INNOVATIVE APPROACHES TO GAUGE RESILIENCE OF MANAGED RAINFED AGRICULTURAL SYSTEMS

By

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ABSTRACT

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Increasing climate extremes have devastated both crop yields and farm economies, especially in the rainfed agricultural systems of the Midwestern United States. Furthermore, these extreme events are projected to increase in the future due to climate change. As a result, alternative agricultural practices are becoming more common in efforts to mitigate the impacts of extreme climatological events. Nevertheless, the level of resiliency of these practices has not yet been adequately quantified due to the lack of robust metrics available to address the complexity of agricultural systems while being simple enough to be measured at different scales. To this end, three studies were conducted and compiled into this dissertation. These studies were carried out in a long-term cropping system experiment at the W.K. Kellogg Biological Station and the Kalamazoo River Watershed located in the Southwestern Michigan of the United States.

The first study was designed to evaluate the applicability of soil moisture metrics to gauge resiliency of four differently managed rainfed agricultural treatments at the field scale. The robustness of these metrics was assessed over a long-period (1993-2018) for a corn-soybean-wheat rotation by monitoring crop growth and yield in response to climate variability. Results demonstrated that the soil moisture metrics can be used as indicators of resilience at the field scale. The no-till treatment had the highest level of resilience as quantified by soil moisture retention, effectiveness of reducing drought severity, crop yields, and stability of yields. Although the organic treatment substantially improved resiliency in terms of soil moisture conservation and drought mitigation than the conventional treatment, the limitation of available nitrogen

significantly reduced corn and wheat yields. Meanwhile, the reduced input treatment was the least resilient as it was vulnerable during extreme climate conditions.

The second study was performed to evaluate the climate resilience of four rainfed agricultural treatments in terms of profitability and farm risks for the same corn-soybean-wheat rotation. Crop production and management data were used to conduct enterprise budgeting and risk analysis. The means and volatility of estimated net returns and risk preferences were used as the evaluation metrics. According to the results of this study, the organic and the no-till treatments had higher resilience than the conventional and the reduced input treatments as they were projected to generate greater net revenues with higher stability. Furthermore, these treatments were promising to cater to a large group of farmers with different risk preferences. Meantime, conventional and reduced inputs treatments were found to be adversely affected by climate extremes.

The goal of the third study was to examine the impacts of large-scale adaptation of conservation agricultural practices (i.e., no-till treatment) on resilience in comparison to traditional practices (i.e., conventional treatment). Similar to the previous two studies, the corn-soybean-wheat rotation was applied on all agricultural land use in the Kalamazoo River Watershed during the period of 1993-2019. Crop and groundwater models were integrated to derive the resilience metrics, namely recharge, groundwater level, soil moisture, yield, and net return. Results showed clear improvement in all metrics under the no-till treatment. Therefore, the adoption of the no-till could improve the overall resilience of the corn-soybean-wheat rotation.

Together, these studies present a set of robust metrics to quantify the resilience of diverse rainfed agricultural systems both at the field and watershed scale.

This dissertation is dedicated to my loving parents, wife, and brothers for all the love and care they have given me.

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KEY TO ABBREVIATIONS

ADI: Accumulated Drought Index

AMSL: Above Mean Sea Level

APSIM: Agricultural Production Systems Simulator

ARMS: Agricultural Resource Management Survey

BD: Bulk Density

COBRA: Community Based Resilience Assessment

CON: Conventional

COSA: Committee on Sustainability Assessment

CRISTAL: Community-based Risk Screening Tool Adaptation and Livelihood

CV: Coefficient of Variation

DEM: Digital Elevation Model

DSSAT: Decision Support System for Agrotechnology Transfer

EMV: Expected Monetary Value

ET: Evapotranspiration

ET_0: Reference Evapotranspiration

ETDI: Evapotranspiration Deficit Index

FAO: Food and Agriculture Organization

FC: Field Capacity

HBV: Hydrologiska Byråns Vattenbalansavdelning

IFOAM: International Federation of Organic Agriculture Movements

IGW: Interactive Groundwater

IISD: International Institute for Sustainable Development

ITS: Index of Temporal Stability

KBS: Kellogg Biological Station

KRWC: Kalamazoo River Water Council

LTER: Long-Term Ecological Research

MAGNET: Multi-scale Adaptive Global Network

MCSE: Main Cropping System Experiment

MDEQ: Michigan Department of Environmental Quality

MEA: Millennium Ecosystem Assessment

MRD: Mean Relative Difference

MW: Monitoring Well

NCEI: National Centers for Environmental Information

NLCD: National Land Cover Database

NOAA: National Oceanic and Atmospheric Administration

NRMSE: Normalized Root Mean Square Error

NSE: Nash-Sutcliffe Model Efficiency Coefficient

NT: No-till

OR: Organic

PDSI: Palmer Drought Severity Index

PET: Potential Evapotranspiration

RATALF: Resilience, and Adaptation and Transformation Assessment Framework

RDI: Reconnaissance Drought Index

RHEAS: Regional Hydrological Extremes Assessment System

RI: Reduced Input

RIMA: Resilience Index Measurement and Analysis Model

RSD: Relative Standard Deviation

RWD: Relative Water Deficit

SALUS: System Approach to Land Use Sustainability

SHARP: Self-evaluation and Holistic Assessment of climate Resilience of farmers and Pastoralists

SMDI: Soil Moisture Deficit Index

SWAT: Soil and Water Assessment Tool

SWDI: Soil Water Deficit Index

SWL: Static Water Level

UNDP: United Nations Development Program

US: United States

USDA: United States Department of Agriculture

USGS: United States Geological Survey

VIC: Variable Infiltration Capacity

VRD: Variance of Relative Difference

WEAP: Water Evaluation and Planning System

WMO: World Meteorological Organization

WP: Wilting Point

WS: Water Stress Ratio

WSA: Water Stress Anomaly

1. INTRODUCTION

Sustainably increasing the production of edible crops by 60-120 percent to feed the increasing global population by 2050 is a major challenge of the 21st century (Berners-Lee et al., 2018; Pradhan et al., 2015; Tilman et al., 2011). Food crops are produced both under rainfed and irrigated agricultural systems around the world. Remarkably, rainfed agriculture contributes to 60 percent of the total food production throughout the world (FAO, 2017), while in the United States, the majority of cropland (≈94%) is planted under the rainfed system (USDA, 2014). The rainfed agricultural system is dominant in the Midwestern United States, which is highly productive, economically vital, technologically advanced, and predominantly produces row crops of corn, soybean, and wheat (Franzluebbers et al., 2011). Unfortunately, the regional climate of the Midwestern States is changing as a result of anthropogenic global climate change, and the increasing frequencies of climate extremes such as droughts, floods, and heatwaves have been documented (Andresen et al., 2012; Hatfield et al., 2018; Pryor et al., 2014). These extreme events significantly impact crop yields and may offset the productivity increment achieved through genetics and management advancements within the past few decades (Hatfield et al., 2018; Wang et al., 2016).

Soil moisture is the most limiting factor of productivity in rainfed agriculture. The availability of soil moisture is dictated by the seasonality of precipitation (i.e., onset, intensity, and frequency) and its interactions with the soil-plant-atmosphere continuum (Rost et al., 2009). This dependency on precipitation makes the rainfed system very vulnerable to climate extremes. For example, the 2012 drought devastated the crops and economies of rainfed farmers in the US Midwest (Boyer et al., 2013; Rippey, 2015). It is projected that climate extremes, such as these, will only increase in frequency and intensity in the future (Jin et al., 2018).

There is an increasing consensus among stakeholders that the resilience of these production systems must be improved. Resilience can be defined as the ability of a system to maintain its structure and functions in the face of climate perturbations (Holling, 1973; Walker et al., 2004). Resiliency allows the system to continue to provide its services, which in agriculture, means the growth and yield of crops, stress tolerance, profits, and other ecosystem services offered by agricultural systems. Nevertheless, increasing evidence demonstrates that conventional agriculture, which is currently widely practiced around the world, has become vulnerable to the stressors associated with climate change and variability (Adhikari et al., 2015; Lesk et al., 2016). Moreover, conventional agriculture has been shown to contribute to global environmental change and therefore be unsustainable (Foley et al., 2011). As a result, alternative agricultural practices, such as conservation agriculture, have been proposed. However, the resilience of these practices against climate extremes is not yet well understood and the risk levels and profitability concerns associated with adoption have prevented widespread implementation (Eeswaran, 2018; Mausch et al., 2017; Roesch-McNally et al., 2018).

Resilience is applicable to a wide range of disciplines (e.g., biological systems, engineering, economics, social welfare, politics, etc.), and these disciplines determine how resilience should be quantified and what metrics should be used to gauge the resiliency (Quinlan et al., 2016). Although several metrics have been previously applied to measure the resilience of agricultural systems, most of them have been qualitative. Moreover, these metrics often fail to capture the temporal dynamics at both the field and regional scales. Therefore, this dissertation aims to advance the understanding of the following knowledge gaps and thereby contribute to the crop and soil sciences to better manage agricultural systems in a changing environment.

Knowledge Gap 1: Lack of a robust resilience metric to address the complexity in agricultural systems as related to temporal variabilities while being simple enough to be measured at the field scale.

Knowledge Gap 2: Resilience matrices are needed to account for long-term profitability and risks at the farm scale for alternative management systems (treatments).

Knowledge Gap 3: Absence of knowledge on how the conservation agriculture (i.e., no-till) affects the overall resiliency at large scales (e.g., a large watershed).

To address the ***knowledge gap 1***, the following objectives were accomplished: (1) rank the relative resilience of different rainfed agricultural systems using the metrics of temporal dynamics of soil moisture; (2) evaluate the robustness of the soil moisture metrics of temporal dynamics on crops growth and yield under climate extremes; and (3) compare the effectiveness of different rainfed agricultural systems on reducing agricultural drought severity.

To fulfill the ***knowledge gap 2***, the following objectives were studied: (1) evaluate the effects of climate variability on farm net returns under different production and treatment systems; and (2) assess the risk level for the adaptation of different production systems under different treatments.

To ascertain the ***knowledge gap 3***, the following objectives were examined: (1) assess recharge, groundwater table, and soil moisture variabilities for the long-term corn-soybean-wheat rotation under the conventional and the no-till practices at a watershed scale; (2) estimate yields and net returns under the conventional and the no-till practices within a large, diverse watershed; (3) evaluate the overall changes in resiliency as affected by the adaptation of no-till for row crop agriculture in the watershed.

2. REVIEW OF LITERATURE

2.1 Overview

Global environmental changes pose far-reaching challenges to our food production systems (Campbell et al., 2016; Myers et al., 2017; Wheeler and von Braun, 2013). With the increasing frequency of climatic extremes, farmers face a daunting task to maintain their crop productivity. Impacts of these extreme climatic events disproportionately affect the rainfed agricultural systems because of its total dependency on precipitation to rebuild the soil moisture required for crop growth (Kuwayama et al., 2019; Minoli et al., 2019; Rost et al., 2009; Sweet et al., 2017). Meanwhile, the conventional practices that are commonly implemented to manage rainfed agricultural systems have become more unreliable in certain regions (e.g., Midwestern United States) to climate change and variability. In fact, conventional practices are known to exacerbate extreme events via contributing to global environmental changes (Bennett et al., 2014; Lesk et al., 2016).

To overcome these challenges, alternative agricultural practices have been introduced as agronomic interventions to improve the resilience of crop production systems (Branca et al., 2013; Michler et al., 2019). However, the resilience of these management practices for climate risk management in rainfed agriculture should be quantified using appropriate set of metrics to assess their benefits. Therefore, the goal of this review is first to explore the challenges and opportunities in rainfed agricultural systems, then to understand the concept of resilience while learning how the resiliency can be measured, and finally to identify the knowledge gaps within the context of managed rainfed agricultural systems.

2.2 Rainfed Agriculture

Agriculture can be classified into two types, namely, rainfed agriculture and irrigated agriculture, depending on the source of water used to grow crops. Rainfed agriculture entirely relies on infiltrated precipitation (predominantly rainfall) for crop production, while irrigated agriculture depends on full or supplementary irrigation. Globally, rainfed agriculture accounts for 80% of the cultivated lands and contributes to nearly 60% of total food production in a wide range of production systems (FAO, 2017). Furthermore, the majority of the cereals are cultivated as rainfed crops. The percentages of corn, wheat, rice, and other coarse grains produced in rainfed systems are 82%, 66%, 40%, and 86%, respectively (Rosegrant et al., 2002).

Regionally, rainfed farmlands account for more than 95% in sub-Saharan Africa, almost 90% in Latin America, 60-65% in Asia, and 75% in East and North Africa (Wani et al., 2009). Meanwhile, in the United States, about 94% of farmland acres are under rainfed agriculture (USDA, 2014). The productivity of rainfed agriculture in temperate regions such as in Europe and North America is much higher than the productivity in humid and dry tropical regions. (FAO, 2011). This discrepancy in productivity is associated to the variations in soil fertility, climate, and biotic stressors (Rosenzweig and Liverman, 1992).

2.2.1 Global Challenges in Rainfed Agriculture

Water stress is the major challenge in rainfed agriculture systems. Meanwhile, since producers do not have a control over the timing and amount of the precipitation, the water use efficiency of rainfed systems is generally low (Rao et al., 2015; Wani et al., 2009). Other constraints that substantially reduce the productivity of rainfed agriculture are soil degradation, soil organic matter depletion, soil erosion, nutrient deficiencies, environmental pollution, low external inputs, low investment capacity, and poor market linkages (Rao et al., 2015; Wani et al., 2009). Moreover, increase in rainfall variability (due to climate change) is becoming another important challenge in rainfed farming systems (Kassie et al., 2014).

2.2.2 Rainfed Agriculture in the Midwestern United States

Rainfed agriculture systems in the Midwestern United States are highly productive than the rainfed systems in Africa, Asia, and Latin America (Rosegrant et al., 2002). Moreover, they are ecologically diverse, practice a high level of farm technology, and receiving annual precipitation of greater than 500 mm (Franzluebbers et al., 2011). In this region, the rainfed production systems are economically important, and most of the corn and soybean crops, are produced either as a monocrop or in rotation (Hatfield, 2012). The productivity of rainfed crops steadily increased in the past as a result of genetic improvements (closer to 70%) and management intensification (closer to 30%) such as plant populations, row spacing, soil fertility, cover crops, rotation, farm mechanization and advancements in crop protection (Franzluebbers et al., 2011; Hatfield et al., 2018). Moreover, with the development of herbicide-resistant crop varieties, adoption of conservation agriculture practices such as no-tillage has been substantially increased to counteract with the problems of soil erosion, nutrient leaching, runoff, and yield instability (Franzluebbers et al., 2011).

2.2.3 Challenges of Rainfed Agriculture in the US Midwest

Regardless of the overall increase in productivity, crop yields in the US Midwest have shown to be vulnerable to interannual variability in the climate (Hatfield et al., 2018; Hatfield, 2012; Ortiz-Bobea et al., 2018). This phenomenon can be explained by the fact that the water availability for rainfed agriculture is determined by the seasonal characteristics of precipitation (i.e., intensity and frequency) and its interaction with the soil-plant-atmosphere continuum (Rost et al., 2009). Therefore, rainfed agriculture is much vulnerable to the effects of climate variability and extremes.

Changes in the Midwest regional climate associated to the anthropogenic activities resulted in increased frequencies of extreme climatic events such as droughts, floods, and heatwaves (Andresen et al., 2012; Dai et al., 2016; Pryor et al., 2014). For example, the 2012 Midwest drought devastated major crops and the economic base of rainfed farms in this region (Fuchs et al., 2015; Mallya et al., 2013; Otkin et al., 2016). As a result of this drought, corn yield in the US has fallen for three consecutive years (2010-2012) for the first time since 1928-1930 (Rippey, 2015). These climate extremes will continue to have substantial impacts not only on the national economy but also on international trade (Boyer et al., 2013), since the share of Midwestern region on U.S agricultural exports are relatively large, especially for corn and soybean.

Nitrate leaching is identified as a major threat to environmental quality and human health (Bowles et al., 2018). Since intensive agricultural management is practiced in this region, nitrate leaching has been found to be another important challenge in this system (Hussain et al., 2019; Martinez-Feria et al., 2019). However, the adoption of conservation agriculture practices has been shown to minimize the leaching losses of nitrogen and increase the nitrogen use efficiency of crops (Palm et al., 2014; Syswerda et al., 2012).

2.3 Resilience in Rainfed Agriculture

Resilience was first defined by Holling (1973) in the context of ecological systems. Accordingly, resilience is the capacity of a system to absorb disturbances and reorganize while changing. Thus, it can still maintain essentially the same function, structure, identity, and feedbacks (Holling, 1973; Walker et al., 2004). In rainfed agriculture, resilience can be defined as the ability of a rainfed system to maintain its structures and patterns of behavior in the face of stressors such as climate perturbations so it can continue to provide its services and desirable outcomes such as crop growth, yield and other ecosystem services (Tendall et al., 2015; Urruty et al., 2016). Resilience also refers to the ability of an agricultural system to develop capacities to cope and adapt to a new condition (e.g., climate shocks and extremes) via appropriate management practices (Bousquet et al., 2016).

Since soil moisture is the key determinant of productivity in rainfed agriculture, Tow et al. (2011) argued that the ability of a system or its components to recover from water stress could also be considered as a measure of resilience. This could be achieved by implementing management interventions that can alleviate the exposure and severity of water stress in a way that an extreme climatic event shall not reduce the crop yields significantly.

2.4 Interventions to Improve Resilience in Rainfed Agriculture

Interventions to enhance the resilience in rainfed agriculture can be broadly categorized as agronomic interventions, genetic interventions, and decision support systems. As climate change is already hampering agriculture around the world, these interventions are also known to support the key objectives of climate-smart agriculture (Lipper et al., 2014). Below, each of these interventions is described in detail.

2.4.1 Agronomic Interventions

Agronomic interventions may include crop, soil, and water management options aimed at improving resilience in agricultural systems. Agronomic interventions such as adjustment of planting and harvesting times, altering fertilizer and water application rates (Howden et al., 2007; Nouri et al., 2017; Rurinda et al., 2015), mulching (Erenstein, 2003; Qin et al., 2015), crop diversification and agroforestry (Altieri et al., 2015; Gan et al., 2015; Lin, 2011; Mbow et al.,

2014) and adoption of conservation agriculture (Delgado et al., 2013; Michler et al., 2019) have varying potentials to build resilience in rainfed agriculture.

2.4.2 Genetic Interventions

Genetic interventions involve the development of novel crop germplasms with improved tolerance to environmental stresses such as drought and heat and/or genotypes with phenological adjustments so that they can escape and/or avoid overlapping with the occurrences of such stress events (Ainsworth and Ort, 2010; Ceccarelli et al., 2010; Davies et al., 2011). The introduction of these crop genotypes with improved stress tolerance has substantially increased the climate-resilience of major crops such as corn and soybean around the world (Cairns et al., 2012; Chapman et al., 2012; Sadok and Sinclair, 2011).

2.4.3 Decision Support Interventions

Decision support interventions mainly refer to the utilization of weather and seasonal climate forecast information to make agricultural decisions in the face of uncertainties in the upcoming days/season (Hansen et al., 2011; Klemm and McPherson, 2017; Meinke et al., 2006). Forecast products can potentially influence many steps throughout the agricultural production such as selection of crops and varieties, changing planting dates, input management, changing land management practices, adjusting marketing practices, and determining index-based insurances to farmers thereby improve the climate-resilience in rainfed agriculture (Crane et al., 2011; Klemm and McPherson, 2017). With increasing real-time or near-real-time earth and environmental observations and modeling tools, decision support systems such as Regional Hydrological Extremes Assessment System (RHEAS) offers agricultural practitioners and policymakers a framework to estimate onset, severity, recovery, and duration of regional droughts and their impacts on expected crop yield outlooks in the vulnerable regions (Andreadis et al., 2017).

2.5 Promising Agricultural Systems to Improve Resilience

To improve resilience, agricultural systems should be persistent, adaptive, and transformative at appropriate times and places. Persistence may include absorbing shocks of agricultural risks like weather extremes, invasive species, pest/disease outbreaks, and price fluctuations. Agriculture also needs to be adaptive to the long-term changes in the environment, such as the effects of climate change, soil degradation, and environmental pollution. Finally, a resilient agriculture system must be able to transform into new modes of operation without harming the human and natural environment (Bennett et al., 2014). Conservation and organic agriculture systems have many promising characteristics that could improve resiliency (Michler et al., 2019; Milestad and Darnhofer, 2003).

2.5.1 Conservation Agriculture

Conservation agriculture consists of three agronomic principles, namely, minimum soil disturbance/no-till, permanent soil cover by crop residues/cover crops, and crop rotations (Hobbs et al., 2008; Palm et al., 2014). Conservation agriculture was originated in response to the US Dust Bowl in 1930’s to counteract soil erosion by wind and water (Baveye et al., 2011) and significantly expanded during mid-to late-1990’s with the development of herbicides, herbicide-tolerant crop species, and improved farm mechanization (Derpsch et al., 2010). Since then, it has been rapidly adopted in North America, South America, and Australia primarily on large-scale mechanized farms, with heavy applications of herbicides to control weeds that are otherwise normally controlled by tillage (Palm et al., 2014). Although it was originally designed for high-input agricultural systems in temperate regions, it has gained momentum with smallholder farmers in Asia and Africa (Brouder and Gomez-Macpherson, 2014) due to its numerous benefits beyond soil erosion control.

