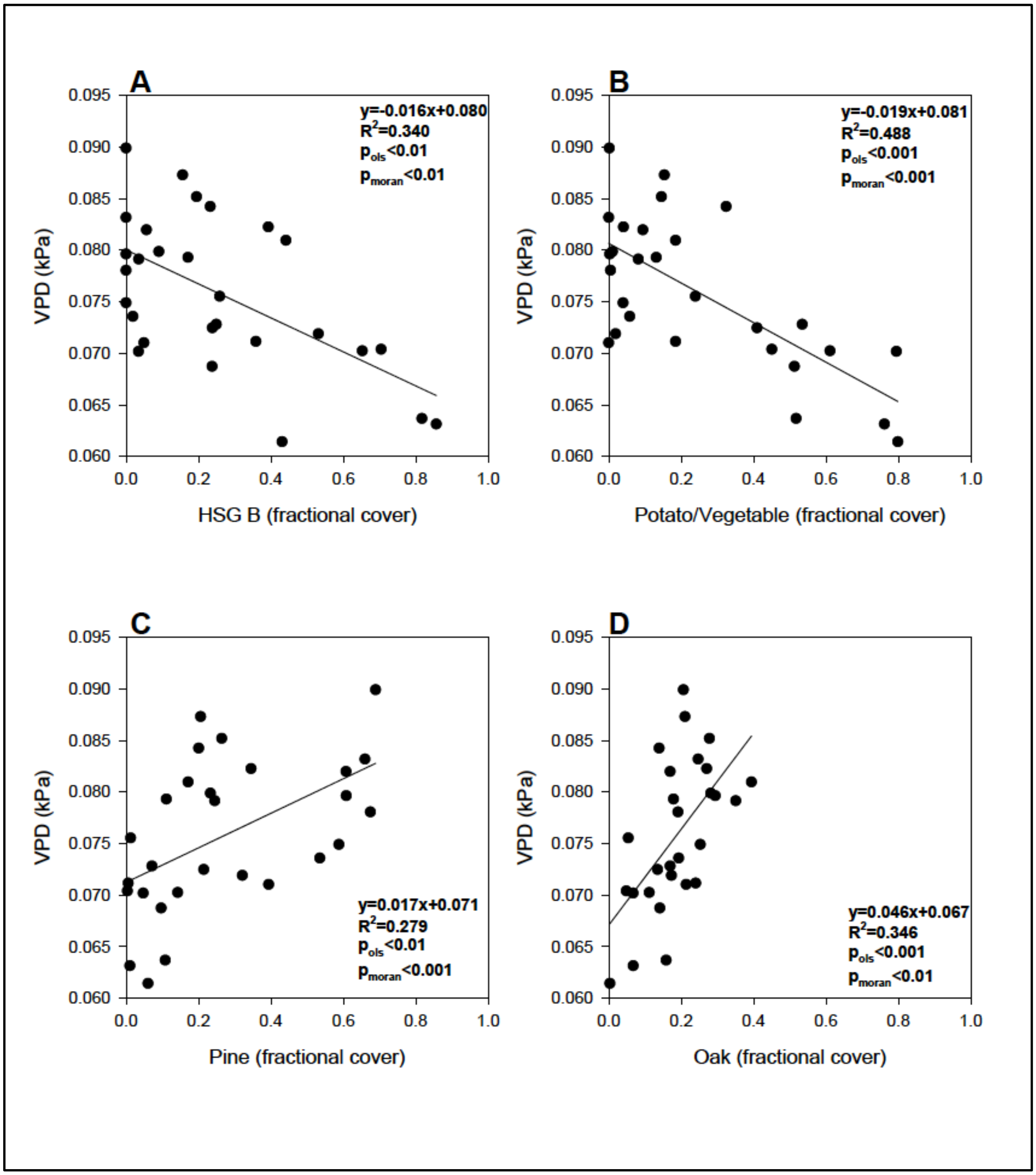


Figure 5. January 2015 Ordinary Least Squares regression results for (A) vapor pressure deficit (VPD, kPa) vs. USDA hydrologic soil category B (fractional cover), (B) VPD vs. potato/vegetable (fractional cover), (C) VPD vs. pine (fractional cover), and (D) VPD vs. oak (fractional cover).

