WATER INTEGRITY IN THE FOOD-ENERGY-WATER (FEW) NEXUS: SOLUTIONS FOR WATER RESOURCES IN A CHANGING WORLD

by

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Dedicated to my family.

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ABSTRACT

The Food-Energy-Water (FEW) nexus conceptualizes the interactions and tension between production and consumption of food, energy, and water. With increasing uncertainties due to climate change, there is a need to address these tensions within the nexus and better comprehend the existing interdependencies and tradeoffs. Water integrity – considering both water availability and quality – is of critical concern within the FEW nexus. Thus, it is important to develop robust decision-making strategies using a FEW nexus lens. This study focuses on addressing water integrity concerns through FEW nexus assessment using an agricultural watershed in northeastern Indiana, with predominantly corn-soybean rotations, as a pilot site. Historical and futuristic climate and hydrological data were used for hydrological modeling using SWAT to quantify water quantity, quality, and crop production. Scientific literature values for farm machinery fuel requirements and their carbon emissions were implemented to obtain values based on the implemented agronomic practices. Results showed that integrating water integrity into FEW nexus assessments has potential for improving water resources management at the nexus. Additionally, when data is not readily-available, inferences can be made with limited data to better comprehend when periods of stress – defined as critical periods – may occur within the nexus. Finally, climate change projections indicate potential shifts in critical periods through the growing season in deficits and surpluses of water availability and for nutrients of concern (surface and subsurface nitrate and soluble phosphorus). The end of the 21st century shows relative increases in these nutrients, despite smaller shifts in deficits and surpluses, attributable to shifts in hydro-climatic patterns. Results of this study provide methodologies and information that can be implemented to evaluate water resources management, as well as inform policymaking for more sustainable agricultural management practices. Further studies are required to provide tools for communication to stakeholders and provide more assessment incorporating additional climate change projections, varying model set-ups, and additional data to provide better comprehension of the FEW nexus.

Keywords: Food-energy-water nexus, water resources management, critical periods, climate change, decision-making

1. INTRODUCTION

Food, energy, and water are necessary for human well-being (Pahl-Wostl et al., 2018). With growing uncertainties in their security with climate change, rapid urbanization, growing populations and economic crisis (Mohtar and Daher, 2012; Schull et al., 2020), it is more crucial to understand the interactions, dependencies, and tradeoffs related to food and energy production and consumption in relation to water. The Food-Energy-Water (FEW) nexus emerged from the understanding that natural resources are limited, and impact economic growth and human well-being (Hoff, 2011; Ringler et al., 2013). Estimates demonstrate that the agricultural sector will be pushed to produce 60% more food by 2050. Anthropogenic increases in nitrogen (Zhang et al., 2015) and phosphorus (Parry, 1998) fertilization, though critical for agricultural production, have also created serious water quality concerns, particularly related to eutrophication (Carpenter et al., 1998; USEPA, 2005). Along with increases of temperature and phosphorus, excess nitrogen levels may lead to harmful algal blooms (Chaffin et al., 2013; Gobler et al., 2016; Jankowiak et al., 2019; Kleinman et al., 2011). Because the agricultural sector consumes about 70% of the global water withdrawals and 90% of overall water use for irrigation (Haddeland et al., 2014; WWAP, 2015), it is critical to not only understand how water quantity will fluctuate with such stress, but also impacts on water integrity and agricultural production (Rosa et al., 2020; Rosa et al., 2018a; Rosa et al., 2018b). Understanding this dynamic not only has the potential to improve resource use efficiency, but to also provide a pathway for innovative solutions for mitigating competition and improving harmony within the nexus.

Water resources management plays an underlying role in the Food-Energy-Water nexus due to the constraints in relation to energy consumption and production, as well as food production (Cai et al., 2018; Rosa et al., 2020). Furthermore, with global climate change, it is important to be able to comprehend historical stressors within the FEW nexus, and how these may change through time. Managing the FEW nexus in an agricultural system may be complex, due to various stakeholders and social, economic and environmental factors (Li et al., 2019). Nevertheless, robust, sustainable solutions for agriculture are not possible without access to unpolluted freshwater (Debnath, 2020; Velasco-Muñoz et al., 2018). When addressing concerns of sustainable agriculture, it is necessary to move away from “silo” decision-making approaches (Märker et al., 2018), and shift towards interdisciplinary collaboration through the nexus. This may be done through the implementation of natural resources management tools as well as laying out methodology for FEW nexus assessments. Additionally, it is important to be able to synthesize the information of the FEW nexus assessments to decision-makers and stakeholders in an accessible manner to ease collaborations across various disciplines.

1.1 Objectives

The overall goal of this study is to incorporate water quantity and water quality impacts of growing demand for food, energy, and water within FEW nexus analysis, with a view to improving sustainability of water resources in a changing world. Specifically, to:

1. Assess the implementation of Food-Energy-Water (FEW) nexus modeling tools for more robust decision-making and address how to better integrate water quantity and quality into these models.
2. Construct critical periods for water management in the FEW nexus based on periods of surplus and deficits and associated water quality by analyzing historical data.
3. Evaluate climate change impacts on patterns and extents of critical periods for water management within the FEW nexus framework.

1.2 Rationale

One of the major concerns of previous methods of FEW nexus analyses is lack of fully capturing the concept of water integrity in the FEW nexus. Though these studies have captured water scarcity and water quantity concerns, there is also the need to incorporate water quality into the FEW nexus framework along with general impacts on the water resource. In this study, FEW nexus assessments evaluated the shortcomings as well as enhanced water resources management representation needs within the nexus at the watershed-scale. Furthermore, working within a FEW framework requires an understanding of how nexus components will be impacted due to climate and social changes and a comprehension of how the system will be affected. Both historical data and futuristic climate change scenarios were assessed to address impacts on the FEW nexus at the watershed-scale.

1.2.1 Thirsty for Water Resources Management in the FEW Nexus

There are various methods that have been implemented to take steps towards a more holistic approach to water resources management. In this section, we will explore and further explain how the conceptualization of water usage and quality degradation to communicate environmental concerns and the need for more robust decision-making has evolved. The target audience for all these methods of quantifying trade-offs based on water management are professionals and decision-makers.

Life-Cycle Analysis

Life-cycle analysis (LCA), also known as "cradle-to-grave" analysis (Duda and Shaw, 1997), is a method in which all of the stages of a product's or service's life are examined. It focuses on quantifying the environmental burdens that are due or related to creation of a product or service from raw materials to its end and waste removal (Klöpffer, 1997; Oberbacher et al., 1996). Conceived in the late 1960s and early 1970s in the United States, this was perhaps the first time that the American scientific community attempted to quantify the complexity of environmental issues. However, the formal analytical scheme that laid down the foundation of the concept known today as LCA was developed in 1969 (Hunt et al., 1996), though similar work was developed in Europe soon afterwards (Boustead, 1996; Fink, 1997; Oberbacher et al., 1996).

Created by Harry E. Teasley, Jr. with the assistance of the Midwest Research Institute (Klöpffer, 1997), the LCA method was established as a means for quantifying energy, material, and environmental impacts of the life cycle of a Coca-Cola Company package. Surprisingly, the study demonstrated that over their life cycle, plastic bottles consumed less hydrocarbon than glass bottles, which has led to the shift to today's common use of plastic bottles for refreshment beverages (Duda and Shaw, 1997; Hunt et al., 1996). However, it was not until 1974, when the United States Environmental Protection Agency (USEPA) produced the report "Resource and Environmental Profile Analysis of Nine Beverage Container Alternatives" that the public domain gained access to the development of LCA through a peer-reviewed document (Hunt et al., 1996). Though incorporating a lens of conserving energy with resource conservation due to package production was revolutionary, none of the models considered water consumption. In 2009, Pfister et al. (2009) developed a method for assessing the environmental impacts of freshwater consumed that considered human health, ecosystem quality, and resources (Cooney, 2009; Pfister et al., 2009). This was the first time that water usage had been assessed using the LCA method. Since then, LCA has been implemented to assess how water consumption impacts the environment, such as in biodiversity (Verones et al., 2015), potential natural vegetation (Núñez et al., 2013), as well as area changes in critical wetlands (Verones et al., 2013).

Integrated Water Resource Management

Integrated water resource management (IWRM) was developed in the 1980s as a solution to contemporary water concerns (Al Radif, 1999). In 1992, the concept of IWRM gained attention following international conferences on water and environmental issues in Dublin and Rio de Janerio (Agarwal et al., 2000). IWRM is the broad scope of processes of formulating and implementing shared vision planning and management strategies for sustainable water resource utilization while considering spatial and temporal interdependencies among natural processes and water uses (Al Radif, 1999), as well as linking social, cultural, and political context of an area (McDonnell, 2008). This was perhaps the first method that incorporated stakeholders in water resources management approaches. With the methodology of LCA to water consumption, IWRM was able to develop as the focus on the life cycle of water (Endo et al., 2017; Ringler et al., 2013).

However, one of the major flaws that has been seen with the IWRM approach is that although IWRM incorporates ecosystems as important users of water, it does not necessarily consider the importance of ecosystem goods and services in terms of water resources (Al Radif, 1999). Furthermore, due to its silo approach, IWRM focuses solely in the water sector, and mostly works at the micro-scale with dependence on stakeholder agreement (Biswas, 2008). Water resource management has been strengthened by IWRM, and has highlighted the linkages between food, energy, and water security (Cai et al., 2018; Hoff, 2011). Hence, the IWRM has established a starting point for assessing the environmental, social, and political contexts of water resource management.

Virtual Water and Water Footprint

The concepts of virtual water and water footprint are closely related. Virtual water is the concept of "hidden water" that flows through trade from one region to another. In comparison, water footprint is the amount water that is used to produce goods and services that we use (Allan, 2003; Hoekstra, 2003).

Virtual water is calculated using individual crop demand with the FAO Penman-Monteith equation. The next portion of the calculation is the amount of virtual water consumed by a nation by using the amount of crop produced. Water footprint of a nation is simply defined total domestic water use and the net virtual water import of a country (Hoekstra, 2003). The amount of virtual water that a person, company, or country imports and exports can play a role in how large their water footprint is. Through these concepts, we were able to tie a price and economic cost to the way we consume water (Zimmer and Renault, 2003).

1.2.2 Moving Towards the Nexus

Figure 1 shows a conceptualization of the FEW nexus and its critical stressors. The purpose of this work was to develop a water-centric perception of the FEW nexus, ensuring that water integrity – both water quantity and quality – are taken into consideration within the FEW nexus framework.

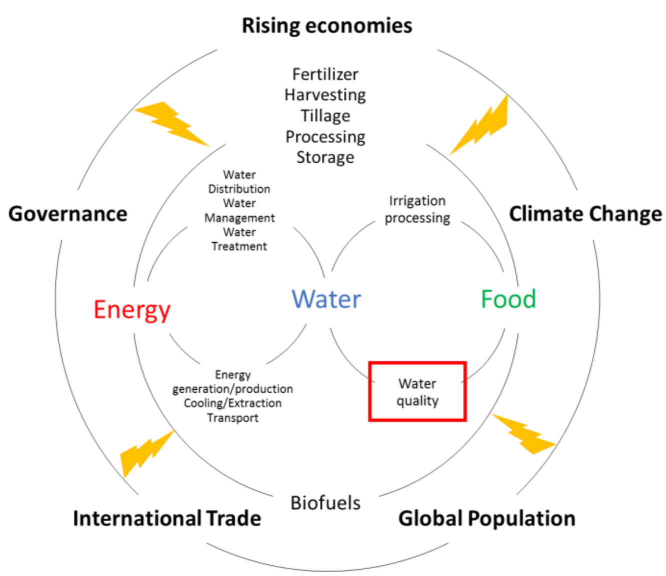

Figure 1 Conceptualization of the FEW Nexus and its critical stressors (Flammini et al., 2014; Mohtar and Daher, 2012)

With the limitations of the concepts of Life Cycle Analysis, Integrated Water Resources Management, Virtual Water, and Water Footprint, the FEW nexus concept has gained traction in various sectors of environmental management (Al-Saidi and Elagib, 2017), with water communities being amongst the strongest proponents (Pahl-Wostl, 2019), as the lack of coordination across the sectors of the nexus have the strongest repercussions for water integrity (Bogardi et al., 2012; Pahl-Wostl, 2019; Pahl-Wostl et al., 2013). However, collaboration across the sectors is necessary for ensuring that stakeholders in the FEW nexus are considered. Thus, as water resources management plays a central role in FEW nexus assessments, holistic solutions that are accessible should be a priority from the start.

1.3 Study Area

With an aerial extent of 4,610 ha (11,392 acres), the Matson Ditch Watershed (Figure 2) is a subsurface drainage-dominated agricultural study site, and is a sub-watershed of Cedar Creek, which is a part of the larger basin of the St. Joseph River (Boles, 2015; Smith et al., 2008). The USDA-ARS National Soil Erosion Research Laboratory has been monitoring streamflow and nutrients (Steiner et al., 2008) there as part of various of initiatives including the USDA-ARS Conservation Effects Assessment Project (CEAP) (Tomer et al., 2014), the St. Joseph River Watershed Initiative (SJRWI) (DeGraves, 2005; SJRWI, 2020), and the Source Water Protection Initiative (SWPI) (Flanagan et al., 2003). The monitoring of water integrity, along with meteorology, in the St. Joseph River watershed has been ongoing since 2002 (Smith et al., 2015).

This predominantly agricultural, precipitation-fed, tile-drained watershed in DeKalb County in northeastern Indiana (Tetra Tech, 2017) has land use that is predominantly row crops, with corn and soybeans (Boles, 2015; Mehan et al., 2019; Smith et al., 2008) making up 62.6% of the agricultural land (Schull et al., 2021). Developed land (5%), deciduous forest (9%), pasture (13%), along with other land uses (<10%) also make up the watershed. Agricultural tillage systems in DeKalb County are predominantly conventional tillage for corn and no-till for soybeans. The corn and soybean growing season in the Matson Ditch Watershed runs from May through October, with most agronomic management operations such as tillage, planting, fertilizer, and pesticide applications occurring at the beginning of the growing season, with harvesting occurring at the end.

With respect to water quantity, losses in crop growth and yield could occur due to stresses from deficits in the amount of water available in the soil (Walthall et al., 2013). Water quality concerns stem from the agricultural practices and the resulting pollutants, including excess nutrients and pesticides (Johnson et al., 2004; Sekaluvu et al., 2018). Nitrogen and phosphorus are nutrients that are of concern due to agricultural practices, as well as atrazine, a water-soluble herbicide (Johnson et al., 2004). Watershed modeling addressing these concerns of the Matson Ditch Watershed has been extensive, with various hydrological models implemented, including the Agricultural Policy Environmental Extender (APEX) (Feng et al., 2016; Michael, 2017), the Soil and Water Assessment Model (SWAT) (Boles, 2013; Mehan et al., 2019; Wallace et al., 2017), the Annualized Agricultural Non-Point Source (AnnAGNPS) (Flanagan et al., 2008), and the Distributed Hydrological Model for Watershed Management (DHM-WM) (Li et al., 2017). Thus, knowledge of agricultural management practices, hydrological water balance, and crop production of the region is ample. Because of historical water integrity issues, as well as the amount of data and assessment of the watershed, the Matson Ditch Watershed provides a suitable study area for piloting FEW nexus assessments for both historical agricultural practices, as well as futuristic scenarios.

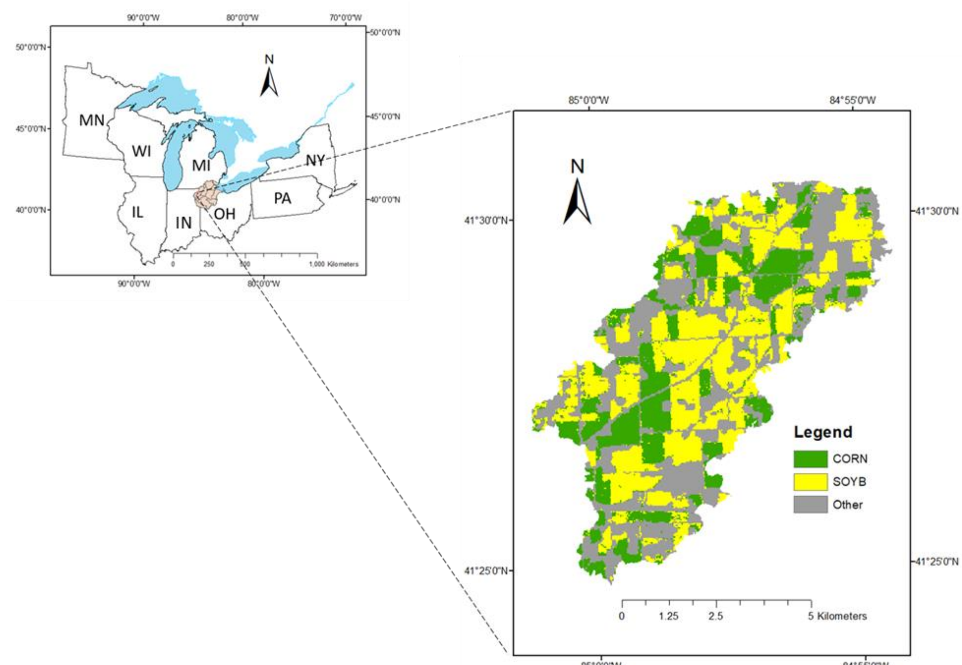

Figure 2 Study site location (Matson Ditch Watershed) in northeastern Indiana and its 2011 land use.

1.4 Graphical Abstract

Figure 3 summarizes the objectives achieved in this study through a graphical abstract. The need for understanding the role in which water integrity – both water quantity and quality – plays in the FEW nexus is a catalyst for the three objectives. By understanding the FEW nexus modeling tools available for informing decision-makers, a methodology may be developed using historical data. Once this methodology is established, futuristic scenarios can be evaluated to determine the impacts of climate change on the FEW nexus in agricultural systems.

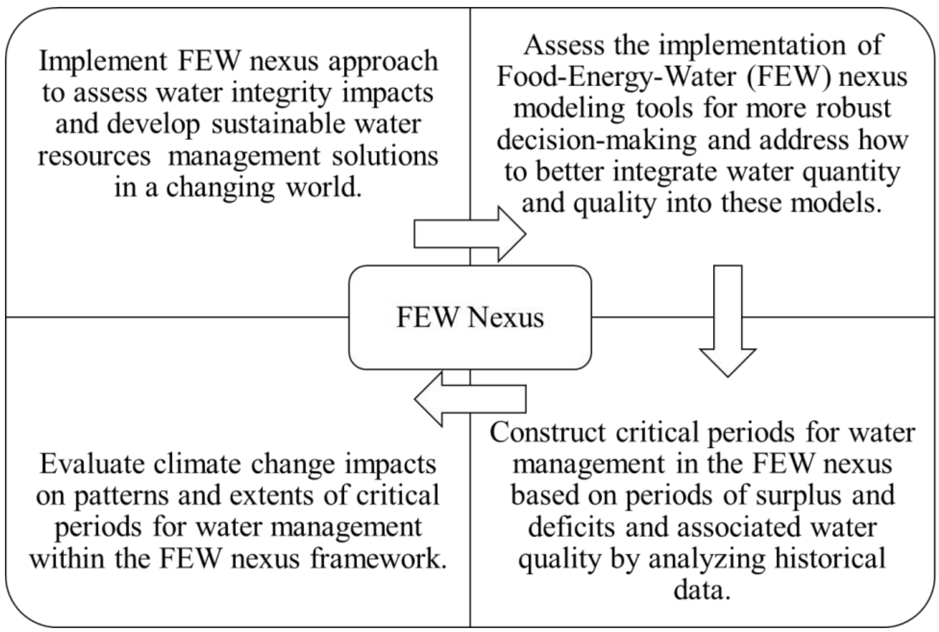

Figure 3 Graphical abstract of objectives achieved in this study.

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2. ANALYZING FEW NEXUS MODELING TOOLS FOR WATER RESOURCES DECISION-MAKING AND MANAGEMENT APPLICATIONS

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2.1 Abstract

Social changes such as growing population, urbanization, globalization, and economic growth, compounded with uncertainties due to climate change are expected to result in substantial shifts in the demand for food, energy, and water. Food, energy and water resource systems are tightly interconnected. Addressing challenges facing any of these resource systems requires a holistic understanding and quantification of the existing interdependencies and trade-offs. This study is aimed at analyzing FEW nexus modeling tools with a specific focus on addressing issues

of water management through a nexus lens. In particular, an exploratory approach is taken to assess available FEW nexus modeling tools to determine their accessibility, knowledge gaps, and potential for including aspects that provide better insight into the nexus such as water quality, futuristic scenarios due to climate change, and varying scales within the nexus. A case study in an agricultural watershed in northeastern Indiana is presented which builds on the WEF Nexus Tool 2.0 framework and assessment criteria. For this case study, spatial and temporal analysis based on SWAT was implemented. This provided a water quality component to the framework enabling a more representative analysis of the FEW nexus.

Keywords: Food-Energy-Water nexus, FEW nexus tools, water management, water quality, decision-making

2.2 Introduction

With the rising concern for how the world will be shaped by social changes such as growing population, urbanization, globalization, and economic growth, as well as with the uncertainties in future temperatures and precipitation due to climate change, there has been a shift towards holistic approaches to developing solutions for the future (Biggs et al., 2015; Mohtar, 2017). Estimates show that by 2030, expected global demand for food, energy, and water are expected to increase by 50%, 50%, and 40%, respectively (Martinez-Hernandez et al., 2017a). Given the interconnectedness among these sectors, the food-energy-water (FEW) nexus has recently emerged as critical framework for solidifying discussions regarding goals for a once ambiguous concept of "sustainable development" (Biggs et al., 2015). This framework is crucial to sustainable water, food, and energy security at different scales (Cai et al., 2018; D'Odorico et al., 2018), spanning from local through national to global scales. Globalization renders the FEW nexus much more complex due to sector interconnectedness across vast distances (D'Odorico et al., 2018). During the Bonn 2011 Nexus Conference, the concept of the FEW nexus was developed (Hoff, 2011; Endo et al., 2017) highlighting the need for a cross-sectoral dialogue around trade-offs associated with different resource allocation and planning decisions.

Water management is a critical component in natural resource management. Within the FEW nexus framework, water may be considered a driver; it is necessary for agricultural production and plays a role in energy production primarily as related to cooling (Daher and Mohtar, 2015; Rao et al., 2017). Both sectors (food and energy) can have adverse effects on water quality; for example, nitrogen and phosphorus continue to be among the most common pollutants in freshwater systems, these originating largely from agricultural sources (WWAP, 2009); energy production can result in increased water temperatures with associated negative impacts on aquatic ecosystems (Madden et al., 2013) even where the net water consumption might be zero. Furthermore, water availability is affected by pollution (WWAP, 2015). Without proper assessment and application of sustainable approaches for food and energy production, serious environmental degradation will continue to occur. In particular, unsustainable use and management of water resources in these two sectors can lead to: competition for water resources between food and energy production (Rosa et al., 2018a, 2018b); increasingly impaired waters (Cai et al., 2018); loss of biodiversity (Poff et al., 1997); and political tensions between communities sharing water resources (Richter, 2014), all of which negatively impact efforts towards environmental sustainability. Often, policy-making within the FEW nexus tends to occur without much consideration of the resulting effects of decisions made within other sectors on the water system (Mohtar and Daher, 2012; IRENA et al., 2015). Amongst the earliest attempts to incorporate the interconnections of the sectors within the FEW nexus was integrated water resources management (IWRM), which strives to analyze the life cycle of water within a system (Al Radif, 1999). The FEW nexus approach builds on IWRM, energy efficiency, and water input for crop production, and provides a cross-cutting platform which allows dialogue across sectors (Mohtar and Daher, 2016).

Currently, there are a limited number of FEW nexus modeling tools with which to quantify the interconnections and stressors both in and between each of the respective FEW sectors (IRENA et al., 2015; FAO, 2014a,b). These tools allow for more quantitative analysis of the intricacies of the FEW nexus, thus aiding policy- and decision-makers in understanding the complexities in securing FEW sources in an efficient, robust, and holistic manner. Nevertheless, they tend to rely on a static, singular scaling, which make it difficult to implement the tools at the local, regional and national scales simultaneously. Most also lack the ability to generate futuristic scenarios of the interrelationships that would give a better understanding of the shifts that could be expected and their impacts. These shortcomings could be due to the level of uncertainty due to climate change, as well as the reality that the development of these modeling tools is relatively new. Hence, the design of the framework of FEW nexus modeling tools must not only be informed by the significance of the interactions, but by how system boundaries are defined when assessing the suitable spatio-temporal scales for decision-making. Thus, there is a need to better understand how to outline these system boundaries as well as to develop a more unified framework to address the varying levels of scaling, significance of interactions, and sector perspectives that are present within these tools (Bazilian et al., 2011). One of the major concerns related to current FEW nexus tools is their failure to address the quality of water within a system. Thus, there is also a need to incorporate a water quality component into the FEW nexus framework for a better representation of the interconnectedness among the sectors of the nexus.

The aim of this study was to analyze FEW nexus modeling tools and provide a framework by which to better integrate water management—including water quality—as a primary component of the nexus. Specifically to: (1) review the availability of tools that model the FEW nexus; (2) determine the benefits and shortcomings of available tools for understanding potential tradeoffs; and, (3) use a state-of-the-art FEW nexus modeling tool in a case study to demonstrate potential applications incorporating water quality and futuristic scenarios related to climate change.

2.3 Methodology

A literature-based exploratory approach was taken as an initial step to assess the potential of incorporating FEW nexus tools in the development of necessary resource allocation strategies, as well as to better understand the trade-offs between the different sectors. This study included recently developed tools and demonstrated how to select a tool based on certain criteria. Finally, a scenario-based case study was conducted to assess how a chosen tool would perform in representing the interconnections between the FEW sectors including future perspectives, the flexibility in scale through assumptions and inputs and outputs of the framework, and its ability to capture potential trade-offs in various resource allocation strategies. Because water quality is a crucial component in water management, the study also assessed the extent to which water quality could be incorporated in FEW nexus modeling. The case study site was the Matson Ditch Watershed, a primarily agricultural catchment in DeKalb County in northeast Indiana, thus demonstrating the feasibility of incorporating a developed tool’s framework to an agricultural-based site.

2.3.1 FEW nexus modeling tools description

Among the most commonly used FEW nexus modeling tools are the Climate Land Use Energy and Water (CLEW) model (Hermann et al., 2011), the Water Energy Food (WEF) Nexus Tool (Daher and Mohtar, 2015), the Water Evaluation and Planning system (WEAP)/Long-range Energy Alternatives Planning system (LEAP) (Sieber, 2006; Hoff et al., 2007; Sieber and Heaps, 2010), MuSIASEM (MultiScale Integrated Analysis of Societal and Ecosystem Metabolism) (Giampietro et al., 2009), and the Global Biosphere Management Model (GLOBIOM) (Ermolieva et al., 2015).

Developed by the International Atomic Energy Agency (IAEA), CLEW (https://www.iaea.org/topics/economics/energy-economic-and-environmental-analysis/climate-land-energy-water-strategies) is a systematic framework approach that uses multiple, unintegrated tools to illustrate synergies and trade-offs for decision making (Kaddoura and El Khatib, 2017). It provides outputs based upon collected data, assumptions, and user-defined scenarios (Hermann et al., 2011). The WEF Nexus Tool 2.0 (http://wefnexustool.org/) is a dynamic model that attempts to shift from silo decision-making to more integrative approaches. The model was originally developed to attempt to assess resource allocation due to national-level agricultural production, importation and exportation, as well as using desalinization and renewable resources as long-term solutions for Qatar. The tool provides comparisons between scenarios and provides a sustainability index for these scenarios (Daher and Mohtar, 2015). WEAP/LEAP **(**https://www.weap21.org) are scenario-based modeling tools developed by the Stockholm Environment Institute (SEI). WEAP incorporates water quality and quantity assessment, ecological and social demands, and water management policies (Kaddoura and El Khatib, 2017). LEAP is the energy planning software also developed by SEI and can be linked with WEAP. These tools' licenses are available for a fee for scientists from developed countries and for free for those in developing countries.

MuSIASEM (http://iaste.info/musiasem/) is an open framework tool that aids in determining feasibility and desirability of socio-economic systems (Giampietro et al., 2009). Developed in 1997 by Mario Giampietro and Kozo Mayumi (IASTE, 2019), the tool is managed by the Integrated Assessment: Sociology, Technology, and the Environment (IASTE). It uses Complex System Theory concepts, as well as a flow-fund model to encompass FEW nexus and social parameters. This can be used for diagnostics or simulations, and has been used in FEW nexus assessments (Kaddoura and El Khatib, 2017). There have been various applications in different countries with this model (IRENA et al., 2015).

GLOBIOM (http://www.globiom.org) is a global-scaled dynamic model that integrates the FEW nexus sectors for policy analysis and was developed by the International Institute for Applied Systems Analysis (IIASA, 2019). GLOBIOM incorporates price and trade flows for all the countries of the world, aggregating into 30 larger regions for convenience (Ermolieva et al., 2015; Havlík et al., 2012). Additionally, there are regional versions of the model, such as GLOBIOM-BRAZIL and GLOBIOM-EU, which were designed with stakeholder involvement to provide a more detailed analysis.

Other tools that have been used in FEW nexus modeling include: the Diagnostic, Financial, and Institutional Tool for Investment (DTI) (Salman, 2013) which provides a national framework for agriculture and energy, with a predominant focus on water management based on irrigation and hydropower (Kaddoura and El Khatib, 2017).; the Q-Nexus Model (Karnib, 2017; Karnib, 2018), which categorizes the FEW nexus sectors through a set of inflows, including irrigated crops and other agricultural products for the food sector; petroleum, electricity, and renewable energy for the energy sector; and groundwater, surface water, wastewater reuses and desalination for water (Karnib, 2018); Data Envelopment Analysis (DEA) (Li et al., 2016), a nonparametric framework for measuring the relative efficiencies of a set of "black box" decision-making units that have various inputs to yield multiple outputs; the Platform for Integrated Modeling and Analysis (PRIMA) (Kraucunas et al., 2015), a modeling system developed at the Pacific Northwest National Laboratory (PNNL) that integrates with models that simulate climate, energy, water and land use interactions for decision-making (Kraucunas et al., 2015); the Global Change Assessment Model (GCAM) (Edmonds et al., 1994), a dynamic-recursive model representing the economy and energy sectors, with particular interest in how climate change mitigation policies will impact the sectors (JGCRI, 2019); and, the Nexus Simulation System (NexSym) (Martinez-Hernandez et al., 2017a), a spreadsheet-based simulation tool (Yao et al., 2018) that simulates processes and local production systems to analyze the FEW nexus at a smaller scale.

With the DTI analysis is conducted at the country level through three different tools (context tool, institutional and policy tool, financial tool), that work synergistically. These are open-access and readily available at http://www.fao.org/land-water/databases-and-software/diagnostic-tools-for-investment/en/. The Q-Nexus Model uses an input-output Leontief matrices framework that integrates societal demands and technical efficiencies within the nexus (Martinez-Hernandez et al., 2017a; Karnib, 2017). This model has been used to analyze the FEW nexus in Lebanon (Karnib, 2017; Karnib, 2018). The DEA is integrated with the C2R, BC2, and Malmquist Index Model to provide more holistic analyses (Dai et al., 208) and has been applied to analyze the water and energy source consumption in cities in China (Li et al., 2016; Martinez-Hernandez et al., 2017a). External factors, such as environmental systems and social economic systems can be integrated into the framework (Li et al., 2016). PRIMA has been applied to assess how energy infrastructure in the U.S. Gulf Coast is effected by climate change (Dai et al., 2018). The modeling system, which takes into account stakeholder engagement (Kraucunas et al., 2015), is available through the open-source software platform, Velo (https://im3.pnnl.gov/platform-regional-integrated-modeling-and-analysis-prima). Aside from being an open source tool, GCAM (http://www.globalchange.umd.edu/gcam/) has tutorials, a community listserv, and a Github repository. The NexSym tool allows users to build system diagrams and provides summary outputs of the model. It has been applied to a bioenergy production system (Martinez-Hernandez et al., 2017a,b).

2.3.2 Initial Evaluation

Several criteria were used to evaluate existing tools as follows:

Availability and accessibility: open-access tools allow decision-makers to conduct assessments or analysis in a manner that is affordable. Thus, modeling tools that require licensing and/or a subscription fee were not included in this study, as cost can be a major hindrance. Ease of access for potential users facilitates the use of the tool in decision-making processes (IRENA et al., 2015). Therefore, only tools that are readily available online were considered in this study.

User friendliness and simplicity: decision-making tools that are simple and easy to use are implemented more readily. One of the major drawbacks of many FEW nexus modeling tools is their need for large amounts of data (IRENA et al., 2015; Kaddoura and El Khatib, 2017). This requires that users be well-informed of where to access required data, and puts a burden on users to process, format, and import the data into the model. Additionally, due to the complexity of the nexus, it becomes challenging for the user to collect comprehensive data for all sectors of the nexus (Kaddoura and El Khatib, 2017; IRENA et al., 2015). Furthermore, learning how to use a tool due to said complexity may require time and effort and may not be feasible. In a review by IRENA et al. (2015), two models considered simple and user friendly are the WEF Nexus Tool 2.0 and the FAO's nexus assessment methodology (FAO, 2014b).

Flexibility: some tools are static in terms of the scaling they propose; for example, DTI requires the user to select the country that they are interested in modeling. Other tools allow static scaling to be used across different boundary conditions; this is seen in the Q-nexus Model, which is based on Leontief matrices that have the potential for being altered for local or regional scales. For this analysis, we looked at the flexibility of boundary conditions for the FEW nexus modeling tools.

Comprehensiveness: although there are various types of models for a specific sector or sector interconnections such as LEAP (Long-range Energy Alternatives Planning System), WEAP (Water Evaluation and Planning), MuSIASEM, and GLOBIUM, finding tools that encompass the FEW nexus in a way that is representative, accessible, and easy to use presents a challenge (Daher and Mohtar, 2015; Kaddoura and El Khatib, 2017; Martinez-Hernandez et al., 2017a). Therefore, tools that have a fully-integrated approach and account for all three sectors of the FEW nexus and, to some extent, establish interconnections between them were preferable.

Predictive component: with the uncertainty of climate change, there is a need to assess how scenarios could change in the future, and how one could create robust solutions. Thus, the ability to use the tools to incorporate and compare futuristic scenarios was evaluated.

According to Kaddoura and El Khatib (2017) and Dargin et al., (2019), tools that are open-access, available online, simple, and user-friendly are more likely to find wide application. Thus these were considered as the primary criteria in the evaluation. Comprehensiveness was the next criterion, and was applied to the tools that were readily available. Tools that did not include all three sectors of the FEW nexus were eliminated from the analysis. The next factor considered was ease of use; tools that require extensive programming, multiple software usage, or a steep learning curve along with a high time investment were removed from the analysis. Finally, considerations were made as to whether the tool would be intuitive to use or had a tutorial and/or community resources available for the user to be able to guide themselves in using the tool effectively. Finally, user ability to input various scenarios and specify sectors within the FEW nexus was evaluated.

2.3.3 Decision Matrix Analysis

The tools selected for further evaluation were subjected to a multi-criteria decision analysis (MCDA) using a decision (or performance) matrix analysis (Dodgson et al., 2009) and based on the seven qualitative criteria as previously described. The decision matrix allowed for a systematic analysis and rating of the FEW nexus tools. The criteria were unweighted, given that priorities could change depending on the analysis objectives. The grading system was based on a ten-point scale, from 1 being poor to 10 being excellent. The overall score was then averaged across the criteria, and the model with the highest average score was selected as the tool that would be used for the case study.

2.4 Results and Discussion

In this study, selected FEW nexus models were subjected to a preliminary screening based on pre-established criteria to determine the ones best suited for use in FEW nexus modeling and assessments. From this initial evaluation (Appendix Table A1), tools which require a financial input were eliminated, as were tools with extensive data requirements, that were complex, with multiple software requirements, and limited scenario parameters. Based on the evaluation, three tools—GCAM, NexSym, and The WEF Nexus Tool 2.0—were selected for further evaluation and were subjected to a more thorough analysis through a multi-criteria decision analysis. Based on the evaluation criteria (Table 1), the WEF Nexus Tool 2.0 was ranked as the best fit (with a total score of 6.86/10), with the GCAM tool coming in second (6.14/10), and NexSym ranked as the least implement (5.57/10).

Table 1 Decision matrix for FEW nexus modeling tools

TOOL	USER-FRIENDLINESS	FLEXIBILITY	COMPREHENSIVE	AVAILABILITY	PREDICTIVE ELEMENT	ECONOMIC COMPONENT	WATER QUALITY	RANK
WEF Nexus Tool 2.0 (Daher and Mohtar, 2015)	Intuitive, easy to understand 9	Limitations on user-defined energy sources and agricultural practices 6	Nation-wide (Qatar), agricultural sector 8	Online 10	Multiple scenarios can be used as a predictive assessment 6	Incorporated for Qatar 8	Needed 1	1
GCAM (Edmonds et al., 1994)	Tutorials, Wiki, requires understanding in LINUX 2	Limitations on user-defined energy sources and agricultural practices with some user-defined components 9	Region-wide (USA, others) 8	Online, but requires downloading to computer for usage 6	Multiple scenarios can be used as a predictive assessment 6	Incorporated through policy files 6	Incorporated 6	2
NexSym (Martinez-Hernandez et al., 2017a)	GUI interface, allows for user inputs 6	User-defined components 10	Local (UK-town), limited spatial analysis 8	Not in a shareable format 2	Multiple scenarios can be used as a predictive assessment 6	Needed 1	Water-treatment and nutrient surplus integrated in model 6	3

The WEF Nexus Tool 2.0 is a great example of a user-friendly tool that is available in open-access and facilitates trade-off perspectives of sustainable solutions with a focus on food security and agricultural production (Daher and Mohtar, 2015). This tool received a 9/10 in the "user-friendly" category, with NexSym receiving a 6, and GCAM receiving a 2 an inadequate user interface. The user interface for GCAM was not well established and required extensive time and tutorials to implement for water resource management. The complexity of the WEF Nexus Tool 2.0 was deemed moderate. It was the most intuitive of the three tools, as well as the tool that required the least amount of user inputs.

While NexSym had potential in allowing users to define their boundaries and interconnections, the software was not available in a shareable format at the time of this study. Hence, NexSym availability was scored a 2. The WEF Nexus Tool 2.0 received a 10, as it was readily available online and can be accessed after the end user creates a profile, which is done in order for the user to be able to save any simulations they are generating. GCAM received a score of 6, because though one can access it online, it requires end users to download the program. For flexibility, though both the WEF Nexus Tool 2.0 and GCAM have similar limitations in both the agricultural and energy components, GCAM received a higher score despite these limitations, as the user has the ability to define some aspect of these sectors.

The WEF Nexus Tool 2.0 incorporates an economic component through the type of crops being produced. There are limitations to implementing policies and future pricing, and thus the tool received an 8. Policy files can be user-defined in GCAM, and taxes and subsidies can be represented. However, the user has to develop these files, which can become difficult if they are unfamiliar with the process. This tool, thus, received a score of 6.

In terms of comprehensiveness, all three tools received a score of 8 because each of these modeling tools have sufficient sector inputs and interconnections based on the scale and purpose; The WEF Nexus Tool 2.0 focuses on food security and has interconnections based on agricultural production and water consumption within Qatar at an annual basis (Daher and Mohtar, 2015). GCAM is a regional-scale model that is meant for coarse 5-year intervals (JGCRI, 2019). The NexSym tool focuses on more local systems, at the city scale (Martinez-Hernandez et al., 2017a). These systems account for necessary interconnections between the nexus despite the differing question and scales, and thus have appropriate comprehensive levels for the respective scale.

Though GCAM has the potential for climate change predictive analysis, the coarse interval time periods could make assessment of crop production difficult as crop growth varies seasonally. There are a variety of climate change projection data sets available, with differing radiative or climate forcings; the ability to incorporate these climate change projections into GCAM would be beneficial for robust decision making. One of these climate change scenarios, RCP 4.5 (Representative Concentration Pathway, 4.5 W/m^2), was simulated successfully with GCAM (Thomson et al., 2011), However, the learning curve for GCAM is steep for novice programmers and decision-makers with minimal coding experience, making predictive analysis challenging.

NexSym has a predictive component for consumption and nutrient modeling through bioenergy production, and provides flexibility in terms of user input and defining the system at hand. Additionally, it includes nitrogen and carbon cycling within the locally-scaled model, as well as a climate input. However, the tool currently does not have a spatial modeling component, but holds promise for incorporating one, as well as integrating aspects of uncertainties and connections with FEW modeling tools based on larger scales (Martinez-Hernandez et al., 2017a,b).

Though the WEF Nexus Tool 2.0 does not have a built-in predictive component, an end user could develop various scenarios in order to assess future climate conditions (Daher and Mohtar, 2015). The annual basis at which output is generated provides a coarse assessment – though finer than that from GCAM – that may be beneficial for decision-makers. Nevertheless, having a more fine-scaled assessment of the predictive component would aid in further developing the water component of the tool, as water availability may shift based on seasonal variations.

In general, FEW nexus tools span not only a range of modeling frameworks and system depths, but also a range of complexity, user-friendliness, and comprehensiveness in modeling FEW nexus interactions, underlying assumptions, and applicability with respect to location. While some tools are more comprehensive than others, there is not yet a single nexus modeling tool that simulates the FEW nexus holistically (Dargin et al. 2019). Furthermore, existing tools were built considering specific regions or localities and there applicability elsewhere may need to be tested more broadly. There is, thus, still room to enhance and expand existing tools and models. In this study, we demonstrate how one could narrow down on tools initially based on broadly applicable criteria, and then further based on their knowledge, expertise, resources, needs, and the range of tools available. Inherently, this process has elements of subjectivity; thus, it is not our intent to endorse one tool over another or others. With these considerations in mind, we present a case-study example application of the WEF Nexus Tool 2.0 framework.

2.5 Case Study: Matson Ditch Watershed

This study used information from the Matson Ditch Watershed in DeKalb County in northeast Indiana, USA, to illustrate the use of the WEF Nexus Tool 2.0 at the watershed scale, and incorporation of a water quality impacts component. The study integrated the methodologies of the WEF Nexus Tool 2.0 and the 7-Question Guideline to Modeling the Water-Energy-Food Nexus developed by Daher and Mohtar (2015) and Daher and Mohtar (2012), respectively. Additionally, the case study integrated future climate projection scenarios to demonstrate how the WEF Nexus Tool 2.0 can be used to assess climate change effects on the stressors within the FEW nexus framework.

2.5.1 Site Description

The Matson Ditch Watershed (Fig. 4) is an agricultural subsurface drainage-dominated catchment with an aerial extent of 4610 ha (11,392 acres). Cultivable agricultural land (67.8%) is primarily used to produce corn, soybeans, and winter wheat. About 5% of the land is developed area that includes residential properties (Mehan 2018), 13% of the watershed is in pasture, and 9% in deciduous forest. Other land uses, such as barren, evergreen forest, range-brush, wetlands, water, and other crops including alfalfa, rye, oats, hay, constitute up to 4% of the area. The annual average precipitation over the entire watershed based on 2003–2012 data was around 1000 mm. The two major soil types in this watershed are a silt loam Alfisol (Blount: somewhat poorly drained) and a clay loam Mollisol (Pewamo: Poorly drained) (Mehan 2018).

The Matson Ditch Watershed is monitored by the USDA-Agricultural Research Service (ARS) National Soil Erosion Research Laboratory (NSERL), and has sufficient data available to allow the application of the WEF Nexus Tool 2.0 methodology. Previous work in the watershed (Mehan, 2018) used the Soil and Water Assessment Tool (SWAT, Arnold et al., 1998), to assess how climate change would affect both surface and subsurface water and nutrient mechanisms. Using historical and projected climate data, the previous study was also able to demonstrate effects on crop yield. Modeling outputs for the 21st century indicated that there could be greater nutrient losses from this agriculturally dominated watershed, and that changing conditions could affect future crop yields, with corn yields potentially decreasing by 2%–50% and soybean yields increasing by 20%–60% (Mehan 2018).

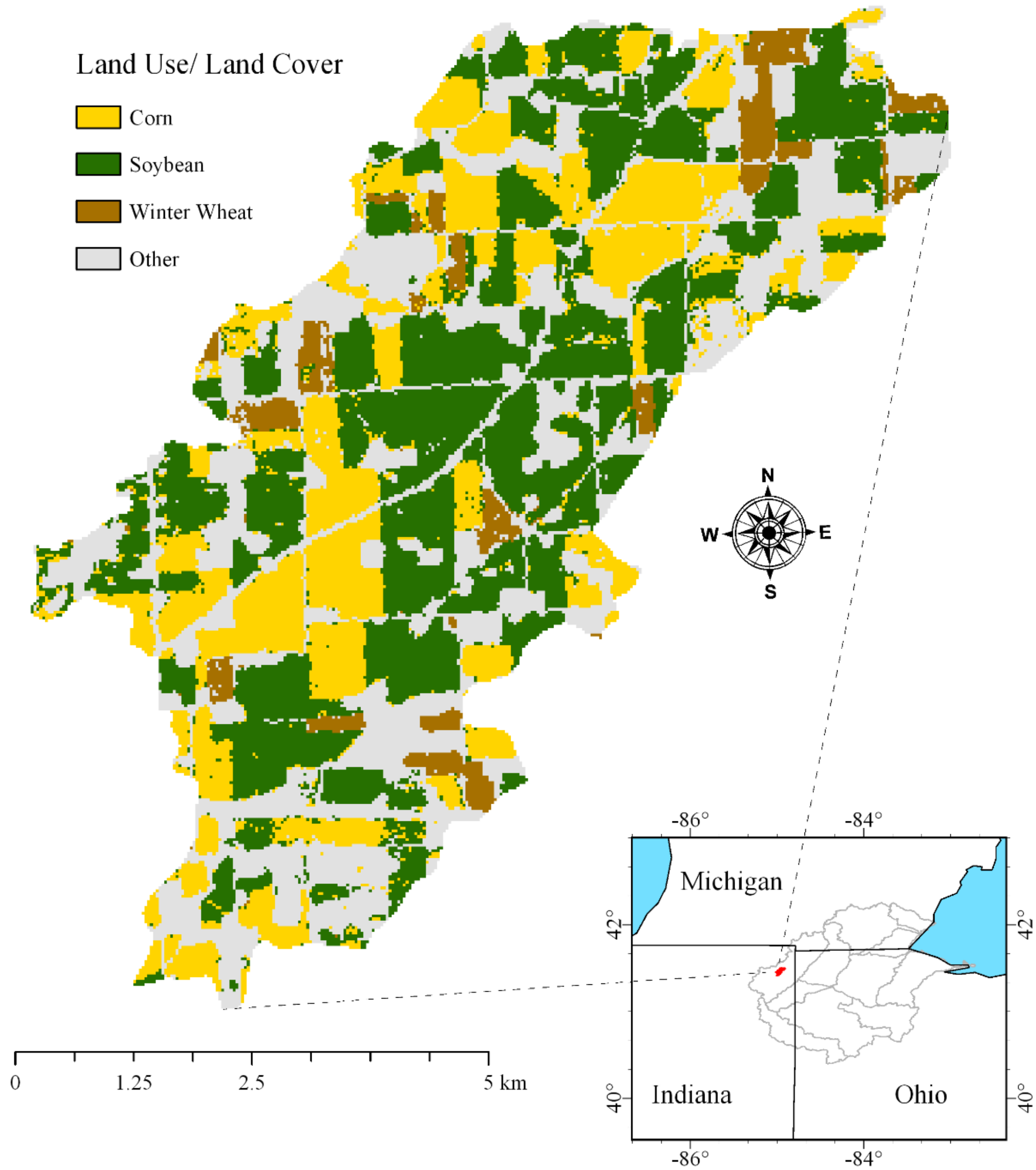

Figure 4 Matson Ditch Watershed in DeKalb County, IN, USA.

2.5.2 WEF Nexus Tool Considerations

This study included answering the 7-Question (7Q) Guideline to Modeling the Water-Energy-Food Nexus by Daher et al. (2017). Because water quality is a crucial component in water management, the study also assessed the extent to which water quality could be incorporated in FEW nexus modeling. A scenario-based case study was conducted to assess how the chosen tool would perform in representing the interconnections between the FEW sectors including future perspectives, the flexibility in scale through assumptions and inputs and outputs of the framework, and its ability to capture potential trade-offs in various resource allocation strategies.

2.5.3 The 7Q guideline: Systems of Systems Analysis

The 7Q Guideline provide a guide to conceptualize the necessary framework for decision-making to quantify interconnections between the sectors of food, energy, and water, as well as to develop scenarios and tradeoffs (Daher et al., 2017). Following is a summary of the responses to the questions, which enabled comprehension of the system within the Matson Ditch Watershed:

- What is the critical question?

  How can we assess water resources impacts within the FEW nexus framework, based on varying renewable energy deployment options and sustainable agricultural practices while taking climate change into account?

- Who are the players/stakeholders?

  Those interested in long-term projections of water quality and climate change would be considered major stakeholders. These involve local farmers, environmental entities, and academics.

- At what scale?

  The scale for this assessment is at the watershed scale.

- How are we defining our systems of systems?

  In this case study, the framework is water-centric considering both water quality and quantity. Fig. 5 shows the FEW nexus framework for this analysis. Because the WEF

Nexus Tool 2.0 was developed to focus on food production (Daher, 2012), the interconnections represented in this tool focus on the process and dependencies for this goal. Agricultural production is critical to water quality in the food-water portion of the nexus (D'Odorico et al., 2018), thus, including water quality considerations in the analysis introduces an additional interaction where food production affects water by impairing its quality. Water quality is considered at both spatial and temporal scales. Crop location, rotations, and type are included. Additionally, energy requirements and carbon emissions for fertilizer production, tillage, harvesting, and transportation due to crop production are considered. The pilot site, the Matson Ditch Watershed, is a predominantly agricultural research watershed with no competing usage of resources other than the concern of water quality impairment. Because the site is predominantly precipitation-fed, energy for securing water will only be used to demonstrate the energy and carbon emission trade-offs.

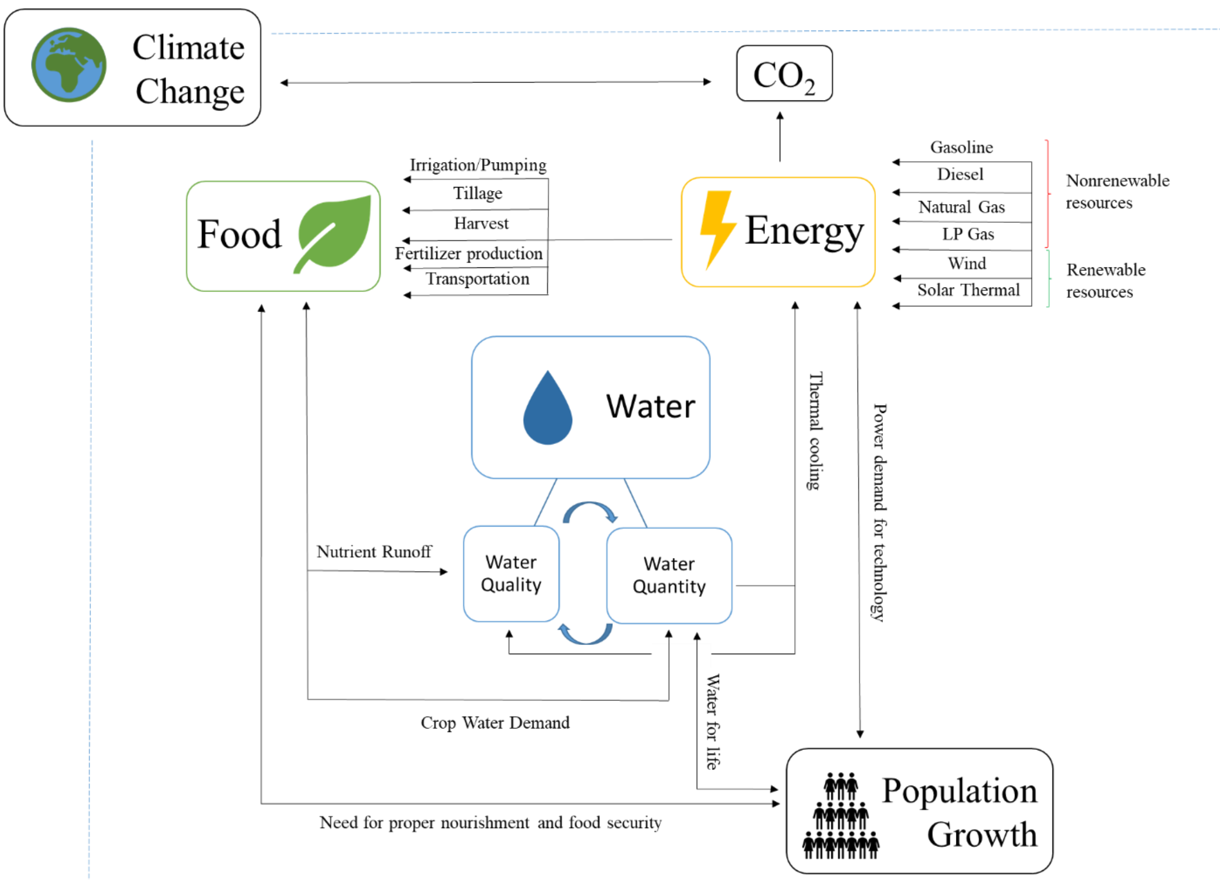

Figure 5 Diagram demonstrating the FEW nexus framework.

- What do we want to assess?

  The analysis will include the type of crops being grown, along with their rotations, the sources of energy for agricultural production and securing water, the sources of water, the quality of the water within the watershed, and what climate change projections indicate through the 21st century.

- What data is needed?

  Among the data required for the assessment were, water requirement (m3), spatial-temporal distributions of water resources, the watershed water budget, energy requirement for water (kJ/ m3), energy requirement for agricultural production (kJ/ha), carbon footprint (ton/kJ), and climate change projection data.

- How do we communicate it? Where do we involve the decision maker in the process?

  Through this case study, a holistic assessment of the Matson Ditch Watershed will be provided. Moving forward, it is possible to incorporate more strict constraints and strategies to remove impractical scenarios.

2.5.4 FEW Nexus Framework and Assumptions

In order to model the FEW nexus, relationships between the food-energy, energy-water, and water-food sectors needed to be assessed, in addition to inputs and assumptions within each of the respective sectors. The sector and inter-connection assumptions were based upon the equations used in the WEF Nexus Tool 2.0 (Table 2). Because this case study was conducted at the watershed level, the constraints set by Daher (2012) were not incorporated. For assessing outputs of the model, no bounds were included for the equations used. Though the WEF Nexus Tool 2.0 has restraints set for each of the amount of water, land, and energy sources, these were not necessary for the case study since, on an annual basis, the Matson Ditch Watershed receives sufficient rainfall to sustain agricultural production. It was also not necessary to account for importation/exportation of crops, political risks associated with trade, or transportation of the crops being produced, which simplified the modelling.

Table 2 FEW Nexus Equations and Assumptions (Source:[47])

Sector	Equation / Assumptions					No.
Food-Energy		Tillage		Harvest		
	Fuel Type	Consumption (gal/acre)	CO_2 Emissions ton CO_2 /gal	Consumption (gal/acre)	CO_2 Emissions ton CO_2 /gal	
	Gasoline	0.56	0.00892	0.63	0.00892	
	Diesel	0.4	0.01	0.45	0.01	
	LP Gas	0.67	0.008672	0.76	0.008672	
Energy[a,b]	$\text{Energy Total}_t = \sum_{i=1}^{n} E_{1,i,t} + E_{2,i,t}$					(1)
	$E_{1,i,t} = E_{R,i,t} + E_{GW,i,t} + E_{TWW,i,t}$					(2)
	$E_{2,i,t} = E_{till,i,t} + E_{harv,i,t} + E_{fert,i,t}$					(3)
Carbon Emissions[c]	$CO_{2_t} = \sum_{i=1}^{n} CO_{2_{1,i,t}} + CO_{2_{2,i,t}}$					(4)
	$CO_{2_{1,i,t}} = CO_{2_{R,i,t}} + CO_{2_{GW,i,t}} + CO_{2_{TWW,i,t}}$					(5)
	$CO_{2_{2,i,t}} = CO_{2_{till,i,t}} + CO_{2_{harv,i,t}} + +CO_{2_{fert,i,t}}$					(6)

[a] $E_{1,i,t}$ (KJ/year) is the energy needed for either pumping or treating water for irrigation for crop i (KJ/year), and $E_{2,i,t}$ is the energy (KJ/year) needed for tillage (till), harvest (harv), fertilizer production (fert), and local transport (considered negligible and thus not included).

[b] Associated energy values were obtained from Daher (2012), with energy requirements for nitrogen, phosphorus, and potassium/atrazine fertilizers at 78,230, 17,500, and 13,800 (KJ/kg) and the carbon emission was assumed 0.0026 ton/year. Groundwater energy requirement being 4,271 KJ/m^3 and treated wastewater requires 1,656 KJ/m^3.

[c] Carbon emission from different energy sources for water retrieval were taken into account, including diesel (778 g CO_2/kWh), natural gas (443 g CO_2/kWh), wind (10 g CO_2/kWh), and solar thermal (13 g CO_2/kWh).

Data Development

Data used in this case study were obtained primarily from Mehan (2018), who used the SWAT model and provided modeling information at both watershed and Hydrologic Response Unit (HRU) levels. HRUs are the smallest modeling unit in SWAT, and are defined as approximately homogenous areas of land use, soil type, and slope (Mehan, 2018). Bias-corrected climate projections from nine different general circulation models (GCMs) and data from two climate change emissions scenarios, (RCP 4.5 and RCP 8.5) were applied to the Matson Ditch Watershed for the 21st century (2006–2099). The climate data through 2099 were separated into three major segments (2006–2019, 2020–2069, 2070–2099) developed using change-point detection algorithms such as the Pruned Exact Linear Time (PELT) algorithm (Killick et al., 2012) to detect points throughout the 21st century where there were inflections in the dataset. The overall analysis was separated into five time periods: 2006–2012; 2006–2019; 2020–2069; 2070–2099; and, 2006–2099. The 2006–2012 period was included to determine hydrologic and nutrient response in the recent past, while the 2006–2099 period was included to determine how the inputs and outputs within individual time periods differed from those of the entire dataset (Mehan, 2018).

For uniformity purposes, the FEW nexus modeling was performed for each of the five time periods outlined in Mehan (2018). Outputs were obtained at the HRU level to provide data based on land use as needed for this study. As the Matson Ditch Watershed is predominantly agricultural, data were extracted for HRUs that had the major crops—corn, soybeans, and winter wheat—and used for evaluations. Nine GCM climate change datasets were applied with two radiative forcing climate scenarios (RCP 4.5 and RCP 8.5). The annual aggregated mean values from the models for precipitation, actual evapotranspiration, nutrient runoff, and crop yields for each of the corn, soybean, and winter wheat HRUs were used.

Fig. 6 shows the integration of the WEF Nexus Tool 2.0 and SWAT for assessment of the Matson Ditch Watershed. In this application, the two are used as stand-alone applications with SWAT model output and watershed representation being used to provide input to WEF Nexus Tool 2.0. The tool incorporates water quantity, energy demand and consumption, and overall food production, while quantities such as water demand based on the evapotranspiration, and water quality contaminant values were taken from the calibrated SWAT model. Furthermore, the SWAT model was used to provide climate change projections through the 21st century.

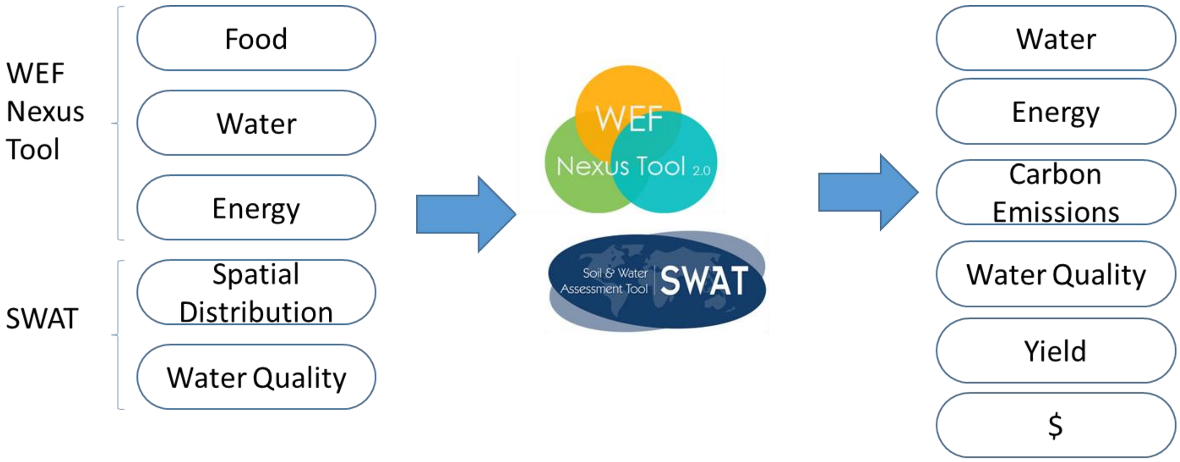

Figure 6 Integrating the WEF Nexus Tool 2.0 and SWAT for assessment of the Matson Ditch Watershed.

Food Sector

The areas for the assumed initial crop production for corn, soybeans, and winter wheat were 1123 ha (2775 acres), 1723 ha (4258 acres), and 238 ha (588 acres), respectively. Land use has not changed much within the region (Sekaluvu et al., 2018), so calculations could be based reliably on the number of hectares of current crop production. Thus, the land use was assumed to be consistent throughout the 2006–2099 analysis period. The amount of crops produced on an annual basis for each of the time scales was calculated using Eq. (7).

$$\text{Crop Production}_{i,t} = \text{Yield}_{i,t} \cdot \text{Crop Area}_{i} \qquad (7)$$

where production of crop i during time period t is in tons, yield of crop i is in tons/ha (Table 3) for each time period t, and crop area is given in hectares. Historical and future yields for each of the crops were obtained by separating the HRUs for each of the time periods by crop type across the watershed, then taking the average of the yields based on the HRU land use indication. A crop rotation of corn-soybeans-winter wheat (in sequence, one crop per year) was modeled in the analysis conducted by Mehan (2018) and thus these HRU yield values were indicative of the rotational crop production between the years 2006–2099.

Table 3 Yield based on mean yield/ha of watershed Crop-Based Hydrologic Response Units

Time Period	Corn (ton/ha)	Soybeans (ton/ha)	Wheat (ton/ha)
RCP 4.5			
2006 – 2012	4.70	4.68	2.95
2006 – 2019	5.11	4.75	3.87
2020 – 2069	4.79	4.61	3.53
2070 – 2099	4.93	4.93	3.86
RCP 8.5			
2006 – 2012	4.45	4.82	3.05
2006 – 2019	4.86	4.79	3.83
2020 – 2069	4.55	4.43	3.56
2070 – 2099	3.50	3.68	2.87

Energy Sector and Carbon Emissions

The energy assumptions for this case study were those developed in Daher (2012). Energy requirements within the watershed were determined by Equation 2 (Table 2). The study watershed is a freshwater, primarily rainfed system. Thus, the main water source that was considered was rainfall (energy requirement = 0 KJ/year). Additional analysis was conducted on groundwater and treated wastewater to assess the energy and carbon emission tradeoffs if precipitation was not the primary source of water for the watershed.

In the study area, the primary energy requirements and CO_2 emissions for crop production are tied to fertilizer, tillage and harvesting. For tillage and harvesting, it was assumed that only one type of fuel type was used. Energy assumptions for tillage from Daher 2012 were assumed for all the agricultural crops. The fertilizer demands for each of the crops were averaged through all the crop HRUs to take into consideration the crop rotations. Unless otherwise noted, the carbon emissions were based on one energy source. The diesel and natural gas (D + NG) energy source is considered the baseline value for Indiana. According to Dillon and Slaper (2015), Indiana's energy consumption in 2012 was broken down as: 44.7% coming from coal, 24.6% from natural gas, 27.2% from petroleum, and 3.5% from other sources. For simplicity, we assumed that the baseline consumption for Indiana was 75% of the D + NG energy source coming from diesel and 25% from natural gas. The more sustainable combination scenario, consisting of wind and solar thermal (W + S), assumed that energy was coming from renewable resources of wind (50%) and solar thermal (50%). In comparison to nonrenewable sources, wind, solar, and the wind-solar combination have almost minimal carbon emissions. For the Matson Ditch Watershed, wind and solar were considered to be the most probable renewable resources for the region. Carbon emissions were calculated in a similar manner to energy (Eq. (5), Table 2), where total carbon emissions were in tons/year for time period t, $CO_{21,i,t}$ were the carbon emissions from pumping or treating water for irrigation for crop i (tons/year), and $CO_{22,i,t}$ were the carbon emissions from tillage, harvest, fertilizer production, and local transport, all multiplied by the years in time period t. $CO_{21,i,}$t was calculated using Eq. (6) in Table 2, where the energy was the sum of the amount required to retrieve clean water from rainfall (R), groundwater (GW), and treated wastewater (TWW) to satisfy the crop water demand of crop i during time period t.

The sources of emissions that were considered were those of groundwater and treated wastewater, as rainfall as a water source does not require an extensive energy input. CO22,i,t was calculated using Eq. (7) in Table 3, where the total carbon emissions are the sum of the amount of energy required for tillage (till), harvesting (harv), producing fertilizer (fert), and local transportation (local tr). However, just like for the energy consumption, the transportation CO_2 emission component was assumed to be zero. Additionally, the energy and carbon emissions assumptions for the potassium (K) fertilizers, which are not applied in the watershed based on Mehan (2018), were implemented for atrazine for simplification purposes. For these crop production energy sources, the energy sources that were considered were diesel, gasoline, and liquid petroleum fuel, in accordance with the WEF Nexus Tool 2.0. For water retrieval, some of the renewable energy alternatives that were integrated in the WEF Tool 2.0, primarily solar and wind, were maintained in order to incorporate renewable energy initiatives in the region.

Water Sector

Water Quantity

Water quantity and quality values were used from Mehan (2018) for the area. In addition to components of groundwater and waste water, which are included in the WEF Nexus Tool 2.0, this analysis added precipitation as a water source as this is the primary water source in the Matson Ditch Watershed. The application of the WEF Nexus Tool 2.0 in this region, thus, entailed reframing the water component to include precipitation. One of the more simplified methods for estimating crop water demand is through calculating evapotranspiration of the plant. The total actual evapotranspiration (ET_a) values had been calculated per HRU of the watershed and were aggregated based on the crop designation.

Water Quality

In addition to water quantity, it was critical to consider the water quality status within the Matson Ditch Watershed. For this case study, the total loads of soluble phosphorus from the entire (surface, subsurface) system, as well as the nitrate-nitrogen and soluble phosphorus in subsurface drainage waters from the cropland were calculated using Eq. (8):

$$\mathrm{WQc}_{i,t} = \mathrm{WQcY}_{i,t} \cdot \mathrm{Crop\ Area}_{i} \quad (8)$$

where $WQc_{i,t}$ is the water quality contaminant coming from cropland i at time period t, WQcY is the water quality contaminant yield (ton/ha) from crop land i at time period t being multiplied by its area (m^2) given the crop rotation. Water quality contaminant values were obtained through a comprehensive modeling effort using SWAT (Mehan, 2018), which included water quality projections through the 21st century.

WEF Nexus Tool Outputs

Throughout the span of 2006–2099, the average annual crop production (tons/year) that was determined is shown in Fig. 7. There was a gradual decline in the average yield for the soybean HRUs, as well as for corn for the RCP 8.5 scenario, with an opposite projection being shown for the soybean HRUs in the RCP 4.5 scenario. The winter wheat HRUs stayed relatively constant throughout the time periods between 2006 and 2099. Though the average values provide an indication of climate impacts, it would be beneficial to be able to also address the extrema of the output to show the full variation from these scenarios.

Table 4 shows the average demand of each of the crops throughout the five time periods in the 21^{st} century for both RCP 4.5 and 8.5. The amount of water required (ETa) would ensure that the crops are not as stressed throughout the time period on an annual basis. As mentioned before, precipitation is the primary water source in this region; on an annual basis, the amount of rainfall that the watershed receives surpasses the amount of water required to ensure that crops are not stressed. For both scenarios, the corn, soybean, and winter wheat HRUs showed little variation through the 21st century; this was because the SWAT analysis conducted by Mehan (2018) accounted for crop rotations; thus, with expected spatial variation, there was not much difference between the HRU averages. However, it was interesting to note that there were not as large of variations in the water demands, despite the notable changes in the soybean and corn HRU crop yield values throughout the 21st century.

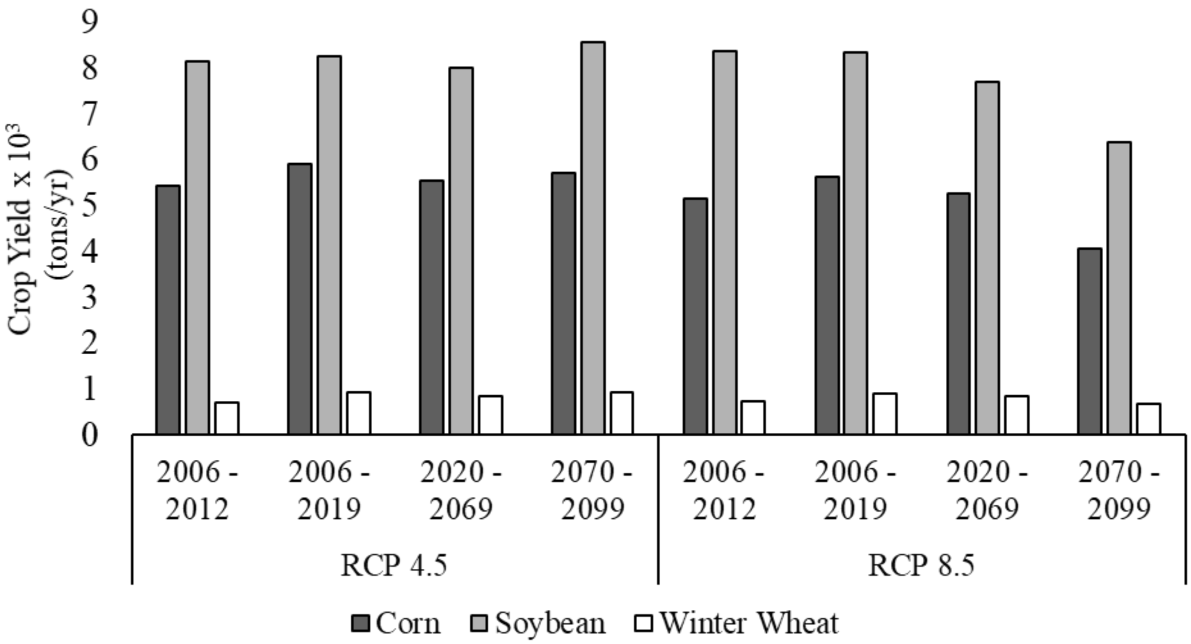

Figure 7 Average annual crop production for Crop-Based HRUs in tons/year predicted for time periods between 2006 and 2099.

The amount of water that would be required for each of the HRUs could be assessed by multiplying the average crop demand by the area of each crop. There are various methods with which to determine water valuation; for example, Chapagain and Hoekstra (2004) introduced the concept of the water footprint to determine the amount of water that is consumed through the lifetime of a product. An additional step would be to address the source from which the water is being consumed for a product, and the additional inputs and environmental impacts from using one water source over another.

For comparison, the energy and carbon emissions of water sources other than precipitation were calculated. Fig. 8 shows the amount of energy that would be required if the water was coming from some source other than precipitation. In the following scenarios, the calculations were done to assess a hypothetical scenario of how to meet this need through groundwater and treated wastewater. This was done in order to comprehend the tradeoffs of energy if securing water from an alternative source. Groundwater would be more energy intensive than treated waste water because the average well depth of Indiana ranging from 9.7 to 31 m deep (32–102 ft) (Indiana Department of Natural Resource, IDNR, 2019), is similar to the assumptions made in the WEF Nexus Tool 2.0 model.

Table 4 Average crop water demand for Crop-Based HRUs in mm/year for time periods between 2006 and 2099.

Scenario and Time Period	Corn	Soybean Crop H_2O Demand (mm/yr)	Winter Wheat
RCP 4.5			
2006 – 2012	514.1	486.9	436.2
2006 – 2019	515.6	490.2	442.2
2020 – 2069	492.2	496.2	428.9
2070 – 2099	497.6	493.9	449.9
RCP 8.5			
2006 – 2012	497.3	484.7	436.6
2006 – 2019	498.4	496.9	440.1
2020 – 2069	481.2	481.3	433.4
2070 – 2099	461.3	466.7	444.1

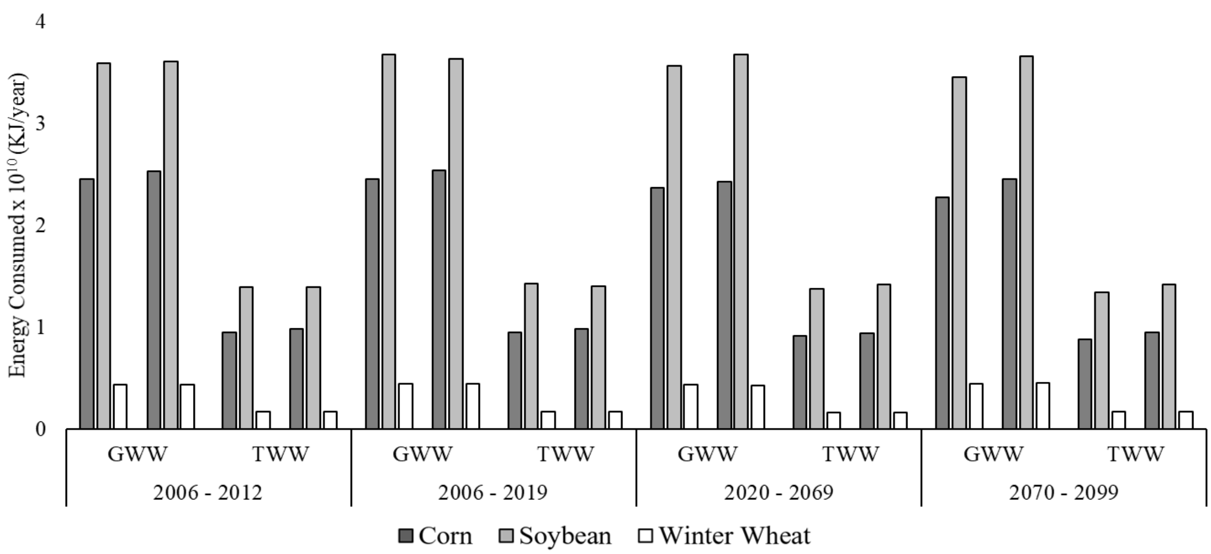

Figure 8 Energy that would be required (KJ/year) to meet total water demand for each crop if the primary water sources were ground water (GW) or treated wastewater (TWW); the first set of bars in each of the series are the results of the RCP 4.5 scenario and the second set are the results from the RCP 8.5 scenario.

Table 5 Carbon Emissions x 10^{10} (tons CO_2/year) for nonrenewable energy based on alternative water source

Scenario and Time Period	Alternative Water Source	Diesel			Natural Gas			D + NG*		
		Corn	Soybean	Winter Wheat	Corn	Soybean	Winter Wheat	Corn	Soybean	Winter Wheat
RCP 4.5										
2006 – 2012	GW	7.83	11.14	1.36	4.46	6.34	0.77	6.99	9.94	1.21
	TWW	3.04	4.32	0.53	1.73	2.46	0.30	2.71	3.85	0.47
2006 – 2019	GW	7.85	11.21	1.38	4.47	6.38	0.79	7.01	10.01	1.23
	TWW	3.05	4.35	0.53	1.73	2.48	0.30	2.72	3.88	0.48
2020 – 2069	GW	7.50	11.35	1.34	4.27	6.46	0.76	6.69	10.13	1.19
	TWW	2.91	4.40	0.52	1.66	2.51	0.30	2.59	3.93	0.46
2070 – 2099	GW	7.58	11.30	1.40	4.32	6.43	0.80	6.76	10.08	1.25
	TWW	2.94	4.38	0.54	1.67	2.49	0.31	2.62	3.91	0.49
RCP 8.5										
2006 – 2012	GW	7.58	11.09	1.36	4.31	6.31	0.78	6.76	9.89	1.21
	TWW	2.94	4.30	0.53	1.67	2.45	0.30	2.62	3.84	0.47
2006 –2019	GW	7.59	11.36	1.37	4.32	6.47	0.78	6.77	10.14	1.22
	TWW	2.94	4.41	0.53	1.68	2.51	0.30	2.63	3.93	0.47
2020 – 2069	GW	7.33	11.01	1.35	4.17	6.27	0.77	6.54	9.82	1.21
	TWW	2.84	4.27	0.52	1.62	2.43	0.30	2.54	3.81	0.47
2070 – 2099	GW	7.03	10.67	1.38	4.00	6.08	0.79	6.27	9.53	1.24
	TWW	2.72	4.14	0.54	1.55	2.36	0.31	2.43	3.69	0.48

*This was assumed to be the baseline consumption for the state of Indiana, with 75% of energy for the alternative water source coming from diesel and 25% of the energy being retrieved from natural gas.