Globally, conservation agriculture was practiced in 180 Million hectares of cropland (12.5% of total cropland) by 78 countries during the period of 2015-2016 (Kassam et al., 2019). During the same period, the adoption of conservation agriculture in the United States was 43.2 Million hectares, which corresponds 35% of total cropland (Kassam et al., 2019). However, in the US Midwest, farmers practice various intensities of conservation agriculture with different combinations of agronomic principles (Denny et al., 2019), making them varying degrees of resilience to climate shocks and extremes.

In comparison to conventional tillage, the no-till systems showed the highest level of resilience as a result of improved water availability and soil quality, that helps to avoid substantial reductions in crop yields during extreme climatic events (Delgado et al., 2013; Harrington and Tow, 2011; Lal et al., 2012; Michler et al., 2019). In contrast, few other studies (e.g., Pittelkow et al., 2015a; Powlson et al., 2014) have shown yield reductions with no-till and limited potential to improve resilience. Interestingly, a recent global meta-analysis highlighted that the no-till system, when it is combined with other two conservation agriculture principles (residue retention and crop rotation), significantly increases crop yields, especially in rainfed crops (Pittelkow et al., 2015b). This could be due to the capture of snow, reduction of runoff and soil evaporation (with the retention of crop residues), and creation of better soil structure and rooting patterns through crop rotations to store more water in the root zone (Franzluebbers et al., 2011; Lal et al., 2012; Lampurlanés et al., 2016; O'Leary et al., 2011).

2.5.2 Organic Agriculture

The movement for organic agriculture began in the first half of the 20th century and have been expanded in the 1970's with the formulation of organic standards. International Federation of Organic Agriculture Movements (IFOAM) institutionalized four principles of organic agriculture, namely, health, ecology, fairness, and care, with the main focus of protecting mankind and environment in the process of food production (Luttikholt, 2007). Organic agricultural systems are well known to improve soil organic matter, especially when practiced for a long-term (Pimentel et al., 2005). It has been estimated that for every 1% organic matter, soil can hold approximately 10,000-11,000 liters of plant-available water per ha down to about 30 cm of soil depth (Gomiero et al., 2011). Therefore, the water holding capacity of soils under organic agriculture is greater than the soils under conventional agriculture (Lotter et al., 2003; Mäder et al., 2002).

Moreover, organic agriculture has shown number of promising features to build resilience and reduce environmental impacts in various food systems thus serves as climate-friendly farming (Milestad and Darnhofer, 2003; Scialabba and Müller-Lindenlauf, 2010; Tuomisto et al., 2012). Even though the yield gap between organic and high input conventional agriculture is larger mainly due to nutrient limitation (De Ponti et al., 2012), organic systems achieve comparable or even higher yields in many developing countries, as compared to the current conventional systems (Scialabba and Müller-Lindenlauf, 2010). In contrast, the production cost of certified organic farms is generally higher as the producers spend more on labor, insurance, certification, and marketing costs than the conventional farmers (Uematsu and Mishra, 2012).

2.5.3 Reduced Input Agriculture

Reduced input agriculture or low external input agriculture is aimed at minimizing the environmental pollution of conventional agriculture practices (Odum, 1987). Therefore, direct or indirect use of petrochemicals-based inputs (e.g., fertilizers, pesticides) are substantially reduced in this system in comparison to a conventional system (Buttel et al., 1986). Reduced input agriculture can be considered as a step toward sustainable agriculture since it improves ecological processes within the agricultural systems (Stinner and House, 1987). However, it has limited potential to improve the overall profit of agricultural productions (Kessler and Moolhuijzen, 1994). To improve the productivity of reduced input agriculture, several management practices were introduced such as integrating leguminous cover crop and intercropping (Robertson et al., 2014).

2.6 Metrics of Resilience in Agricultural Systems

Appropriate metrics are required to quantify the resiliency of promising agricultural systems. The measure of resilience can be used to maintain or shift a system towards a more desirable and sustainable state, track thresholds of potential concerns, and help with assessments on how the system is being managed and can be further improved (Quinlan et al., 2016). Meantime, evaluation of resilience often involves a holistic approach that incorporates social, economic, and environmental dimensions of resilience (COSA, 2017). Because of the complexity and interactions in these three dimensions, food system resilience is generally assessed qualitatively (Toth et al., 2016). However, qualitative assessments are case-specific, and their applicability across scales varies based on the assumptions.

Various organizations and individuals have developed and employed several tools to measure the resilience of farming systems in many regions of the world (Douxchamps et al., 2017). These tools have been generally applied to large socioeconomic units (e.g., households/ communities/ administrative units/ national scale). For example, the Food and Agriculture Organization of the United Nations (FAO, 2016) developed the Resilience Index Measurement and Analysis Model (RIMA), which has been applied in many African countries to measure the climate-resilience of agricultural communities (Serfilippi and Ramnath, 2018). Few other examples are; Community Based Resilience Assessment (CoBRA) developed by United Nations Development Program (UNDP, 2013), Self-evaluation and Holistic Assessment of climate Resilience of farmers and Pastoralists (SHARP) adopted by the Food and Agriculture Organization of the United Nations (Choptiany et al., 2017), Community-based Risk Screening Tool-adaptation and Livelihood (CRiSTAL) developed by International Institute for Sustainable Development (IISD, 2014), Climate Vulnerability and Capacity Analysis (CVCA) established by Care International (Care, 2009) and Resilience, and Adaptation and Transformation Assessment Framework (RATALF) developed by The Commonwealth Scientific and Industrial Research Organization (O'Connell et al., 2015).

These tools consist of a combination of measurement indices to quantify the resilience of the different aspects of agricultural systems, called 'resilience metrics'. Generally, these metrics include the means and variance of agricultural production (Di Falco and Chavas, 2008; Zampieri et al., 2020), crop yields (Birthal et al., 2015; Li et al., 2019; Martin and Magne, 2015), profit (Browne et al., 2013; Komarek et al., 2015; Seo, 2010), revenue (Kandulu et al., 2012; Rigolot et al., 2017; Tibesigwa and Visser, 2015), labor productivity (Komarek et al., 2015), crop failure (Jones and Thornton, 2009), dietary diversity (Dillon et al., 2015), farming risks (Komarek et al., 2015), agricultural gross domestic product (Hsiang and Jina, 2014) and expenditure for food consumption/food security (Alfani et al., 2015). In the context of agricultural development, climate-resilience was monitored and evaluated using income, food availability, land area, and labor force (Douxchamps et al., 2017). Nevertheless, these indicators are often used at a large scale and show non-linear responses to climate variability depending upon various characteristics of farms and farmers (Di Falco and Chavas, 2008; Tittonell, 2014).

Although there is a growing interest in the concept of resilience in the face of global environmental changes, there is no pragmatic guidelines available to quantify the overall resilience of farming systems (COSA, 2017). Moreover, existing tools and frameworks often fail to capture the spatial and temporal dynamics of resilience at various scales (Dixon and Stringer, 2015; Douxchamps et al., 2017). Therefore, new metrics are needed to address the complexity in agricultural systems while being simple enough to be measured at different scales.

2.6.1 Soil Moisture

Soil moisture primarily controls the productivity of crops in rainfed agricultural systems (Jägermeyr et al., 2016), and is considered among 27 key indicators of climate-resilience proposed by the committee on sustainability assessment (COSA, 2017). Precipitation is the source of soil moisture in rainfed farming; therefore, the seasonality of rainfall, such as onset, intensity, and frequency, determines the availability of water resources to crops (Robinson et al., 2019). Moreover, soil moisture affects several hydrological processes such as evapotranspiration, runoff, and recharge to aquifers hence considered as one of the components of hydrological cycle (Robinson et al., 2019). Meanwhile, irregular rainfall associated to the climate variability has reduced the plant available water, and water stress has been identified as an important abiotic stress that significantly affects crop yields (Dinar et al., 2019; Ortiz-Bobea et al., 2019; Rossato et al., 2017). That is why Rockström et al. (2010) argued that any investment that focuses on the improvement of rainfed agriculture should primarily consider water management.

Spatiotemporal dynamics of soil moisture should be taking into account in order to evaluate soil moisture as a metric of resilience. Mean relative difference (MRD) of soil moisture, Spearman's rank correlation coefficient, and the Index of Temporal Stability (ITS) are used as indices of the spatiotemporal variabilities of soil moisture (Liu et al., 2018; Vachaud et al., 1985). These indices were commonly used to identify temporally stable or representative locations to employ soil moisture monitoring equipment (Barker et al., 2017; Brocca et al., 2010; Starks et al., 2006; Zhou et al., 2007) and/or to validate remotely sensed soil moisture products (Cosh et al., 2008; Jacobs et al., 2004; Wagner et al., 2008). Moreover, these indices were also used to study the spatiotemporal dynamics of soil moisture in hillslope (Gao et al., 2016; Liu et al., 2018) or under diverse land uses (Hu et al., 2010) or in different depths of the soil (Gao and Shao, 2012; He et al., 2019). In contrast, the applicability of these indices to quantify the resilience of different agricultural systems has not been studied before.

2.6.2 Drought Indices

Shortage of soil moisture to the crops for a few weeks due to the absence of rainfall can lead to the development of agricultural droughts (Esfahanian et al., 2017). Drought affects both quantity and quality of crop yields depending on the following factors; timing of drought in relation to the crop's growth stage, reliability of water resources, vulnerability of cropping system, and socioeconomic conditions of farmers (Rey et al., 2017). Hence, drought indicators can be used as metrics of resilience in agricultural systems and building drought resilience is essential to sustain agricultural production in the United States (Brusberg and Shively, 2015). The agricultural drought indices, which are commonly used are presented in Table 2.1 (Esfahanian et al., 2017; Moorhead et al., 2015).

Table 2.1. Commonly used available agricultural drought indices.

Agricultural Drought Index	Inputs Required	Reference
Soil Water Deficit Index	Soil moisture, field capacity, wilting point	Martínez-Fernández et al., 2015
Soil Moisture Deficit Index	Soil moisture	Narasimhan and Srinivasan, 2005
Evapotranspiration Deficit Index	Actual Evapotranspiration (ET), potential evapotranspiration (PET)	Narasimhan and Srinivasan, 2005
Palmer Drought Severity Index (PDSI)/ Palmer Z index	Precipitation, temperature, available soil water capacity, and latitude of the location	Palmer, 1965; Alley, 1984
Reconnaissance Drought Index	Actual ET, PET	Tsakiris and Vangelis, 2005
Accumulated Drought Index	Precipitation, reference ET (ET_0)	Sivakumar et al., 2011
Relative Water Deficit	Actual ET, PET	Sivakumar et al., 2011
Crop Moisture Index	Same as PDSI	Palmer, 1968
Vegetation Condition Index	Satellite images	Kogan, 1995
Standardized Vegetation Index	Remote sensing data	Peters et al., 2002

Soil Water Deficit Index (SWDI): SWDI can be used to quantify the agricultural drought when temporal soil moisture data is available (Martínez-Fernández et al., 2015). SWDI can be calculated using the following formula:

$$SWDI = \left\{\frac{\theta v - \theta_{fc}}{\theta_{fc} - \theta_{wp}}\right\} \times 10 \qquad (2.1)$$

where, Θ_v is the percentages of the volumetric soil moisture (cm^3/cm^3), Θ_{fc} is the percentage of the field capacity (cm^3/cm^3) of the soil and Θ_{wp} is the percentage of the permanent wilting point (cm^3/cm^3). When SWDI is positive, the soils have excess water; when it equals zero, the soil is at the field capacity (i.e., no water deficit). Negative values indicate drought, and the soil reaches the wilting point when the SWDI reaches ≤ -10. At this point, the soil water content is below the lower limit of water available for plant uptake (Savage et al., 1996).

According to calculated SWDI values, drought severity in agricultural systems can be classified as “no drought” if SWDI > 0, as “mild” if 0 > SWDI > -2, as “moderate” if -2 > SWDI > -5, as “severe” if -5 > SWDI > -10, and as “extreme” if -10 ≥ SWDI (Martínez-Fernández et al., 2015).

Although the annual and monthly time scales of evaluation seem adequate to monitor the effects of meteorological and hydrological droughts (Sharma, 1997), a shorter period of analysis is required to evaluate the effects of agricultural drought. A weekly period is commonly recommended for cropping systems as their growth stages show different levels of sensitivity to drought, and farmers require a sufficient window of time for management interventions such as irrigation planning (Purcell et al., 2003). For this purpose, SWDI is appropriate to evaluate the effects of droughts in agricultural systems. Moreover, the SWDI is more comprehensive compared to the Soil Moisture deficit Index (SMDI) in capturing soil moisture deficit since it uses several soil parameters. In contrast, the SMDI only uses one parameter – soil moisture (Esfahanian et al., 2017).

Soil Moisture deficit Index (SMDI): SMDI only requires the soil moisture in the root zone as input (Narasimhan and Srinivasan, 2005). The weekly percentage of soil moisture deficit or excess can be calculated as follows:

$$SD_{ij} = \frac{SW_{ij} - MSW_j}{MSW_j - minSW_j} \times 100,\ if\ SW_{ij} = MSW_j \tag{2.2}$$

$$SD_{ij} = \frac{SW_{ij} - MSW_j}{maxSW_j - MSW_j} \times 100,\ if\ SW_{ij} > MSW_j \tag{2.3}$$

where, SD_{ij} is the soil water deficit (%), SW_{ij} is the mean weekly soil water (mm) in the soil profile, MSW_j is the long-term median of available soil water (mm) in the soil profile, $max.SW_{ij}$ is the long-term maximum of available soil water (mm) in the soil profile, and

$min. SW_{ij}$ is the long-term minimum of available soil water (mm) in the soil profile. *i* denotes the year while *j* denotes the week. Using the above equation, the seasonality inherent in soil water is removed, and the deficit values can be compared across seasons. The soil water deficit (SD) values during a week could range from – 100 to +100, indicating very dry to very wet conditions, respectively. As the SD values for all the subbasins were scaled between – 100 and +100, they are also spatially comparable across different climatic zones (Narasimhan and Srinivasan, 2005). Thereafter, SMDI for any given week can be calculated by:

$$SMDI_j = \frac{\sum_{t=1}^{j} SD_t}{25_t + 25} \tag{2.4}$$

where, *t* is the time in weeks. SMDI during any week will range from -4 to +4, representing the worst drought and no drought conditions, respectively.

Evapotranspiration Deficit Index (ETDI): ETDI is calculated using a procedure similar to the calculation of SMDI. However, a water stress ratio is initially computed rather than using the evapotranspiration (ET) alone (Narasimhan and Srinivasan, 2005). The weekly water stress ratio (*WS*) is calculated as follows:

$$WS = \frac{PET - AET}{PET} \tag{2.5}$$

where, *PET* is the weekly potential evapotranspiration of the crop, and *AET* is the weekly actual evapotranspiration. Values of *WS* may range from 1 to 0, where 1 indicating zero actual evapotranspiration and 0 indicating the evapotranspiration occurring at potential rates. After calculating *WS*, the maximum, minimum, and median water stresses are used to calculate the weekly water stress anomaly (WSA). The WSA values will range from -100 to +100, with negative values indicating dry conditions and positive values indicating wet conditions (Narasimhan and Srinivasan, 2005).

Under water-limited conditions, crop transpiration will not occur at the potential rates. Therefore, the ratio of actual ET to PET can indicate the stress on the plant, thus, ETDI may be more suitable to evaluate the impacts of agricultural drought than the indices that use precipitation. Meanwhile, the major limitation to this drought index is that the actual crop ET data may not often be measured in agricultural settings. Furthermore, the PET must be available for the same crop as the actual ET. Although the reference ET (ET_0) can replace PET, ET_0 is only applicable for the reference crop, and different crops will have different relationships to ET_0 depending on their growth stage-specific crop coefficients (Moorhead et al., 2015).

Palmer Drought Severity Index (PDSI)/ Palmer Z index: As part of the original work done by Palmer in the early 1960s, the Palmer Moisture Anomaly Index (Z Index) is usually calculated on a monthly basis along with PDSI output as the moisture anomaly. The PDSI addresses two of the most elusive properties of droughts namely, intensity and their beginning and ending time (Alley, 1984). However, this index is computationally intensive and less transparent compared to the SWDI, SMDI, and ETDI, because it requires a total of eight parameters such as precipitation, temperature, available soil water capacity, and latitude of the location of interest (Alley, 1984; Ficklin et al., 2015; Jacobi et al., 2013; Palmer, 1965). Moreover, the Z-index has been used with a coarse spatial resolution of 7000-100,000 km^2 and monthly temporal resolution, while SMDI and ETDI were used with a finer spatial resolution (16 km^2) and weekly temporal resolution (Narasimhan and Srinivasan, 2005).

Reconnaissance Drought Index (RDI): RDI was introduced by Tsakiris and Vangelis (2005) with the objective of developing an agricultural drought index accounting for both precipitation and ET. RDI first calculates the aridity index using precipitation and potential evapotranspiration. The aridity index is calculated as the ratio between the long-term annual mean of precipitation and the annual mean of ET_0. RDI will then be calculated as a standardized or normalized ratio between the cumulative precipitation and cumulative ET_0 for a given period (Tsakiris and Vangelis, 2005). RDI can be also calculated for various time scales; however, ET data may not be available in all the locations, and an accurate estimation of ET requires numerous inputs (Moorhead et al., 2015).

Accumulated Drought Index (ADI): ADI was formulated by the Integrated Center of Agrometeorological Information in Brazil (Sivakumar et al., 2011). ADI is calculated as follows:

$$ADI = \sum DI/(3nN) \tag{2.6}$$

where, *DI* is derived from the relationship between precipitation and ET as detailed in Sivakumar et al. (2011), *n* is the number of time periods, and *N* is the number of periods with less than 10 mm of precipitation. Even though this index uses both precipitation and ET to assess the drought conditions, it was not well-established and verified in the drought assessment literature (Moorhead et al., 2015).

Relative Water deficit (RWD): RWD is calculated as the ratio of actual ET to PET (Sivakumar et al., 2011).

$$RWD = \left(1 - \frac{AET}{PET}\right) \times 100 \tag{2.7}$$

The RWD will be zero if actual ET is occurring at the rate of PET, that indicates no water stress to crops. RWD can be calculated for different time scales; nonetheless, the actual ET data is difficult to obtain, and it varies for different crops. This is the major drawback of this index to implement it across different landscapes.

2.6.3 Farm Economics

Farm profit is the key concern of producers since the livelihood of most of the farmers is primarily depends on their farming enterprises. Farm profits are generally measured as the earnings before interest taxes and amortization. Additionally, net farm revenue, operating profit margin ratio, rate of return on farm assets, and rate of return on farm equity can be used to quantify the profitability of agricultural enterprises (Langemeier, 2016). Farmers depend on net farm income for; living expenses, to pay their debts, and to purchase new assets to continue their farming operations.

The United States had 6.8 million farms in 1935; however, according to a recent survey conducted in 2019, there were 2.02 million farms located in 897 million acres of land, with an average farm size of 444 acres (ERS, 2020). This decline in the number of farms highlights the increasing agricultural productivity and opportunities for nonfarm employment. Therefore, agricultural production in the United States is currently concentrated to a smaller number of large, specialized farms, mostly in rural areas. Technological advancements in crop and animal genetics, agrochemicals, farm machinery, and management were the driving force for the growth in agricultural outputs (ERS, 2020).

The net farm income of the whole country is calculated by subtracting total farm expenses from gross farm income. Net farm income (inflation-adjusted) was forecasted to increase by 21.7% in 2020, to 102.7 billion US dollars by the United States Department of Agriculture. Total cash receipts from major row crops corn, soybean, and wheat were 50.1 billion, 34.2 billion, and 9.0 billion US dollars, respectively, in 2019. The median of the total household income from all farming households was 72,481 US dollars in 2018. In contrast, the annual farm sales of around half of the US farms were under 10,000 US dollars, and these farm families mostly rely on off-farm employment for their family income. Meantime, large-scale farms had an annual farm income of 348,811 US dollars (ERS, 2020).

Farm economics is one of the three pillars of sustainable agriculture (Pham and Smith, 2014). Crop productivity, profitability, and stability are the indicators used to gauge sustainability in farming systems (Pham and Smith, 2014). For the households depending on farming for their livelihood, the gross farm income should be able to compensate both fixed and variable costs involved in their farming operation. Meanwhile, most of the developing countries have tropical climates and smallholdings, where farm families cannot meet their income needs alone from farming. Therefore, they need to seek off-farm income to maintain their farming operations (Li et al., 2012).

According to Tey and Brindal (2015), the farm profit is determined mostly by the scale of operation, operational efficiency, and output prices. Improving the operational efficiency through precision management of resources such as irrigation water and nutrients has substantially improved the profitability in farming systems (McConnell and Burger, 2011; Sapkota et al., 2014; Spencer et al., 2019). Conservation management systems also have improved the profitability of farming systems (Jat et al., 2014; Ngwira et al., 2013); however, some other studies have shown mixed results (Mafongoya et al., 2016; Plastina et al., 2020).

Farmers' interventions to address the challenges of climate extremes, such as implementing any resilient practices, maybe costlier and riskier than the business-as-usual practices; therefore, the long-term profitability is the most important factor that determines adaptation of such practices (Kumar et al., 2016; Mausch et al., 2017; Sain et al., 2017).

Moreover, farmers demonstrate different preferences toward risks, depending on the socioeconomic factors. (Brink and McCarl, 1978; Lu et al., 2003). For example, a highly profitable production system may also be highly risky because of the variabilities on net revenues and/or market demands, thus may not be preferred by a risk-averse farmer. Farm profitability also determines the costs and benefits of farm insurance policies, which are important tools for climate risk management (Annan and Schlenker, 2015; Tack and Ubilava, 2015).