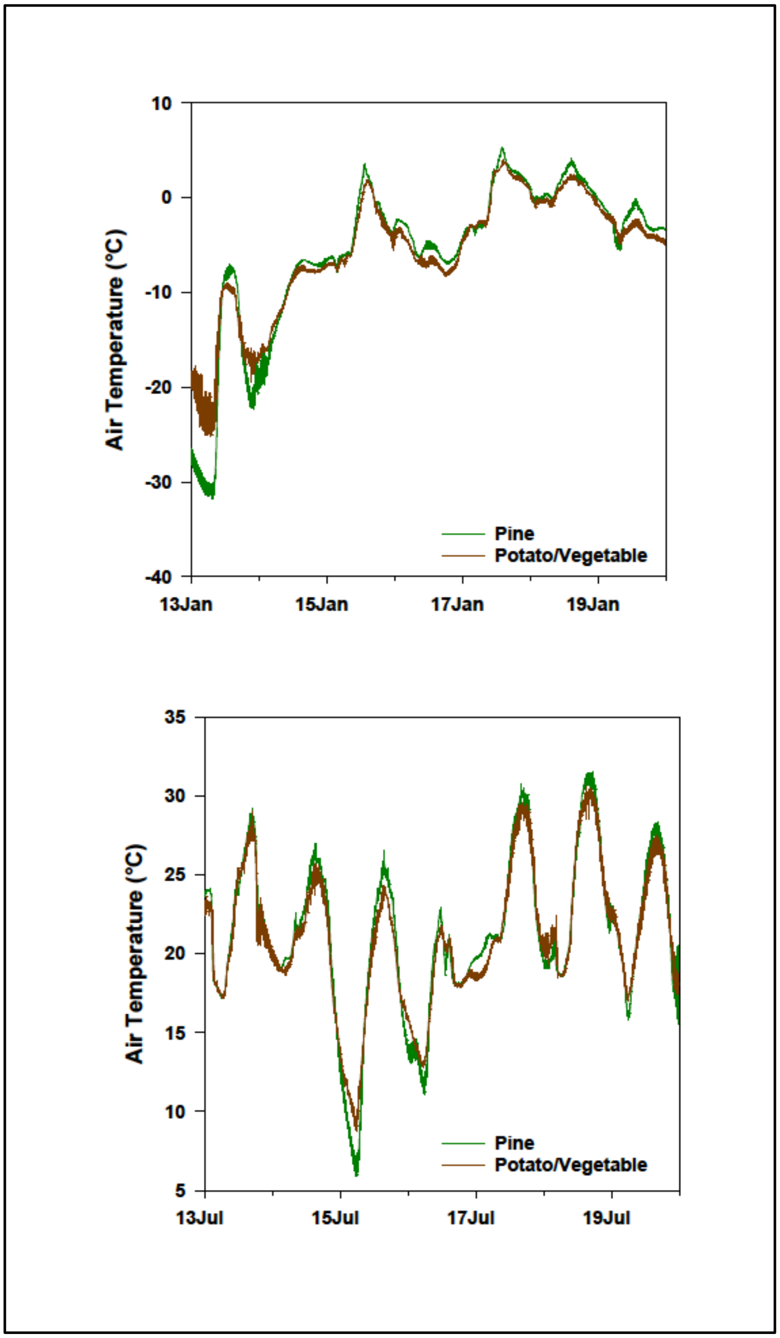


Figure 6. Time-series temperature comparison (°C) over a warm week in (A) January 2015 and (B) July 2015 between three temperature/humidity sensors located with 67-69% pine cover ('Pine') within a 2-km radius and three sensors with 76-80% potato/vegetable cover ('Potato/Vegetable') within a 2-km radius. Error bars represent standard deviation between three measurements.

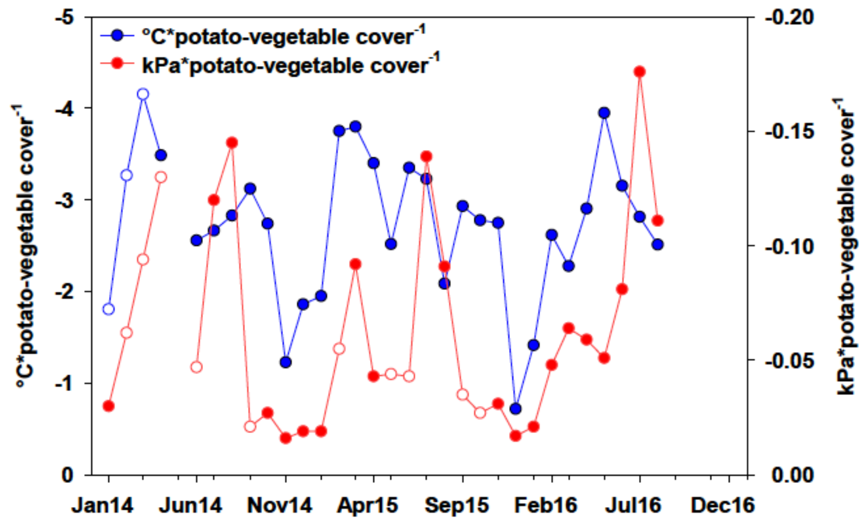


Figure 7. Monthly differences in the slope of Ordinary Least Squares regressions using potato/vegetable cover (fraction) as the explanatory variable for diel temperature range (blue, °C) and vapor pressure deficit (red, kPa). Filled circles are statistically significant at $p < 0.05$.