Table 6 Carbon Emissions x 10^{10} (tons CO_2/year) for renewable energy based on alternative water source

Scenario and Time Period	Alternative Water Source	Wind			Solar Thermal			W + S		
		Corn	Soybean	Winter Wheat	Corn	Soybean	Winter Wheat	Corn	Soybean	Winter Wheat
RCP 4.5										
2006 –	GW	0.10	0.14	0.02	0.13	0.19	0.02	0.12	0.17	0.02
2012	TWW	0.04	0.06	0.01	0.05	0.07	0.01	0.05	0.06	0.01
2006 –	GW	0.10	0.14	0.02	0.13	0.19	0.02	0.12	0.17	0.02
2019	TWW	0.04	0.06	0.01	0.05	0.07	0.01	0.05	0.07	0.01
2020 –	GW	0.10	0.15	0.02	0.13	0.19	0.02	0.11	0.17	0.02
2069	TWW	0.04	0.06	0.01	0.05	0.08	0.01	0.04	0.07	0.01
2070 –	GW	0.10	0.15	0.02	0.13	0.19	0.02	0.11	0.17	0.02
2099	TWW	0.04	0.06	0.01	0.05	0.08	0.01	0.04	0.07	0.01
RCP 8.5										
2006 –	GW	0.10	0.14	0.02	0.13	0.19	0.02	0.11	0.17	0.02
2012	TWW	0.04	0.06	0.01	0.05	0.07	0.01	0.04	0.06	0.01
2006 –	GW	0.10	0.15	0.02	0.13	0.20	0.02	0.11	0.17	0.02
2019	TWW	0.04	0.06	0.01	0.05	0.08	0.01	0.04	0.07	0.01
2020 –	GW	0.09	0.14	0.02	0.13	0.19	0.02	0.11	0.17	0.02
2069	TWW	0.04	0.05	0.01	0.05	0.07	0.01	0.04	0.06	0.01
2070 –	GW	0.09	0.14	0.02	0.12	0.18	0.02	0.11	0.16	0.02
2099	TWW	0.04	0.05	0.01	0.05	0.07	0.01	0.04	0.06	0.01

Table 5, Table 6 show the amount of carbon emissions based upon the energy source for each of these water source alternatives. This allows for better comparisons of the differences in carbon emissions between conventional energy sources such as diesel and natural gas, and renewable sources such as wind and solar thermal. Out of the four energy sources for water, diesel emitted the most carbon, followed by natural gas. Wind and solar thermal were close in terms of carbon emissions, but wind was the least carbon intensive of the energy sources.

In terms of energy and carbon emissions associated with crop production, we found that fertilizer production required the greatest amount of energy (8.51×10^9, 1.21×10^9, and 1.74×10^9 KJ/year for the corn, soybean, and winter wheat HRUs, respectively). The CO_2 emissions from fertilizer consumption was 393 tons/year for corn HRUs, 589 tons/year for soybean HRUs, and 80 tons/year for wheat HRUs. For tillage, the amount of energy required per crop HRU was 3.45×10^7, 5.18×10^7, and 0.71×10^7 KJ/year for corn, soybean, and wheat, respectively. The carbon emissions for tillage and harvest are outlined in Table 7.

Table 7 Tillage and harvest energy requirements and carbon emissions per season.

Crop	Crop Production Stage	Energy Requirement (x 10^7 KJ/year)	Carbon Emission (ton CO_2/year) Energy Source		
			Gasoline	Diesel	LP Gas
Corn	Tillage	3.45	14.26	11.42	16.59
	Harvest	4.60	16.04	12.85	18.82
Soybean	Tillage	5.18	21.41	17.15	24.91
	Harvest	6.90	24.09	19.29	28.25
Winter Wheat	Tillage	0.71	2.92	2.34	3.40
	Harvest	0.94	3.28	2.63	3.85

Lastly, water quality was incorporated into the analysis. Fig. 9 shows the annual amount of total soluble phosphorus (Sol P) and nitrate (NO_3) from subsurface drainage from each of the crop areas. The largest annual loads came from soybeans, followed by corn, and finally wheat, largely because values were based on crop area. For soluble phosphorus loads level showed gradual decline through the mid-21st century, with a noticeable increase in the amount of soluble phosphorus output at the end of the 21st century for both the RCP 4.5 and 8.5 scenarios. Soluble phosphorus losses predicted for 2070–2099 under RCP 8.5 were substantially greater than the projected value for RCP 4.5. Based on Mehan (2018), annual soluble phosphorus loads during 2070–2099 could range between a decrease of 45% to an increase of 70% under RCP 4.5, and a decrease of 60% to an increase by 75% under RCP 8.5. The mean value of subsurface NO_3 losses for the crop HRUs demonstrated a decline which is consistent with the overall results of Mehan (2018), in which projected decreases from the baseline based on 9 GCMs ranged between 25–75% for RCP 4.5 and 25–60% for RCP 8.5 during 2070–2099.

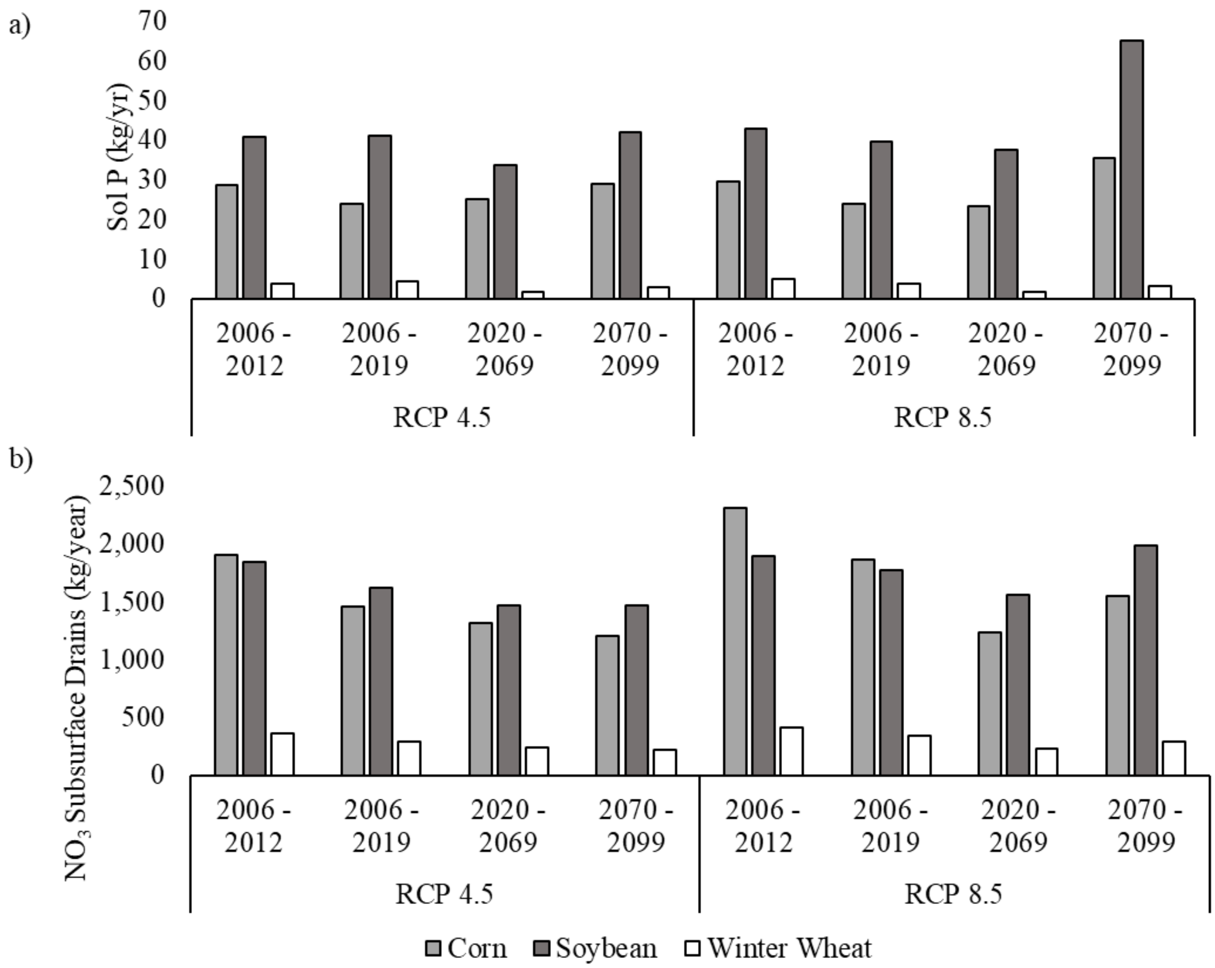

Figure 9 Water quality contaminant loads per year from corn, soybean, and wheat crop areas predicted from the Matson Ditch Watershed from 2006–2099. a) Soluble Phosphorus (Sol P); b) Nitrate in subsurface drains (NO_3).

2.6 Discussion

The variety of FEW nexus modeling tools evaluated in this study demonstrate the wide range of applications of FEW nexus modeling and how certain sectors may be of more interest than others. Additionally, the varying levels of scale and data requirements indicate a wide breadth of knowledge in terms of accessing data, computing and programming skills, and assumptions that can be made about the system. Dai et al. (2018), Kaddoura and El Khatib (2017), and IRENA et al. (2015) have developed literature reviews of available FEW nexus modeling tools and demonstrated their potential in the integration of a more sustainable future. These reviews give a broad overview of the tools, however our review provided a demonstration of how a user can attempt to assess which tool would be the most implementable given a set of priorities, limitations, and skill set. This study took a water-centric view given the importance of water to both the food and energy sectors. Although there are FEW nexus tools that assess water in terms of both quality and quantity, these are generally missing other portions of the FEW nexus. Nutrient modeling within the FEW nexus is rather limited, even though it plays a critical role in its interconnections (Yao et al., 2018). This, thus, points to the need to enhance and expand existing tools to represent the FEW nexus in a way that is more holistic.

Tools that are open-access, available online, simple, and user-friendly will generally be used more than those that are not (Kaddoura and El Khatib, 2017; Dargin et al., 2019). Traditionally, software development has focused on defining methods and processes through data specification. Even though design and implementation of user interfaces are recognized to be among the most energy- and time-intensive steps of any software production process, modeling software is not considered to the same extent (Calvary et al., 2007), at times making the software nonintuitive. With the progression of computational technologies, end users have a wider range of data types available (Vogel, 2011). Thus, it is critical that modeling tools have streamlined instructions for data input, ample explanation of input parameters, data visualization capabilities, and other analysis techniques that support interactive exploration of data, in addition to an appealing graphical user interface.

The case study presented provides a demonstration of FEW nexus assessment using the WEF Nexus Tool 2.0 based on a watershed (Matson Ditch Watershed) in the Midwestern United States. Results of the assessment demonstrate various trade-offs that can be considered by decision-makers when analyzing scenarios of the FEW nexus (Mohtar and Daher, 2016). For this case study, the average annual values for different time periods were taken into consideration to demonstrate that minimum inputs at a coarse scale can provide a starting point to understand the underlying stressors within the FEW nexus of the system at hand. Focusing on a watershed-scale analysis has benefits; previous studies show that this type of analysis can be conducted using a FEW nexus approach with a similar framework, along with the development of future scenarios (Degirmencioglu et al., 2019). It is important to note, that the Matson Ditch Watershed is a single-use area and interactions and mutual constraints among different sectors are not pronounced. In more complex, multi-use systems, such competition and trade-offs among the sectors would need to be explored in greater depth.

For crop production, the annual average yields from each of the SWAT model HRUs output was based on the mean values from the RCP 4.5 and 8.5 scenarios. Incorporating an average value provides a starting point for assessing how crop production will be affected throughout the 21st century, however, it is necessary to evaluate outputs from several climate realizations in order to get a better indication of the range of crop output that is possible with a changing climate.

For the energy required for crop production, it is important to note that though the average tillage energy and carbon emission values are useful estimations, the WEF Nexus Tool 2.0 could incorporate more specific tillage practices; different tillage systems can affect soil carbon and CO_2 emissions. For example, less intensive tillage systems could reduce CO_2 emissions and improve soil conditions (Al-Kaisi and Yin, 2005). Calculations from West and Marland (2002) show that CO2 from agricultural operations account for 137 kg CO2 for no-tillage methods compared to 168 kg CO2 for conventional tillage. Diversifying the tillage methods simulated would allow for a better estimation of carbon output, better quantify the differences between the tillage and harvest energy requirements, and could demonstrate how agricultural conservation practices affect the FEW nexus. Degirmencioglu et al. (2019) demonstrates how fuel consumption based on tillage practice can be improved upon through a case study in the Gediz Basin in Turkey.

The energy required for alternative water sources was calculated to demonstrate a potential trade-off between precipitation and energy if securing water from an alternative source. The amount of energy was based on the volumetric requirement of water by the crops. Though the WEF Nexus Tool 2.0 can account for desalination, for the Matson Ditch Watershed, only groundwater and treated wastewater were considered based on what is practical for the region. The assumed average depth of a well that could be implemented for groundwater extraction was 30 m (98 ft), with an assumed efficiency of the pump motor at 80%. The energy demand of groundwater pumping in the model was reflective of that within the state of Indiana, where there are more than 300,000 wells (Indiana Geology, 2019), ranging from 9.7 to 31 m deep (32–102 ft) (Indiana

Department of Natural Resource, IDNR, 2019). The energy requirement may be greater in areas with lower water tables; for example in California's Central Valley, which is predominantly irrigated agriculture, energy consumed for agricultural practices in 2012 was slightly under 7000 GW hours (2.52×10^{13}) with aquifers of depths up to 61 m (200 ft) (Dale, 2016). For agricultural areas near coastlines, desalination may potentially be a reasonable alternative, especially if precipitation is insufficient to satisfy crop water demand.

Based on Daher (2012), it was assumed that treated wastewater, if used, would be processed using screens and grit removal, with biological treatment of conventional activated sludge and a sequence batch reactor followed by sand filters. The water could then be used for landscape, farms, or ground injection. One of the major concerns with treated wastewater, is health and contamination (Pescod, 1992). However, wastewater is already a common source in countries around the world, such as Pakistan, Vietnam, Ghana, Mexico, Spain, and Greece. Treated wastewater totals 1.5% of water withdrawn in the United States (Pedrero et al., 2010). In California, for example, 656 million cubic meters of water are reused annually (Pedrero et al., 2010). In Indiana, there have been two case studies to assess the feasibility of incorporating treated wastewater as a form of irrigation, demonstrating low risk from land application, but mixed responses from farmers (Dare, 2015). A more practical scenario for Indiana farmland is the use of recycled drainage water, which can generally be used without treatment unless the biological quality was of concern.

For treated wastewater, Rao et al. (2017) reported the average energy requirement to treat one cubic meter of water with aerobic sludge treatment and anaerobic sludge digestion was 0. kwh (2160 KJ), with the average in the United States at 0.43 kwh (1548 KJ), consistent with the value assumed by Daher (2012). Additionally, municipal wastewater holds a large amount of energy which could partially be recovered, with a chemical energy content per unit of wastewater of 2.1 kW h/m^3 (7560 KJ/m^3) and 4.7 kW h/m^3 (16,920 KJ/m^3) for domestic and mixed wastewater, respectively. Nitrogen and phosphorus recovery could also be implemented to develop fertilizers (Rao et al., 2017; Yao et al., 2018). This holds potential for further developing FEW nexus tools to capture chemical energy and nutrient recovery. One aspect that was not taken into consideration was the amount of water required for energy supply; water is used in most stages of energy production (Rao et al., 2017), and ensuring that water is being accounted for in the water–energy connection will allow for better assessment of the FEW nexus.

In Daher (2012), the water consumption for crops in the WEF Nexus Tool 2.0 were based on data from the Water Footprint Network and the Agricultural Sector in the Ministry of Environment of Qatar. Due to differences in climate and agricultural production between Qatar and other areas where the tool might be applied, site-specific values of water demand need to be calculated. The Matson Ditch Watershed is a rainfed agricultural region, where on an annual basis the effective rainfall, that is, the rain which is readily available for crop usage, exceeds crop water demand. From Mehan (2018), a baseline value of 819 mm of average annual precipitation was considered at the watershed level, comprising baseline values of actual evapotranspiration (water demand from crops and plants) of 519 mm, surface flow of 161 mm, groundwater flow of 36 mm, subsurface drainage flow of 81 mm, and lateral flow of 22 mm. Evapotranspiration is roughly 63% of the total water available from rainfall. Conventional methods for calculating effective precipitation are on a monthly basis (Brower and Heibloem, 1986). Furthermore, crop water needs vary by crop growth stage. In the study area, for example, excess water due to rainfall and snowmelt in the spring is drained off so as to allow crop production. However, crops may suffer water stress in later growth stages due to insufficient rainfall in summer months—implying that the excess depicted by the annual picture could be deceiving. Thus, in order to fully capture critical aspects of water management in the FEW nexus, the modeling needs to be done on a monthly basis. Using monthly values would allow for finer-scale assessments of the water surpluses and shortages for the crops within the watershed.

Water quality is a critical component that could benefit FEW nexus modeling tools to better address the health of water bodies that impact and are impacted by food and energy production. Without a water quality component, it may not be possible to obtain the full picture of the FEW nexus. Assessment of water quality in a region requires extensive knowledge of the site location, as well as water quality data (Mijares et al., 2019). Though implementing water quality into a model potentially enhances its performance by allowing a more comprehensive assessment of the FEW nexus, the model becomes much more data intensive. Nevertheless, components can be simplified; Yao et al. (2018), for example, developed nutrient flows and stocks in a local FEW nexus system, accounting for inlets and outlets of annual loads of nitrogen, thus, demonstrating the potential of modeling nutrient flows in a simplified FEW nexus system.

It is important that FEW nexus models provide decision-makers the ability to integrate all these components for a single strategy for natural resource management (Mohtar, 2016). One strategy, which is implemented by the WEF Nexus Tool 2.0, is to incorporate a sustainability index, which aggregates the resources through indices that have the potential to be weighted as the stakeholder or decision-maker sees fit (Daher and Mohtar, 2015). Through the incorporation of water quality, an implementation of water quality indices developed for the Western Lake Erie Basin, such as those by Mijares et al. (2019), could be incorporated into a sustainability index to be more reflective of the water resource management in the region.

One aspect that this case study did not mention was the financial obligation for implementing certain scenarios, as these may change with policies based on the type of energy inputs one may use, and with some of the energy markets, such as electricity, as prices are volatile. In the state of Indiana, for example, policies would have to be further developed in order to incentivize solar energy production (Sesmero et al., 2016). Wind, on the other hand, has policies in place that allow it to continue to thrive in Indiana, accounting for $40 million annually (Tegen et al., 2014). In the future, it would be beneficial to make profit or financial projections throughout the 21st century to strengthen the long-term assessments for decision-making. Additionally, trade policies, subsidies, import and export policies, and other unique economic structures may all impact the financial obligations of a scenario (Kaddoura and El Khatib, 2017).

Although it may seem that data are readily available, one of the major limitations in modeling the FEW nexus is extensive data requirements (Kaddoura and El Khatib, 2017). In order to employ the WEF Nexus Tool 2.0, it requires detailed knowledge of the site of interest. Data sources for crop production can be found from sites like the United States Department of Agriculture National Agricultural Statistics Service (USDA-NASS), and the Food and Agriculture Organization (FAO) of the United Nations. However, these databases contain crops that are currently produced on a large scale and data on specialty crops may be not be readily available. Determining tillage, harvest, and fertilizer application methods may be difficult, as this can vary by individual farming facility. Data can be sparse if it is on the local level in terms of crop production, which may require connecting with stakeholders or nongovernmental organizations. The FAO provides various resources for assessing crop growth periods, water demand, and rough yield estimates, which could aid in generating estimates for crop production. National energy and water consumption data may be readily available, but again, may be difficult to downscale. Water quality is spatially dependent and finding long-term reliable data can prove difficult. All of these considerations should be taken into account when assessing FEW nexus modeling tools.

This work provides a starting point for better integrating water management (both quantity and quality) into a FEW nexus framework, and for integrating climate change responses based on climate change projections for the 21st century. While there has been interest in addressing climate change impacts in recent years, the focus in strategic planning has remained "silo-based" or highly sectoral, thereby not addressing the competition among food, energy, and water demands within the nexus (Rasul and Sharma, 2016; Daher and Mohtar, 2015). Without properly addressing the interconnection and interdependence within the FEW nexus, decision-making would not be robust, solutions would not be sustainable, and substantial environmental degradation may result. Analysis on monthly or seasonal basis would allow for finer-scale assessments capturing periods of water surpluses and deficits, and provide deeper insights into nexus responses at different times of the year. A dynamic link between FEW nexus tools and hydrologic and water quality models would help with streamlining the analysis.

2.7 Conclusion

With various tools for modeling the FEW nexus, it is critical to assess the feasibility of incorporating a model for an area of study. Developing the scope and framework of the food-energy-water nexus may seem daunting, but with the 7-Question Guideline to Modeling the Water-Energy-Food Nexus and available tools, it is possible to integrate a portion, if not all, of a chosen tool's framework into an assessment The goal of this study was to analyze FEW nexus modeling tools with a specific focus on their potential for addressing water resources management issues at the nexus. Through this work, the framework of the WEF Nexus Tool 2.0 and the SWAT model were implemented in a case study in the Matson Ditch Watershed in Indiana to demonstrate potential growth in modeling the FEW nexus for water resource management while capturing uncertainties due to climate change. Results showed that through the integration of the WEF Nexus Tool 2.0 and a comprehensive watershed model such as SWAT, a more holistic view of the FEW nexus can be developed to improve decision-making. Incorporating futuristic climate data in the analysis demonstrated the potential of FEW nexus tools in assessing future stressors and informing water resource management strategies for the development of robust solutions. Additionally, the analysis showed how spatial, temporal, and water quality components could be integrated in further assessments of sites using a FEW nexus framework approach.

2.8 Supplementary Materials

Table S.8 Literature-based analysis of FEW nexus tools: system components and considerations.

	Water Analysis			Energy		Food	Climate Change		Simplicity
Modeling Tool	Quantity	Quality	Spatial-temporal distribution	Renewable Energy	Non-Renewable Energy	Crop Production	Carbon Footprint	Predictive Component	Minimal Data Input
CLEW	√			√	√	√	√		
WEF Nexus Tool 2.0	√			√	√	√	√	√	√
WEAP/ LEAP	√	√	√	√	√				
MuSIASEM	√			√	√	√			
GLOBIOM	√	√	√	√	√	√	√	√	
PRIMA	√	√	√	√	√	√	√	√	
NexSym	√	√		√	√	√	√	√	

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3. CONSTRUCTION OF CRITICAL PERIODS FOR WATER RESOURCES MANAGEMENT AND THEIR APPLICATION IN THE FEW NEXUS

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3.1 Abstract

Amidst the growing population, urbanization, globalization, and economic growth, along with the impacts of climate change, decision-makers, stakeholders, and researchers need tools for better assessment and communication of the highly interconnected food–energy–water (FEW) nexus. This study aimed to identify critical periods for water resources management for robust decision-making for water resources management at the nexus. Using a 4610 ha agricultural watershed as a pilot site, historical data (2006–2012), scientific literature values, and SWAT model simulations were utilized to map out critical periods throughout the growing season of corn and soybeans. The results indicate that soil water deficits are primarily seen in June and July, with average deficits and surpluses ranging from −134.7 to +145.3 mm during the study period. Corresponding water quality impacts include average monthly surface nitrate-N, subsurface nitrate-N, and soluble phosphorus losses of up to 0.026, 0.26, and 0.0013 kg/ha, respectively, over the growing season. Estimated fuel requirements for the agricultural practices ranged from 24.7 to 170.3 L/ha, while estimated carbon emissions ranged from 0.3 to 2.7 kg CO_2/L. A composite look at all the FEW nexus elements showed that critical periods for water management in the study watershed occurred in the early and late season—primarily related to water quality—and mid-season, related to water quantity. This suggests the need to adapt agricultural and other management practices across the growing season in line with the respective water management needs. The FEW nexus assessment methodologies developed in this study provide a framework in which spatial, temporal, and literature data can be implemented for improved water resources management in other areas.

Keywords: food-energy-water nexus; water resources management; critical periods; decision-making; life cycle analysis; agricultural management

3.2 Introduction

With a changing climate, rapid population growth, and urbanization, robust and innovative solutions are needed to address the increasing and competing needs for food, energy, and water. The interdependence among food, energy, and water systems [1] and the competition between energy and food production for limited water resources [2], are the basis for the framework of the food–energy–water (FEW) nexus. Water resource allocation and water quality are especially critical within the FEW nexus framework, as clean water is required for both food and energy production [2–4], yet both food and energy production have negative impacts on water quality [5]. Adverse impacts on water quality, in turn, have implications on the amount of water available for anthropogenic and ecosystem allocations. Thus, both aspects of water resources integrity (quantity and quality) need to be considered in FEW nexus assessments so as to avoid misconceptions related to the availability of water resources. In previous work [6] Schull et al. (2020) showed how a FEW nexus decision-making model—the WEF Nexus Tool 2.0 [3]—and results from the Soil and Water Assessment Tool (SWAT) [7] could be combined to give water-centric insights into interactions among FEW nexus sectors in an agricultural watershed through to the end of the 21st century. In the study, average annual values were obtained and used to provide a broad picture of the interactions among FEW nexus components. The results, however, show the need for finer-scaled evaluations as assessments on an average annual level could potentially mask the periods of time during which tradeoffs within the FEW nexus might be most critical for water management. In particular, a detailed tracking of water availability and water quality on a monthly basis through the growing season would provide actionable insights on water-related aspects at the different crop-growth stages. Crop production requires not only water, but also energy. Farmers use a variety of tillage, planting, chemical application, and harvesting methods, and thus the amount of energy consumed is dependent on these practices. Evaluating energy usage and carbon emission across the growing season would provide a more accurate picture of how energy is consumed at the different crop growth stages, than would average annual values. For field operations, the most commonly used fuels are gasoline, diesel, and liquified petroleum gas [8]. With the use of fossil fuels as energy sources, it is necessary to calculate the carbon equivalent to gauge the environmental impact of agricultural production. Thus, even while addressing water resources management, it is important to quantify relationships and tradeoffs among the different sectors of the nexus [2] such that decision making is robust, and solutions are sustainable [9].

This study aims to identify critical periods for water resources management at the watershed scale and explore their potential for improving decision-making at the nexus; specifically, to: (1) develop critical periods for water quantity and quality management in an agricultural system by identifying periods of water surplus and deficits based on historical data; (2) integrate energy, environmental, and cost impacts of agricultural production in water resources management; and, (3) make recommendations on the use of critical periods in developing sustainable and robust solutions at a watershed scale. This study uses the 4610 ha (11,392 acres) Matson Ditch Watershed (Figure 10) in DeKalb County, northeastern Indiana, U.S., as a pilot site. The watershed was selected as it has sufficient data on land cover, crop yield, soil, management operations, and hydrological conditions to allow the different FEW nexus components in the watershed to be captured. Methodologies and approaches are applicable to other agricultural watersheds.

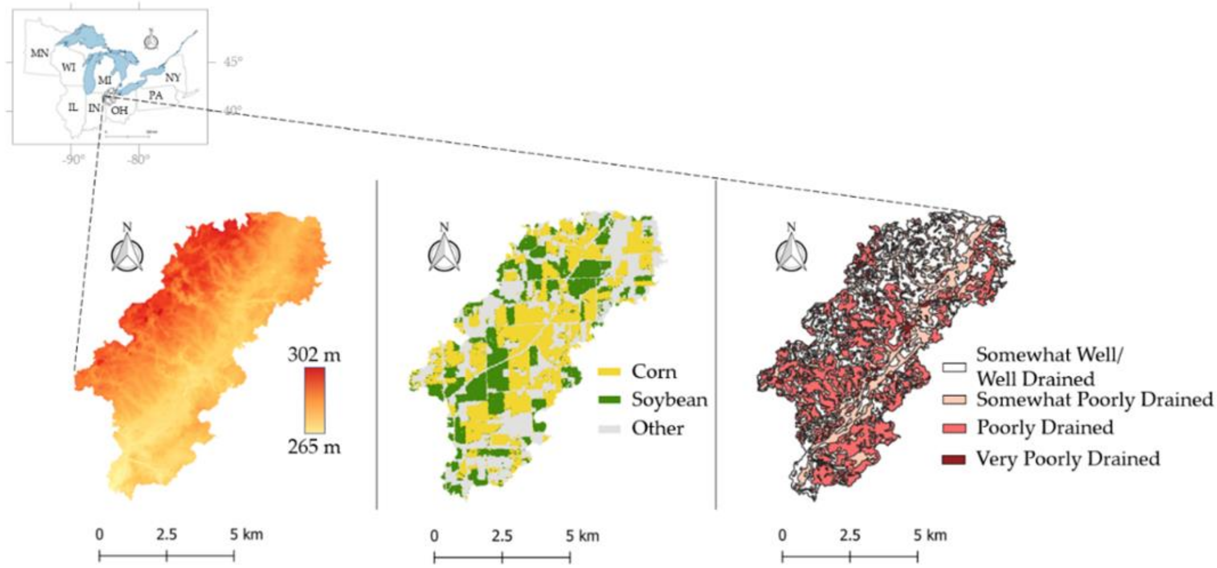

Figure 10 Topography, land cover (2011), and soil drainage classification of the Matson Ditch Watershed, Dekalb County, IN, USA.

3.2.1 FEW Nexus System for the Matson Ditch Watershed

The Matson Ditch Watershed FEW nexus system through the growing season is represented using Figure 11. The outer dashed line shows the system boundary and captures aspects of the FEW nexus that are being considered in the study. Due to the fluctuation in water, energy, and fertilizer demands, as well as prices and costs for each crop, the system schematic has been presented at the per hectare scale. The watershed is a rainfed predominantly sub-surface drained agricultural watershed [10]. Based on historical data from 2003–2012, annual precipitation averages around 1000 mm (39.4 in) [6,11–13]. Crop production in the watershed is reflective of the U.S. Midwest [14,15], with largely corn-soybean rotations covering 62.6% of the available agricultural land. Other land uses in the watershed include developed land (5%), pasture (13%), and deciduous forest (9%), with smaller land uses occupying <10% of the land use area. This study focused only on corn and soybeans.

With respect to water quantity, losses in crop growth and yield could occur due to stresses from deficits in the amount of water available in the soil [16]. As with the larger Western Lake Erie Basin (WLEB) in which the study watershed is located, water quality concerns stem from pollutants from agricultural lands and include nutrients and pesticides [17,18]. The corn and soybean growing season in the study region runs from May through October, with most field operations occurring in early (tillage, planting, fertilizer, and pesticide applications) and late season (harvesting). Agricultural tillage systems in DeKalb County are predominantly conventional tillage for corn and no-till for soybeans. According to the United States Energy Information Administration [19], in the state of Indiana the dominant energy sources are coal, natural gas, and gasoline. In terms of carbon emissions, Indiana is ranked as the eighth highest state based on 2017 data, and 11th highest in energy consumption per capita. The energy consumption and carbon emissions embedded in fertilizer and pesticide production are also included within the system boundary.

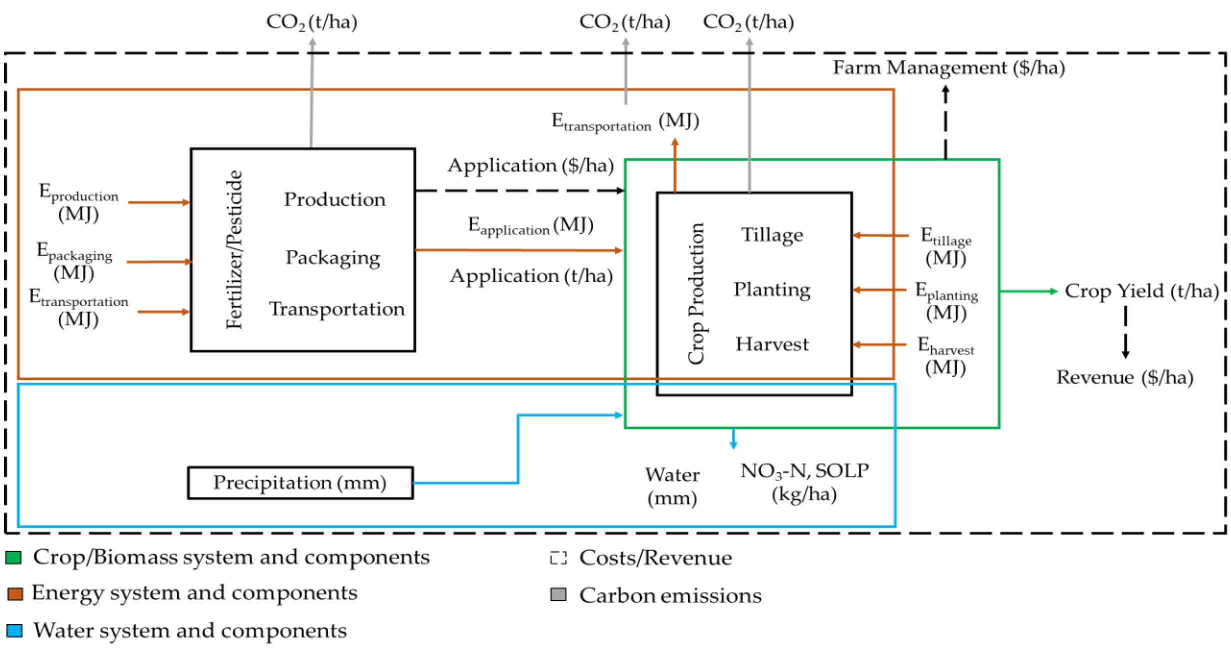

Figure 11 Schematic showing system and boundaries of the FEW nexus framework for the Matson Ditch Watershed downscaled on a hectare scale. As the Matson Ditch Watershed is precipitation-fed, the water source comes only from precipitation (mm), with the nutrients of interest in this study being surface and subsurface nitrate (NO3-N, kg/ha) and soluble phosphorus (SOLP, kg/ha). The energy use of each component is represented by Ecomponent (e.g., Etillage) in MJ from fuel or electricity, with carbon emissions (CO2, t/ha) being an output. Food production is represented by crop yield (t/ha) along with associated revenues (USD/ha). Costs (USD/ha) include fertilizer and pesticide application, and general costs of farm management.

Details on how the different components are evaluated in this study are presented in the materials and methods sections. As assumptions, processes, and equations vary across the different sectors, each of the components is analyzed individually. Later, we discuss how the components interact with each other and combine results to provide an overall interpretation on critical periods for water management in the watershed.

3.2.2 Materials and Methods

Identifying Critical Periods for Water Quantity and Quality

In this study, critical periods for water quantity were determined through water balance evaluations and identification of periods of water surpluses and deficits based on results from SWAT. Critical periods for water quality were identified from periods in which the highest losses of phosphorus and nitrogen occurred, also based on SWAT model simulations. The analysis was conducted on a growing season basis (May through October), so as to better capture interactions among FEW nexus components. The study built on prior SWAT model assessments conducted in the watershed [12], in which the model had been set up to allow detailed evaluations of hydrology and nutrient yields in the watershed. In this prior work, the SWAT model was set up for the period between 2003 and 2012 with the first three years comprising a warm-up period. Crop management and other field operations were simulated based on current practice in the watershed. The model was calibrated for 2006–2009, using standard parameter optimization procedures, and validated for 2010–2012. Additional evaluations based on soft data were conducted for subsurface flow and crop yields, and the model was checked for accuracy in spatial representation. As the model had already been set up and had undergone a thorough calibration and validation in the previous work, this aspect of modeling was not repeated in this study. However, the model was re-run to provide the level of data needed for the planned analysis. To maintain consistency with the previous work, historical data from the period 2003–2012 were used to provide baseline runs for the watershed, with 2003–2005 being maintained as a warmup period.

Water Quantity

Figure 12 shows the hydrological system of the Matson Ditch Watershed. The input into the system is the precipitation, with the losses from the system being a summation of surface runoff, lateral flow, tile (subsurface drainage) flow, groundwater flow, and deep aquifer recharge. Effective precipitation is the amount of precipitation remaining after accounting for all losses; it is the precipitation that is stored in the root zone and is available for use by plants. The percentage of precipitation that is effective depends on factors such as climate, soil texture and structure, and the depth of the root zone [20]. The effective precipitation in any one month was calculated as (Equation (9)):

$$P_{eff,m} = P_m - \left(SURQ_m + GWQ_m + TILEQ_m + LATQ_m + DA_{rchg,m}\right). \quad (9)$$

where, for any month m, $P_{eff,m}$ is the effective precipitation (mm), P_m is the precipitation (mm), $SURQ_m$ is the amount of surface runoff (mm), GWQ_m is the amount of groundwater flow (mm), $TILEQ_m$ is the amount of tile (subsurface drainage) flow (mm), $LATQ_m$ is the lateral flow (mm), and $DA_{rchg,m}$ is the deep aquifer recharge (mm).

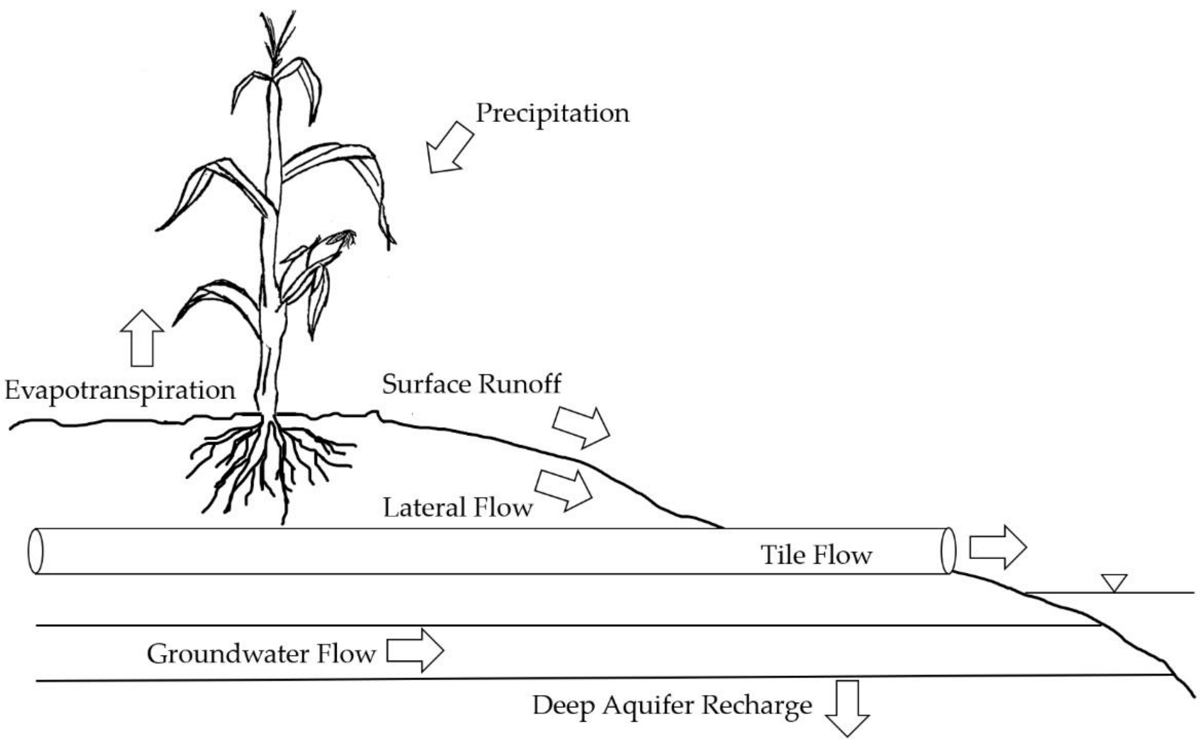

Figure 12 Hydrological system for the Matson Ditch Watershed.

The water surplus or deficit was determined as the difference between the effective precipitation and the amount of water required by the crops as determined based on the evapotranspiration (Equation (10)):

$$\mathrm{D_{S,m}} = \mathrm{P_{eff,m}} - \mathrm{ET_m}. \tag{10}$$

where, for any month m, $D_{s,m}$ is the surplus or deficit (mm), $P_{eff,m}$ is the effective precipitation as calculated in Equation 8 (mm), and ET_m is the actual evapotranspiration (mm). If $D_{S,m}$ is positive, this means the effective precipitation is higher than the evapotranspiration and, thus, there is a surplus and water requirements for the crop are met effectively through precipitation; if $D_{S,m}$ is negative, the effective precipitation is less than the evapotranspiration thus there is a deficit and the crop would need to extract from available soil water reserve, if any, or depend on external inputs.

Water Quality

The water quality parameters that were evaluated in this study were soluble phosphorus (SOLP) and surface and subsurface nitrate (NO_3, TNO_3). As with water balance components, water quality parameter values were based on the model developed by Mehan et al. (2019a) [12]. Values were extracted and analyzed for all Hydrologic Response Units (HRUs) that had corn or soybeans land cover. In primarily sub-surface drained agricultural watersheds such as the Matson Ditch Watershed, water quality impacts of agricultural production are typically associated with the application of agricultural chemicals (fertilizers, pesticides) on agricultural fields [21,22], which typically coincides with the beginning of the growing season and the start of the spring rains. Thus, for this analysis, water quality parameters were aggregated and evaluated on a monthly basis for May through October of each year, and over the entire study period (2006–2012). The water quality parameters were then visualized across the growing seasons to determine the var-iation over the entire period.

Crop Growth

In SWAT, plant growth is modeled through simulating leaf area development, light interception, and conversion of intercepted light into biomass through the assumption of radiation-use efficiency based on the species of plant. Yield is calculated using an adjusted harvest index for a given day and the aboveground biomass [23]. For corn and soybeans, Equation (11) was used to calculate the yield,

$$\mathrm{yld} = \mathrm{bio}_{\mathrm{ag}} \times \mathrm{HI}. \tag{11}$$

where yld is the crop yield (kg ha^{-1}), bioag is the aboveground live biomass on the day of the harvest (kg ha^{-1}), and HI is the adjusted harvest index on the harvest date (<1). Values obtained for yield during the period 2006–2012 were checked against historical data for the Matson Ditch Watershed. The historical data were obtained from the USDA National Agricultural Statistics Service (NASS).

Energy Usage and Carbon Emissions

As values for energy use and carbon emissions specific to the watershed were not available, regional values were used in this study. Generally, Cooperative Extension fact sheets, such as Downs and Hansen (1998) [8] and Hanna (2001) [24] provide farmers with guidance on inputs into their agricultural production, such as recommended fertilizer, pesticides, and fuel. In this study, fuel requirements for diesel were obtained from Hanna (2001) [24]. This author provided the fuel requirements for diesel; hence it was necessary to calculate equivalent values for the two other most common fuels used in agriculture, gasoline and liquified petroleum (LP) gas based on their respective energy content in comparison to diesel (Equation (12), [8]):

$$\mathrm{fuel}_{\mathrm{est}}\left(\frac{\mathrm{L}}{\mathrm{ha}}\right) = 9.35394 \times \mathrm{diesel}_{\mathrm{req}}\left(\frac{\mathrm{gal}}{\mathrm{ac}}\right) \times \mathrm{E}_{\mathrm{ratio}} \cdot \tag{12}$$

where the fuel estimate ($\mathrm{fuel}_{\mathrm{est}}$) for the alternative fuel is calculated by multiplying the required amount of diesel ($\mathrm{diesel}_{\mathrm{req}}$) by the energy content ratio ($\mathrm{E}_{\mathrm{ratio}}$) between diesel and the alternative fuel. The value 9.35394 is a factor to convert values from imperial to metric units.

The type of fuel selected as an energy source will affect the amount of carbon being emitted during a specific agricultural practice. Estimates for carbon equivalents or carbon footprints associated with usage of fuel, fertilizers, and pesticides in agricultural systems were obtained based on greenhouse gas equivalencies calculations by government-level environmental protection agencies, such as the United States Environmental Protection Agency (USEPA) [25–27] and academic institutions [3,28–33]. Ranges of carbon emission equivalents for each of the farming practices, as well as the carbon equivalents per kilogram of energy source were obtained from Lal

(2004) [28]. These carbon equivalent values were provided by kg of fuel. Using the values of average weight from Downs and Hansen (1998) [8], Equation 13 was used to convert values from Lal (2004) [28]:

$$\mathrm{CO_2}_{\mathrm{est}}\left(\frac{\mathrm{kg}}{\mathrm{L}}\right) = \frac{\mathrm{kg\ CO_2}}{\mathrm{kg_{fuel}}} \cdot \frac{\mathrm{lb}}{\mathrm{gal_{fuel}}} \times \frac{0.454\ \mathrm{kg}}{1\ \mathrm{lb}} \times \frac{1\ \mathrm{gal}}{3.78541\ \mathrm{L}}. \quad (13)$$

Cost Analysis in Decision-Making in the FEW Nexus

In order to understand the impacts on cost of agricultural production, it was necessary to assess the economic costs of agricultural production. Both monthly and annual averages for price received for corn and soybeans in the state of Indiana were obtained from NASS. "Price received" for the crops is based on the data collected and the information received from the Agricultural Marketing Service. Monthly average state and national prices that producers received including market year averages are available from NASS. Monthly crop price received by farmers are available for the period 1970–2018. These values were implemented to provide indications on how the price received by farmers has changed over both the long-term and short-term. For this study, the Purdue Crop Cost and Return Guide archive was used to obtain estimates for earnings and losses for the period of 2006–2012. The Center for Commercial Agriculture has provided an archive since 2002 to project costs for the upcoming cropping year [34]. The costs that were taken into consideration included fertilizer, seed, pesticides, machinery (fuel, repairs, and ownership), hauling, interest, insurance, labor, as well as land. A range of potential values of earnings and losses across the state of Indiana were obtained by calculating earnings and losses per hectare for each crop, based on the assumptions of a 404.7 ha (1000-acre) farm with corn and soybeans crop rotations. Overall market revenue per crop was calculated using Equation (14):

$$\text{Market Revenue}_{\text{crop}} = \text{Yield}_{\text{crop}} \times \text{Harvest Price}_{\text{crop}}. \quad (14)$$

Government payments for the crops were based on the direct payment per crop, as shown in Equation (15):

$$\text{Gov Pay}_{\text{crop}} = \text{Direct Payment Yield}_{\text{crop}} \times \text{Direct Payment Price}_{\text{crop}}. \quad (15)$$

The direct payment for corn was USD 11.02/metric ton (USD 0.28/bu) for corn and USD 16.17/metric ton (USD 0.44/bu) for soybean, with the direct payment based on direct payment yields for low, average, and high productivity soil.

Overhead costs—which include machinery ownership, family and hired labor, as well as land rent—for crop production were subtracted from the summation of the market revenue and government payment to obtain the overall earnings or losses, as indicated by Equation (16):

$$\mathrm{EL_{crop}} = \left(\mathrm{Market\ Revenue_{crop}} + \mathrm{Gov\ \ Pay_{crop}}\right) - \mathrm{Overhead_{crop}}. \tag{16}$$

3.3 Results

3.3.1 Water Quantity

Figure 13 shows the range of values for monthly deficits and surpluses (a, b), along with average monthly precipitation, effective precipitation, and evapotranspiration (c, d) for the same crops. Data shown are averages for the period of 2006–2012. In Figure 13a,b, the shaded region indicates the range of distribution of the D_S across all years. While both deficits and surpluses occurred throughout the growing season, for both corn and soybeans, deficits were more pronounced in mid-season, particularly in June and July (Figure 13). Deficits were also seen in August, although this month also tended to have somewhat higher rainfall than the other two months, and hence the deficits were generally less severe. These patterns were thought to be due to the green leaf area, as it plays an important role for evapotranspiration [35,36]. Stone (2003) [37] provides insight on which growth stages are most sensitive to water stress. For corn, water stress should be lessened in particular during the silking period, while for soybeans, it should be lessened during early to mid-bean fill [37]. Silking occurs about 69–76 days (mid-July) after seeding for a typical 120-day hybrid in the Corn Belt of the United States [38]. Early pod development for soybeans starts about 74–88 days (early to mid-August) from planting, with an additional 15–20 days to the middle of the seed filling [39]. Though these periods correlate with the highest number of days of stress per month according to the SWAT output, these sensitive growth stages correlate with a water deficit for corn at −23.50 mm (−0.93 in) and surplus for soybeans at 14.04 mm (0.55 in). As the Matson Ditch Watershed is a precipitation-fed watershed with rapid aquifer recharge, a deficit does not necessarily mean that the crop is experiencing water stress, but that the crop needs from evapotranspiration exceed what is available through effective precipitation and, thus, that the crop would be drawing from storage.

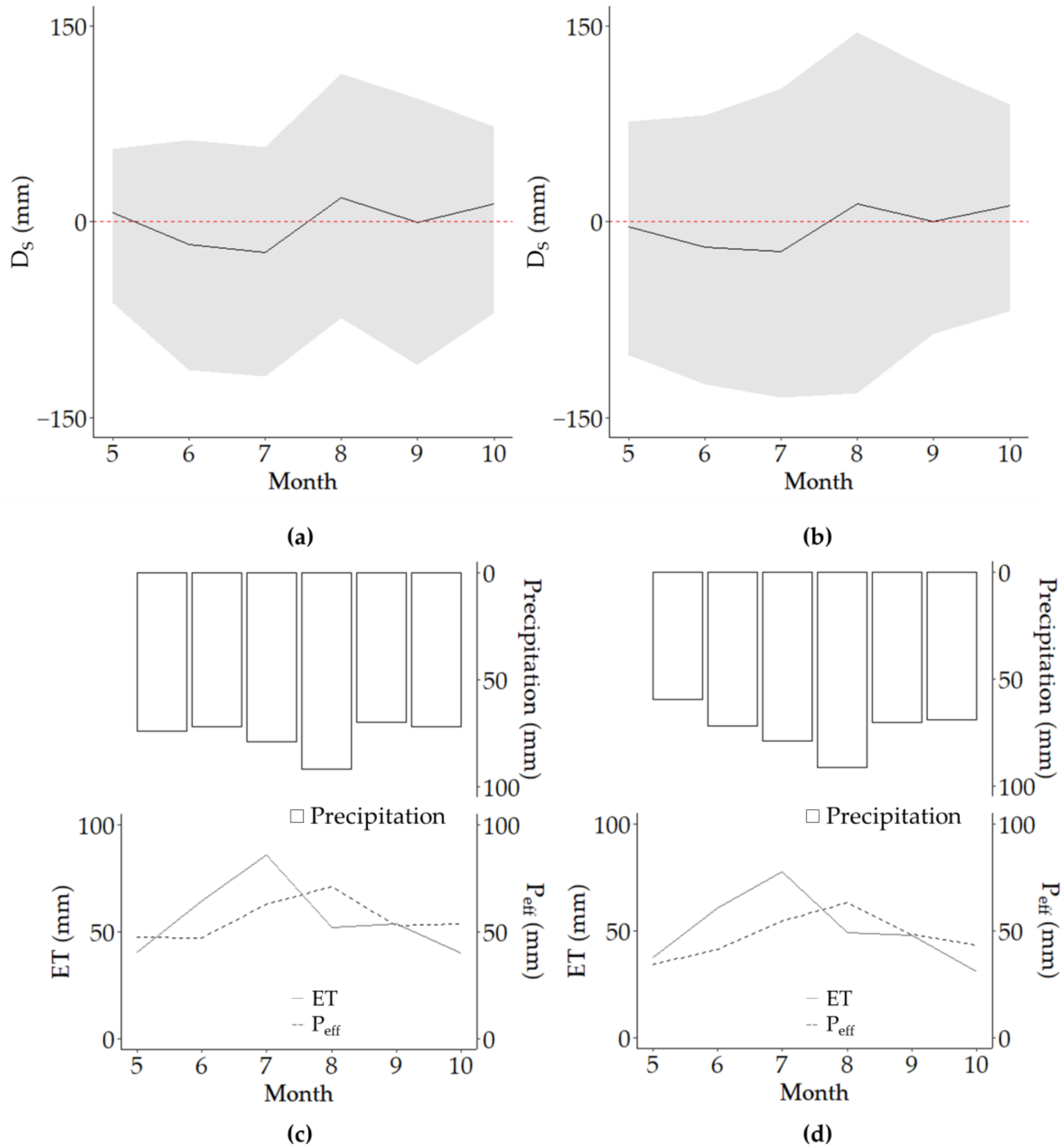

Figure 13 (a) Average monthly deficits (−ve) and surpluses (+ve) for corn; (b) Average monthly deficits (−ve) and surpluses (+ve) for soybeans; (c) Average monthly precipitation, effective precipitation (black dotted line), and evapotranspiration (grey solid line) for corn; (d) Average monthly precipitation, effective precipitation (black dotted line), and evapotranspiration (grey solid line) for soybeans. Shaded region indicates the range of distribution of the monthly D_S across all years.

As P_{eff} is calculated based on the differences between the precipitation and the losses from the system, the amount of effective precipitation may vary with the hydrological conditions in the system. In the Matson Ditch Watershed, the variation in P_{eff} is mainly driven by the surface and subsurface drainage for both corn and soybeans. Losses for corn were highest in May, with surface runoff being highest on average during this month (14.39 mm; 0.57 in). Average subsurface flow for corn ranged from 8.61– to 10.75 mm (0.34–0.42 in), with the highest flow occurring in August. For soybeans, May had surface runoff averaging 12.27 mm (0.48 in) and subsurface flow averaging 8.37mm (0.33 in). The largest combined losses occurred in June, with surface flow averaging 10.39 mm (0.41 in) and subsurface flow averaging 11.77 mm (0.46 in). Subsurface flow for soybeans peaked in August (13.21 mm; 0.52 in), with the end of the growing season having levels at 12.83 mm (0.51 in).

Figure 14 shows the average evapotranspiration and effective precipitation, as well as deficits or surpluses through each growing season in 2006–2012 for both the corn and soybean crops. For corn, the smallest range of D_S was seen in 2012, with the range of the deficit and surplus being −91.27 – +54.94 mm (−3.59 – +2.16 in). For soybeans, the smallest range of D_S occurred in 2006, with deficit values between −68.35and 101.68 mm (−2.69 in – 4.00 in). The largest range of the deficit and surplus for corn was in 2007, with a range of −109.65 – +113.49 mm (−4.32 – +4.47 in). For soybeans, this was also in 2007, with a range of −124.56 – +145.34 mm (−4.90 – +5.72 in).

Variations in temperature, frequency, antecedent soil moisture conditions, and intensity in rainfall can all affect the range for deficits and surpluses for crops. In 2006, the maximum temperature was 34.1 °C (93.4 °F) in July during the growing season, with a minimum of −3.33 °C (26 °F) in October. The maximum temperature for 2012 for the growing season was 38.5°C (101.3 °F) in July, with a minimum in the growing season at −2.4 °C (27.68 °F) in October. Mehan (2018) indicated that the critical daily average temperatures for crop growth range from 20 to 25 °C [11]. From 2006 to 2012, the number of days within this optimal temperature during the growing season ranged between 46 (2009) and 85 (2010). Higher daily temperatures could lead to heat stress and higher evapotranspiration rates [40]. Such climate shifts have already been documented [41–47] and could have effects on soil water reserves and other characteristics that affect water availability for cropland. It should be noted that the range of values for soybeans is much more pronounced than that of corn. This could be because soybeans are not as severely affected by drought as corn [48], and thus may be more adaptable to changes in climate. This inference aligns with findings from Mehan et al. (2019a) [12] indicating that future yields for soybeans in the Matson Ditch Watershed were projected to be higher than baseline values. Hatfield et al. (2018) [43] showed that corn yields would significantly decrease in the Midwest due to increases in temperature, while soybeans would be more affected by water availability.

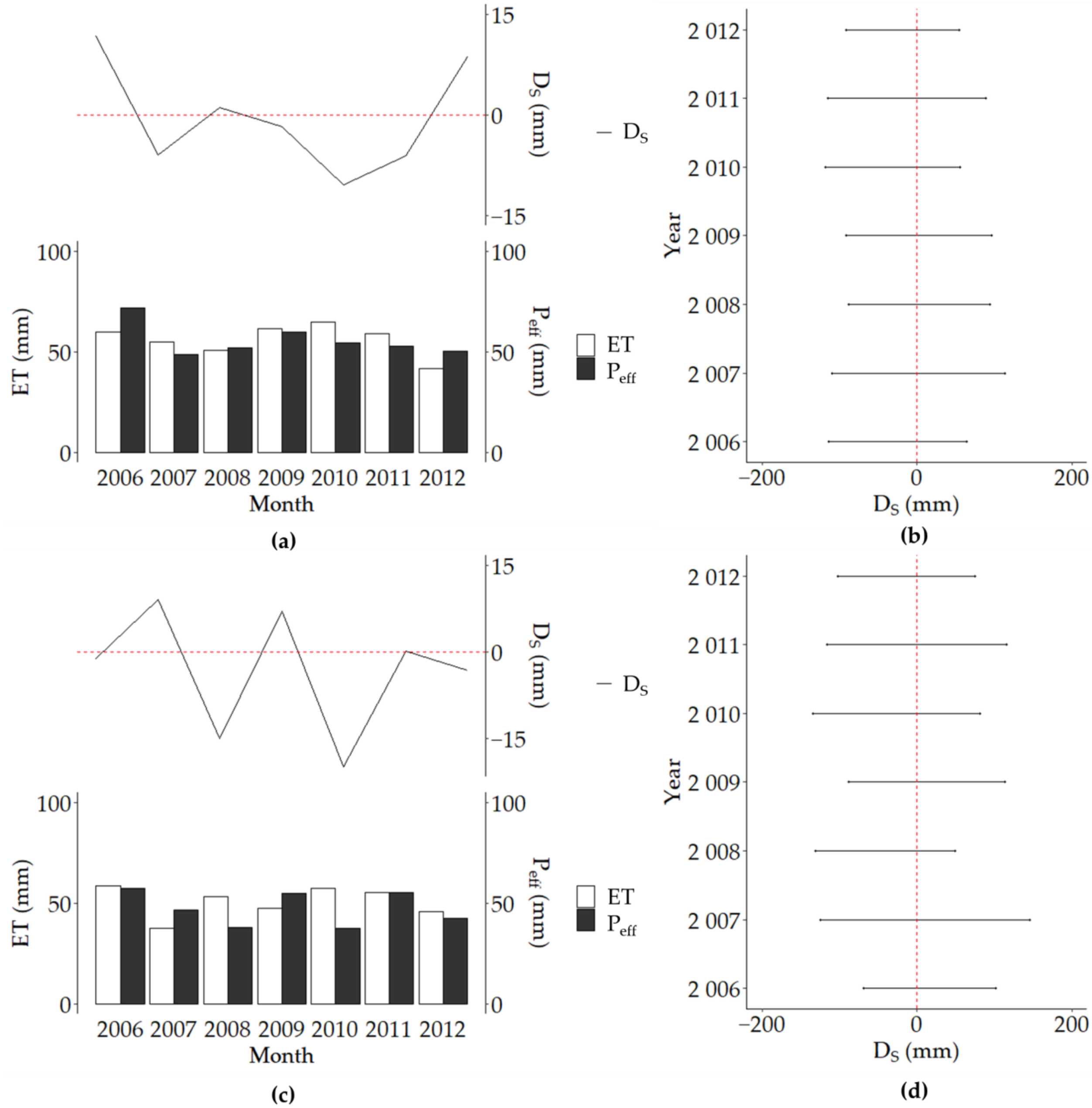

Figure 14 (a) Average effective precipitation (P_{eff}), evapotranspiration (ET), and deficit/surplus (D_S) for corn; (b) Annual range in deficit/surplus for corn; (c) Average effective precipitation (P_{eff}), evapotranspiration (ET), and deficit/surplus (D_S) for soybeans; (d) Annual range in deficit/surplus for soybeans.

3.3.2 Water Quality

Figure 15 shows the monthly averages for nitrate-N losses in surface runoff (NSURQ), tile (subsurface drainage) nitrate-N losses (TNO_3), and soluble phosphorus losses (SOLP) losses from each crop type. The shaded region indicates the range of monthly average distributions across all the growing periods for 2006–2012. For surface nitrate-N losses, the average values in May were 1.48×10^{-1} and 1.22×10^{-3} kg/ha for corn and soybeans, respectively. For corn, there was a decline for June (4.47×10^{-3} kg/ha) and July (1.49×10^{-6} kg/ha), but a slight increase in August (9.39×10^{-5} kg/ha) and September (8.47×10^{-5} kg/ha) with the October average of surface nitrate at 1.66×10^{-4} kg/ha. For soybeans, the values of surface nitrate decreased after May, with the lowest value in June at 2.49×10^{-5} kg/ha and increasing in July (4.97×10^{-5} kg/ha) and August (7.65×10^{-5} kg/ha). There was a slight dip in the average in September (5.77×10^{-5} kg/ha) and then an increase in the harvesting month of October (2.58×10^{-2} kg/ha). The average value of subsurface nitrate-N losses during May was 1.89×10^{-1} kg/ha for corn and 1.09 x 10^{-1} kg/ha for soybeans. For corn, the average declined in June (2.72×10^{-2} kg/ha), with the lowest value being simulated in July (2.68×10^{-3} kg/ha). Increases were seen in August (2.55×10^{-2} kg/ha) and September (8.40×10^{-2} kg/ha), with the value at the end of the growing season (October) being 1.27×10^{-1} kg/ha. For soybeans, there was an increase in the monthly average of June to 2.58×10^{-1} kg/ha. In July, the monthly average declined to 1.25×10^{-1} kg/ha and decreased in August (4.14×10^{-2} kg/ha) and September (3.78×10^{-2} kg/ha). A slight increase was observed for October (7.25×10^{-2} kg/ha). For soluble phosphorus losses, there was a decline in monthly averages through the growing periods of soybeans, with a slight increase in monthly averages for corn. For corn, the average soluble phosphorus loss at the start of the growing season was 5.67×10^{-4} kg/ha and the season ended with an average value of 8.40×10^{-4} kg/ha. For soybeans, the monthly values of soluble phosphorus losses began at 7.73×10^{-4} kg/ha and ended at 5.95×10^{-4} kg/ha. The increases during the late summer months of July (corn: 1.56×10^{-4} kg/ha; soybean: 8.94×10^{-4} kg/ha) and August (corn peak at 1.29×10^{-3} kg/ha; soybean peak at 9.40×10^{-4} kg/ha) were due to subsurface flow. For both soluble phosphorus and nitrate-N, higher loadings were simulated during the months in which agronomic practices occurred, making these critical periods for water quality. The results, however, suggest the need to monitor contaminant transport during the growing season particularly as related to subsurface losses. Capturing these critical periods allows decision-makers to understand the relationships in water quantity and quality issues on a watershed-scale basis.

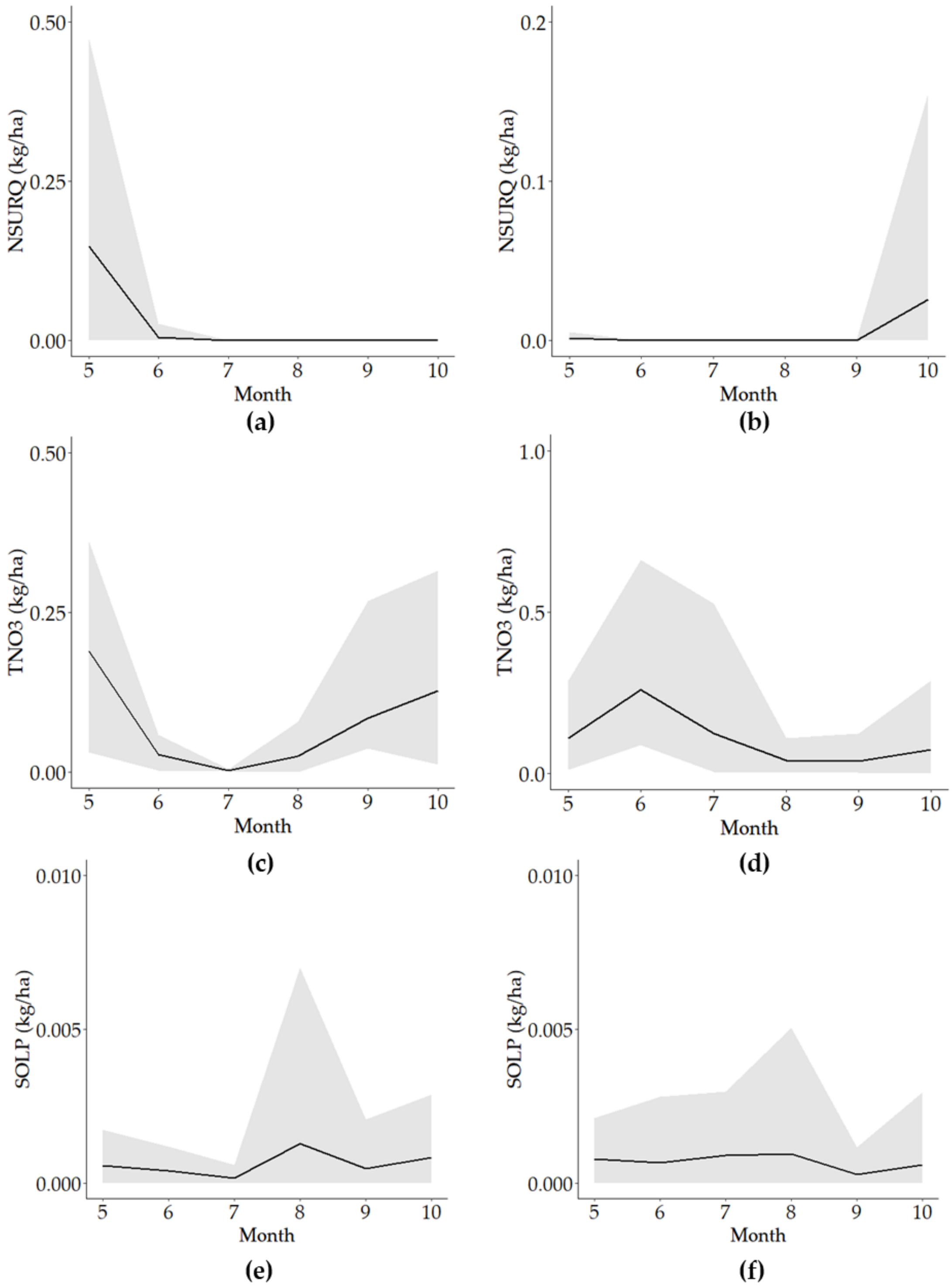

Figure 15 Monthly average nutrient losses from crops in the Matson Ditch Watershed for 2006–2012: (a) surface NO_3-N for corn; (b) surface NO_3-N for soybeans; (c) subsurface drainage NO_3-N for corn; (d) subsurface drainage NO_3-N for soybeans; (e) soluble P for corn; (f) soluble P for soybeans. Shaded regions indicate the range of distribution of the monthly nutrient load across all years.

3.3.3 Crop Growth

Yield values from the SWAT output, as well as the observed values from NASS, are shown in Table 9. The observed NASS crop yield averages for 2006–2012 were 8.1 ± 1.3 t/ha for corn and 2.8 ± 0.3 t/ha for corn and soybean, respectively, compared to 6.5 ± 1.3 and 2.6 ± 1.4 t/ha for the simulated value. Overall, the comparison between the observed and simulated yields indicated that the SWAT model adequately captured crop growth in the Matson Ditch Watershed. It also provided confirmation that though deficits were experienced within the watershed, the crops did not experience stress and had enough water to sustain their growth. This is reasonable, as the Matson Ditch Watershed is a precipitation-fed system with adequate yields being obtained without the need for irrigation. The output of crop yields is important in relation to critical periods as it provides context on why there are stressors within the nexus. By temporally mapping the harvest of these crops in October, it provides a tradeoff that occurs in the nexus; the yield of the crops comes at the cost of water quality, in which several water quality parameters are seen to increase in the month of October.

Table 9 USDA NASS DeKalb County crop yields for 2006–2012.

Year	Yield (t/ha)			
	Corn		Soybeans	
	Observed	Simulated	Observed	Simulated
2006	9.2	6.5	3.0	1.5
2007	9.2	4.5	3.0	3.8
2008	7.6	6.5	2.1	0.5
2009	9.4	8.1	3.0	1.5
2010	7.7	8.2	2.6	4.2
2011	7.8	5.8	2.7	3.7
2012	5.7	5.6	3.0	2.7

3.3.4 Energy Consumption and Carbon Emissions

The agronomic practices and management operations for corn and soybeans are shown in Table 10. This outlines the timeline for which nutrient and pesticide application occurs, as well as the type of tillage that is used with each crop type within the watershed. The timing of these practices captures critical periods for both energy usages and carbon emissions as these are associated with tillage, planting, fertilizer, and pesticide applications, and harvesting. No energy is required for water application, as the watershed is precipitation-fed. Furthermore, this timing is associated with the water balance through the growing stages of the crop—discussed earlier in the text—and affects the amount and availability of nutrients for transport within the system. Table 11 shows the gallons of fuel required per crop hectare based on the agronomic activities for the Matson Ditch Watershed and the calculated values for carbon emission per liter based on the fuel type found in various sources. The carbon footprint per hectare was calculated by summing the most appropriate fuel requirement based on the field operation as documented in Downs and Hansen (1998) [8], Hanna (2001) [24], and Lal (2004) [28], including fertilization application, tillage, planting, harvesting, and hauling. It was assumed that the crop would be hauled up to half a mile (0.805 km) off the field. The range in carbon emission coefficients shows there is uncertainty in calculating the carbon equivalent for various energy sources, and thus for the Matson Ditch Watershed, decision-makers can estimate the total amount of fuel and carbon emissions based on site-specific agronomic practices.

Table 10 Agronomic practices or management operations for different land use/ land cover for the Matson Ditch Watershed [11,49].

Crop	Date	Management Operation	Rate
Corn	22–April	Nitrogen Application (as Anhydrous Ammonia)	176.0 kg/ha
	22–April	(P_2O_5) Application (DAP/MAP)	54.0 kg/ha
	22–April	Pesticide Application	2.2 kg/ha
	6–May	Tillage–Offset Disk (60% mixing)	
	6–May	Planting–Row Planter, double disk openers	
	10–October	Harvest	
Soybeans	10–May	(P_2O_5) Application (DAP/MAP)	40.0 kg/ha
	24–May	No–tillage planting–Drills	
	7–October	Harvest	
	20–October	Tillage, Chisel (30% mixing)	

Table 11 Estimated range of fuel required (L/ha) for agronomic practices and management operations based on crop and fuel type.

Crop	Fuel Type	Fuel Required (L/ha) Downs and Hansen (1998); Hanna (2001) [8,23]	Fuel Required (L/ha) Lal (2004) [28] †
Corn	Diesel	(36.7, 58.9)	(36.9, 69.3)
	Gasoline	(40.8 *, 42.1)	(46.1, 85.5)
	LP Gas	(54.9 *, 70.8)	(90.8, 170.3)
Soybeans	Diesel	(26.2, 49.1)	(24.7, 42.8)
	Gasoline	(29.1 *, 35.0)	(30.9, 53.4)
	LP Gas	(39.2 *, 59.0)	(61.6, 102.0)

	Carbon Emissions (kg CO_2/L)					
Fuel Type	**Daher (2012) [3]**	**Lal (2004) [28]**	**USEPA (2008) [25]**	**USEPA (2014) [26]**	**USEIA (2019) [50]**	**USEPA (2020) [27]**
Diesel	2.6	0.8 **		2.7	2.7	2.7
Gasoline	2.4	0.6 **		2.3	2.3	2.3
LP Gas	2.3	0.3 **	1.7	1.5		

* Calculated from diesel requirements and Equation (3). ** Calculated using Equation (4). † Converted from kg CE values based on fuel weight.

Table 12 outlines the estimated energy required and the carbon equivalent per kg of active ingredient (ai) estimated for the Matson Ditch Watershed based on literature for carbon footprint and equivalent of these chemicals. As inputs for energy are outlined based on the agronomic practices occurring throughout the year, these values are applicable to the growing season in general. For irrigated systems, it would be important to also calculate monthly energy use requirements of pumping and transporting the water to fields through the growing season. Furthermore, carbon emissions from different energy sources could be assessed to provide watershed managers and decision-makers an understanding on the tradeoffs in renewable and nonrenewable energy sources.

Table 12 Estimates of total energy (MJ/kg ai) and carbon equivalent (kg CO_2/kg ai) for fertilizer and pesticide production, packaging, and transport for the Matson Ditch Watershed.

Estimates	**Chemical**			**References**
	Anhydrous Ammonia	P_2O_5 (DAP/MAP)	Atrazine	
Total MJ/kg ai	63	18	208	[29,51,52]
	67	17.4	189	[29,51,52]
	-	-	190	[29,53]
Total kg CO_2/kg ai	(0.9–1.8)	(0.1–0.3)	3.8	[28]
	4.8	0.73	23.1	[30]
	2.52	0.73	-	[31]
	1.3	0.2	6.3	[32]
	1.74	0.33	-	[33]

ai = active ingredient.

3.3.5 Cost Assessment of the FEW Nexus

Based on the analysis of all available NASS data (1970–2018) there was an increase in price received for corn and soybeans over time ($\tau = 0.3749$, $p < 0.0001$ for corn, $\tau = 0.5732$, $p < 0.0001$ for soybeans). However, this does not necessarily consider potential increases in costs for agronomic inputs, such as machinery maintenance, chemical application, labor, rent, etc. Hence these inputs were taken into account through short-term assessment. The earnings and losses shown in Table 13 were based on a 1000-acre (404.7 ha) farm in Indiana with corn and soybeans rotations, as previously discussed. These values reflect the profitability, which is the difference between the price received multiplied by the yield and the government subsidies (thus, revenue) and the cost of the crop. While the revenue from a crop is not realized until after the growing season, the cost inputs of agronomic practices tend to occur at the beginning of the growing season, thus, these values reflect the costs over the growing period.

The earnings and losses can be explained by historical context. In 2003, a summer drought in the Midwest caused yields for corn and soybeans to be reduced [54], which meant crops were severely stressed. Though still operating at losses in 2004, losses were not as great as those in 2003. According to the Committee on Water Implication of Biofuels Production in the United States in the National Academies of Sciences, Engineering, and Medicine [55], after Hurricane Katrina in 2005, there was a surge in the price of oil, causing an interest in ethanol production due to the low corn prices. The federal government encouraged corn and soybean production with an ethanol subsidy through the Energy Act of 2005 [55]. In 2006, the governor of Indiana announced plans for the state to shift to cellulosic and biomass fuel production. With Indiana being one of the top soy and corn producers in the country, this made the state a suitable candidate for biodiesel production [56]. This, in combination with policies implemented by several countries that constrained corn and soybean supply in the world market, likely added upward pressure to the price of corn and soybean prices [57], which is reflected in the results found. After 2008, there was a decline in demand for agricultural commodities due to the recession, so the profitability of corn and soybeans was reduced [54,55]. These values correspond with insights from Langemeier (2017), that indicated that from 2007–2013, corn production was relatively more profitable than soybeans on an average farm in Indiana [58].

Table 13 Ranges of estimated earnings (+ve) or losses (−ve) per ha for 2003–2012 for a medium-sized farm in Indiana.

	Earnings/Losses per ha	
Year	**Corn**	**Soybeans**
2003	(USD −126.67, USD −65.04)	(USD −212.00, USD −152.69)
2004	(USD −116.83, USD −97.38)	(USD −123.70, USD 12.17)
2005	(USD −196.55, USD −166.66)	(USD −236.77, USD −171.57)
2006	(USD −199.37, USD −184.03)	(USD −207.62, USD −125.37)
2007	(USD 216.90, USD 559.50)	(USD 17.02, USD 240.80)
2008	(USD 151.87, USD 687.56)	(USD 211.39, USD 609.74)
2009	(USD −297.86, USD 45.09)	(USD −290.97, USD −115.02)
2010	(USD −52.24, USD 317.40)	(USD −142.46, USD 87.85)
2011	(USD 259.76, USD 838.84)	(USD 149.81, USD 571.39)
2012	(USD 72.80, USD 614.92)	(USD −20.64, USD 310.49)

3.3.6 Interactions Among FEW Nexus Components in the Matson Ditch Watershed

Figure 16 shows how critical periods for the different FEW nexus components can be mapped out across the growing period for decision-making. Inputs and outputs associated with the food and energy components typically occur at the beginning and the end of the growing season as they are associated with farming operations including tillage, planting, and fertilizer applications—which occur at the beginning of the growing season—and harvesting and yields—which occur at the end of the growing season. However, operations occurring mid-season could also have impacts. For example, a post-emergence herbicide application occurring around June is a typical agronomic practice for soybeans in Indiana [59]. While not included in this study, such operations would have associated energy consumption and carbon emissions that would occur during the growing season. Depending on the operation, there could be water quality implications associated with the application or with any soil disturbances that occur. In contrast, both water quantity and quality components varied across the growing season and for the different crops. Nonetheless, there were distinct periods in which water deficits occurred, generally during the period when the crop is actively growing. In the study watershed, the crops were generally able to draw from soil storage when deficits occurred. In areas where substantial deficits occur, irrigation would be necessary to avoid yield losses. Introducing irrigation to a system has implications on energy use and carbon emissions [60]. Furthermore, irrigation has implications for pollutant transport and, thus, could introduce critical periods for water quality in mid-season. Even in areas such as the study watershed, supplemental irrigation has been shown to increase crop yields. Thus, opportunities for potentially water quality-friendly practices—such as drainage water recycling [61]—could be explored. With respect to water quality, key management interventions would be needed at the beginning and towards the end of the growing season. Some of these could entail changes in farming operations, for example, the timing or method of fertilizer applications to minimize pollutant availability for transport thorough surface and/or subsurface pathways. This could have implications on energy use and carbon emissions. Regardless, farmers would be concerned about the implications of changing management practices on yields and overall costs of crop production. Thus, concerted efforts would be needed to optimize management practices so as to minimize water quality impacts while ensuring farming remains profitable [62].