Resilience in terms of farm economics can be measured using both the mean and volatility of the expected net revenues or profitability, where a system with higher mean and lower volatility can be taken as a relatively resilient system (Abson et al., 2013; Browne et al., 2013). The volatility, as it measures the variations in farm income, can also capture the risk associated with the system (Browne et al., 2013). It is essential that the producers make informed decisions considering the most appropriate risk management strategies tailored to their adaptation systems and the probability of risks (Vigani and Kathage, 2019). Conversely, an appropriate cost-benefit analysis or enterprise budgeting is required to reasonably estimate the net return in farming enterprises (Plastina et al., 2020). To perform an accurate enterprise budgeting, correct data on the quantities of inputs, outputs, and associated costs during the time of operation are essential for the period of analysis, which may not adequately available from farm records.

2.6.4 Ecosystem Services

Ecosystems are a vital part of the environment, and all the benefits that humans receive from the natural environment are called ecosystem services (Costanza et al., 1997; Mengist et al., 2020). Agricultural ecosystems are managed to primarily produce food, fodder, fiber, and fuel;

however, they also offer various ecosystem services that are essential for the functioning of the environment (Dale and Polasky, 2007; Swinton et al., 2007; Tancoigne et al., 2014; Wood et al., 2015). According to the Millennium Ecosystem Assessment, ecosystem services can be broadly grouped into four categories, namely, provisioning services, regulating services, supporting services, and cultural services (Fisher et al., 2009; MEA, 2005).

Provisioning services include any goods that are directly consumed by people, such as food, water, energy, raw materials, timber, ornamentals, genetic and medicinal resources. Regulatory services comprise carbon sequestration, climate regulation, mitigation of floods, control of soil erosion, management of pest/disease outbreak, purification of water, air, and soil, decomposition, and detoxification. Supporting services involve natural processes such as photosynthesis, cycling of water and nutrients, soil formation, pollination, and biodiversity. Tangible benefits such as recreation, education, inspiration, ecotherapy, and other spiritual values of the ecosystems come under the cultural services (Garbach et al., 2014; MEA, 2005; Wei et al., 2021).

Although the food production systems have the potential to offer numerous ecosystem services, the current trend of conventional agriculture deliberately aimed on maximizing few provisioning services (e.g., food, fodder, fuel) with the simplification of agricultural landscapes rather than harnessing a range of ecosystem services (Bommarco et al., 2013; Gaba et al., 2015; Robertson and Swinton, 2005) which in turn affects the resilience and sustainability of the agricultural systems.

Remarkably, ecosystem services and system resilience are strongly related to each other. Resilient ecosystems can withstand or quickly recover from environmental disturbances such as climate perturbations and continue to supply ecosystem services. On the other hand, the ecosystem with lower resilience may be vulnerable to extreme events (Biggs et al., 2012; Fedele et al., 2017; Montoya and Raffaelli, 2010). Therefore, the loss of ecosystem resilience could compromise ecosystem services that are indispensable for agricultural systems, especially in the face of increasing climatic extremes (DeClerck et al., 2016; El Chami et al., 2020; Swift et al., 2004).

For example, recharge is an important water-related ecosystem service in agricultural systems (Coates et al., 2013; Serna-Chavez et al., 2014). Recharge is the deep percolation of water leaving the vadose zone from agricultural farms and contribute to replenishing the aquifers and the groundwater-dependent ecosystems such as wetlands and streams (Gordon et al., 2010; Sampath et al., 2015). A significant portion of the land area is utilized to grow agricultural crops; thus, large quantities of recharge to groundwater occurs from the cropland areas. In the meantime, groundwater resources are highly exploited to cater to the requirements of increasing human population. Extraction of groundwater above the rate of local recharge has significantly reduced the groundwater storage in the aquifers that has affected the baseflow to streams, groundwater-fed wetlands, and other dependent habitats and species (Dalin et al., 2017; Scanlon et al., 2012; Wada et al., 2010).

Recharge may behave differently in response to various tillage practices (O’Leary et al., 2011; Owens, 1994). Since reduced tillage or zero tillage is one of the important principles of conservation agriculture, it is important to understand how recharge responds to such tillage regimes when conservation practices are implemented at regional scales. If conservation tillage could increase the recharge and thereby improve groundwater levels, it will increase the resiliency in the face of declining groundwater resources.

2.7 Modeling Resilience at a Large Scale

Resilience in agricultural systems not only confined to farm scales but also expand across regional scales (Bailey and Buck, 2016; Scherr et al., 2012). To evaluate the resilience at larger scales, appropriate metrics should be measured. However, it is often impossible to measure the resilience metrics at regional scales due to the lack of resources to collect data. Meanwhile, modeling approaches can be implemented to solve this problem.

Model is the representation of a conceptualized system, which consists of a set of equations to mimic the system's behavior. Models assist in understanding and explaining the performance of the systems at different scales. Depending on the structure, functions, and purposes, models can be classified as statistical, mechanistic, deterministic, stochastic, dynamic, static, process-based, descriptive, and explanatory models (Murthy, 2004).

Statistical models are based on historical observations, and the relationships between inputs and outputs are developed using statistical techniques (Jones et al., 2017a). Mechanistic models explain not only the relationships between model parameters but also detail the mechanisms of the modeling process. Deterministic models simulate predictions on dependent variables without any associated probability distribution, variance, or random element, while a probability element is attached to each output in stochastic models. Dynamic models represent the behavior of a system; therefore, time is included as a variable; however, static models do not include time as a variable; hence dependent and independent variables will have constant values over a given period of time. Process-based models are often computer models that use several mathematical equations to detail the processes occurring at different levels in a system. Descriptive models are used to describe the system without much emphasis on the mechanisms, while explanatory models describe the mechanisms and processes that cause the functioning of the systems (Murthy, 2004).

Most of the crop and hydrological models that are used to evaluate the performances of agricultural systems are process-based models (Jones et al., 2017a; Siad et al., 2019). Therefore, these models can be implemented to produce resilience metrics such as crop growth, yield, revenues, and soil water balances at different scales ranging from field to region.

2.7.1 Crop Modeling

Development of crop models to characterize the processes of crop growth began between 1950-1960 and currently achieved remarkable improvements in agricultural system models (Boote et al., 2013; Jones et al., 2017a). Crop models can be broadly categorized into predictive and explanatory models (Di Paola et al., 2016). Predictive models are used to predict the yield mostly based on empirical functions (i.e., statistical relationships) between environmental variables and crop yield using few easily derived parameters. Meanwhile, explanatory models are built by considering plant-environment interactions and ecophysiological processes (e.g., photosynthesis, leaf area expansion, biomass partitioning) that govern the growth and yield formation of crops (Di Paola et al., 2016). Explanatory models are also called process-based models and continue to be updated. Meanwhile, the number of parameters that are required to explain each process within the model has been increased that ultimately elevate the complexity of these models compared to predictive models. Therefore, hybrid models (i.e., mixing both empirical and mechanistic approaches) are often used to evaluate the performance of different agricultural systems (Di Paola et al., 2016).

Crop models require weather, soil, crop cultivar, and management information to simulate the processes such as photosynthesis, respiration, water and nitrogen balances, phenology, partitioning, and senescence generally at a daily time scale (Boote et al., 2013; Jones et al., 2003). Numerous crop models have been developed in various countries. Each of these models has its own strengths and weaknesses (Di Paola et al., 2016). Some of the popular crop models are; Agricultural Production Systems Simulator (APSIM) (Keating et al., 2003), AquaCrop (Vanuytrecht et al., 2014), CropSyst (Stöckle et al., 2003), Daisy (Abrahamsen and Hansen, 2000), Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), EPIC (Williams et al., 1984), InfoCrop (Aggarwal et al., 2006), MONICA (Nendel et al., 2011), Oryza (Bouman et al., 2001), System Approach to Land Use Sustainability (SALUS) (Basso et al., 2006), STICS (Brisson et al., 1998), and WOFOST (Diepen et al., 1989).

Among these crop models, DSSAT and APSIM operate as a platform for multiple crop modules for major food crops. For example, within the DSSAT framework, CERES-Rice, CERES-maize, CERES-wheat, and CROPGRO-soybean modules are available to model rice, maize, wheat, and soybean crops, respectively (Jones et al., 2003). DSSAT currently consists of process-based simulation modules for 42 major crops, and the APSIM has a unique capability of modeling intercropping systems (Hoogenboom et al., 2019; Jones et al., 2017b; Keating et al., 2003).

DSSAT is the most widely used crop modeling system in the world. The applications of DSSAT include the evaluation of genetic improvement (Boote et al., 1996), assessment of the impacts of climate change and variability (Fodor et al., 2017; Rosenzweig et al., 2014), optimization of management practices such as tillage, water, and nutrients (Iocola et al., 2017; Joshi et al., 2017; Kropp et al., 2019; Liu et al., 2013; Malik and Dechmi, 2019; Roy et al., 2019), evaluation of crop responses to environmental stresses (Liu et al., 2016; Saseendran et al., 2015) and yield gap analysis (Teixeira et al., 2019). Meanwhile, DSSAT was applied for yield forecasting, disease management, precision farming, decision support, and policy analysis in agriculture (Boote et al., 1996; Jha, 2019; Shelia et al., 2015; Thorp et al., 2008). Meanwhile, the sequence modeling procedure in DSSAT enables us to simulate crop rotations (Bowen et al., 1998; Liu et al., 2013; Salmerón et al., 2014).

Crop models have been successfully used to implement hypothetical experiments and/or to simulate field experiments to assess various genetic × environment × management (G×E×M) interactions from field to regional scales (Adnan et al., 2019; Balboa et al., 2019; Eitzinger et al., 2017; Jin et al., 2019; Peng et al., 2020). Increasing access to biophysical data from remote sensing and integration of data assimilation techniques have substantially improved the scale of implementation of crop models (Jin et al., 2018). Therefore, crop modeling can help to evaluate the resilience of different production systems and to quantify their responses to different adaptation measures (Challinor et al., 2018; Rötter et al., 2018).

2.7.2 Hydrological Modeling

Hydrological models are used to predict and manage the distribution and fluxes of water as a function of various climate, soil, and physiographical characteristics that are used to describe the system within the model (Siad et al., 2019). Hydrological models that describe the land surface processes are called rainfall-runoff models, and those that describe the processes in the saturated zone are referred to as groundwater models. A large number of hydrological models are currently available to model hydrological processes from the scale of small catchments to the globe (Siad et al., 2019). Some of these models are; Variable Infiltration Capacity (VIC) model (Liang et al., 1994), MIKE-SHE (Refsgaard and Storm, 1995), Hydrologiska Byråns Vattenbalansavdelning (HBV) (Lindström et al., 1997), Soil and Water Assessment Tool (SWAT) (Gassman et al., 2007), Water Evaluation and Planning System (WEAP) (Sieber and

Purkey, 2015), Soil Water Atmosphere Plant (SWAP) (Van Dam et al., 2008) and HYDRUS (Šimůnek et al., 2012). MODFLOW (Harbaugh, 1995) and Interactive Groundwater (IGW) (Li and Liu, 2006) are the commonly available hydrological models to simulate groundwater systems. Each model has its unique features and applications, and their choice and implementation depend on data availability and modeling objectives. Furthermore, hydrological models can be coupled with crop models to better evaluate the water movement through the plant-soil-atmosphere continuum (Siad et al., 2019).

Groundwater models use the finite difference approximation of the governing partial differential equation to solve flow conditions in confined and unconfined aquifers as follows (Heath, 1983):

$$S_s \frac{\partial h}{\partial t} = \nabla(K \cdot \nabla H) + q \tag{2.8}$$

where, S_s is the specific storage coefficient, h is the hydraulic head, t is time, K is the saturated hydraulic conductivity, ∇ is the mathematical gradient operator, and q is the net flux (i.e., source (+) or sink (-) term).

Regional groundwater modeling requires numerous data inputs, which include aquifer properties, lithology, hydrographic information, land use, climate data, topography, recharge, and static water levels (Liao et al., 2020). Calibrated groundwater models are very useful tools to evaluate the impacts of land use changes and pumping on the groundwater flow dynamics (Sampath et al., 2015), groundwater quality (Curtis et al., 2018), and contaminant transport in the saturated zone (Hadley and Newell, 2014).

2.8 Adaptation of Resilient Practices

The adaptation usually refers to the process, action, or outcome of farmers and farming systems to better cope with the changing condition, stress, hazard, or risk (Smit and Wandel, 2006). Climate change adaptation in the context of agriculture could be identified as the adjustment of agronomic practices, agricultural processes, and capital investments in response to extreme events (Ainsworth and Ort, 2010). Depending on the timing of implementation, adaptations can be proactive (anticipatory) or reactive. Based on their degree of spontaneity, they could be either autonomous or planned. Adaptation in farming communities is closely related to their respective adaptive capacity and vulnerability. The concepts of adaptation, adaptive capacity, vulnerability, resilience, exposure, and sensitivity are closely related and have wide applications to global environmental changes and its impacts on agricultural systems. Vulnerability is determined by both the differential exposure and sensitivity of farming communities to climate change and to the adaptive capacities of those communities to deal with the effects associated with exposures. Exposure and sensitivity signify the likelihood of experiencing detrimental effects, while the livelihood characteristics of agricultural systems influence its sensitivity to such exposure (Smit and Wandel, 2006).

Agriculture has evolved through centuries in different regions of the world; therefore, it has an immense diversity of management practices to be used for adaptation to the impacts of climate variability. Such practices may involve adjustment of the timing of planting and harvesting, replacing crop species and cultivars with more appropriate thermal duration or stress tolerance, developing new crop varieties with improved traits, precision management of agricultural inputs such as water and nutrients and improvement of climate forecasting to reduce the production risks (Delgado et al., 2013; Howden et al., 2007; Minoli et al., 2019).

Many agricultural systems can provide both adaptation and mitigation benefits synergistically if they are designed and managed appropriately in a large landscape (Harvey et al., 2014). This is because most of the agricultural adaptation options for climate extremes have positive impacts on mitigation. These include measures that reduce soil erosion, reduce leaching of nitrogen and phosphorous, conserving soil moisture, increasing the diversity of crop rotations, and modification of microclimate to reduce temperature extremes (Smith and Olesen, 2010). Cooper et al. (2009) argued that, the development of temperature-adapted varieties, together with improved farm management practices, could result in practically complete mitigation of the negative impact of temperature rise and rainfall variability.

According to Smit and Skinner (2002), the adaptation strategies of farming communities in response to climate change can be categorized into four groups namely, technological developments (e.g., crop improvement, weather and climate information systems, and resource management innovation), government programs and insurance (e.g., agricultural subsidies and livelihood support programs, farm insurance, and resource management programs), farm practices (e.g., farm production, irrigation, and timing of operation) and farm financial management (e.g., crop insurance, crop shares, income stabilization, and household income).

The ability of farmers to adapt to climate change will depend on several socioeconomic factors. Land tenure, farm size, ownership of agricultural assets and livestock, gender, age, and availability of inputs decide the technology adoption under climate change (Asfaw et al., 2014). In Africa, the adaptation of conservation farming practices (minimum tillage, permanent soil cover, and crop rotations) determine by the availability of extension services and rainfall variability (Arslan et al., 2014). This shows the role of agro-ecological and socioeconomic constraints in explaining adoption, as well as the potential role and effectiveness of outreach programs to support it.

Recent survey studies among the farmers in the Midwestern United States indicate that most of the producers recognized the changing climate (Arbuckle et al., 2013; Doll et al., 2017; Mase et al., 2017) and have, therefore, implemented different climate adaptation measures (Denny et al., 2019; Morton et al., 2015). For example, farmers who better understand the causes and casualties of climate change are increasingly using climate information, conservation practices, crop insurance, and other alternative options for mitigating risks to climate change (Arbuckle et al., 2013; Haigh et al., 2015; Mase et al., 2017; Morton et al., 2017). However, recognition of the threats due to climate change and the rate of uptake of climate-resilient practices still inadequate compared to the rate of changes in climate variability (Church et al., 2017; Lemos et al., 2014). This is because there are many barriers to adaptation and operating at different levels. Barriers are the obstacles that hinder the planning and implementation of adaptation measures. Generally, farmers are constrained by financial barriers, socio-cultural barriers, institutional barriers, technological barriers, and a lack of information on the impacts of climate extremes (Antwi-Agyei et al., 2015). To overcome these barriers, a comprehensive and dynamic policy approach is required considering all the aspects ranging from individual farmer awareness to the establishment of efficient markets (Howden et al., 2007). Moreover, there is a need to engage stakeholders at different levels from different sectors with diverse and often contesting types of expertise, experience values, and interests (Vervoort et al., 2014).

2.9 Summary

Overall, increasing climate extremes have become the major challenge for the rainfed agricultural systems in the Midwestern United States. Although farmers have realized the causes and casualties of these extreme climatic events, the uptake of adaptation measures was not adequate to face the challenges. Alternative agricultural practices such as conservation agriculture and organic agriculture have been introduced and endorsed for adaptation to counteract the effects of climate change and variability. However, the resilience of these promising management systems has not been adequately quantified due to the lack of metrics to capture the temporal variabilities both at field and regional scales. Therefore, carrying out research studies to explore the metrics that are practical and able to quantify the resilience of different rainfed systems would aid in identifying appropriate options for climate risk management in agriculture.

3. INTRODUCTION TO METHODOLOGY

This dissertation comprised of three research studies that are critically important to quantify the level of resiliency in agricultural settings. The first paper, entitled "Evaluating the Applicability of Soil Moisture-based Metrics for Gauging the Resiliency of Rainfed Agricultural Systems," aimed to develop appropriate metrics to measure the resiliency of rainfed agricultural systems at the field scale. Soil moisture is the major limiting factor of crop productivity in rainfed agriculture. Hence, the spatiotemporal dynamics of soil moisture is one of the key indicators of resilience. We hypothesized that above-average soil moisture during the growing season could improve the resiliency of rainfed agricultural systems. Thus, the elevated soil moister content can positively affect the growth and yields of crops, especially during climate extremes such as droughts. This hypothesis was tested in a long-term crop rotation (corn-soybean-wheat) setting. The experimental fields were managed under four treatments, namely, conventional, no-till, reduced input, and organic treatments. This long-term cropping system experiment was located at the W.K. Kellogg Biological Station in the temperate humid climate of Southwest Michigan, United States. The data on precipitation, soil moisture, total crop biomass, crop yield, and soil organic carbon were collected for the duration of this study. Four soil moisture-based metrics, namely, the mean relative difference, Spearman's rank correlation coefficient, the index of temporal stability, and the soil water deficit index, were computed for each treatment. Next, the robustness of these metrics under long term (1993-2018) climate variabilities was evaluated for reducing drought severity and maintaining/improving growth and yield of crops using different statistical techniques.

The second study, entitled "Evaluating the Climate Resilience in terms of Profitability and Farm Risk Management for a Long-Term Corn-Soybean-Wheat Rotation under Different

Treatment Systems," examined the climate resilience of alternative agricultural treatments in terms of profitability and risks that are essential concerns of producers. Three alternative treatments include the no-till treatment, the reduced input treatment, and the organic treatment, were compared against the conventional treatment for the same crop rotation (i.e., corn-soybean-wheat). The annual crop management and production data for each treatment were obtained for the period of study (1993-2018) from the W.K. Kellogg Biological Station. Means and volatility of expected net returns and the risk preferences were used as metrics to evaluate the resilience. The net returns for each crop production and treatment systems were estimated using static enterprise budgeting, while the volatility of net returns was calculated using the relative standard deviation. The payoff matrix tool was utilized to assess the risk preferences for each production and treatment systems. A statistical mixed model was used to quantify the effects of long-term climate variability on the estimated net returns. Finally, resilient treatments were defined as those with higher expected net revenues with lower volatility to the conventional treatment and also have a wide range of risk preferences for the adaptation.

The last study, entitled "Quantification of Resilience Metrics as Affected by a Conservation Agricultural Practice at a Watershed Scale," was designed to scale up the quantification of resilience from the field scale to a larger scale (e.g., a watershed). This study was implemented in the Kalamazoo River watershed located in the Southwestern Michigan of the United States. The long-term data collected from the W.K. Kellogg Biological Station for the conventional and the no-till treatments were used to develop a sequence crop model to represent the corn-soybean-wheat rotation, and this model was calibrated using the yield and soil moisture data for the study period (1993-2019). The soil, climate, and land use data were collected for the watershed scale simulation. Meanwhile, yield, soil moisture, and recharge values were obtained from the calibrated crop model for different soils and climate within the study area. The net return was calculated using an enterprise budget for each crop. Yield, net return, and recharge data were analyzed using a mixed model to exploit the statistical significance between two treatments. The daily soil moisture data over the growing season was used to compute soil moisture metrics, namely, the mean relative difference and the soil water deficit index. The annual recharge data comes from the crop model for the agricultural areas, while a calibrated groundwater model was used to calculate a long-term mean recharge values from the non-agricultural areas. This information was integrated to assess the long-term changes in the water table under both treatments. Finally, recharge, groundwater table, soil moisture, yield, and net return were used to evaluate the overall changes in resiliency as affected by the adaptation of no-till as a conservation agriculture treatment in the watershed.

4. EVALUATING THE APPLICABILITY OF SOIL MOISTURE-BASED METRICS FOR GAUGING THE RESILIENCY OF RAINFED AGRICULTURAL SYSTEMS

4.1 Introduction

Rainfed agriculture systems account for 80 percent of the croplands in the world and contribute to nearly 60 percent of total food production (FAO, 2017). Meanwhile, in the United States, about 94 percent of farmland acres are considered rainfed agriculture (USDA, 2014). Rainfed agricultural systems in the United States are economically important, ecologically diverse, technologically advanced, and are most common in the eastern half of the mainland where annual precipitation is greater than 500mm. In this region, the majority of the corn and soybean crops are produced from these systems, either as a monocrop or in rotation. The productivity of these crops steadily increased in the past as a result of genetic improvements (about 70%) and management interventions (about 30%). Moreover, with the development of glyphosate-resistant crop varieties, adoption of conservation agriculture practices such as no-tillage has been substantially increased to counteract the problems of soil erosion, nutrient leaching and runoff, and yield instability (Franzluebbers et al., 2011).