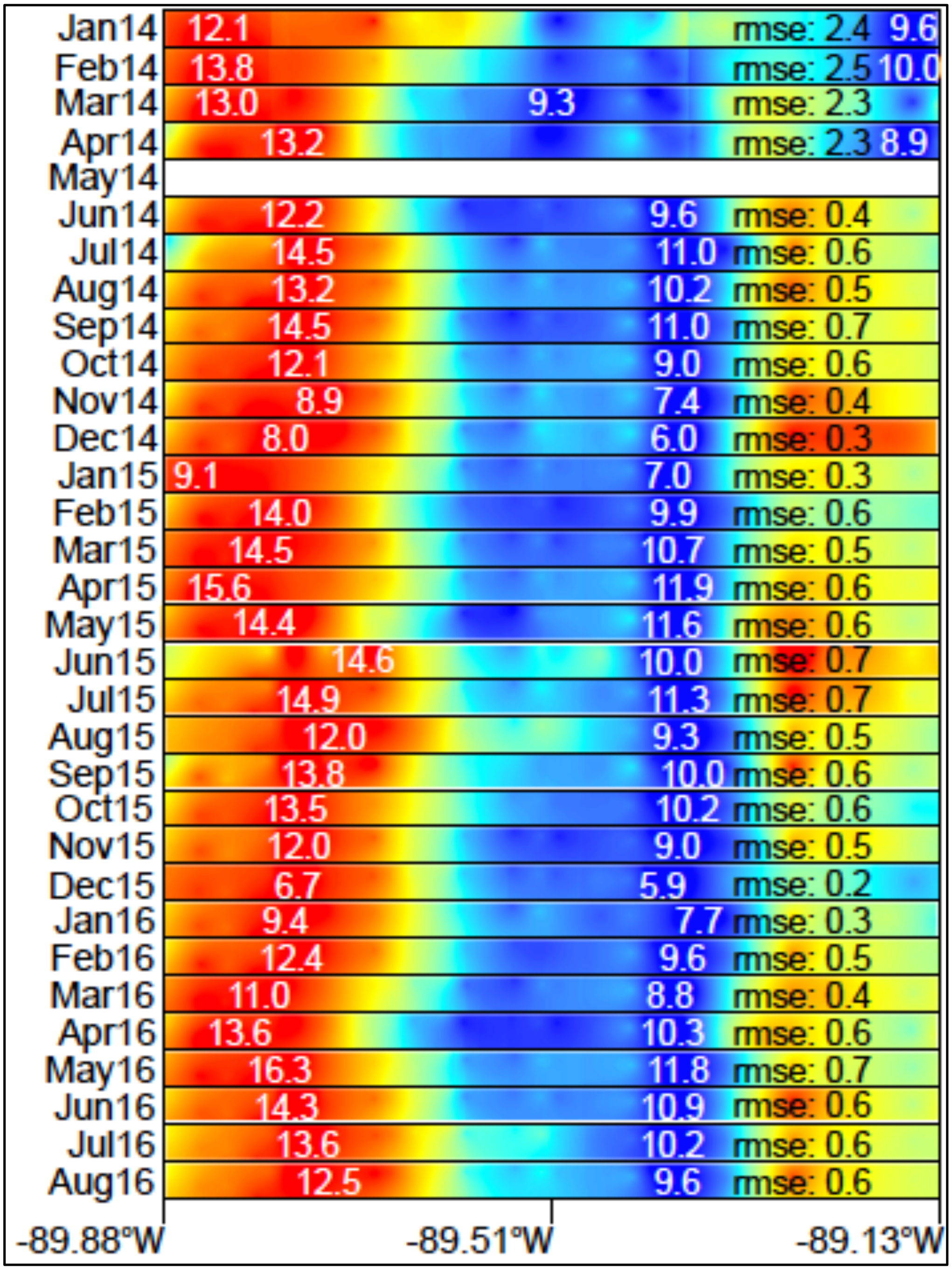


Figure 8. Monthly diel temperature range (DTR, °C) visualized across a 60 x 4 km grid representing the longitudinal transect in the Wisconsin Central Sands for 31 months monitored between January 2014-August 2016. Maximum modeled DTR values are labeled in red regions, while minimum modeled DTR values are labeled in blue regions. Root mean squared error for each regression kriging model is labeled as 'rmse.'