3.4 Discussion

Given the intricate links among food, energy, and water, the competition for water between the food and energy sectors, and the negative effects these two sectors often have on water, assessments considering all three sectors in concert are key to developing long-term solutions for water management. While most associated analyses are conducted on an annual or average annual basis, this study considered monthly timeframes across the crop growing season. This level of analysis provided insights into critical periods for water resources management considering both quantity and quality, and allowed other aspects of the nexus to be integrated at the same level.

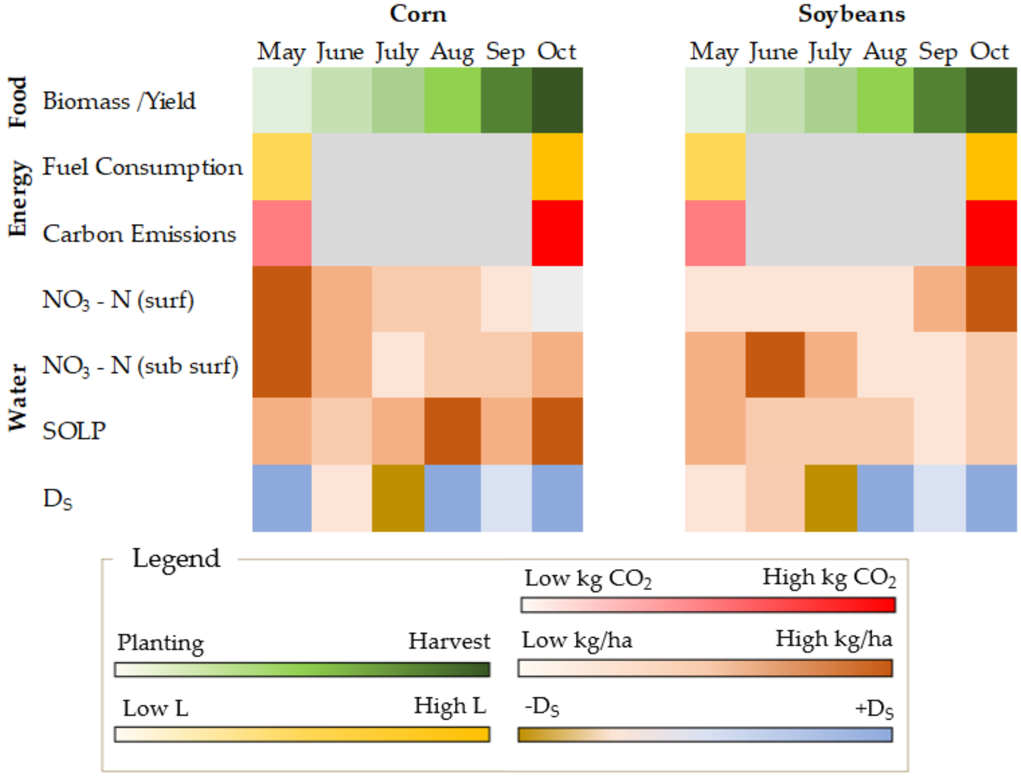

Figure 16 Summary of monthly (May–October) patterns for corn and soybeans in the Matson Ditch Watershed across the various aspects of the FEW nexus during the 2006–2012 time period. The color-scales indicate low values with lighter colors and higher values with darker colors. For food: the crops continue to grow until at the end of the growing season, in this case, in October. For energy: fuel usage and carbon emissions for each year can be determined for the agronomic calendars for each crop, along with their associated carbon emissions. For water: water quality loads for various pollutants (surface nitrate, NO_3-N (surf); subsurface nitrate, NO_3-N (sub surf); and soluble phosphorus, SOLP) are mapped out across the growing season for each crop. For water quantity, deficits and surpluses (D_S) are indicated for each month for each crop.

When addressing the water demands of corn and soybeans, it is necessary to understand that there are various factors that can play a role. According to the FAO, corn requires about 500–800 mm per growing period, with soybeans requiring 450–700 mm [20]. The actual amount of precipitation available to the crop can be determined by calculating the effective rainfall, which can be obtained by subtracting losses other than evapotranspiration from the total precipitation. Site-specific water balances can be obtained using a hydrological modeling approach, which also helps better attribute periods of water stress. However, depending on the model, a substantial amount of data might be required. In the absence of detailed data, the FAO provides a chart that could be used to calculate effective precipitation [20]. However, various factors can affect effective precipitation, including soil moisture status, crop characteristics, climatic conditions, and hydrological conditions due to geographic location [63], and thus the chart might not always provide a representative picture. Correlations between precipitation and effective precipitation (P_{eff}), and those between effective precipitation and deficits or surpluses (D_S) could be constructed for different crops in areas or periods with data (Figure17) and used in subsequent assessments or other assessments in the same or similar region. For the Matson Ditch Watershed, for example, the chart obtained for P_{eff} compared well to that provided by the FAO (Figure 17a), and inferences could potentially be made on D_S based on P_{eff} (Figure 17b). Corresponding correlations (Spearman's ρ) between precipitation and $P_{eff,}$ and P_{eff} and D_S were 0.9239 and 0.6891, respectively, while that between precipitation and D_S was 0.6344. All correlation values were significant ($p < 0.0001$). Thus, in cases where it would be difficult to quantify losses due to data limitations, P_{eff} and/or D_S could still be estimated as long as precipitation data are available.

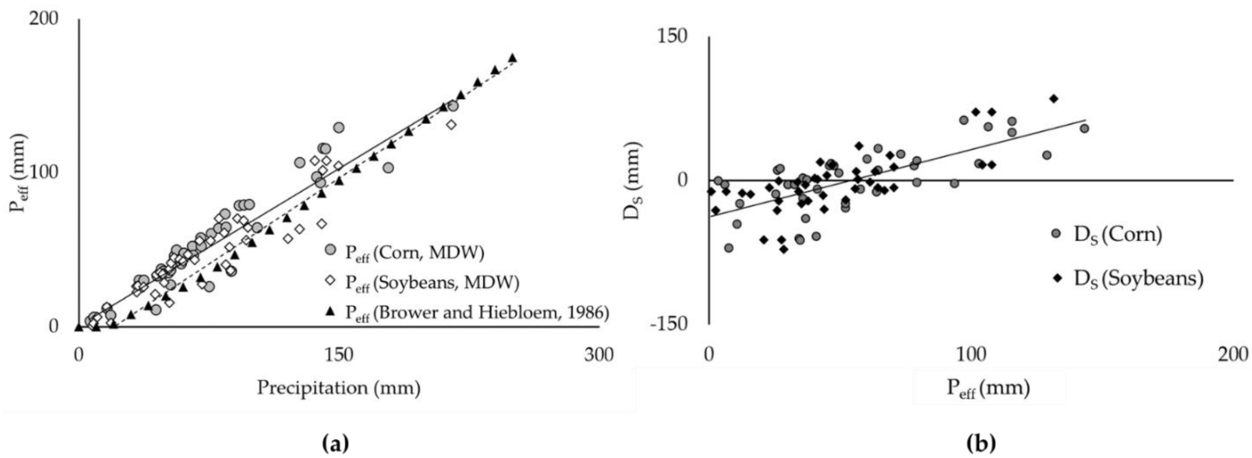

Figure 17 Scatter plots for the Matson Ditch Watershed (MDW) showing: (**a**) effective precipitation (P_{eff}) for corn and soybeans vs. monthly average precipitation compared to the effective precipitation (P_{eff}) vs. precipitation curve provided by the FAO [24]; and, (**b**) deficits or surpluses (D_S) vs. monthly average effective precipitation.

Though the Matson Ditch is a precipitation-fed watershed, the amount of soil water reserve that is available to plants can become significantly reduced, based on study results. Losses in crop growth and yield may occur due to stress from a deficit in the availability in the amount of water in the soil [16]. In our study, although there were months in which deficits were observed, the crops were able to rely on soil moisture storage and were not adversely affected. This might not be the case in other watersheds. Methodologies used in this study can be applied in other areas to identify critical periods and help identify where additional efforts are needed to better manage water availability. With respect to water quality, the situation in the Matson Ditch Watershed is reflective of the agricultural industry. Nonpoint source pollution from agriculture impairs 48% of rivers in the United States [64], with primary concerns being phosphorus and nitrogen. In high concentrations, soluble phosphorus and nitrogen can become detrimental to water quality [65–68]. Phosphorus creates eutrophic water conditions that deplete oxygen and heighten hypoxic conditions [69–72]. Soluble reactive phosphorus, due to its bioavailability, is often the limiting nutrient in fresh waters, thus it is critical to prevent this type of phosphorus from entering susceptible bodies of water [73]. Nitrogen in excessive levels may deplete dissolved oxygen supply and contribute to cyanobacteria growth [73]. Nitrogen paired with phosphorus can affect the prevalence of and toxicity of HABs [74–76]. Due to degradation of land and water resources, individual farmers and communities may have to make critical investments to reverse the situation [77]. Government programs that aid in minimizing the cost of sustainable farming practices are available in the United States. In the larger Western Lake Erie Basin, farmers are implementing Best Management Practices (BMPs) on a voluntary basis [78]. With programs such as the 4R Nutrient Stewardship Program, government agencies and farmers work together to optimize farming practices [79] to minimize environmental impacts while continuing to support the viability of farming.

Carbon footprints and carbon emission assessments for farming operations and energy sources required in the agricultural system of interest provide another context that may be of interest to decision-makers. Most FEW nexus assessments focus on greenhouse gas and carbon emissions in relation to energy consumption [80]. To quantify the relationship pathways outlined, values from literature representative of the Matson Ditch Watershed were implemented for energy efficiency and carbon emission concerns that may be of interest to decision-makers or stakeholders. These included fertilizer and pesticides as they are significant secondary sources of carbon emissions in agriculture [28]. Including aspects of agricultural production that occur outside of the growing period would provide an expanded view of the life cycle of agricultural chemical usage through their energy and carbon emissions. As the focus of this study was on the development of critical periods for water resources management in agricultural systems, analysis was kept to the growing period.

With respect to the cost analysis, it was necessary to not just look at the price received by the farmer, but also to address profits or losses. Using the Purdue Crop Cost and Return Guide allowed us to develop an understanding of realistic scenarios for earnings and losses in crop production. Though the assumption for this study was that everything grown was sold at the end of the season, there is potential for storage of grains for later sale [81]. Additionally, cost assessment is much more complex, as the economic value of crops shifts. As noted previously, policy initiatives can influence the profitability of certain crop production and alter the tradeoffs when selecting which crops to produce. This highlights that though policy could allow for differences in behavior, it can also allow for current practices to continue. It also brings forth the point that policy effects are difficult to predict. When evaluating the cost aspects of the FEW nexus, it is, thus, necessary to understand that policy and other cost factors can play a role in profitability of agricultural production.

3.5 Conclusion

Due to the major role that water quality and quantity play in the FEW nexus, constructing critical periods for water management is important. This study outlined critical periods for various FEW nexus components during the growing season. The amount of water required by crops varied through the season, with needs for corn and soybeans being greatest during the summer months. Water quality was influenced by agronomic practices, with subsurface nitrate-N losses simulated throughout the growing season due to subsurface flow. In general, critical periods for water quality in the study watershed occurred in the early and late season while those for water quantity occurred in mid-season. Any changes to current practice could potentially shift this pattern, particularly as related to water quality. The results suggest the need to adapt agricultural and other management practices across the growing season in line with the respective water resource management needs. It was, however, recognized that such adaptations could have implications for crop yields, energy usage, and carbon emissions which could, in turn, affect farming profitability. This pointed to the need for an optimization approach to finding water management solutions at the nexus. The methodology developed in this study provides a framework through which spatial, temporal, and literature data can be used to conduct FEW nexus-based assessments on a monthly scale with a view to capturing FEW nexus elements as related to critical periods for water management. This provides an additional level of information for decision-makers and stakeholders, apart from the annual or average annual picture, which helps better address water resources concerns. The results show that through the integration of representative values for energy consumption and carbon emissions for field operations and profitability, a more holistic view of component interactions at the FEW nexus could be developed to improve decision-making. Finally, this methodology could be implemented in other areas with similar needs.

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4. EVALUATING CLIMATE CHANGE IMPACTS ON PATTERNS AND EXTENT OF CRITICAL PERIODS FOR WATER MANAGEMENT AT THE FOOD-ENERGY-WATER NEXUS

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4.1 Abstract

Water resources management requires robust, strategic planning to ensure continued access to ample clean water. Long-term strategies for assessing water availability and developing policy decisions require a comprehensive understanding of the impacts of climate change, as well as the uncertainties related to climate change. This study assesses the potential impacts of climate change on critical periods for water resources management, defined as the periods of deficit in terms of water availability and excess nutrient loads for water quality. The study uses the Matson Ditch Watershed in northeastern Indiana, USA, as a pilot site, and Soil and Water Assessment Tool (SWAT) model simulation results obtained using three General Circulation Models (GCMs) and two greenhouse gas scenarios, RCP 4.5 and 8.5 W/m^2, for 2006 – 2099 for analysis. Deficits and surpluses (D_S) changes ranged from -297 to +380% for RCP 4.5 and from -245 to +405% for RCP 8.5. Surface runoff nitrate-N loss changes ranged between -100 to +119,631% and -71 to +199,618% for RCP 4.5 and RCP 8.5, respectively. Subsurface tile flow nitrate-N loss changes ranged from -87 to +3,429% for RCP 4.5 and -88 to +4,138% for RCP 8.5. The ranges for surface

runoff soluble phosphorus loss changes were -100 to +662% and -100 to +876% for RCP 4.5 and RCP 8.5, respectively. Shifts in agronomic practices for food production, such as "climate-smart" practices may occur to mitigate and adapt to climate change. Innovative technologies may provide avenues for decoupling water and energy within the nexus. This study presents implications for water resources management at the Food-Energy-Water (FEW) nexus.

Keywords climate change · food-energy-water nexus · water resources management · critical periods · decision-making

4.2 Introduction

Water deficits are a serious concern for agricultural production. Mitigation against water deficits have included irrigation. A fifth of all crops are irrigated (Döll, 2002), but they account for the largest agricultural demand for water (Elliott et al., 2014). Climate change may play a critical role in threatening water integrity (Hatfield, 2012; Whitehead et al., 2009; Wuebbles and Hayhoe, 2004). With climate change, food and water security become a more critical concern. Climate change can impact global and regional water cycles, runoff, and water scarcity (Rao et al., 2017). Agricultural production introduces an excess amount of nutrients into water systems and is the leading cause of water quality impairments in the United States (USEPA, 2005). With increasing temperatures, more frequent and more toxic algal blooms are occurring, even in areas that did not historically experience algal blooms (Anderson et al., 2002). The Food and Agricultural Organization (FAO) estimates that agriculture accounts for 70% of global freshwater withdrawals (FAO, 2017). Water resources management to allocate sufficient water to meet agricultural demands requires regional knowledge and stakeholder involvement.

In areas such as the Midwestern United States, that are generally water rich but could benefit from innovative water resources management (Schull et al., 2021), water integrity concerns are exasperated by climate change (Wuebbles and Hayhoe, 2004). For example, droughts have become more pronounced in the Midwestern state of Nebraska (Zhang et al., 2018). Excess nutrient loading along with increasing temperatures have been linked to the intensification of cyanobacterial harmful algal blooms in Lake Erie (Jankowiak et al., 2019), along with the rest of the Great Lakes (Pryor et al., 2014). Additionally, with increases in extreme rainfall events and flooding in the Midwest during the last century (Pryor et al., 2014), there are concerns of climate change impacting water integrity and agriculture (Hatfield, 2012). Hence, stakeholders have been interested in mitigating environmental concerns and addressing the impacts of climate change, as water is critical for agricultural development (Fries et al., 2020) and is critical for ecological and anthropogenic well-being (UN-Water, 2019).

Climate change is an identified hindrance to robust decision-making policies and management of water resources (Draper and Kundell, 2007; Munia et al., 2020). Hydrologic and water quality models are commonly used to understand the impacts of future climate change in order to explore potential adaptions for hydrological conditions from futuristic data (Purkey et al., 2008). The consequences of climate change towards water resources management are seen through both dimensions of water integrity – water quantity and quality (Chaturvedi et al., 2021). Additionally, soil moisture deficits are affected by shifts in precipitation and humidity (Turral et al., 2011), which may affect crop growth (Adams et al., 1990). Additionally, the impacts of nonpoint source pollutants from anthropogenic activities, particularly agriculture, have caused eutrophication and toxicity in surface waters (Murdoch et al., 2000). As climate change continues, conditions for severe water quality impairments may become more frequent (Michalak, 2016). Schull et al. (2021) outlined a baseline based on 2006 – 2012 growing seasons of corn and soybean for a Midwestern watershed. One of their findings was to indicate how critical periods – defined as months in which water resources are strained due to agricultural management practices, energy consumption, and nonpoint source pollution – could shift in the future.

Schull et al. (2021) used the Matson Ditch Watershed as a pilot site. Predominantly agricultural and located in DeKalb County in northeastern Indiana, USA, previous research activities in this watershed provide sufficient historical data on land use, crop yield, soil, and hydrological conditions for modeling studies. Future climate scenarios can also be applied, to assess their impact on possible future hydrology, plant growth, and pollutant losses. Thus, this study will use observed precipitation and temperature data from 2003 – 2019 to determine a historical baseline and has the following research objectives: (1) assess how critical periods for water resources management would be impacted by climate change and (2) outline the impacts that these shift in critical periods for water resources management may have on the larger Food-Energy-Water nexus.

4.3 Methodology

4.3.1 Overview of the Methodology

This study builds upon prior work by Schull et al. (2020, 2021). Schull et al. (2020) found that while average annual values were beneficial for long-term climate change impact assessments, stakeholders would find benefits in using a finer-scaled FEW nexus approach through the growing season, rather than across several years. Schull et al. (2021) demonstrated an approach to identify critical periods for water resources management considering both aspect of water integrity – water quantity and quality. Both studies used the Matson Ditch Watershed as a pilot site, with agronomic practices and hydrological processes being modeled using the Soil and Water Assessment Tool (SWAT, Arnold et al., 1998). The Matson Ditch Watershed has been modeled in SWAT in various studies (Boles, 2015; Mehan et al., 2019; Wallace et al., 2017), and with long-term water quality monitoring from the USDA-ARS, it provides a suitable pilot site for the current assessments. In line with the aforementioned studies, this study used the model developed by Mehan et al. (2019a) as a basis. The model had a three year warm up period (2003 – 2005), and was calibrated for 2006 – 2009, using standard parameter optimization procedures, and validated for 2010 – 2012. Additional evaluations based on soft data were conducted for subsurface tile flow and crop yields, and the model was checked for accuracy in spatial representation. This (Mehan et al., 2019a) model was considered the default for this study and no further calibration/validation were then conducted. Updated inputs to the model included temperature and precipitation data from 2003 – 2019. A few model inputs and input files were reconfigured to improve the efficiency of simulations and the SWAT model was re-run to provide the level of data needed for the planned analysis (Figure 18), as described in the ensuing subsection.

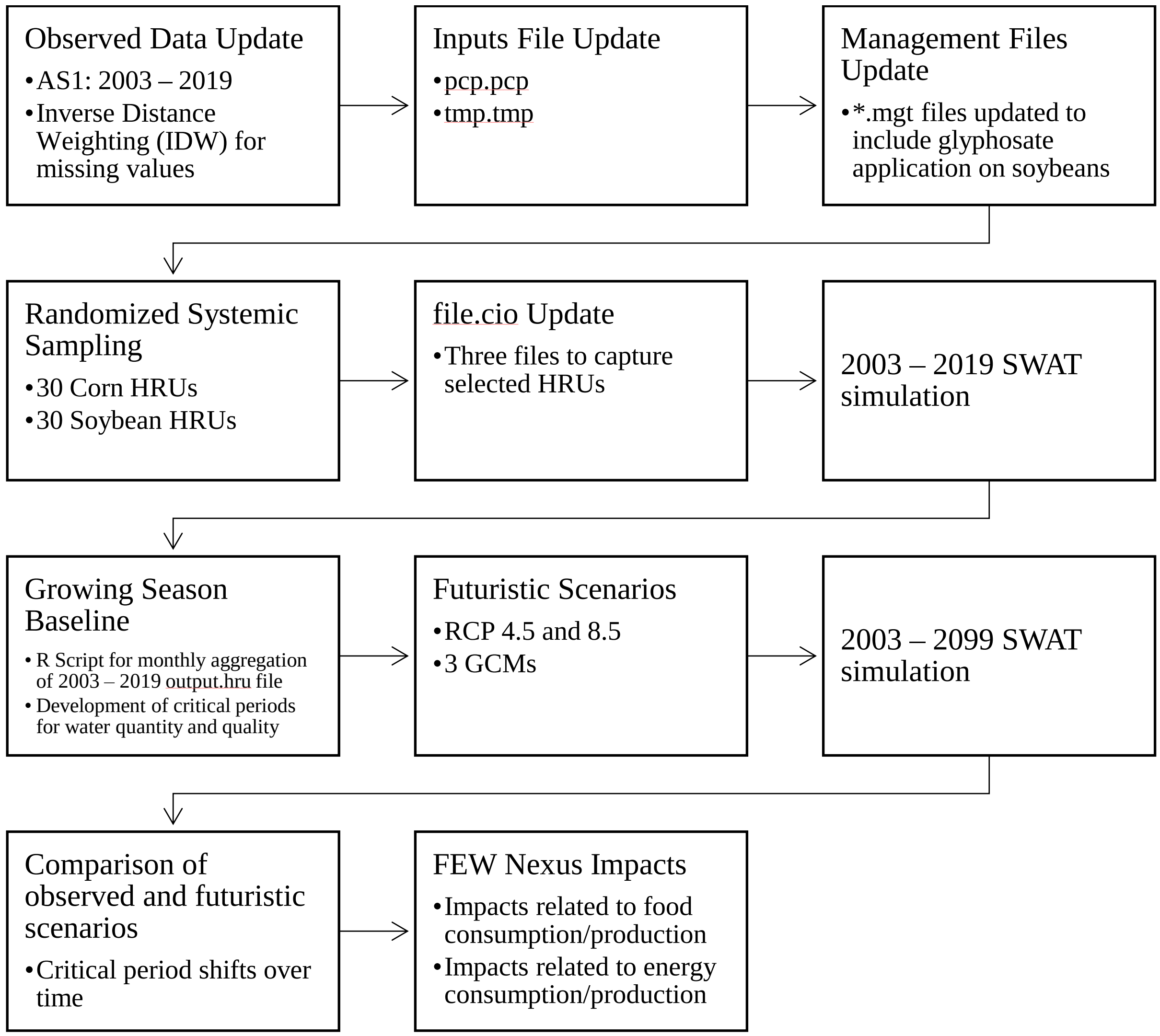


Figure 18 Flow chart of methodology used in the study showing model updates, development of baseline scenarios, evaluation of critical periods for shifts over time, and FEW nexus integration.

4.3.2 Climate Data Inputs

Observed data for 2003 – 2019 from the USDA-ARS gauge station, AS1, were used for the SWAT input files of precipitation and temperature. Pre-processed data were provided in 10-minute intervals for both precipitation and temperature. The precipitation data had been accumulated for each 10-minutes through the day from which the daily values were extracted. For temperatures, the minimum and maximum 10-minute readings per day were considered the daily minimum and maximum, respectively. From the extracted daily values, there was 100% coverage for daily cumulative precipitation and 98% coverage for daily minimum and maximum temperatures. For missing data, inverse distance weighting (IDW) of nearby weather stations as shown in Figure 19, BME (USDA-ARS; 51% coverage for daily cumulative precipitation), BME2 (USDA-ARS; 73% coverage for daily minimum and maximum temperature) and Garrett (NOAA; 98% coverage for both daily precipitation and temperature), were used to fill gaps in the data. These weather stations were selected due to the proximity of the watershed (Figure 19), as well as being able to fill the missing portion of the AS1 datasets.

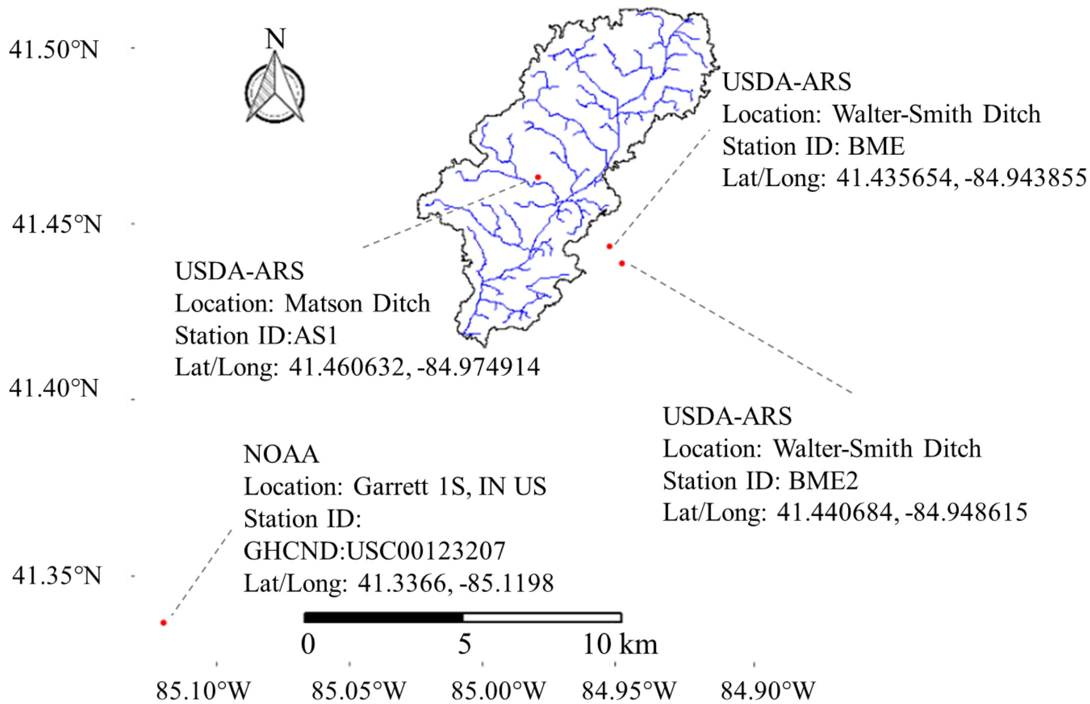


Figure 19 Weather Stations used for developing input temperature and precipitation files for SWAT model; precipitation (AS1, BME, Garrett 1S); temperatures (AS1, BME2, Garrett 1S).

4.3.3 Updates to Agricultural Management

Agricultural management is defined in the .mgt files for each HRU. According to Schull et al. 2021 [17], ensuring that the model accurately represents agricultural practices is beneficial for assessments not just for water resources management, but in other sectors of the FEW nexus. Hence, the agronomic practices of the SWAT model developed by Mehan (2018) were updated (Table 14) using R (R Core Team, 2019) to include a post-emergence herbicide application (Loux et al., 2017) in June, typical in the state of Indiana (Loux et al., 2017; Schull et al., 2021). This was done by adding a line to each file with a land use designation of either corn, soybean, or winter wheat (as these have either corn-soybean rotations or corn-soybean-winter wheat rotations). The line indicated the date of the application, the number designated for glyphosate amine (Round Up) in SWAT, as well as the rate of application.

Table 14 Updated agronomic practices or management operations for different land use/ land cover for the Matson Ditch Watershed (shown in bold).

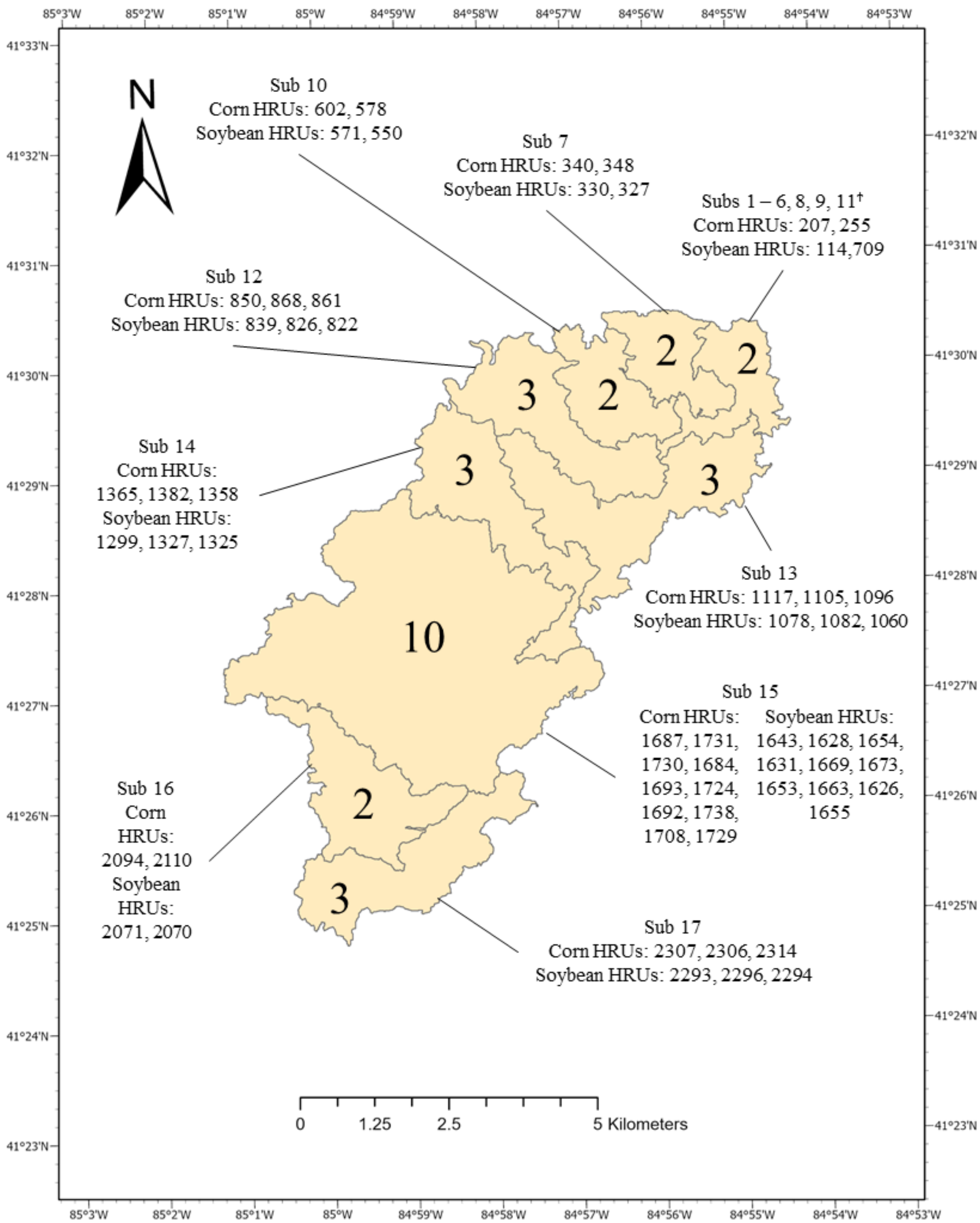
Crop	Date	Management Operation	Rate
Corn	22–April	Nitrogen Application (as Anhydrous Ammonia)	176.0 kg/ha
		(P_2O_5) Application (DAP/MAP)	54.0 kg/ha
		Atrazine Application	2.2 kg/ha
	6–May	Tillage – Offset Disk (60% mixing)	
		Planting – Row Planter, double disk openers	
	10–October	Harvest (Combine)	
Soybean	10–May	(P_2O_5) Application (DAP/MAP)	40.0 kg/ha
	24–May	No-tillage planting (Drills)	
	10–June	**Glyphosate Amine (Round Up) Application**	**0.84 kg/ha**
	7–October	Harvest	
	20–October	Tillage, Chisel (30% mixing)	

4.3.4 Selection of HRUs for Analysis

The Soil and Water Assessment Tool spatial modeling is based upon hydrological response units (HRUs). These are the smallest modeling components for SWAT, and are determined based on land use, spatial location, and the assumption of similar response to weather inputs. If the land use is agricultural, the SWAT management file for each HRU can be configured to indicate crop rotations through time. Based on the model developed by Mehan et al. (2019), there were a total of 2476 HRUs defined for the Matson Ditch Watershed. Of these 883 HRUs had either corn-soybean (670) or corn-soybean-winter wheat rotations (163). For this many HRUs, the daily HRU output file generated by SWAT is typically very large, for example the 1.5 GB output file obtained for the period 2006 – 2012 in previous work (Schull et al., 2021). For the future scenarios planned for this study, a typical run for 2006 – 2099 could result in a file size of 16 GB or larger. To keep the output manageable considering two greenhouse gas emission scenarios using several general circulation models (GCMs) and several distinct time periods as evaluated in this study, a randomized systematic sample was conducted comprising 60 HRUs (30 corn HRUs and 30 soybean HRUs; Table 15) from the HRUs with corn-soybean rotations. Selection was made based on the subbassin area percentage of the overall watershed to ensure that the samples were spatially representative of the entire watershed (Figure 20). SWAT allows the user to adjust the output files to print up to 20 HRUs at a time. Hence, to obtain outputs from the 60 HRUs for each combination of RCP and GCM, the SWAT model was run 3 times per combination, resulting in a total of 64 simulations. The runs for the respective radiative forcings and GCMs were combined and monthly aggregations were obtained for water quantity and quality parameters using R packages dplyr and data.table (Dowle and Srinivasan, 2019; Wickham et al., 2021; R Core Team, 2019).

Table 15 Systematic Sampling Based on Matson Ditch Subbasin Area

Subbasins	Area	% of Watershed Area	# Samples /Subbasin	Corn HRU Number	Soybean HRU Number
1 – 6, 8,9,11	220.5	4.78	2	207, 255	114,709
7	214.3	4.65	2	340, 348	330, 327
10	253.4	5.50	2	602, 578	571, 550
12	415.3	9.01	3	850, 868, 861	839, 826, 822
13	532.8	11.56	3	1117, 1105, 1096	1078, 1082, 1060
14	434.8	9.43	3	1365, 1382, 1358	1299, 1327, 1325
15	1758.2	38.14	10	1687, 1731, 1730, 1684, 1693, 1724, 1692, 1738, 1708, 1729	1643, 1628, 1654, 1631, 1669, 1673, 1653, 1663, 1626, 1655
16	374.1	8.12	2	2094, 2110	2071, 2070
17	406.8	8.82	3	2307, 2306, 2314	2293, 2296, 2294
Total	**4610.1**	**100**	**30**	**-**	**-**



†Subbasins 1 – 6, 8, 9, and 11 were grouped together in order to meet area requirements for systematic sampling.

Figure 20 Subbasin systematic sampling of HRUs across the Matson Ditch Watershed. Number inside subbasins indicate the number of HRU samples taken for each of corn and soybean. The subbasin number is indicated by the label as well as the specific HRUs that were sampled for each respective subbasins.

4.3.5 Master Watershed File (file.cio) Updates

Once the randomized systematic sampling was done to the indicate what HRUs should be printed as output, the hydrological components of interest were determined. Though the user can allow SWAT to output all the default hydrological components, the user can also explicitly state the parameters of interest to simplify data processing. The following components were printed for each HRU output file (Arnold et al., 2013):

- Precipitation (PRECIPmm): total amount of precipitation falling on the HRU during the daily timestep (mm H_2O)
- Evapotranspiration (ETmm): actual evapotranspiration (mm H_2O) (soil evaporation and plant transpiration) from the HRU during the daily timestep
- Deep aquifer recharge (DA_RCHGmm): deep aquifer recharge; the amount of water (mm H_2O) from the root zone that recharges the deep aquifer during the daily timestep
- Surface runoff (SURQ_GENmm): surface runoff (mm H_2O) generated in the HRU during the daily timestep
- Lateral runoff (LATQGENmm): lateral flow (mm H_2O), or the water flowing laterally within the soil profiles that enters the main channel, in the HRU during the daily timestep
- Ground water flow (GW_Qmm): baseflow (mm H_2O) or groundwater contribution to the streamflow during the daily timestep
- Subsurface tile flow (QTILEmm): tile drainage flow (mm H_2O) from the soil profile for the day
- Surface nitrogen (NSURQkg/ha): NO_3-N in surface runoff (kg N/ha); nitrate transported with surface runoff into the reach during the daily timestep
- Subsurface nitrogen (TNO3kg/ha): NO_3-N in tile flow (kg N/ha); nitrate transported with subsurface tile flow discharge into the reach during the daily timestep
- Soluble phosphorus (SOLPkg/ha): soluble phosphorus yield (kg P/ha); soluble mineral forms of phosphorus transported by surface runoff during the daily runoff
- Water stress days (W_STRS): fraction of days crop is stressed by water deficit
- Temperature stress days (TMP_STRS): fraction of days crop is stressed by extreme temperatures
- Nitrogen stress days (N_STRS): fraction of days crop is stressed by nitrogen deficiency

- Phosphorus stress days (P_STRS): fraction of days crop is stressed by phosphorus deficiency

Furthermore, from this output, the water component of deficits and surplus (D_S) was calculated. The deficits or surplus (D_S) in a system is the difference in the effective precipitation (or the amount of precipitation available to the crop after removing losses within the system) and the evapotranspiration needs of the crop (Schull et al. 2021). This provided a method for which to capture the water quantity available for agricultural production.

4.3.6 Futuristic Scenarios

To capture periods where distinct change points were expected to occur, the simulation period was broken down into five timelines for assessment: 2006 – 2019, 2020 – 2069, 2070 – 2099, and 2006 – 2099 (Mehan, 2018; Mehan et al., 2019).

Bias-corrected climate change projections by Mehan (2018) and Mehan et al. (2019) for 9 General Circulation Models (GCMs) (Table 16) and two greenhouse gas emissions scenarios, Representative Concentration Pathways (RCP) 4.5 W/m^2 (medium emissions scenario) and 8.5 W/m^2 (high emissions scenario) were available to simulate the Matson Ditch Watershed for 2006 – 2099. Based on the models that were down-scaled and bias-corrected for the Matson Ditch Watershed by Mehan (2018) and those with similar variability in precipitation and climate based on the work by Byun and Hamlet (2018), the Beijing Climate Center Climate System Model (BCC-CSM1.1), the Community Climate System Model (CCSM4), and the Norwegian Earth System Model (NorESM1M) were selected for further analysis.

Table 16 Different General Circulation Models (GCM) studied for Representative Concentration Pathways (RCP) 4.5 and 8.5

Model No.	Model	References
1	Beijing Climate Center Climate System Model, Beijing, China (BCC-CSM1.1)	[28, 29]
2	Community Climate System Model, USA (CCSM4)	[30, 31]
3,4	Geophysical Fluid Dynamics Laboratory, USA (GFDL ESM2G and GFDL ESM2M)	[32, 33]
5,6	Institut Pierre Simon Laplace Climate Modeling Center, France (IPSL CM5ALR and IPSL CM5AMR)	[34, 35]
7,8	MIROCESM and MIROCESMCHEM, Japan	[36]
9	Norwegian Earth System Model, Norway (NorESM1)	[37]

4.3.7 Output Data Analysis

Output from the SWAT model was analyzed for both the baseline (2006 – 2019) and future timelines as previously described. The output was analyzed using several approaches, including: an exploratory approach of patterns and distributions; a comparative approach based on relative differences; an interpretative approach through the assessment of indices including the ratio between effective precipitation to precipitation and crop stress days for nitrogen, phosphorus, water, and temperature.

Patterns and Distributions

To determine if there might be changes in the patterns observed for water quantity and quality parameters, visualizations of the distributions and monthly patterns were generated. Violin plots were overlaid with boxplots for both the baseline model and the futuristic model. This allowed visualization of density and statistical summaries across the growing period.

Relative Differences

After initial visualization of pattern and distribution shifts, it was important to understand what the relative differences were between the baseline model and the futuristic scenarios. The main relative difference was calculated using Equation (17).

$$\mathrm{RD} = \frac{\mathrm{WQP_t} - \mathrm{WQP_{baseline}}}{\mathrm{WQP_{baseline}}} \tag{17}$$

where WQP_t is the average water quality parameter for timeline t, $WQP_{baseline}$ is the average water quality parameter for the 2006 – 2019 baseline. A positive relative difference value indicates that the futuristic scenario was greater than that of the baseline, with a negative value indicating that the opposite. For D_S, because the comparative values may be either negative (indicating a deficit of water in the system) or positive (indicating a surplus of water in the system), Equation (18) was used to calculate the relative difference.

$$
\mathrm{RD} = \begin{cases} if\ D_{S,b} < 0\ and\ \ D_{S,t} < 0 & \dfrac{WQP_t - WQP_{baseline}}{WQP_{baseline}} \\ if\ D_{S,b} < 0\ and\ \ D_{S,t} > 0 & \dfrac{WQP_t - WQP_{baseline}}{|WQP_{baseline}|} \\ if\ D_{S,b} > 0\ and\ \ D_{S,t} < 0 & \dfrac{WQP_{baseline} - WQP_t}{WQP_{baseline}} \\ if\ D_{S,b} > 0\ and\ \ D_{S,t} > 0 & \dfrac{WQP_t - WQP_{baseline}}{WQP_{baseline}} \end{cases} \tag{18}
$$

P_{eff}/Precipitation Ratio

The ratio between effective precipitation—the portion of precipitation that is readily available to the crops—and precipitation provides further details on the water balance in futuristic scenarios. Through the calculation of the ratio between effective precipitation and precipitation, insights to water availability and water stress can be understood. For example, this ratio can provide an understanding of the proportion of water that is available for crop production (Schull et al., 2021). Furthermore, when the ratio is subtracted from 1, the difference is the ratio between the losses in the system and precipitation, which could provide insight to movement of water outside the system as well. Comparing the P_{eff}/Precipitation ratio across time periods standardizes the water availability. This ratio can be considered the slope for the precipitation versus effective precipitation curve, such as that shown by Schull et al. (2021).

Stress Days

Additional assessment of stress, or growth constraints, can be shown through SWAT output of crop stress days for water, temperature, nitrogen, and phosphorus. Depending on the parameter, the calculation of the stress may change across time periods. The amount of stress for each of these parameters is calculated on a daily basis. The following information is from the Soil and Water Assessment Tool Theoretical Documentation (Arnold et al., 2013).

Water Stress Days

Water stress ranges from 0 to 1 as soil water conditions vary and are calculated using Equation (19).

$$\text{wtrs} = 1 - \frac{E_{t,act}}{E_t} \tag{19}$$

where wtrs is the amount of stress for a given day, E_t is the maximum plant transpiration on the given day, and $E_{t,act}$ is the actual amount of transpiration on the given day.

Temperature Stress Days

Temperature stress also ranges from 0 to 1 and is a daily function of average air temperature and the optimal temperature for plant growth. Equation (20) shows the temperature values used for temperature stress.

$$\text{tstrs} = \begin{cases} \text{if } \overline{T}_{avg} \le T_{base} & 1 \\ \text{if } T_{base} < \overline{T}_{avg} \le T_{opt} & 1 - e^{\frac{-0.1054(T_{opt}-\overline{T}_{avg})^2}{(\overline{T}_{avg}-T_{base})^2}} \\ \text{if } T_{opt} < \overline{T}_{avg} \le 2T_{opt} - T_{base} & 1 - e^{\frac{-0.1054(T_{opt}-\overline{T}_{avg})^2}{(2T_{opt}-\overline{T}_{avg}-T_{base})^2}} \\ \text{if } \overline{T}_{avg} > 2T_{opt} - T_{base} & 1 \end{cases} \tag{20}$$

where tstrs is the temperature stress for a given day, $\overline{T}_{avg}$,is the mean temperature for the day (°C), T_{base} is the plant's base temperature (°C) for growth, and T_{opt} is the plant's optimal temperature (°C) for growth.

Nitrogen Stress Days

Nitrogen stress is only calculated for non-legumes, as the SWAT model does not allow legumes to experience nitrogen stress. This is because in agricultural fields, legumes are considered the main natural contributors to usable nitrogen (Valentine et al., 2011). The SWAT model calculates nitrogen stress using Equation (21), which outputs a value for nstrs between 0 for optimal nitrogen content and 1 when nitrogen content is at or less than the 50% threshold:

$$\text{nstrs} = 1 - \frac{\varphi_n}{\varphi_n + e^{3.535-0.02597\varphi_n}} \tag{21}$$

where $\varphi_n = 200\left(\frac{bio_N}{bio_{N,opt}} - 0.5\right)$ and $bio_{N,opt}$ is the optimal mass of nitrogen stored in the current growth stage of the plant, and bio_N is the actual amount of nitrogen stored, both in kg N/ha.

Phosphorus Stress Days

Phosphorus stress compares optimal and actual plant storage values in a similar manner to that of nitrogen. Equation (22) shows the equation used to calculate P stress, ranging from 0 – 1.

$$\mathrm{pstrs} = 1 - \frac{\varphi_{\mathrm{p}}}{\varphi_{\mathrm{p}} + e^{3.535 - 0.02597\varphi_{\mathrm{p}}}} \tag{22}$$

where $\varphi_{\mathrm{p}} = 200\left(\frac{\mathrm{bio}_{\mathrm{P}}}{\mathrm{bio}_{\mathrm{P,opt}}} - 0.5\right)$ and $\mathrm{bio}_{\mathrm{P,opt}}$ is the optimal mass of phosphorus stored in the current growth stage of the plant and $\mathrm{bio}_{\mathrm{P}}$ is the actual amount of phosphorus stored, both in kg P/ha.

4.4 Results

In this section, patterns and distributions, relative differences, P_{eff}/Precipitation ratios and crop stress days simulated based on three climate models (BCC-CSM1.1, CCSM4, and NorESM1) and separated by crop type (corn and soybean), time period, and greenhouse gas emission scenario are presented. These results show potential changes in critical periods for corn and soybeans through the growing season for future periods in comparison to the baseline period.

Patterns and Distributions

The patterns and distributions for the three climate models are shown monthly for precipitation, effective precipitation, evapotranspiration, and deficits/surplus, as well as water quality parameters (surface and subsurface nitrate and soluble phosphorus). Figures 21– 23 show the minimum and maximums across the three climate models and for each of the greenhouse gas scenarios. Figures A.1 – 40 in the Appendix have additional information, with each of the months having a box plot that shows the 25^{th}, 50^{th}, and 75^{th} monthly quartiles through the bottom, middle, and top of the box, respectively. The average for each month is indicated with a diamond. Additionally, the box plots have outliers connected to the box, shown by circles. The monthly distributions are shown using a violin plot. The violin plot adds the additional dimension to the pattern component for the data, the box plot; the box plot provides a statistical summary for each month, whereas the violin plot shows the kernel density of the data. Using both the box plot and violin plots allow the reader to visually notice shifts not just in range, but also distribution of the data across varying time periods and greenhouse gas scenarios for each crop type. For the water quantity parameters, the data is overall normally distributed, with clear boxplots and violin plots. For water quality parameters, the distributions are very skewed, as the box plots and violin plots are flattened with outliers being the most noticeable.

Results from the historical baseline for 2006 – 2019 correspond with the work by Schull et al. (2021) showing the largest deficit and largest demand of crop evapotranspiration during the month of July for water quantity. Thus, for the water quantity parameters (precipitation, effective precipitation, evapotranspiration, and deficits/surpluses) the month of July is highlighted to demonstrate how this historical period of stress for water quantity shifts through the 21st century. For water quality, the critical period differs depending on the contaminant and the crop type. Table 17 indicates the critical period for the contaminant and crop type through the growing season. These were selected by the period for which the average monthly level was largest based on the 2006 – 2019 baseline. These critical periods aligned with the work from Schull et al. (2021), except that for subsurface tile flow nitrate-N, where Schull et al. (2021) found the critical period to be at the end of the growing season, but this study found it to be at the beginning.

Table 17 Water Quality Historical Critical Periods

Soil Moisture or Contaminant	Crop	
	Corn	Soybean
Soil Moisture Deficits/Surplus (D_S)	July	July
Surface Runoff Nitrate-N (NSURQ)	May	May
Subsurface Tile Flow Nitrate-N (TNO3)	May	June
Surface Runoff Soluble Phosphorus (SOLP)	August	August

Monthly average water deficits/surpluses (D_S) for corn under the three climate models ranged from -143.2 mm to +305.4 mm during the medium emissions scenario and from -165.2 mm to +337.7 mm during the high emissions scenario for 2006 – 2099. For soybeans, the ranges were -137.3 mm to +282.7 mm and -137.9 mm to +375.6 mm for RCP 4.5 and RCP 8.5, respectively. When comparing the historical critical period of July for both crops for D_S, the RCP 8.5 scenario simulation results indicated that the lowest range of D_S may occur in July, while with the RCP 4.5 results indicating that the lowest range of D_S may shift to occur in August. However, across both greenhouse gas emissions scenarios, July is the month with the widest range of values for both corn and soybeans across 2020 – 2069 and 2070 – 2099 in comparison to other months in the growing season.

For surface runoff nitrate-N losses, the month of May remained the critical period for both corn and soybeans through the different greenhouse gas emissions scenarios. The monthly average values ranged between 0 – 59.9 kg-ha^{-1} (RCP 4.5) and 0 – 73.4 kg-ha^{-1} (RCP 8.5) for corn across the growing season for 2006 – 2099. For soybeans, the monthly average values across the growing season through the 21st century were 0 – 4.46 and 0 – 3.952 kg-ha^{-1}. For 2020 – 2069, the range for corn was relatively similar across the greenhouse gas scenarios during the historical critical period of May (0 – 60 kg-ha^{-1} for RCP 4.5 and 0 – 66.8 kg-ha^{-1} for RCP 8.5). However, for soybeans, the range during RCP 4.5 was greater (0 – 4.5 kg-ha^{-1}) than that during RCP 8.5 (0 – 2.0 kg-ha^{-1}), though nitrate-N losses under soybean cropping were much lower than those from the corn. During the end of the 21st century, the surface runoff nitrate-N losses during May in the medium emissions scenario (0 – 48.2 kg-ha^{-1}) was almost half of that of the high emissions scenario (0 – 73.4 kg-ha^{-1}) for corn. In contrast, the ranges for soybean for the end of the 21st century were comparable for both greenhouse gas scenarios (RCP 4.5: 0 – 3.1 kg-ha^{-1}, RCP 8.5: 0 – 4.0 kg-ha^{-1}).

The historical critical period for subsurface tile flow nitrate-N losses for corn was in May. The monthly averages for 2006 – 2099 for RCP 4.5 and 8.5 were 0 – 10.0 kg-ha^{-1} and 0 – 14.5 kg-ha^{-1}, respectively. During 2020 – 2069, the range during the medium scenario (0 – 8.9 kg-ha^{-1}) was slightly greater than that of the high emissions scenario (0 – 6.9 kg-ha^{-1}). Additionally, though the month of June during RCP 4.5 did not have a range (0 – 3.8 kg-ha^{-1}) as large as that of May, for RCP 8.5, the range (0 – 6.9 kg-ha^{-1}) was similar to May. June may be an emerging critical period for subsurface nitrate for 2020 – 2069 for the high emissions scenario. For 2070 – 2099, the medium emissions scenario corn nitrate-N loss ranged from 0 – 8.2 kg-ha^{-1} and 0 – 13.7 kg-ha^{-1} for the historical critical period, with the month of June having loss values up to 3.4 and 3.5 kg-ha^{-1} for RCP 4.5 and RCP 8.5, respectively.

For soybeans, the historical critical period for subsurface tile flow nitrate-N losses was in June. During this month, the average monthly values ranged 0 – 13.1 kg-ha^{-1} and 0 – 20.9 kg-ha^{-1} for the medium and high emissions scenarios for 2006 – 2099. However, the month of July had larger ranges across both greenhouse gas emissions scenarios (RCP 4.5: 23.3 kg-ha^{-1}, RCP 8.5: 11.2 kg-ha^{-1}). For the 2020 – 2069 period, the ranges for subsurface tile flow nitrate-N losses in June were 12.2 kg-ha^{-1} in both greenhouse gas emission scenarios, with July ranging up to 10.0 kg-ha^{-1} for RCP 4.5 and up to 11.2 kg-ha^{-1} for RCP 8.5. in the latter portion of the 21st century.

June remained the month with the largest ranges through the growing season, with monthly averages of 0 – 10.4 kg-ha^{-1} for RCP 4.5 and 0 – 12.1 kg-ha^{-1} for RCP 8.5. The higher range values seen across the 21st century during July may be due to 2006 – 2019 projected values, and thus demonstrates the importance of separation of time periods based on shifts, as well as further analysis to determine the critical period during the growing period.

August was the surface runoff soluble phosphorus loss historical critical period for both crop types. Through 2006 – 2099, the range during August for corn was 0 – 0.016 kg-ha^{-1} for RCP 4.5 and 0 – 0.035 kg-ha^{-1} for RCP 8.5. However, the month with the largest range was July, with ranges of 0 – 0.08 kg-ha^{-1} for RCP 4.5 and 0 – 0.038 kg-ha^{-1} for RCP 8.5. For soybeans, the range in August (0 – 0.019 kg-ha^{-1}) for RCP 4.5 was much less than that of July (0 – 0.079 kg-ha^{-1}), but that was not the case for RCP 8.5 (July: 0 – 0.028 kg-ha^{-1}, August: 0 – 0.03 kg-ha^{-1}). For 2020 – 2069, the month with the largest range for corn was September for RCP 4.5 (0 – 0.026 kg-ha^{-1}; August: 0 – 0.01 kg-ha^{-1}) and RCP 8.5 (0 – 0.024 kg-ha^{-1}; August: 0 – 0.019 kg-ha^{-1}), whereas for soybeans it was September (0 – 0.024 kg-ha^{-1}; August: 0 – 0.008 kg-ha^{-1}) for RCP 4.5 and July for RCP 8.5 (0 – 0.028 kg-ha^{-1}; August: 0 – 0.005 kg-ha^{-1}). For 2070 – 2099, July had the largest range for surface runoff soluble phosphorus losses for corn for both RCP 4.5 (0 – 0.019 kg-ha^{-1}; August: 0 – 0.007 kg-ha^{-1}) and RCP 8.5 (0 – 0.038 kg-ha^{-1}; August: 0 – 0.032 kg-ha^{-1}). For soybeans, the month of May had the largest range for RCP 4.5 (0 – 0.018 kg-ha^{-1}; August: 0 – 0.008 kg-ha^{-1}), with August having the largest range for soluble phosphorus losses for RCP 8.5 (0 – 0.02 kg-ha^{-1}). Soluble phosphorus loss critical period shifts seem to be more abrupt in comparison to other hydrological parameters. However, ranges alone do not provide a complete picture of critical periods. The relative differences, or the percentage changes, may also provide insight to how these parameters are changing through the 21st century.

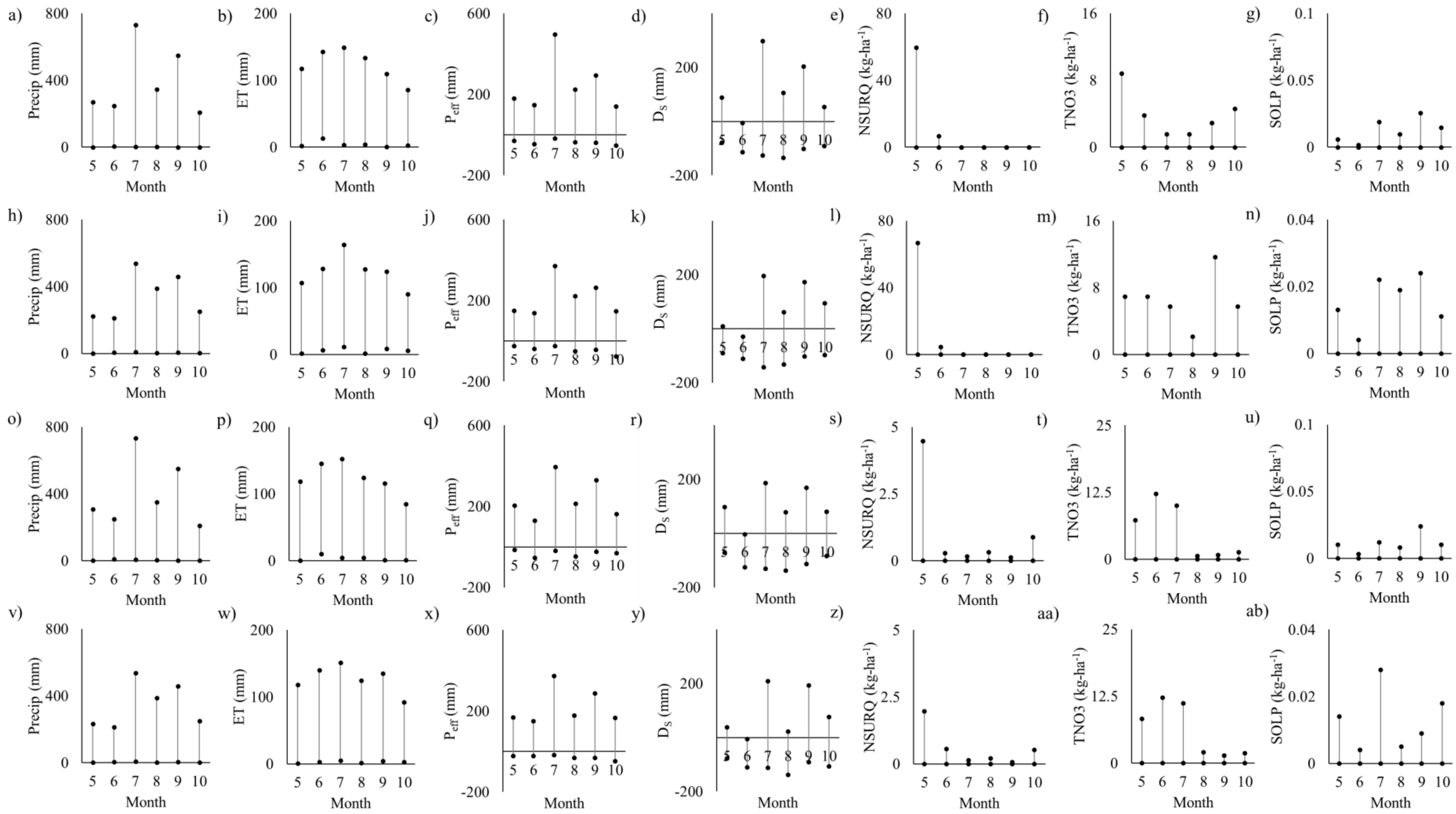


Figure 21 2020 – 2069 a - g) monthly minimum and maximum distributions through the growing season for corn HRUs for RCP 4.5; h - n) monthly minimum and maximum distributions through the growing season for corn HRUs for RCP 8.5; o - u) monthly minimum and maximum distributions through the growing season for soybean HRUs for RCP 4.5; v - ab) monthly minimum and maximum distributions through the growing season for soybean HRUs for RCP 8.5.

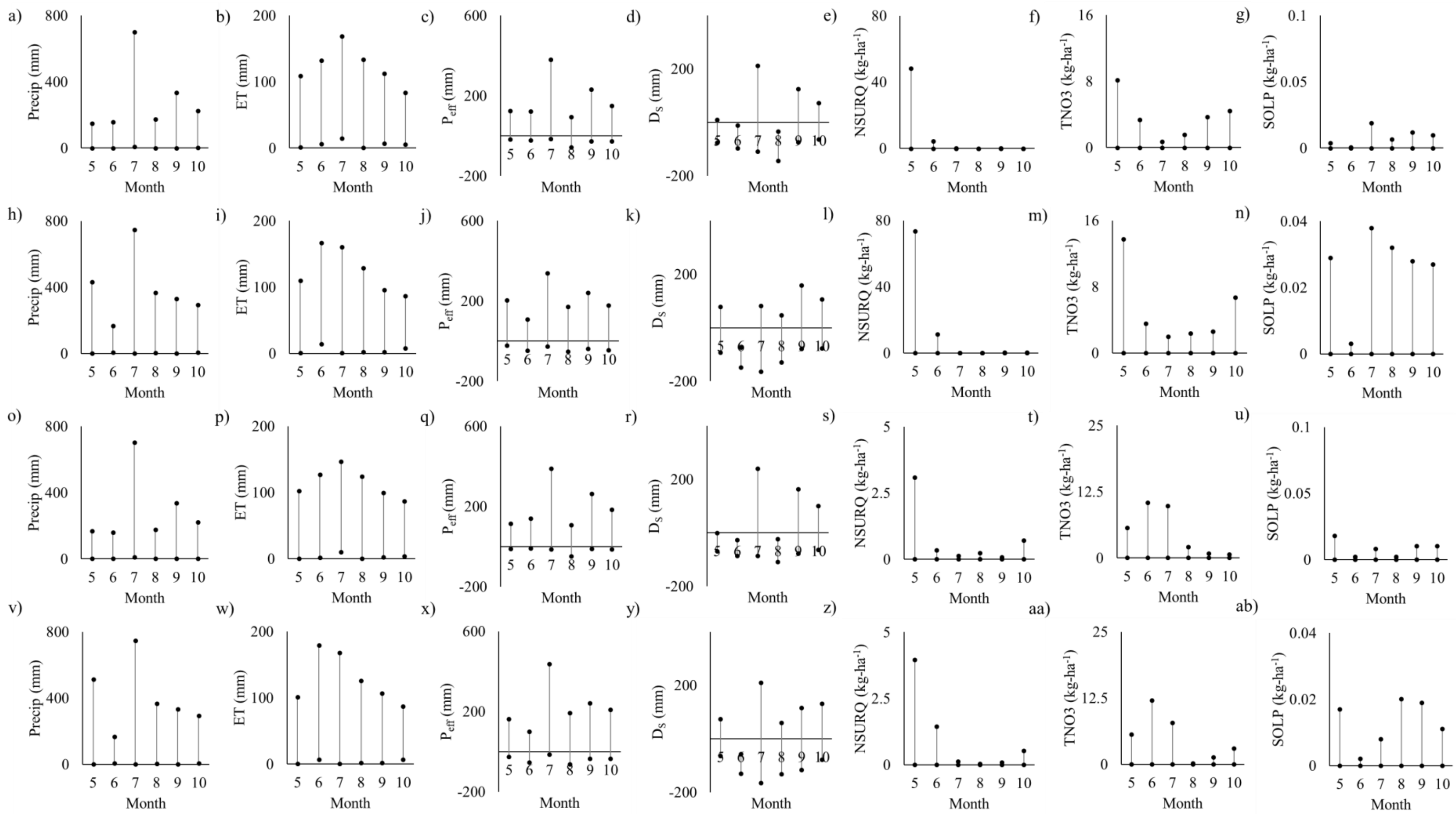


Figure 22 2070 – 2099 a - g) monthly minimum and maximum distributions through the growing season for corn HRUs for RCP 4.5; h - n) monthly minimum and maximum distributions through the growing season for corn HRUs for RCP 8.5; o - u) monthly minimum and maximum distributions through the growing season for soybean HRUs for RCP 4.5; v - ab) monthly minimum and maximum distributions through the growing season for soybean HRUs for RCP 8.5.

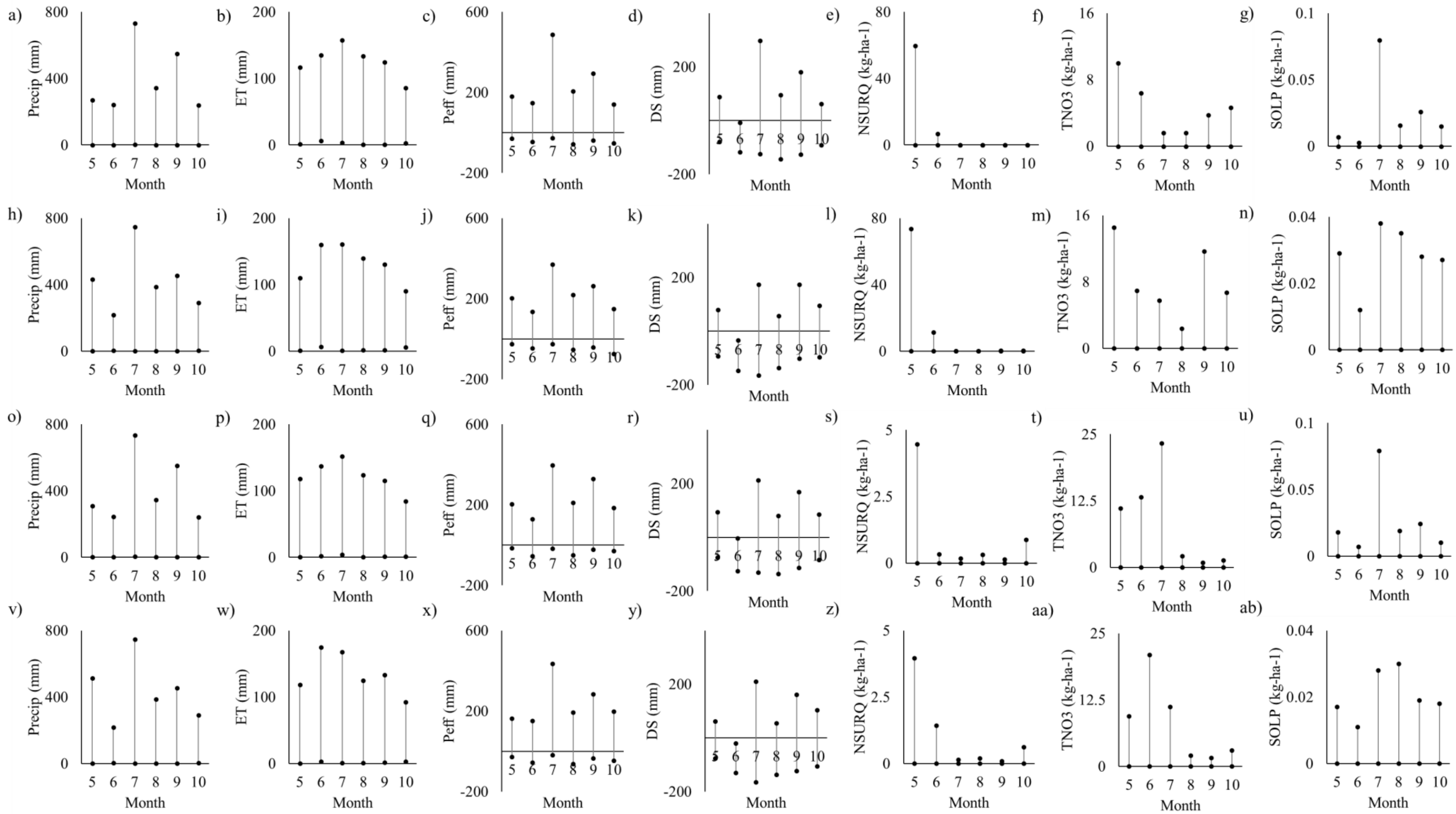


Figure 23 2006 – 2099 a - g) monthly minimum and maximum distributions through the growing season for corn HRUs for RCP 4.5; h - n) monthly minimum and maximum distributions through the growing season for corn HRUs for RCP 8.5; o - u) monthly minimum and maximum distributions through the growing season for soybean HRUs for RCP 4.5; v - ab) monthly minimum and maximum distributions through the growing season for soybean HRUs for RCP 8.5.

Relative Differences

Table A.1 indicate the minimum and maximum relative difference for hydrological and water quality parameters through the growing season months for corn and soybean. A positive relative difference value indicates that the futuristic scenario hydrologic or water quality parameter was greater than the baseline, whereas a negative value indicates that it was lower. For RCP 4.5 during the 2020 – 2070 time period, the evapotranspiration potential minimal relative differences ranged from -15 to +24% for corn and from -18 to +27% for soybean. Comparatively for RCP 8.5, the same time period may have relative differences ranging between -11 to +25% for corn and between –18 to +26% for soybean. For 2070 – 2099, the evapotranspiration relative differences range for RCP 4.5 may be -16 to +31% for corn and -28 to +34% for soybean, with RCP 8.5 ranges between -25 to +31% for corn and -24 to +30% for soybeans. This may indicate that the water needs of the crops will stay within a certain threshold, even in times of stress.

For effective precipitation, the 2020 – 2069 RCP 4.5 ranges for corn were projected to be -33 to +129% for corn and -24 to +123% for soybeans, with RCP 8.5 ranges being -30 to +143% and -27 to +138%, respectively. For the later portion of the 21st century, ranges for effective precipitation for RCP 4.5 ranged from -47 to +149% for corn and -47 to +150% for soybeans. For RCP 8.5, these ranges were-27 to +143% and -25 to +139%, respectively. Deficits and surpluses relative differences were also calculated. For the middle portion of the 21st century, the relative differences ranged from -202 to +216% for corn and -177 to +325% for soybeans for RCP 4.5 and -245 to +269% for corn and -228 to +408% for soybeans for RCP 8.5. At the end of the 21st century, the ranges for corn were -297 to +235% and -223 to +228% for RCP 4.5 and RCP 8.5, respectively. For soybean, these ranges were -264 to +380% and -196 to +270%. These values may be high on both the negative and positive side, as the magnitude of slight deficits and surpluses may be < 1 mm, so any increases or decreases may show a large magnitude of relative differences.

For the historical critical period of July, the medium emissions scenario relative differences for evapotranspiration, effective precipitation, and deficits and surpluses may range from -6 to +17%, +44 to +129%, and -99 to +188% for corn, and -3 to +16%, +41 to +123%, and -94 to +207% for soybeans for the 2020 – 2069 period, respectively. During the latter portion of the 21st century, the ranges for these hydrological parameters were estimated to be -6 to +14% (evapotranspiration), +76 to +149% (effective precipitation), and +138 to +235% (D_S), respectively. Hence, though the evapotranspiration relative difference ranges stayed relatively constant through both periods, the effective precipitation and D_S relative difference ranges were higher. Thus, the monthly values for these hydrological components were typically higher at the end of the 21st century than the baseline and compared to the values during the 2020 – 2069 period.

There was a slight increase in the evapotranspiration relative difference ranges for the month of August for 2020 – 2069 (corn ET: 2 – 24%; soybean ET: 0 – 27%) and 2070 – 2099 (corn ET: 6 – 31%; soybean ET: 8 – 34%), but for effective precipitation and deficits and surpluses, there were further negative shifts in the range of relative differences between 2020 – 2069 (corn EP:-33 to 0%, D_S: -202 to +71%; soybean EP: -32 to -1%, D_S: -177 to -88%) and 2070 – 2099 (corn EP: -47 to -11%; D_S: -264 to -113%; soybean EP: -47 to -11%; D_S: -264 to -113%). Thus, it may be possible that along with increases in evapotranspiration demands, there may also be increases in hydrological losses, resulting in less effective precipitation and soil moisture deficits in the system into the latter portion of the 21st century. This indicates that there is a shift in the critical periods and August may be a period of concern under the medium emissions scenario.

For RCP 8.5, the relative difference ranges for these hydrological components during the historical critical period of July were -1 to +15% for corn evapotranspiration, 71 to 143% for corn effective precipitation, and 108 to 220% for corn D_S; and 0 to 12% for soybean evapotranspiration, 64 to 138% for soybean effective precipitation, and 117 to 250% for soybean D_S for the 2020 – 2069 period. For the latter portion of the 21st century, the ranges of the relative differences became -10 to +12% and -9 to +6% for the evapotranspiration for corn and soybeans, respectively. The ranges for effective precipitation were 41 to 143% for corn and 38 to 139% for soybeans. For D_S, the ranges for 2070 – 2099 were 104 to 228% for corn and 107 to 270% for soybeans. However, for the month of August and the higher emissions scenario, the evapotranspiration relative difference range widened in the latter portion of the 21st century (corn ET: -6 to +31%; soybean ET: -2 – 30%) compared to that during the 2020 – 2069 period (corn ET: 5 – 25%; soybean ET: 4 to 26%) for both crops. The relative difference ranges for effective precipitation (2020 – 2069 corn EP: -22 to +4%, 2070 – 2099 corn EP: -21 to -8%; 2020 – 2069 soybean EP: -25 to -2%; 2070 – 2099 EP: -21 to -11%) and D_S (2020 – 2069 corn D_S: -245 to +55%, 2070 – 2099 corn D_S: -223 to -91%; 2020 – 2069 soybean D_S: -228 to -77%; 2070 – 2099 D_S: -94 to -196%) narrowed in the latter portion of the 21st century, but both periods have negative relative difference values. Hence, in the high emissions scenario, the month of August is a concern for effective precipitation and

D_S. Additionally, during the 2020 – 2069 period for September, there is a large range in the relative difference in D_S, with corn D_S values ranging between 9 to 269% and soybean values ranging from 42 to 408%. Compared to the range in the 2070 – 2099 period (-54 to +104% and 55 to 176%), the large range may be a reason to flag September as a month of concern for surpluses in those increases as these may cause ponding in a field, as compared to August which is shifting to declining in water availability.

For the water quality parameters, for corn for the medium emissions scenario, the relative differences for surface runoff nitrate-N losses (NSURQ) were greatest in July during the 2020 – 2069 period, ranging from 74 to 1841% increases. However, the range widened during the latter portion of the 21st century for the month of July, with the relative differences ranging between – 100 to +2,507%. Additionally, though the relative differences for the months of August and September during the 2020 – 2069 for surface runoff nitrate-N losses were not as wide as those in July (-26 to +508% and 225 to 581%, respectively), they showed shifts to higher relative differences during the end of the 21st century (418 to 1,032% and 915 to 1,580%, respectively). This parallels with the average annual results reported by Mehan et al. (2019). Randall and Mulla (2001) indicated that surface runoff nitrate-N losses are influenced by long-term patterns in precipitation, hence, as the region gets wetter (Cherkauer et al., 2021), there is potential for increases in surface nitrate-N losses. For the high emissions scenario, the largest range in relative differences in surface runoff nitrate-N losses for corn occurred in July for 2020 – 2069 at 16 to 1,870%. The range shifted to 962 to 2,507% during the 2070 – 2099 period, but also had larger relative difference increases for the entire growing season.

For subsurface tile flow nitrate-N (TNO3) losses in the medium scenario, the largest increases in relative differences for corn were during the month of July through the 2020 – 2069 period (1,110 to 1,980%), as well as through 2070 - 2099 (1,603 to 3,429%). During September and October, there were negative ranges for the relative differences for both 2020 – 2069 and 2070 – 2099, but they were not as large as compared to that of the prior months. The months of September and October had the largest increases in relative differences, ranging for the 2020 – 2069 period from 664 to 1,999% and 671 to 1,717%, respectively. For the 2070 - 2099 period, the relative difference ranges during 2070 – 2099 were 502 to 2,051% for September and 652 to 1,688% for October.

For RCP 8.5, subsurface tile flow nitrate-N losses for corn showed the greatest increase in relative differences in July, ranging 592 to 3,929% for 2020 – 2069 and 328 to 3,429% for 2070 – 2099. During September and October, there were decreases in relative differences, ranging from -54 to -17% and -64 to -39%, respectively, for 2020 – 2069 and -49 to -41% and -52 to +7% for 2070 – 2099. Soils with high organic manner may be susceptible to nitrate loss when wet years are followed by dry years (Randall and Mulla, 2001), so it is possible that with the fluctuation of precipitation, increases in subsurface tile flow nitrate losses would occur.