Regardless of this overall increase in productivity, crop yields have been shown to be vulnerable to interannual variability in the climate (Hatfield et al., 2018; Hatfield, 2012; Lesk et al., 2016; Thornton et al., 2014). Like in other areas around the world, changes in the regional climate in the Midwestern states result in increasing the frequencies of extreme events such as droughts, floods, and heatwaves (Andresen et al., 2012; Hatfield et al., 2018; Pryor et al., 2014). The water availability for rainfed agriculture is primarily controlled by the seasonal pattern of precipitation (intensity and frequency) and its interactions with the soil-plant-atmosphere continuum (Rost et al., 2009). This makes rainfed crop production much vulnerable to the effects of climate variability and extremes. For example, the flash drought in 2012 devastated major crops and economic base of rainfed farms in the Midwestern region (Fuchs et al., 2012; Mallya et al., 2013; Otkin et al., 2018, 2016). Flash droughts are associated with decreased precipitation and humidity, increased solar radiation, and elevated temperatures, leading to reduced availability of soil water to crops (Ford and Labosier, 2017). As highlighted by Rippey, (2015), due to this drought development, corn yield in the US has fallen for three consecutive years from 2010-2012 for the first time since 1928-1930. These climate extremes will have substantial impacts not only on the national economy but also on international markets (Boyer et al., 2013).

Resilience can be generally defined as a capability of a system to recover from stressors (Holling, 1973). Therefore, climate-resilience can be considered as the ability of a system to maintain its structures and patterns of behavior in the face of climate perturbations. This allows the system to continue to provide its services, which in the case of agriculture, is the growth and yield of crops (Tendall et al., 2015; Urruty et al., 2016; Walker et al., 2004). It also refers to the ability of a system to develop capacities to cope with, adapt, and potentially transform the appropriate management practices to face the challenges of the climate shocks and extremes (Bousquet et al., 2016). Specific to rainfed agriculture, climate-resilience can be used to describe the ability of the components of the system to recover from water stress (Tow et al., 2011). This could be achieved by implementing management interventions that will keep the soil moisture at relevant levels in a way that extreme climatic events shall not reduce the crop yields significantly. Such actions to enhance the climate-resilience in rainfed agriculture can be broadly categorized as genetic interventions, informed decisions, and agronomic interventions.

Genetic interventions involve developing new germplasm with improved tolerance to environmental stresses such as drought and heat stress and/or crop genotypes with phenological adjustments to avoid such stresses (Ainsworth and Ort, 2010; Ceccarelli et al., 2010; Davies et al., 2011). Adoption of these genotypes with improved stress tolerance has increased the climate-resilience of corn and soybean production systems around the world (Cairns et al., 2012; Chapman et al., 2012; Sadok and Sinclair, 2011). *Informed decisions* refer to the utilization of seasonal climate forecast information (Hansen et al., 2011; Meinke et al., 2006). Forecast products such as those of NOAA's climate prediction center (e.g., three-month outlooks) can potentially influence most of the agronomic and genetic interventions. *Agronomic interventions* may include, adjustment of planting and harvesting times, altering fertilization rates and irrigation practices (Howden et al., 2007; Nouri et al., 2017; Rurinda et al., 2015), mulching (Erenstein, 2003; Qin et al., 2015), crop diversification and agroforestry (Altieri et al., 2015; Gan et al., 2015; Lin, 2011; Mbow et al., 2014) and adoption of conservation agriculture (Delgado et al., 2013; Michler et al., 2019). There is also evidence for the improvement of climate-resilience under organically managed agricultural systems (Scialabba and Mller-Lindenlauf, 2010; Tuomisto et al., 2012) due to the enhancement in soil quality and reduction in environmental impacts.

In this study, we are mainly focusing on agronomic interventions, especially conservation agriculture as climate-resilience practices. Conservation agriculture comprises of three management principles: minimum soil disturbance/no-till, permanent soil cover by crop residues/cover crops, and crop rotation (Hobbs et al., 2013; Pittelkow et al., 2015a). These conservation practices are adopted at various intensities and combinations in the Midwestern states to provide varying degrees of resilience to climate shocks and extremes (Denny et al., 2019). In comparison to conventional tillage, the no-till/zero-tillage systems showed the highest level of climate-resilience as a result of improved water availability and soil quality, that helps to avoid substantial reductions in crop yields during extreme climatic events (Delgado et al., 2013;

Harrington and Tow, 2011; Michler et al., 2019). In contrast, some other studies (e.g., Pittelkow et al., 2015a; Powlson et al., 2014) have shown that no-till reduces crop yields compared to conventional tillage and their potential for climate-resilience is limited. Interestingly, Pittelkow et al., 2015b, in their comprehensive review, highlighted that no-till, when combined with the other two principles of conservation agriculture (residue retention and crop rotation), significantly increases the crop yields in rainfed systems. This could be due to the ability of the system to capture snow, reduction of runoff and soil evaporation (with the retention of crop residues), and creation of better soil structure and rooting patterns through crop rotations to store more water in the root zone (Franzluebbers et al., 2011; O'Leary et al., 2011).

To evaluate responses of varying agronomic interventions of climate-resilience practices, there is a need for quantification metrics for system resiliency. Resilience metrics can be used to shift a system towards more desirable and sustainable states, track thresholds of potential concerns, and help with assessments on how the system is being managed (Quinlan et al., 2016). The Committee on Sustainability Assessment (COSA) stated that gauging resilience generally involves a holistic approach that incorporates social, economic, and environmental dimensions of resilience (COSA, 2017). Because of the complexity and interactions in these three dimensions, food system resilience is often assessed qualitatively (Toth et al., 2016). However, qualitative assessments are region-specific and subject to variations in assumptions. Therefore, multiple tools have been developed to evaluate the climate resilience of food production systems in many parts of the world (Douxchamps et al., 2017). These tools have often been applied to large socioeconomic units (e.g., households/communities/administrative regions/national scale). For example, the Resilience Index Measurement and Analysis Model (RIMA) developed by the Food and Agriculture Organization of the United Nations (FAO, 2016), is increasingly used to measure the climate-resilience of agricultural communities in many African countries (Serfilippi and Ramnath, 2018). Other such tools are Community Based Resilience Assessment (CoBRA) developed by United Nations Development Program (UNDP, 2013), Self-evaluation and Holistic Assessment of climate Resilience of farmers and Pastoralists (SHARP) used by FAO (Choptiany et al., 2017), Community-based Risk Screening Tool-adaptation and Livelihood (CRiSTAL) developed by International Institute for Sustainable Development (IISD, 2014), Climate Vulnerability and Capacity Analysis (CVCA) developed by Care International (Care, 2009) and Resilience, Adaptation and Transformation Assessment Framework (RATALF) developed by The Commonwealth Scientific and Industrial Research Organization (O'Connell et al., 2015).

In general, these tools use indices known as resilience metrics to evaluate the flexibility of a system. Means and variance of agricultural production (Di Falco and Chavas, 2008), crop yields (Birthal et al., 2015; Martin and Magne, 2015), profit (Browne et al., 2013; Komarek et al., 2015; Seo, 2010), revenue (Kandulu et al., 2012; Rigolot et al., 2017; Tibesigwa and Visser, 2015), labor productivity (Komarek et al., 2015), crop failure (Jones and Thornton, 2009), dietary diversity (Dillon et al., 2015), farming risks (Komarek et al., 2015), agricultural gross domestic product (Hsiang and Jina, 2014), and expenditure for food consumption/food security (Alfani et al., 2015) have been used as resilience metrics. These metrics are often used in combination and have shown non-linear responses to climate variability depending upon various characteristics of farms and farmers (Di Falco and Chavas, 2008; Tittonell, 2014). Despite the growing knowledge in this area, there is still no consensus on how resilience should be measured and no universal tool available to quantify resilience at different scales. Moreover, existing tools and frameworks often fail to capture the spatial and temporal dynamics of resilience (Dixon and Stringer, 2015; Douxchamps et al., 2017).

To address these challenges, there is a need for new metrics to address the complexity in agricultural systems while being simple enough to be measured and adopted by individual farmers. Therefore, we propose a new measure to overcome these challenges and constraints by providing a case-specific definition of resilience and confining our focus to long-term agronomic performance (soil moisture, growth, and yield of crops) under different rainfed agricultural systems in an experimental farm scale. However, it is important to note that this study is only focusing on farm-scale resiliency and therefore is not considering other sociological/institutional characteristics that are important beyond farm-scale, which can be evaluated through existing resilience metrics, which were discussed earlier. In order to achieve this goal, three objectives need to be satisfied: 1) rank the relative resilience of different rainfed agricultural systems using the metrics of temporal dynamics of soil moisture; 2) evaluate the robustness of the soil moisture metrics of temporal dynamics to growth and yield under climate extremes; and 3) compare the effectiveness of different rainfed agricultural systems on reducing agricultural drought severity.

4.2 Materials and Methods

Root zone soil moisture is the key determinant of productivity in rainfed agricultural systems (Jägermeyr et al., 2016). The ability of a system to store a substantial amount of soil moisture is one of the key indicators of resilience, as recommended by COSA, (2017). In this study we applied a combination of soil moisture-based metrics to gauge the resiliency of rainfed agricultural systems. Long-term (1993-2018) agricultural experiment data on soil moisture, total crop biomass, crop yield, and soil organic carbon were collected, which provides an excellent opportunity to conduct an exhaustive evaluation of resiliency in agricultural systems. We hypothesize that a rainfed agricultural system has a higher degree of resilience if it can maintain above-average soil moisture; thus, this relative resilience will beneficially affect the yields, especially during periods of climate variabilities (e.g., drought). We test this hypothesis using soil moisture-based metrics in four differently managed long-term rainfed row crop treatments, namely, conventional treatment (CON), no-till treatment (NT), reduced input treatment (RI), and organically managed treatment (OR). These soil moisture-based metrics include three metrics of the temporal stability of soil moisture and an agricultural drought index. The soil moisture temporal dynamics metrics were selected to evaluate the relative resilience of different rainfed agricultural treatments (Objective 1), then we examined the robustness of these soil moisture metrics for different crops under climate extremes (i.e., dry and wet years) during the growing season. The results of this section can prove whether the soil moisture temporal dynamics metrics can be used to evaluate the resiliency of different agricultural systems as measures of growth and yield (Objective 2). Finally, an agricultural drought index was selected to evaluate the effectiveness of different rainfed agricultural treatments on reducing the agricultural drought severity (Objective 3).

4.2.1 Study Location and Site Description

This study was conducted at the Kellogg Biological Station (KBS), where Long-Term Ecological Research (LTER) experiment is implemented to evaluate the performance of different annual and perennial crops under varying management intensity gradients (Robertson and Hamilton, 2015). KBS is located in Southwest Michigan at 288 AMSL, within the northern boundary of the U.S. Corn Belt (42.41˚ N, 85.37˚ W). For the period of 1981-2010, the mean annual air temperature is 10.1 ˚C, and the mean annual precipitation is 1,005 mm, with 511 mm of the total precipitation falling as rain during the summer growing season (May-September) (NCEI, 2019). The evapotranspiration in this region is water-limited during the warmer part of the year and energy-limited during the colder months (Mcvicar et al., 2012). The soil of this experimental station is classified as fine-loamy, mixed, mesic Typic Hapludalf (Kalamazoo loam series) developed on glacial till and outwash (Syswerda and Robertson, 2014). The texture of the Ap horizon (0-30 cm) of this soil is loam or sandy loam (43% sand, 38% silt, and 19% clay). The pH, bulk density, and total soil carbon are 5.5, 1.6 g cm^{-3}, and 12.85 g kg^{-1}, respectively (Crum and Collins, 1995). The Main Cropping System Experiment (MCSE), established in 1988 (Figure 4.1), is comprised of seven model ecosystems namely, four annual row crop systems with different management intensity (treatments), Poplar (*Populus deltoides* × *P. nigra*), continuous Alfalfa (*Medicago sativa*), and an early successional vegetation community (Robertson and Hamilton, 2015). For this study, we selected the first four annual row crop treatments that were designed in a management intensity gradient.

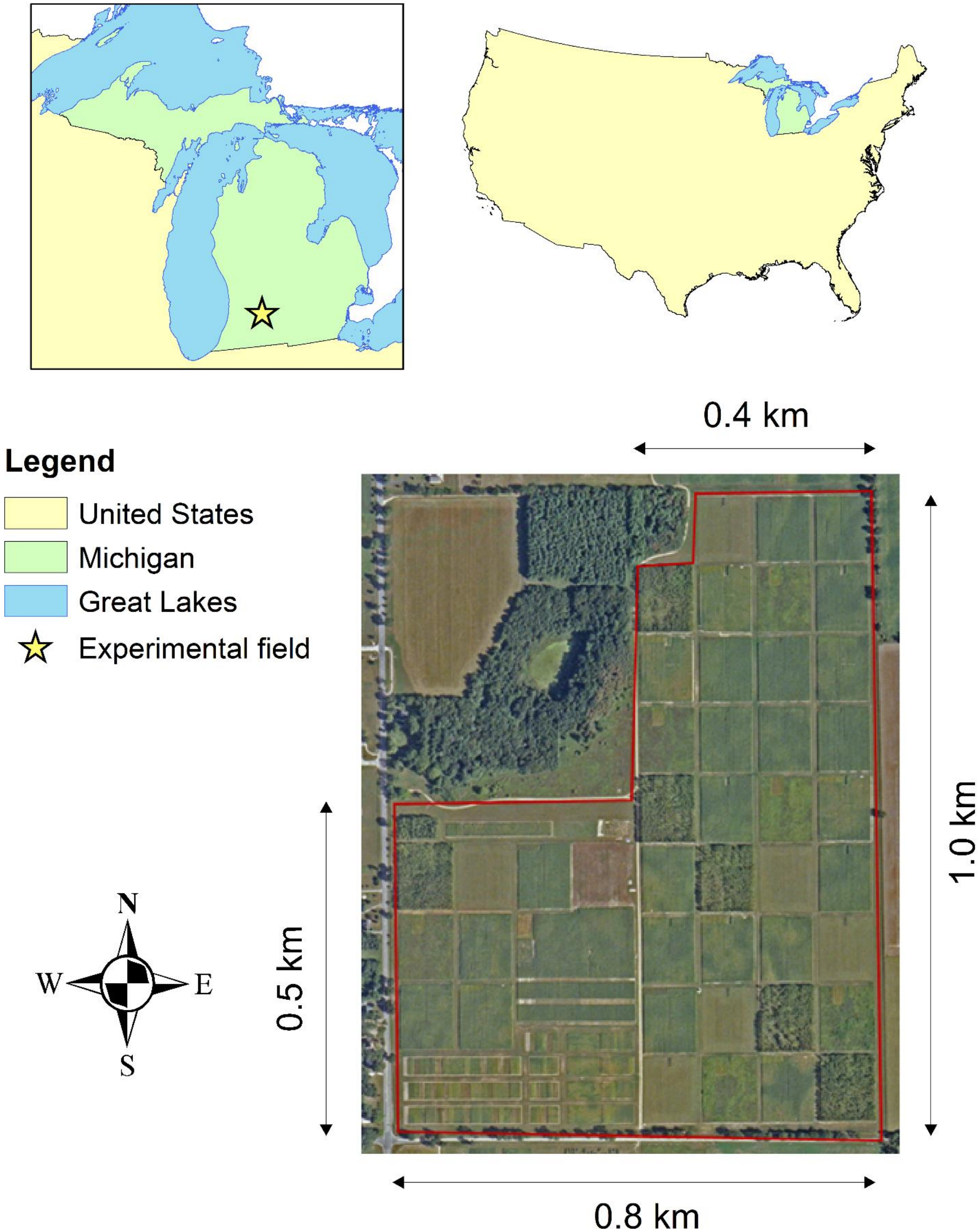

Figure 4.1. The experimental fields of the Main Cropping System Experiment (MCSE) at the Kellogg Biological Station (KBS) in Michigan, United States.

Crops were established and measurements began in 1989. All agricultural systems within the experiment have been managed as rainfed and each of them is assigned to six replicates (blocks) of one-ha, plots (87 × 105 m) in a randomized complete block design. The four annual row crop treatments consisted of maize (*Zea mays*)-soybean (*Glycine max*)-winter wheat (*Triticum aestivum*) rotations managed as (i) conventional treatment (CON), (ii) no-till treatment (NT), (iii) reduced input treatment (RI), and (iv) organically managed (USDA certified organic) treatment (OR). The conventional treatment is considered as the control. This allows us to measure the resilience of selected agricultural systems in comparison to the conventional system. The reasons behind the selection of the conventional treatment as control are; 1) majority of the croplands (>85% globally and >65% in the United States) are under conventional agriculture (Kassam et al., 2019) and 2) conventional system has been identified as the significant contributor of pollutions to the environment (Foley et al., 2011; Meier et al., 2015).

All row crop treatments were planted and harvested at the same time. A routine experimental design was followed only from 1993; therefore, we confined this study for the period of 1993-2018. The detailed description of the four annual row crop treatments is presented in the Supplementary Materials section (Table S4.1).

4.2.2 Data Collection

To achieve the objectives of this research, gravimetric soil moisture, soil organic carbon, total crop biomass, and yield were measured for the period (1993-2018) from the experimental plots at KBS. Gravimetric soil moisture data were collected, and then respective bulk density data were used to convert it into volumetric soil moisture. This volumetric soil moisture data was used to calculate the metrics of soil moisture temporal dynamics to evaluate the relative resilience of different rainfed agricultural treatments (Objective 1). In addition, soil organic carbon data were collected to explore its associations with observed soil moisture dynamics. Total crop biomass and yield data were collected to evaluate the robustness of the soil moisture metrics to gauge resiliency to climate extremes in terms of growth and yield of crops (Objective 2). Finally, the volumetric soil moisture data was used to calculate the drought index to evaluate the effectiveness of different rainfed agricultural treatments on reducing the agricultural drought severity (Objective 3).

Soil moisture: Gravimetric soil moisture measurements began in 1989 in all MSCE agricultural treatments. These measurements were employed each year, typically biweekly throughout the growing season (April-October). Soils were collected from five permanent sampling stations established in each replicate (plot). Two soil cores were taken from each sampling station using soil augers to represent 0-25 cm depth. These ten samples then composited by the physically mixing of individual soil cores taken within a replicate into one homogenous sample. Composite soil samples were sieved through a 4 mm screen to remove debris and homogenize the sample. About 40-50 g of sieved composite samples were taken into soil moisture cans, and then oven-dried to a constant weight, at least 24 hours at 105 ˚C. The gravimetric soil moisture (θ_g) was calculated as follows (Reynolds, 1970):

$$\theta g = \frac{Weight\ of\ moist\ soil - Weight\ of\ dry\ soil}{Weight\ of\ dry\ soil} \tag{4.1}$$

Bulk density: Bulk density is used to convert gravimetric soil moisture into volumetric soil moisture. It was measured by taking core samples at different soil horizons (Blake and Hartge, 1986). In this study, we used the gravel-free bulk density values measured at 0-25 cm depth. Bulk density (*BD*) was calculated as follows (Carter and Gregorich, 2008):

$$BD = \frac{Weight\ of\ dry\ soil}{Volume\ of\ soil\ core\ (Cylindrical\ volume)} \tag{4.2}$$

Bulk density measurements were available for MCSE during the years of 1996, 2001, 2010 and 2013. Therefore, bulk density measurements from the years 1996, 2001, 2010 and 2013 were used to convert gravimetric soil moisture measurements for the periods of 1993-2000, 2001-2009, 2010-2012, and 2013-2018, respectively. Equation 4.3 (Evett, 2008) was used to covert gravimetric soil moisture into volumetric soil moisture (θ_v), assuming the density of water is 1 gcm^{-3}.

$$\theta\mathrm{v} = \theta\mathrm{g} \times BD \tag{4.3}$$

Soil organic carbon: Soil organic carbon from the surface soils for each treatment and respective replicates was available for the period of 1989-2001. Even though the measurements have been made for total soil carbon (organic and inorganic forms), extensive testing of KBS surface soils has shown soil inorganic carbon to be non-detectable; thus, total soil carbon is identical to total organic carbon. To measure the total soil carbon, subsamples were oven-dried at 60 ˚C for at least 48 hours until no further mass loss occurs. Dried and finely grounded soil samples are weighed into small foil capsules which are combusted in an automated CHN (carbon, hydrogen and nitrogen) analyzer that measures the amount of released CO_2 using gas chromatography. Soil carbon values are expressed as a percentage of carbon in dry soil. We utilized these soil organic carbon values to explore its associations with soil moisture dynamics.

Crop biomass and yield: Total crop biomass was measured from 1993 at peak growth of biomass. Aboveground biomass hand-clipped within 1 m^2 quadrat at each of the five sampling stations per replicate, once in a growing season. Collected biomass was oven-dried at 60 ˚C for 48 hours and weighed. Seed yield of crops was measured during crop harvest determined by machine harvesters appropriate to each crop. The standardized moisture content for yield measurement was 15.5% for corn and 13% for wheat and soybean.