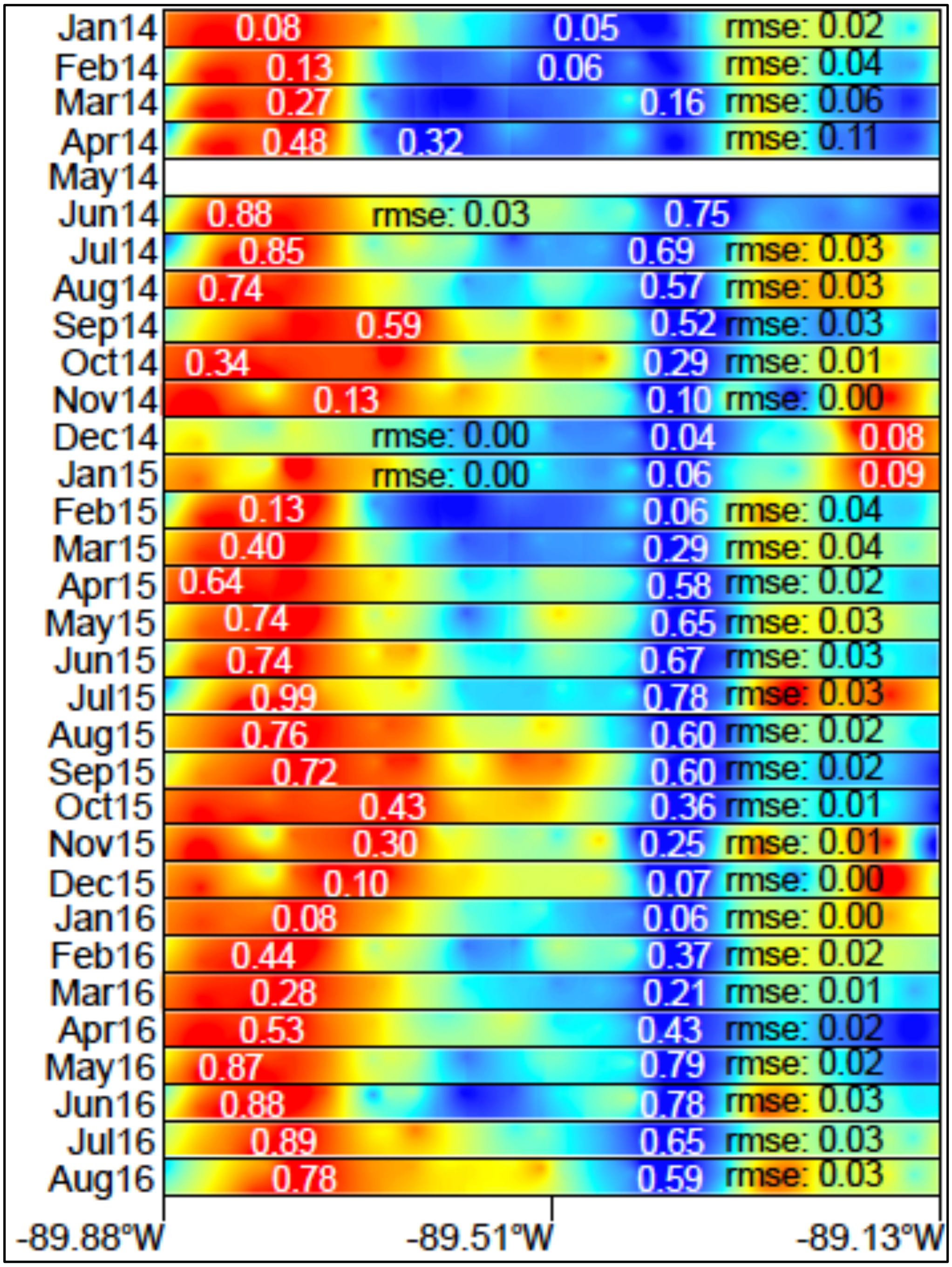
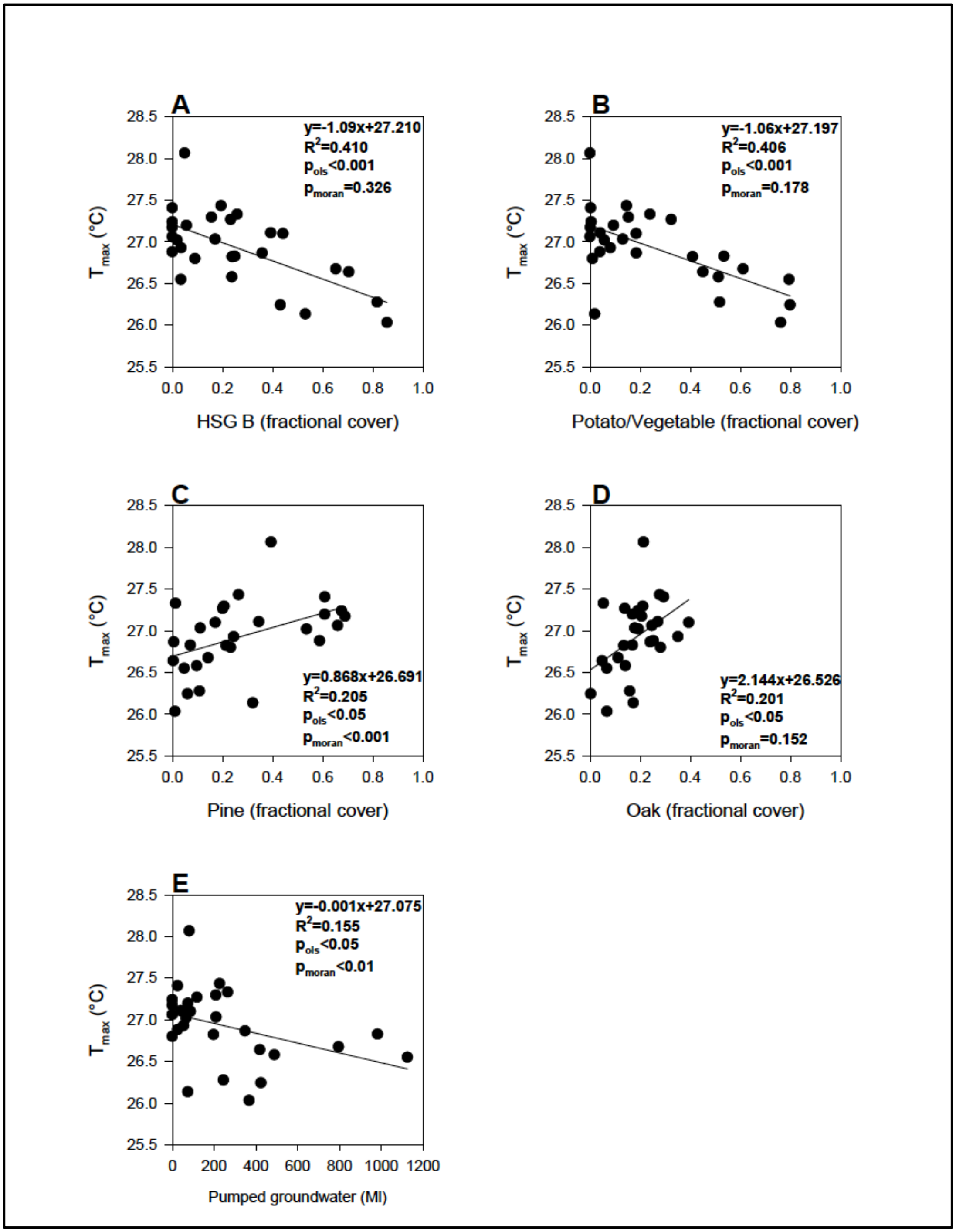