During the medium emissions scenario, surface runoff soluble phosphorus losses did not have as large of a relative difference range in comparison to that of surface and subsurface tile flow nitrate. For corn, there were negative relative differences for the months of June (2020 – 2069: -98 to -86%; 2070 – 2099: -95 to -82%), August (2020 – 2069: -93 to -41%; 2070 – 2099: -100 to -52%), and October (2020 – 2069: -88 to -80%; 2070 – 2099: -100 to -80%). Additionally, in July, during the 2020 – 2069 period, the relative difference range was 5 to 407%, but for 2070 – 2099, the range widened to -90 to 662%. For soybeans, this occurred in May (2020 – 2069: -81 to -11%; 2070 – 2099: -79 to -36%), June (2020 – 2069: -100 to -95%; 2070 – 2099: -100 to -91%) and August (2020 – 2069: -92 to -50%; 2070 – 2099: -92 to -22%). The months with the greatest increases in the relative difference for projected surface runoff soluble phosphorus losses during 2020 – 2069 were September (19 to 398%) and October (41 to 303%). These ranges also widened at the end of the 21st century. For 2070 – 2099, the ranges were -72 to +348% for September and -27 to +424% for October.

For the high emissions scenario, the soluble phosphorus losses demonstrated a similar pattern of having negative relative differences for the month of June (2020 – 2069: -98 to -69%; 2070 – 2099: -96 to -36%), August (2020 – 2069: -82 to -70%; 2070 – 2099: -100 to -70%), and October (2020 – 2069: -93 to -76%, 2070 – 2099: -100 to -57%) for corn. Again, July had the greatest increase in relative differences, with a range of 151 to 668% for 2020 – 2069, which also widened in 2070 – 2099 (-69 to +815%) as seen in the medium emissions scenario. Similarly, the months with the largest increases in relative differences during 2020 – 2069 were September (100 to 535%) and October (96 to 588%). These ranges increased during the 2070 - 2099 period, with the relative differences in September and October ranging from -46 to +623% and 22 to 876%, respectively.

Overall, the potential relative difference for water quality parameters were much larger than those of water quantity, as was indicated in the distributions and patterns. Surface and subsurface tile flow nitrate-N losses relative differences may indicate large increases for soybeans due to the magnitude change and how small baseline values were. However, the baseline values were reasonable in comparison to those found by Schull et al. (2021) as, typically, little or no fertilizer is applied to soybeans nitrate-N losses were relatively low or zero at times and, thus, associated relative differences are not shown in the document. The default model was not calibrated with the new baseline expanding the observed precipitation and temperature data for an additional 7 years, these relative differences for both water quantity and water quality are subject to change with calibration. Once the model is calibrated, it is expected that there may be slight shifts in the relative difference values.

Figure 24 provides a visual representation for the need to ensure to provide a more granular assessment for monthly averages across the growing season. Though surface runoff nitrate-N losses had the largest ranges of relative difference values, the mostly positive ranges show interesting patterns between the different greenhouse gas emissions scenarios and crop types. For corn, there are similar patterns between RCP 4.5 and 8.5 for 2020 – 2069, but this is not the case for RCP 4.5 and 8.5 during 2070 – 2099. However, when simply looking at the 2006 – 2099 relative differences, it appears as if the patterns across the greenhouse gas scenarios are similar for corn.

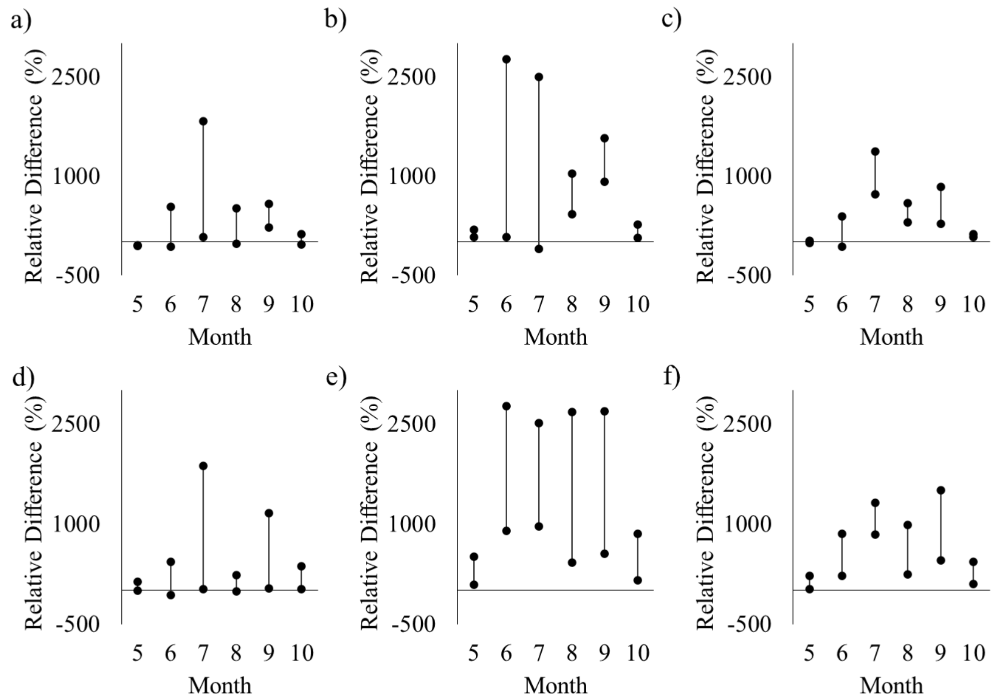


Figure 24 Relative difference percentages of average monthly values of surface runoff nitrate-N losses (NSURQ) through the 21st century for corn a) RCP 4.5 2020 – 2069; b) RCP 4.5 2070 – 2099; c) RCP 4.5 2006 – 2099; d) RCP 8.5 2020 – 2069; e) RCP 8.5 2070 – 2099; f) RCP 8.5 2006 – 2099.

P_{eff}/Precipitation Ratio

For the baseline scenario, the P_{eff}/Precipitation ratio was greatest in September for corn with ratios ranging from 0.59 – 0.81 during the growing season, as this was when the largest portion of precipitation would be available for crop use. For soybeans, the ratio was greatest in August and September, ranging from 0.63 – 0.79, as there are slight differences in water availability between the two crops. For 2020 – 2070, the range for corn was projected to be 0.63 – 0.8 and 0.59 – 0.79 for RCP 4.5 and 8.5, respectively. For soybeans, the ratio range may be 0.6 – 0.78 for RCP 4.5 and 0.58 – 0.77 for RCP 8.5, respectively. At the end of the 21st century, potential ratio ranges for corn for RCP 4.5 could be 0.54 – 0.79, and 0.49 – 0.77 for RCP 8.5. For soybeans, the ratio ranges may be 0.56 – 0.78 and 0.51 – 0.76.

Figure 25 demonstrate the differences between the baseline average for each crop and the ranges for each greenhouse gas emissions scenarios. For corn RCP 4.5, across the 21st century there may be a shift in the drop in the ratio value that is seen in the baseline that historically would be in June but would potentially occur in July, with the end of the season having lower P_{eff}/Precipitation ratios in comparison to the baseline. For corn RCP 8.5, there is potential that there will be an initial low P_{eff}/Precipitation in the month of May (due to this large range in the potential ratio) as well as that in July, with a similar pattern of lower P_{eff}/Precipitation ratios at the end of the growing season. For soybeans RCP 4.5, the peak of the curve may shift to June in comparison to July and August in the baseline. For 2020 – 2069, July – October may have lower ratio values than that of the baseline. For 2070 – 2099, there is a large range in the month of July, but it is lower than the baseline scenario. The months of September and October appear to be on par with the baseline scenario. For RCP 8.5, the peak of P_{eff}/Precipitation ratio may also shift to June, however, along with the large range in July during 2070 – 2099, there will also be a large range in the potential ratio in May.

The fluctuation of the minimums and maximums through the 21st century may indicate when there may be the lowest and highest uptakes of precipitation in a standardized format. Due to the strong correlation between precipitation and effective precipitation, this ratio would be a good starting point for outlining critical periods if the only information available are these hydrological parameters. For example, because these values may be considered slopes, an inference approach like that outlined in Schull et al. (2021) may provide insights on deficits/surpluses if that information is not available.

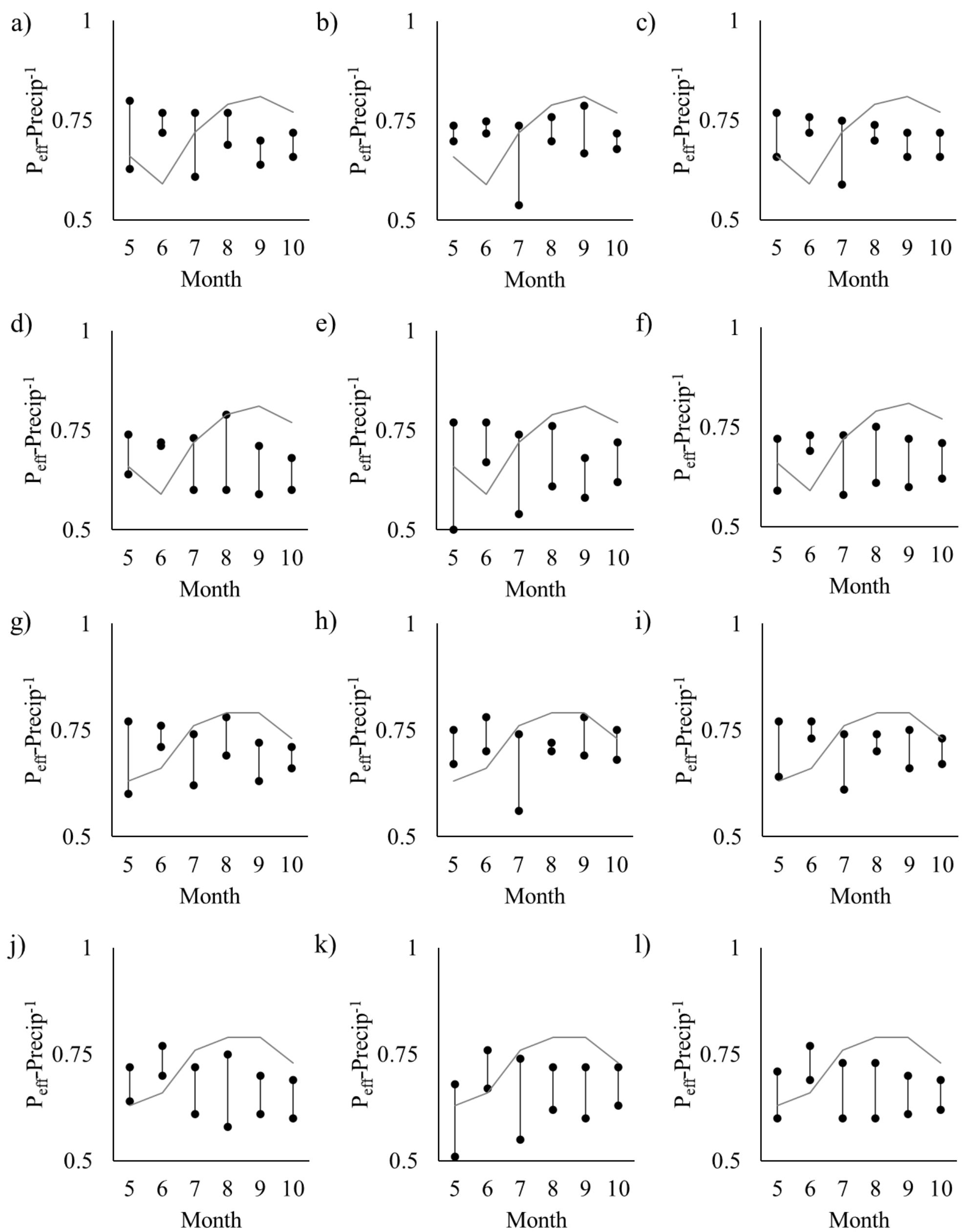


Figure 25 P_{eff}-$Precip^{-1}$ ratio across the growing season. The grey line indicates the baseline (2006 – 2019) ratio for the respective crop. a) 2020 – 2069 RCP 4.5 ratio across the growing season for corn; b) 2070 – 2099 RCP 4.5 ratio across the growing season for corn; c) 2006 – 2099 RCP 4.5 ratio across the growing season for corn; d) 2020 – 2069 RCP 8.5 ratio across the growing season for corn; e) 2070 – 2099 RCP 8.5 ratio across the growing season for corn; f) 2006 – 2099 RCP 8.5 ratio across the growing season for corn; g) 2020 – 2069 RCP 4.5 ratio across the growing season for soybeans; h) 2070 – 2099 RCP 4.5 ratio across the growing season for soybeans; i) 2006 – 2099 RCP 4.5 ratio across the growing season for soybeans; j) 2020 – 2069 RCP 8.5 ratio across the growing season for soybeans; k) 2070 – 2099 RCP 8.5 ratio across the growing season for soybeans; l) 2006 – 2099 RCP 8.5 ratio across the growing season for soybeans.

Stress Days

Stress days were rounded to the nearest day and found in Table A.3. Average water stress days range from 5 – 8 for corn and 3 – 9 for soybean with the baseline but range from 1– 6 and 3 – 5, respectfully, for 2020 – 2069 RCP 4.5, and 1 – 5 and 2 – 4 for RCP 8.5. For the end of the 21st century, the average water stress days through the growing season ranged from 1 – 5 for RCP 4.5, and 1 – 7 for RCP 8.5 for corn. For soybeans, the range through the growing season was 0 – 3 days for RCP 4.5 and 1 – 5 days for RCP 8.5. Figure 26 demonstrates the average range of water stress days for both corn and soybean for both greenhouse gas emissions scenarios. Overall, compared to the baseline number of water stress days, both crop types have less stress days for both greenhouse gas emissions scenarios.

Historical temperature stress days are from 1 – 16 for corn and 0 – 4 for soybean, but futuristic scenarios indicate a potential range of 0 – 14 days for corn and soybean for RCP 4.5 for the mid-21st century, and 0 – 13 days for corn and 0 – 12 days for RCP 8.5 soybean. Figure 27 demonstrates the average range of temperature stress days for both corn and soybean for both greenhouse gas scenarios. Though corn shows less stress days for both greenhouse gas scenarios when compared to the baseline values, soybeans show an increase of temperature stress days at the end of the growing season (September and October).

Nitrogen stress days for corn ranged from 0 – 31, with the first half of the growing season (May – July), having the crops being nitrogen stressed and September not being stressed at all. The number of nitrogen stress days were 0 – 28 for RCP 4.5 and 0 – 27 for RCP 8.5. Corn showed less nitrogen stress days than compared to the baseline scenario. While soybeans do not experience nitrogen stress, drought may impact the soybean root development and nodule traits (Kunert et al., 2016), which may result in less optimal plant growth. Further research should be conducted in understanding how water stress and climate change may affect nitrogen stress for soybeans. Figure 28 demonstrates the average range of nitrogen stress days for both corn and soybean for both greenhouse gas scenarios.

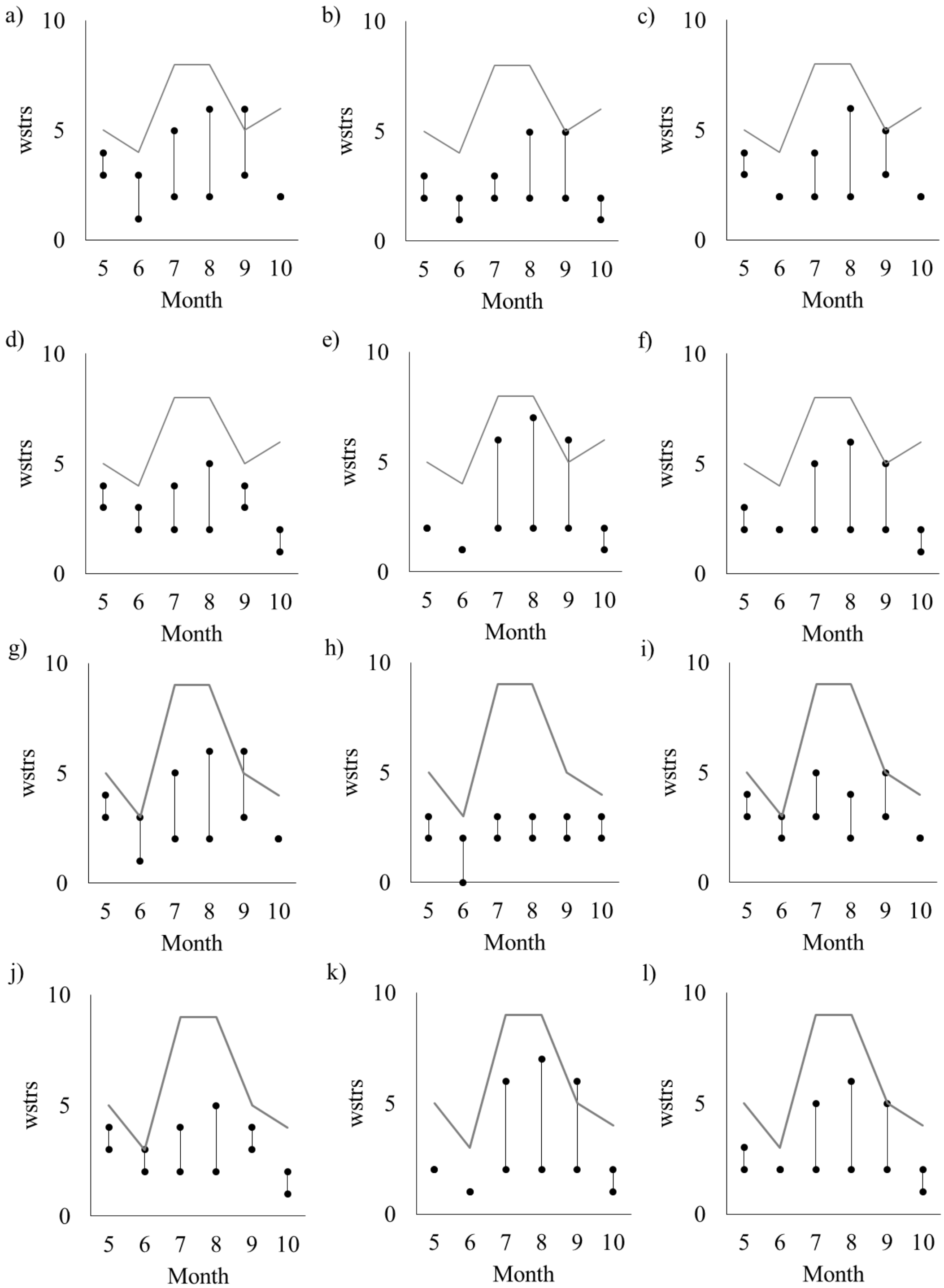


Figure 26 Water stress days (wstrs) through the growing season, with the grey line being the baseline; a) RCP 4.5 2020 – 2069 for corn; b) RCP 4.5 2070 – 2099 for corn; c) RCP 4.5 2006 – 2099 for corn; d) RCP 8.5 2020 – 2069 for corn; e) RCP 8.5 2070 – 2099 for corn; f) RCP 8.5 2006 – 2099 for corn; g) RCP 4.5 2020 – 2069 for soybean; h) RCP 4.5 2070 – 2099 for soybeans; i) RCP 4.5 2006 – 2099 for soybeans; j) RCP 8.5 2020 – 2069 for soybeans; k) RCP 8.5 2070 – 2099 for soybeans; l) RCP 8.5 2006 – 2099 for soybeans.

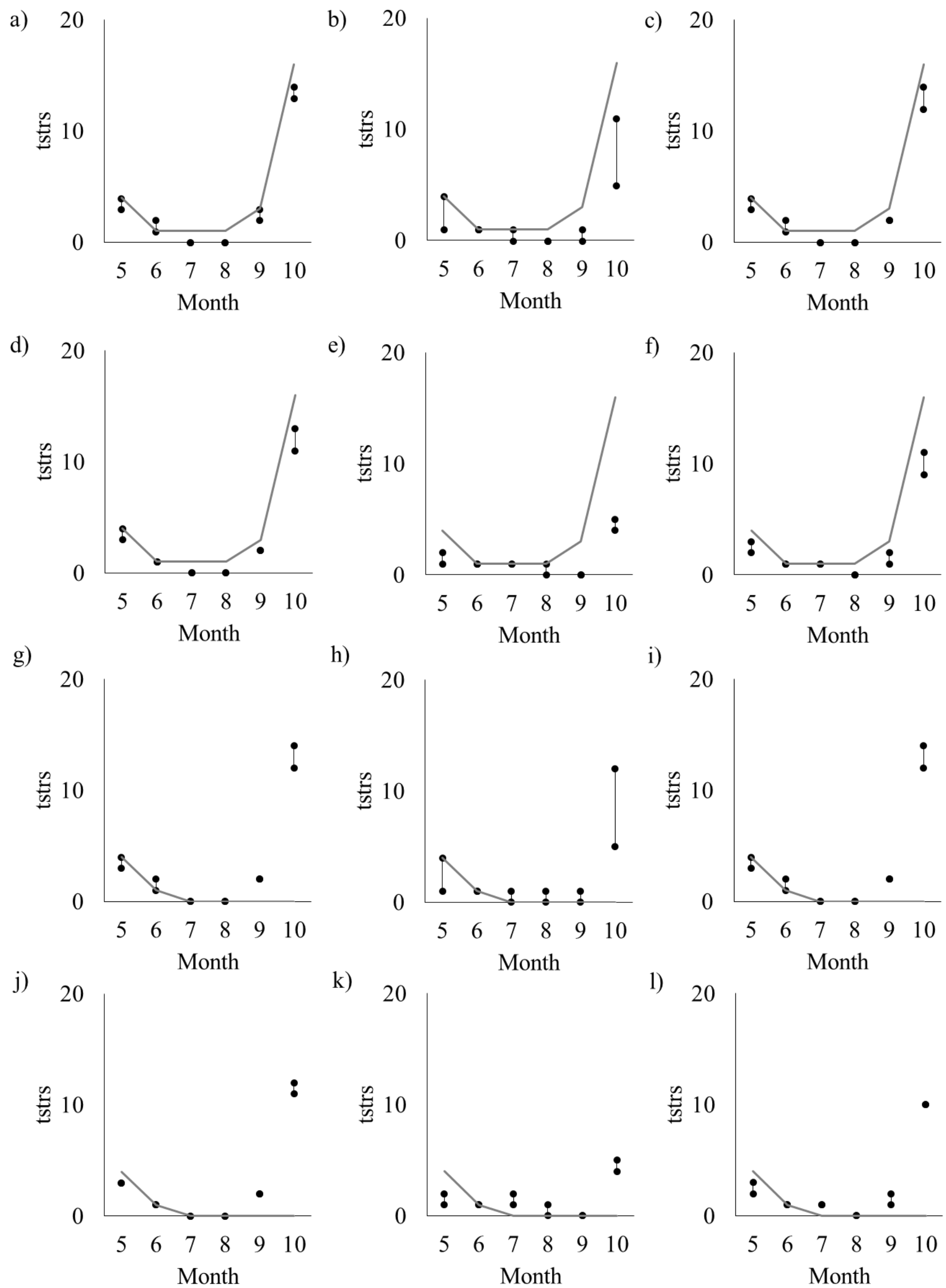


Figure 27 Temperature stress days (tstrs) through the growing season, with the grey line being the baseline; a) RCP 4.5 2020 – 2069 for corn; b) RCP 4.5 2070 – 2099 for corn; c) RCP 4.5 2006 – 2099 for corn; d) RCP 8.5 2020 – 2069 for corn; e) RCP 8.5 2070 – 2099 for corn; f) RCP 8.5 2006 – 2099 for corn; g) RCP 4.5 2020 – 2069 for soybean; h) RCP 4.5 2070 – 2099 for soybeans; i) RCP 4.5 2006 – 2099 for soybeans; j) RCP 8.5 2020 – 2069 for soybeans; k) RCP 8.5 2070 – 2099 for soybeans; l) RCP 8.5 2006 – 2099 for soybeans.

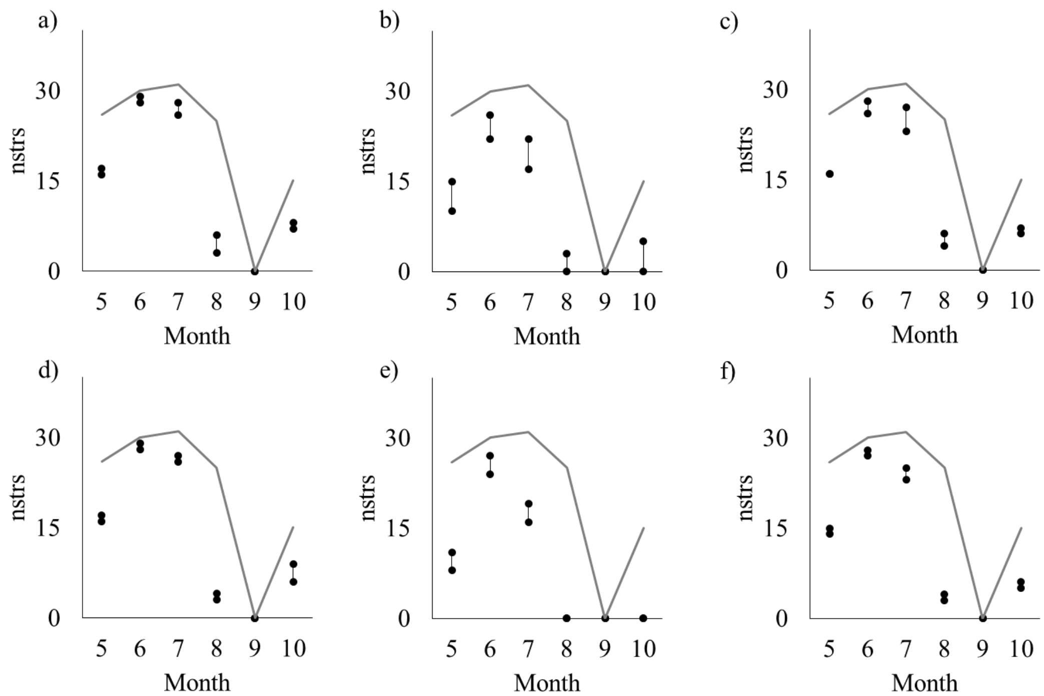


Figure 28 Nitrogen stress days (tstrs) through the growing season, with the grey line being the baseline; a) RCP 4.5 2020 – 2069 for corn; b) RCP 4.5 2070 – 2099 for corn; c) RCP 4.5 2006 – 2099 for corn; d) RCP 8.5 2020 – 2069 for corn; e) RCP 8.5 2070 – 2099 for corn; f) RCP 8.5 2006 – 2099 for corn.

Phosphorus stressed days were historically 0 – 16 for corn and 0 – 8 for soybean, with the futuristic values potentially ranging between 0 – 25 and 1 – 23 for corn and soybean across both greenhouse gas emissions scenarios. For both corn and soybeans, historical baseline indicated that these mostly occurred at the start of the growing season, which is true in the futuristic scenario, but there are more days of stress through the growing season in months that had none. Figure 29 shows the number of phosphorus stress days for both crop types for both greenhouse gas emissions scenarios. Both corn and soybean show increases in phosphorus stress days through the 21st century in comparison to the baseline scenario. Nitrogen and phosphorus stress may be influenced by fluctuation of wet and dry seasons. When rapid fluctuations in precipitation patterns occur, it may cause greater nutrient losses (Randall and Mulla, 2001).

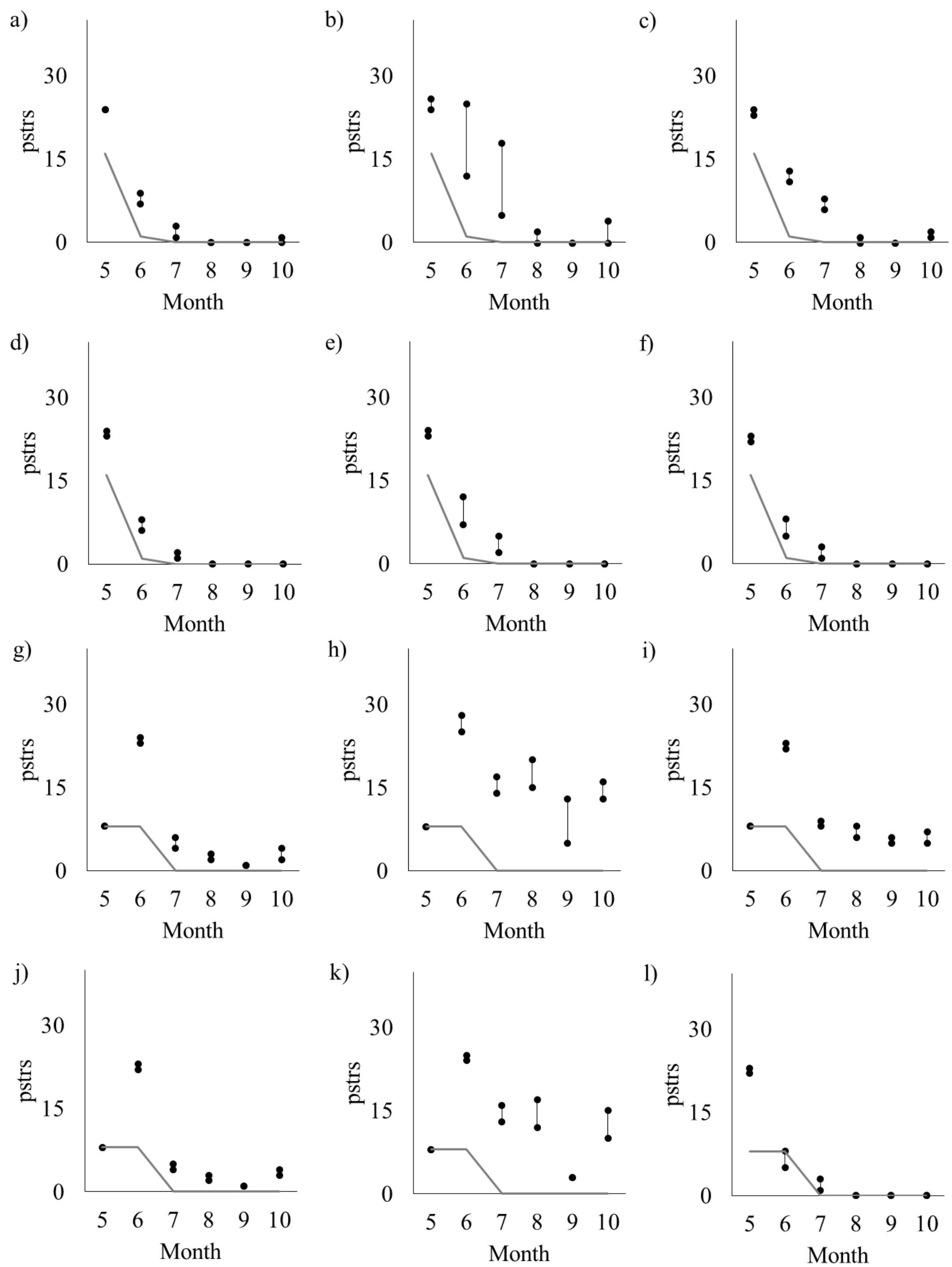


Figure 29 Phosphorus stress days (tstrs) through the growing season, with the grey line being the baseline; a) RCP 4.5 2020 – 2069 for corn; b) RCP 4.5 2070 – 2099 for corn; c) RCP 4.5 2006 – 2099 for corn; d) RCP 8.5 2020 – 2069 for corn; e) RCP 8.5 2070 – 2099 for corn; f) RCP 8.5 2006 – 2099 for corn; g) RCP 4.5 2020 – 2069 for soybean; h) RCP 4.5 2070 – 2099 for soybeans; i) RCP 4.5 2006 – 2099 for soybeans; j) RCP 8.5 2020 – 2069 for soybeans; k) RCP 8.5 2070 – 2099 for soybeans; l) RCP 8.5 2006 – 2099 for soybeans.

4.4.1 Precipitation, Effective Precipitation, and Evapotranspiration

Figures A.41 – A.49 demonstrate the precipitation, evapotranspiration, and effective precipitation critical periods for both the baseline and the futuristic scenarios for corn and soybean. The change in average precipitation shows a similar pattern change for effective precipitation for both corn and soybean in the futuristic scenario, where it may increase in July and September. This may alter the effective precipitation curve in the future. Whereas the baseline scenario has a more gradual curve that peaks in August for both corn and soybean, the futuristic scenario has more abrupt fluctuations, which may cause water stress for the crops, as the evapotranspiration monthly curve stays relatively the same.

4.4.2 Deficit and Surplus (D_S)

Figures A.50 – A.58 show the changes in patterns in the deficits and surpluses, with the range mostly widening to surpluses for each month. The black line indicates the average deficit/surplus (D_S) values from the baseline, and the blue line indicates the average D_S for the futuristic scenarios. The pattern for both corn and soybeans shift, with the month of July, which in the baseline was on average the lowest in deficit for both crops (-25.1 mm for corn; -27.1 mm for soybean) but demonstrating a system surplus for this month in the futuristic baseline scenarios. August, which in the baseline had a surplus for both crops (10.4 mm corn; 11.96 mm for soybean), had slight deficits in the futuristic scenarios. CCSM4 demonstrates a deficit at the end of the growing season, unlike the baseline and the other futuristic scenarios.

4.4.3 Water Quality Parameters

Figure A.59 shows the monthly average nutrient loss from crops for the baseline scenario, with Figures A.60 – A.78 illustrating the projected monthly average nutrient losses from crops for the futuristic scenarios. Average ranges are higher for the futuristic scenario surface and subsurface tile flow nitrate-N losses for both crops when compared to the baseline, but lower for surface runoff soluble phosphorus losses. This may indicate further need to assess water quality strategies for the watershed, particularly for nitrogen. The overall average trends across the growing seasons are similar, but the ranges change between the greenhouse gas scenarios and GCMs used.

4.4.4 Critical Periods Through the End of the 21st Century

When looking at the three general circulation models – BCC-CSM1.1, CCSM4, and NorESM1 – there was a large range in both the water quantity and quality components through a seasonal basis, even when breaking them up across time periods through the 21st century. Though this large amount of data provides a beneficial understanding of the possible outcomes and impacts due to climate change, without thorough synthesis and summarization, stakeholders may be overwhelmed by the amount of information here to formulate data-driven solutions.

Based on comparisons between the baseline and future scenarios, fluctuations in months with the largest water quantity and quality stress may shift. The baseline scenario (2006 – 2019) has the largest surplus during the month of October and the largest deficit in July for corn and soybean. Surface runoff nitrate-N losses were greatest at the beginning of the growing season for both corn and soybeans. However, for subsurface tile flow nitrate-N losses, corn and soybean had different patterns. For corn, the greatest losses of subsurface tile flow nitrate-N were in May, declining until July, and then increasing through the end of the growing season. For soybeans, the peak levels of subsurface tile flow nitrate-N losses were in June, declining in July and August, and remaining relatively negligible for the rest of the growing season. For surface runoff soluble phosphorus losses, corn showed a gradual increase over the growing season, with the largest peak in August, and a smaller one in May. For soybeans, soluble phosphorus losses stayed relatively constant through July, then declined through the rest of the growing season. For deficits and surpluses, the average deficit was largest for both crops in July, with the monthly averages indicating the system was in surplus at the end of the growing season.

Figures 30 – 32 provide an example to demonstrate how shifts can occur through the 21st century. Across the three GCMs, the projected water quality parameters increased in comparison to the baseline. The BCC-CSM1.1 results demonstrate greater surpluses at the end of the growing season, with CCSM4 showing shifts in surpluses in July and September. NorESM1 shows a shift in surpluses in July as well.

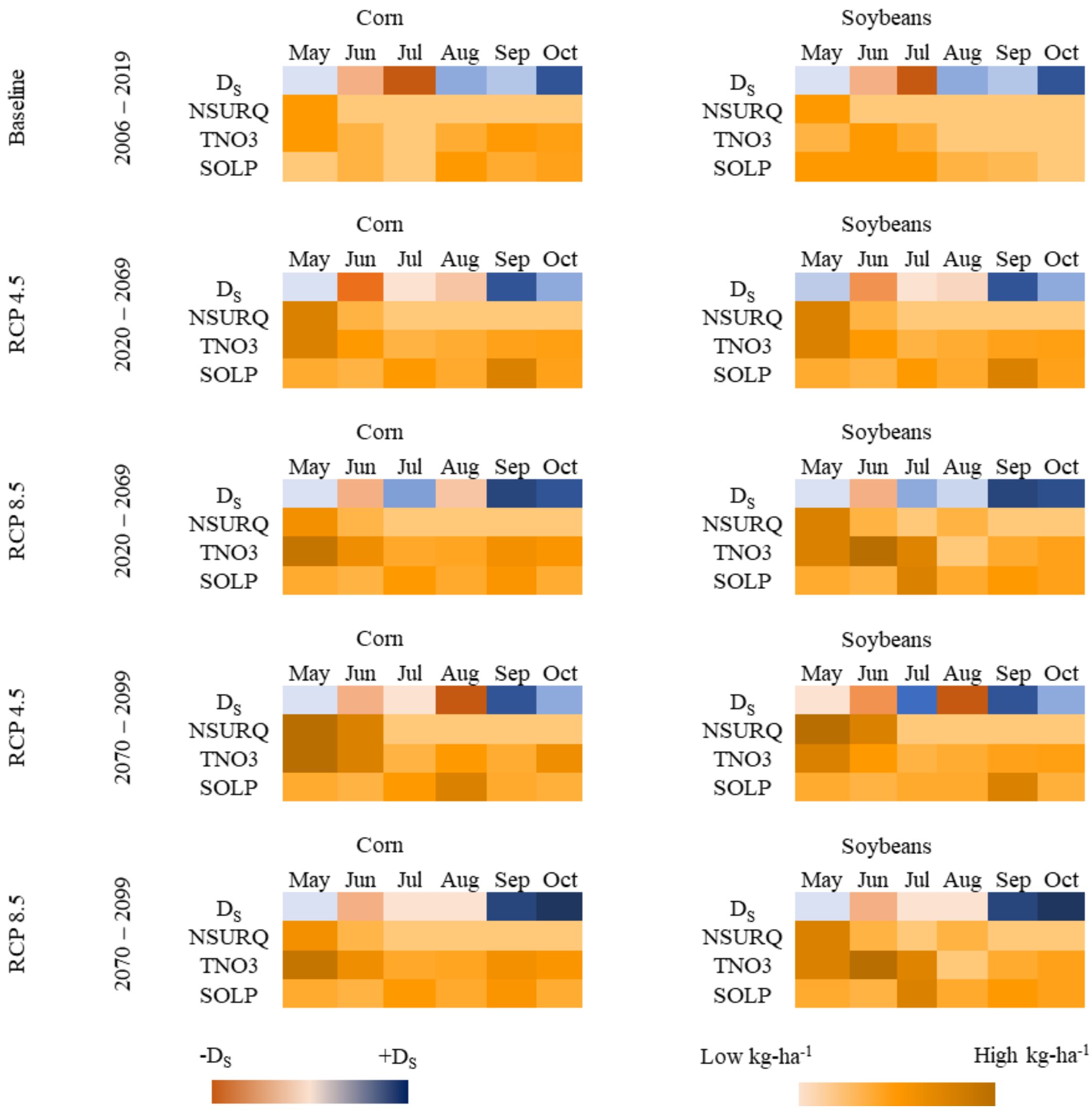


Figure 30 Critical periods through the 21st century for BCC-CSM1.1. For water quantity, deficits and surpluses (D_S) are indicated for each month for each crop, with blue indicating surpluses and brown indicating deficits. For water quality, losses for various pollutants (surface runoff nitrate-N, NSURQ; subsurface tile flow nitrate-N, TNO3; and surface runoff soluble phosphorus, SOLP) are mapped out across the growing season for each crop. The color-scales indicate low values with lighter colors and higher values with darker colors.

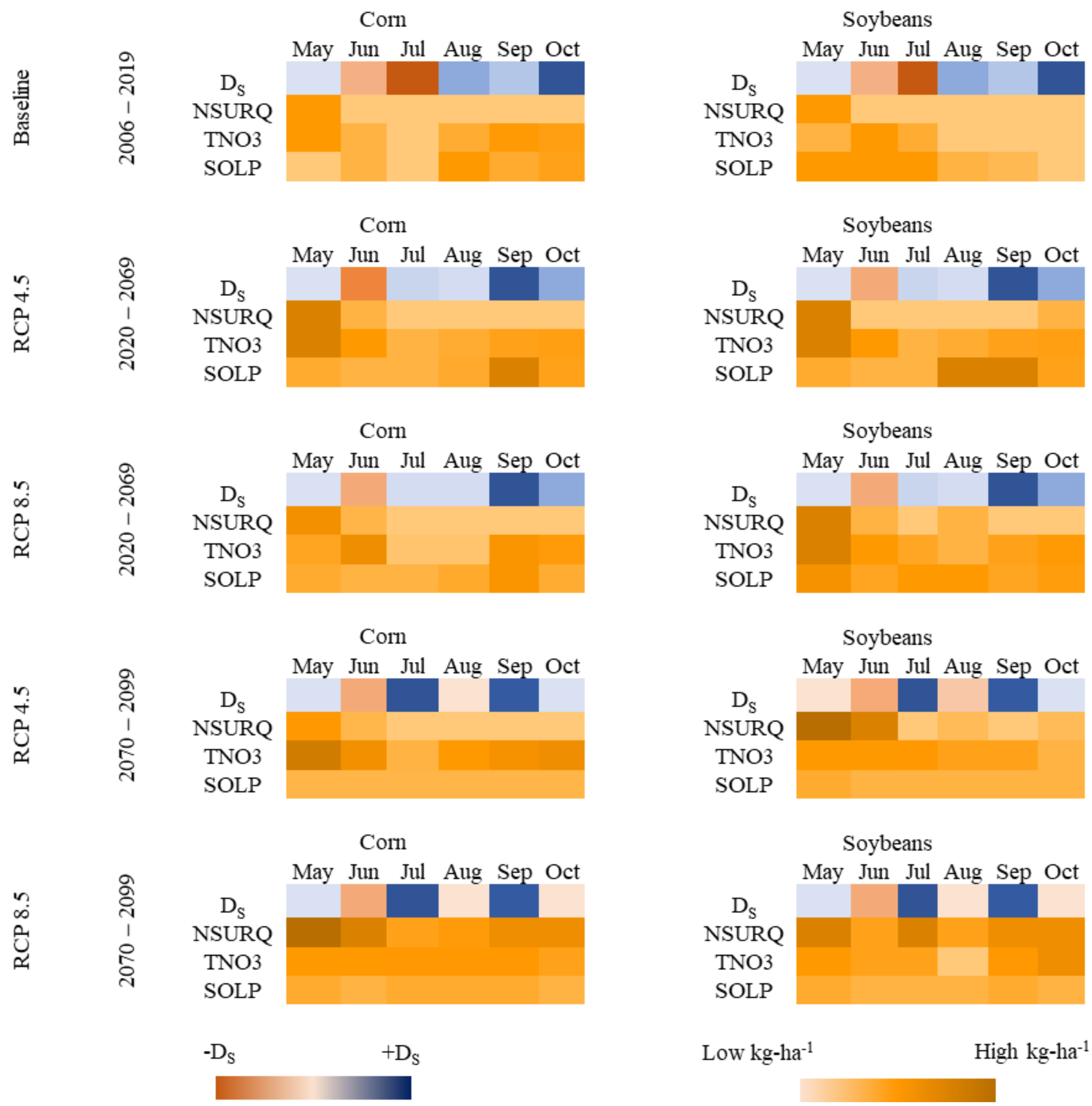


Figure 31 Critical periods through the 21st century for CCSM4. For water quantity, deficits and surpluses (D_S) are indicated for each month for each crop, with blue indicating surpluses and brown indicating deficits. For water quality, losses for various pollutants (surface runoff nitrate-N, NSURQ; subsurface tile flow nitrate-N, TNO3; and surface runoff soluble phosphorus, SOLP) are mapped out across the growing season for each crop. The color-scales indicate low values with lighter colors and higher values with darker colors.

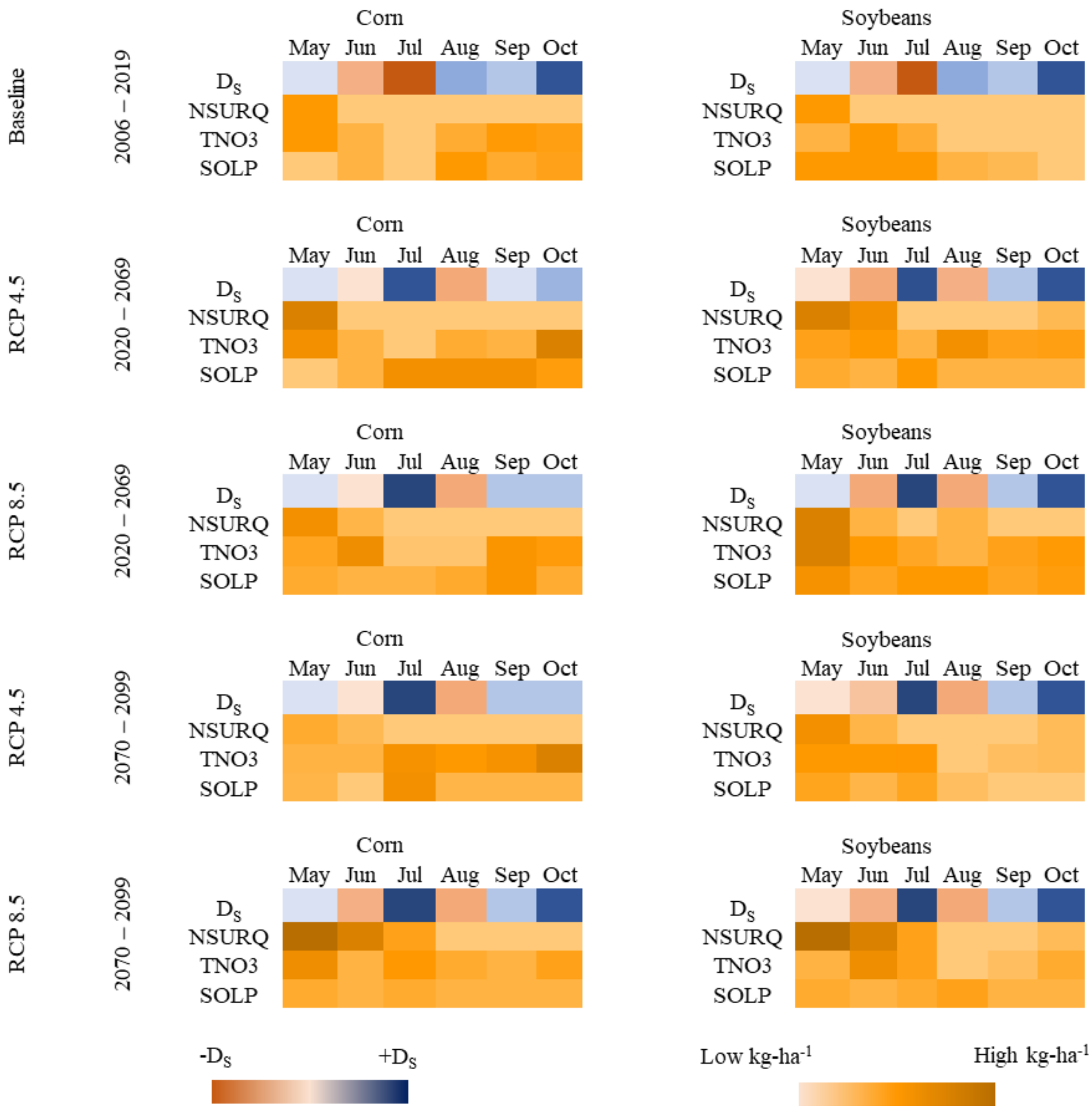


Figure 32 Critical periods through the 21st century for NorESM1. For water quantity, deficits and surpluses (D$_S$) are indicated for each month for each crop, with blue indicating surpluses and brown indicating deficits. For water quality, losses for various pollutants (surface runoff nitrate-N, NSURQ; subsurface tile flow nitrate-N, TNO3; and surface runoff soluble phosphorus, SOLP) are mapped out across the growing season for each crop. The color-scales indicate low values with lighter colors and higher values with darker colors.

4.5 Implications for Water Resources Management at the FEW Nexus

Climate change is expected to magnify pressures on resources within the nexus (Mortada et al., 2018), thus making it more critical to take proactive approaches to ensuring security within the FEW nexus that is environmentally sustainable (Cai et al., 2018). This section will indicate the implications of water resources management at the Food-Energy-Water nexus by discussing the smaller nexuses individually.

4.5.1 Water – Food Nexus

The reliance of cropping systems for water and the interconnection of water and food security is what is known as the water – food nexus (Mortada et al., 2018). With climate change, food and water security become a more critical concern. Climate change can impact global and regional water cycles, surface runoff, and water scarcity (Rao et al., 2017). Because of extreme weather events due to climate change, temporal and spatial variability in precipitation may be more complex in the future (Cai et al., 2018), causing uncertainty in crop production predictions. Crop growth windows may shift or be altered due to regional weather patterns shifts due to climate change. Furthermore, because of more frequent, more extreme events, periods of drought and excess water will affect the critical crop growth periods (USDA, 2019). The water-food nexus also captures the affect that agricultural systems have on water resources (Cai et al., 2018), which is why current ongoing research focuses on this aspect when it comes to sustainable farming practices and environmental regulations that are tied to nonpoint source pollution.

4.5.2 Water – Energy Nexus

The water-energy nexus refers to the multiple points of reliance of water and energy for societal use. Because water is not evenly distributed and requires varying amount of treatment depending on its usage, energy is required for water acquisition, use, and disposal. Energy for water ranges from 3 – 4% of electric consumption in the United States (Rao et al., 2017). Because climate change makes water security more variable, technologies such as desalinization have become more common, though they are energy intensive (Daher and Mohtar, 2015; Rao et al., 2017). Water is used in every step of fossil-fuel extraction and processing, though 87% of electric supply is generated through water-cooled technology, with 45% of water withdrawals in the United States for power plant cooling (Allen et al., 2012; Daher and Mohtar, 2015; Rao et al., 2017). It is estimated that coal produced in 2009 required 1.3 – 4.5 billion cubic meters (m^3) of water, with oil refining requiring 4 – 8 million cubic meters daily in the United States. Furthermore, as climate change causes hydroclimatic variability, this may cause a shift in energy output, and limit power plant operations due to water and temperature limitations imposed by droughts and heat waves (Cai et al., 2018). Additionally, shifts in temperature and precipitation due to climate change may cause a demand in energy for ensuring water allocation in areas that were once water secure. Water quality impairments have been well documented due to fossil-fuel development, causing concerns for water for human consumption, as well as the impacts for aquatic ecosystems (Allen et al., 2012). With countries across the globe developing initiatives to begin to minimize dependence on fossil fuels, two alternatives that have been implemented but are considered just as, if not more, water-intensive have been biofuel and nuclear energy production (Cai et al., 2018; Daher and Mohtar, 2015). However, wind and solar initiatives demonstrate great potential for minimizing the demand of water for energy production, as well as providing energy to supply clean water (Jones and Olsson, 2017). Being able to "decouple" the water-energy nexus – harness renewable energy sources that do not require water cooling nor cause water quality impairment – would be beneficial if more energy may be required to transport water to water insecure areas (Mohtar and Daher, 2012).

4.5.3 Food – Energy Nexus

Agriculture uses energy from both direct and indirect forms; energy from fuel and electricity to power buildings and operate machinery and equipment (Schnepf, 2004), as well as indirect energy-usage through the production of fertilizers and pesticides (Ketzer et al., 2020). Because of the noted dependence fossil fuels have for water, there has been a shift towards growing biofuels (Mohtar and Daher, 2012). However, along with controversy over the water intensity of this alternative to fossil-fuels, this creates competition for land for food production (Harvey and Pilgrim, 2011; Tilman et al., 2009), demonstrating an example of a tradeoff and tension within the food-energy nexus. Thus, there have been research initiatives to ensure that energy and food production can occur simultaneously. Innovative technology, such as agrophotovoltaics – the practice of maximizing land use efficiency by producing both food and solar energy simultaneously (Beckman et al., 2013; Elborg, 2017; Hitaj and Suttles, 2016) – demonstrate how interdisciplinary research can provide solutions to tensions within the food-energy nexus while being cognizant of water requirements for both food and energy production. Miskin et al. (2019) demonstrate that maximizing land use efficiency through the co-production of food and renewable energy has potential across the United States. The FEW nexus is a good method for which to temporally map strategies, and comprehend how to better address problems, giving a better understanding as to how these interconnections play out across both space and time. Thus, there is a lot of potential for addressing the FEW nexus connections, particularly in agricultural systems. When attempting to outline system boundaries, socially constructed boundaries such as counties, states, and nations may be beneficial for financial allocations, however, these may not necessarily make the most sense for natural resources management.

By providing a watershed-scale framework, this provides a water-centric context for decision-makers but requires collaboration amongst the various stakeholders across these said socially constructed boundaries to ensure that solutions are sustainable and beneficial to all.

4.5.4 Overall Takeaways

The ranges for the deficits and surpluses show net increases in surpluses. However, these values are based on futuristic projections over a century, so it would be important to have proactive solutions. If there are surpluses, there may be an indication to implement water catchment and redistribution to ensure that in case there are instances of deficits, the water can be redistributed back into the system to ensure that crops are not stressed. However, as indicated by Figures 30 – 32, surpluses occur during the end of the growing season. Water storage until the next growing season may not necessarily be beneficial in these cases. However, when surpluses are followed by deficits, a water catchment system may aid in ensuring that flooding and ponding does not occur in fields and limit the amount of crop stress in periods of deficit. Furthermore, diversification of crops and other proactive approaches may be worth exploring. Additionally, water quality mitigation techniques would be beneficial to address shifts in critical periods through the growing period. Though best management practices require continuous data collection and monitoring (Liu et al., 2017), the Matson Ditch Watershed is an example of collaborating with stakeholders to understand ongoing agronomic practices. Through a FEW nexus approach, new technology and innovative approaches may be identified to mitigate water quality concerns.

4.6 Discussion

4.6.1 Caveats, Limitations, and Recommendations for Future Work

SWAT Modeling Future Work

The SWAT model setup, as designed by Mehan (2018), assumed that everything but climate remained constant through the analysis period. This was because the interest was in discerning the impacts of climate change apart from other changes that could occur, thus, the status quo in terms of farming practices was not changed. A range of outputs was obtained by using data from different climate models to account for uncertainty in futuristic projections.

However, with climate change, these practices may not necessarily be representative of what agricultural practices may occur to adapt to climate change. Because of the lengthening of the growing season due to climate change (USEPA, 2016; Walthall et al., 2013; Widhalm et al., 2018), farming management operations may shift to earlier in the year than historically considered the norm.

A first step to developing realistic climate change scenarios is to maintain the same set farm management operations in the management (.mgt) file but implement Potential Heat Units for their timing. Because the PHU theory requires daily mean temperature for management scheduling, this approach may consider the temporal shifts due to climate change. Because of some issues with the PHU scheduling, the usage of the SWATfarmR program to write the management file (.mgt) and randomize operations within a span of five days and only set during the days in which no rainfall occurs could make this method more reliable (Odusanya et al., 2019; Schürz et al., 2017). Another option to consider is taking an approach like that of Woznicki et al. 2015, in which management practice dates are shifted earlier and later and show the effects on yield and hydrological conditions.

A second step to developing realistic scenarios requires local knowledge and collaboration with farmers. Overall, farmers' views and perceptions indicate a willingness to implement climate change adaptions and mitigation strategies (Chatrchyan et al., 2017; Mase et al., 2017). However, it is important to note the importance of collaboration with farmers as stakeholders when developing climate change adaption strategies and policy, as basing policy solely on models may disempower farmers and over-simplifies complex realities that these stakeholders face (Crane et al., 2011). Mase et al. (2017) indicates that the most important factor in farmers' adaption behavior to climate change is their level of concern with on-farm environmental risks. Some of these on-farm mitigation strategies, at times called "climate-smart agriculture," include furthering sustainable practices that are accepted both by scientific literature and farmers, such as conservation tillage, agroforestry, and residue management (Scherr et al., 2012). Social norms also play a role, so understanding current ongoing management practices may be beneficial for proposing agricultural operations for a region of interest. Thus, it is important for extension educators, private agricultural advisors, and farmers to foster their respective relationships with each other to continue to disseminate information about climate change (Prokopy et al., 2015).

By better understanding the needs and behaviors of farmers, viable strategies can then be modeled in SWAT (Neitsch et al., 2011), to assess their effectiveness, as well as propose methods which have not been implemented at a larger-scale, such as diversification of crops (Morton et al., 2017). Though Mase et al. (2017) indicates that the United States crop insurance program may be causing inaction from farmers, futuristic projections demonstrate that inaction would not be the most economical or practical. For Indiana in particular, there has been an increase in average daily air temperature of 1.2°F (0.66°C) since 1895, with projections showing a rise of more than 5 – 6°F (2.78 – 3.33°C) by the end of the 21st century. Additionally, average annual precipitation has increased 5.6 in (142 mm) since 1895, with more extreme events predicted in the future (Widhalm et al., 2018). This has the potential to stress the crops due to longer dry periods and drought, increased heat stress, and soil erosion from more extreme events. Increase of yields for some crops may occur, but in extreme hot summers, corn yields may be reduced (USEPA, 2016), with similar trends occurring through the Midwest region (Walthall et al., 2013).

Future work is proposed to maintain current management operation practices and indicate how climate change may change their timing. Once this is done, climate change mitigation and adaption strategies should be implemented to be able to understand how shifts in critical periods are being affected by climate change, followed by assessment of the effectiveness of the implementation of "climate-smart" practices.

Sustainability Indices

Sustainability indices are one method of breaking down the information in a way in which is easy to disseminate and summarize scenarios that are being assessed. Table 18 shows commonly used sustainability indices. These indices have provided examples in how to address concerns in a changing world and can be developed for local to global scales.

Table 18 Common Sustainability Indices (Ramos and Caeiro, 2010; Siche et al., 2008)

Index	Description	Variables	Reference
Ecological Footprint (EF)	Normalized, weighted ratio to determine ecological sustainability that is based on required amount of resource to sustain a national living standard	As many as desired	(Siche et al., 2008; Wackernagel et al., 1999)
Environment Sustainability Index (ESI)	Normalized, aggregated scalar value (0 – 100) from most unsustainable to most sustainable for a nation to preserve environmental resources	76 variables	(Babcicky, 2013; Esty et al., 2008; Siche et al., 2008)
Environmental Performance Index (EPI)	Weighted, complimentary scalar (0 – 100) based on environmental results of countries against specified policy targets	16 variables	(Esty et al., 2006; Hsu et al., 2013)
City Development Index (CDI)	Normalized, weighted composite index composed of 5 sub-indices such as city product, infrastructure, waste, health, and education	11 variables	(Ebert and Welsch, 2004; Lee et al., 2020; UN-Habitat, 2001)

Schull et al. (2020) has demonstrated the need to include water quality into the sustainability index. Mijares et al. (2019) provided a framework for the region for the development of understanding how water quality indices can be formulated, while considering management standards and thresholds. Ebert and Welsch (2004) outlined rules for aggregation for variables depending on the comparability of measurements and properties of the index (whether interval or ratio). If values cannot be compared and a ratio scale is being implemented, then a geometric mean should be used for the index. However, if there is some comparability possible, then any homothetic function may be used. If an interval scale is being used, then dictatorial ordering should be implemented for non-comparability and an arithmetic mean examined for full comparability (Böhringer and Jochem, 2007).

Thus, it is necessary to ensure that one assesses the viability of the index formulation when deciding which indices to use. However, one of the major concerns for various sustainability indices in the literature is the fact these indices have weights that are assigned to parameters. The derivation of weights and normalization of indicators within sustainability indices in particular does not comply with scientific criteria, as it implies a value judgement (Böhringer and Jochem, 2007). Furthermore, the assignments of weights make the index static, in that new weights must be assigned when new parameters are introduced. Further critique of the sustainability indices is that various factors that are compared with each other are not necessarily translatable; in attempting to generalize "sustainability", the meaning of the index becomes obsolete. Improper use of indicators, even those as common as the gross national product (GNP), individual resources, or contamination measurements do not provide adequate indications of sustainability (Siche et al., 2008), causing many sustainability indices, including the Ecological Footprint and Environmental Sustainability Index, to not meet fundamental scientific requirements for an index.

To get meaningful use out of indices, one must fully define what the end goals of sustainability should be when developing them, and how one begins to weigh these sustainability development goals. For agricultural practices, the sustainability goals can be based on minimizing carbon emissions through the use of renewable energy, adhering to water resource standards, and/or assessing earnings and losses based on crop production and management. Accordingly, in order to successfully implement a sustainability index, one should outline a threshold or goal for each resource of the sustainability index (e.g., reduce carbon emissions by 20%), and then calculate the index based on these goals.

Daher and Mohtar (2015) developed an index for FEW nexus assessments, which included land requirements, water and energy consumption, crop yields, economic costs, and carbon emissions. The resource index is a simple equation, as shown in Equation 23:

$$\mathrm{RI_{i,p}} = \frac{\mathrm{R_{scenario,i,p}}}{\mathrm{R_{goal,i,p}}}, \tag{23}$$

where $R_{i,p}$ is the resource index for resource i in scenario p. $R_{scenario,i,p}$ is the scenario output for resource i in scenario p, and $R_{goal,i,p}$ is the set goal for resource i in scenario p. Daher and Mohtar (2015) summarize the sustainability of each scenario through the aggregation of resource indices. The sustainability index (SI) is calculated by a geometric mean as shown in Equation 24:

$$\mathrm{SI_p} = \left(\prod_{\mathrm{i}=0}^{\mathrm{n}} \mathrm{RI_{i,p}}\right)^{\frac{1}{\mathrm{n}}}. \tag{24}$$

Hence, from the information that has been provided, a FEW nexus sustainability index that uses the Matson Ditch Watershed may in fact be developed once the SWAT model has been calibrated and validated.

Model Re-calibration and Re-validation

Because the SWAT model has not been re-calibrated or re-validated for the extended baseline period, the futuristic yield was not assessed. However, future work should use a calibrated and validated model's yield to be able to assess yield changes, as well as how fuel consumption may shift over time. Mehan (2018) indicated that the time periods were divided based on different change-point detection algorithms. If a recalibration and re-validation were to occur, this time-intensive algorithm would need to be executed to ensure that the updated information has not altered the predetermined inflections in the datasets. Water quality modeling is challenging (Ejigu, 2021), particularly when a watershed is ungauged (Qi et al., 2020; Sivapalan, 2003). Though SWAT was developed for ungauged watersheds, using observed data for streamflow and water quality may further improve the model to account for responses that were perhaps not captured in previous studies (Mehan et al., 2019; Schull et al., 2020; Schull et al., 2021). The water balance for the model with the new input data is comparable to that of previous work, thus the water quality transport and patterns may shift in comparison to that outlined in this study. However, modeling is a re-iterative process that requires constant updating and adjustment to ensure that the area of interest is being represented accurately. Thus, the importance of continued data collection and processing allows for decision-makers and policy-makers to have all information relevant to water resources management.

Water Quality Fluctuations Beyond the Growing Season

Though this study addresses the water quality fluctuations that occur during the growing season, this is not necessary indicating that there are not critical periods beyond the growing season. High nitrogen levels have been attributed to agricultural systems that leak nutrients and inefficient uptake of nitrogen fertilizers by monoculture cropping (Gentry et al. 1998). Leaching losses can be substantial, however they can depend on the rate of fertilization, soil type, and hydrological conditions (Gentry et al., 2009). Results from this study align with reported nitrate-N losses from fields being higher for corn than soybean (Tyler and Peterson, 2020). Nevertheless, for subsurface tile nitrate-N losses in the Midwest, most of the exports are occurring during the months of January and June, which coincide with increases in hydrological losses as well as fertilizer applications (Hanrahan et al., 2018). Elevated post-harvest soil nitrate is an indication that excess nitrogen fertilizer was applied to corn (Gehl et al., 2006). Thus, it is important to comprehend the hydrological systems at play and how management practices would affect what is seen in the growing window, in this case, during the months of May through October. If there is an interest in outlining critical periods of subsurface nitrate-N through the entire year, particularly with the addition of winter cover crops, such as ryegrass, would be another application that may be applicable for future projects. However, such analysis is beyond the scope of this work.

4.7 Summary and Conclusions

Water deficits and water quality impacts due to agriculture are historical issues, with climate change potentially further exasperating impacted regions. Water resources management using proactive approaches may be a beneficial approach to mitigating these impacts on water integrity. Areas such as the Midwestern United States, that are generally water rich, may be severely impacted with shifts in water availability and quality due to climate change. In this study, the Matson Ditch Watershed was used as a pilot site for developing a 2006 – 2019 baseline scenario for critical periods for water resources management. From this study, it was demonstrated how critical periods can be formulated with futuristic data for different crop types. Critical periods for water resources are complex, however through thoroughly analyzing futuristic projection distributions, patterns, as well as stress days may provide insight for decision-making. Increases in surpluses, as well as nitrate and phosphorus, indicate a need for continuing to develop solutions to address water integrity concerns. The Food-Energy-Water nexus provides a method to better comprehend the complexity of local systems to provide such solutions. Additionally, there is potential for using sustainability indices for improving communication, assessment, and prediction of concerns for regions like the Matson Ditch Watershed. A water-centric approach to the FEW nexus provides a more complete understanding of the underlying driver of the nexus, as well as innovative, sustainable approaches within agricultural production.

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5. GENERAL DISCUSSION AND CONCLUSIONS

The Food–Energy–Water (FEW) nexus concept emerged from the aim to address the Sustainable Development Goals (SDGs) developed by the United Nations (Bhaduri et al., 2015; Cai et al., 2018; Ringler et al., 2013; Scanlon et al., 2017). These connections between energy and food production, as well as competition with limited water resources drive the systems approach of the FEW nexus (Cai et al., 2018; Hoff, 2011; Schull et al., 2021). The United Nations have begun to integrate food, energy, and water systems in the UN Sustainable Goals (SDGs), which highlight the need to understand these interactions and how they not only promote a sustainability (Laspidou et al., 2020), but environmental justice and human well-being. The FEW nexus has provided a method for which to bring together stakeholders, decision-makers, and scientists across the sectors of the nexus to develop innovative, interdisciplinary and transdisciplinary solutions for environmental resource scarcity and security (Endo et al., 2020). Water resource integrity, that is, water allocation and quality, plays an integral role in the FEW nexus. This is due to the need for clean, readily-available water for both food and energy production (Cai et al., 2018; Daher and Mohtar, 2015; Rao et al., 2017). Including only a single component of water integrity in water resource management can provide inaccurate assessments (Schull et al., 2020; Schull et al., 2021). Because water integrity is a driving factor in the interactions within the FEW nexus, it is crucial to assess how both water quantity and quality are impacted through climate change and how this translates to the larger scope of the FEW nexus.

One method for which decision-makers may better understand the nexus is through modeling tools. FEW nexus modeling tools, as presented in Chapter 2 of this dissertation provide a method to be able to plan natural resources management policies. However, these FEW nexus tools should also incorporate water resources integrity, that is both water availability (quantity) as well as water quality. Using the Matson Ditch Watershed as a pilot site, spatial and temporal assessment using SWAT as well as the energy and carbon footprint assumptions from the WEF Nexus Tool 2.0 provided a methodology for implementing water quality into these FEW nexus assessments for evaluating annual average values through the 21st century.

However, stakeholders that are interested in these tools may find it beneficial to look at the growing period, rather than over large time periods. Thus, this led to Chapter 3, which developed a methodology for identifying critical periods for water resources management through the crop growth periods in the Matson Ditch Watershed using historical data for 2006 – 2012. Corresponding water availability was demonstrated in terms of deficits and surpluses (DS), with water quality components of surface runoff and subsurface tile flow nitrate-N losses and surface runoff soluble phosphorus losses being reported monthly across the growing season. Additionally, scientific literature values for energy usage and carbon emissions were incorporated to estimate the requirements based on the agricultural management practices of the watershed.

Finally, Chapter 4 addressed how these critical periods would shift in the future through the incorporation of a new baseline of historical data (2006 – 2019) and use of three bias-corrected and downscaled general circulation models (BCC-CSM1.1, CCSM4, and NorESM1) and two greenhouse gas emissions scenarios (RCP 4.5 and RCP 8.5). Monthly averages for the crop growth periods within the Matson Ditch Watershed through the 21st century for water availability and quality were determined. Proactive solutions to minimize stress on crops should be implemented, such as continuing best management practices, water catchment and redistribution systems, and diversification of crops.

This portion of the study required a large amount of data, with extensive output as shown in Appendix A. To expand the number of GCMs or greenhouse gas emissions scenarios, highly skilled personnel with extensive computational resources and high-performance processors with a LINUX/UNIX environment (Mehan, 2018) would be needed. However, the purpose behind the development of the critical periods here was to be able to communicate with decision-makers in a simple manner. Thus, personnel need to have a background in development of policy and natural resource management tools to ensure that the scientific background of the data is still maintained when attempting to summarize key points for stakeholders.

Results of this study provide information of how to develop water-centric FEW nexus assessments using both historical and futuristic climate and greenhouse gas scenarios on a watershed scale. Using FEW nexus natural resources management tools, as well as hydrological modeling tools, a methodology was outlined to demonstrate how to incorporate both components of water integrity – water quantity and quality – into a FEW nexus assessment. Additionally, assessments both at a coarse (average annual) and fine (monthly) scale for the FEW nexus were implemented using both historical and futuristic data. As decision-makers and policy makers move forward, it will be critical to adapt agricultural and other management practices across the growing season in line with the respective water resource management needs. Such adaptations could have implications for crop yields, energy usage, and carbon emissions which could, in turn, affect farming profitability. This pointed to the need for an optimization approach for finding water management solutions at the nexus. The integration of representative values for energy consumption and carbon emissions for field operations and profitability, and a more holistic view of component interactions at the FEW nexus could be developed to improve decision-making in the Matson Ditch Watershed as well as other areas with similar needs. Solutions to concerns of water integrity require stakeholder collaboration through the Food-Energy-Water nexus to better comprehend the complexity of local systems. Finally, there is potential for using sustainability indices and user-friendly virtual tools for improving communication, assessment, and prediction of concerns for regions like the Matson Ditch Watershed.

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6. RECOMMENDATIONS FOR FUTURE WORK

Results from this study were based on the outputs from SWAT model simulations using both historical data and three general circulation models for the hydrological components. The new baseline of data covered 7 additional years from previous work (Mehan, 2018; Mehan et al., 2019; Schull et al., 2020; Schull et al., 2021). Future work should ensure that the model is calibrated and validated for this new baseline, both for the hydrological component as well the crop yields for the model. Once this is done, the GCMs can be used to assess crop yields through the end of the 21st century and provide a method for which to calculate energy and carbon emissions based on harvest levels (Hillier et al., 2011) and other agronomic practices (Downs and Hansen, 1998; Hanna, 2001; Lal, 2004).

Furthermore, future work can also assess how critical periods may shift through the year; as the model is currently set up, the farm management operations are set for a specific date. However, the modeler has the option to automate the operations using what is known as the Potential Heat Unit theory (Neitsch et al., 2011). This would allow assessments of how shifts in the growing season would occur due to climate change and how the critical periods for water resources management would be impacted.

With the calibration and validation of the SWAT model, a sustainability index may be developed. Sustainability indices provide a method to compare different resources of the FEW nexus and assess performance of sustainable agricultural practices through these resources. Daher and Mohtar (2015) developed a comprehensive sustainability index that can be adjusted for the requirements of the user. Suggestions for improvement of this index include using a geometric mean rather than weights to ensure that the index can be malleable to a wider range of resources or parameters (Mijares et al., 2019), as well as excluding costs, as this is more difficult to model for futuristic scenarios.

Lastly, it would be beneficial to develop a web-based tool that can be used for similar regions such as the Matson Ditch Watershed that would be free and simple to use. This would allow decision-makers to look at historical critical periods for food, energy, and water for their watershed, as well as look at how climate change projections may impact the critical periods. The tool could provide alternative scenarios, with varying sources of energy or diverse crops to select through the growing season. The tool might also include a sustainability index for purposes of communication, tracking progress, and predictive purposes. With the methodology outlined in this study (Schull et al., 2021), such a tool could be made for users without extensive hydrological modeling expertise and provide them with the information required for data-driven decision-making for sustainable water resources management.