4.2.3 Calculating the Metrics of temporal Dynamics of Soil Moisture to Examine the Relative Resilience of Different Rainfed Agricultural Treatments

Metrics of the temporal dynamics of soil moisture are the mean relative difference (MRD), index of temporal stability (ITS), and non-parametric Spearman's rank correlation coefficient (r_s). MRD is used to present the relative ranks of different rainfed agricultural treatments in terms of root zone soil moisture content, ITS is used to show the variability of the MRD ranking over the growing season and r_s was used to indicate the persistence of the relative MRD ranks over the period of study (Jacobs et al., 2004; Joshi et al., 2011; Vachaud et al., 1985). In the past, temporal stability analysis of soil moisture was used to identify time-stable points or representative locations to employ monitoring networks/sensors (Barker et al., 2017; Brocca et al., 2010; Starks et al., 2006; Zhou et al., 2007) and/or to validate remote sensing soil moisture products (Cosh et al., 2008; Jacobs et al., 2004; Joshi et al., 2011; Wagner et al., 2008). In other studies, the metrics were used to study the spatiotemporal dynamics of soil moisture in hillslope (Gao et al., 2016; Liu et al., 2018) or under different land use (Hu et al., 2010) or in diverse soil layers (Gao and Shao, 2012; He et al., 2019). In this study, we will use these metrics to gauge the relative resilience of different rainfed agricultural treatments.

Mean Relative Difference: MRD was introduced by Vachaud et al. (1985) to study the temporal stability of spatially measured soil moisture. The mean relative difference (equation 4.4) together with the index of temporal stability (equation 4.7) have been used in the spatiotemporal analysis of soil moisture (Gao and Shao, 2012; He et al., 2019; Joshi et al., 2011; Liu et al., 2018). Here, we use these metrics to evaluate the spatiotemporal dynamics of soil moisture across different agricultural treatments. The MRD (% cm^3/cm^3) for treatment in a particular growing season (year) is defined as:

$$MRD = \frac{1}{Nt}\sum_{t=1}^{Nt}[(\Theta v - \overline{\Theta})/\overline{\Theta}] \tag{4.4}$$

$$\overline{\Theta} = \frac{1}{NT}\sum_{T=1}^{NT}\Theta v \tag{4.5}$$

where, θv is the volumetric soil moisture (% cm^3/cm^3) measured in a treatment T at time t. $\overline{\Theta}$ is the mean volumetric soil moisture of all treatments. N_T is the number of treatments. Nt is the number of soil moisture measurements (sampling days) during the particular growing season.

A negative MRD value indicates that the treatment is *drier* than the field-averaged soil moisture, whereas a positive MRD value signifies that the treatment is *wetter* than the field mean soil moisture (Joshi et al., 2011).

Variance of Relative Difference (VRD): The variance of the relative difference for each treatment is calculated as:

$$VRD = \frac{1}{nt-1}\sum_{t=1}^{Nt}\left\{\frac{\Theta v-\overline{\Theta}}{\overline{\Theta}} - MRD\right\}^2 \tag{4.6}$$

The MRD quantifies the deviation of the soil moisture in a particular treatment, and the VRD quantifies the accuracy of that measurement (Joshi et al., 2011). Here we calculated VRD to derive ITS in the next step (equation 4.7).

Index of Temporal Stability: ITS can be derived by considering both MRD and VRD (He et al., 2019; Jacobs et al., 2004; Liu et al., 2018); therefore, ITS represents both bias and accuracy metrics.:

$$ITS = \sqrt{MRD^2 + VRD} \tag{4.7}$$

In a rank ordered MRD and ITS plot, treatments with MRD values close to zero and with smaller ITS values can be considered temporally more stable (He et al., 2019; Joshi et al., 2011;

Liu et al., 2018). However, our intention in this work is to find out relatively *wetter* treatment (i.e., positive MRD). Because we hypothesized that if an agricultural system can hold more soil moisture due to conservation practices (e.g., no-till) during the growing period than a conventional system, it would positively be affecting the growth and yield of crops in rainfed agricultural systems.

Non-parametric Spearman's rank correlation coefficient: The non-parametric Spearman's rank test (Vachaud et al., 1985) was used to examine the persistence of MRD ranks over the 26-year study period for each treatment. The r_s is expressed as:

$$r_s = 1 - \frac{6\sum_{i=1}^{n}(R_{ij} - R_{ik})}{n(n^2-1)} \tag{4.8}$$

where, R_{ij} is the rank of MRD in treatment i on the year j, R_{ik} is the rank of MRD in treatment i on the following year k, and n is the number of years. The r_s was calculated for each agricultural system where r_s of 1, for any treatment, represent the MRD having the same rank between the years j and k. Therefore, higher values of r_s (values closer to 1) represent higher temporal persistence of relative ranking over the study period (Liu et al., 2018).

4.2.4 Evaluate the Sensitivity of the Mean Relative Difference of Soil Moisture to Climate Variability and its Reflections on Crop Growth and Yield in Different Treatments

Long-term experimental data on soil moisture, total crop biomass, crop yield, and soil organic carbon were collected from KBS-LTER data catalog and processed using a python script in Wing Pro Version 7.1.2 (Wingware, Cambridge, Massachusetts, USA) and Microsoft Excel Version 2016 (Microsoft Corporation, Redmond, Washington, USA). In this study, a mixed model (Milliken and Johnson, 2009) was used to explore the statistical significance of random and fixed effects of independent variables on selected response variables.

The statistical model for evaluating the effects of treatment, climate variability and year on selected response variables (i.e., MRD, total crop biomass and yield) was specified as:

$$y_{ijk} = \mu + clim + trt_i + yr_k + trt_i \times clim + blk_j(yr_k) + trt_i \times yr_k + e_{ijk} \tag{4.9}$$

where, y_{ijk}: is the vector of observation (response variable) collected for the ith treatment, within jth block on the kth year. μ: is the overall mean, *trt*: is the fixed effect of treatments, which represents different agricultural systems, *blk*: is the random effect of the replications (blocks) nested within years, *clim*: is the fixed effect of the climate variability (dry, normal and wet), *yr*: is the random effect of the year, *trt* × *clim*: is the interaction between the effects of treatment and the fixed effect of climate variability, *trt* × *yr*: is the interaction between the effects of treatment, the random effect of the year, and *e* is the residual. The effect of seasonal mean temperature was also initially included in the statistical model as a fixed effect; however, the temperature effect and all the interaction terms with temperature were non-significant at $p \leq 0.05$ for all studied response variables. Thus, we decided not to include the effect of seasonal mean temperature in the final statistical model. The non-significant effect of seasonal mean temperature was most likely a result of a little coefficient of variation (CV = 4.8%) observed for this continuous variable. The normality of the residuals and homogeneity of variances were checked for each response variable (Milliken and Johnson, 2001). The data for all response variables were normal, and their variances were homogenous.

Analyses were performed by crop (separately for each crop), using PROC GLIMMIX procedure (Milliken and Johnson, 2009) in SAS software version 9.4 (SAS Institute Inc. Cary, North Carolina, USA). Fixed effects were tested using F-test (Steel et al., 1980), and random effects were tested using Wald test for covariance (Wald, 1943). Tukey Test for mean separation was performed when significant differences were detected for the fixed effects (Lee and Lee, 2018), and significant differences were evaluated at the 0.05 probability level (Steel et al., 1980). Pearson's correlation analysis (Weaver et al., 2017) was performed using MINITAB 15 (Minitab, LLC. State College, PA, USA) to determine the relationship between MRD vs. soil organic carbon.

4.2.5 Compare the Effectiveness of Different Treatments on Reducing Agricultural Drought Severity

Agricultural drought is defined as a period of soil moisture deficiency resulted in the shortage of precipitation that occurs for a few weeks of duration (Esfahanian et al., 2017). Drought is the major growth- and yield-limiting abiotic stress in rainfed agricultural systems. A U.S. based study estimated yield reductions in row crops as high as 8% in the rainfed agriculture counties of Midwest due to recent drought events (Kuwayama et al., 2019). Moreover, increasing climate variability and extremes make rainfed agriculture more vulnerable to droughts (Hatfield et al., 2018), which increases the adoption of conservation practices among farmers (Ding et al., 2009). Therefore, we decided to evaluate the impacts of these treatments on agricultural drought severity and occurrence using the Soil Water Deficit Index (SWDI). SWDI was considered for this study since it requires fewer inputs and is more widely used than other agricultural drought indices such as Palmer Moisture Anomaly Index (Alley, 1984; Palmer, 1965), Soil Moisture Deficit Index (Narasimhan and Srinivasan, 2005), and Evapotranspiration Deficit Index (Narasimhan and Srinivasan, 2005). In addition, when time-series soil moisture measurements are available from the root zone, SWDI can be successfully implemented at field scale to assess agricultural drought

(Martínez-Fernández et al., 2015) with the additional information on field capacity and permanent wilting point of that particular soil. Ultimately, the evaluation of the agricultural drought severity will enable us to gauge the relative resilience of different rainfed agricultural systems.

Categorization of climate variability: Total seasonal precipitation (April-October) for the period of 30 years (1989-2018) was collected from the KBS weather station located within the experimental site, and the probability distribution was calculated to categorize the climate variability, namely dry years (cumulative probability less than 33.3%), normal years (cumulative probability in between 33.3% and 66.6%) and wet years (cumulative probability greater than 66.6%) as shown in Figure 4.2.

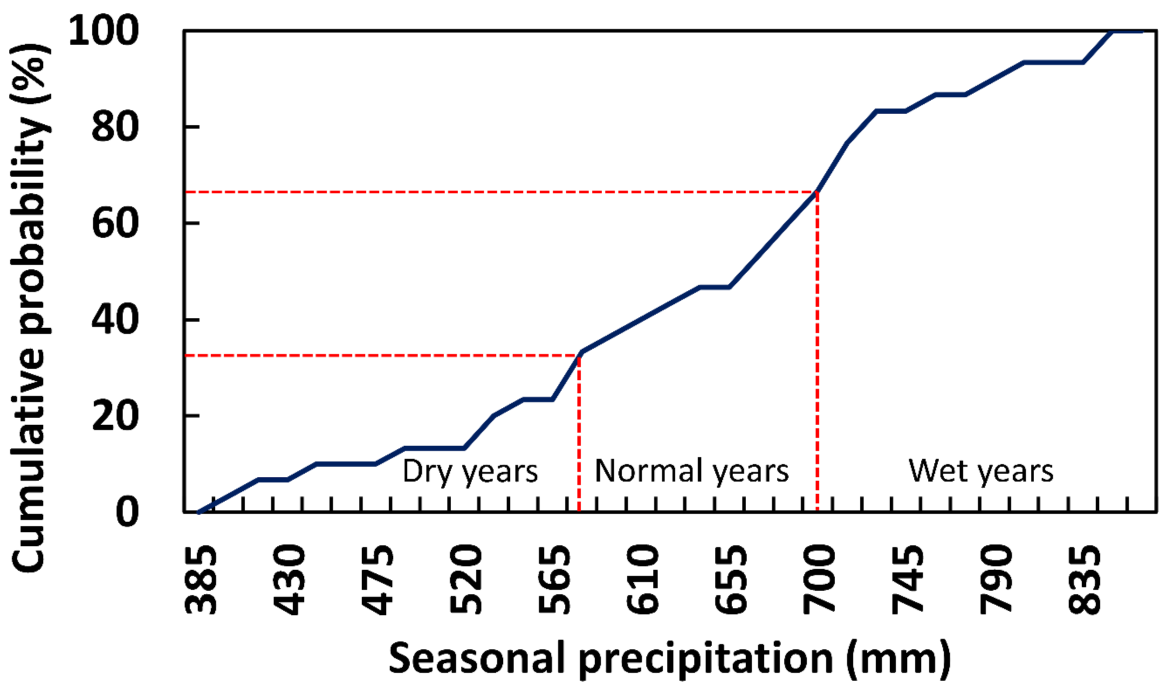

Figure 4.2. Cumulative probability distribution of seasonal precipitation for the period of 30 years (1989-2018) at KBS weather station.

Based on the frequency analysis explained above, dry years were categorized as the years that the seasonal precipitation ≤ 580 mm, wet years were categorized as the years that the seasonal precipitation ≥ 700 mm and normal years were categorized as the years that seasonal precipitation is in between. Classification of the entire experimental period (1993-2018) into the above climate variability categories for each crop in the rotation is given in Table 4.1.

Table 4.1. Climate variability for each crop in the rotation.

Crop	Categories of climate variabilities	Years
Corn	Dry years	1996, 1999, 2002, 2005
	Normal years	1993, 2014, 2017
	Wet years	2008, 2011
Soybean	Dry years	1997, 2012
	Normal years	2003, 2009
	Wet years	1994, 2000, 2006, 2015, 2018
Wheat	Dry years	1995, 1998, 2007
	Normal years	2004, 2010, 2016
	Wet years	2001, 2013

Soil Water Deficit Index (SWDI): Soil water deficit index is an agricultural drought indicator developed by Martínez-Fernández et al. (2015) based on water deficit accumulation or soil water storage. SWDI is the fraction between the differences of i) volumetric soil moisture and field capacity, and ii) plant available water content, which is the difference between field capacity and permanent wilting point. This fraction is then multiplied by 10 to obtain SWDI (equation 4.10), and the respective drought severity levels:

$$SWDI = \left\{\frac{\theta v - \theta_{FC}}{\theta_{FC} - \theta_{WP}}\right\} \times 10 \tag{4.10}$$

where, θv is the volumetric soil moisture (% cm3/cm3), θ_{FC} is the field capacity (% cm3/cm3) of the soil, and θ_{WP} is the permanent wilting point (% cm3/cm3). The SWDI is calculated for the root zone on all the dates of soil moisture measurement for each treatment during the growing season. The median volumetric soil moisture of six replicates was used to calculate SWDI. Since the soil texture of this experimental station is fine-loamy, we selected the field capacity value of 27% and the wilting point of 12% as proposed by Ratliff et al. (1983) and Hanson et al. (2000). When SWDI is positive, the soils have excess water; when it equals zero, the soil is at the field capacity (i.e., no water deficit). A negative MRD indicates the drought, and the water deficit is absolute (wilting point) when the SWDI reaches ≤ -10. After this point, the soil water content falls below the lower limit of plant-available water (Savage et al., 1996). Based on calculated SWDI, drought severity can be categorized as "no drought" if SWDI > 0, as "mild" if 0 > SWDI > -2, as "moderate" if -2 > SWDI > -5, as "severe" if -5 > SWDI > -10, and as "extreme" if -10 > SWDI (Martínez-Fernández et al., 2015).

The number of droughts in each severity category was added for each treatment during the study period 1993-2018, and the percentage of drought events was calculated and compared under the categories of climate variability (dry, normal, and wet years). Moreover, SWDI for the entire study period (1993-2018) was organized in descending order for each treatment to perform probability analysis as described by Alizadeh (2013). This would allow analyzing the behavior of drought severity under different treatments in response to climate variability.

4.3 Results and Discussion

4.3.1 Ranking the Resilience of Soil Moisture in Different Treatments

As discussed earlier, we hypothesize that if soil moisture in an agricultural system can remain wetter than the conventional (control) system over the growing season due to treatment, it would beneficially affect the growth and yield of crops in rainfed agriculture. Therefore, treatments were ranked on the ascending order of MRD for the study period (1993-2018) and presented together with ITS for each climate variability category as dry years (Figure 4.3), normal years (Figure S4.1), and wet years (Figure S4.2).

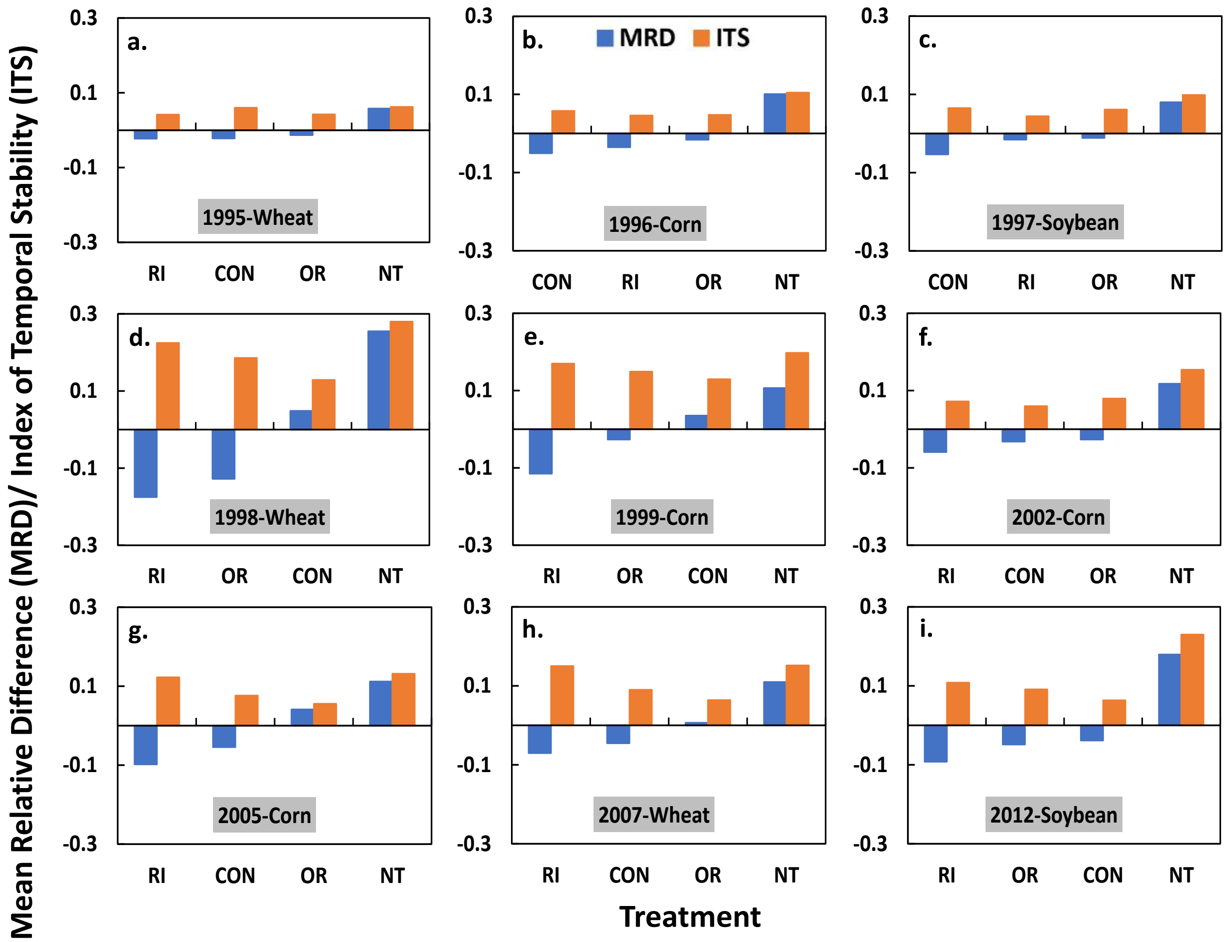

Figure 4.3. Ranked MRD of volumetric soil moisture and ITS for each treatment during the dry years. *Note: Crop grown is given next to the respective year for each plot. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

According to the relative positions of MRD during dry years (Figure 4.3), a no-till treatment maintained higher soil moisture (and higher MRD) than a conventional treatment. Similarly, the organic treatment always performed better than the reduced input treatment, while the conventional treatment performed better than the reduced input treatment in the majority of years. During normal and wet years, no-till and organic treatments were better than the conventional treatment, while reduced input treatment performed equally to the conventional treatment in most of the normal and wet years (Figures S4.1 and S4.2).

Table 4.2 presents the number of occurrences in each rank, based on MRD and the relative positions of MRD (either negative or positive) for different categories of climate variability. The rankings are based on the ascending order of MRD in which a wetter system is represented by the highest-ranking (rank=4). During dry and normal years, the majority of the times, the conventional treatment represents the second rank, the no-till treatment represents the fourth rank, reduced input treatment represents the first rank, and the organic treatment represents the third rank. This indicates that the no-till treatment is the wettest and organic treatment is wetter than the conventional treatment; however, the reduced input treatment is drier than the conventional treatment during dry and normal years. During wet years, the majority of the times conventional treatment represents the lowest rank (i.e., rank 1) thus it was the driest of the treatments, while no-till treatment represents the highest rank (i.e., rank 4) thus wettest of the treatments. Organic and reduced input treatments fall in between; however, the organic treatment is still wetter than the reduced input treatment.

Concerning the relative positions of MRD, the no-till treatment is wetter (100% of years having positive MRD) than all other treatments during dry, normal, and wet years. The organic treatment performs similar to the conventional treatment, while the reduced input treatment is drier than conventional treatment in dry years (100% of years having negative MRD). During normal and wet years, the organic treatment is wetter in ≥50% of years, which is higher than the conventional treatment. Meanwhile, the reduced input treatment performs equally to the conventional treatment during normal and wet years.

Table 4.2. Relative positions and ranking based on MRD, and their respective percentages for each agricultural system under each climate variability category.