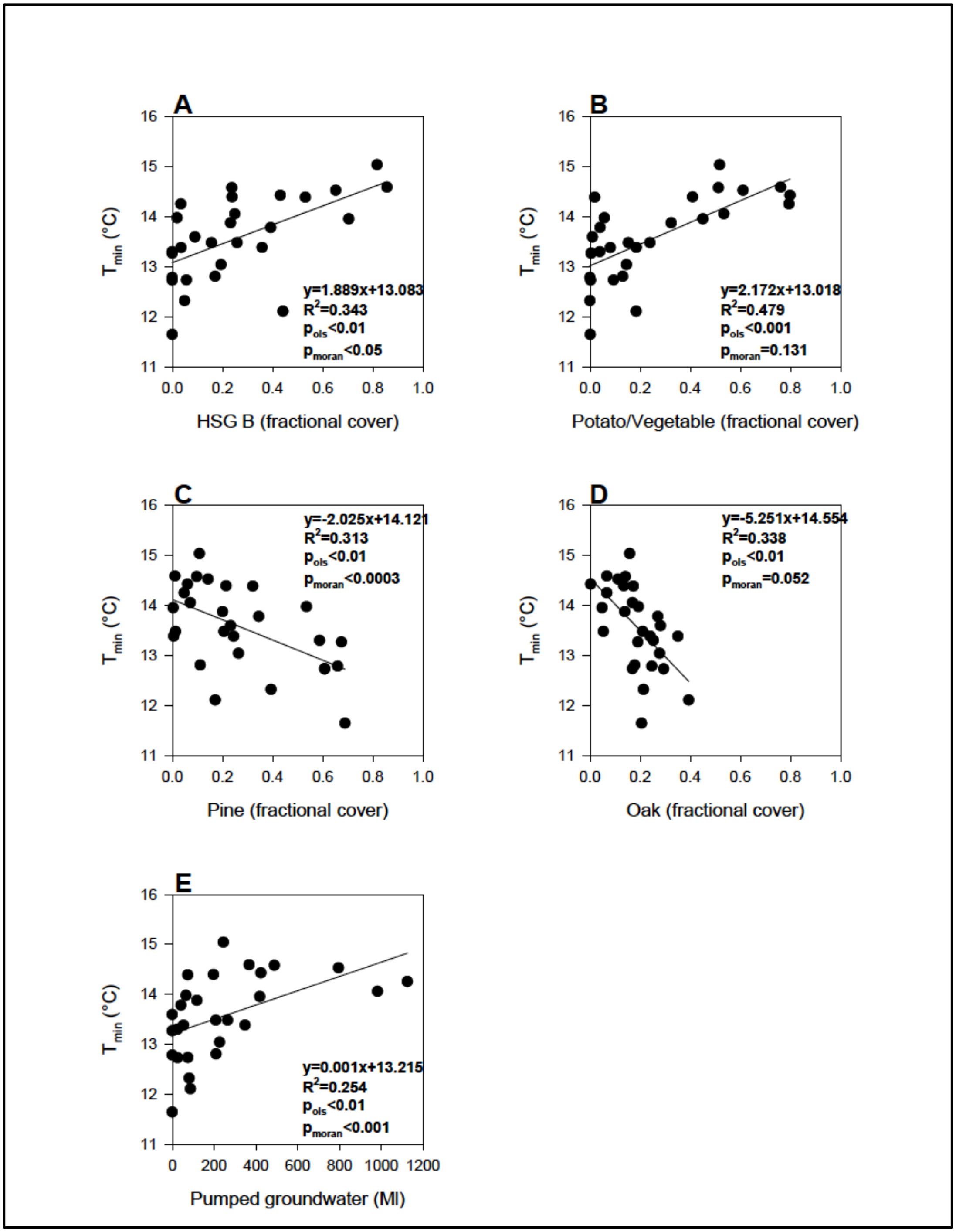