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APPENDIX A. ADDITIONAL FIGURES AND TABLES

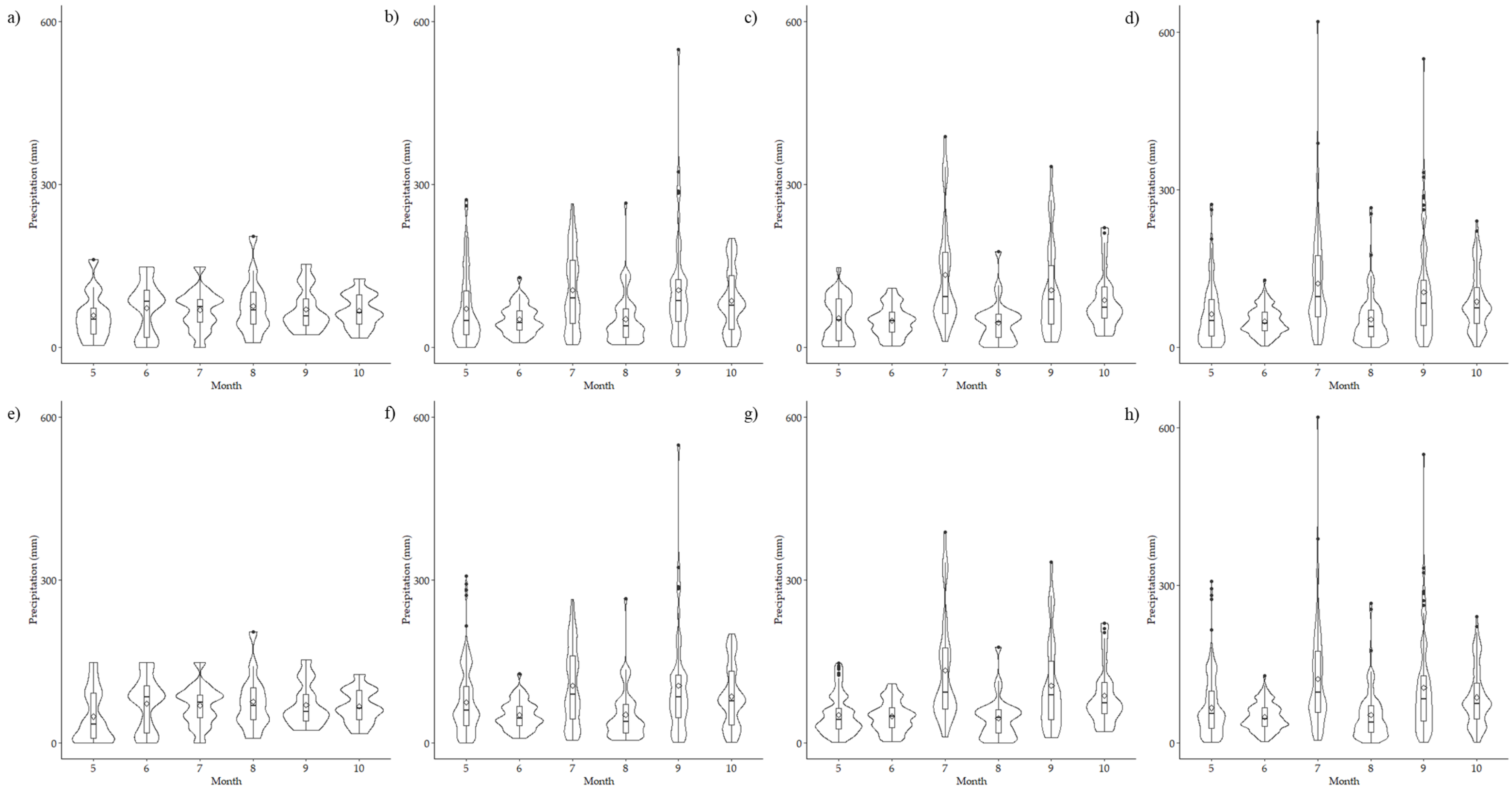

Figure A.1 Precipitation distribution for BCC-CSM1.1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

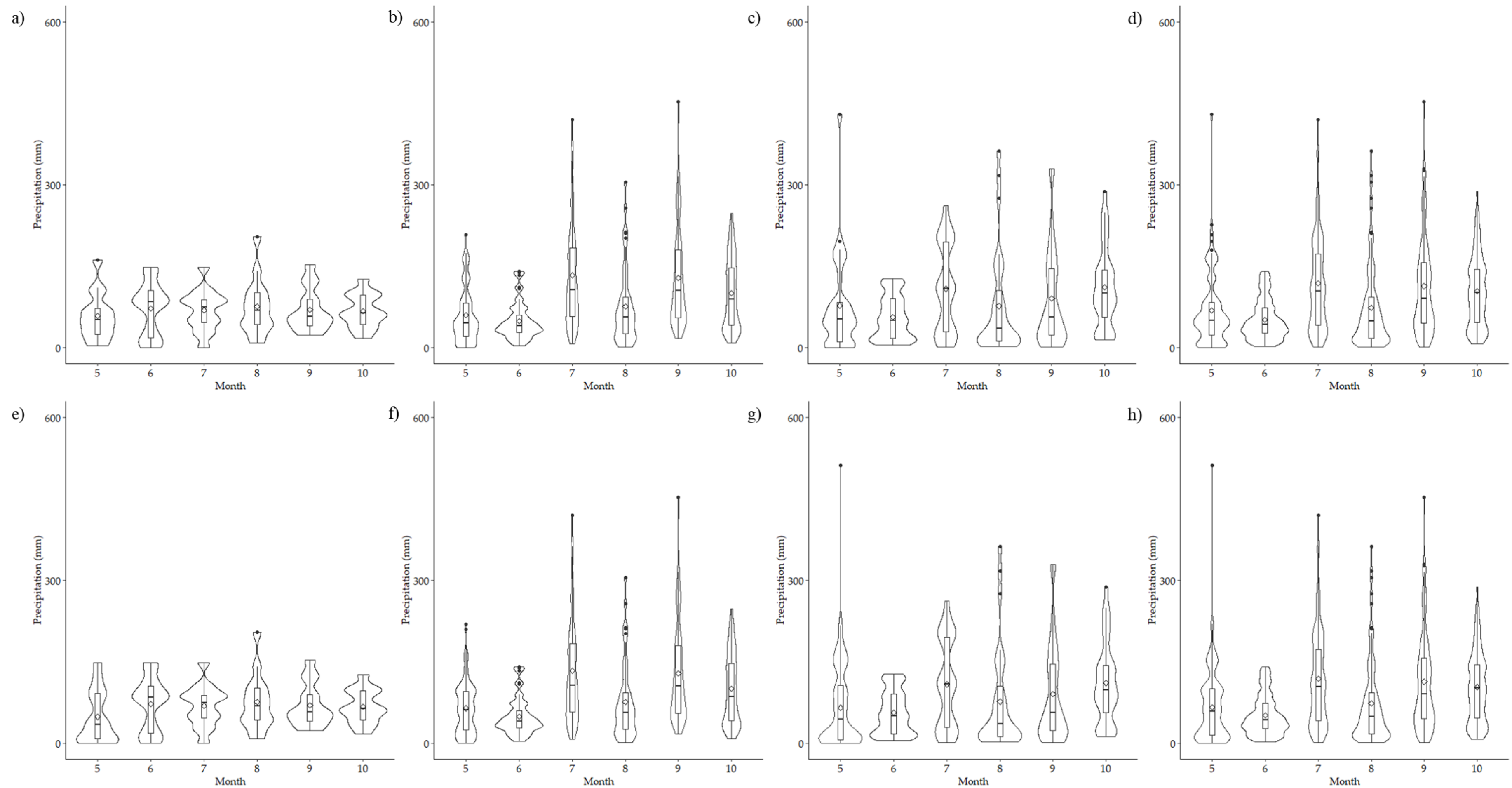

Figure A.2 Precipitation distribution for BCC-CSM1.1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

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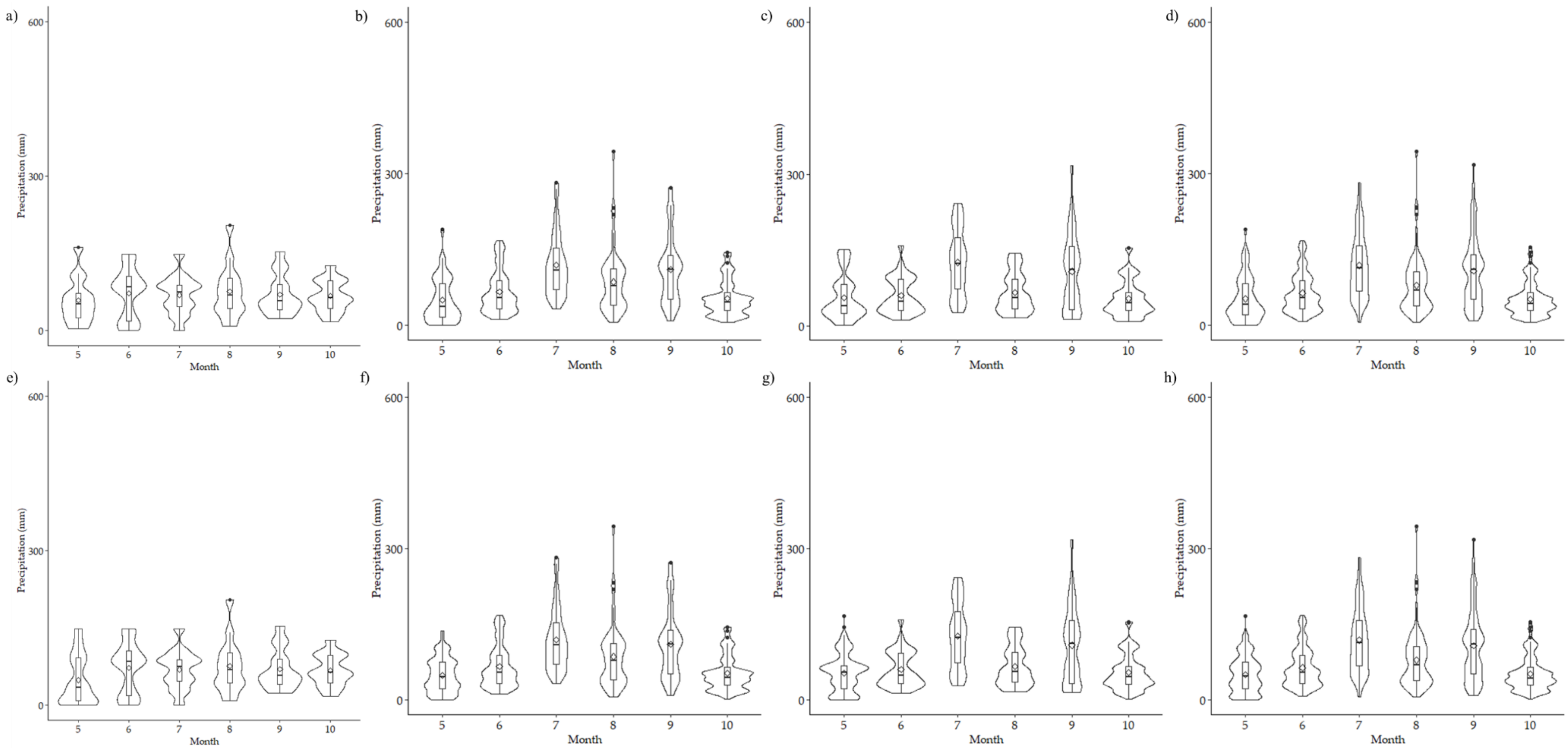


Figure A.3 Precipitation distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

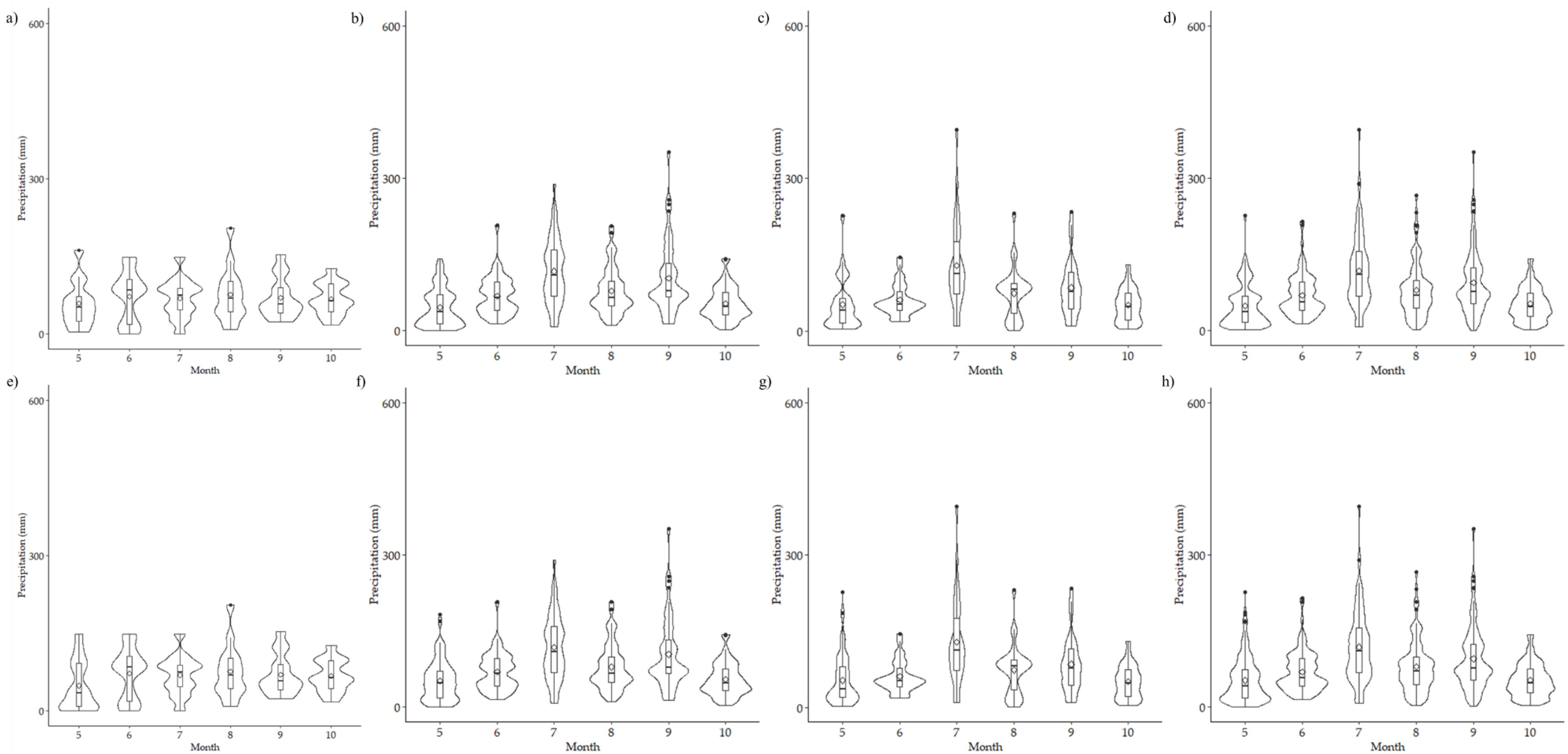


Figure A.4 Precipitation distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

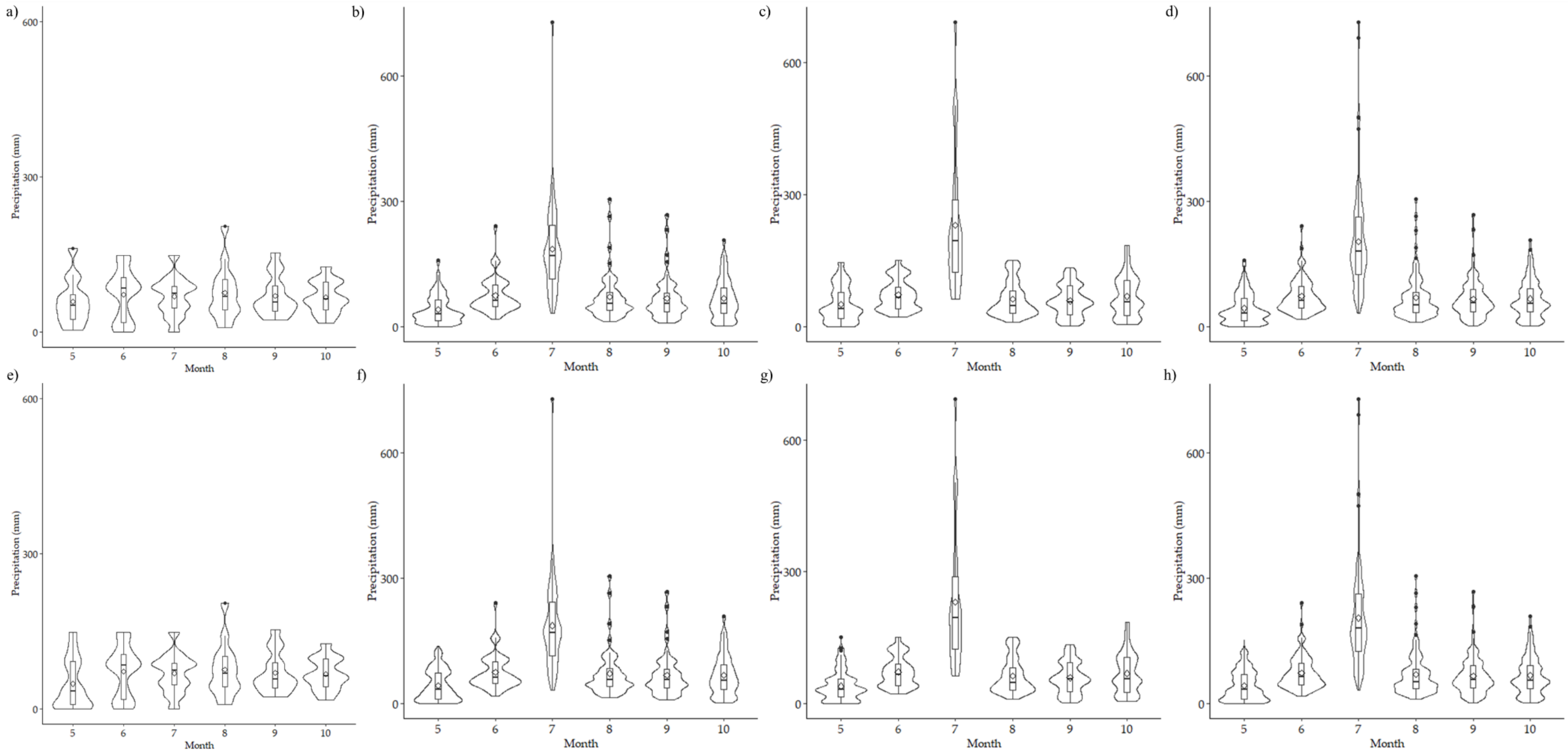


Figure A.5 Precipitation distribution for NorESM1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

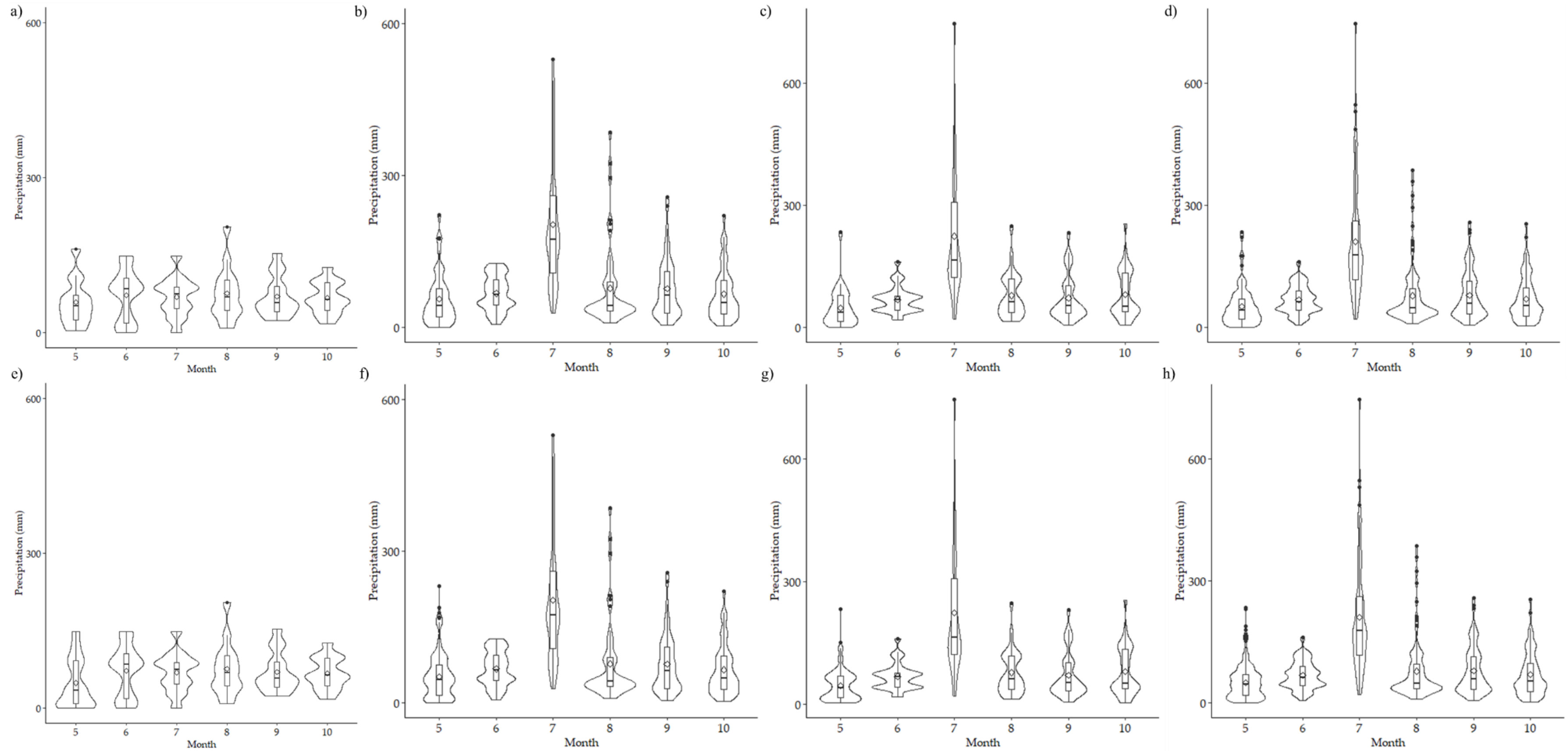


Figure A.6 Precipitation distribution for NorESM1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

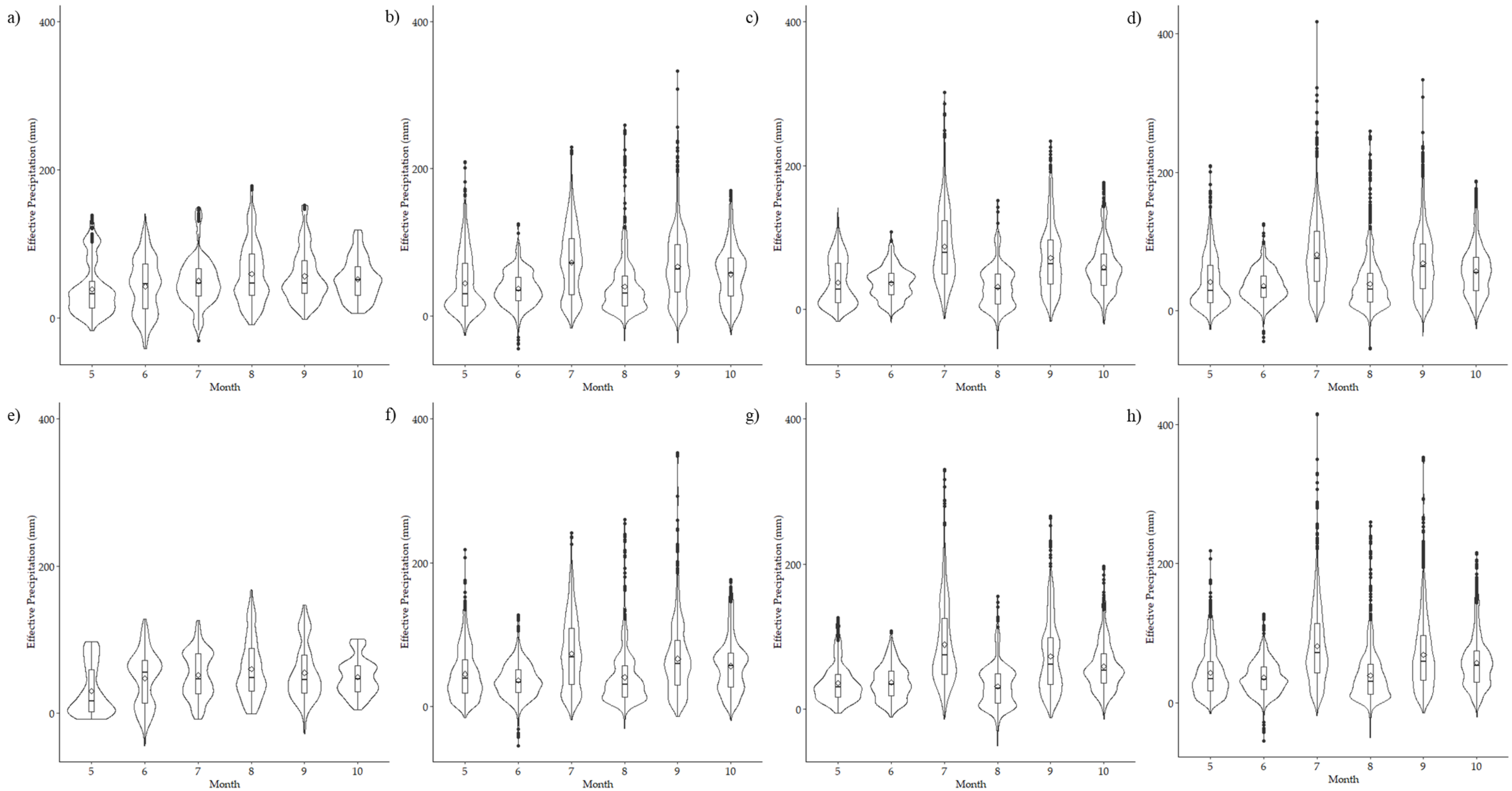


Figure A.7 Effective precipitation distribution for BCC-CSM1.1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

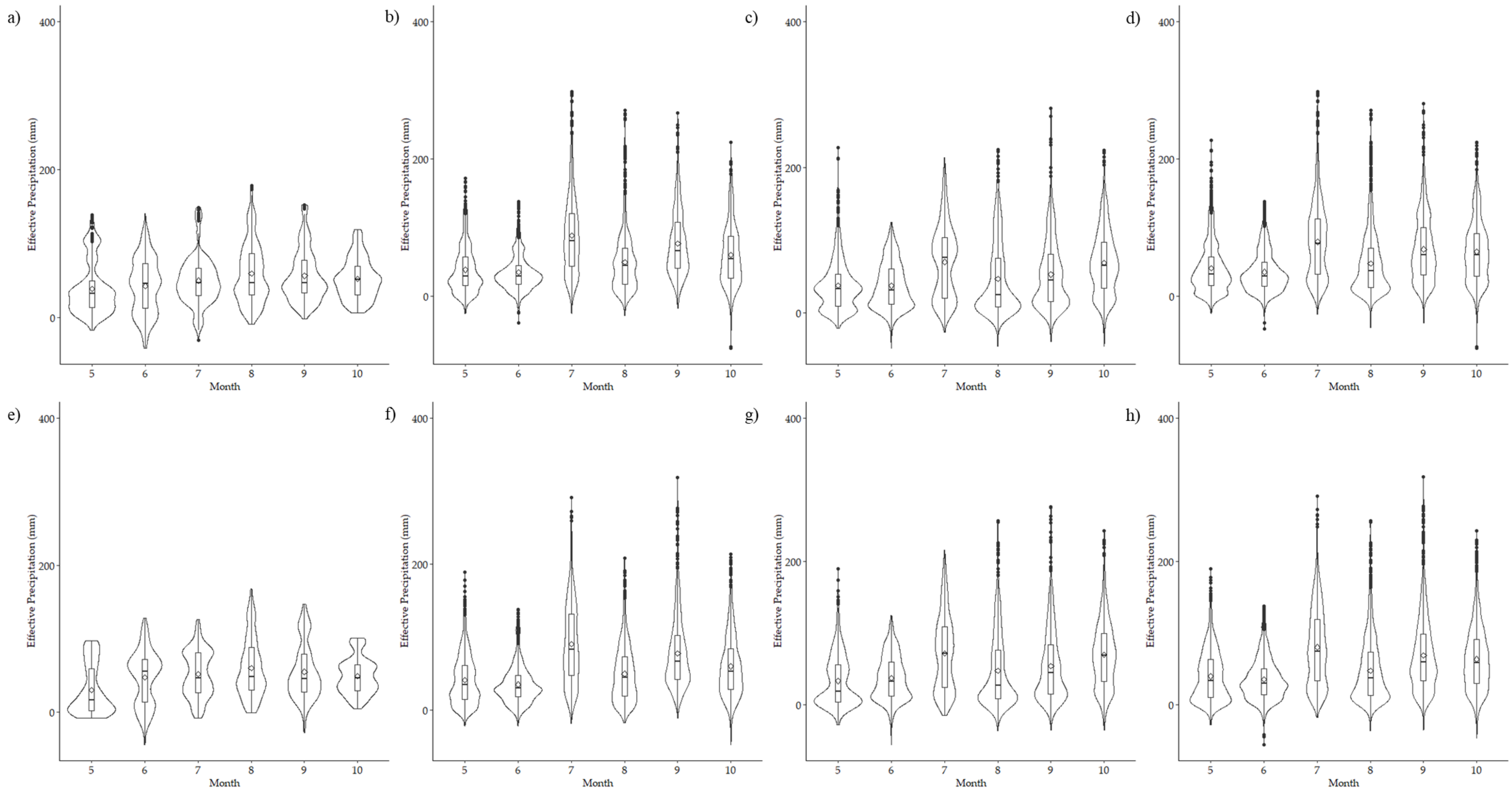


Figure A.8 Effective precipitation distribution for BCC-CSM1.1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

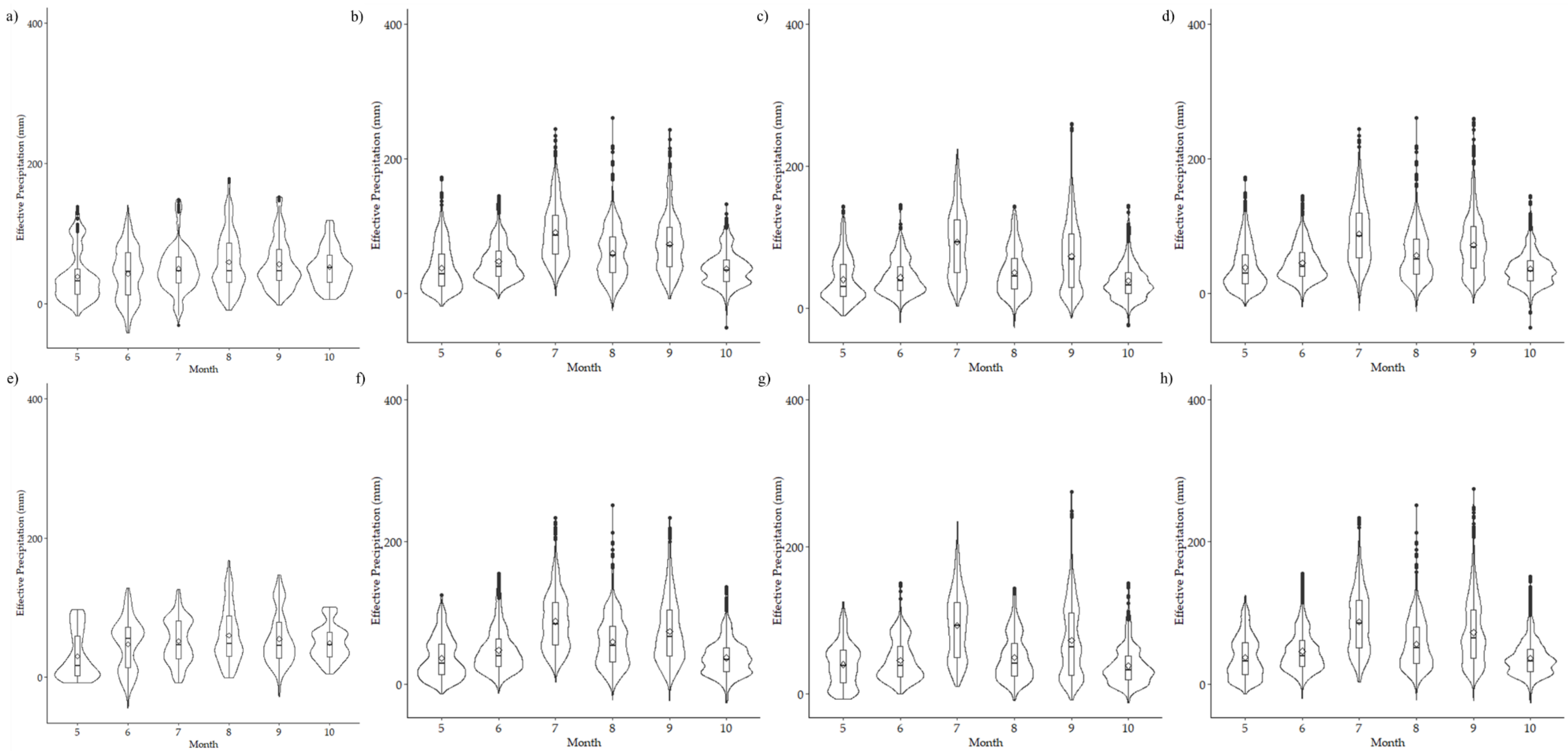


Figure A.9 Effective precipitation distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

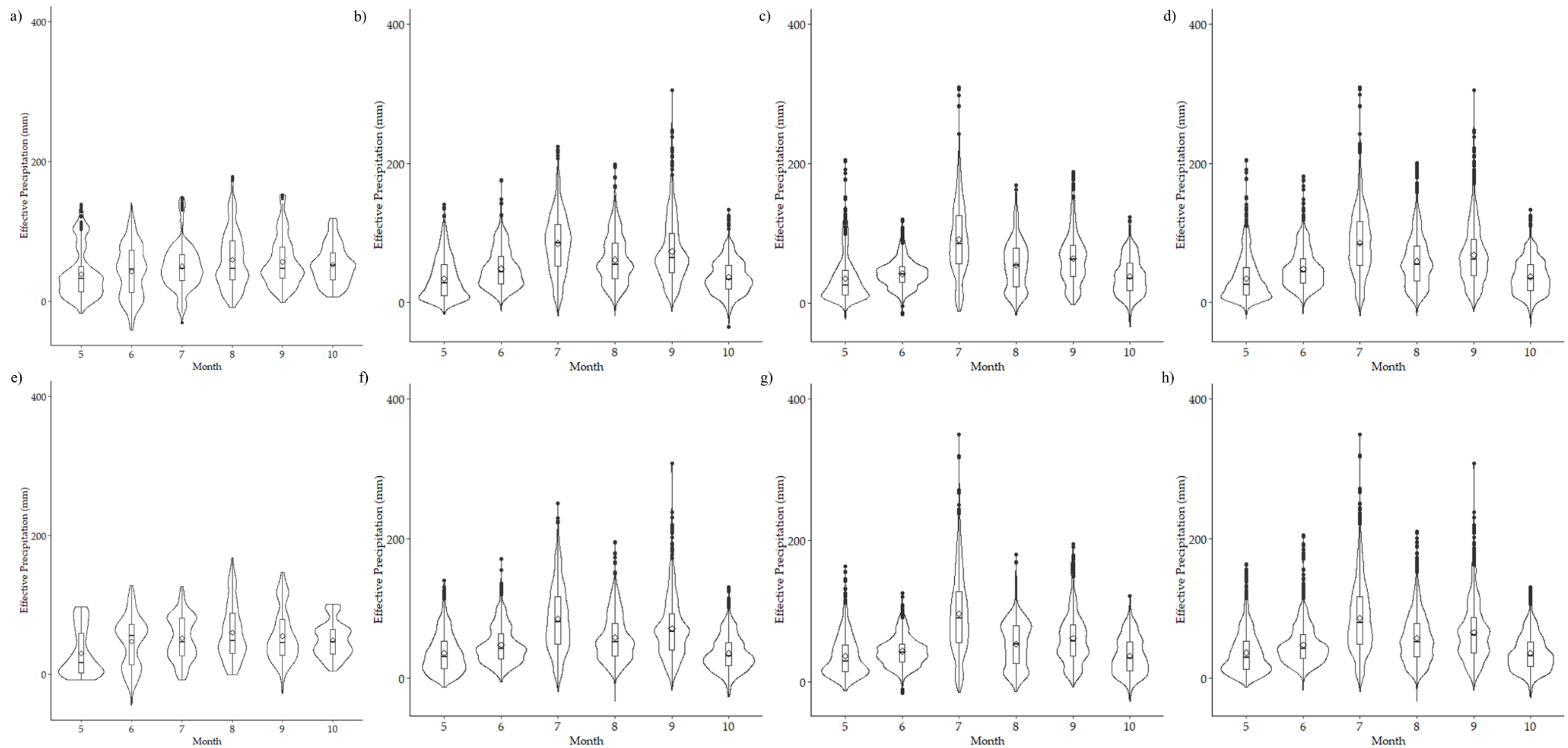


Figure A.10 Effective precipitation distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

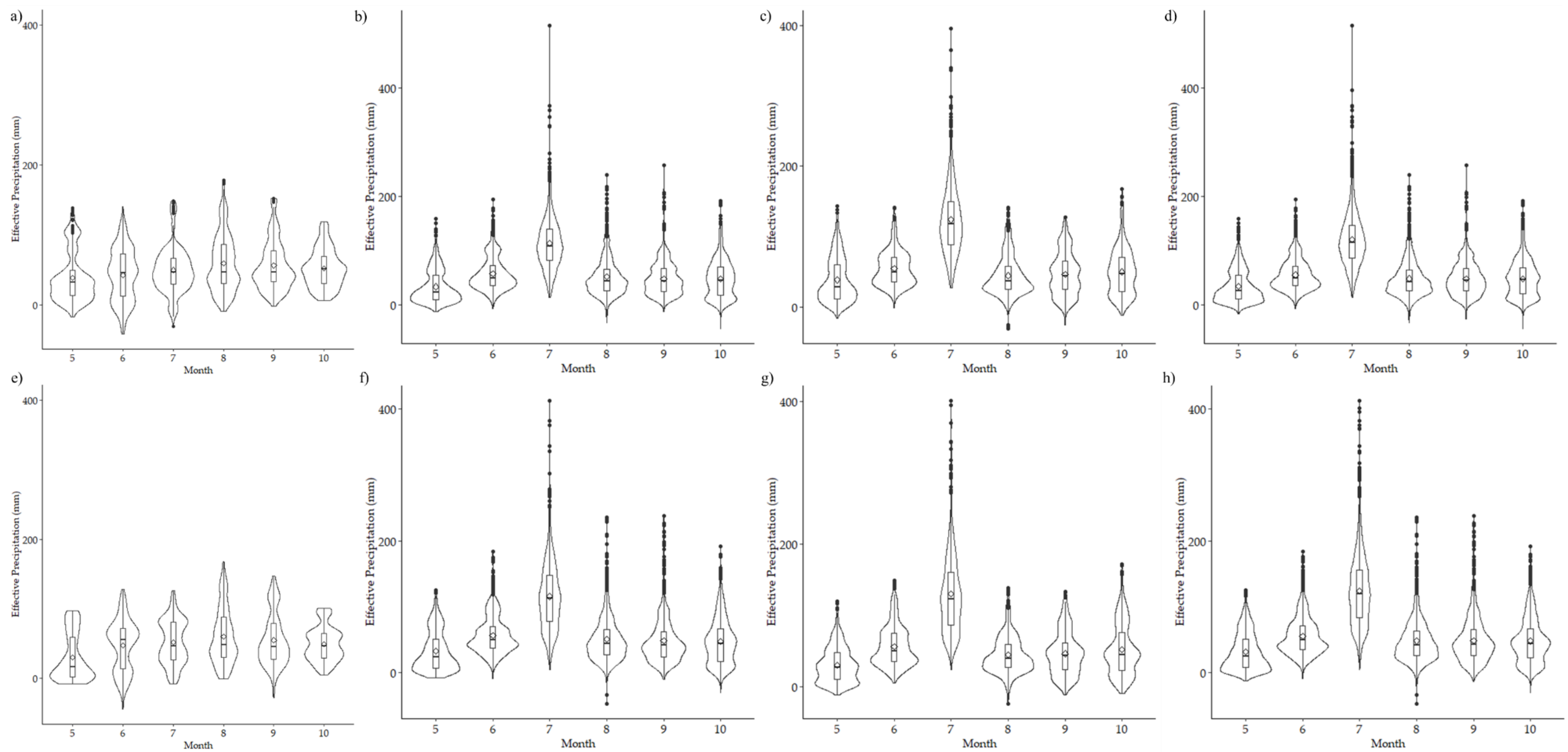


Figure A.11 Effective precipitation distribution for NorESM1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

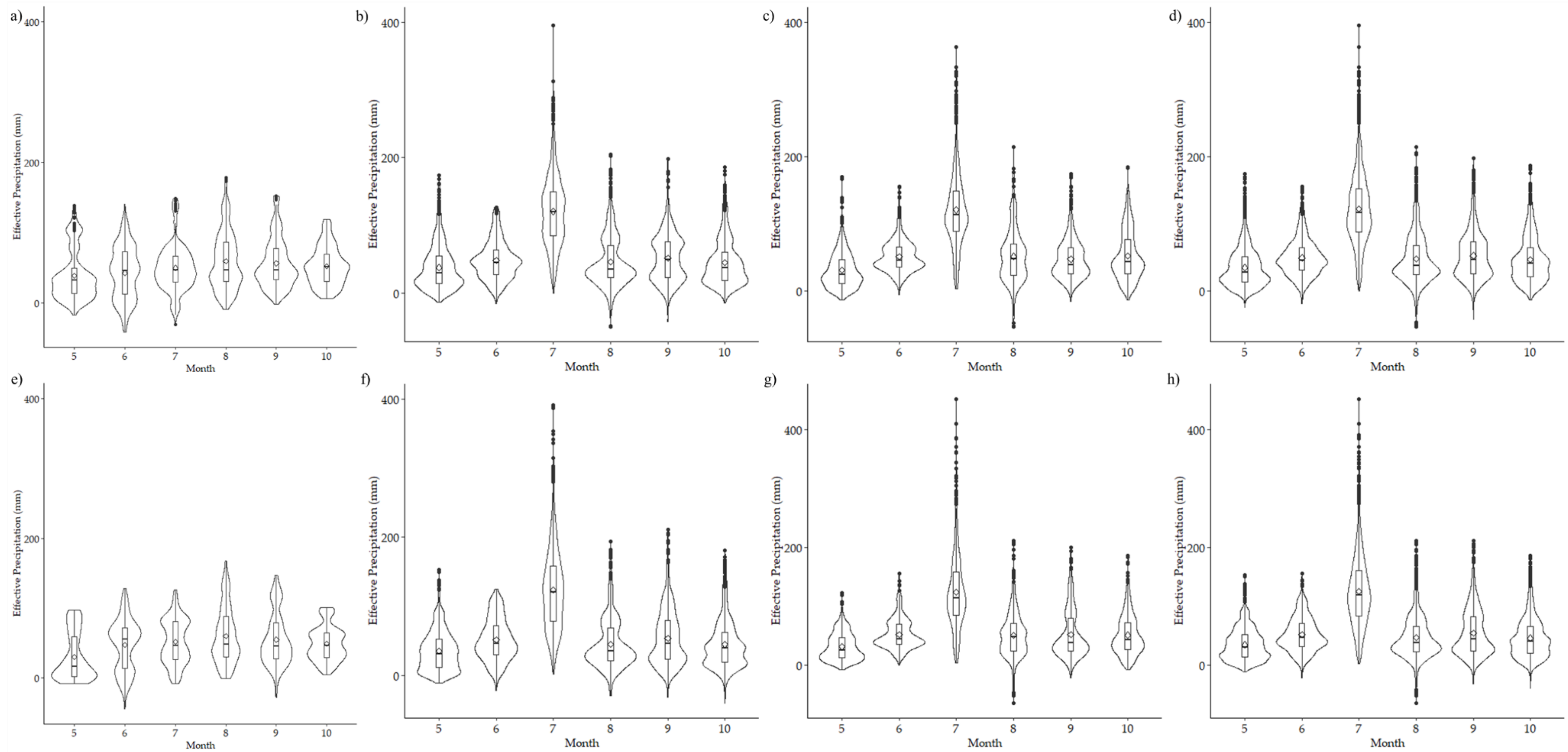


Figure A.12 Effective precipitation distribution for NorESM1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

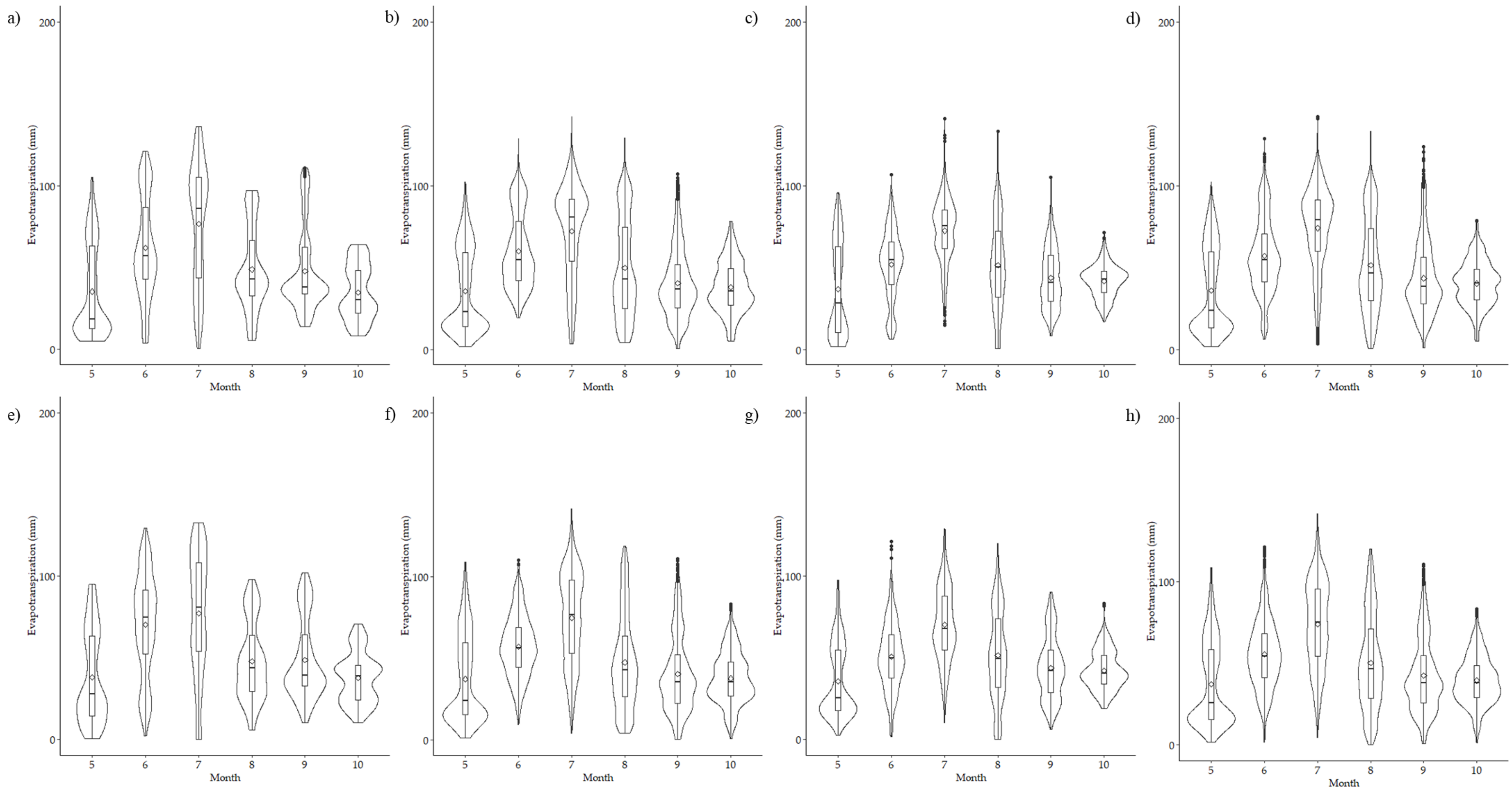


Figure A.13 Evapotranspiration distribution for BCC-CSM1.1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099)

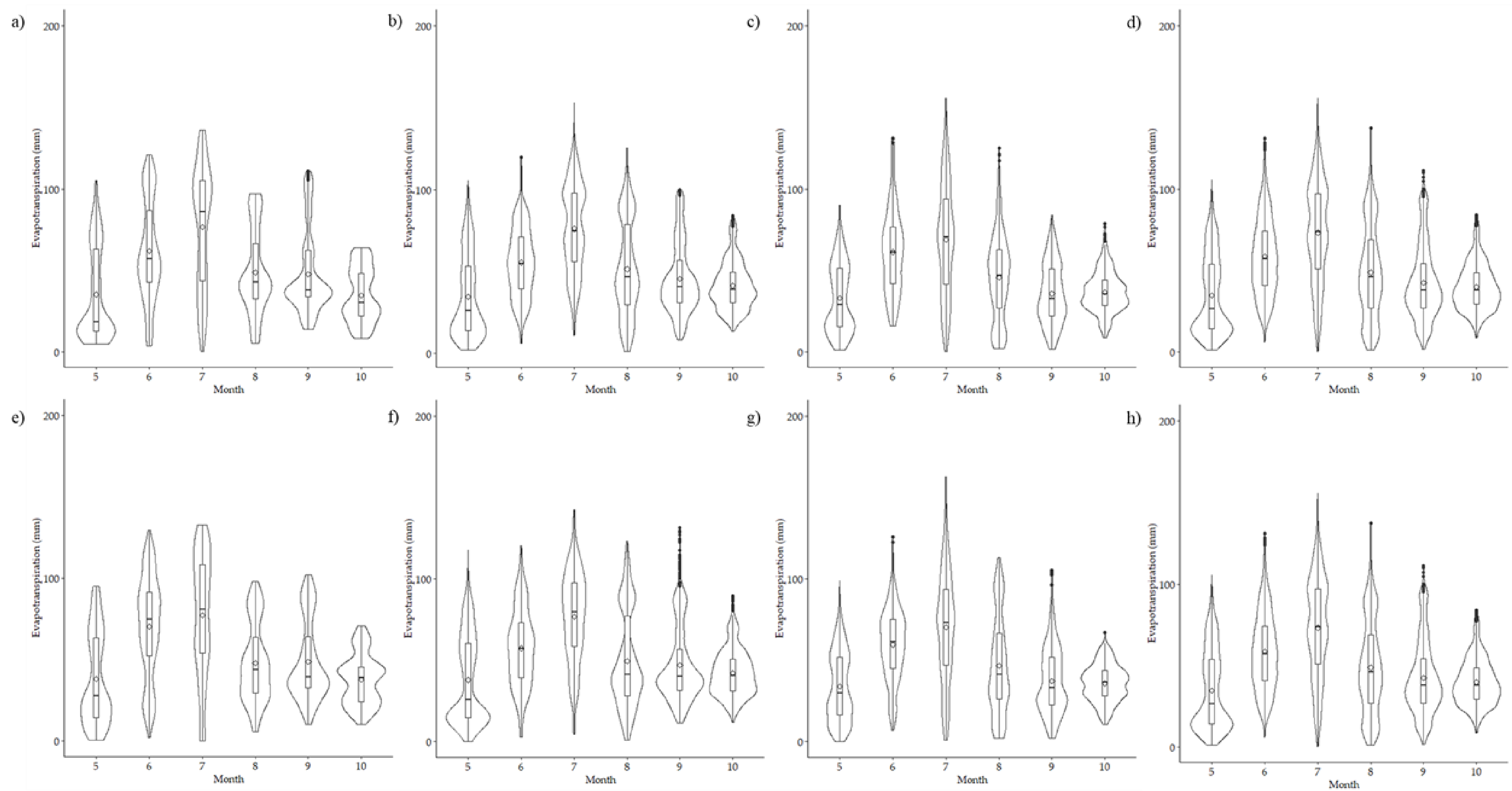


Figure A.14 Evapotranspiration distribution for BCC-CSM1.1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

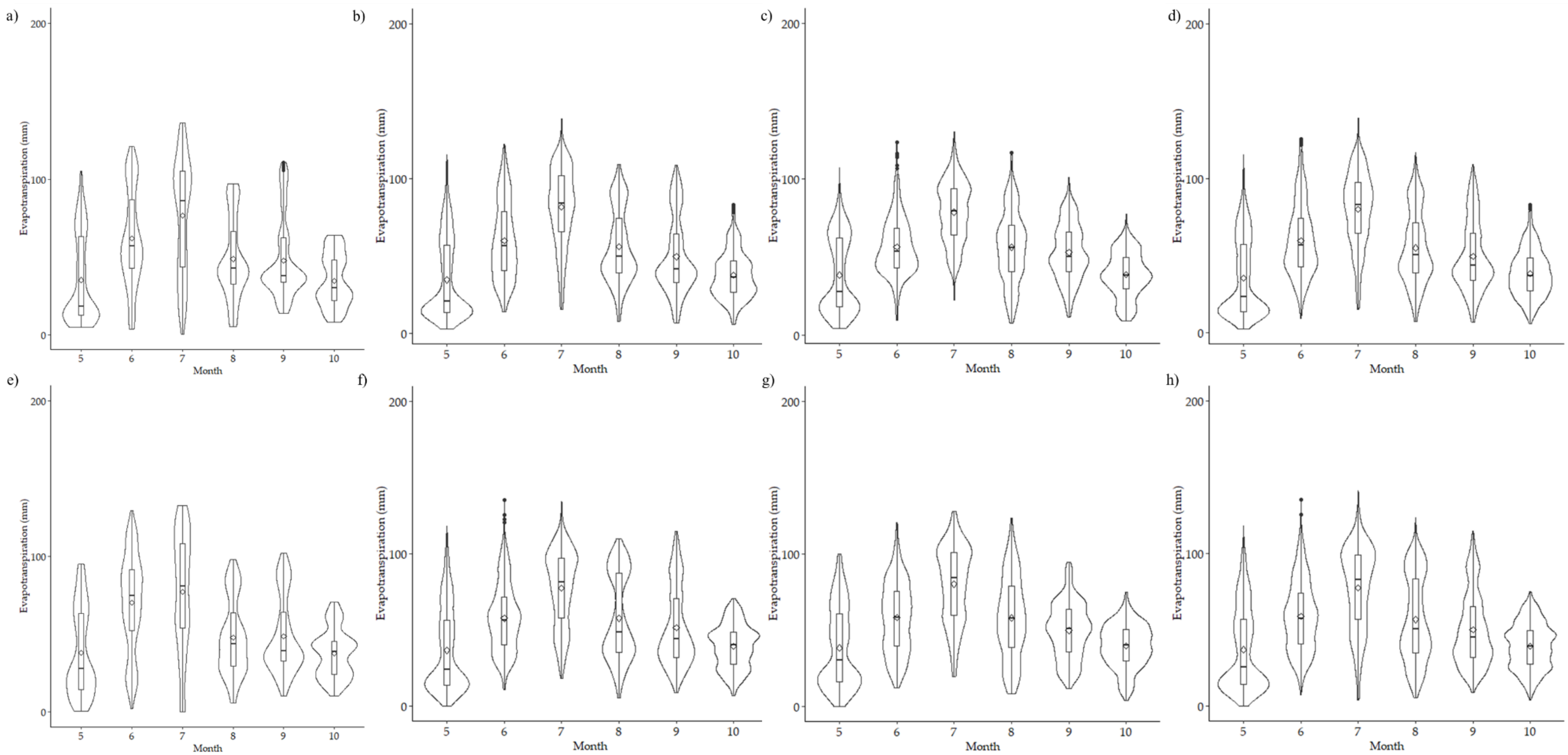


Figure A.15 Evapotranspiration distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

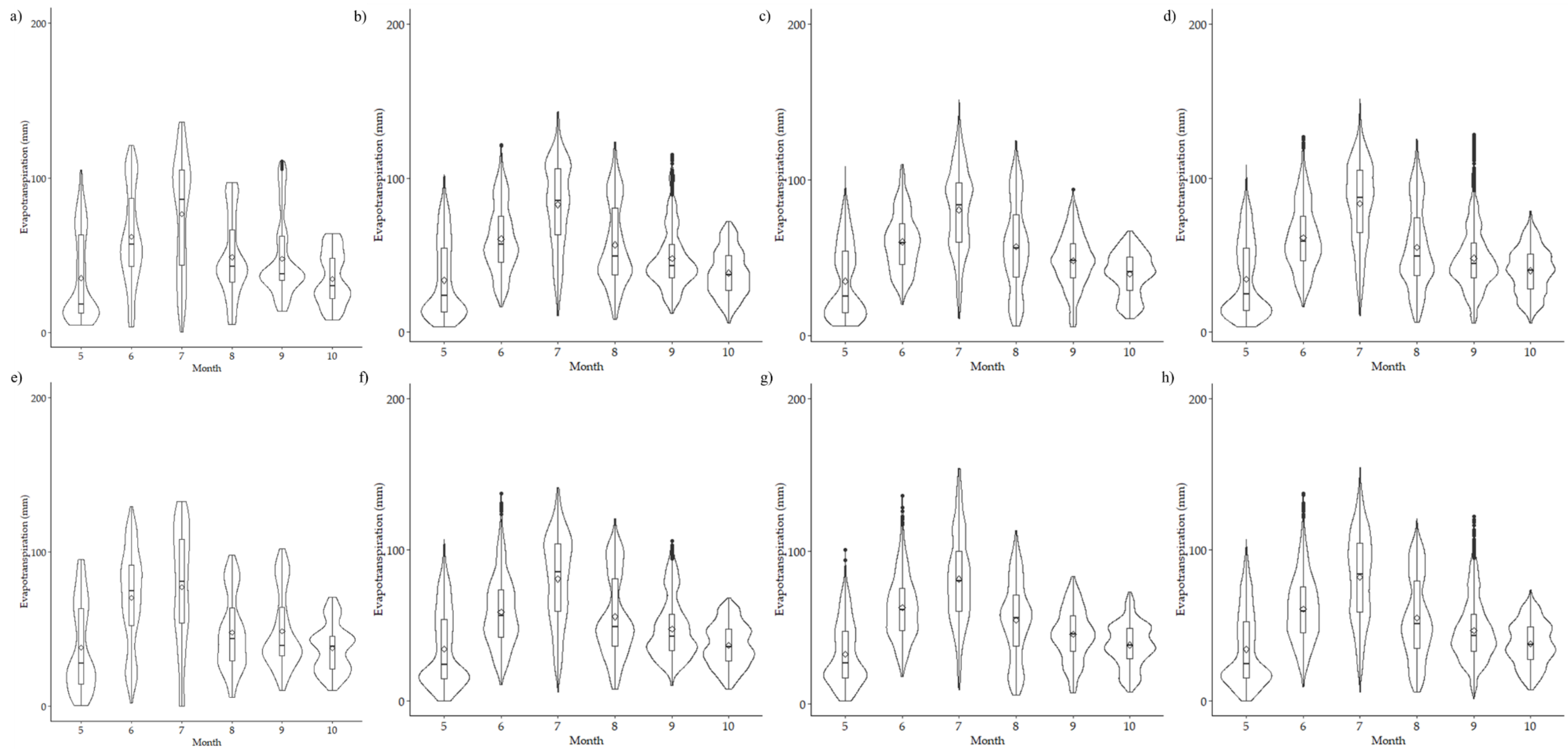


Figure A.16 Evapotranspiration distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

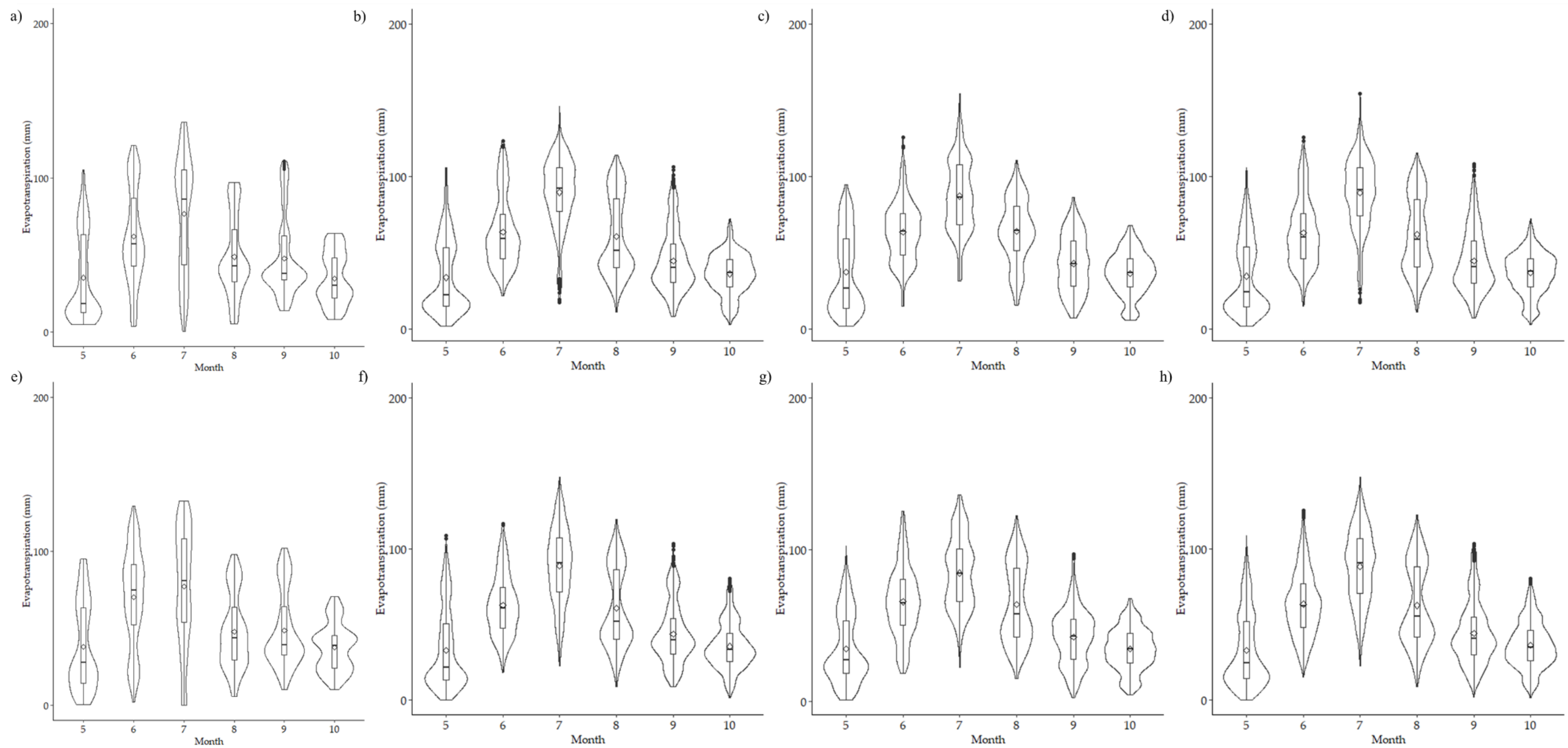


Figure A.17 Evapotranspiration distribution for NorESM1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

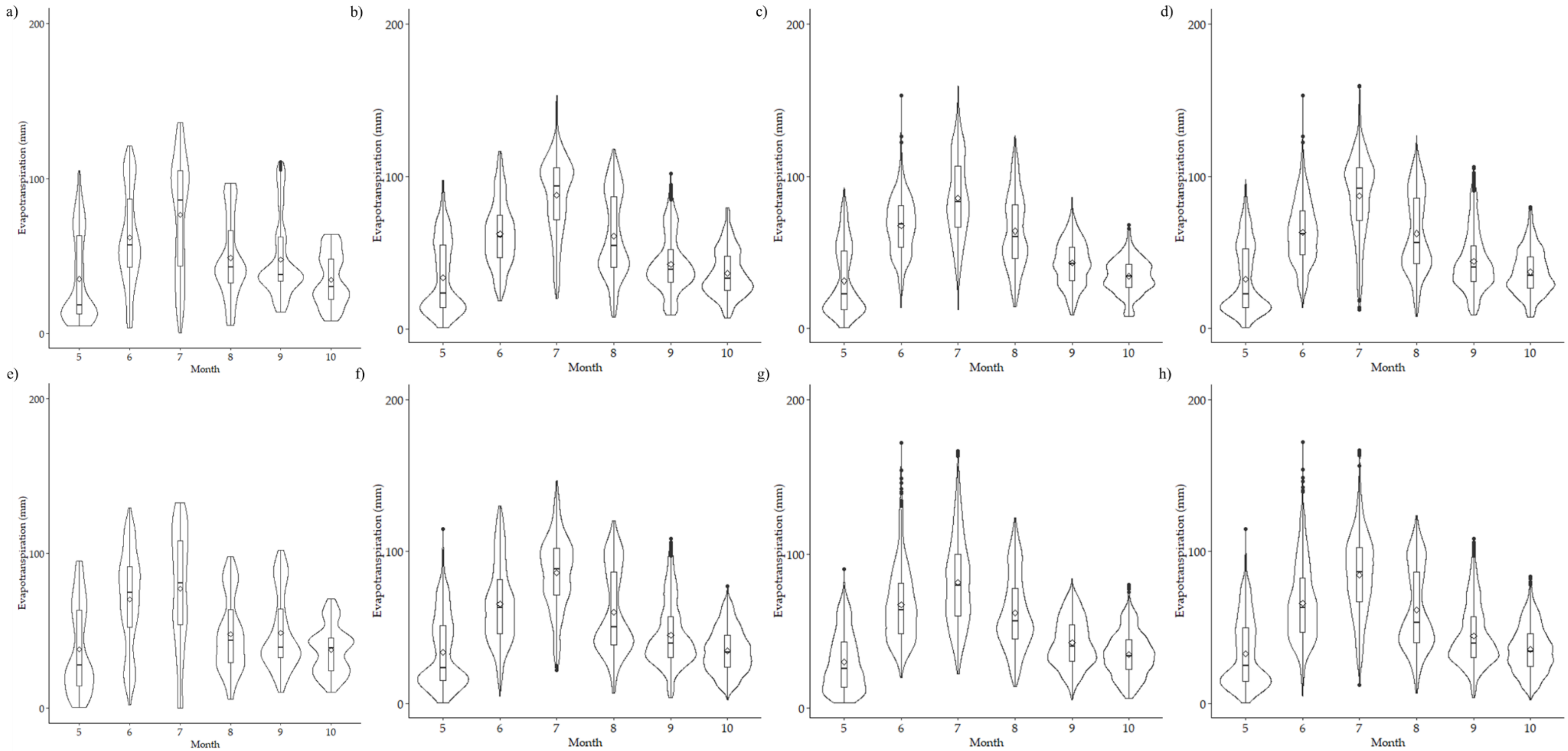


Figure A.18 Evapotranspiration distribution for NorESM1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

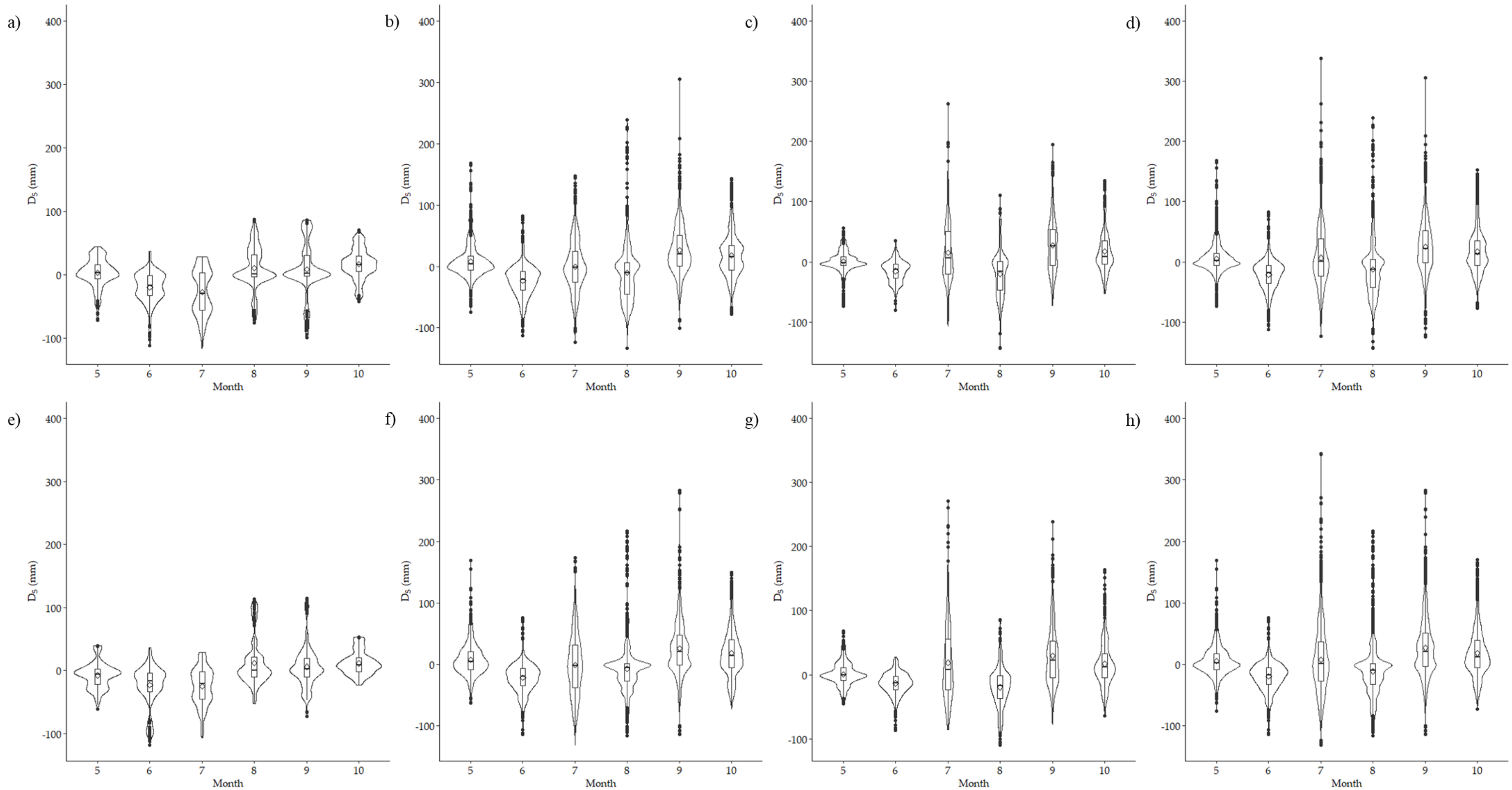


Figure A.19 D_S distribution for BCC-CSM RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

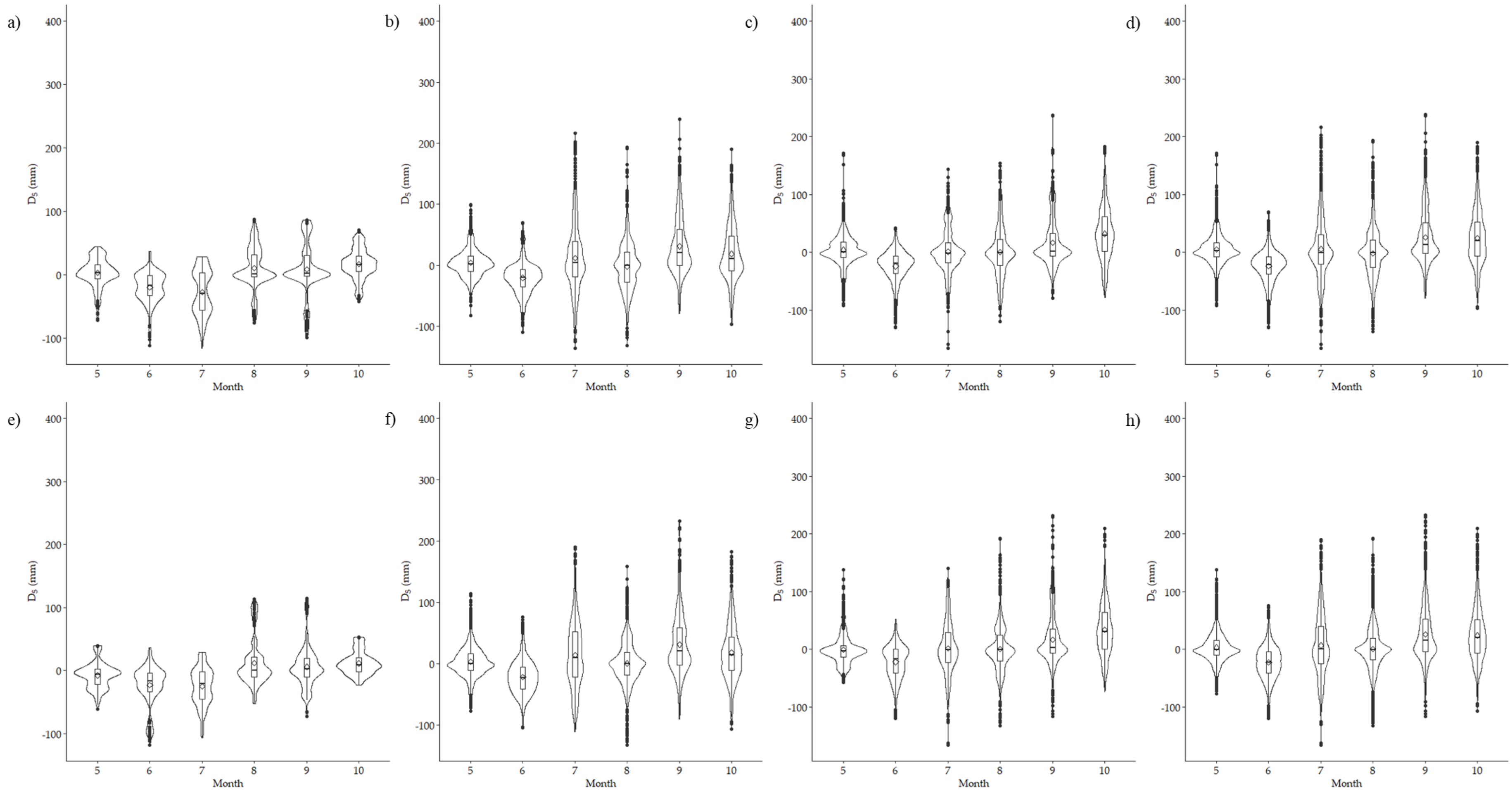


Figure A.20 D_S distribution for BCC-CSM RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

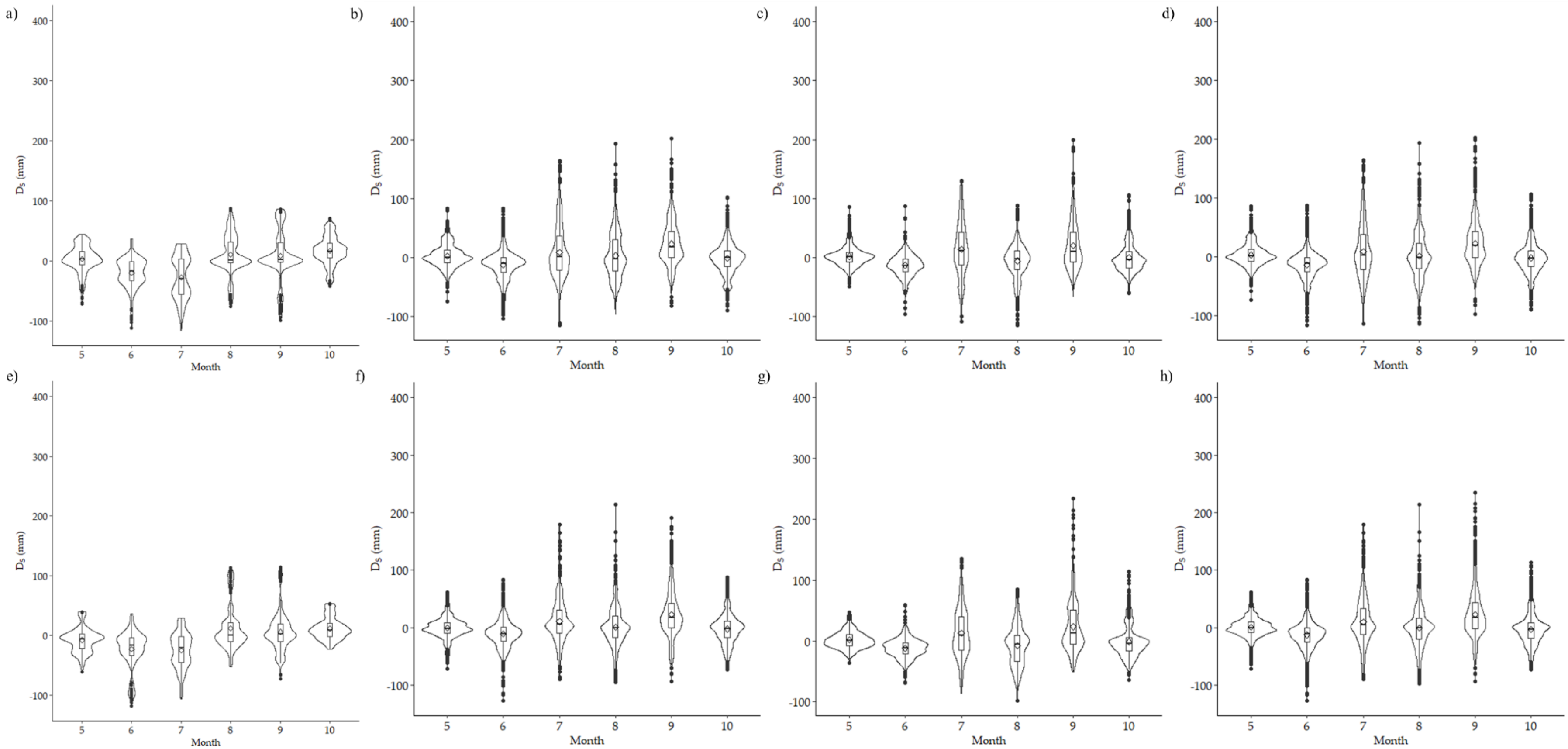


Figure A.21 D_S distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

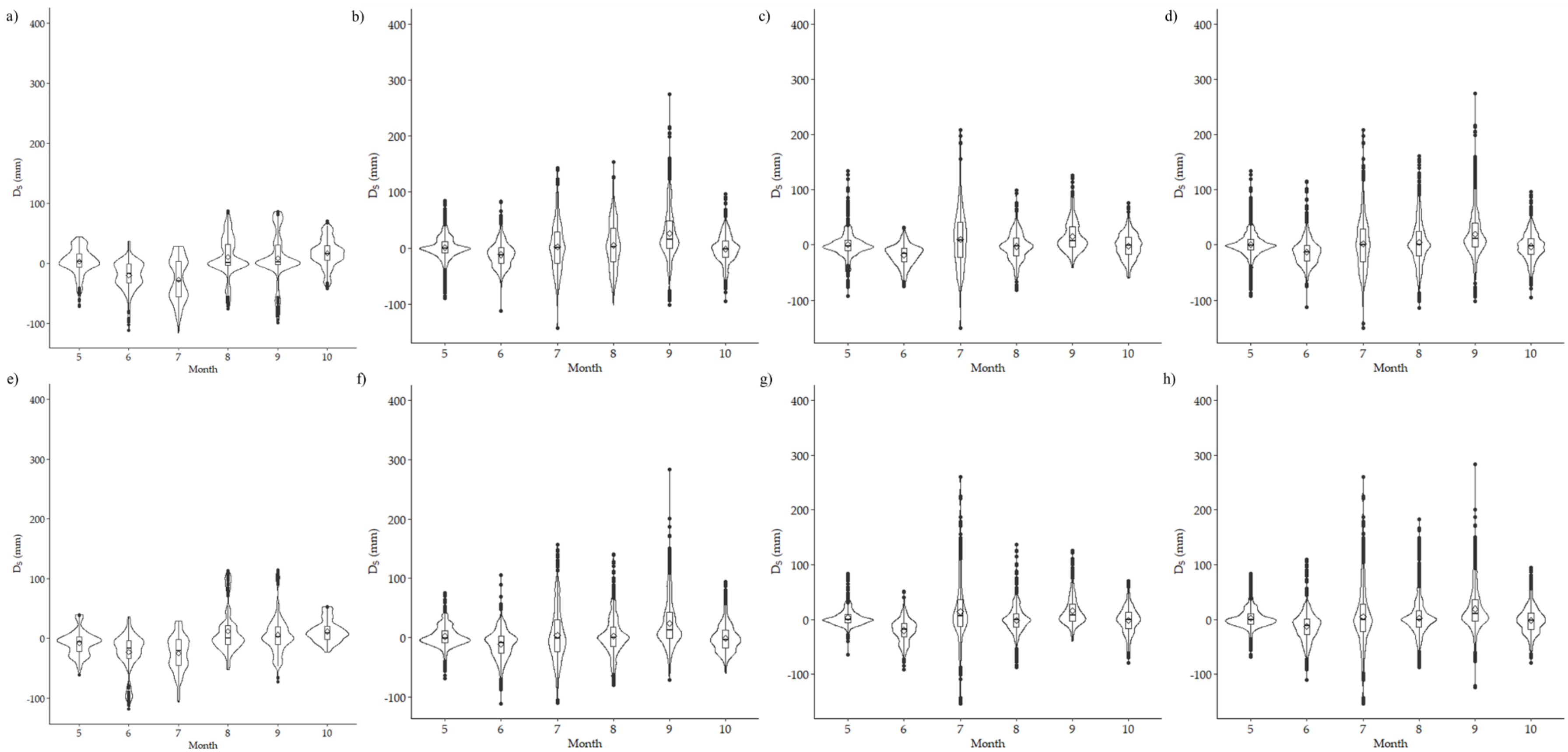


Figure A.22 D_S distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

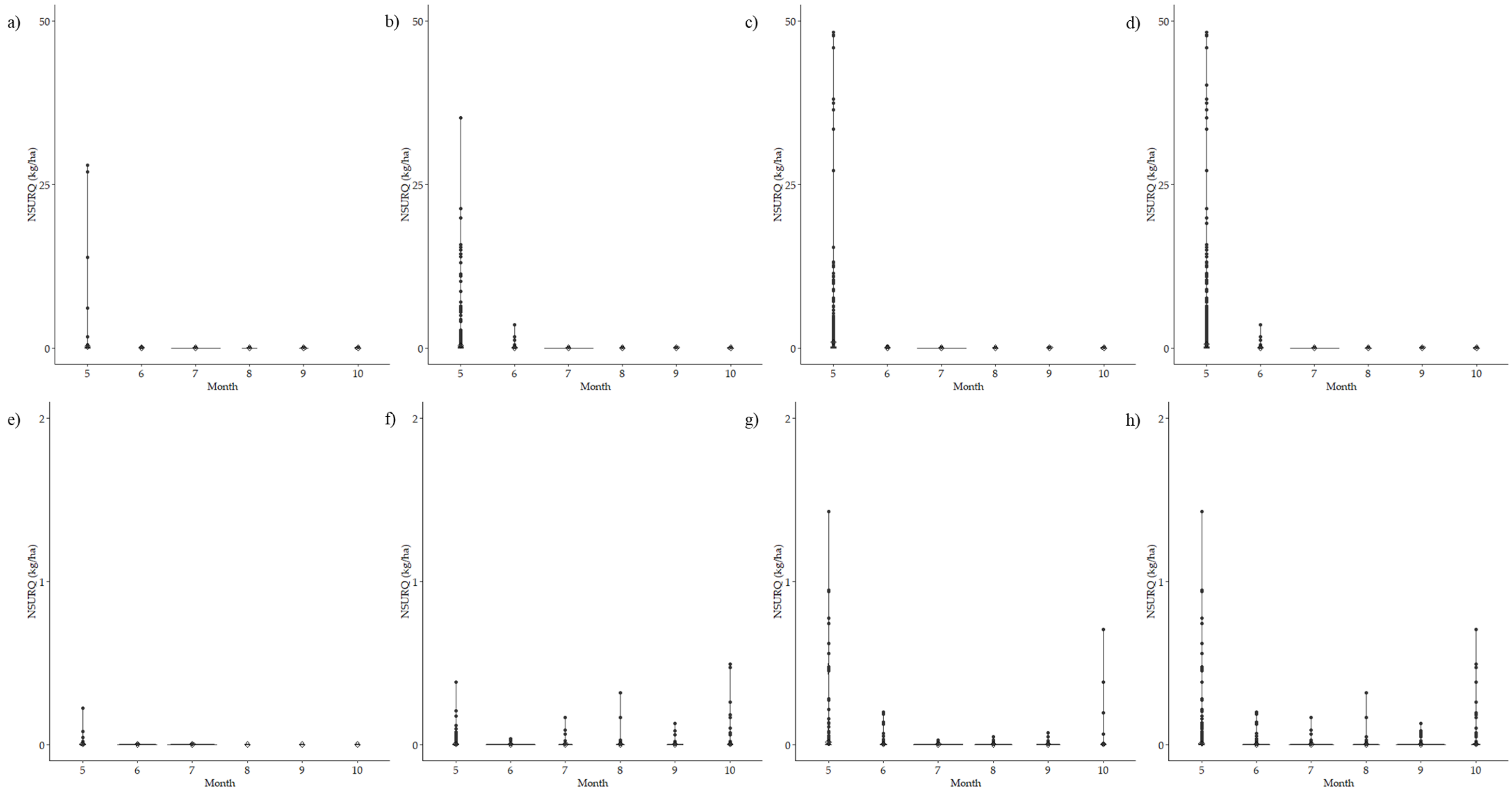


Figure A.23 Surface nitrate (NSURQ) distribution for BCC-CSM1.1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