Category of climate variability	**Treatment***	**Relative positions of MRD** (Percent of the total years)		**Ranking based on MRD** Number of occurrences in each rank (Years)			
		MRD<0	MRD>0	1	2	3	4
Dry years	CON	77.8	22.2	2	4	3	0
	NT	0	100	0	0	0	9
	RI	100	0	7	2	0	0
	OR	77.8	22.2	0	3	6	0
Normal years	CON	87.5	12.5	2	5	1	0
	NT	0	100	0	0	1	7
	RI	87.5	12.5	6	2	0	0
	OR	50	50	0	1	6	1
Wet years	CON	100	0	5	4	0	0
	NT	0	100	0	0	0	9
	RI	100	0	3	5	1	0
	OR	44.4	55.6	1	0	8	0

**CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

The highest level of soil moisture resilience shown by the no-till treatment irrespective of climate variability. This can be due to improved soil water dynamics. In the no-till treatment, a greater amount of crop residues is retained in the soil compared to the conventional treatment (Palm et al., 2014; Pittelkow et al., 2015b). As a result, organic matter and biotic activity significantly increase in the topsoil, which leads to greater wet aggregate stability and macropore connectivity while reducing soil compaction (Blanco-Canqui and Ruis, 2018; Palm et al., 2014; Perego et al., 2019). Therefore, water infiltration increases, surface runoff, and soil evaporation decreases, which results in an increased amount of plant-available water (Liu et al., 2013; Palm et al., 2014; Thierfelder et al., 2013; Thierfelder and Wall, 2009). The impact of the no-till treatment on higher soil moisture and water use efficiency is also evident under irrigation (Gathala et al., 2013; Grassini et al., 2011). The average measured soil organic carbon in our experiment for the 13-year period (1989-2001) supports these arguments where the no-till treatment had significantly higher soil organic carbon than the conventional treatment (Figure S4.3). Additionally, the organic treatment and the reduced input treatment also had significantly higher soil organic carbon compared to the conventional treatment. However, accumulation of soil organic carbon in tilled reduced input and organic treatments are unlikely and may be a result of leguminous winter cover crop established in these treatments (Robertson et al., 2014). We also found a significant positive correlation between the mean relative difference (MRD) of volumetric soil moisture and the soil organic carbon (Figure S4.4). This highlights the increase in soil moisture retention with increasing soil organic carbon, which was observed in the no-till and the organic treatments. This is one of the main reasons for the increasing yield of crops with increasing soil organic carbon (Oldfield et al., 2019) unless other resources are limited. The next best treatment in terms of soil moisture resilience was the organic treatment. This can be due to increased biological activity such as an abundance of earthworms that could beneficially affect the soil water dynamics; however, activity of earthworms will be limited in other systems as a result of the application of herbicides (Bai et al., 2018). Moreover, leguminous winter cover cropping may also have beneficially affected the soil water dynamics in the organic system (Basche et al., 2016). Even though the reduced input system had a leguminous winter cover crop, it had the lowest soil moisture resilience may be because of the impacts of herbicides on soil structure by reducing soil biological activities (Basche and DeLonge, 2019).

As we look for an agricultural system with higher MRD, most of the time, the system with greater MRD also has higher ITS (Figures 4.3, S4.1, and S4.2). However, under a few instances, lower MRD can obtain a higher ITS. This can be explained by Equation 4.7 in which the ITS is always a positive value regardless of whether MRD is a positive or negative number.

Therefore, ITS is not a suitable metric for gauging the resilience of an agricultural system as related to soil moisture temporal dynamics in a growing season.

4.3.2 Temporal Persistence of Soil Moisture in Different Treatments

Spearman's rank correlation coefficient (r_s) of different treatments for the duration of the study (1993-2018) is shown in Figure 4.4. Accordingly, the no-till treatment showed the highest temporal persistence ($r_s \approx 1$), highlighting its ability to maintain greater resilience of soil moisture among other treatments for the long-term (26-years). The conventional treatment showed the lowest temporal persistence. This is due to its ranking of the MRD, which behaves differently in different years (Figures 4.3, S4.1, and S4.2). Thus, the ability of the conventional treatment to maintain the resilience of soil moisture for an extended period is limited. The temporal persistence of the organic treatment and the reduced input treatment fall in between conventional and no-till treatments; however, the organic treatment performs a little better than the reduced input treatment. Therefore, the ability of the organic treatment to maintain the resilience of soil moisture for a long period is greater than the reduced input treatment. This observation is in support of the long-term effects of the no-till treatment in soil moisture conservation (Bai et al., 2018; Lampurlanés et al., 2016). Moreover, Castellini et al. (2019) detected a significantly higher number of micropores under the long-term no-till treatment compared to the conventional treatment. This can be another reason for the highest temporal persistence of soil moisture in the no-till treatment. Meanwhile, the moderate level of temporal persistence of soil moisture observed for organic and reduced input treatments can be attributed to increased soil moisture conservation with the winter cover crop applied to these treatments (Basche et al., 2016). Cover crops are also beneficial in reducing annual deep drainage and soil evaporation (Yang et al., 2020), thereby increasing soil water availability in the root zone.

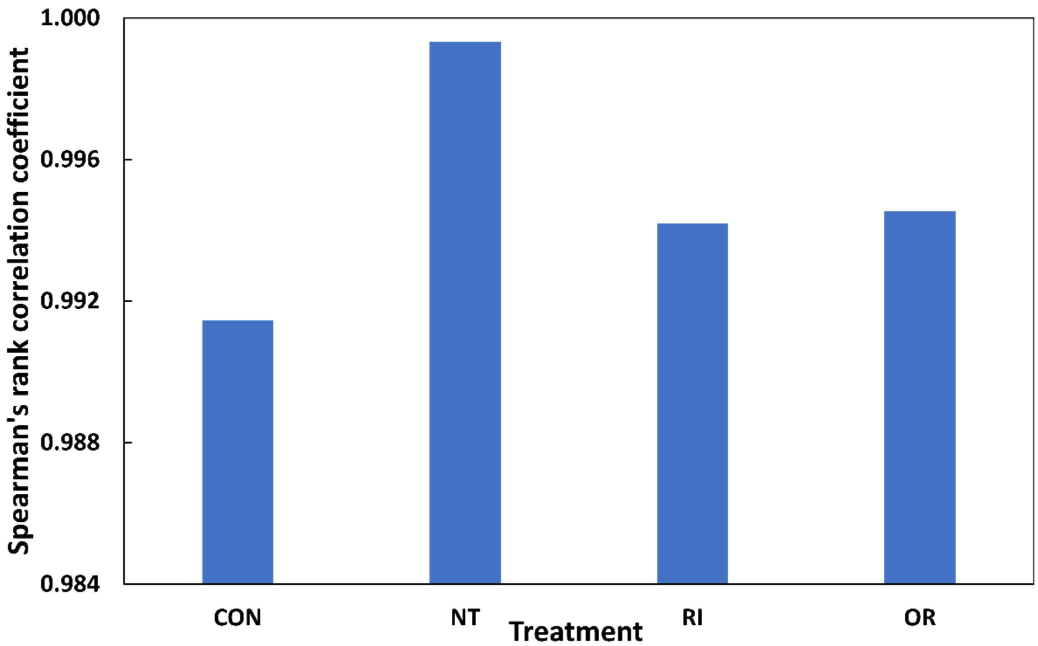

Figure 4.4. Spearman's rank correlation coefficient of different treatments for the duration of the study. *CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

4.3.3 Evaluating the Effects of Treatments and Climate Variability on Mean Relative Difference of Soil Moisture and its Reflections on Growth and Yield of Crops

The mixed model (equation 4.9) explained in Section 2.5 was used to analyze the MRD, total biomass (at peak growth), and yield, considering them as response variables for individual crop types. The probability of the effects on the above response variables on each crop is presented in Table S4.2. Accordingly, the effect of treatments (*trt*) on MRD was strongly significant ($p<0.0001$) for all crops. However, the effect of climate variability (*clim*), year (*yr*), and interaction terms ($trt \times clim$ and $trt \times yr$) were not significant. This means that MRD can be used to differentiate the impacts of different treatments regardless of climate variabilities and the random yearly effects. For total biomass and yield the effect of treatment (*trt*) was strongly significant ($p<0.0001$) in corn and wheat while it was significant ($p<0.05$) in soybean. Therefore, we first compared the treatments against the means of MRD, means of total biomass, and means of yield for each crop type in Table 4.3:

Table 4.3. The means of MRD, total biomass and yield for different treatments and crop types*.

Treatment	Corn			Soybean			Wheat		
	MRD	Total biomass ($Mgha^{-1}$)	Yield ($Mgha^{-1}$)	MRD	Total biomass ($Mgha^{-1}$)	Yield ($Mgha^{-1}$)	MRD	Total biomass (Mgha-1)	Yield (Mgha-1)
CON	-0.0549[c]	14.26[a]	6.78[b]	-0.0551[c]	5.33[a]	2.40[b]	-0.0202[b]	8.07[a]	3.74[a]
NT	0.1121[a]	15.08[a]	7.80[a]	0.1055[a]	5.46[a]	2.83[a]	0.1293[a]	8.45[a]	3.90[a]
RI	-0.0602[c]	14.45[a]	6.81[b]	-0.0492[c]	5.21[ab]	2.62[ab]	-0.0742[b]	6.86[b]	3.38[b]
OR	0.0136[b]	10.14[b]	4.30[c]	0.0072[b]	4.81[b]	2.33[b]	-0.0204[b]	4.59[c]	2.08[c]

** Means with the same letter in each column are not significantly different at p<0.05. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

The comparison of treatments versus means of MRD (Table 4.3) showed that the no-till treatment had significantly higher MRD than the conventional treatment, which was ultimately reflected on the yield where it was significantly greater under the no-till treatment in corn and soybean. However, significantly higher MRD was not reflected in the growth where the biomass under the no-till treatment was not significantly different from the biomass under the conventional treatment. MRD in the reduced input treatment was not significantly different from the conventional treatment, which was reflected in the growth and yield of corn and soybean, where their biomass and yield were not significantly different (Table 4.3). Meanwhile, the MRD in the organic treatment was significantly greater than that in the conventional system for corn and soybean (Table 4.3). This was not reflected in the growth as it was significantly lower in the organic treatment for both crops. Furthermore, the yield of corn was significantly lower in the organic treatment than the conventional treatment. In contrast, the yield of soybean in the organic treatment was not significantly different from the yield in the conventional treatment. In wheat, MRD was significantly higher in the no-till treatment than the conventional treatment; however, growth and yield were not significantly different. Moreover, MRD in the reduced input and organic treatments was not significantly different from the conventional treatment in wheat; however, growth and yield were significantly lower in these two treatments than the conventional treatment.

In addition to significant treatment effects (*trt*), the interaction between treatment and climate variability (*trt* × *clim*) was also significant for the total biomass and yield of crops (Table S4.2). The occurrence of treatment by climate interaction (*trt* × *clim*) highlights that the performances of treatments change in different categories of climate variability; thus, worthy of an investigation. As shown in Figure S4.5, the cereals (corn and wheat) presented the highest growth and largest grain yield in the normal years, while the wet years produce higher growth and yield for soybean. Furthermore, we are particularly interested in the total biomass and yield performances of treatments under dry extreme of the climate variability. Total biomass of corn and soybean were not different among the treatments (Figure S4.5; a and b) during dry years. However, the no-till treatment had equivalent total biomass for wheat to that in the conventional treatment, while wheat growth was smaller in the reduced input and organic treatments (Figure S4.5; c). The no-till treatment produces higher yields than the conventional treatment for soybean and wheat during dry years (Figure S4.5; e and f) while corn yield in the no-till treatment was similar to that in the conventional treatment (Figure S4.5; d). Dry year yields of corn and soybean under the reduced input treatment and the organic treatment were comparable to the yields under the conventional treatment (Figure S4.5; d and e); however, these treatments did not perform well on the yield of wheat compared to the conventional treatment (Figure S4.5; f). Furthermore, the interaction between treatment and year (*trt* × *yr*) was also significant for the total biomass and yield of corn (Table S4.2). The occurrence of treatment by years interaction (*trt* × *yr*) is expected due to the number of years evaluated (26-years). In addition, this can be originated from interannual variations on other above- and below-ground environmental variables (e.g., solar radiation, vapor pressure deficit, and nutrient dynamics) which could also affect the growth and yield but were not included in the model (equation 4.9) used for this study.

In summary, significantly greater soil moisture retention, as quantified by MRD under the no-till treatment, was reflected on the significantly higher yields in corn and soybean than the conventional treatment when averaged across all the years. Moreover, the no-till soybean and wheat produced substantially higher yields than the conventional soybean and wheat during dry years. Similar to our study, significantly higher yields under the no-till treatment were also observed in several previous studies when combined with crop residue retention in long-term crop rotations (Corbeels et al., 2014; Deines et al., 2019; Pittelkow et al., 2015b; Rusinamhodzi et al., 2011). Moreover, Syswerda et al. (2012) found significantly lower nitrate leaching loss under the no-till treatment than the conventional treatment in this same experiment at KBS-LTER. Hence, the no-till treatment has the ability to use a greater amount of nitrogen in the process of yield formation.

Although the organic treatment had significantly greater MRD in corn and soybean than the conventional treatment, it did not produce significantly higher biomass or yield. However, organic soybean yield was equivalent to the conventional treatment even during dry years. Significantly higher MRD for no-till and organic treatments in corn and soybean than the conventional treatment signifies a greater soil moisture retention over the growing season under no-till and organic treatments. As previously discussed, this can be attributed to the improvement in soil physical properties and soil organic carbon with these conservation systems (Hobbs et al., 2008; Valkama et al., 2020; Verhulst et al., 2010; Williams et al., 2017). Additionally, the decrease in evaporation, increase in infiltration, and the ability to store more soil moisture under no-tillage produces greater soil water storage (Blevins et al., 1971; Lal et al., 2012; Lampurlanés et al., 2016). Meanwhile, the major reason behind the significant growth and yield reduction, especially in cereal crops (i.e., corn and wheat) with the organic treatment versus the other treatments, was nitrogen deficiency as organic treatment lacks exogenous nitrogen fertilizer application (Robertson et al., 2014). Growth and yield reduction were evident even if though higher soil water retention was shown to be higher for organic treatment than the conventional and reduced input treatments in our study. Interestingly, the yield of soybean in the organic treatment was comparable to that in the conventional and reduced input treatments even during dry years. This is because soybean has a synergistic relationship with nitrogen fixing bacteria, which reside on its roots and fix atmospheric nitrogen (Hungria and Mendes, 2015).

The equal performance of MRD in the reduced input treatment to the conventional treatment was reflected as the equivalent growth and yield of corn and soybean but not in wheat. In wheat, growth and yield were significantly lower in the reduced input treatment than the conventional treatment. Although reduced input treatment had the potential for soil quality improvement as a result of leguminous winter cover crop, this potential was limited because of herbicide and inorganic fertilizer application that substantially reduces the activities of soil biota (Bai et al., 2018; Tsiafouli et al., 2015). Therefore, the reduced input treatment performs inferior to the organic treatment on MRD in corn and soybean even though its performance is comparable to the conventional treatment. Equal performance of the reduced input treatment to the conventional treatment on crop growth and yield of corn and soybean is due to its equal performance on soil moisture retention, as it was shown in this study. Nonetheless, the growth and yield of wheat in the reduced input treatment were significantly lower than the conventional treatment. This is associated to the lack of nitrogen to wheat as it is planted in the fall immediately following the soybean harvest, which leaves a relatively low amount of nitrogen-rich crop residue for the wheat crop in the reduced input treatment, whereas corn and soybean follow nitrogen-fixing red clover winter cover crop (Robertson et al., 2014) that can supplement a reduced rate of nitrogen fertilizer application. This proves the ability of the winter red clover cover crop (Gentry et al., 2013; Vyn et al., 2000) to supply sufficient nitrogen to the reduced input system.

Interestingly, the coefficient of variation (CV) of total crop biomass and yield for different treatments under two extremes of climate variability (i.e., dry and wet) showed that the no-till treatment had the lowest CV values among other treatments except for wheat during wet years (Table S4.3). The lowest CV value indicates fewer variations, hence greater stability of growth and yield of these crops, which also highlights the resilience of the no-till treatment. This finding was in support of Verhulst et al. (2011), where they have shown that higher soil moisture retention by the zero-tillage practice resulted in a more stable agronomic system than the conventional system, as it utilizes rainfall more efficiently. In contrast, Rusinamhodzi et al. (2011) argued that yield stability was not substantially improved by the no-till system.

4.3.4 Comparing the Effectiveness of Different Treatments on Reducing Agricultural Drought Severity

According to the classification of drought severity (Martínez-Fernández et al., 2015), the drought categories that are crucial for crop production are moderate, severe, and extreme. This is because the loss of soil moisture as a percentage of total plant available water is 20-50%, 50-100%, and 100% for moderate, severe, and extreme droughts, respectively (Martínez-Fernández et al., 2015). These losses of plant available soil moisture are translated to *some* crop damages under moderate drought, *likely* crop damages under severe drought, and *major* crop damages under extreme drought (Svoboda et al., 2002). Mild drought is not associated with significant crop damages; therefore, the effectiveness of different treatments on reducing moderate, severe, and extreme droughts are only assessed here.

In general, the numbers of severe and extreme drought events were decreased in all treatments when climate variability shifted from dry to wet (Figure 4.5). This is because increasing precipitation improves the availability of soil moisture to crops, thus reduces severe and extreme categories of agricultural drought, while increasing the drought events with lower severity (i.e., moderate/mild) or no drought. In terms of having drought-free events/no drought, no-till treatment is superior and organic treatment is better than the conventional treatment, while reduced input treatment is the worst. For example, the no-till treatment and the organic treatment had 467% and 67% higher drought-free events than the conventional treatment, respectively, during dry years, while the reduced input treatment had no drought-free events during dry years. The above observations were also noticed during normal and wet years where the no-till treatment and the organic treatment had substantially higher drought-free events than the conventional treatment, while the reduced input treatment had substantially lower drought-free events than the conventional treatment. Moreover, the effectiveness of the no-till system, especially on reducing moderate, severe, and extreme drought events is much higher than any other treatment irrespective of climate variability. During dry years where the drought can be prominent, the no-till treatment had 4%, 23%, and 57% lower severity than the conventional treatment, respectively, for the moderate, severe, and extreme droughts.

The effectiveness of the organic system on reducing moderate, severe, and extreme drought events is still better than the conventional system. The percentages of moderate and severe drought events in the organic treatment were 20% and 17% lower than the conventional treatment during dry years, respectively. Nonetheless, the effectiveness of the reduced input system is broadly limited. The reduced input treatment had 12% and 50% higher moderate and extreme drought events than the conventional treatment during dry years, respectively. However, it had 10% lower severe drought events than the conventional treatment during the dry years (Figure 4.5).

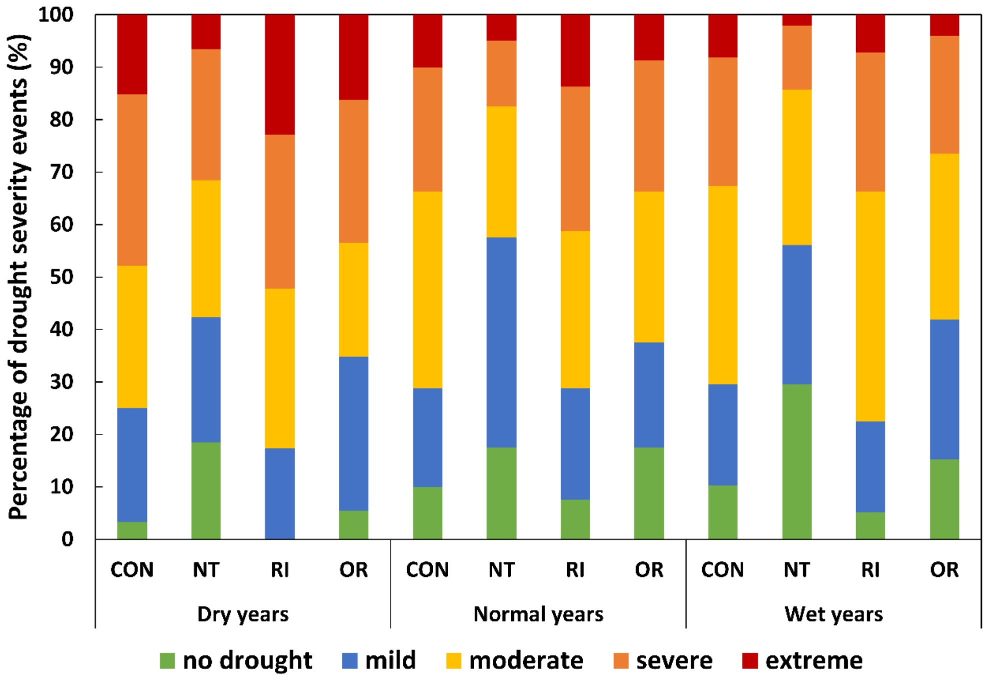

Figure 4.5. Percentage of agricultural drought severity events based on different treatments and climate variabilities during the experimental period (1993-2018). *Note: The numbers of soil moisture measurements (events) available to calculate the percentage of different drought severities in the dry, normal, and wet years were 92, 80, and 98, respectively. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

Probability analysis of SWDI for the entire experimental period showed that no-till treatment has the highest probability (22%) to have drought-free events (Figure 4.6). Meanwhile, the organic, the conventional, and the reduced input treatments are ranked next with a probability of 12.5%, 7.8%, and 4%, respectively. The no-till treatment and the organic treatment had substantially lower probabilities under the impactful drought events (i.e., moderate, severe, and extreme) than the conventional treatment, while these probabilities were larger in the reduced input treatment (Figure 4.6).