Figure 9. Monthly vapor pressure deficit (VPD, kPa) visualized across a 60 x 4 km grid representing the longitudinal transect in the Wisconsin Central Sands for 31 months monitored between January 2014-August 2016. Maximum modeled VPD values are labelled in red regions, while minimum modeled VPD values are labeled in blue regions. Root mean squared error for each regression kriging model is labeled as ‘rmse.’

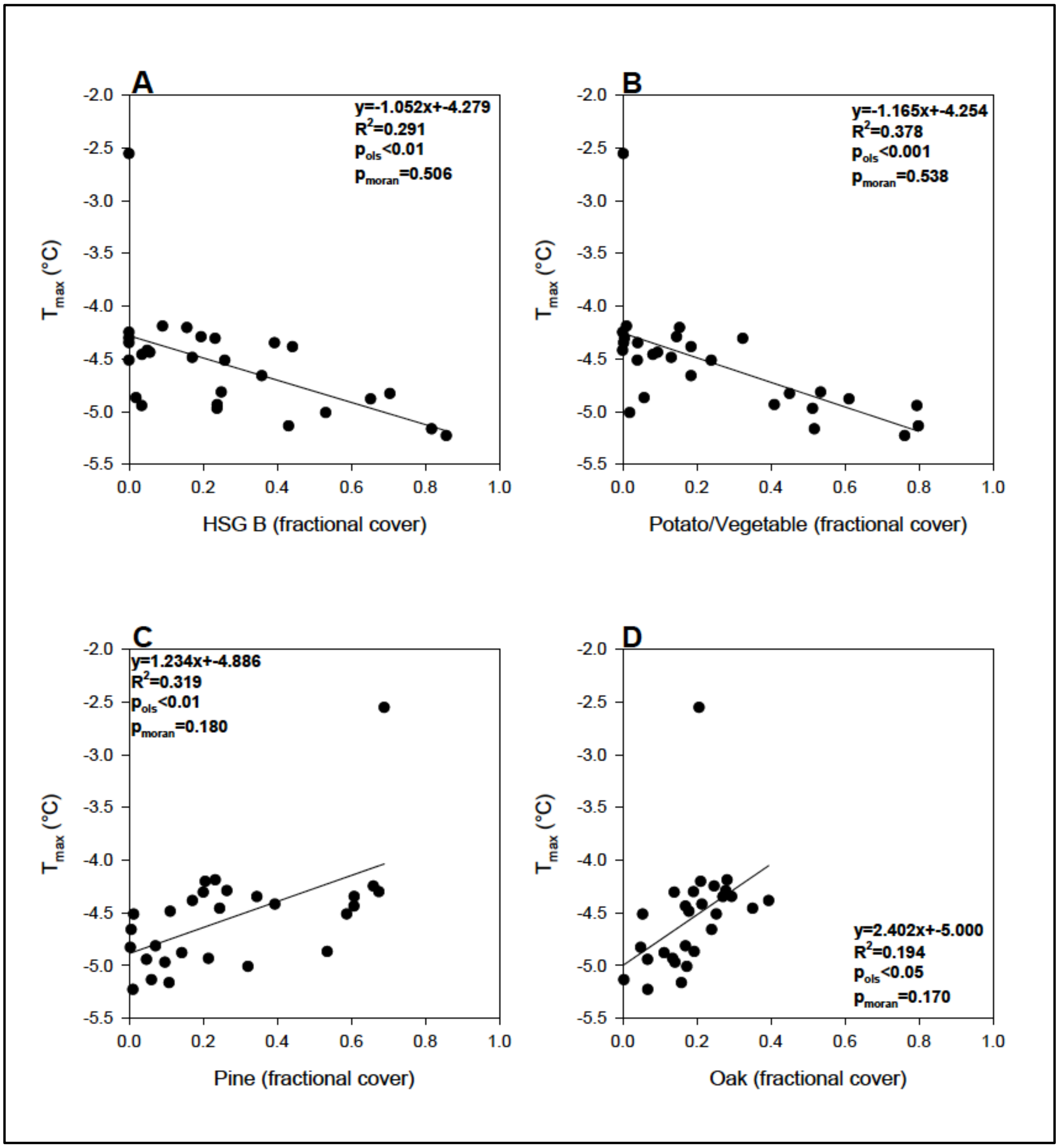
5.9. Supplementary Information



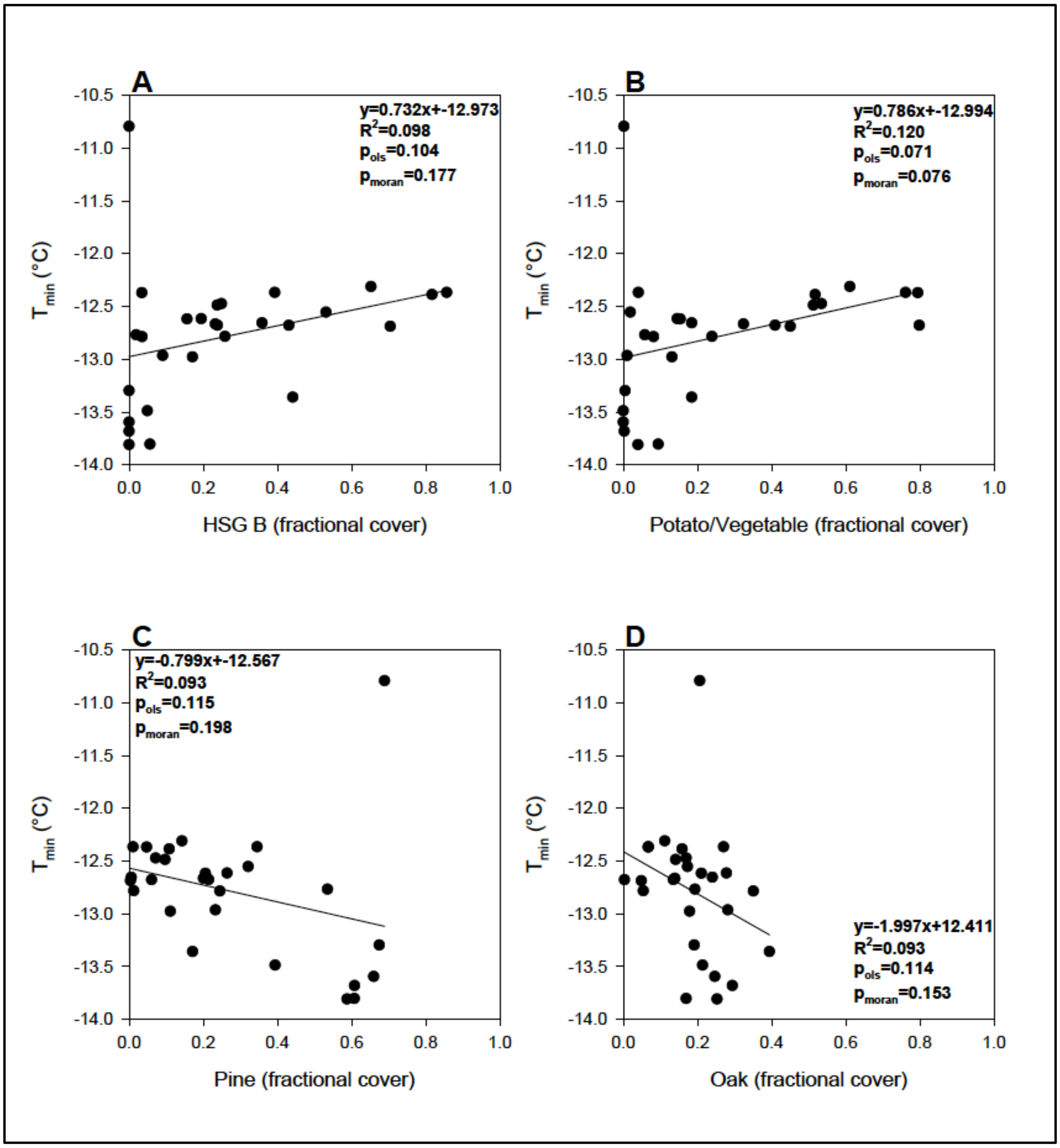
Supplemental Figure 1. July 2015 Ordinary Least Squares regression results for (A) daily maximum temperature (T_{max}, °C) vs. USDA hydrologic soil category B (fractional cover), (B) T_{max} vs. potato/vegetable (fractional cover), (C) T_{max} vs. pine (fractional cover), (D) T_{max} vs. oak (fractional cover), and (E) T_{max} vs. pumped groundwater (Ml).



Supplemental Figure 2. July 2015 Ordinary Least Squares regression results for (A) daily minimum temperature (T_{min}, °C) vs. USDA hydrologic soil category B (fractional cover), (B) T_{min} vs. potato/vegetable (fractional cover), (C) T_{min} vs. pine (fractional cover), (D) T_{min} vs. oak (fractional cover), and (E) T_{min} vs. pumped groundwater (Ml).



Supplemental Figure 3. January 2015 Ordinary Least Squares regression results for (A) daily maximum temperature (T_{max}, °C) vs. USDA hydrologic soil category B (fractional cover), (B) T_{max} vs. potato/vegetable (fractional cover), (C) T_{max} vs. pine (fractional cover), and (D) T_{max} vs. oak (fractional cover).