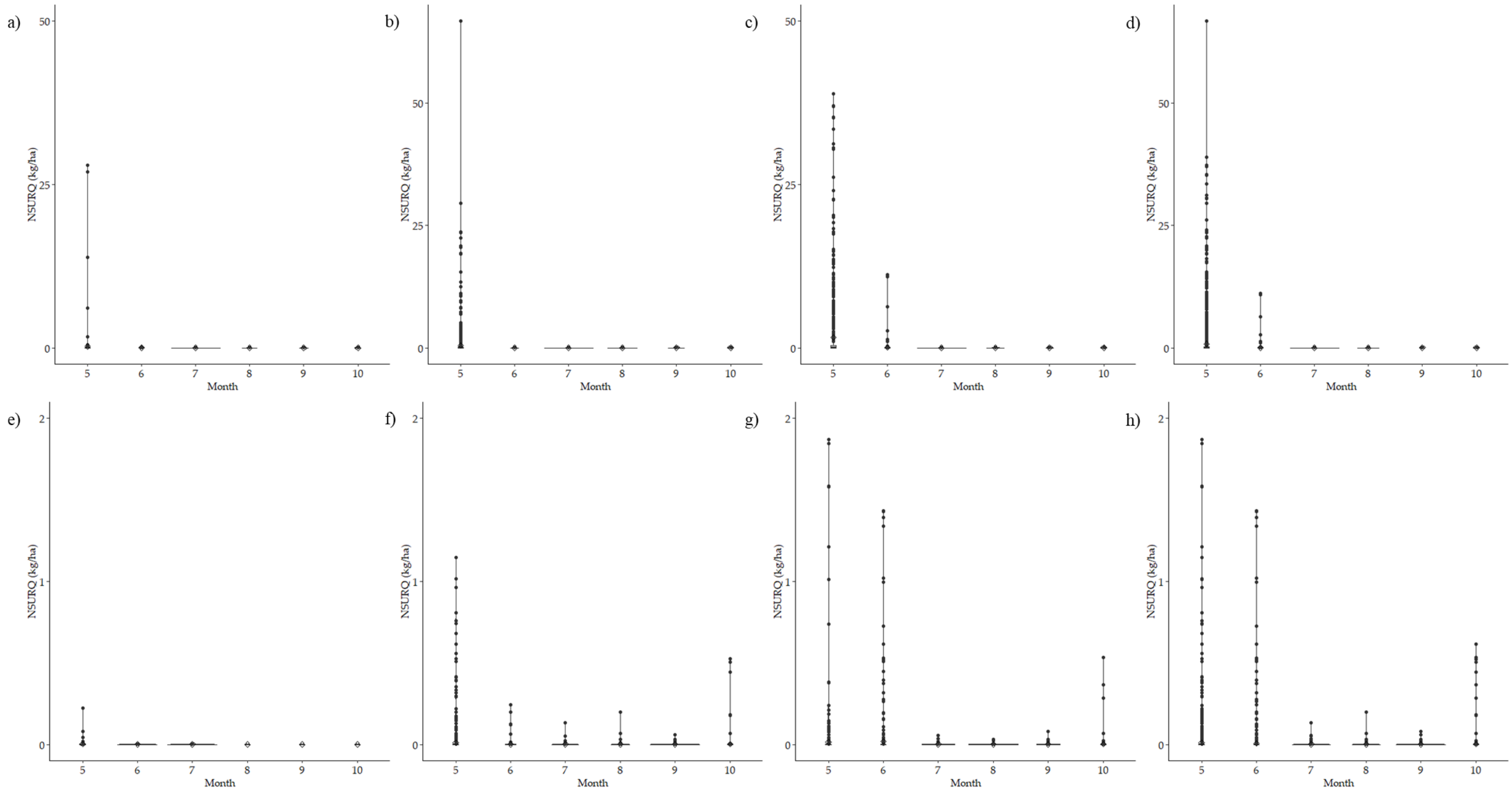


Figure A.24 Surface nitrate (NSURQ) distribution for BCC-CSM1.1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

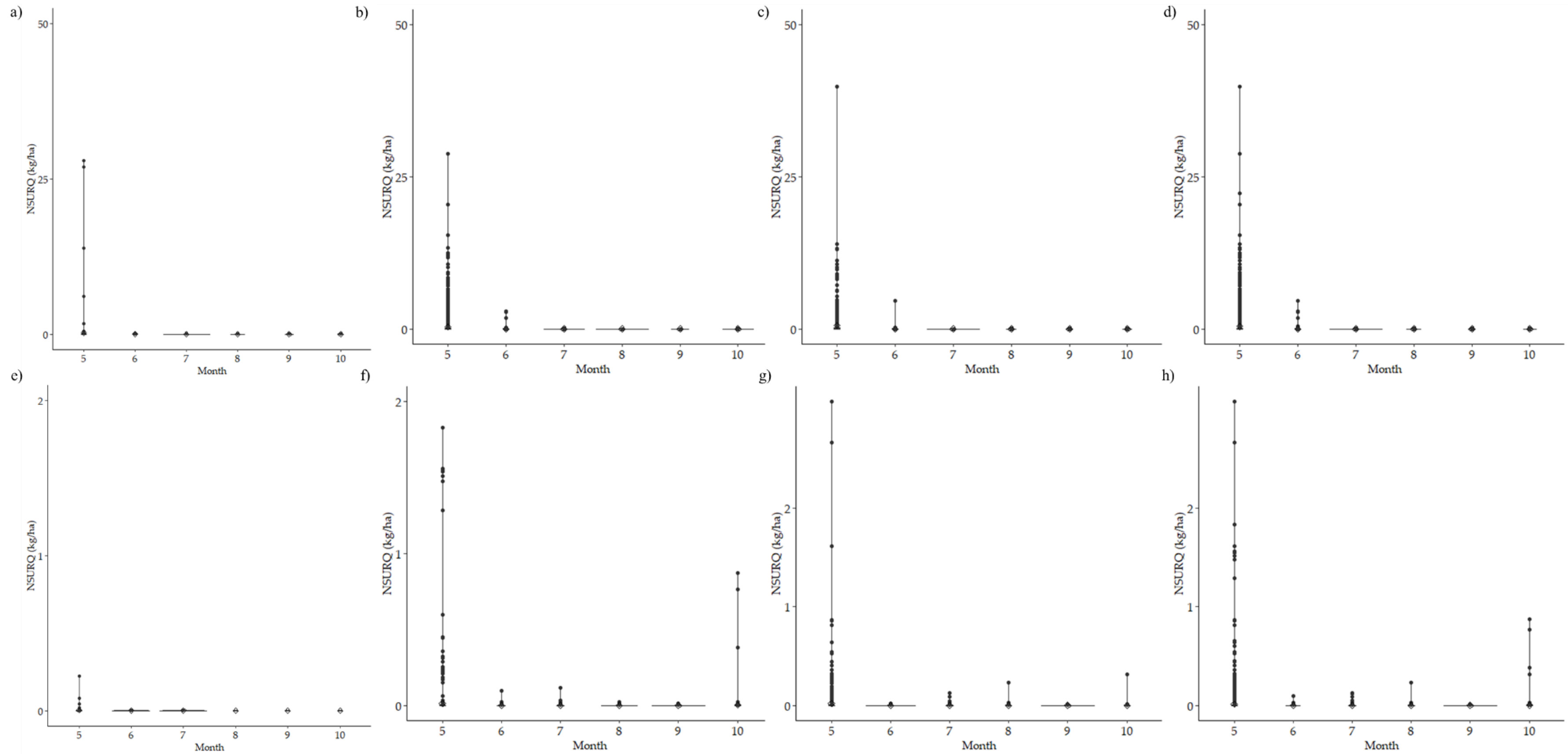


Figure A.25 Surface nitrate (NSURQ) distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

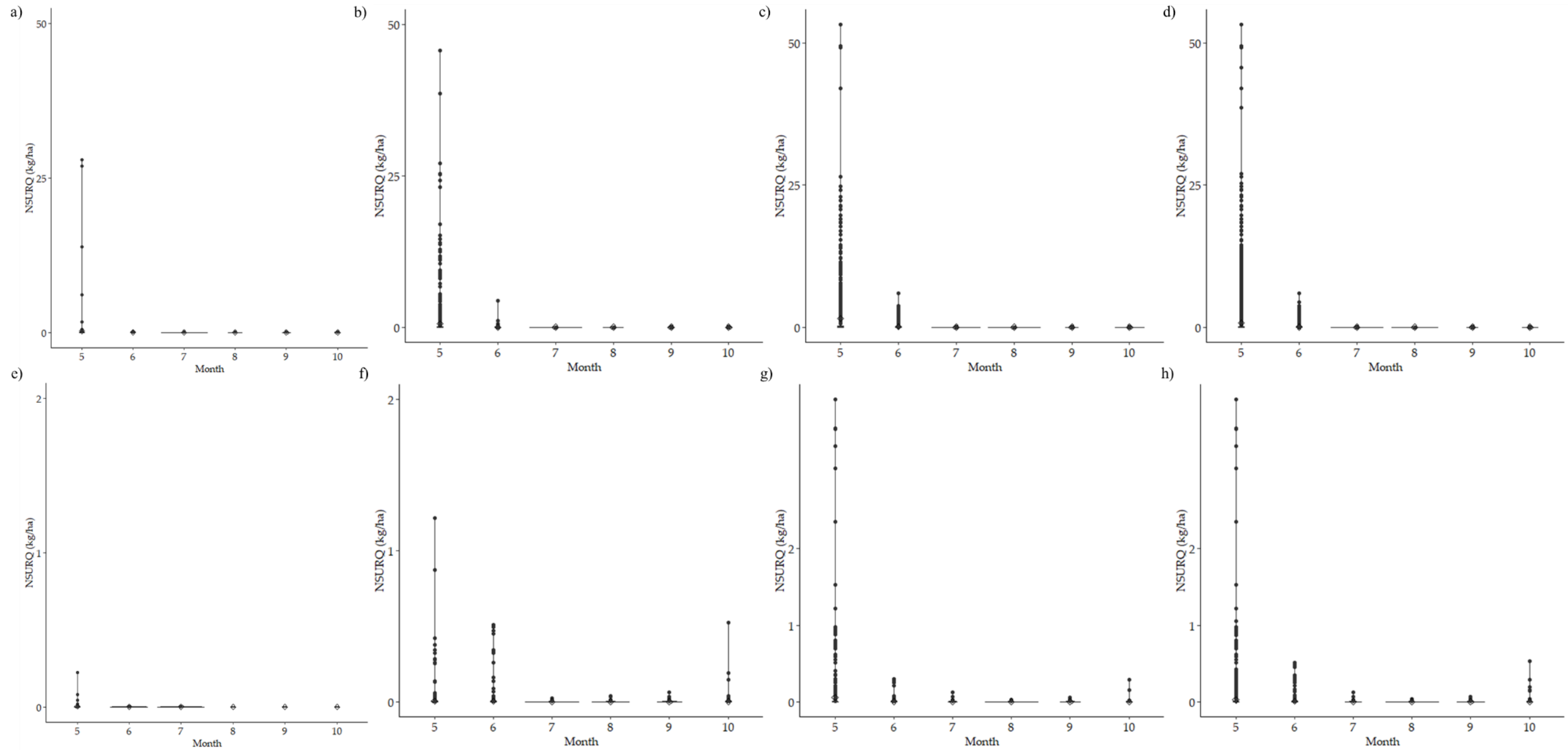


Figure A.26 Surface nitrate (NSURQ) distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

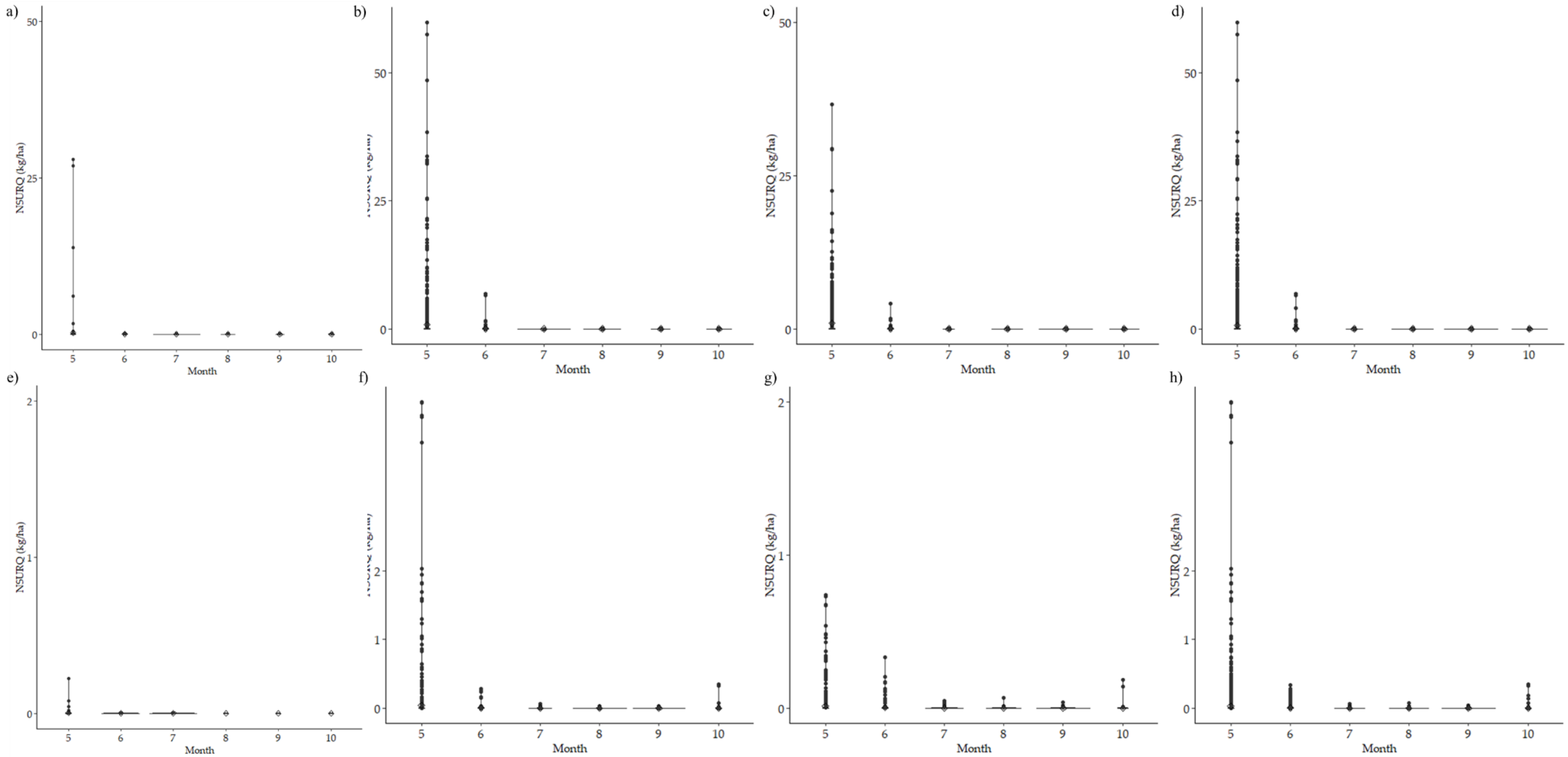


Figure A.27 Surface nitrate (NSURQ) distribution for NorESM1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

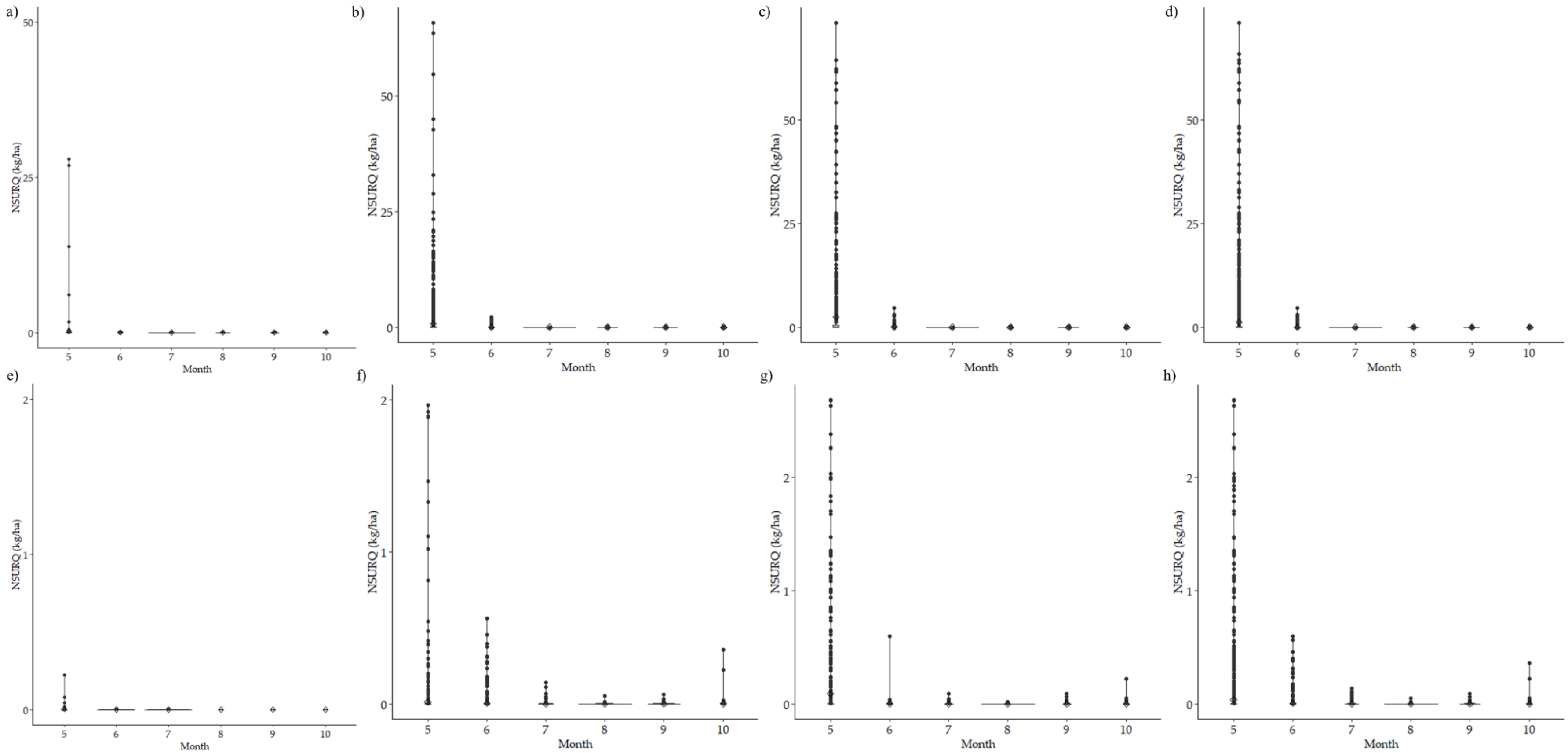


Figure A.28 Surface nitrate (NSURQ) distribution for NorESM1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

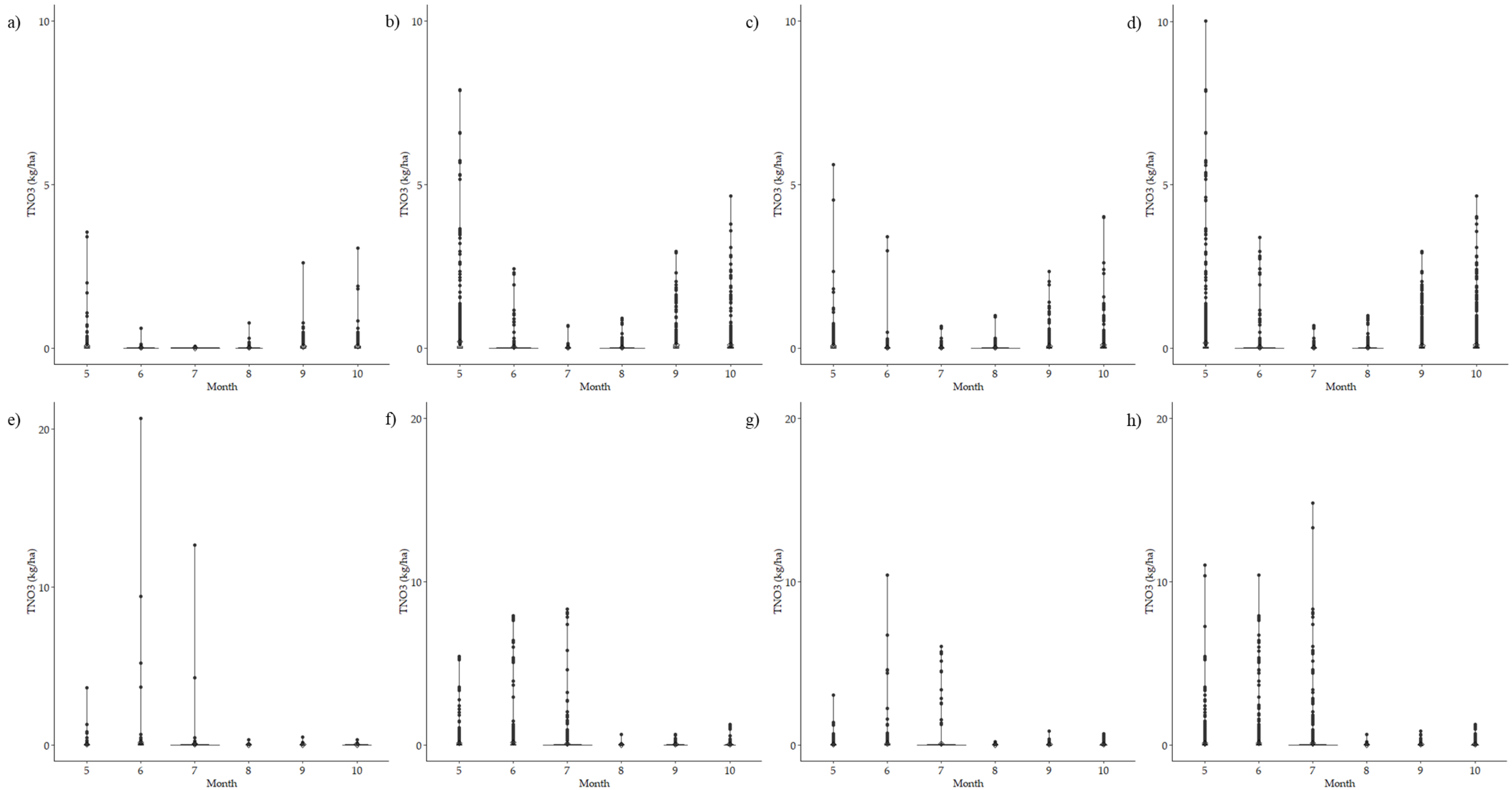


Figure A.29 Subsurface nitrate (TNO3) distribution for BCC-CSM RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

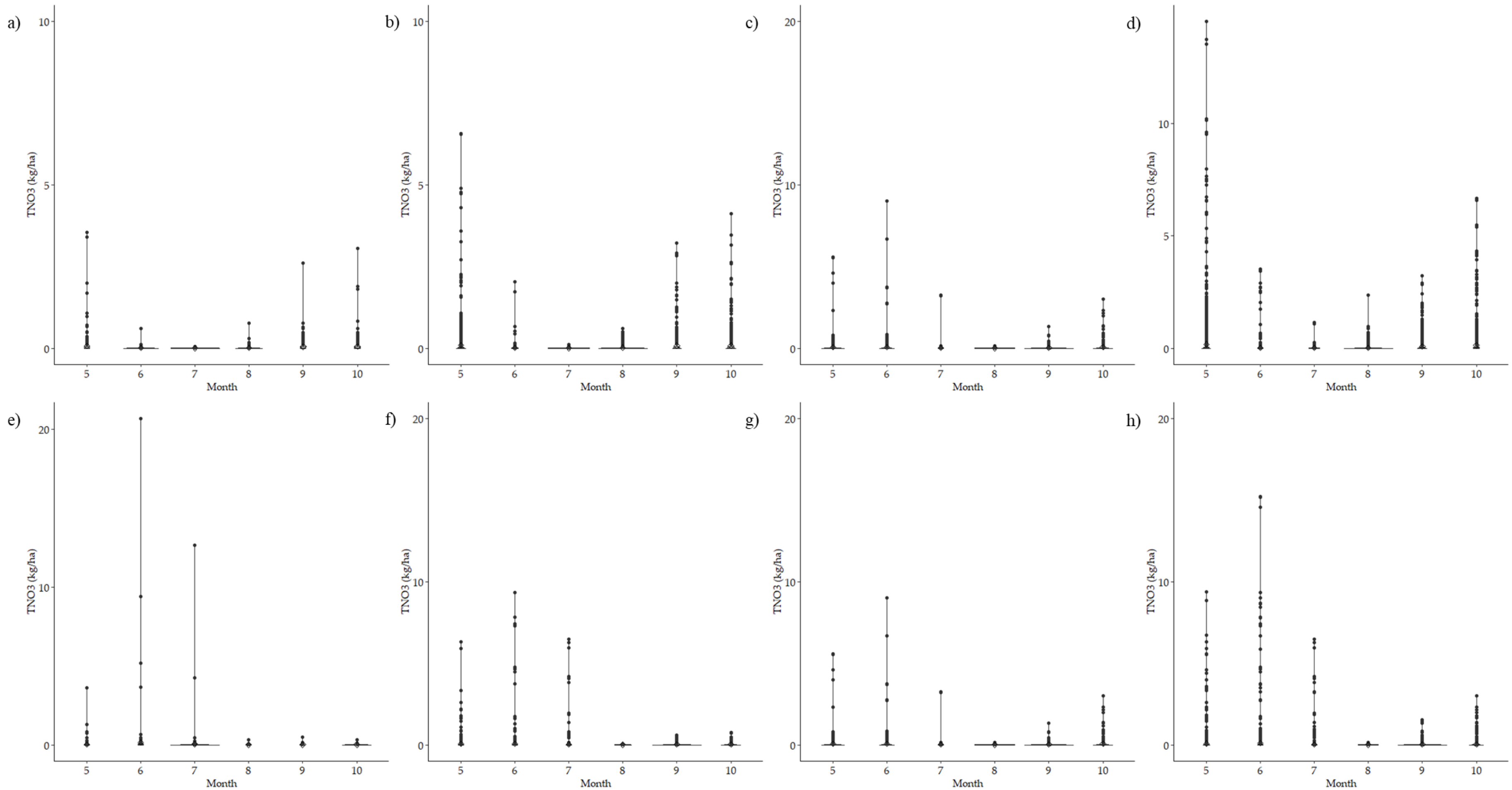


Figure A.30 Subsurface nitrate (TNO3) distribution for BCC-CSM RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

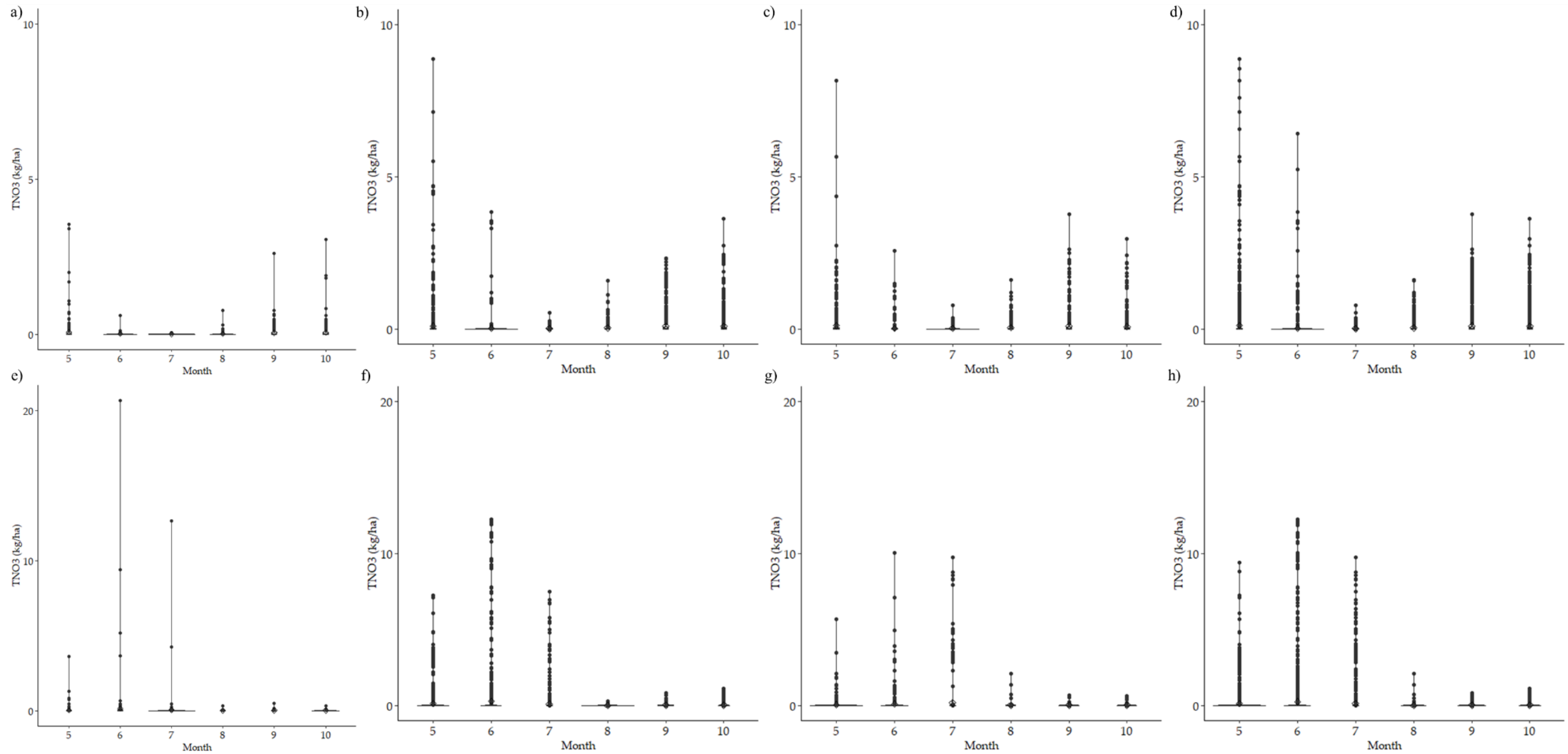


Figure A.31 Subsurface nitrate (TNO3) distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

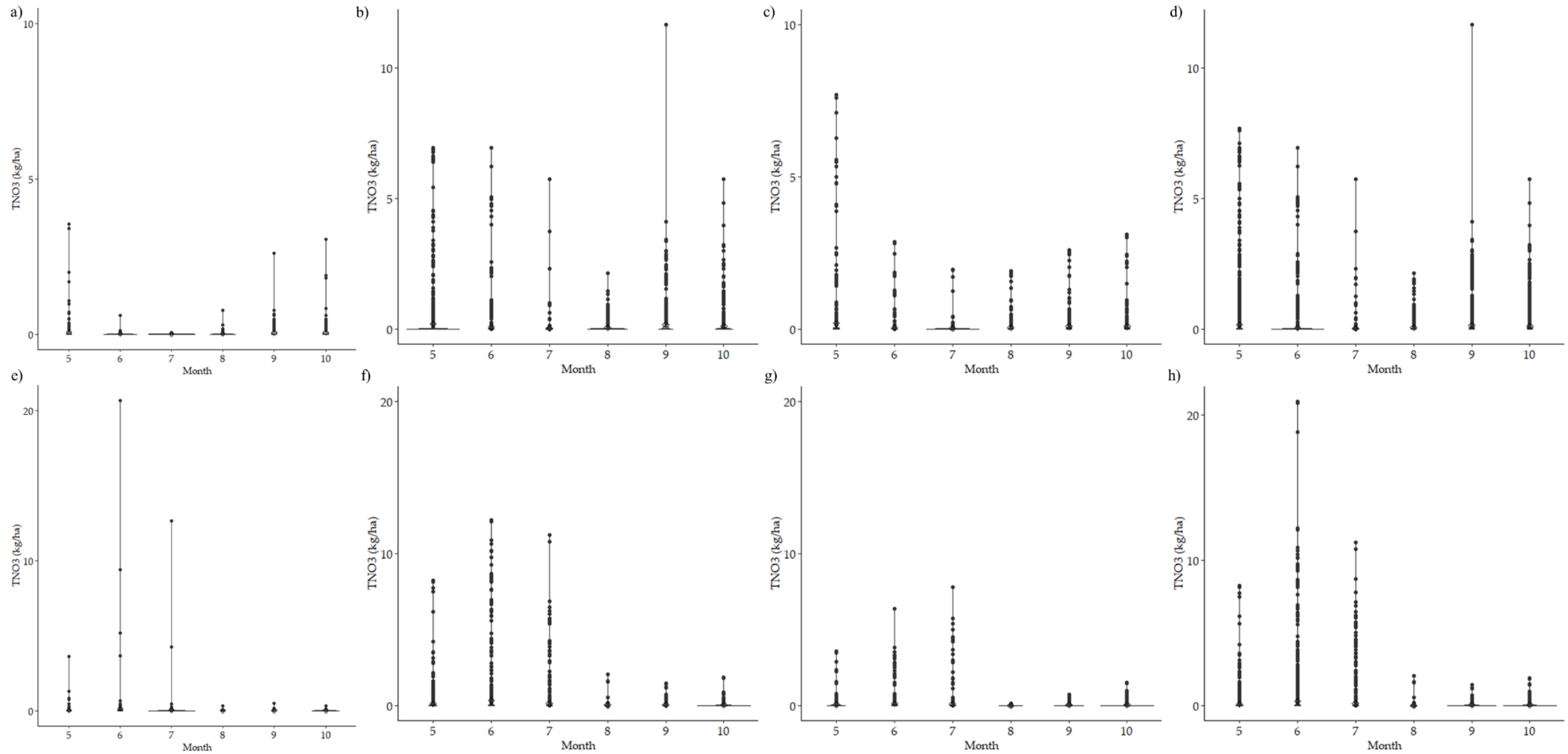


Figure A.32 Subsurface nitrate (TNO3) distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

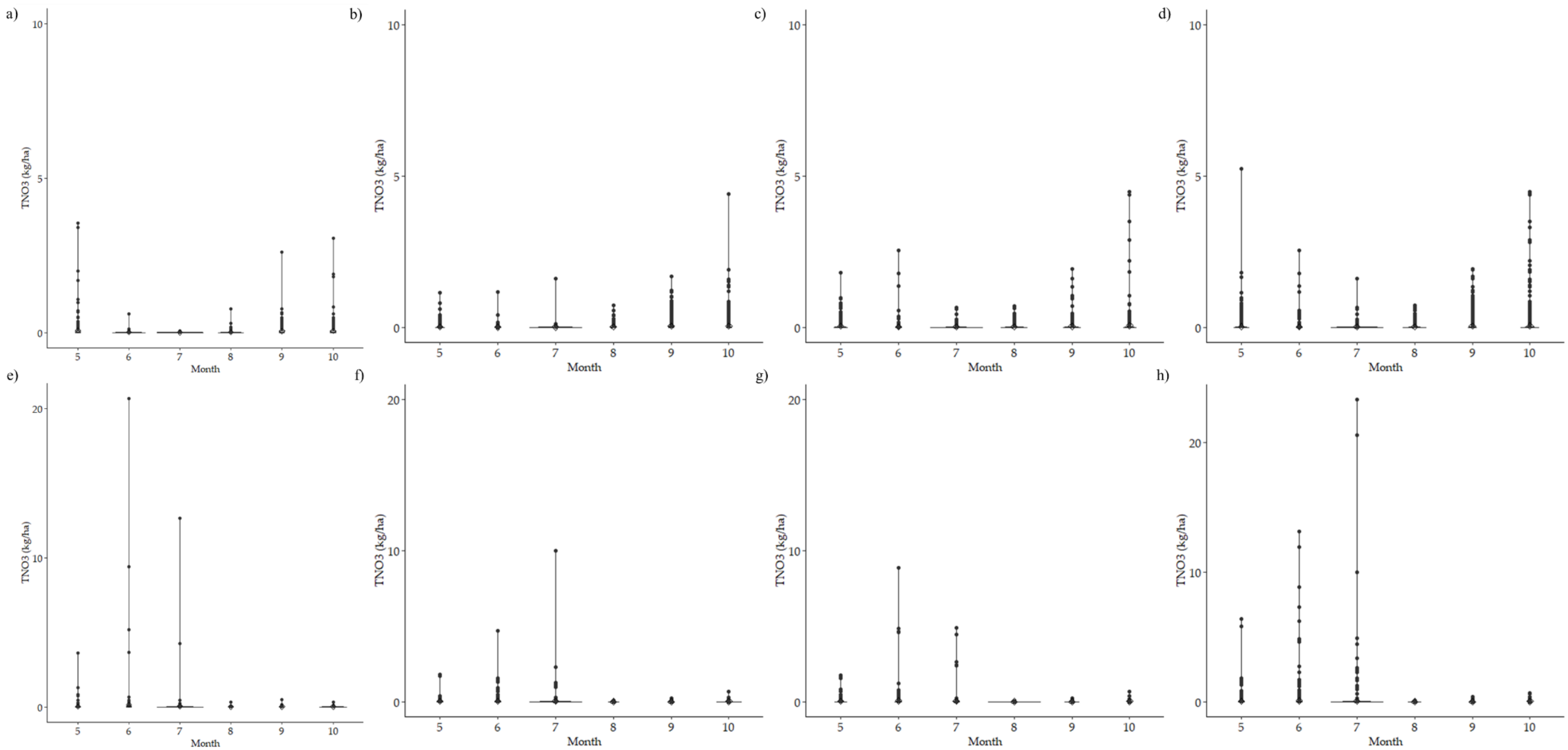


Figure A.33 Subsurface nitrate (TNO3) distribution for NorESM1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

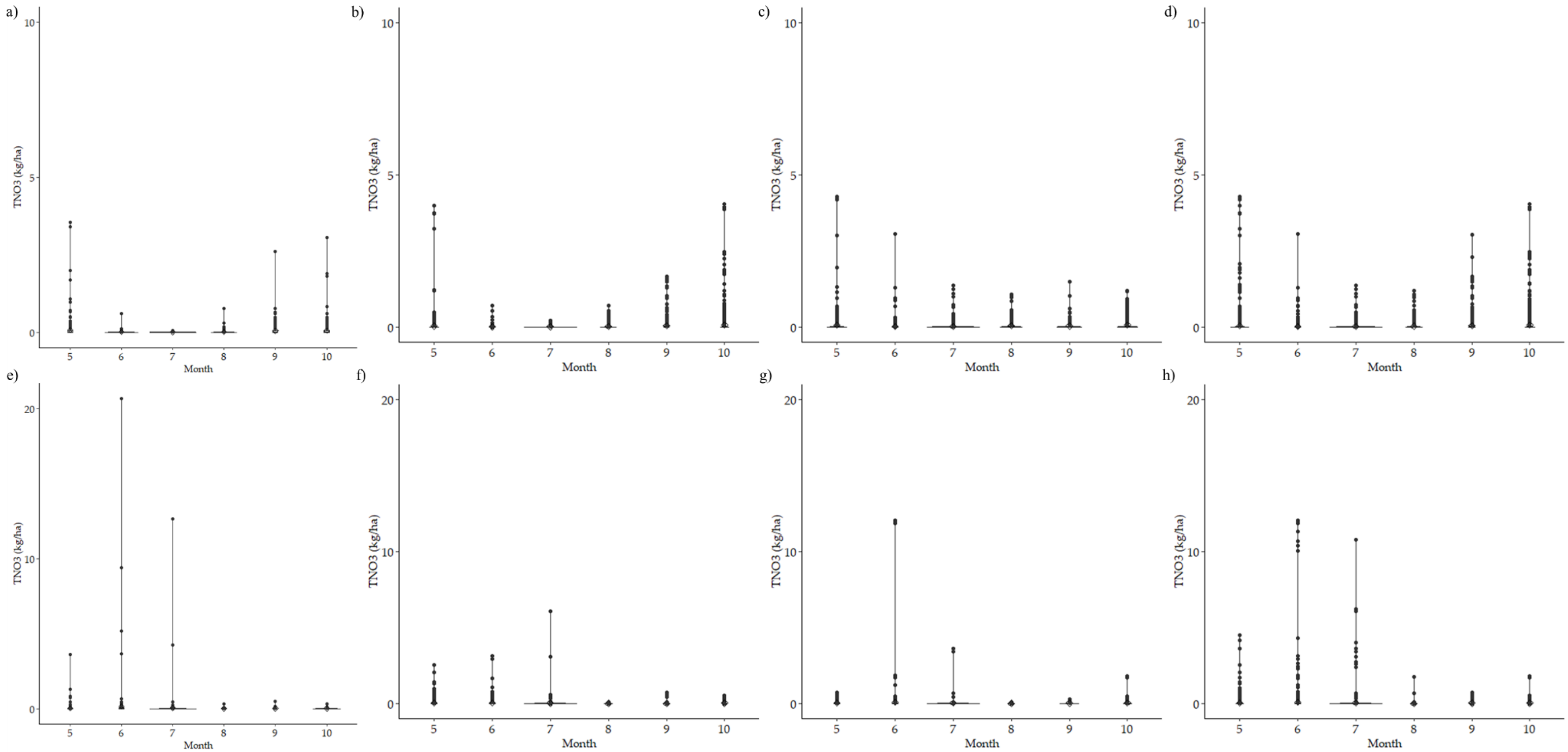


Figure A.34 Subsurface nitrate (TNO3) distribution for NorESM1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

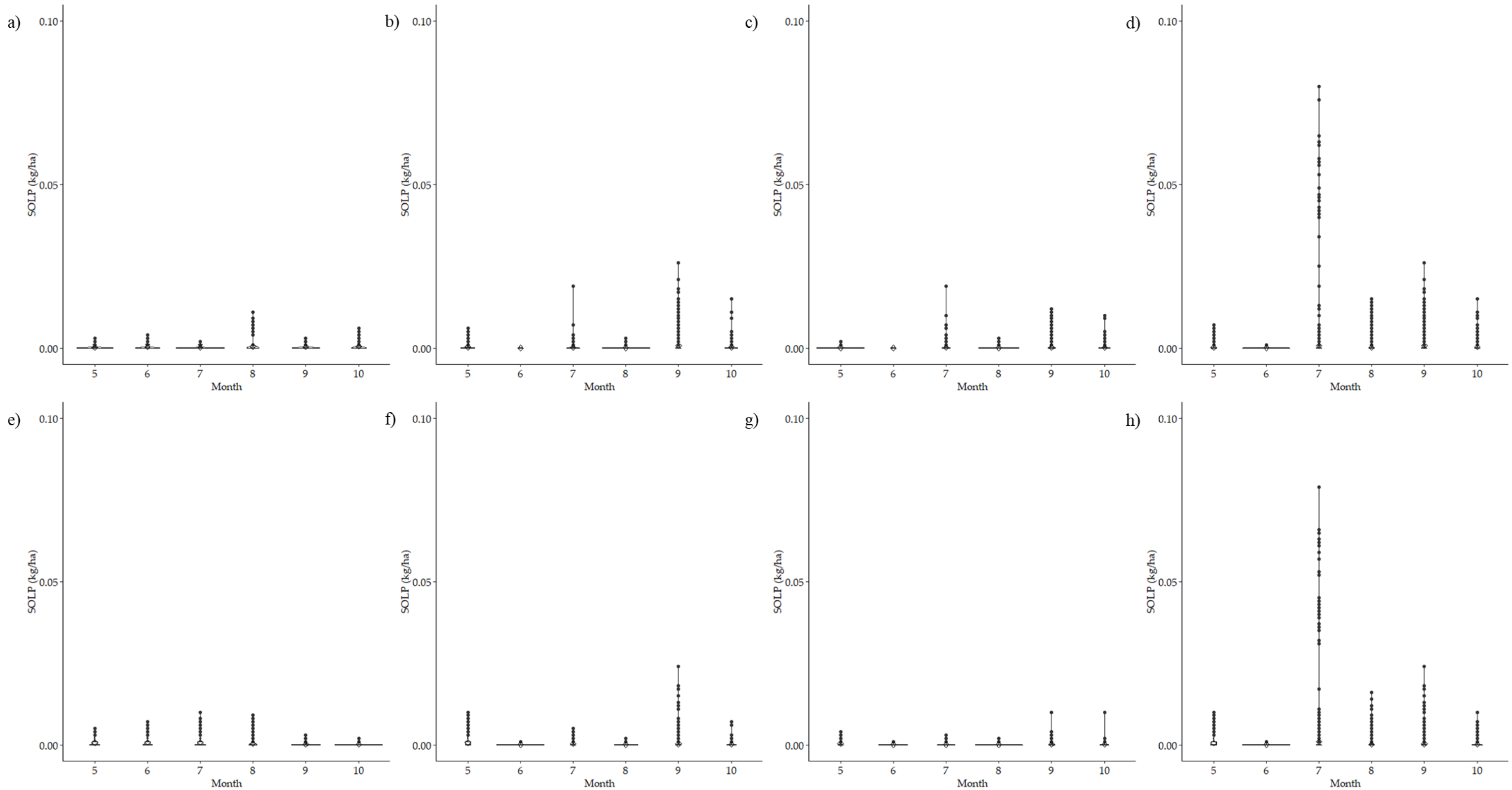


Figure A.35 Soluble phosphorus (SOLP) distribution for BCC-CSM RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

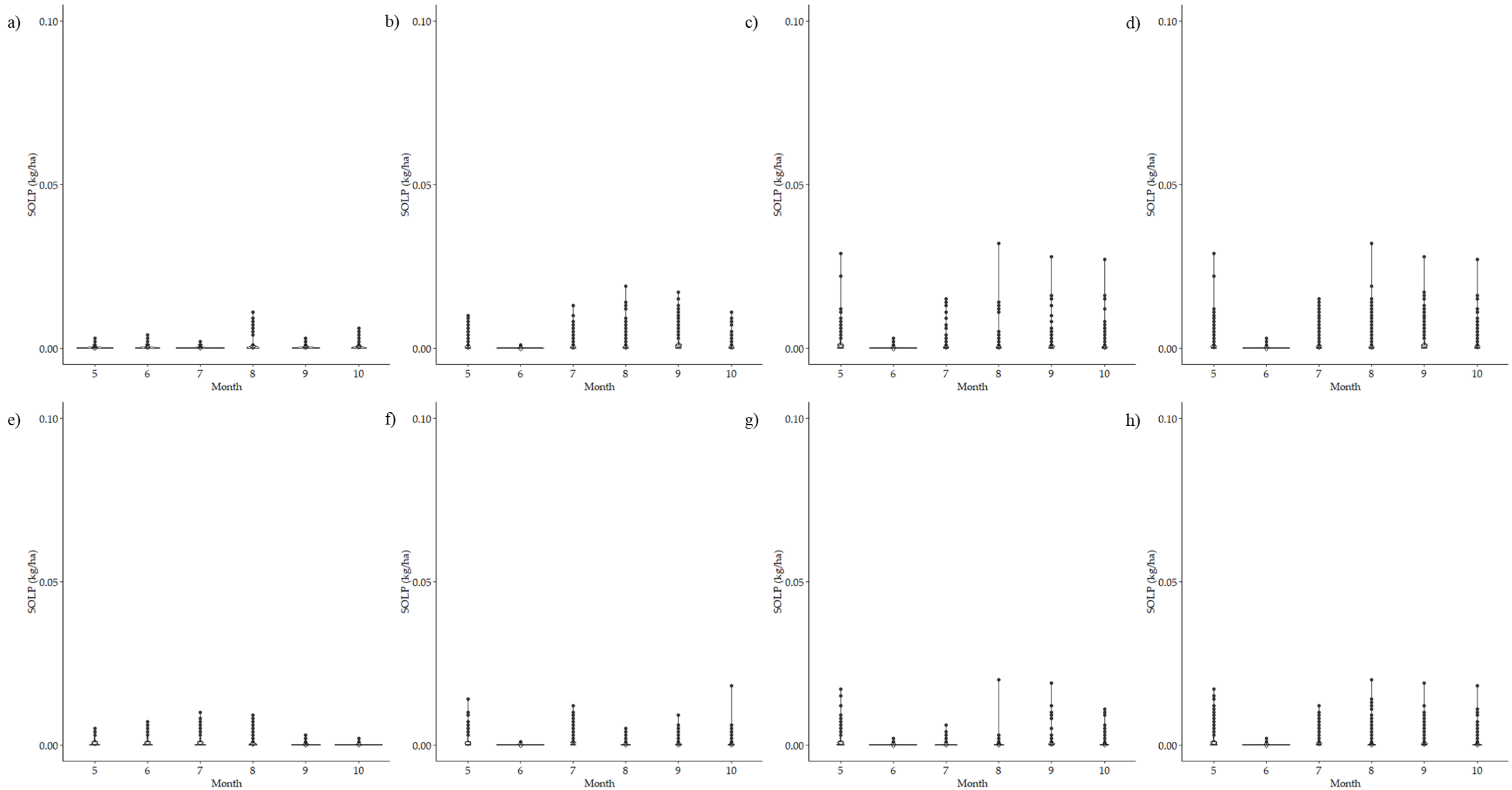
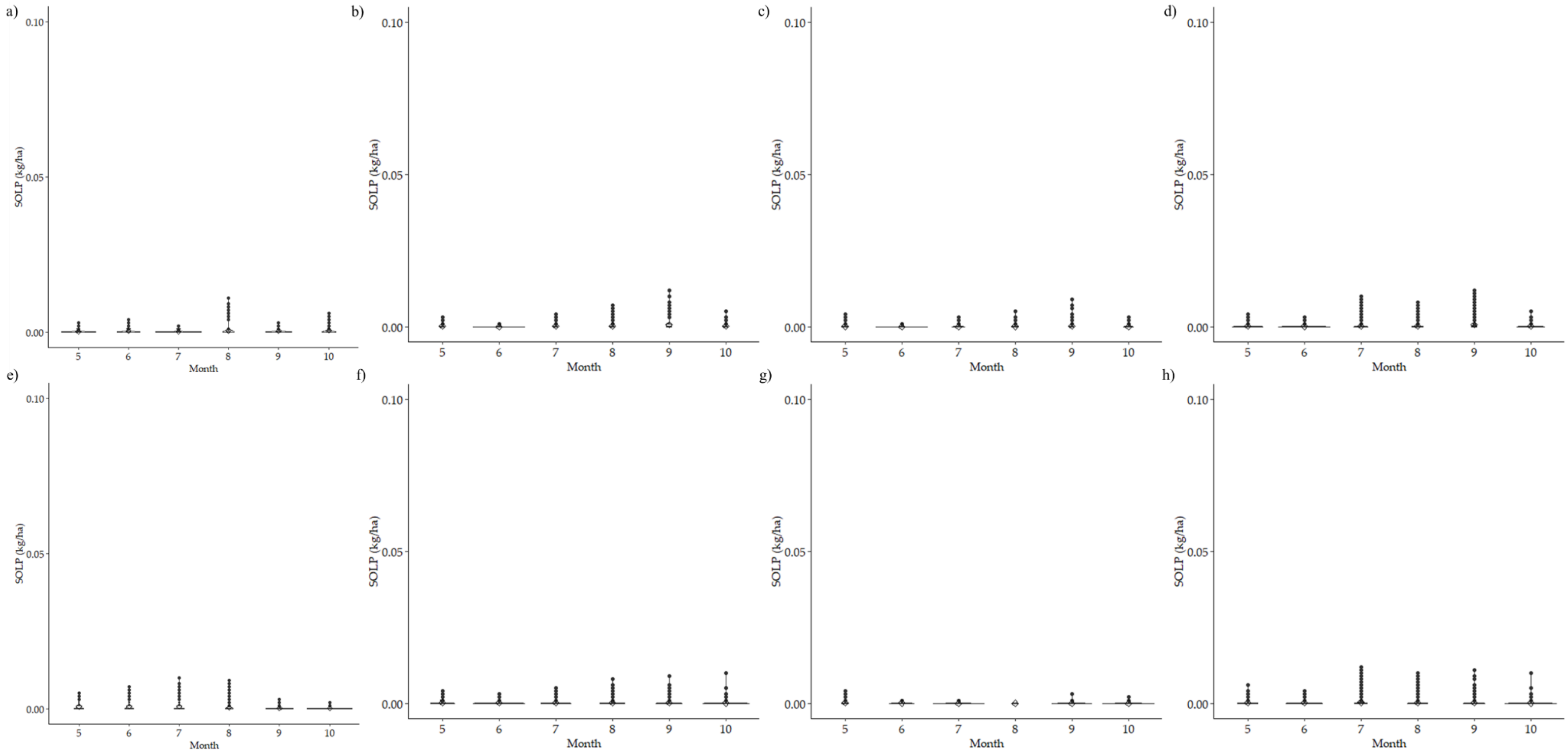


Figure A.36 Soluble phosphorus (SOLP) distribution for BCC-CSM RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).



FigureA.37 Soluble phosphorus (SOLP) distribution for CCSM4 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

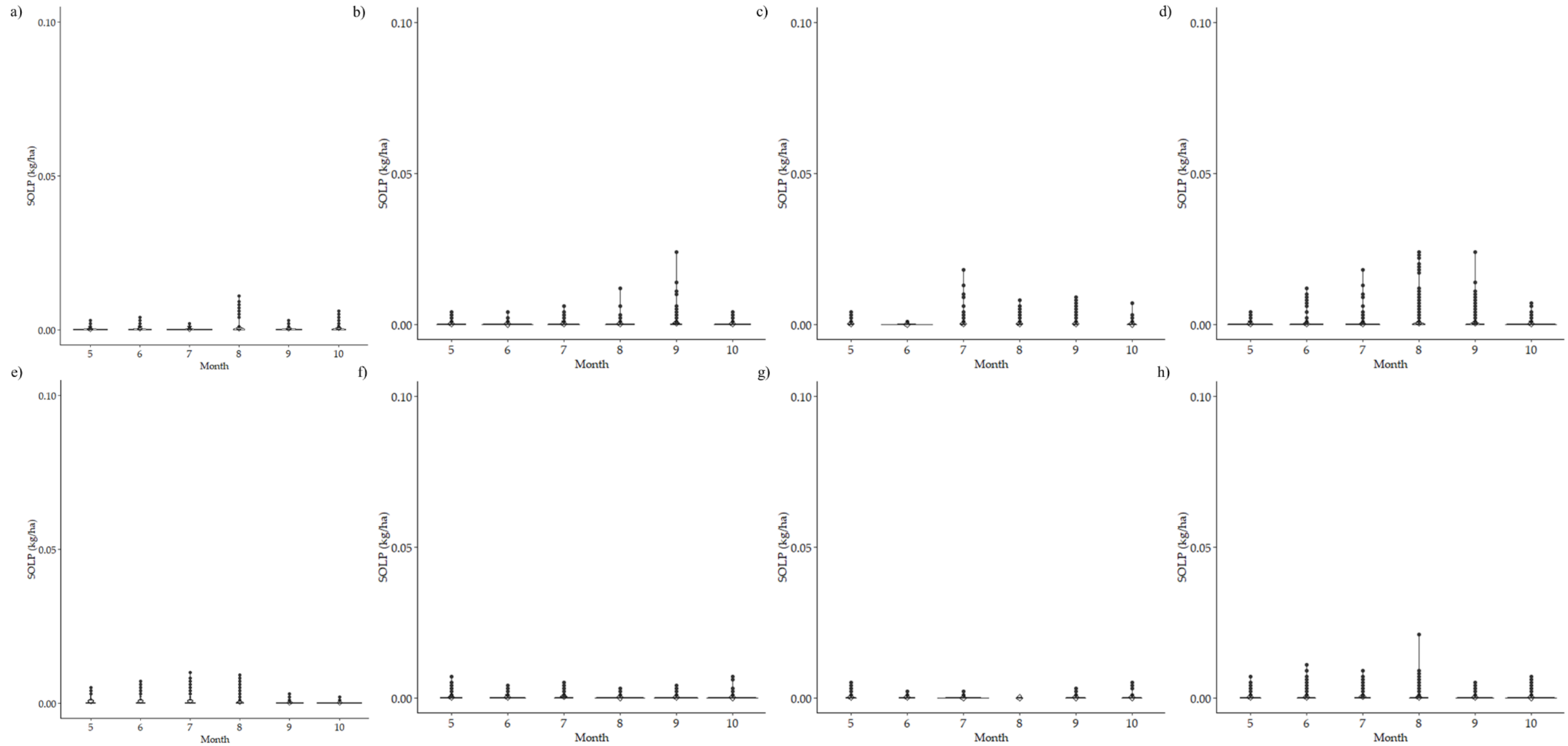


Figure A.38 Soluble phosphorus (SOLP) distribution for CCSM4 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

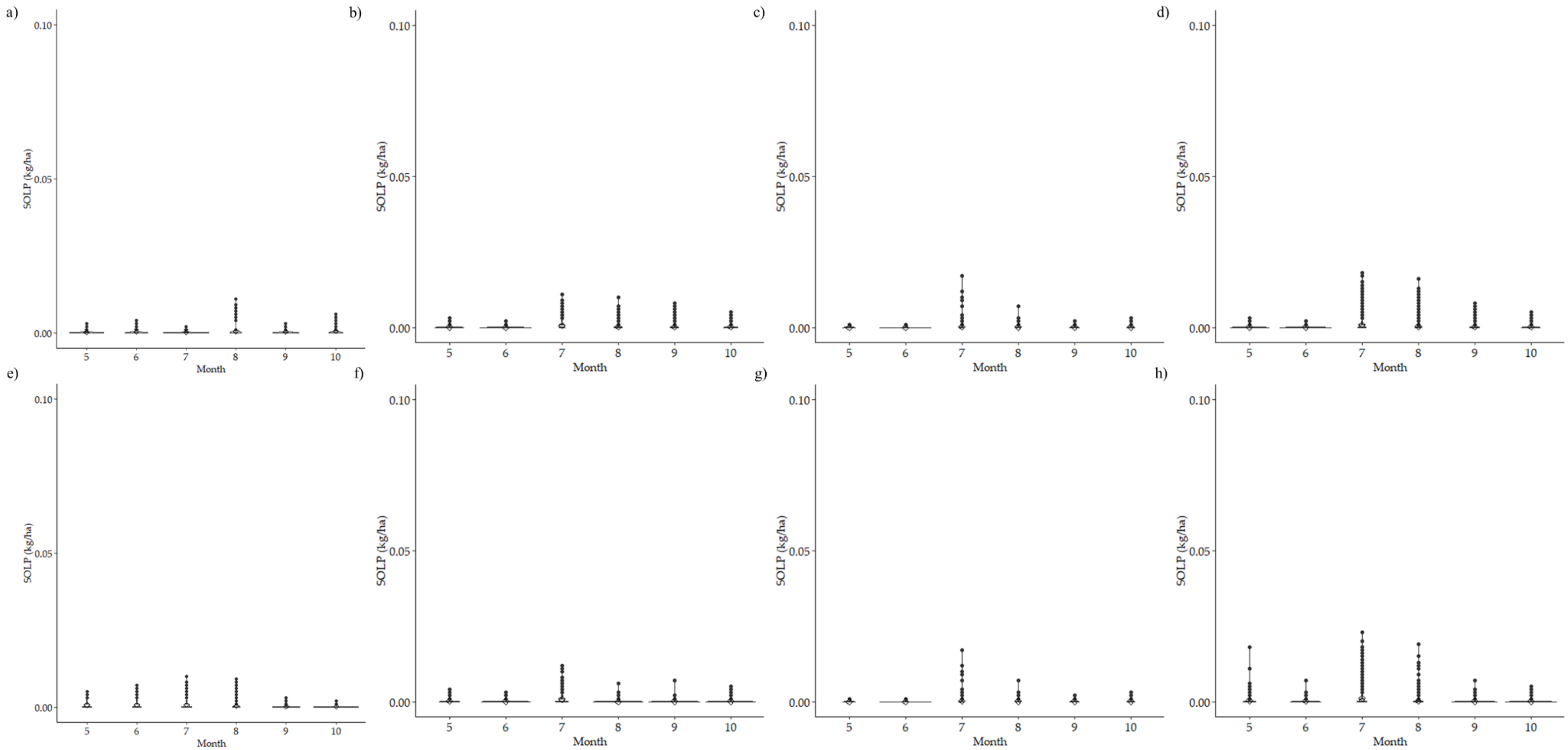


Figure A.39 Soluble phosphorus (SOLP) distribution for NorESM1 RCP 4.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

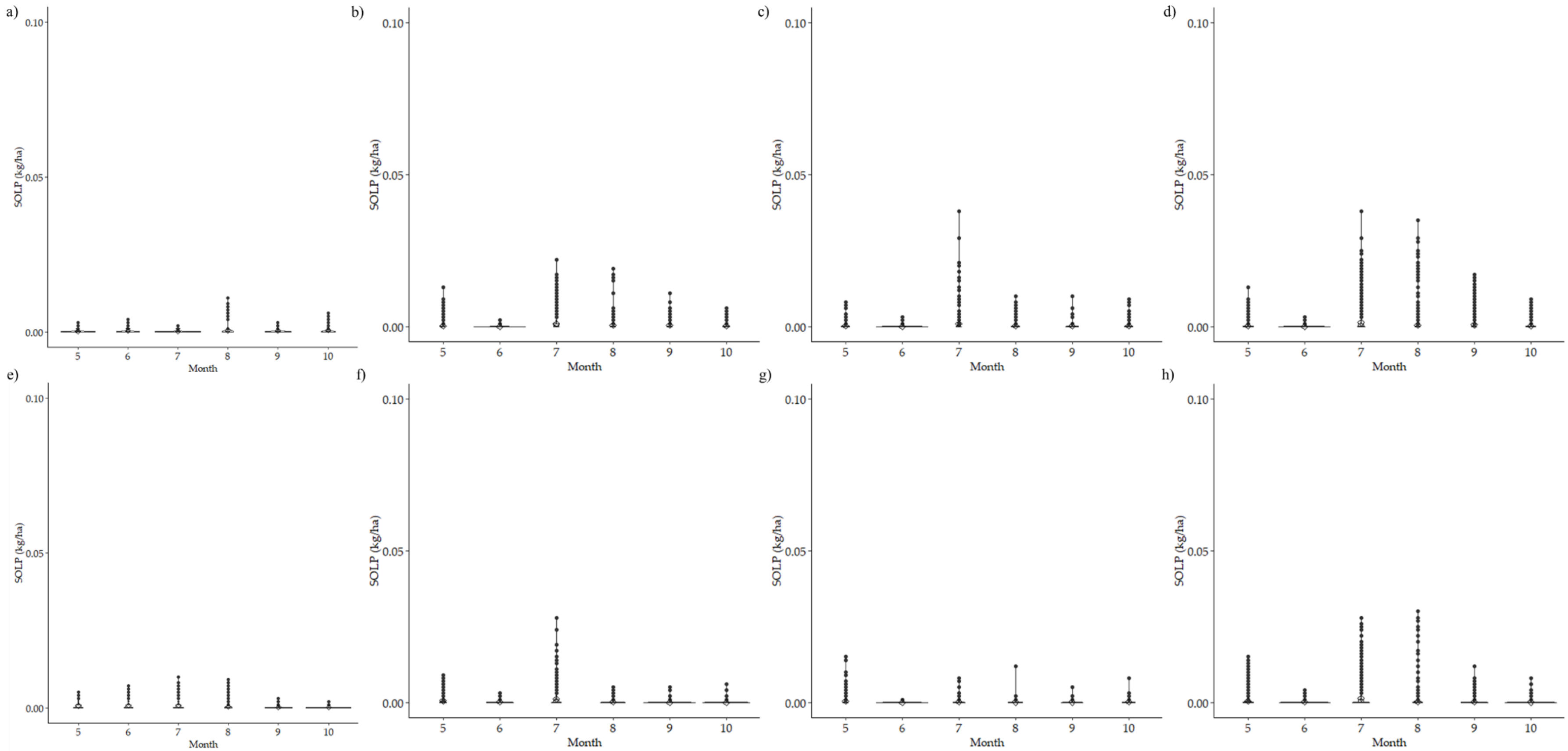


Figure A.40 Soluble phosphorus (SOLP) distribution for NorESM1 RCP 8.5; (a) corn (2006 – 2019), (b) corn (2020 – 2069), (c) corn (2070 – 2099), (d) corn (2006 – 2099), (e) soybean (2006 – 2019), (f) soybean (2020 – 2069), (g) soybean (2070 – 2099), (h) soybean (2006 – 2099).

Table A.1 Relative Differences for Water Quantity and Quality Parameters Range of Selected GCMs

RCP 4.5	MO	ET						EP						D_S*					
		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	-4	1	-1	6	-2	2	-14	15	-8	0	-12	8	-122	181	-90	-70	-125	77
	6	-3	3	-16	2	-8	2	-14	35	-14	28	-16	30	-67	20	-53	-7	-53	9
	7	-6	17	-6	14	-3	16	45	129	76	149	63	142	-99	188	138	235	138	214
	8	2	24	6	31	5	27	-33	0	-47	-8	-35	-5	-202	-71	-297	-126	-297	-89
	9	-15	4	-10	1	-9	4	-15	30	-18	27	-16	28	-67	216	-60	230	-60	200
	10	4	10	5	20	6	16	-30	9	-27	13	-30	10	-108	7	-110	-1	-110	-1
Soybean	5	-13	-1	-14	-6	-13	-2	9	49	0	20	6	41	-97	198	-42	148	-42	173
	6	-18	-11	-28	-6	-21	-10	-24	20	-21	19	-24	18	-73	-8	-58	-13	-58	-15
	7	-3	16	-9	10	-4	15	41	123	71	150	57	139	-94	207	156	280	156	243
	8	0	27	8	34	5	31	-32	-1	-47	-11	-35	-6	-177	-88	-264	-113	-264	-103
	9	-17	6	-13	-6	-13	3	-11	36	-16	33	-11	33	-16	325	-40	380	-40	336
	10	-5	5	-8	12	-3	5	-24	14	-25	20	-26	17	-118	57	-116	49	-116	56

RCP 4.5	MO	NSURQ						TNO3						SOLP					
		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	-55	-43	74	191	-19	21	-87	-2	-69	6	-77	-4	-23	67	1	97	-7	97
	6	-74	536	73	2770	-73	384	121	678	304	589	231	823	-98	-86	-95	-82	-96	-82
	7	74	1841	-100	2507	717	1379	1110	1980	1603	3429	1238	1992	5	407	-90	662	83	662
	8	-26	508	418	1032	296	591	-27	17	-45	21	-38	16	-93	-41	-100	-52	-62	-52
	9	225	581	915	1580	273	836	-64	-16	-70	-29	-61	-12	-63	62	-99	67	-39	67
	10	-37	120	68	268	77	118	-73	-36	-51	-37	-64	-40	-88	-80	-100	-64	-89	-64

Table A.1 Relative Differences for Water Quantity and Quality Parameters Range of Selected GCMs

RCP 4.5	MO	NSURQ						TNO3						SOLP					
		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Soybean	5	23356	71874	29657	119631	23087	57914	-37	493	3	351	9	386	-81	-11	-79	-36	-78	-36
	6	19435	46019	4281	103754	11931	43424	-80	76	-67	-17	-59	59	-100	-95	-100	-91	-100	-91
	7	596	1324	587	2973	966	1334	-78	95	-52	48	6	151	-86	5	-84	45	-73	45
	8	-	-	-	-	-	-	388	828	443	1672	399	1015	-92	-50	-92	-22	-53	-22
	9	-	-	-	-	-	-	664	1999	502	2051	629	2008	19	398	-72	348	-1	348
	10	-	-	-	-	-	-	671	1717	652	1688	702	1518	42	303	-27	424	38	424

RCP 8.5	MO	ET						EP						D_S*					
		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	-5	-2	-12	-1	-8	-2	-10	-1	-20	-2	-10	5	-74	30	-117	48	-89	84
	6	-10	1	-3	9	-5	2	-18	15	-12	20	-17	15	-39	6	-13	23	-13	21
	7	-1	15	-10	12	-5	14	71	143	41	143	59	145	108	220	104	228	104	227
	8	5	25	-6	31	0	28	-22	4	-21	-8	-21	0	-245	-55	-223	-91	-223	-59
	9	-11	0	-25	1	-11	1	-8	36	-17	14	-7	21	9	269	-54	104	-54	207
	10	5	19	-1	14	6	15	-30	16	-27	33	-28	24	-113	9	-110	89	-110	44
Soybean	5	-11	0	-21	-10	-13	-3	16	37	3	20	15	32	117	143	-91	148	-91	141
	6	-18	-7	-15	-4	-17	-6	-25	9	-21	11	-25	9	-52	-4	-34	-4	-34	0
	7	0	12	-9	6	-4	10	64	138	38	139	55	141	117	250	107	270	107	262
	8	4	26	-2	30	-1	29	-25	-2	-21	-11	-22	-4	-228	-77	-196	-94	-196	-79
	9	-8	-2	-24	-6	-10	-4	-2	43	-5	13	-1	26	42	408	55	176	55	320
	10	-7	13	-7	3	-5	6	-27	23	-25	42	-26	30	-108	54	-116	194	-116	107

Table A.1 Relative Differences for Water Quantity and Quality Parameters Range of Selected GCMs

RCP 8.5	MO	NSURQ						TNO3						SOLP					
		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99		20 – 69		70 – 99		06 – 99	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	-1	128	91	506	23	215	-73	-10	-61	46	-64	7	1	99	10	206	22	206
	6	-71	432	900	2770	225	853	207	1297	207	526	266	1073	-98	-69	-96	-36	-95	-36
	7	16	1870	962	2507	840	1317	592	3939	328	3429	529	3370	151	668	-69	815	92	815
	8	-17	232	418	2678	246	988	-15	29	21	72	13	33	-82	-70	-100	-25	-56	-25
	9	36	1158	550	2690	451	1509	-54	-17	-49	-41	-49	-24	-50	54	-78	98	-10	98
	10	16	363	154	851	97	434	-64	-39	-52	7	-62	-16	-93	-76	-100	-57	-86	-57
Soybean	5	27281	32299	60138	133092	37626	61095	-4	558	24	519	25	476	-65	-21	-78	10	-70	10
	6	3820	36316	102421	199618	41771	65913	-83	110	-56	-17	-53	109	-100	-84	-99	-77	-98	-77
	7	264	1620	960	2973	766	1526	-88	119	-68	48	-56	117	-73	51	-84	104	-66	104
	8	-	-	-	-	-	-	457	1763	562	1672	564	1553	-65	1	-66	45	-34	45
	9	-	-	-	-	-	-	808	4138	400	2051	813	3309	100	535	-46	623	190	623
	10	-	-	-	-	-	-	895	2105	969	3023	923	2260	96	588	22	876	97	876

† Calculated with $RD = \frac{WQP_t - WQP_{baseline}}{WQP_{baseline}}$

$$\text{*Calculated with } RD = \begin{cases} if\ D_{S,b} < 0\ and\ D_{S,t} < 0 & \frac{WQP_t - WQP_{baseline}}{WQP_{baseline}} \\ if\ D_{S,b} < 0\ and\ D_{S,t} > 0 & \frac{WQP_t - WQP_{baseline}}{\left|WQP_{baseline}\right|} \\ if\ D_{S,b} > 0\ and\ D_{S,t} < 0 & \frac{WQP_{baseline} - WQP_t}{WQP_{baseline}} \\ if\ D_{S,b} > 0\ and\ D_{S,t} > 0 & \frac{WQP_t - WQP_{baseline}}{WQP_{baseline}} \end{cases}$$

Positives indicate an increase in relative difference, while negatives indicate decrease.