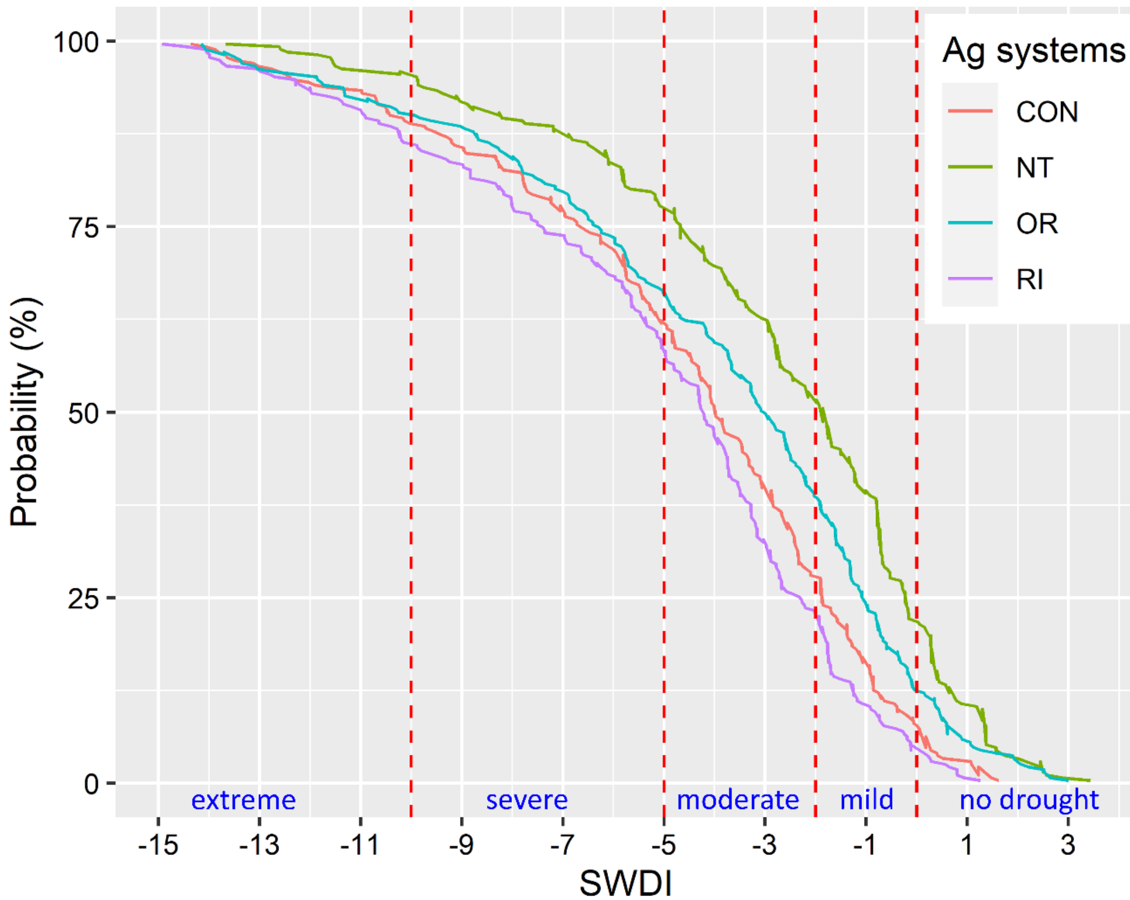

Figure 4.6. Probability distribution of drought experienced by each agricultural system as represented by SWDI during the experimental period (1993-2018). *Note: Red dashed lines represent the boundary of different drought severity levels. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

Both of the above analyses have shown that the effectiveness of the no-till treatment to reduce moderate, severe, and extreme drought events is much greater than all other treatments. In agreement with these findings, Lal et al. (2012) showed that compared to the conventional system, the no-till system had 86 mm more available soil water at planting during drought-hit

(2011-2012) in Akron, Colorado. This is due to greater soil water conservation under the no-till system as resulted by reduced runoff, evaporation rate, and increased capture of snow (Al-Kaisi et al., 2013; Lal et al., 2012). Furthermore, Thierfelder and Wall (2010) found three to five times higher infiltration for no-till plots compared to conventional plots in Africa. They argued that the no-till would increase the soil moisture and enable crops to mitigate the effects of droughts. Therefore, the effectiveness of the no-till treatment to reduce agricultural drought severity is much higher than the conventional treatment.

The organic treatment is inferior to the no-till treatment but superior to the conventional treatment on reducing moderate, severe, and extreme droughts. The primary reason for the higher effectiveness of the organic treatment to reduce agricultural drought compared to the conventional treatment could be due to higher water holding capacity of soils under the organic management (Lotter et al., 2003). In the temperate climate of Switzerland, water holding capacity was reported 20-40% greater in organically managed soils in comparison to those managed conventionally (Mäder et al., 2002). Pimentel et al. (2005) quantified 15-20% higher soil water availability in organic systems than the conventional systems in the long-term Rodale Institute Farming Systems trial in Pennsylvania. This is because of the presence of higher soil organic matter in organically managed soils, and it has been estimated that for every 1% soil organic matter, soil can hold 10,000-11,000 liters of plant-available water per ha of soil down to about 30 cm soil depth (Gomiero et al., 2011). In our organic treatment study, the soil organic matter was 0.3% higher than that in the conventional treatment, when soil organic carbon (Figure S4.3) converted to organic matter. Cover crops are grown under organic treatment also may have contributed to soil moisture conservation (Basche et al., 2016; Yang et al., 2020).

Finally, the effectiveness of the reduced input treatment to mitigate drought occurrences (moderate, severe, and extreme) is limited compared to other treatments (Figures 4.5 and 4.6). This may be due to its poor soil biology resulted from herbicide applications when compared to the organic treatment (Basche and DeLonge, 2019) and tillage operation compared to the no-till treatment. However, it was not clear why the reduced input treatment had lower effectiveness to reduce drought severity than the conventional treatment.

In summary, these findings highlight that the no-till treatment is the best, the organic treatment is better, and the reduced input treatment is worst when compared to the conventional treatment in terms of the effectiveness of lowering agricultural drought.

4.4 Conclusions

Understanding the factors that affect agricultural system resiliency are critical in designing adaptation measures in the face of increasing climate variability and change. Soil moisture primarily controls the productivity of rainfed agricultural systems; soil moisture dynamics can be an indicator of resilience. Building on this, we evaluated the applicability of soil moisture-based metrics to gauge resiliency of three promising rainfed agricultural treatments, namely the no-till, the organic, and the reduced input treatments against the conventional treatment. The results of this study showed that among the metrics of temporal dynamics of soil moisture, MRD, and r_s were suitable to gauge the resiliency of different agricultural systems. In contrast, ITS was not applicable since it cannot capture relative soil moisture dynamics. In addition, SWDI was able to gauge the resiliency of different treatments in terms of the effectiveness of reducing agricultural drought severity.

Based on MRD and r_s, the no-till treatment had the highest resilience to climate variability among the studied treatments due to maintaining the highest level of soil moisture during the growing season. Moreover, the effectiveness of the no-till system on agricultural drought mitigation was superior among the other treatments. This improvement in resilience due to the no-till treatment was reflected not only in the significantly higher yields of crops even during dry years, but also on stable crop growth and yields during years with climate extremes.

Concerning the improvement in resiliency from promising treatments, organic treatment was the second-best treatment after the no-till. Significantly greater MRD in corn and soybean and higher r_s were observed with the organic treatment compared to the conventional treatment. Furthermore, the organic treatment was inferior to the no-till treatment but was superior to the conventional treatment on reducing drought severity. However, this improvement was not evident on significantly higher biomass or yield due to nitrogen limitation to the crops in the organic treatment (Robertson et al., 2014). However, organic soybean yield was equivalent to the conventional treatment even during dry years because of the ability of soybean to fix nitrogen (Hungria and Mendes, 2015).

The greater soil moisture resilience in the no-till and the organic treatments can be attributed to the improvement in soil physical properties and soil organic carbon that improves soil water storage in these management systems (Gomiero et al., 2011; Lal et al., 2012). This was observed in our study as well where we found significant positive correlation between MRD and soil organic carbon.

Equal performance of MRD in the reduced input treatment to the conventional treatment was reflected as the equivalent growth and yield of corn and soybean but not in wheat. The reason for the significant reduction on growth and yield of wheat in the reduced input treatment, compare to the conventional treatment, may be associated to the lack of nitrogen for wheat as it is planted in the fall immediately following the soybean harvest, which leaves the relatively lower amount of nitrogen-rich crop residue for the wheat crop in the reduced input treatment. In contrast, corn and soybean follow nitrogen-fixing red clover winter cover crop (Robertson et al., 2014). Moreover, the effectiveness of the reduced input treatment to mitigate drought occurrences was also limited compared to other treatments.

In summary, this study showed that MRD, r_s, and SWDI are applicable in combination to evaluate resilience in different rainfed agricultural systems as related to the soil moisture content, growth, and yield. The no-till system had the highest resiliency than the conventional treatment in terms of higher soil moisture retention, higher effectiveness for drought mitigation, larger crop yields, and increased stability of yields. The yields in the no-till treatment were 15%, 18% and 4.3% greater than the conventional treatment for corn, soybean and wheat, respectively. Although the organic treatment had substantially higher resiliency in terms of grater soil moisture retention and drought mitigation than the conventional treatment, yields were significantly lower, especially for cereals (i.e., corn and wheat) as a result of nitrogen limitation. Even though the yields of corn and soybean in the reduced input treatment were comparable to those in the conventional treatment, the reduced input treatment had the limited capacity to recover from extreme conditions and improve resiliency in terms of soil moisture retention and drought mitigation. Finally, the proposed approach here can be improved in future studies by increasing the frequency of soil moisture measurements over the growing season at different depths of the root zone. In addition, we are recommending the expansion of the study to larger spatial scales to better capture the robustness of these metrics under a variety of rainfed agriculture systems in the USA Midwestern region and around the world.

4.5 Acknowledgment

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5. EVALUATING THE CLIMATE RESILIENCE IN TERMS OF PROFITABILITY AND FARM RISK MANAGEMENT FOR A LONG-TERM CORN-SOYBEAN-WHEAT ROTATION UNDER DIFFERENT TREATMENT SYSTEMS

5.1 Introduction

Growing anthropogenic activities that generate greenhouse gas emissions have caused global warming and lead to significant changes in the climate system. These changes include increasing ambient temperature, precipitation variability, and the frequency of extreme events such as droughts, floods, and heatwaves (IPCC, 2018). In many regions of the world, climate change and extremes have reduced productivity of major food and feed crops (Adhikari et al., 2015; Challinor et al., 2014; Lesk et al., 2016; Rojas-Downing et al., 2017), leading many commentators to proclaim that climate change, along with the need to feed a human population of about 9.8 billion by the end of 2050, poses a significant threat to regional and global food security (Branca et al., 2013; Pradhan et al., 2015; Rojas-Downing et al., 2017).

US agriculture is not immune to climate change. Despite improved plant genetics and management practices that have brought about long-term improvements in yields, extreme weather events tied to climate change may offset these yield gains (Hatfield et al., 2018; Ortiz-Bobea et al., 2018; Schlenker et al., 2006). Furthermore, climate variability is a major cause for annual variations in crop yields in the Midwestern United States (Hatfield, 2012; Wang et al., 2016) and accounts for more than 60% of the yield variability of major food crops (Ray et al., 2015).

The Midwestern US is one of the most productive and economically important agricultural regions in the world but is increasingly experiencing extreme weather events tied to climate change, including droughts and floods (Andresen et al., 2012; Hatfield et al., 2018). Projecting into the future, an ensemble of eight climate models showed that the frequency of drought in the

US Midwest is to increase from the present rate of once every five years to once every other year by 2050 (Jin et al., 2018). Such projected drought events are expected to drive yield losses of corn, soybean, and wheat – outpacing the rate of productivity gains through improved CO_2 fertilization, cultivars and agronomic practices (Jin et al., 2018; Lobell et al., 2014; Troy et al., 2015; Zipper et al., 2016). Such effects may result in amplified economic swings for consumers and producers. For example, the 2012 North American drought-impacted Southern states the most, where corn prices responded with a 53% increase in 2012-2013 relative to the previous 5-year average price and by 146% compared to the decade of 2000-2009 (Boyer et al., 2013).

The substantial extent of the row crop operations in the Midwest is under rain-fed production. Because precipitation is the primary source of moisture in rain-fed agriculture, the impacts of droughts are much more significant in such systems where farmers have limited options for irrigation (Kuwayama et al., 2019; Sweet et al., 2017). Besides impacting plant available moisture, Midwest growers must contend with the timing of extreme moisture events, as extreme rain events tied to climate change are most apt to occur during planting and harvesting times (Tomasek et al., 2017), – times where timely access to fields is paramount to maintaining productivity and profitability of their farms.

Recent studies of Midwest farmers show that growers recognize the changing climate (Arbuckle et al., 2013; Doll et al., 2017; Mase et al., 2017) and have, therefore, implemented different adaptation measures (Denny et al., 2019; Morton et al., 2015). For example, farmers who better understand the impacts of climate change and are able to attribute it to the anthropogenic activities are increasingly using climate information, conservation practices, crop insurance and other alternative techniques for mitigating risks to climate change (Arbuckle et al., 2013; Haigh et al., 2015; Mase et al., 2017; Morton et al., 2017). However, recognition of the threats due to climate change and the uptake of climate-resilient practices still wanes (Church et al., 2017; Lemos et al., 2014). Therefore, the path to greater food stability and security may be a greater concerted effort to promote climate change-resilient practices.

Climate resilience can be defined as the ability of an agricultural system to keep up with its structures and to ensure provisioning of its functions in the face of climate variability and extremes. For agriculture, this can be done by improving resilience capacities, namely robustness, adaptability, and transformability (Meuwissen et al., 2019; Tendall et al., 2015; Urruty et al., 2016) of agricultural practices. Robustness is the capacity of the agricultural system to withstand climate extremes. Adaptability is the capacity to change the agricultural practices, marketing, and risk management to reduce the impacts of climate extremes without altering the structures and feedback mechanism of the system. Transformability is the capacity to substantially change the structures, feedback mechanisms, and functions in response to climate extremes (Meuwissen et al., 2019). Therefore, the goals of improving climate resilience include not only increasing the productivity of crops in the face of climate extremes but also improving the ecosystem services provided in nature while minimizing the environmental degradation from farm-related activities (Peterson et al., 2018).

Alternative agricultural systems have been endorsed to promote climate resilience compared to the conventional agriculture (Branca et al., 2013; Michler et al., 2019; Scialabba and Müller-Lindenlauf, 2010; Tuomisto et al., 2012). These alternative systems may include no-till/reduced tillage practices, crop rotations, cover crops, reduced applications of inorganic inputs, and certified organic crop production. According to some researchers, such production systems have the potential to mitigate environmental pollution and greenhouse gas emissions, while substantially improving the soil and water quality in the agricultural ecosystems (Behnke et al., 2018; Martens et al., 2015; Syswerda and Robertson, 2014). However, these treatments have not gained sufficient popularity among farmers due to higher risks and profitability concerns (Mausch et al., 2017; Roesch-McNally et al., 2018) and general resistance to changes in farm practices (Fleming and Vanclay, 2010; Takahashi et al., 2016). Some even assert that old practices are strongly reinforced by the markets, legislation, and agribusiness companies that greatly benefit from this intensive system (Roesch-McNally et al., 2018). Hence, conventional agriculture is still widely used regardless of being vulnerable to climate extremes, the cause of environmental pollution, and a source of carbon emissions (Bennett et al., 2014; Foley et al., 2011).

Farm profits are an important source of family and regional incomes. For some, farm income may be the sole source of family earnings. Farm earnings are measured in farm profits or the differences between farm income and farm expenses. Maintaining a consistent and predictable flow of annual earnings is desirable (Martens et al., 2015). Therefore, climate-induced variations in agricultural production should be a motivating factor in growers' willingness to explore and implement climate-resilient practices. However, there are costs and risks to adopting new practices, and growers should target long-term, economic resilience when considering what practices to adopt (Kumar et al., 2016; Mausch et al., 2017; Sain et al., 2017).

Economic resilience can be quantified using both the mean and volatility (Abson et al., 2013; Browne et al., 2013) of the expected net returns or profitability where a system with higher mean and lower volatility can be taken as a relatively resilient system. In general, there are tradeoffs between profitability and farm risk management as different farmers reflect different behaviors towards risk (Brink and McCarl, 1978; Lu et al., 2003). For example, a system may be solidly profitable but risky due to the interannual variations on net returns and/or market demands. Such a venture with high expected returns but a high degree of variation in expected outcomes may not be pursued, depending on risk tolerances (preferences) of the farmer. Profitability also affects the costs and benefits of crop insurance policies, which is considered to be an important tool for climate risk management (Annan and Schlenker, 2015; Tack and Ubilava, 2015). Therefore, both profitability and risks should be evaluated to identify climate-resilient systems that can be successfully transformed into farm-level adaptation.

Data from long-running agricultural experiments are befitting an evaluation of the economic resilience and risks associated with alternative agricultural systems, as they can capture historical climate information and its impacts on farm net returns. The Main Cropping System Experiment (MCSE) of the Kellogg Biological Station's (KBS) Long-Term Ecological Research program provides an effective backdrop to look at the long-term effect of climate on crop resilience under alternative agricultural treatment systems. Three alternative treatment systems (i.e., no-till, reduced input, and organic) for a rotational row crop production system (corn-soybean-wheat) were compared to conventional treatment. In a similar experiment, Swinton et al. (2015) compared the profitability of these treatments for the period of 1993-2007. That study compared the economic values of ecosystem services in the context of climate change. The current study augments Swinton et al. (2015) by broadening the time-scale of analysis and focusing on growers' economic incentives for adopting alternative agricultural practices as it relates to economic returns and risks to those returns.

Accordingly, this study was designed to evaluate the climate resilience of three alternative treatment systems in terms of long-term profitability and risks compared to the conventional system. To accomplish this task, the following objectives and hypotheses were formulated and tested. 1) to evaluate the effects of climate variability on farm net returns under different production and treatment systems – here we hypothesize that climate variability has a significant impact on expected net returns and a treatment system with the higher net return and lower volatility will have greater climate resilience for a production system; 2) to evaluate the risk level for the adaptation of different production systems under different treatments – here we hypothesize that one treatment system dominates the others in terms of both risk and net return and would offer different adaptation alternatives for farmers depending on their risk preferences.

5.2 Materials and Methods

Profitability and associated risks are the outcomes of climate resiliency and determine farm-level adaptation in agricultural systems (Mausch et al., 2017). In this study, we evaluate the climate resilience of three alternative treatment systems implemented in a long-term corn-soybean-wheat rotation in comparison to the conventional treatment. Expected profits and annual variation in expected profits, as a measure of economic risk, are used as evaluation metrics. Annual crop management and production data during the period of 1993-2018 (26 years) were collected, and the net returns for each production and treatment systems were estimated via static enterprise budgeting. First, we quantify the effects of climate variability on the means of net returns using a statistical mixed model and volatility of net returns using relative standard deviation (Objective 1). We judge resiliency based on high expected net revenues and low expected annual variation in net revenues by defining the resilient system as the one which has the highest expected net return and lowest volatility. Finally, we assess the risk level of different production and treatment systems as affected by climate variability using the payoff matrix tool (Objective 2). This will enable us to identify if a climate-resilient system can be welcomed among the farmers with a wide range of risk preferences for adaptation.

5.2.1 Study Location and Details of the Experiment

This study was conducted using long-term data generated at KBS located in Southwest Michigan, United States. This region represents a humid continental climate and the Köppen climate classification subtype of "Dfa" (Peel et al., 2007). Soils at KBS mainly consist of Kalamazoo (fine loamy) and Oshtemo (coarse loamy), both mixed, mesic Typic Hapludalfs that mainly differ in the thickness of the Bt horizon (Syswerda and Robertson, 2014). A series of Long-Term Ecological Research experiments have been established at KBS. One such experiment is the Main Cropping System Experiment (MCSE), which is in the geographic coordinates of 42.41˚ N, 85.37˚ W, and the altitude of 288 m AMSL (Figure 5.1).

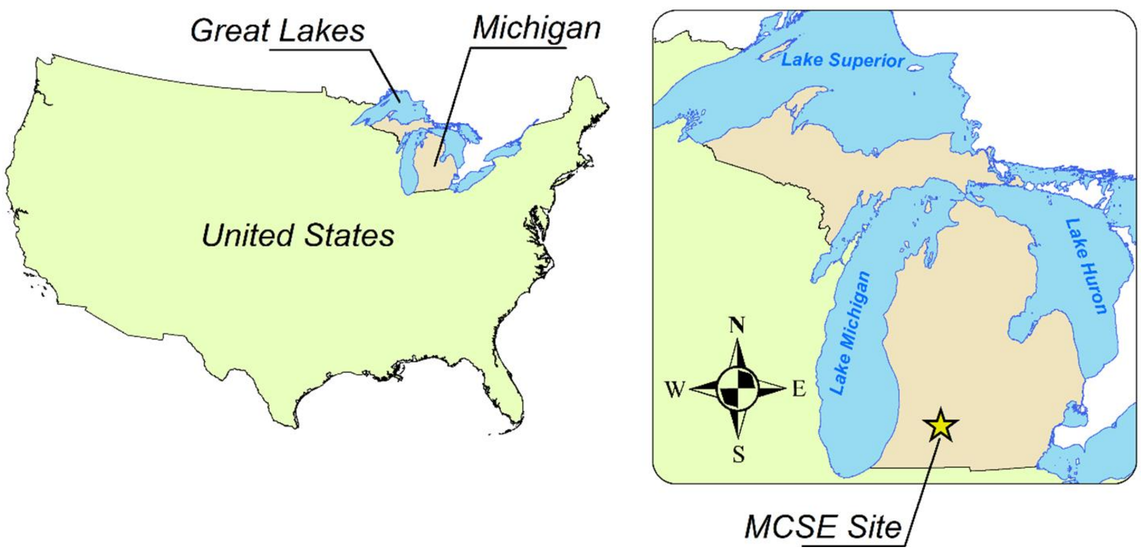

Figure 5.1. The location of the Main Cropping System Experiment (MCSE) in Southwest Michigan, United States.