Supplemental Figure 4. July 2015 Ordinary Least Squares regression results for (A) daily minimum temperature (T_{min}, °C) vs. USDA hydrologic soil category B (fractional cover), (B) T_{min} vs. potato/vegetable (fractional cover), (C) T_{min} vs. pine (fractional cover), and (D) T_{min} vs. oak (fractional cover).

Chapter 6

Conclusion

6.1. Synthesis

My dissertation improves our scientific understanding of the impacts of irrigated potato and vegetable production on water resources and climate in the Wisconsin Central Sands (WCS). In Chapter 2, I identified different types of knowledge and nonknowledge exchanges and production that I encountered while engaging and observing other scientists engage with farmers in the WCS. My results suggest strategies and pitfalls for scientists as they continue to engage with WCS farmers and all scientists who are regularly engaging with wary or oppositional groups to conservation. Additionally, I identified several opportunities throughout this dissertation for better water management in the WCS and similar regions including crop rotational strategies, precision irrigation, and boundary work amongst stakeholders. The findings of Chapter 3 inform the growing body of literature comparing the depletability of aquifers in humid vs. arid regions (Nocco et al., 2017; Bradbury et al., 2017; Kraft et al., 2012). Chapter 3 demonstrates that coarse aquifers in humid regions like the WCS should be managed for ecosystem services rather than depletability. Chapter 4 quantified intrafield variability in crop water availability and use over multiple rotations on multiple fields. The results from Chapter 4 demonstrate that precision irrigation benefits may both field and crop specific in the WCS in order to conserve groundwater and achieve a return on investment. Chapter 5 demonstrates that conversion from pine plantations or rainfed cropland to irrigated agriculture results in lower diel temperature ranges and vapor pressure deficits on a year-round basis. These findings will have implications for water management, crop production, ecological communities, and the incidence of chronic and infectious diseases in humans, plants, and animals in irrigated regions located in humid continental climates (Niles and Mueller, 2016; Jones et al., 2017; Zipper et al., 2016; Kim et al., 2016; Lee et al., 2016).

The most direct outcome of my dissertation will be to inform agricultural and aquatic stakeholders, agencies, and policy makers in the WCS and similar regions in their efforts at equitable groundwater governance. The introspective, social component of this research will provide a framework for more deliberate scientist-farmer communication in long-term community conflicts. Because other areas in the northern Great Lake states are likely to continue expanding agricultural irrigation, this research will also serve as a greater model of how irrigated land use may change the coupled water-energy cycle in these ecosystems. Finally, my mechanistic and methodological findings will be useful for modelers and field scientists interested in quantifying irrigated crop ET, recharge, and effects on climate at a variety of spatiotemporal scales.

6.2. Limitations and future work

Though I collected four seasons of field data, a significant limitation to my findings is the lack of a drought year occurring between 2013-2016. The precipitation conditions for the growing season were 100 mm lower than average in 2013 (not considered a drought), 100 mm wetter than average in 2014, close to average with large, uneven rain events in 2015, and close to average with small, evenly distributed rain events in 2016. The presence of a drought during the study period would have forced Isherwood Farms and farmers throughout the transect to apply an average of 130 mm more irrigation to their fields (Smail, 2013). This additional irrigation would have reduced net groundwater recharge, increased crop ET relative to surrounding rainfed landscapes, and exacerbated freshwater stresses. Because of these impacts, a drought would have increased our understanding of (1) the maximum amount of groundwater that is depleted by crops during the summer and fall seasons, (2) the maximum intrafield ET variability in the conventionally irrigated fields (Chapter 4), (3) the maximum magnitude of irrigation-induced reductions to diel temperature range and vapor pressure deficit compared to surrounding regions, and (4) the most uncomfortable and tense exchanges of knowledge between conservation scientists and farmers, as freshwater stress would also increase during drought. Fortunately, the permanent research infrastructure I installed on Isherwood Farms is being used to quantify long-term water budgets and WCS scientists will be able to quantify the impacts of drought on the water and energy cycle as well as scientist-farmer interactions in the near future. An additional limitation of this body of work is that majority of my stakeholder engagement was with the agricultural stakeholders, which may have set me on a particular path of experimental planning and discovery that is skewed to agriculturally-based water solutions.

There are ample opportunities for future work in the WCS and irrigated regions throughout the northern Great Lake states of Wisconsin, Minnesota, and Michigan. The wicked water resources problems in these regions require extensive collaboration amongst social scientists, scientists from several disciplines and communities, farmers, and other stakeholders. Ideally, these individuals will work together to build a framework for predicting ecosystem services and disservices resulting from changes in land use, water management, and climate for sandy aquifers in the Northern Great Lake States. Specifically, future work could improve ET and recharge estimates at different spatial scales, test precision irrigation interventions, quantify historical climate impacts associated with irrigated agriculture, and investigate whether communication and leadership development for scientists could improve farmer-scientist relations.

6.3. References

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