Table A.2 P_{eff}/Precipitation Ratio Range Throughout the Growing Season of Selected GCMs

RCP 4.5	Month	2006 – 2019	2020 – 2069		2070 – 2099		2006 – 2099	
		Baseline	Min	Max	Min	Max	Min	Max
Corn	5	0.66	0.63	0.80	0.70	0.74	0.66	0.77
	6	0.59	0.72	0.77	0.72	0.75	0.72	0.76
	7	0.72	0.61	0.77	0.54	0.74	0.59	0.75
	8	0.79	0.69	0.77	0.70	0.76	0.70	0.74
	9	0.81	0.64	0.70	0.67	0.79	0.66	0.72
	10	0.77	0.66	0.72	0.68	0.72	0.66	0.72
Soybean	5	0.63	0.60	0.77	0.67	0.75	0.64	0.77
	6	0.66	0.71	0.76	0.70	0.78	0.73	0.77
	7	0.76	0.62	0.74	0.56	0.74	0.61	0.74
	8	0.79	0.69	0.78	0.70	0.72	0.70	0.74
	9	0.79	0.63	0.72	0.69	0.78	0.66	0.75
	10	0.73	0.66	0.71	0.68	0.75	0.67	0.73
RCP 8.5	Month	2006 – 2019	2020 – 2069		2070 – 2099		2006 – 2099	
		Baseline	Min	Max	Min	Max	Min	Max
Corn	5	0.66	0.64	0.74	0.49	0.77	0.59	0.72
	6	0.59	0.71	0.72	0.67	0.77	0.69	0.73
	7	0.72	0.60	0.73	0.54	0.74	0.58	0.73
	8	0.79	0.60	0.79	0.61	0.76	0.61	0.75
	9	0.81	0.59	0.71	0.58	0.68	0.60	0.72
	10	0.77	0.60	0.68	0.62	0.72	0.62	0.71
Soybeans	5	0.63	0.64	0.72	0.51	0.68	0.60	0.71
	6	0.66	0.70	0.77	0.67	0.76	0.69	0.77
	7	0.76	0.61	0.72	0.55	0.74	0.60	0.73
	8	0.79	0.58	0.75	0.62	0.72	0.60	0.73
	9	0.79	0.61	0.70	0.60	0.72	0.61	0.70
	10	0.73	0.60	0.69	0.63	0.72	0.62	0.69

Table A.3 Range of Average Stress Days Throughout the Growing Season of Selected GCMs

RCP 4.5		2006 – 2019				2020 – 2069							
		Baseline Values				Water		Temperature		Nitrogen		Phosphorus	
	MO	Water	Temperature	Nitrogen	Phosphorus	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	5	4	26	16	3	4	3	4	16	17	24	24
	6	4	1	30	1	1	3	1	2	28	29	7	9
	7	8	1	31	0	2	5	0	0	26	28	1	3
	8	8	1	25	0	2	6	0	0	3	6	0	0
	9	5	3	0	0	3	6	2	3	0	0	0	0
	10	6	16	15	0	2	2	13	14	7	8	0	1
Soybeans	5	5	4	0	8	3	4	3	4	0	0	8	8
	6	3	1	0	8	2	3	1	2	0	0	23	24
	7	9	0	0	0	3	5	0	0	0	0	4	6
	8	9	0	0	0	3	4	0	0	0	0	2	3
	9	5	0	0	0	3	4	2	3	0	0	1	1
	10	4	0	0	0	3	4	13	14	0	0	2	4

RCP 4.5		2070 – 2099								2006 – 2099							
		Water		Temperature		Nitrogen		Phosphorus		Water		Temperature		Nitrogen		Phosphorus	
	MO	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	2	3	1	4	10	15	24	26	3	4	3	4	16	16	23	24
	6	1	2	1	1	22	26	12	25	2	2	1	2	26	28	11	13
	7	2	3	0	1	17	22	5	18	2	4	0	0	23	27	6	8
	8	2	5	0	0	0	3	0	2	2	6	0	0	4	6	0	1
	9	2	5	0	1	0	0	0	0	3	5	2	2	0	0	0	0
	10	1	2	5	11	0	5	0	4	2	2	12	14	6	7	1	2
Soybeans	5	2	3	1	4	0	0	8	8	3	4	3	4	0	0	8	8
	6	0	2	1	1	0	0	25	28	2	3	1	2	0	0	22	23
	7	2	3	0	1	0	0	14	17	3	5	0	0	0	0	8	9
	8	2	3	0	1	0	0	15	20	2	4	0	0	0	0	6	8
	9	2	3	0	1	0	0	5	13	3	5	2	2	0	0	5	6
	10	2	3	5	12	0	0	13	16	2	2	12	14	0	0	5	7

Table A.3 Range of Average Stress Days Throughout the Growing Season of Selected GCMs

RCP 8.5		2006 – 2019				2020 – 2069							
		Baseline Values				Water		Temperature		Nitrogen		Phosphorus	
	MO	Water	Temperature	Nitrogen	Phosphorus	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	5	4	26	16	3	4	3	4	16	17	23	24
	6	4	1	30	1	2	3	1	1	28	29	6	8
	7	8	1	31	0	2	4	0	0	26	27	1	2
	8	8	1	25	0	2	5	0	0	3	4	0	0
	9	5	3	0	0	3	4	2	2	0	0	0	0
	10	6	16	15	0	1	2	11	13	6	9	0	0
Soybeans	5	5	4	0	8	3	4	3	3	0	0	8	8
	6	3	1	0	8	2	3	1	1	0	0	22	23
	7	9	0	0	0	3	4	0	0	0	0	4	5
	8	9	0	0	0	3	4	0	0	0	0	2	3
	9	5	0	0	0	3	4	2	2	0	0	1	1
	10	4	0	0	0	3	4	11	12	0	0	3	4

RCP 8.5		2070 – 2099								2006 – 2099							
		Water		Temperature		Nitrogen		Phosphorus		Water		Temperature		Nitrogen		Phosphorus	
	MO	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Corn	5	2	2	1	2	8	11	23	24	2	3	2	3	14	15	22	23
	6	1	1	1	1	24	27	7	12	2	2	1	1	27	28	5	8
	7	2	6	1	1	16	19	2	5	2	5	1	1	23	25	1	3
	8	2	7	0	1	0	0	0	0	2	6	0	0	3	4	0	0
	9	2	6	0	0	0	0	0	0	2	5	1	2	0	0	0	0
	10	1	2	4	5	0	0	0	0	1	2	9	11	5	6	0	0
Soybeans	5	2	2	1	2	0	0	8	8	2	3	2	3	0	0	8	8
	6	1	2	1	1	0	0	24	25	2	3	1	1	0	0	21	21
	7	2	5	1	2	0	0	13	16	3	5	1	1	0	0	6	8
	8	2	2	0	1	0	0	12	17	2	5	0	0	0	0	5	7
	9	2	2	0	0	0	0	3	3	2	4	1	2	0	0	2	2
	10	2	2	4	5	0	0	10	15	1	3	10	10	0	0	5	7

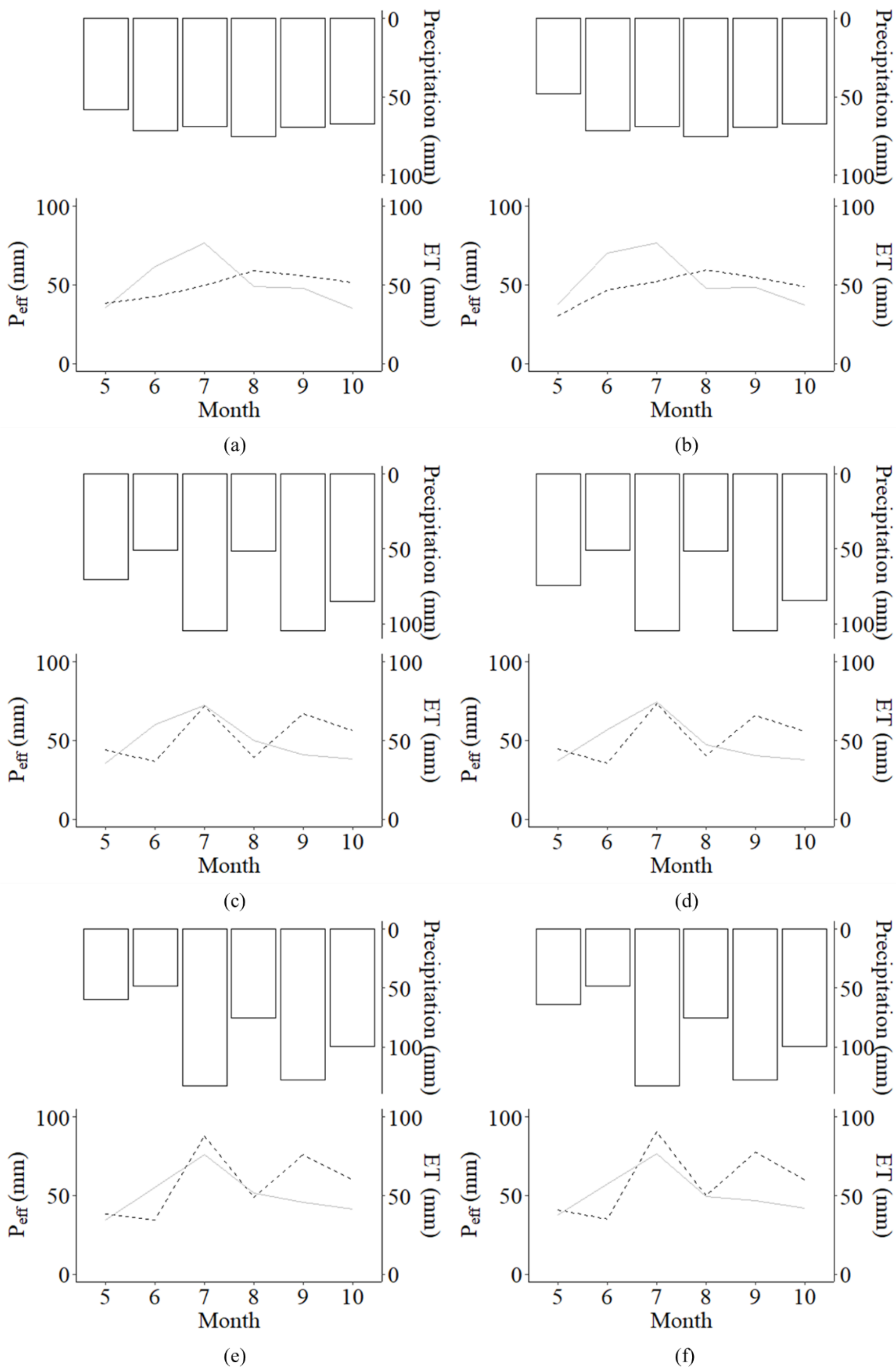


Figure A.41 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and BCC-CSM1.1 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2020– 2069); (d) RCP 4.5 soybean (2020 – 2069); (e) RCP 8.5 corn (2020– 2069); (f) RCP 8.5 soybean (2020 – 2069).

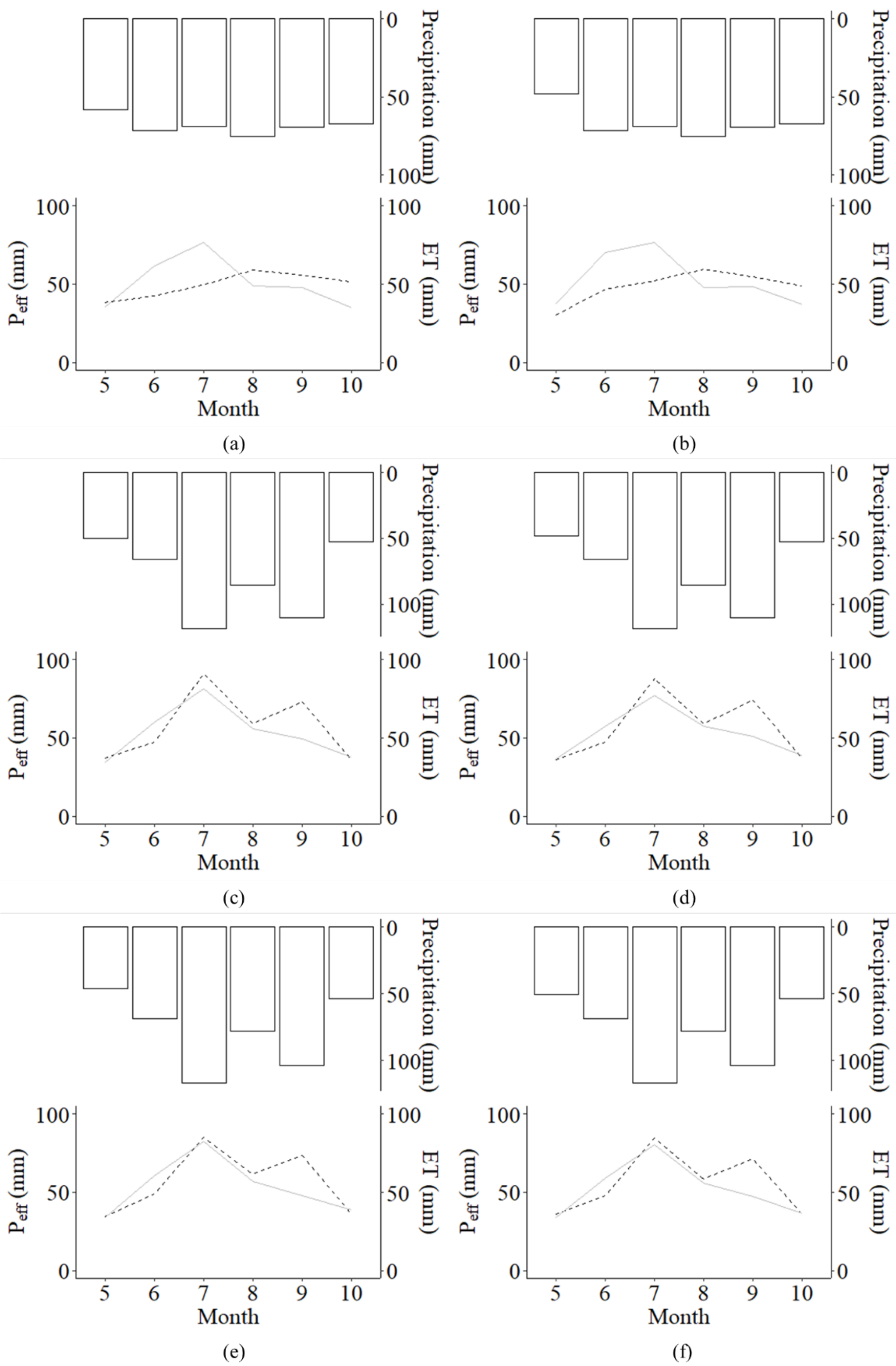


Figure A.42 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and CCSM4 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2020– 2069); (d) RCP 4.5 soybean (2020 – 2069); (e) RCP 8.5 corn (2020– 2069); (f) RCP 8.5 soybean (2020 – 2069).

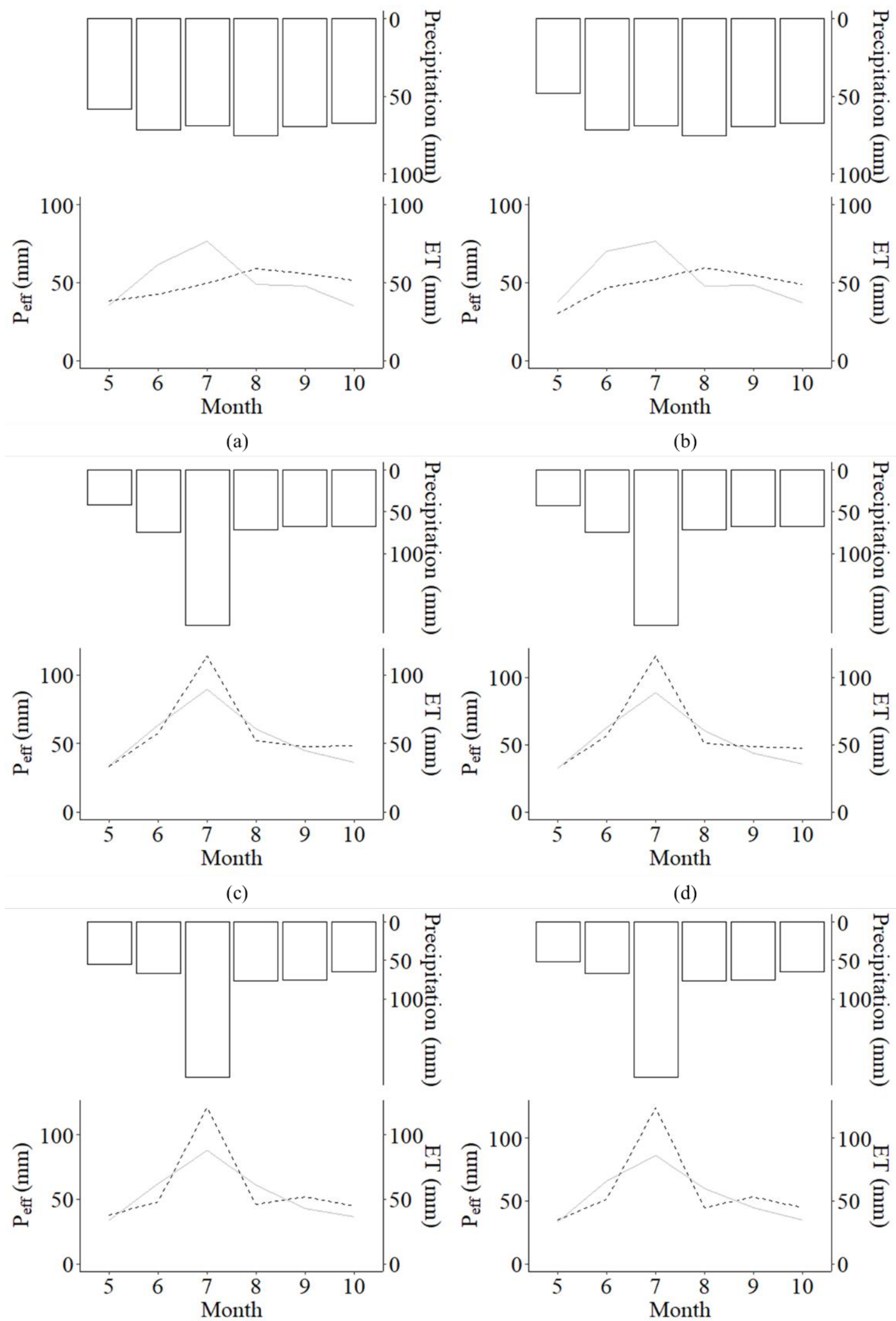


Figure A.43 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and NorESM1 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2020– 2069); (d) RCP 4.5 soybean (2020 – 2069); (e) RCP 8.5 corn (2020– 2069); (f) RCP 8.5 soybean (2020 – 2069).

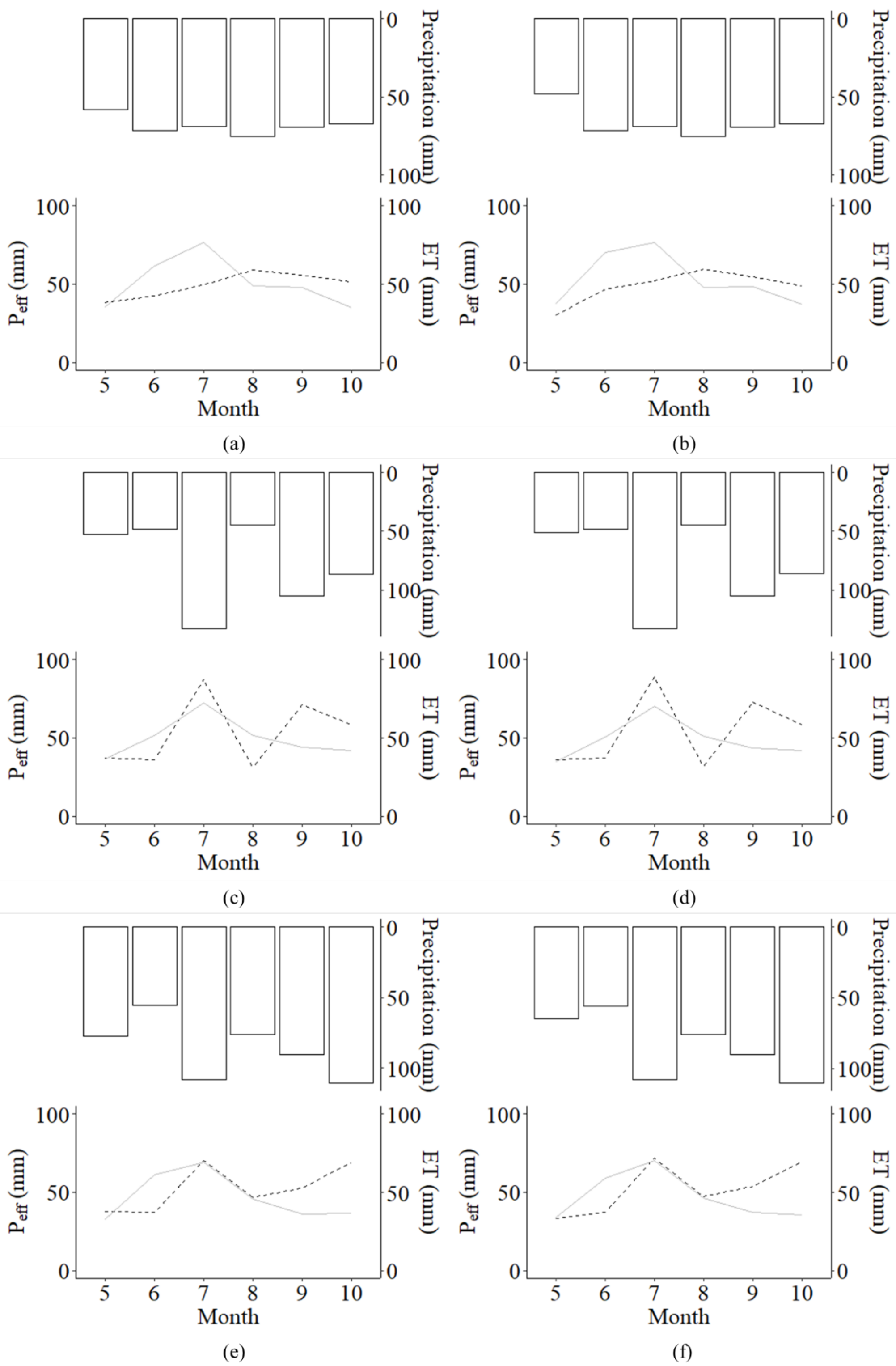


Figure A.44 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and BCC-CSM1.1 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2070– 2099); (d) RCP 4.5 soybean (2070 – 2099); (e) RCP 8.5 corn (2070– 2099); (f) RCP 8.5 soybean (2070– 2099).

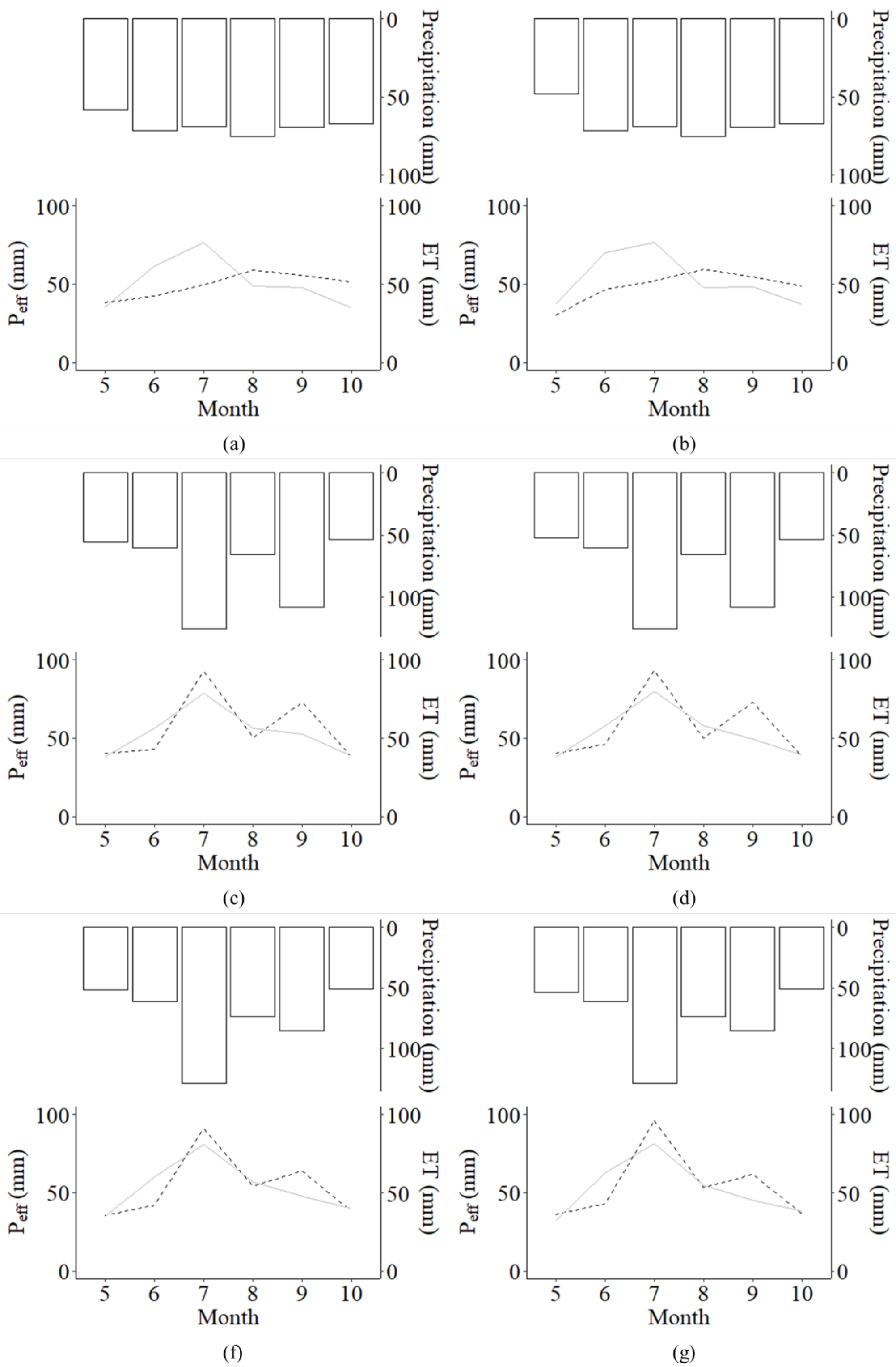
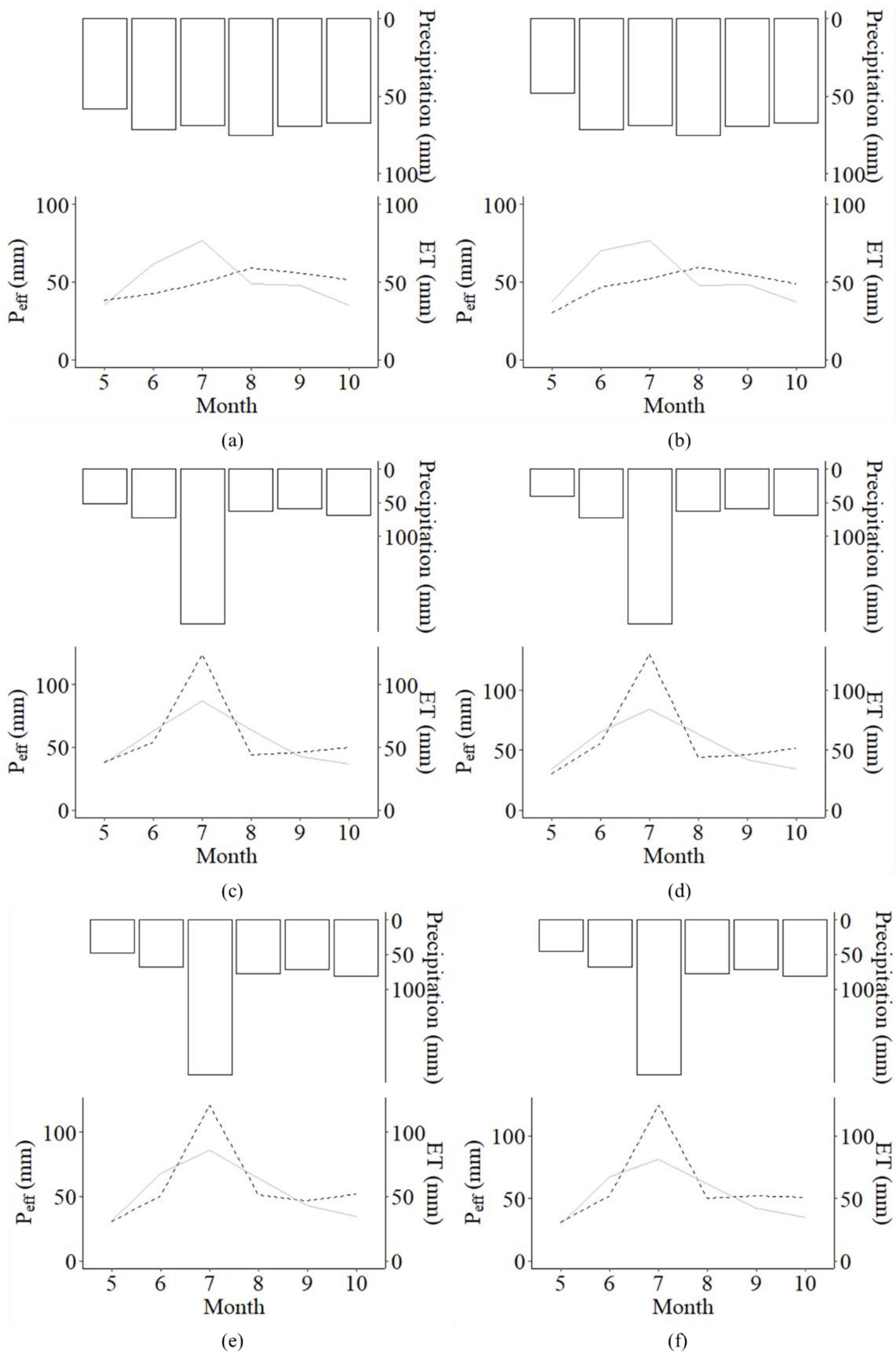


Figure A.45 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and CCSM4 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2070– 2099); (d) RCP 4.5 soybean (2070 – 2099); (e) RCP 8.5 corn (2070– 2099); (f) RCP 8.5 soybean (2070– 2099).



FigureA.46 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and NorESM1 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2070– 2099); (d) RCP 4.5 soybean (2070 – 2099); (e) RCP 8.5 corn (2070– 2099); (f) RCP 8.5 soybean (2070– 2099).

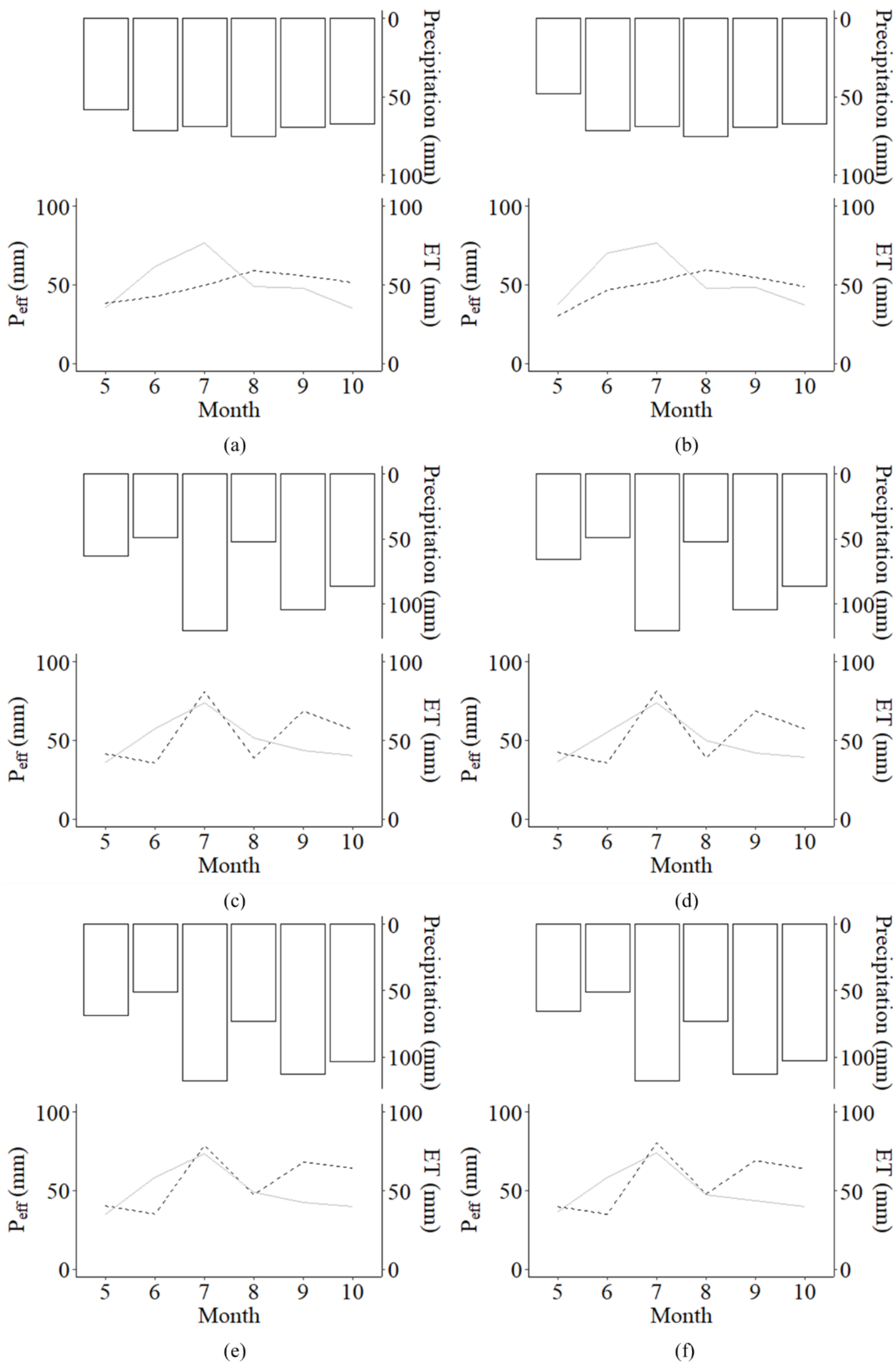


Figure A.47 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and BCC-CSM1.1 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2006– 2099); (d) RCP 4.5 soybean (2006– 2099); (e) RCP 8.5 corn (2006– 2099); (f) RCP 8.5 soybean (2006– 2099).

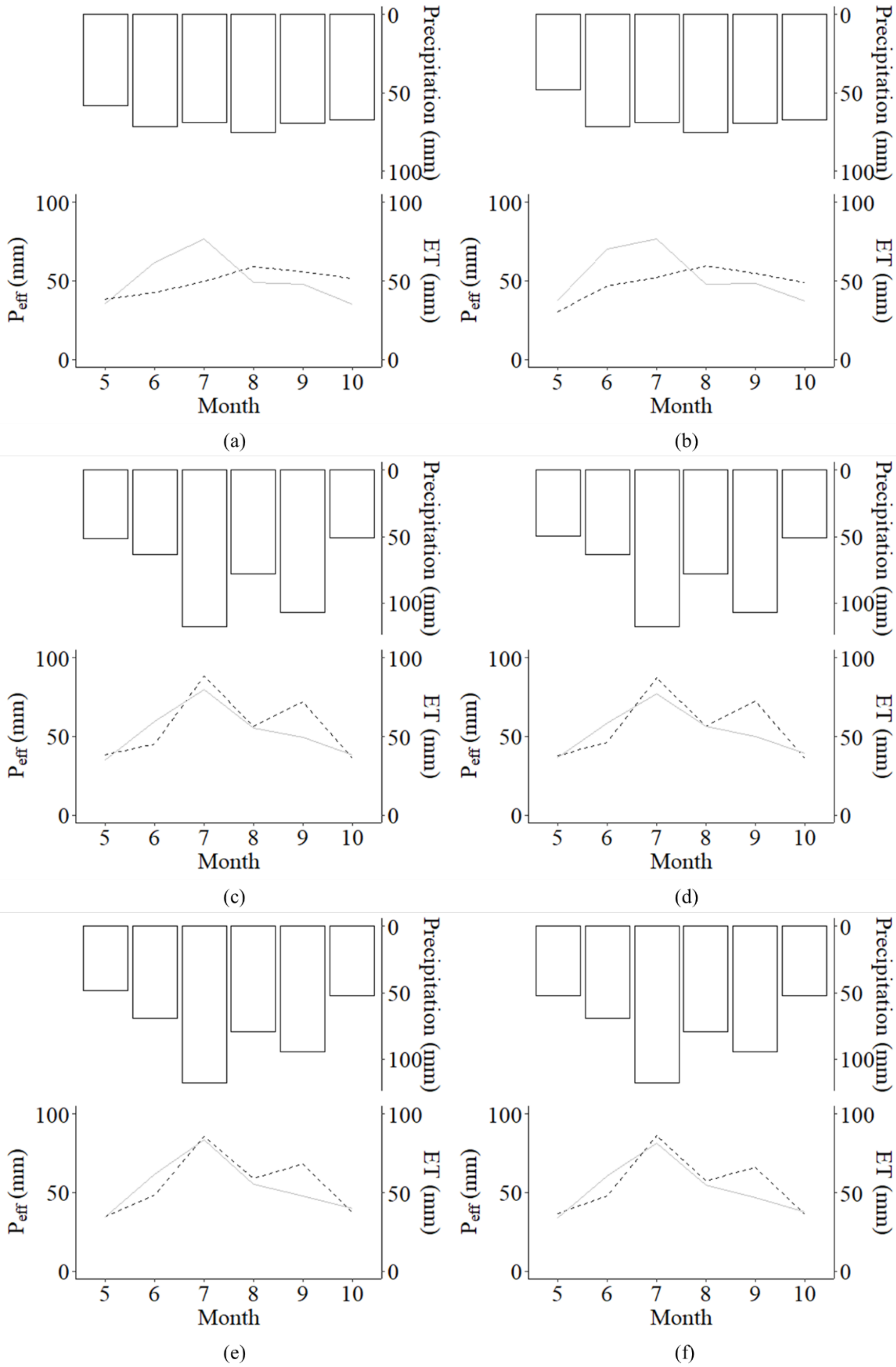
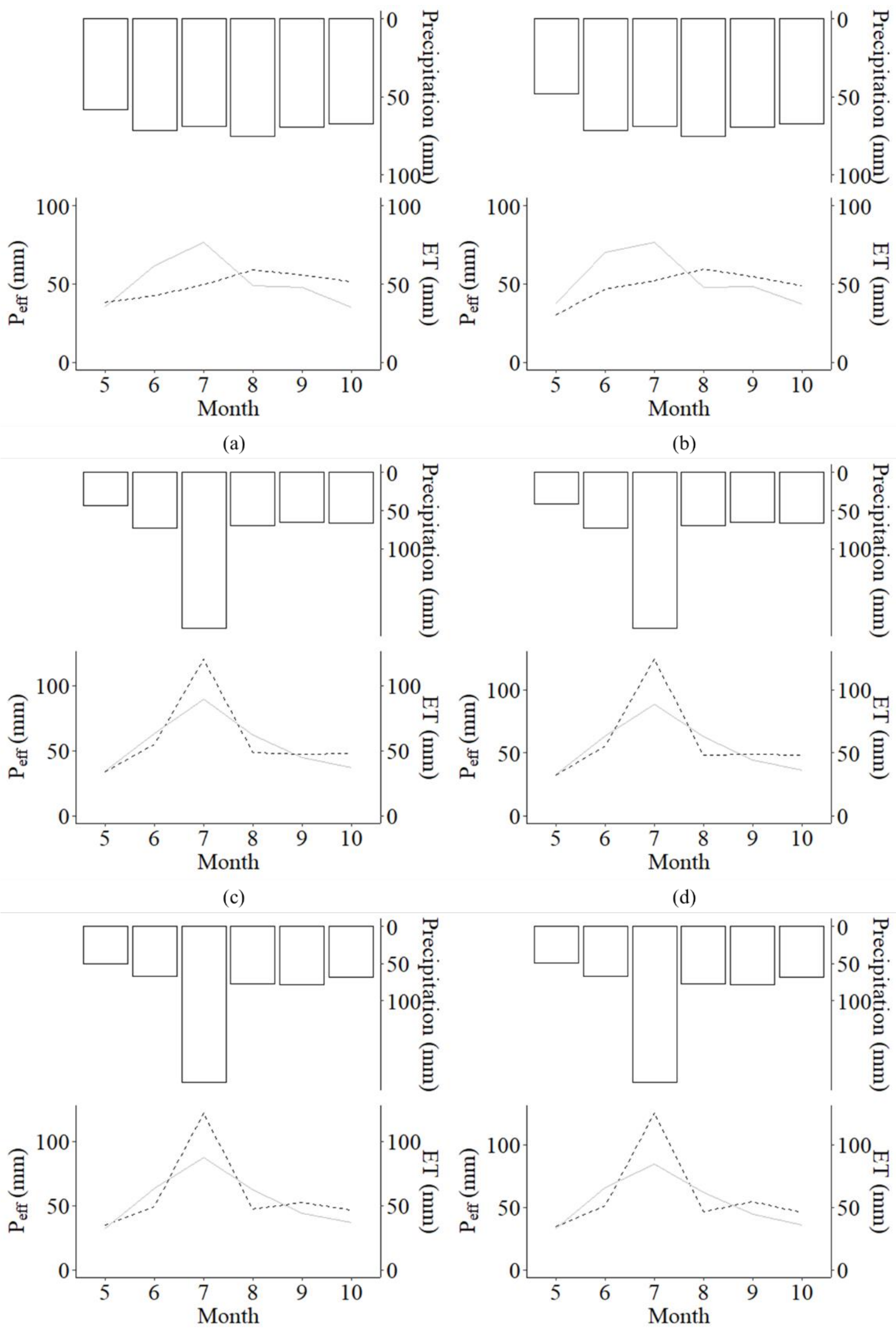


Figure A.48 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and CCSM4 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2006– 2099); (d) RCP 4.5 soybean (2006– 2099); (e) RCP 8.5 corn (2006– 2099); (f) RCP 8.5 soybean (2006– 2099).



(a) (b) (c) (d) (e) (f)

Figure A.49 Monthly precipitation, evapotranspiration (ET), and effective precipitation (P_{eff}) critical periods during an average growing season for baseline (2006 – 2019) and NorESM1 for (a) corn (2006 – 2019); (b) soybean (2006 – 2019); (c) RCP 4.5 corn (2006– 2099); (d) RCP 4.5 soybean (2006– 2099); (e) RCP 8.5 corn (2006– 2099); (f) RCP 8.5 soybean (2006– 2099).

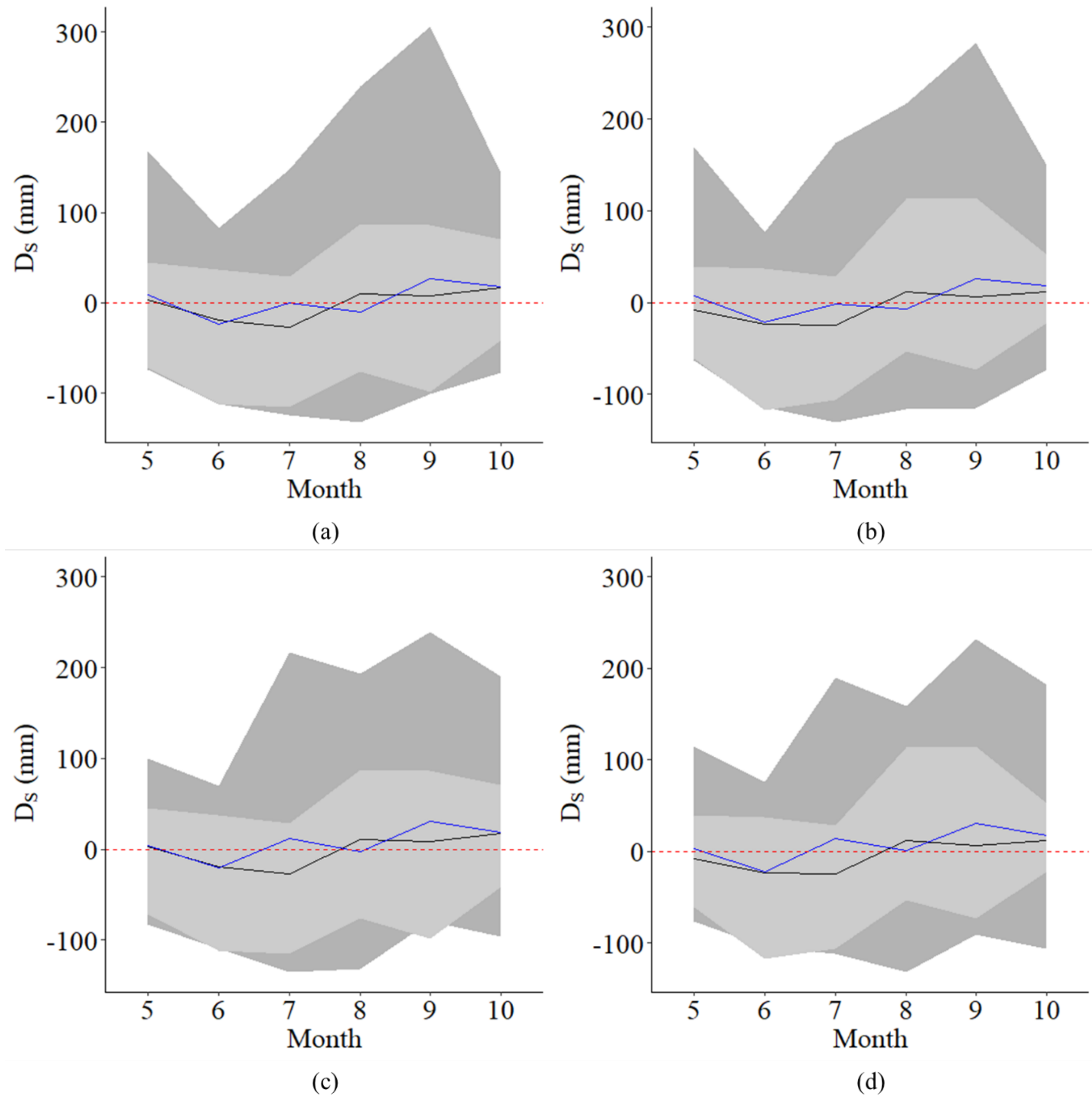


Figure A.50 Baseline (2020–2069) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for BCC-CSM (blue line) (2020 – 2069). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

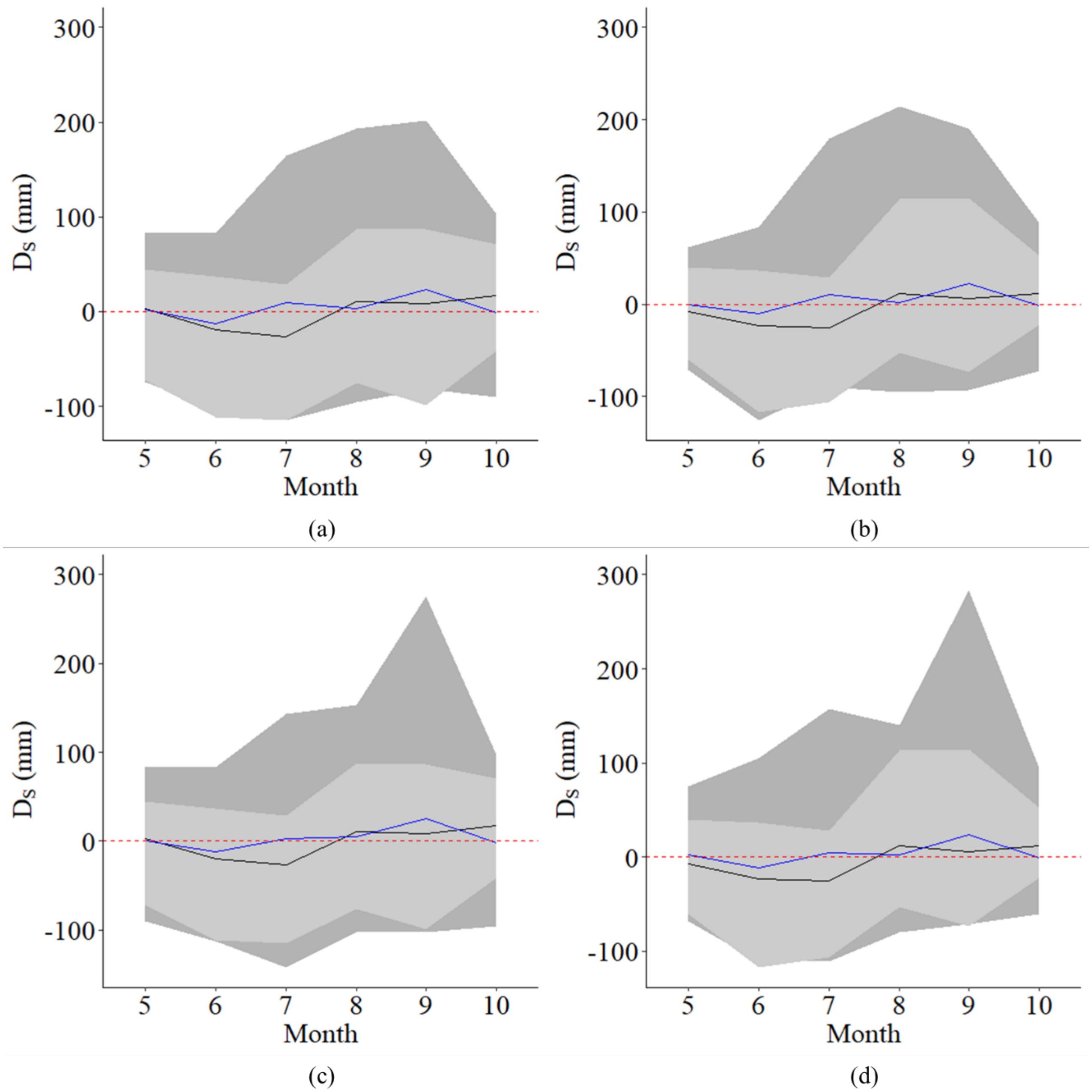


Figure A.51 Baseline (2020–2069) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for CCSM4 (blue line) (2020 – 2069). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

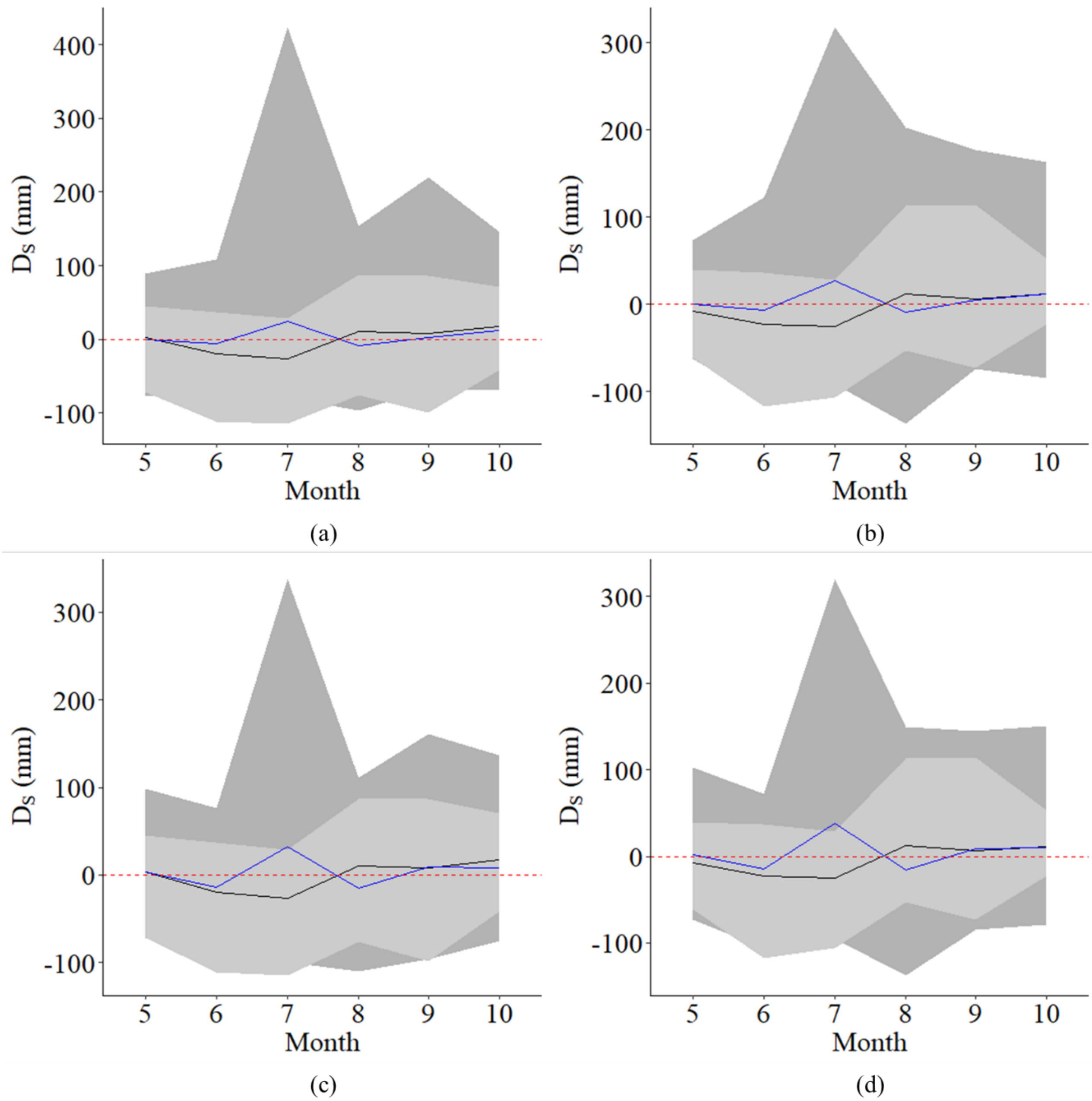


Figure A.52 Baseline (2020–2069) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for NorESM1 (blue line) (2020 – 2069). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

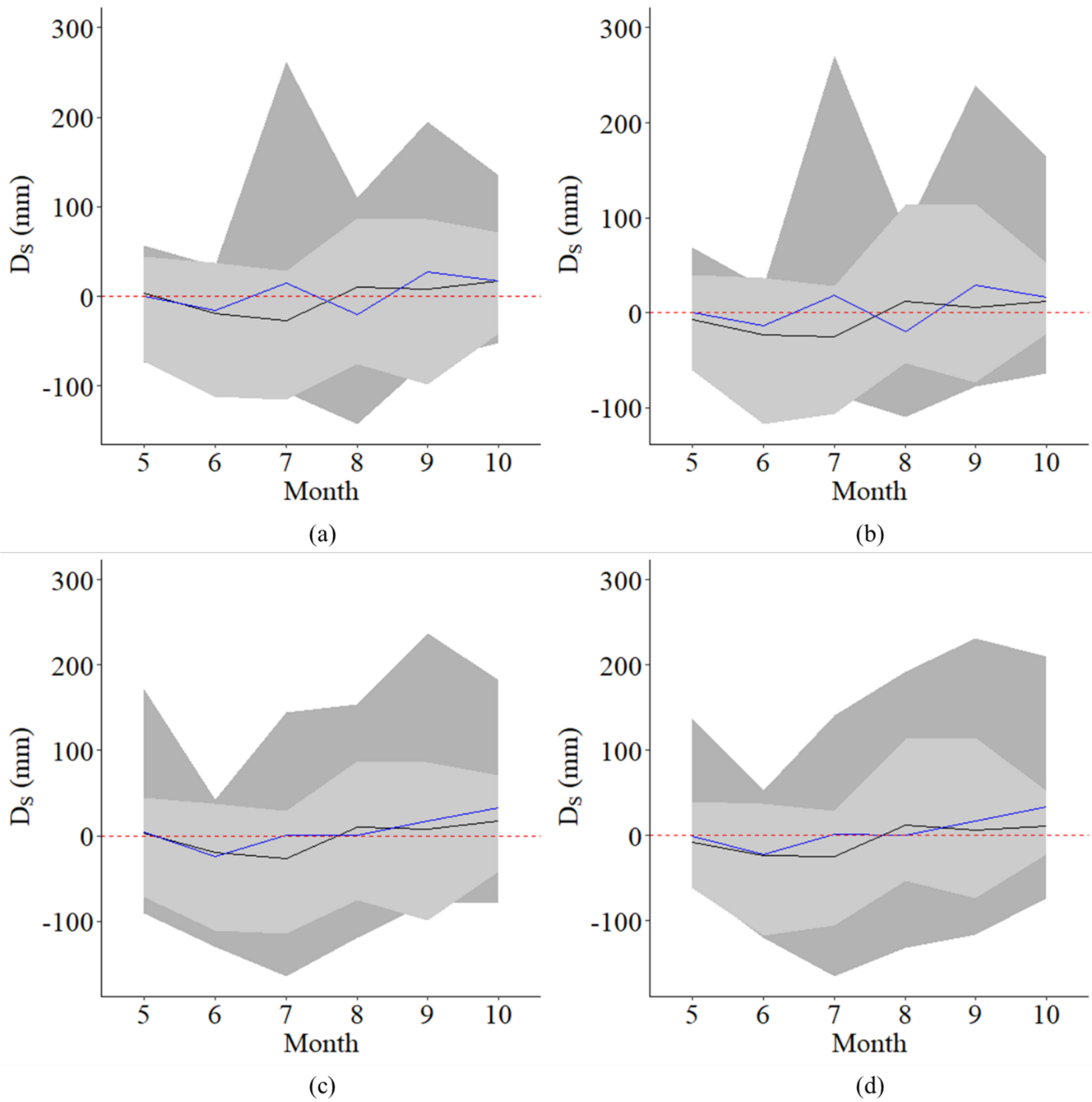


Figure A.53 Baseline (2070–2099) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for BCC-CSM (blue line) (2070 – 2099). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

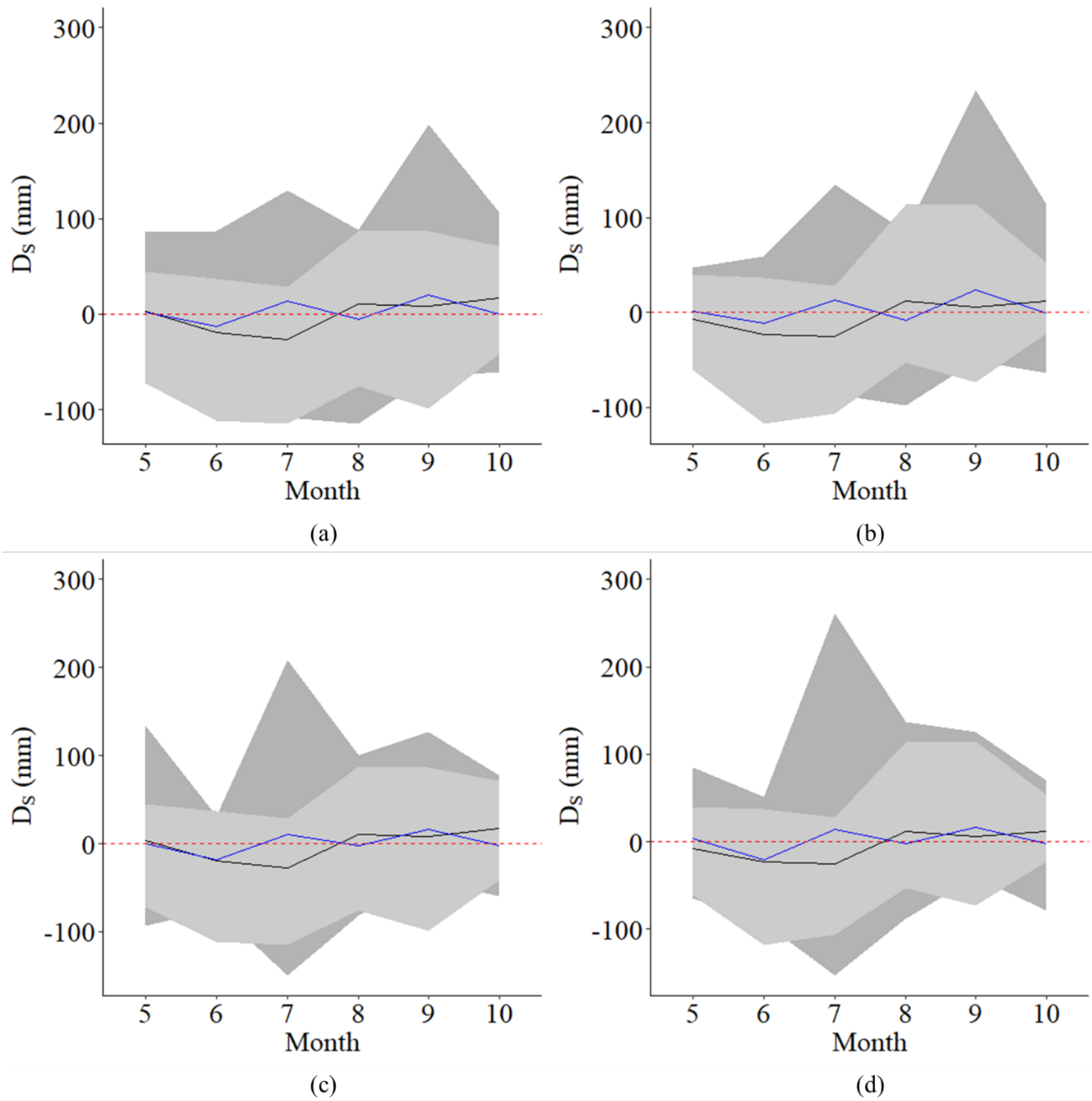


Figure A.54 Baseline (2070–2099) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for CCSM4 (blue line) (2070 – 2099). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

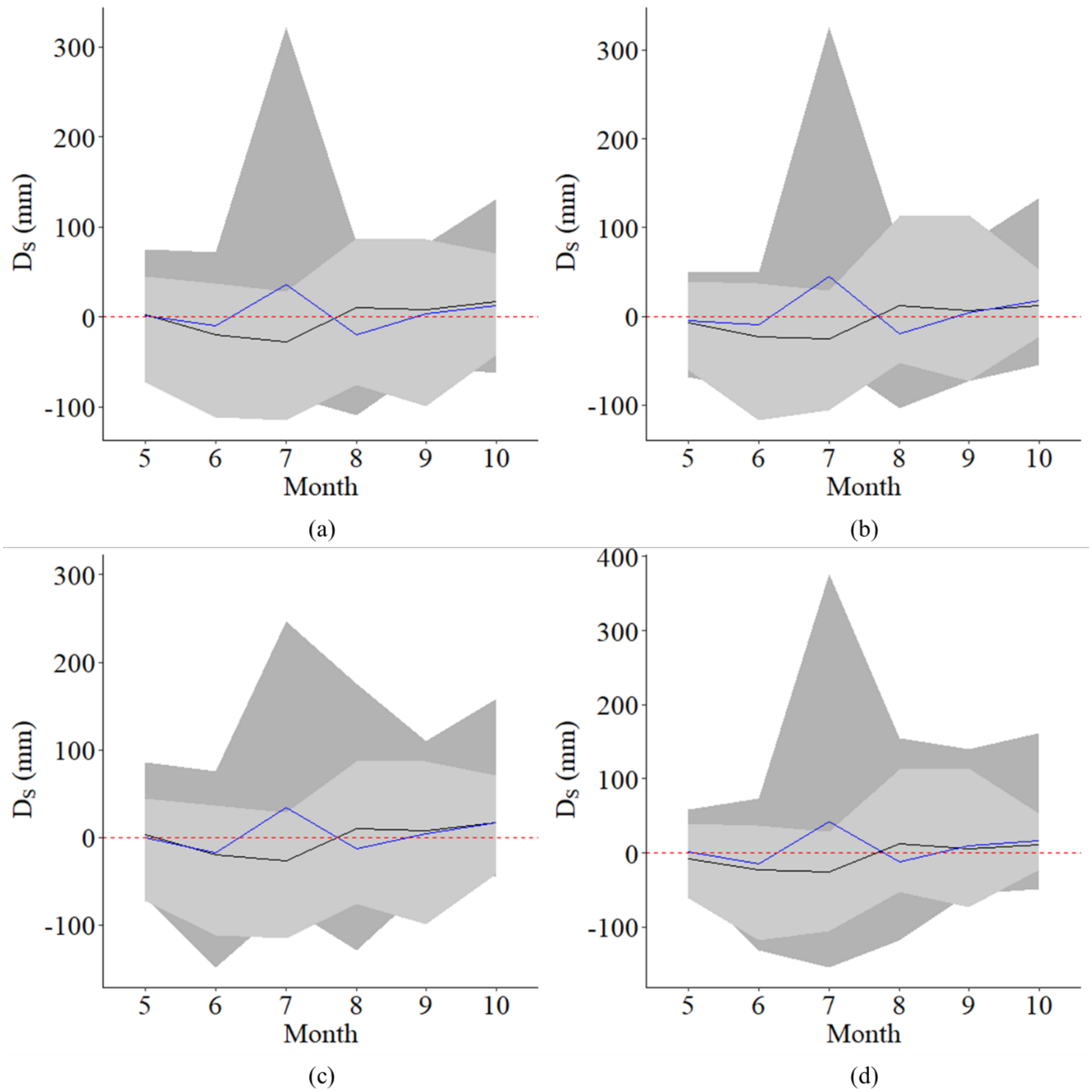


Figure A.55 Baseline (2070–2099) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for NorESM1 (blue line) (2070 – 2099). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

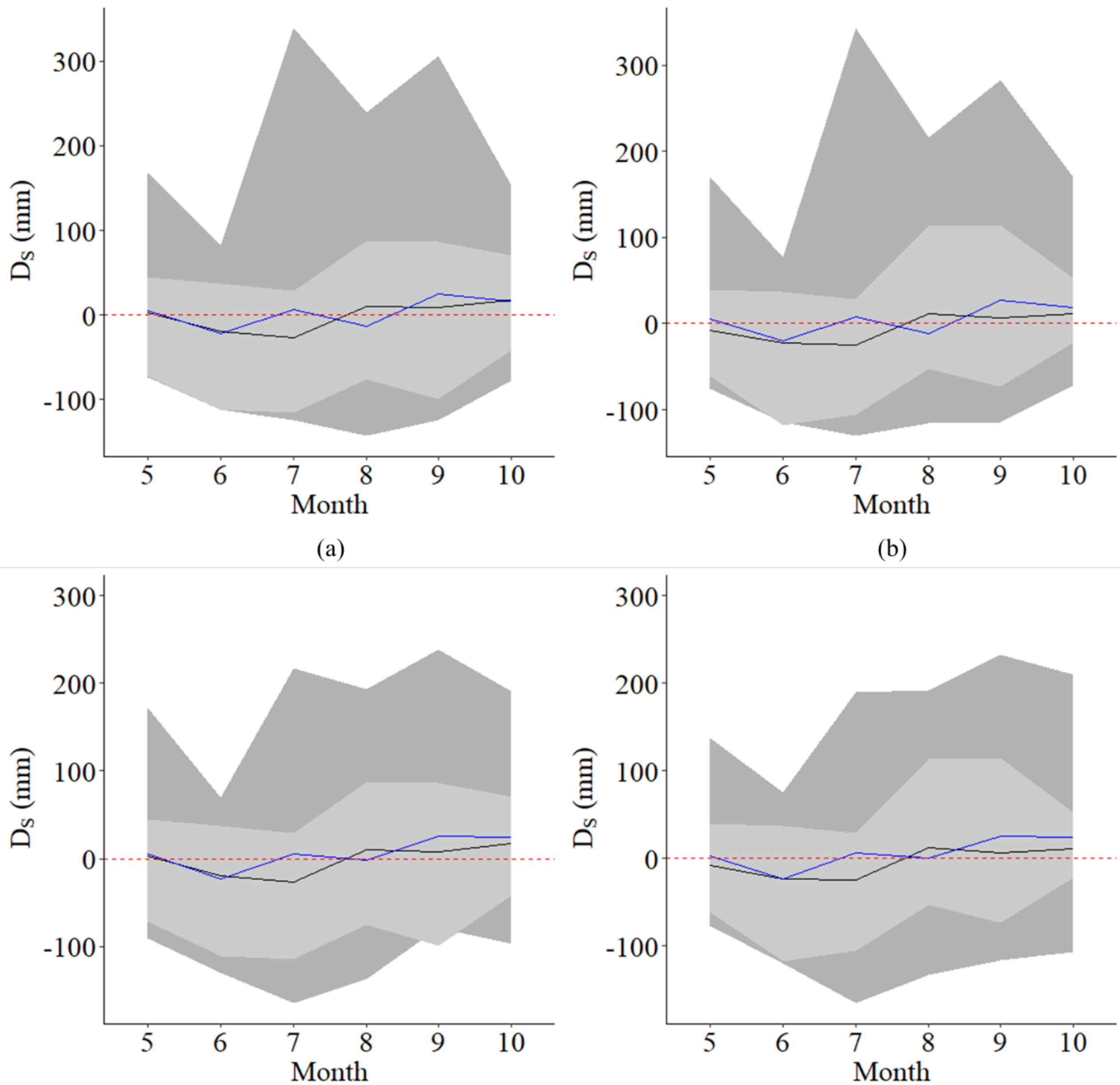


Figure A.56 Baseline (2006–2099) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for BCC-CSM (blue line) (2070 – 2099). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

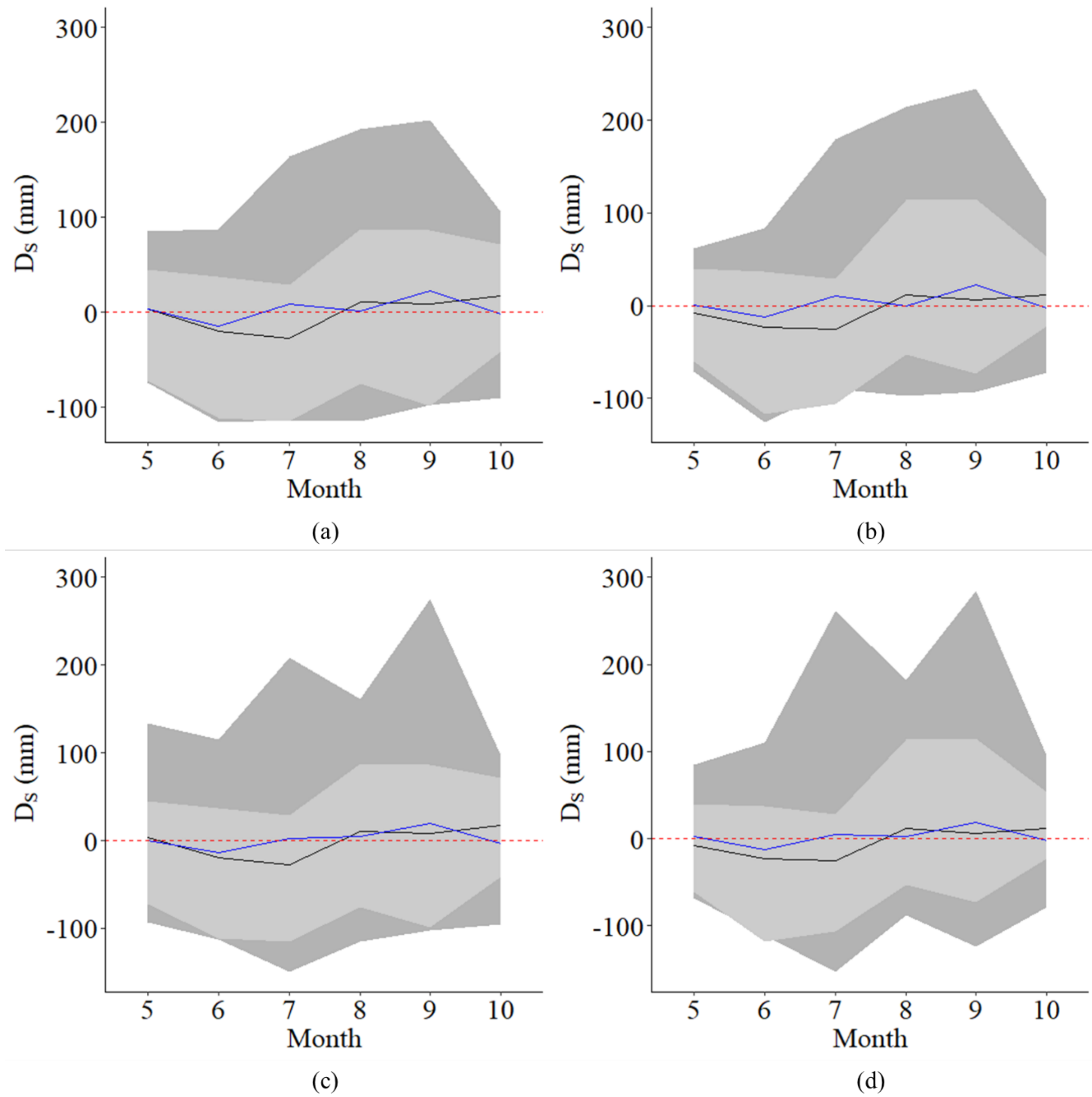


Figure A.57 Baseline (2006–2099) average (black line) for deficits or surplus (D_S) for corn and soybean and respective ranges versus ranges futuristic scenarios for CCSM4 (blue line) (2070 – 2099). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

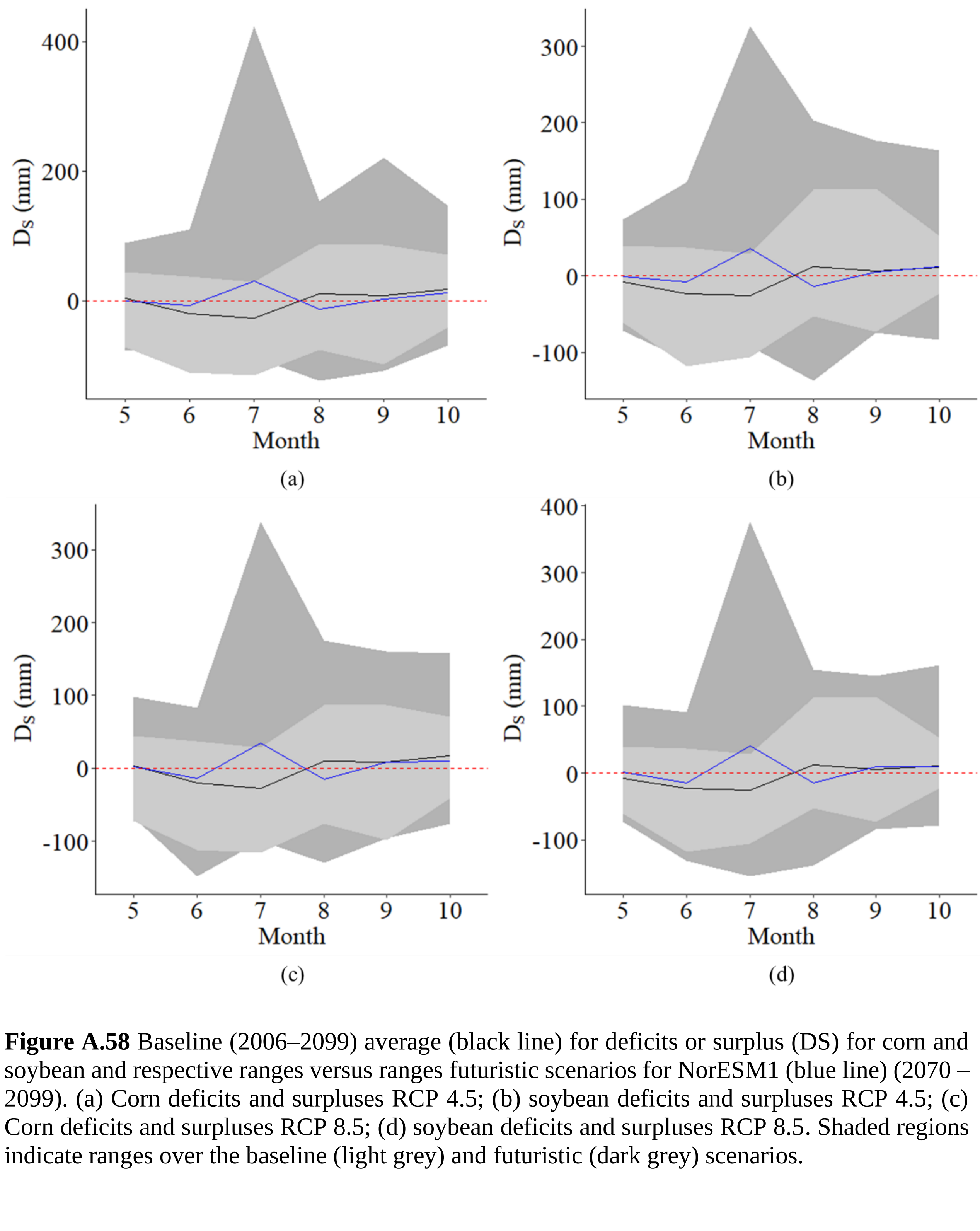


Figure A.58 Baseline (2006–2099) average (black line) for deficits or surplus (DS) for corn and soybean and respective ranges versus ranges futuristic scenarios for NorESM1 (blue line) (2070 – 2099). (a) Corn deficits and surpluses RCP 4.5; (b) soybean deficits and surpluses RCP 4.5; (c) Corn deficits and surpluses RCP 8.5; (d) soybean deficits and surpluses RCP 8.5. Shaded regions indicate ranges over the baseline (light grey) and futuristic (dark grey) scenarios.

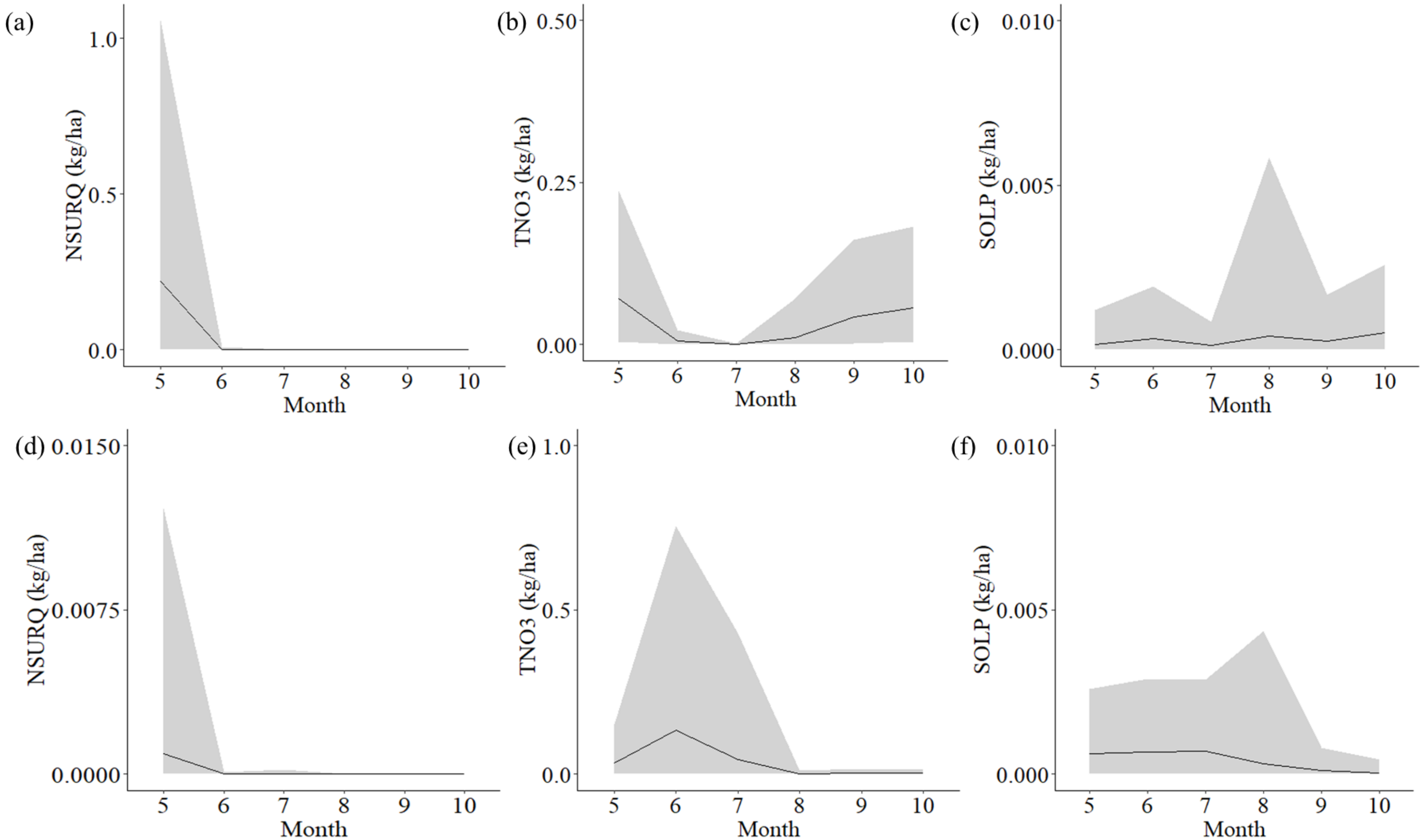


Figure A.59 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for 2006–2019: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the baseline scenario.

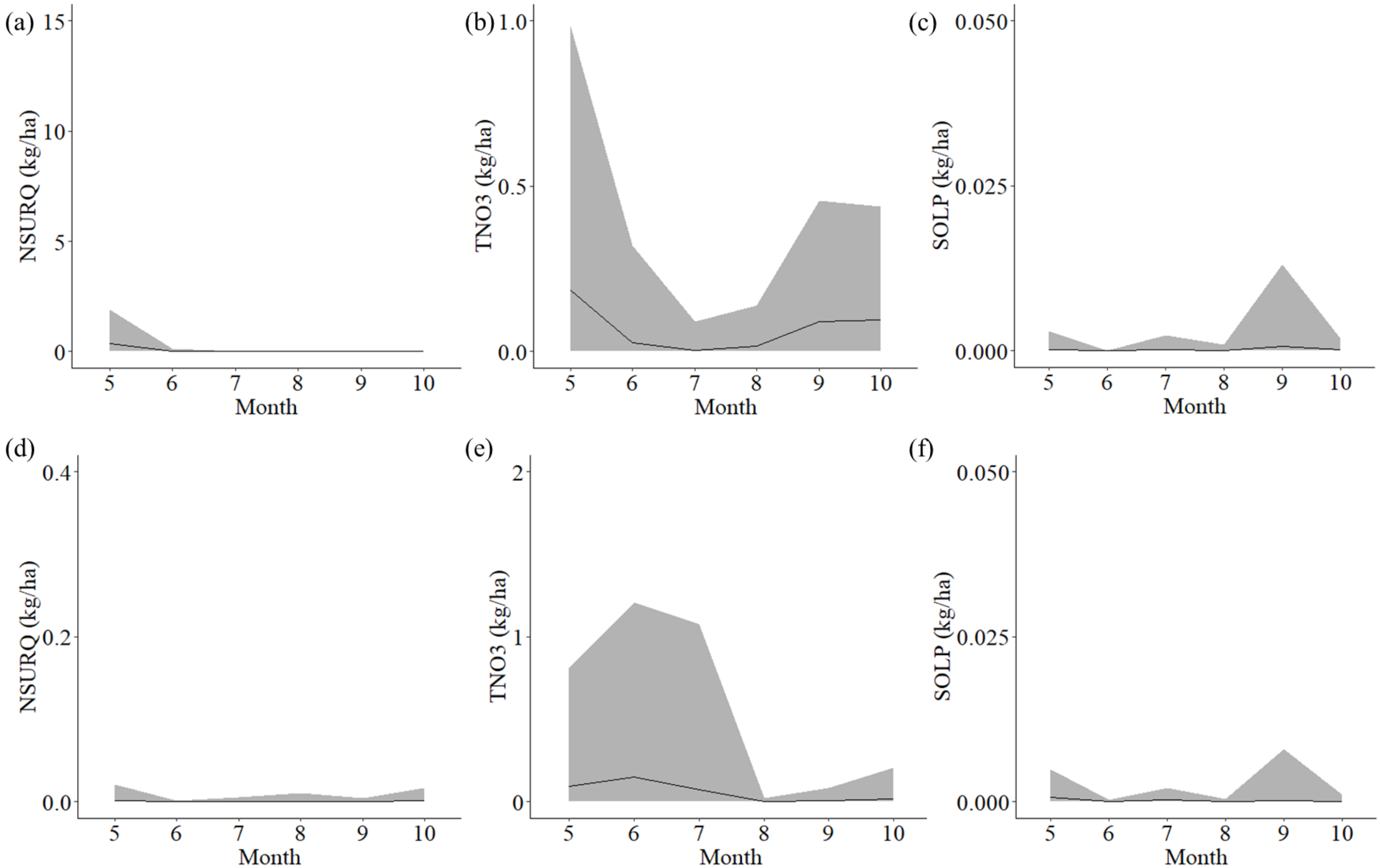


Figure A.60 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for BCC-CSM1.1 RCP 4.5 2020–2069: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

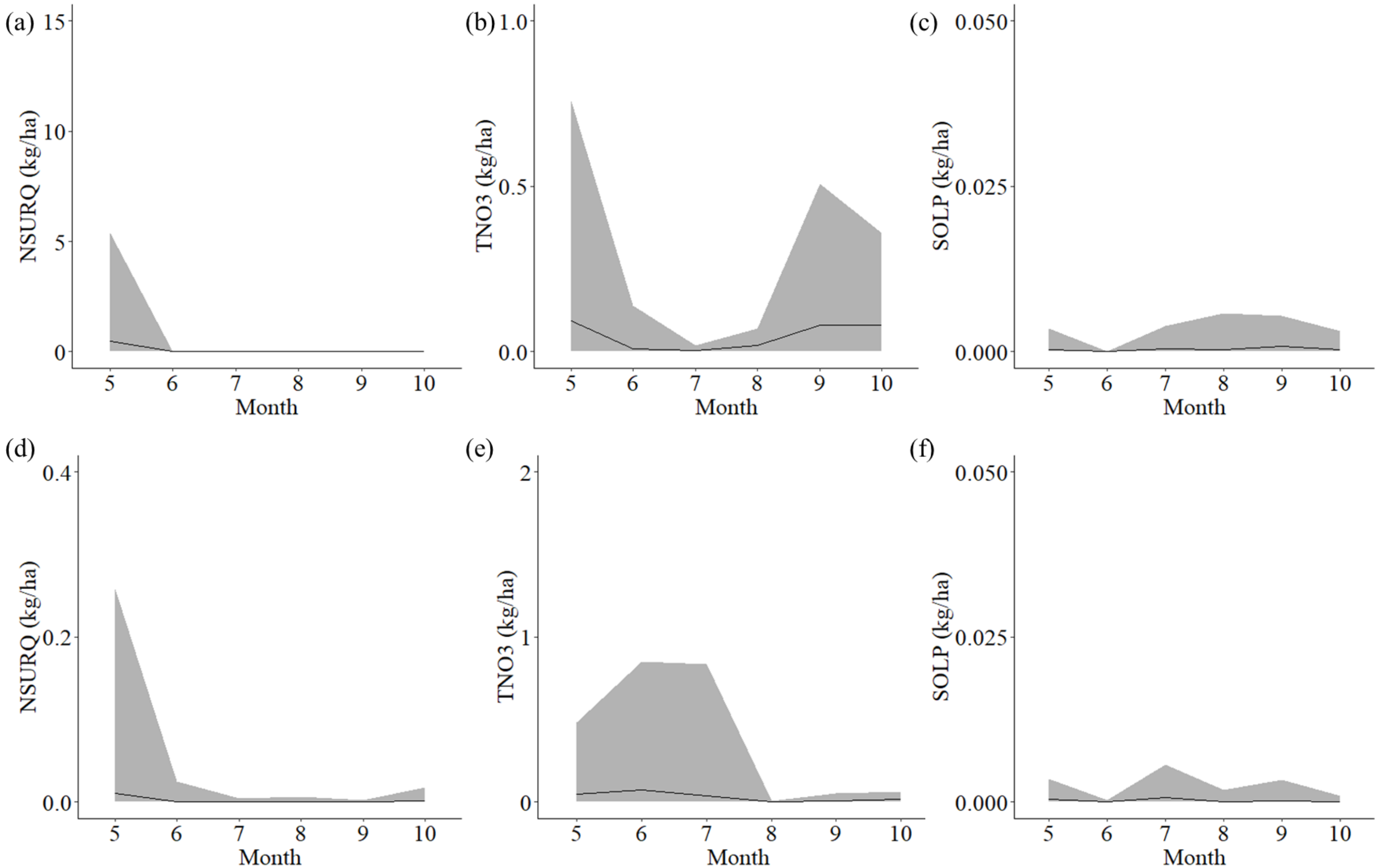


Figure A.61 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for BCC-CSM RCP 8.5 2020–2069: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

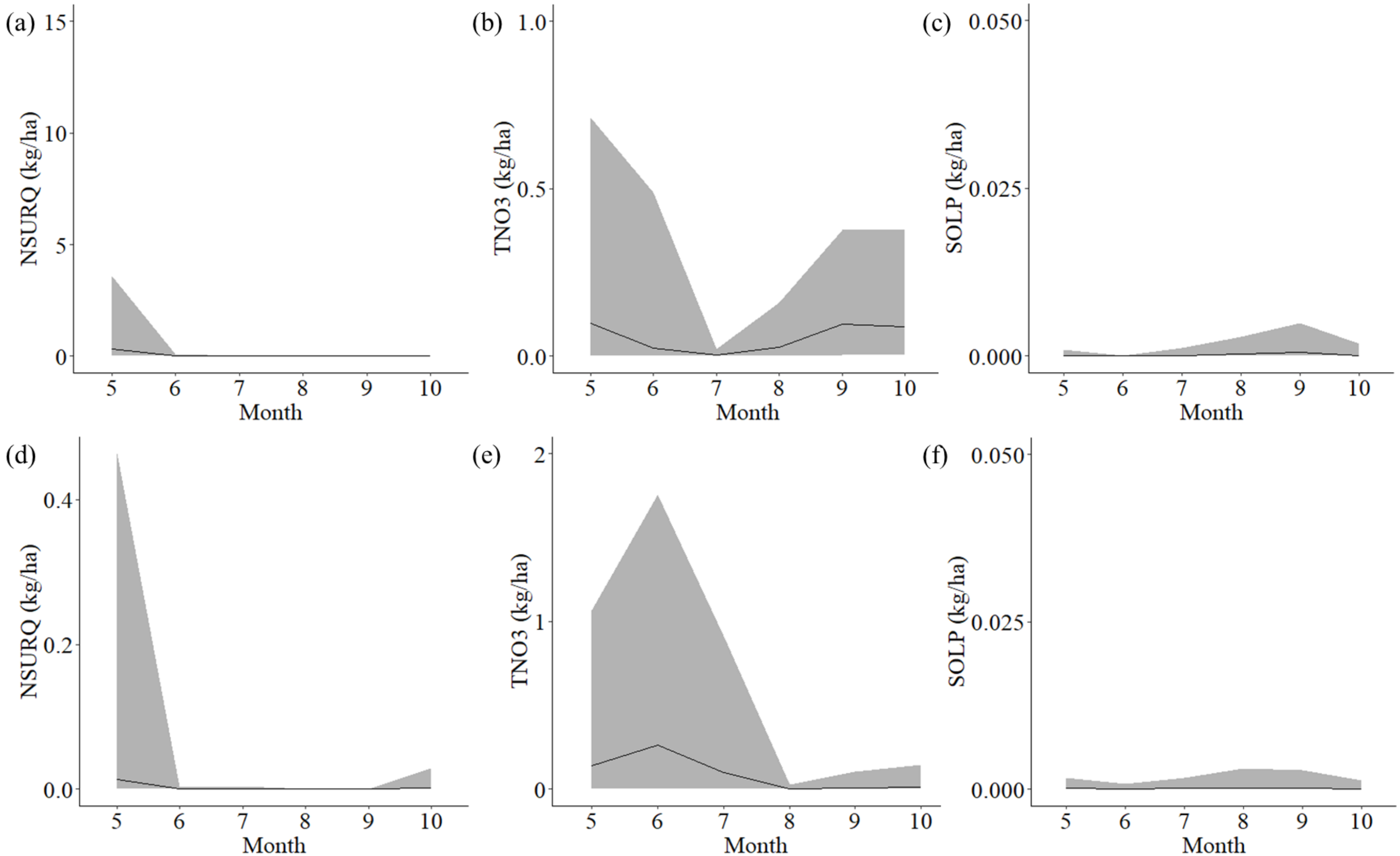


Figure A.62 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 4.5 2020–2069: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

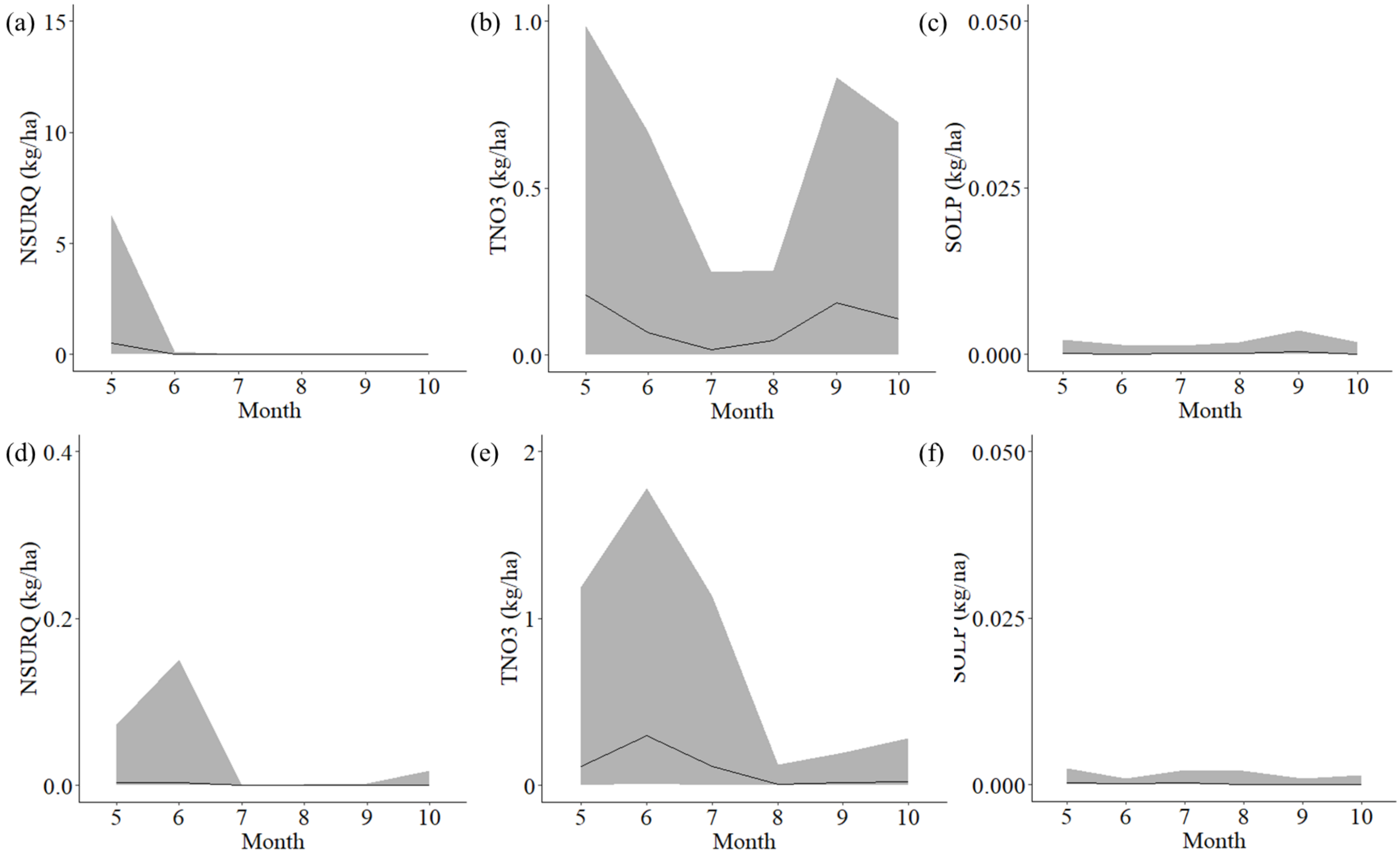


Figure A.63 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 8.5 2020–2069: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

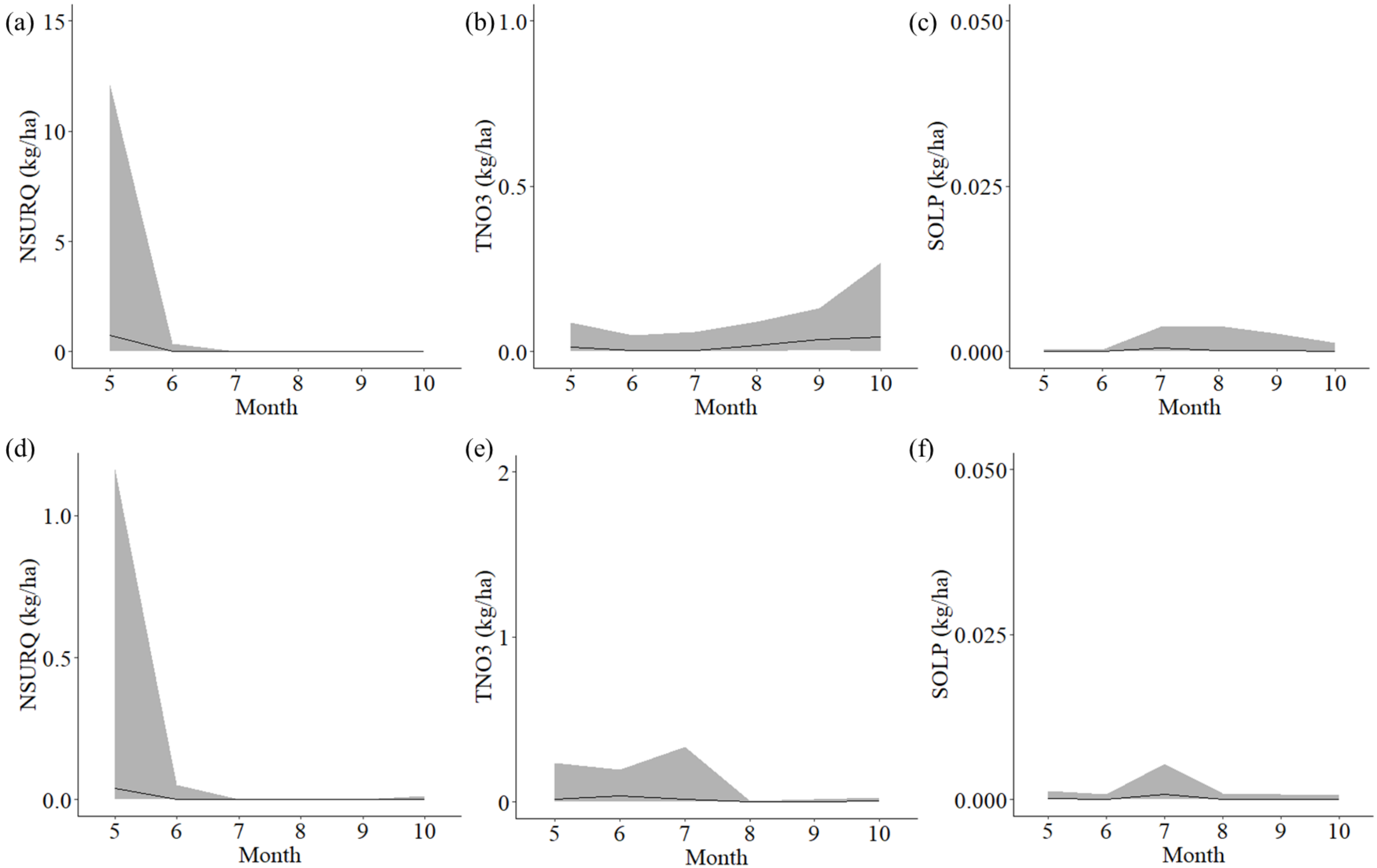


Figure A.64 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for NorESM1 RCP 4.5 2020–2069: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

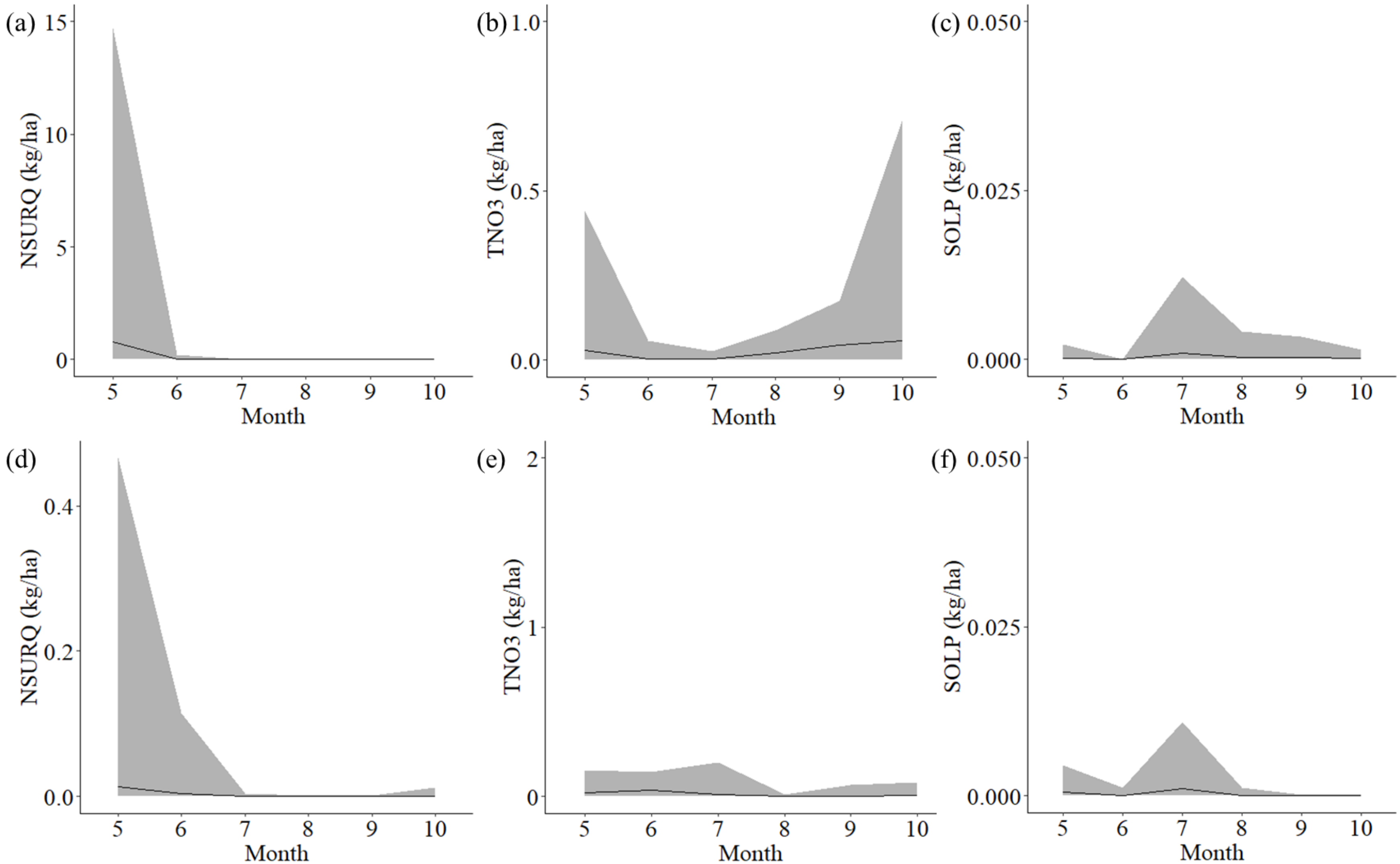


Figure A.65 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for NorESM1 RCP 8.5 2020–2069: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

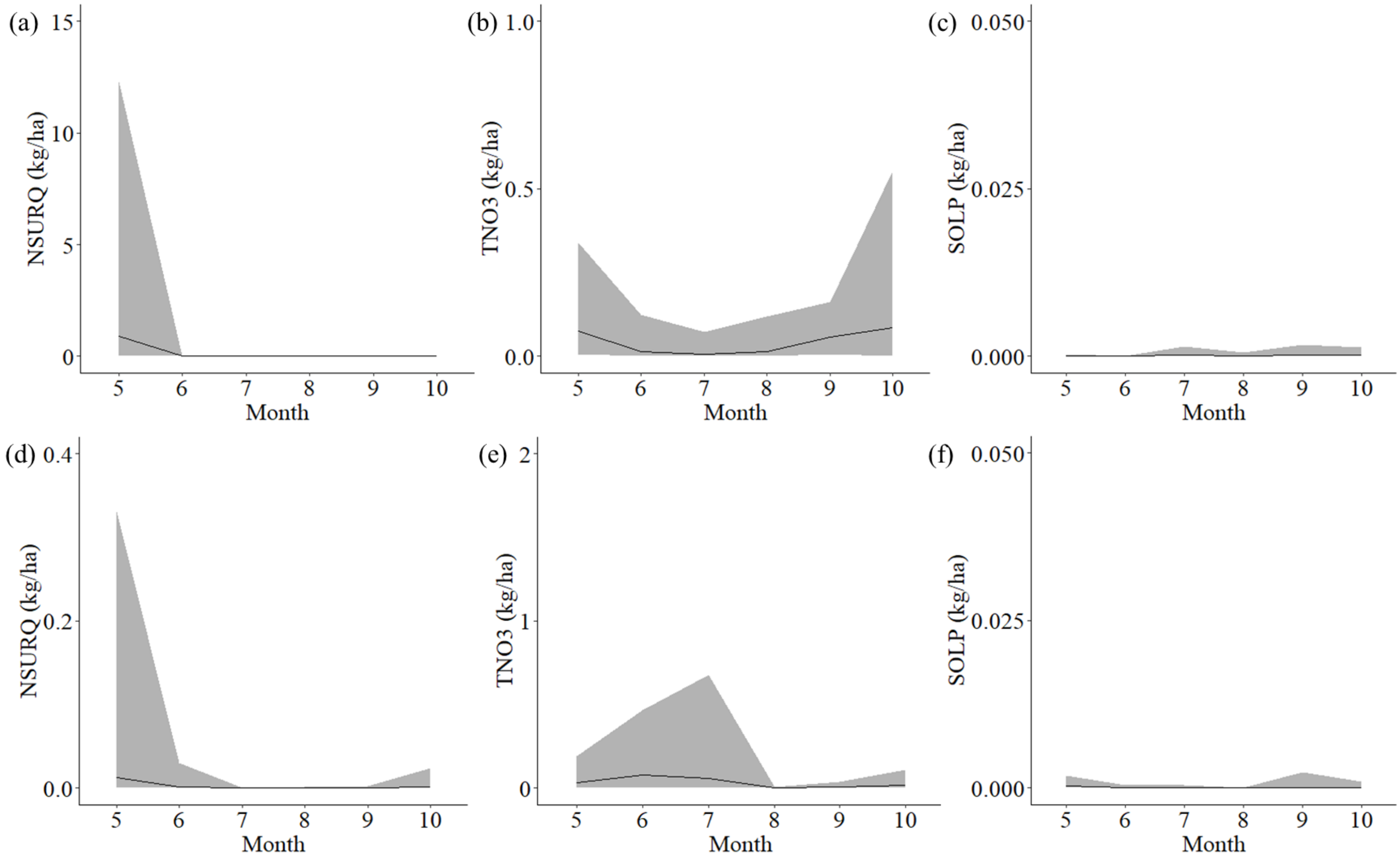


Figure A.66 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for BCC -CSM RCP 4.5 2070–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

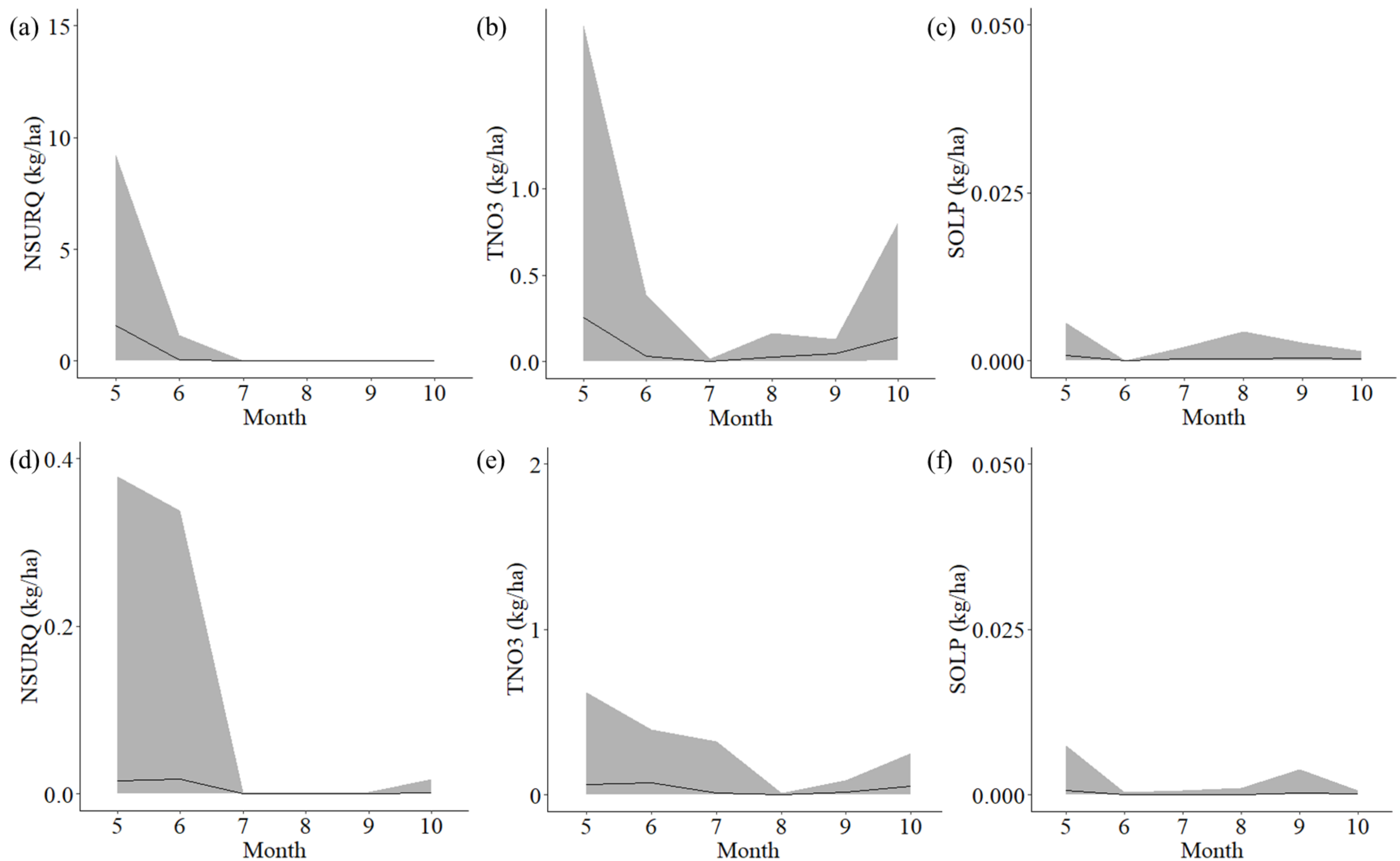


Figure A.67 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for BCC -CSM RCP 8.5 2070–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

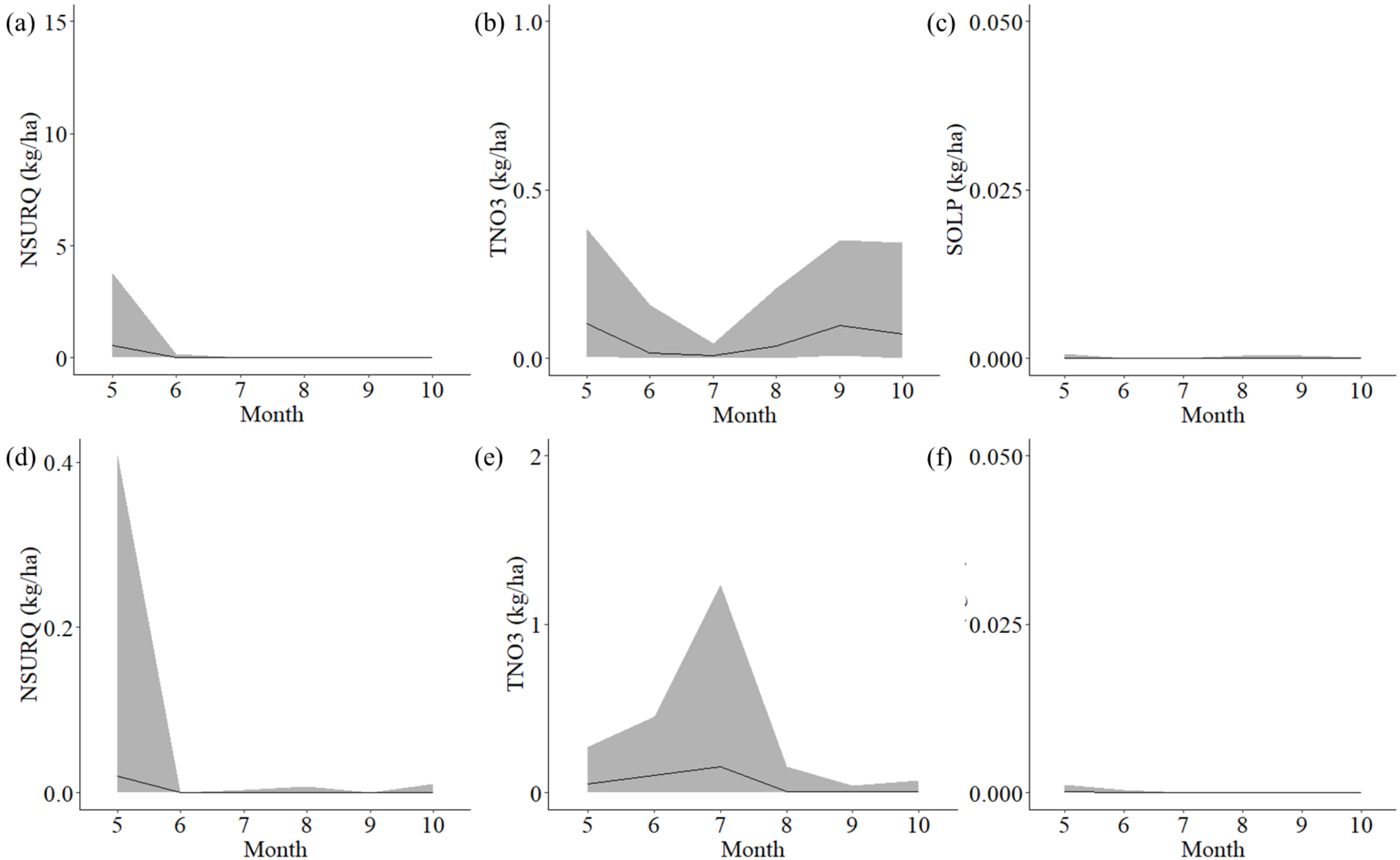


Figure A.68 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 4.5 2070–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

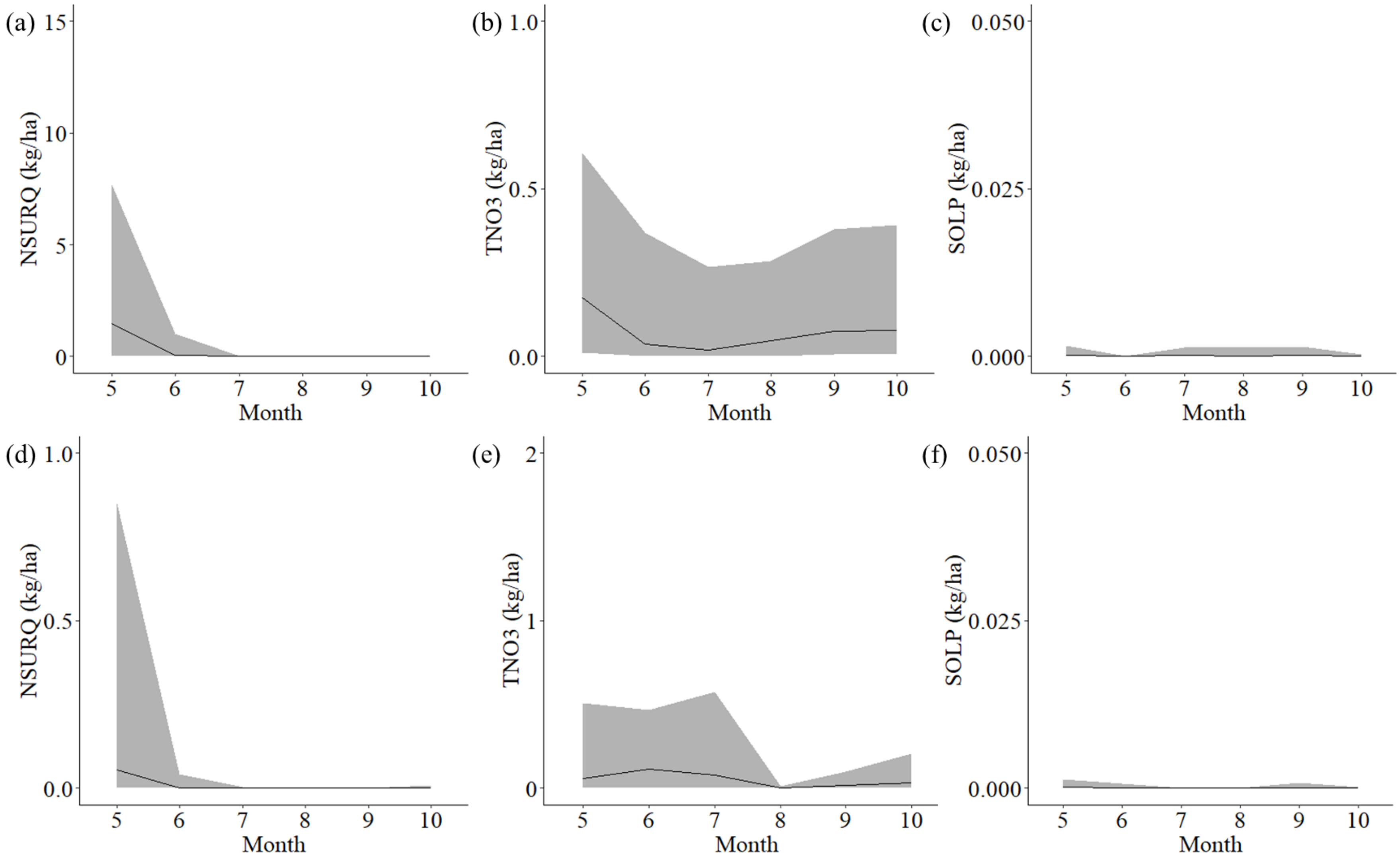


Figure A.69 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 8.5 2070–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

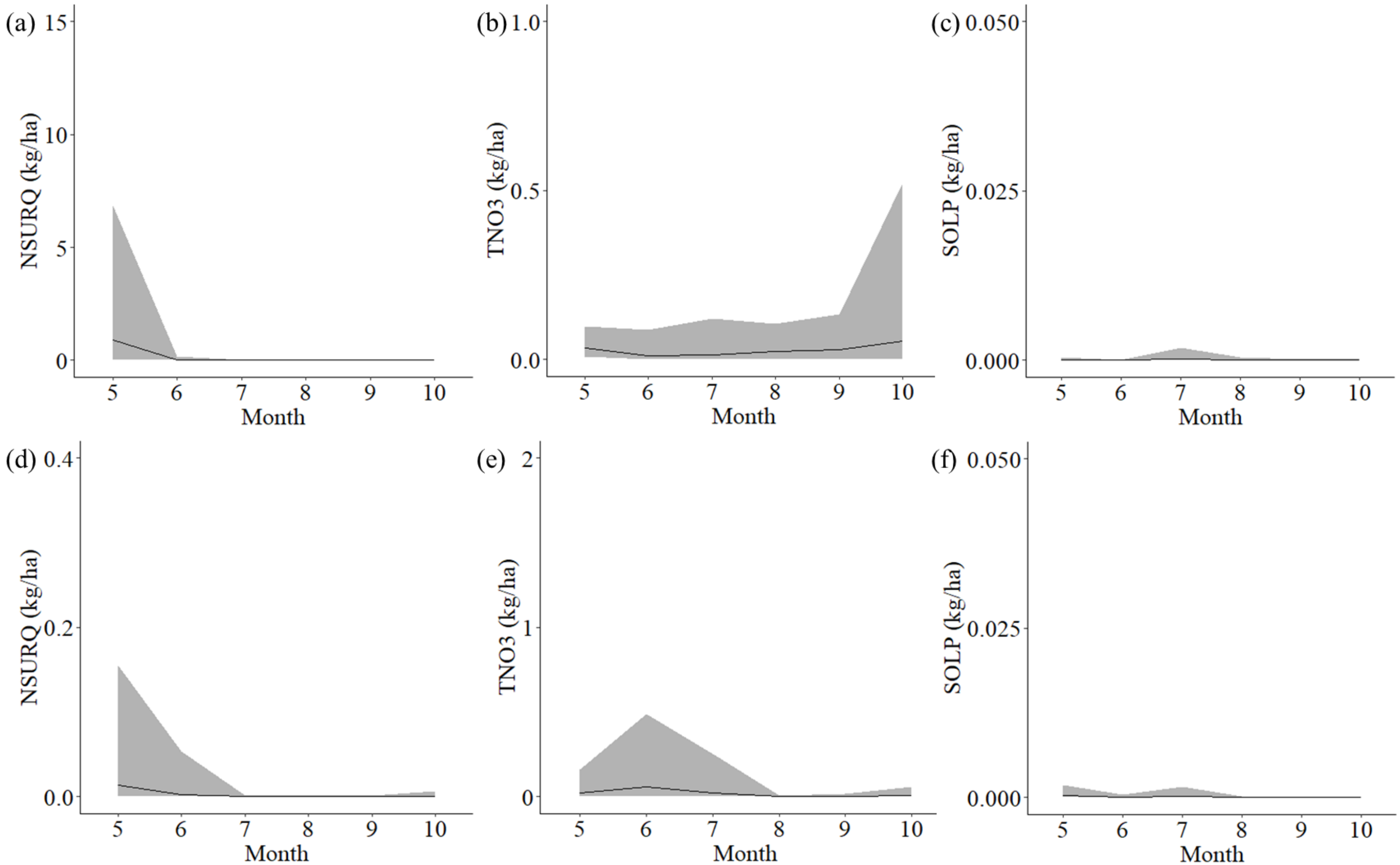


Figure A.70 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for NorESM1 RCP 4.5 2070–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

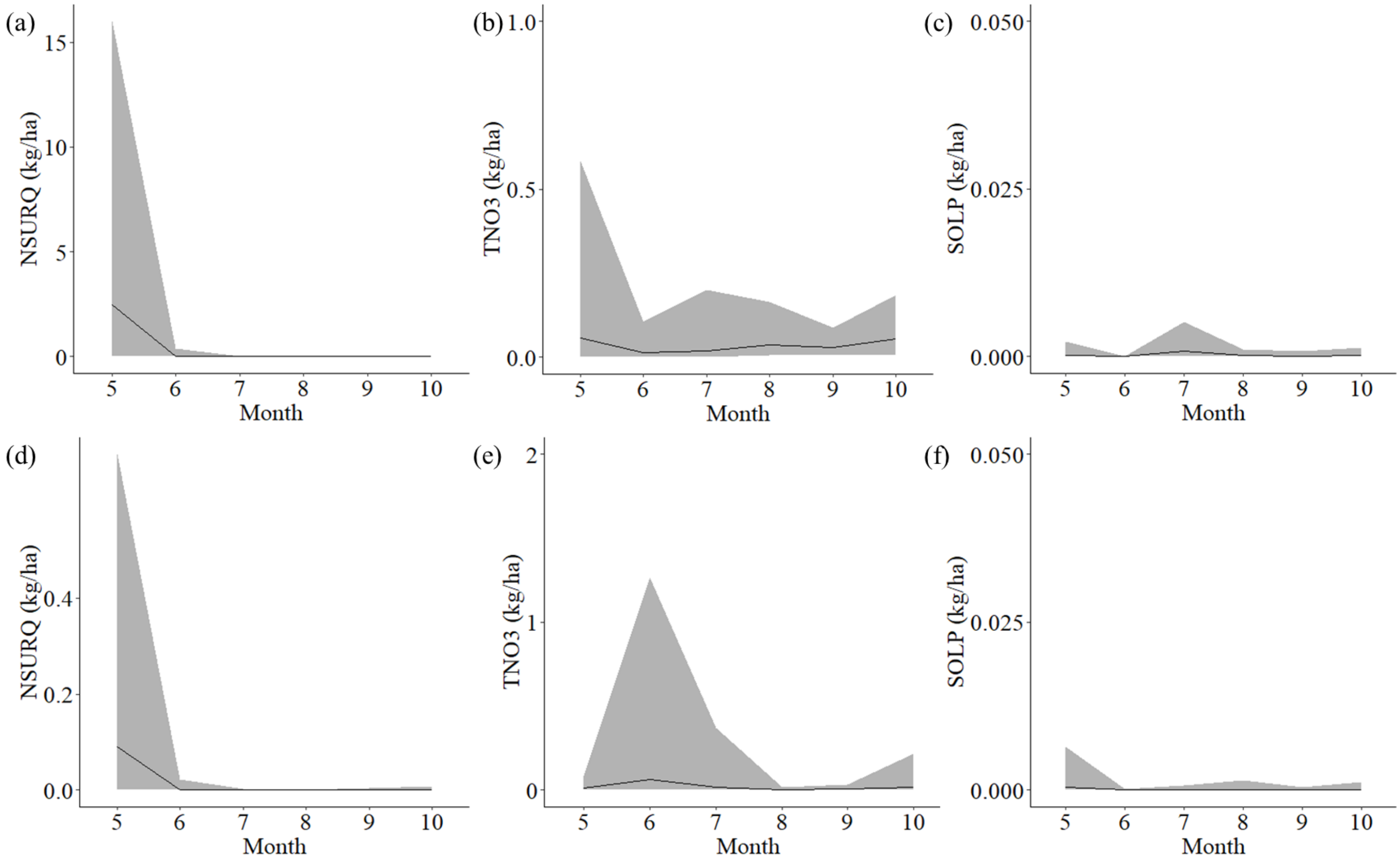


Figure A.71 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for NorESM1 RCP 8.5 2070–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

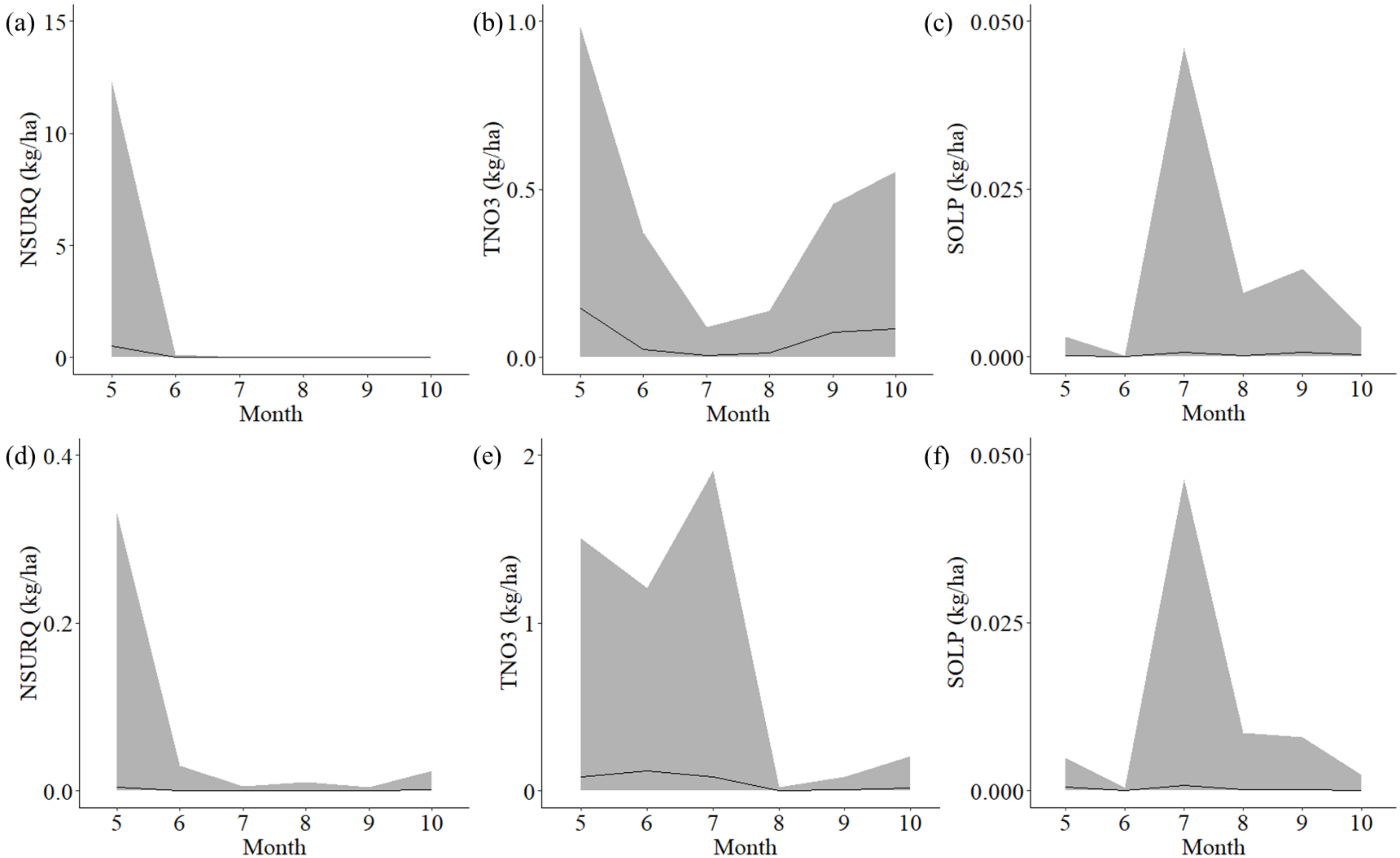


Figure A.72 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for BCC-CSM RCP 4.5 2006 – 2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

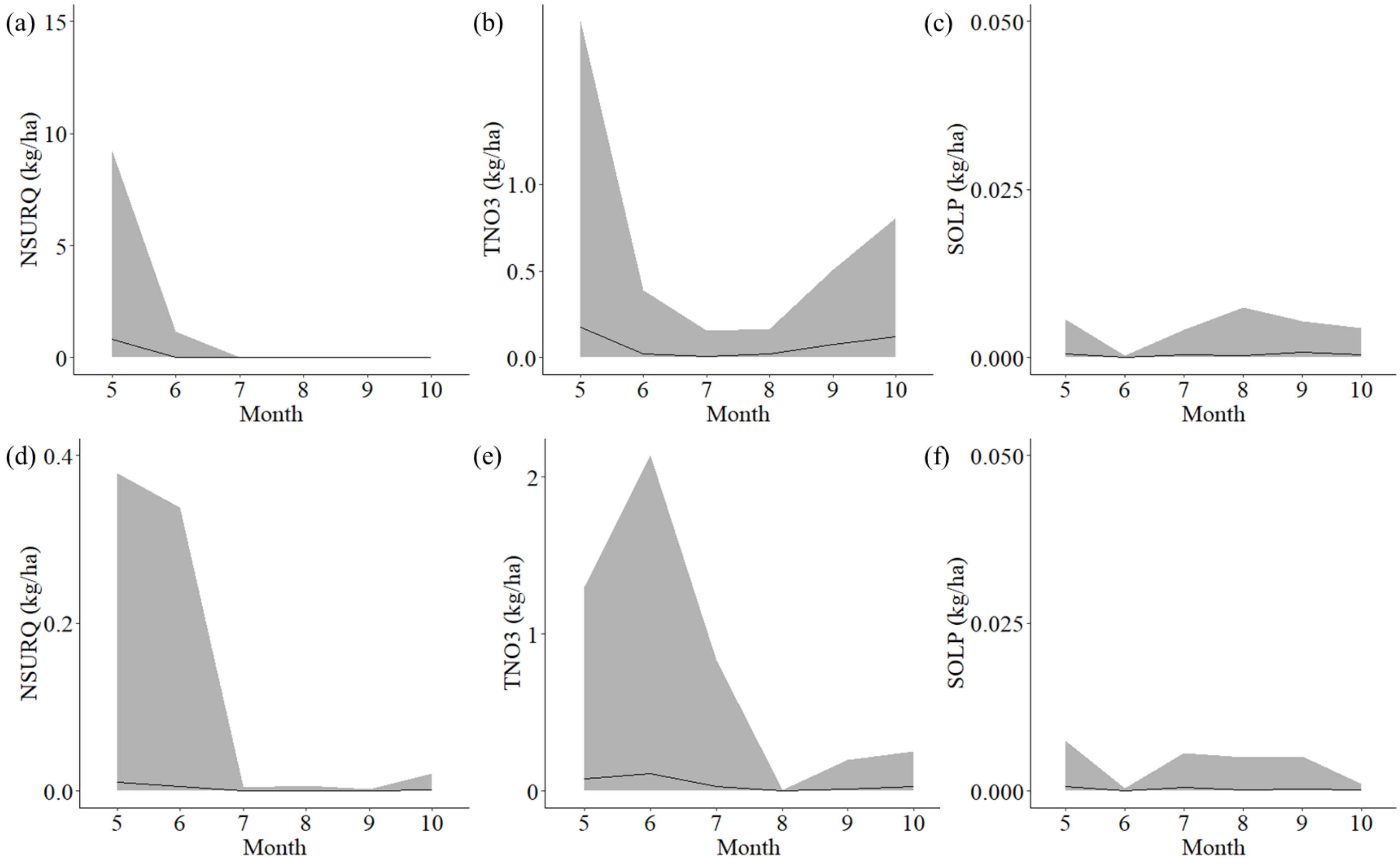


Figure A.73 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for BCC-CSM RCP 8.5 2006–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

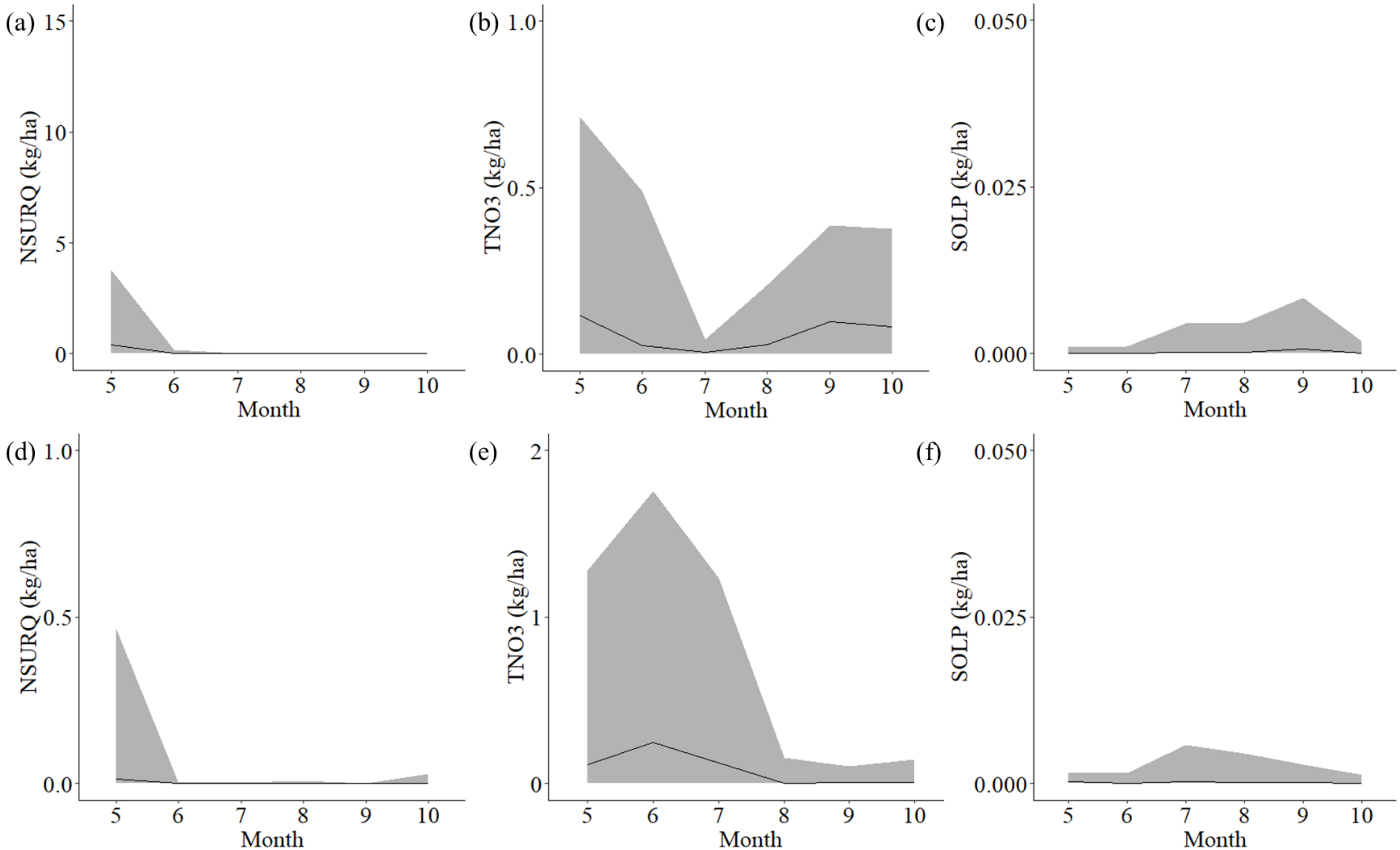


Figure A.74 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 4.5 2006–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

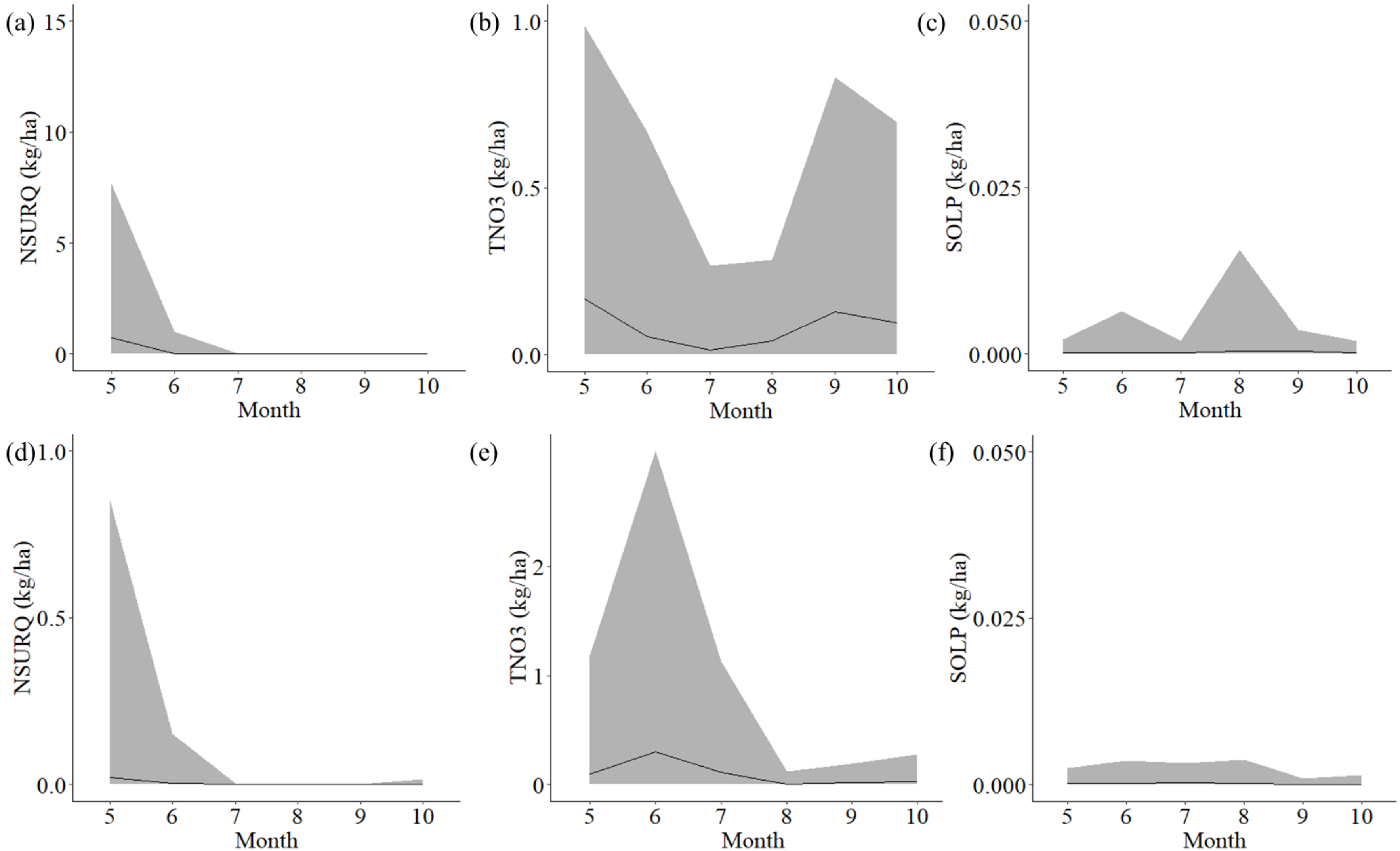


Figure A.75 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 4.5 2006–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

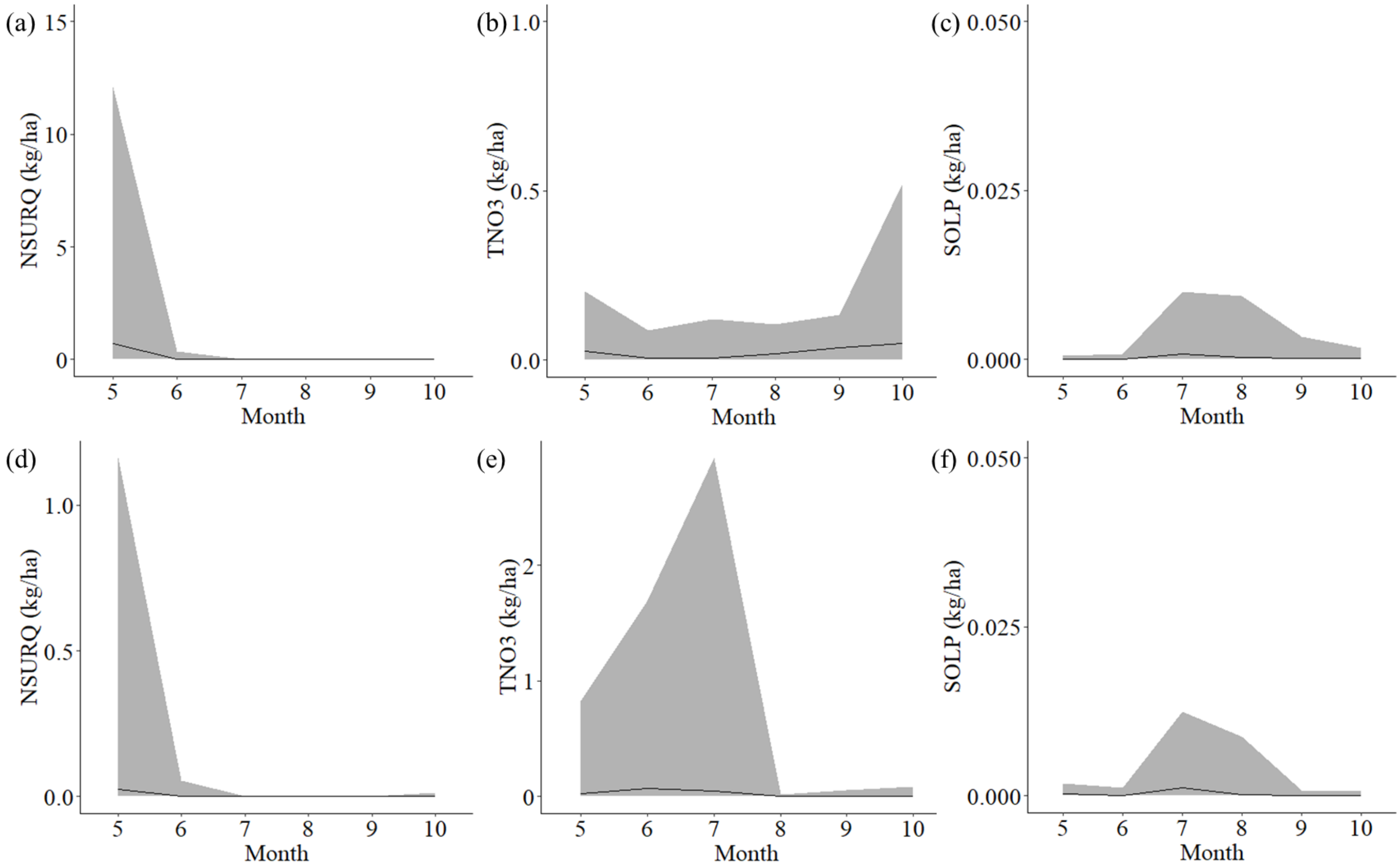


Figure A.76 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for CCSM4 RCP 8.5 2006–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

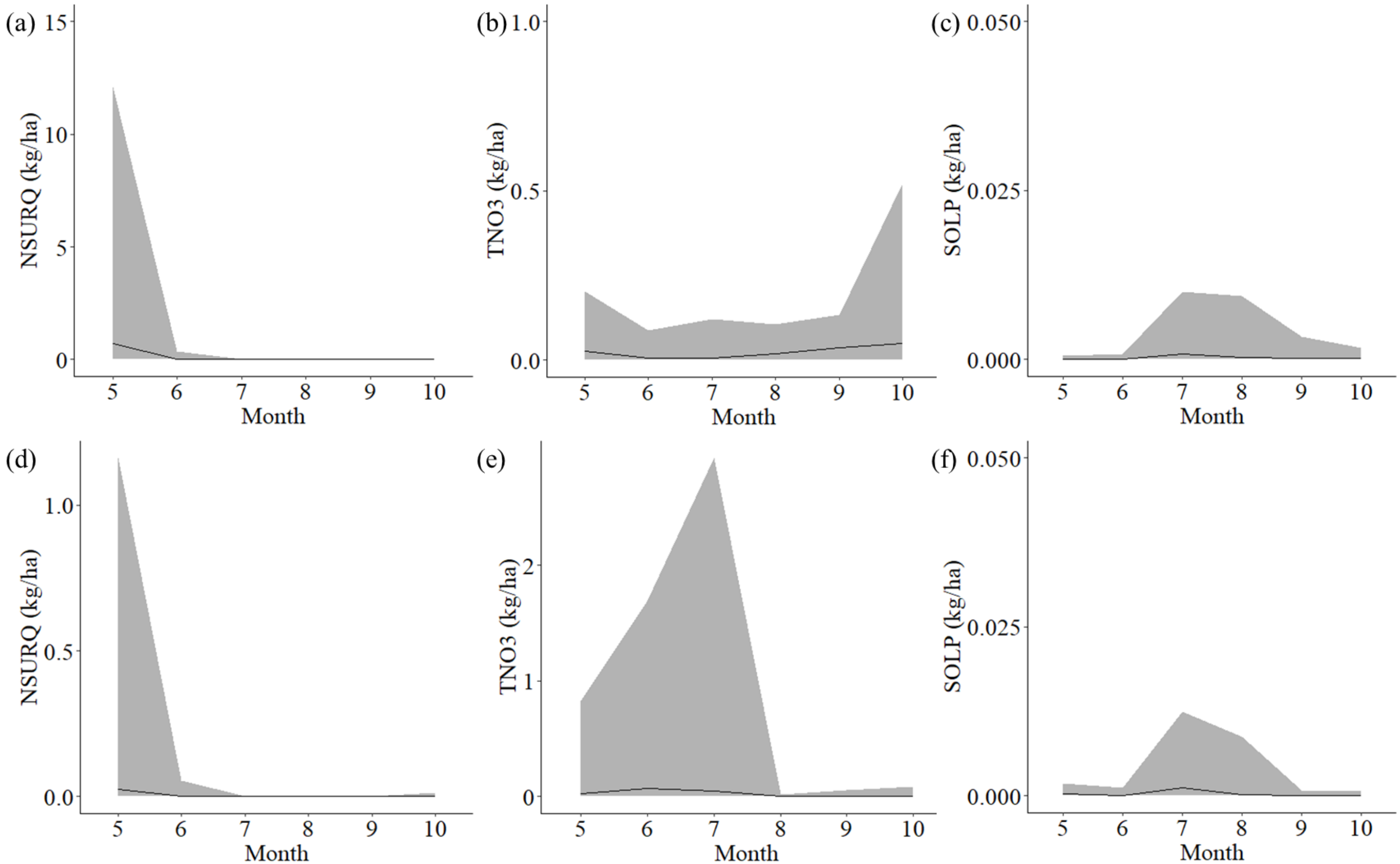


Figure A.77 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for NorESM1 RCP 4.5 2006–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

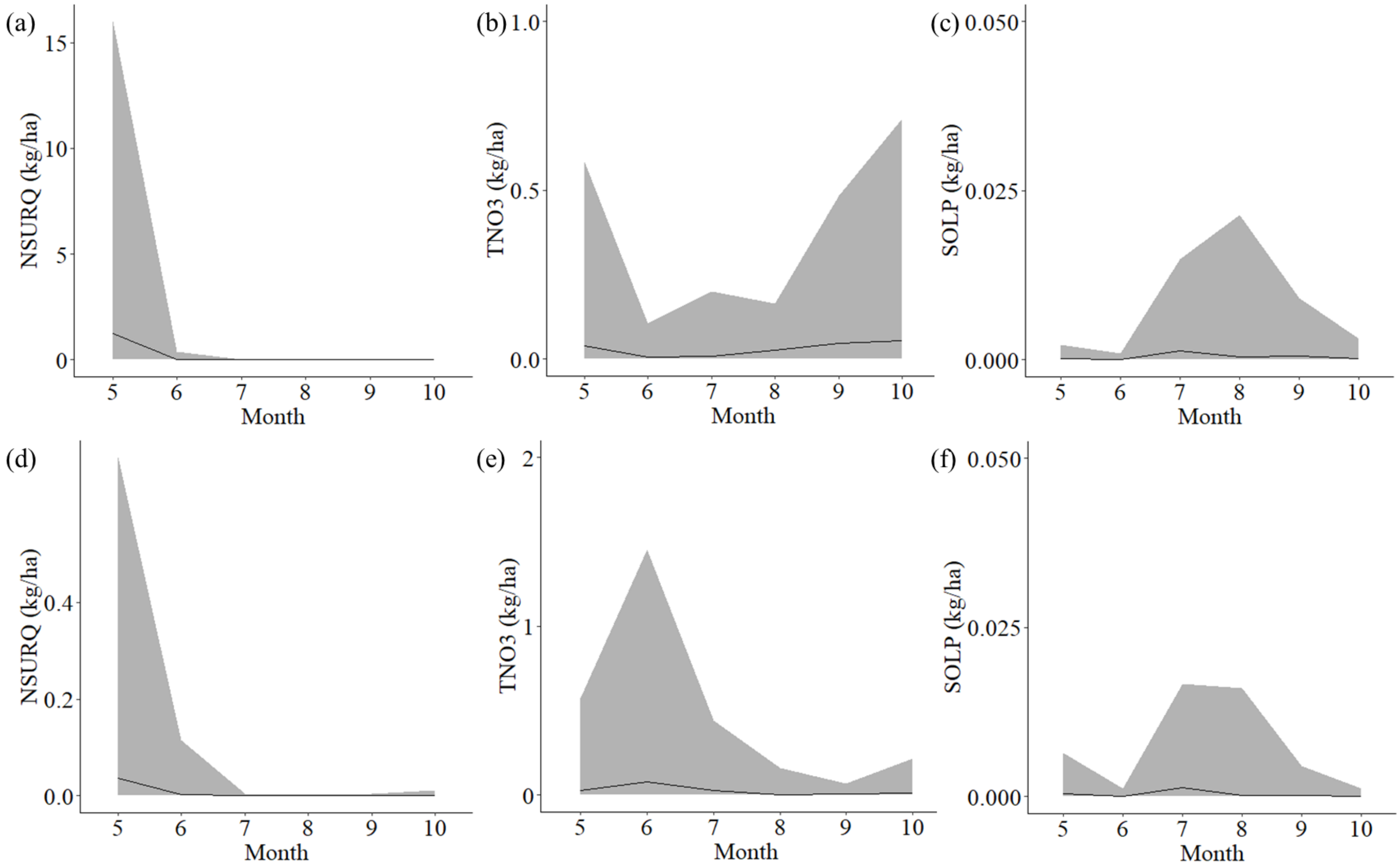


Figure A.78 Monthly average nutrient losses (black line) from crops in the Matson Ditch Watershed for NorESM1 RCP 8.5 2006–2099: (a) surface NO_3-N for corn; (b) subsurface drainage NO_3-N for corn; (c) soluble P for corn; (d) surface NO_3-N for soybeans; (e) subsurface drainage NO_3-N for soybeans; (f) soluble P for soybeans. Shaded regions indicate ranges over the futuristic scenario.

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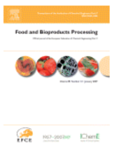

Analyzing FEW nexus modeling tools for water resources decision-making and management applications

Author: Val Z. Schull,Bassel Daher,Margaret W. Gitau,Sushant Mehan,Dennis C. Flanagan
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