The MCSE began in 1989 and consisted of seven agricultural treatment systems. First four are annual row crop production systems (corn-soybean-wheat rotation), which are under different intensities of management and the remaining three are the perennial systems namely, poplar (*Populus deltoides* × *Populus nigra*), continuous alfalfa (*Medicago sativa*) and an early successional vegetation community (Robertson and Hamilton, 2015). Although the MCSE started in 1989, an appropriate experimental design was followed only from 1993; therefore, this study involves the first four annual row crop production systems of the MCSE for the period of 1993-2018.

The four annual row crop production systems comprised of corn (*Zea mays*)-soybean (*Glycine max*)-winter wheat (*Triticum aestivum*) in rotation and managed as (i) conventional (CON), (ii) no-till (NT), (iii) reduced input (RI), and (iv) US Department of Agriculture (USDA) certified organic (OR) treatments. Hence, here we consider different crops as production systems while different management as treatment systems. All these production and treatment systems have been managed as rainfed, and each of them is assigned to six replicates (blocks) of one-ha, in a randomized complete block design. Moreover, crops have been planted and harvested at the same time for each treatment and replicate during their usual growing seasons. During the cropping rotations of corn and soybean, CON, NT, RI treatments have been planted with Roundup-ready seeds while the OR treatment has been planted with conventional and untreated seeds. There was no difference between the treatments on seed types during the winter wheat cycle. The timing of management operations of this corn-soybean-wheat rotation under each treatment is presented in supplementary materials (Table S5.1-S5.4). The detail agronomic management of the different treatment systems is as follows:

Conventional treatment: Crops were planted following the primary tillage and soil finishing. Primary tillage was applied using moldboard plough until 1998 and after that using chisel plough. Secondary tillage was applied by disking before planting during the years when wheat crop is planted. Inter-row cultivation was performed for corn and soybean. Fertilizer application rates were based on the soil-test recommendations for each crop. Weeds were controlled by a broadcast application of appropriate herbicides, depending on the weed intensity in each crop. No type of manure or compost or insecticides was applied.

No-till treatment: Crops were planted under zero tillage operations using a no-till drill. Fertilizer application rates were based on the soil-test recommendations for each crop. Weeds were controlled by the broadcast application of appropriate herbicides, depending on the weed intensity in each crop. No type of manure or compost or insecticide was applied.

Reduced input treatment: Crops were planted following the primary tillage and soil finishing. Primary tillage was applied using moldboard plough until 1998 and after that using chisel plough. Secondary tillage was applied by disking before planting during the years when wheat crop is planted. Inter-row cultivation was performed for corn and soybean. Nitrogen fertilizer and herbicide rates were applied as one-third of nitrogen and herbicides applied to the conventional treatment. Herbicides were not broadcasted but banded within rows. Phosphorus and potassium fertilizer application rates were based on the soil-test recommendations for each crop. A winter cover crop was planted following the corn and wheat crops of the rotation to supply nitrogen to the following crop. Commonly, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted following wheat. No type of manure or compost or insecticide was not applied.

Organic treatment: Crops were planted following the primary tillage and soil finishing. Primary tillage was applied using moldboard plough until 1998 and after that using chisel plough. Secondary tillage was applied by disking before planting during the years when wheat crop is planted. Inter-row cultivation was performed for corn and soybean. A winter cover crop was planted following the corn and wheat crops of the rotation to offer nitrogen to the following crop. Commonly, cereal rye (*Secale cereal*) was planted following corn, while red clover

(*Trifolium pratense*) was planted following wheat. No manure-based fertilizers were applied. This is a USDA certified organic treatment; therefore, no chemical fertilizers/herbicides/insecticides were applied.

5.2.2 Enterprise Budget Analysis to Estimate Net Return under Different Production and Treatment Systems

Calculation of cost component: Data on crop management, quantities of inputs, and the rates of application for all four treatments for the period of 1993-2018 were obtained from the agronomic log of the KBS. Variations in operating costs across treatments were estimated using 2018 enterprise budgets from Clemson University Cooperative Extension for corn, soybean, and wheat (Clemson, 2020). Annual operating costs were static using 2018 prices and reflect the primary operating costs for each treatment. While the use of static prices simplifies the analysis, it also holds constant commodity prices – highlighting the role of variations in cropping systems inputs and practices in determining economic outcomes as affected by climate variability. Additionally, though other well-established crop enterprise budgets exist for modeling economic outcomes, we selected Clemson's budgets because they consistently represented the inputs and practices across all crops in this analysis and provided sufficient detail required to model the economics of different treatments modeled here. Budgets with this level of detail were not available for Michigan-specific farm operations.

Clemson University enterprise budgets were modified based on each production and treatment system. To this end, farm machinery operations, and crop scouting were valued using the 2018 custom machine and work rate estimates of Michigan State University Extension (Battel, 2018). Costs captured for some of the farming activities in the previous year for the following crop were included in the budget of the main cropping year in which the harvest occurs. For example, costs of land preparation and planting needed for wheat and for establishing cover crops to benefit corn and soybean during the previous year were considered in the calculation of the main cropping year budget of the respective crops. Michigan crop insurance payments for each commodity were used to account for the annual crop insurance amounts. The fixed cost, which generally involves land rent, farm machinery, farm insurance, and any overhead costs were excluded in the budget analysis due to complexity in making reasonable estimates for this research experiment-based management system. Therefore, the cost component consists only of the variable cost.

Calculation of returns: Crop yield data was collected from the MCSE for the individual replicates of each production system. Crops from the conventional, no-till, and reduced input systems were priced using conventional commodity prices, while organic crops were priced using the organic commodity prices (Table 5.1). Prices for the conventional and organic commodities were obtained from the Agricultural Resource Management Survey (ARMS) of USDA (USDA, 2020). Recent ARMS commodity price data was available for the corn, soybean, and wheat during the years of 2010, 2006, and 2009, respectively. Hence, ARMS price data was used as static commodity price in this study because of its sufficient statistical reliability and the availability of organic commodity prices. Expected annual profits were estimated as the calculated net returns over the 26 years of data. Expected gross revenues were estimated from projected gross revenues, comprised of yield and crop prices (Table 5.1). Expected costs were fixed based on fixed input costs specific to each treatment. The expected net return was then estimated as the average difference between projected gross revenues and costs.

Table 5.1. Conventional and organic commodity prices used to value the crops in different treatment systems*.

Crop	Conventional price (US dollar/bushel)	Organic price (US dollar/bushel)
Corn	4.33	7.13
Soybean	5.52	14.20
Wheat	4.65	8.02

**Note: Conventional and organic prices of corn, soybean, and wheat were obtained from ARMS conducted during the years of 2010, 2006, and 2009, respectively (USDA, 2020).*

5.2.3 Categorization of Climate Variability

The study period (1993-2018) was classified into dry, normal, and wet categories of climate variability based on seasonal precipitation that covers primary growing season (April-October). To do this, thirty years (1989-2018) of total seasonal precipitation data collected from the KBS weather station located within the experimental site. This is because climate variability should be analyzed for a relatively long period comprising at least three consecutive ten-year periods (WMO, 2017). Annual seasons were categorized as follows:

i) dry years when the cumulative probability of aggregate seasonal precipitation is less than 33.3%;

ii) normal years when the cumulative probability of aggregate seasonal precipitation is in between 33.3% and 66.6% and

iii) wet years when the cumulative probability of aggregate seasonal precipitation is greater than 66.6%.

These breakouts are as shown graphically in Figure 5.2. Accordingly, dry years were categorized as the years that the seasonal precipitation ≤ 580 mm, wet years were categorized as the years that the seasonal precipitation ≥ 700 mm and normal years were categorized as the years that seasonal precipitation is in between. Classification of the study period into the categories of climate variability for each crop in the rotation is also shown in Figure 5.2.

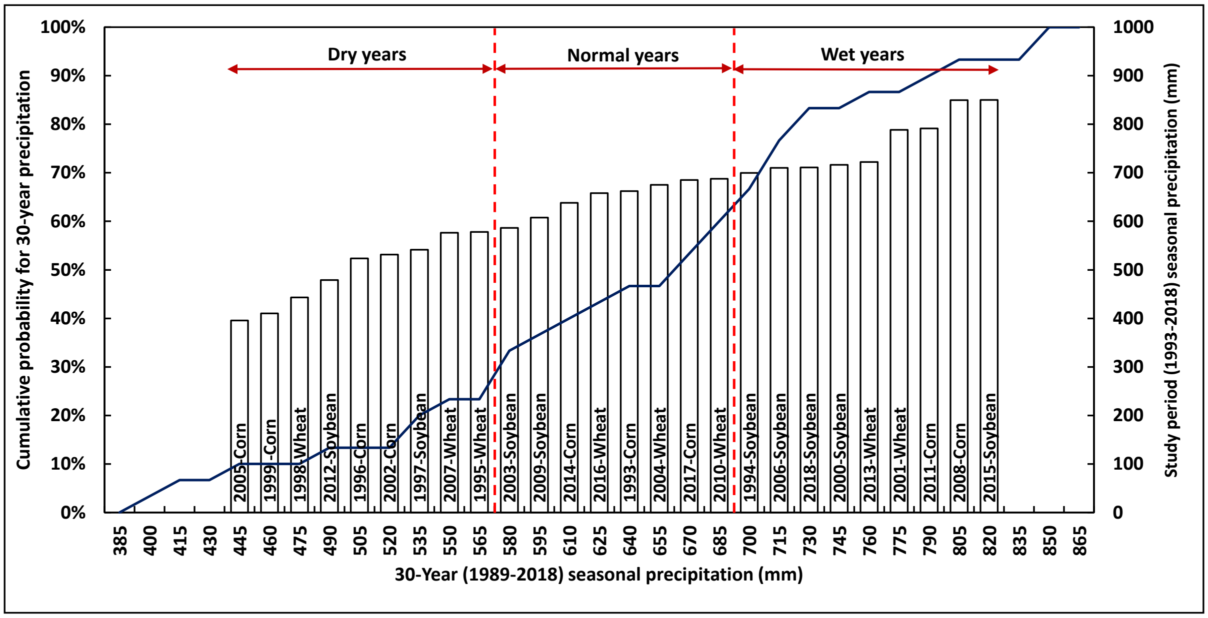

Figure 5.2. The probability distribution of total seasonal precipitation (1989-2018) at the KBS weather station. *Note: The dark solid blue line indicates the cumulative probability, while the bar graph shows the total seasonal precipitation. Years and cultivated crops are given inside the bars following the categorization of climate variability.*

5.2.4 Evaluating the Effects of Different Production and Treatment Systems and Climate Variability on the Expected Net Return

A statistical mixed model, which incorporates both fixed and random effects of relevant independent variables (Milliken and Johnson, 2009), was used to evaluate the effects of the treatment systems and the climate variability on the net return. The statistical model of our estimates (i.e., net return) was specified as:

$$y_{ijk} = \mu + clim + trt_i + yr_k + trt_i \times clim + blk_j(yr_k) + trt_i \times yr_k + e_{ijk}, \quad (5.1)$$

where, y_{ijk} is the vector of expected net returns, or annual profit, calculated for the i^{th} treatment, within j^{th} block on the k^{th} year, μ - is the mean, *trt* - is the fixed effect of treatment, *blk* - is the random effect of the replicates/blocks nested within years (*yr*), *clim* - is the fixed effect of the climate variability (dry, normal and wet), *yr* - is the random effect of the year, *trt* × *clim* - is the interaction term between the effects of treatment and the fixed effect of climate variability, *trt* × *yr* - is the interaction term between the effects of treatment and the random effect of the year, and *e* - is the residual. The estimated net return data passed the normality test for the residuals and temporal homogeneity of variances (Milliken and Johnson, 2001). Statistical analysis was performed by the production system (separately for each crop), using PROC GLIMMIX procedure (Milliken and Johnson, 2009) in the SAS software (Version 9.4 SAS Institute Inc. Cary, North Carolina, US). Fixed effects were tested by F-test (Steel et al., 1980), and random effects were tested by Wald test for covariance (Wald, 1943). Tukey Test for mean separation was performed when significant differences were detected for the fixed effects (Tukey, 1977), and significant differences were evaluated at the 0.05 probability level (Steel et al., 1980).

5.2.5 Defining Climate Resilience

As growers will take into account both the expected returns to a production system and the expected risks, in this section we define climate resilience based on both the means and volatility of the expected net returns.

5.2.5.1 Defining Climate Resilience Based on the Means of Expected Net Returns

Of the four treatments modeled, the conventional tillage is considered as the baseline, or control case, for which alternative treatments are compared. The conventional system was taken as the control because of its widespread practice in present agriculture throughout the world (Kassam et al., 2019) besides being vulnerable to climate change and extremes.

We estimate expected economic returns as a mean of net return for each treatment system. Statistical significance was tested for each climate category-commodity combination (dry, normal and wet – corn, soybean, and wheat), resulting in nine cases for each of the four treatments. A treatment is deemed resilient to a climatic condition if the treatment provides six or more returns that are statistically higher than the conventional system under all climatic conditions. A treatment system was identified as non-resilience if it performs worse than the conventional treatment in four or fewer cases as a measure of the mean of net return. A treatment system with five cases of net returns that significantly higher to the conventional treatment is considered as moderate resilience.

5.2.5.2 Defining Climate Resilience Based on the Volatility of Expected Net Returns

The volatility of expected net return is another indicator of climate resilience where an agricultural system with stable expected revenues can be more resilient while an agricultural system with volatile expected revenues will be less resilient to climate perturbations (Abson et al., 2013; Gil et al., 2017; Urruty et al., 2016). Relative standard deviation (RSD) can be used to quantify the volatility of agricultural outcomes (Rigolot et al., 2017). RSD is the normalized measure of the dispersion of a probability distribution, which is defined as the ratio between the standard deviation and the absolute mean, presented in percentage (Abson et al., 2013). The absolute mean is used in calculating RSD instead of the coefficient of variation to avoid negative measures of variation. In this way, RSD estimates are scale-invariant and comparable across all climate category-commodity combinations. In this study, we calculated the RSD for each treatment under each category of climate variability for all three production systems. Moreover, the distribution of expected profits for each treatment, as affected by climate variability, was also presented. Here, we define the resilient treatment as the one that holds a higher expected return with lower RSD and variability.

5.2.6 Evaluating the Risk Level for the Adaptation of Different Production and Treatment Systems by Producers

Risk is defined as the chance of adverse outcomes associated with an action (Nelson, 1997). While making decisions for the adaptation of different production and treatment systems, producers would prefer to avoid risks. To understand the risks associated with each potential adaptation actions, producers require decision-making tools that permit them to incorporate uncertainty and risk into their adaptation planning. To this end, a payoff matrix can be considered as a suitable decision-making tool to analyze adaptation decisions in terms of alternative actions, possible events, and payoffs (Hoag and Parsons, 2010; Nelson, 1997).

We used the payoff matrix to evaluate the risk level for the adaptation of different production and treatment systems. The producer (decision-maker) can choose among alternative actions with differing predicted reward/risk structures that refer to different treatment systems for each production system. However, the expected outcomes (i.e., net return) from each action may depend on uncertain events, which represents climate variability impacts on grower net returns, for each of the commodity-treatment combinations. This uncertainty information can be incorporated into the payoff matrix as probabilities (Nelson et al., 1978; Senapati, 2020). According to 30-year (1989-2018) seasonal precipitation data from the KBS weather station (section 2.4.1), and the probability of having dry, normal, and wet years for a three-decadal time frame was 0.3, 0.3, and 0.4, respectively.

Producers can make decisions, either by incorporating the probability of uncertain events or not incorporating these events. There are two types of risk preferences among the producers who do not incorporate the probabilities of uncertain events into their decision-making process. i) Risk-averse decision-makers: producers who select the best among the worst outcomes for each adaptation action; ii) Risk-loving decision-makers: producers who select the best among the best outcomes for each adaptation action. Producers who do incorporate the probabilities of uncertain events into their decision-making process can also be classified into two groups. i) Risk-neutral decision-makers: producers who maximize the expected monetary value (EMV), which was calculated based on the probabilities of climate variability; ii) Risk-averse decision-makers: producers who maximize the EMV subject to some minimum level of safety. Here we decided the safety level as a minimum net return of 150 USD for at least 95% of the time. The above decision-rules were based on Nelson et al. (1978) and used to identify the treatment systems which can be selected by the producers with different risk preferences.

5.3 Results and Discussion

5.3.1 Effects of Treatment Systems and Climate Variability on the Net Return of the Different Production Systems

The statistical mixed model (equation 1) was used to analyze the net returns – taking it as a response variable for the individual production system (i.e., crop type). The probability of the fixed and random effects on the net return on each production system is presented in Table 5.2. Accordingly, the effect of treatments (*trt*) on the net return was significant ($p<0.01$) for all crops. The effect of climate variability (*clim*) was strongly significant ($p<0.0001$) in soybean. However, factor variables entered the equation significantly, either directly or through mediated effects, as components of interaction terms. The interaction between treatment and climate variability ($trt \times clim$) was significant ($p<0.01$) for all crops, which indicates that the performances of treatments change in different climate conditions. Therefore, the effects of treatments on each production system were further investigated under the categories of climate variability, and this differential performance was used to evaluate the resilience under section 3.2. Furthermore, the interaction between treatment and year (*trt* × *yr*) was significant (p<0.01) on the net return for corn and soybean. The interaction between treatment and year can be due to the interannual variations of crop yield, types, and rates of the applications of herbicides and fertilizers and that could lead to the interannual variations in the net return.

Table 5.2. Probabilities for the effects evaluated in the statistical mixed model for the net return.

Production system	Effects in the statistical model	Probability (p-value) *
Corn	Treatment (*trt*)	**0.007**
	Climate variability (*clim*)	0.413
	Year (*yr*)	0.051
	Interaction between treatment and climate variability (*trt* × *clim*)	**0.0001**
	Interaction between treatment and year (*trt* × *yr*)	**0.006**
Soybean	Treatment (*trt*)	**<0.0001**
	Climate variability (*clim*)	**<0.0001**
	Year (*yr*)	0.118
	Interaction between treatment and climate variability (*trt* × *clim*)	**0.002**
	Interaction between treatment and year (*trt* × *yr*)	**0.003**
Wheat	Treatment (*trt*)	**0.006**
	Climate variability (*clim*)	0.152
	Year (*yr*)	0.294
	Interaction between treatment and climate variability (*trt* × *clim*)	**0.005**
	Interaction between treatment and year (*trt* × *yr*)	0.278

* *Bold values denote statistical significance at the p<0.05 level.*

5.3.2 Resilience of Production and Treatment Systems as Measured by the Net Return

The means of net returns for different production and treatment systems, as affected by climate variability, are presented in Table 5.3. For a total of nine cases for each treatment, the organic treatment has significantly higher net returns than the conventional system (eight cases). The no-till treatment had seven cases where the net returns were significantly higher than that of the conventional treatment. However, the reduced input treatment had only three cases of significantly higher net returns in comparison to the conventional treatment. Therefore, the findings assert that organic and the no-till treatments are resilient systems, while the reduced input system is not.

Although the no-till treatment performs superior to all other production systems on yield, in the majority of the crop and climate variability combinations (Table S5.5), the organic treatment overrides the economic performance because of the relative revenue-cost differential, driven by higher per-unit selling prices and marginally lower production costs of organics (USDA, 2020). When averaged across crops and the categories of climate variability, the mean net returns for the conventional, no-till, reduced input, and organic treatments were 22 USD ha^{-1}, 187 USD ha^{-1}, 13 USD ha^{-1}, and 454 USD ha^{-1}, respectively. This reinforces the findings of Swinton et al. (2015), who showed that organic treatment dominates on profitability when it has been valued at the organic prices. When the net returns are averaged across treatments and categories of climate variability, the corn production system had the highest net return of 367 USD ha^{-1} followed by wheat (132 USD ha^{-1}) and soybean (2 USD ha^{-1}).

Table 5.3. Means of net return under different production systems as affected by climate variability*.

Production system	Treatment system	Expected Net return (US Dollars per hectare)		
		Dry years	Normal years	Wet years
Corn	CON	(50.30)^{c}	468.40^{b}	463.00^{b}
	NT	**80.10**^{b}	**746.40**^{a}	692.00^{ab}
	RI	**66.30**^{b}	310.70^{c}	478.00^{b}
	OR	**586.60**^{a}	340.60^{bc}	**742.00**^{a}
Soybean	CON	(500.80)^{c}	(318.10)^{c}	(66.30)^{c}
	NT	**(324.60)**^{b}	**(112.60)**^{b}	**74.40**^{b}
	RI	(608.10)^{d}	(405.90)^{d}	(112.70)^{c}
	OR	**99.60**^{a}	**187.40**^{a}	**904.70**^{a}
Wheat	CON	(4.40)^{c}	55.50^{d}	130.10^{b}
	NT	**173.10**^{a}	**193.60**^{b}	58.20^{c}
	RI	**41.20**^{b}	**152.90**^{c}	91.70^{c}
	OR	**158.80**^{a}	**302.30**^{a}	**239.40**^{a}

** Means with the same letter in a single column for each crop are not significantly different at $p<0.05$. Means of net return with negative values are presented in parenthesis. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; and OR: Organic treatment. Means of net return, which are significantly higher in comparison to the conventional treatment, are presented in bold letters.*

The stability of farm profits is directly related to resilience (Cabell and Oelofse, 2012). The volatility, as measured by the RSD was presented against the net return in a scatter plot in Figure 5.3. Accordingly, the organic treatment can be identified as climate-resilient during dry and wet years, while the no-till treatment shows resiliency during the normal years in the corn production system. In the soybean production system, the organic treatment can be found as climate resilience across dry, normal, and wet years. Meanwhile, in the wheat production system, the organic treatment shows climate resiliency during wet and normal years, while the no-till system is climate-resilient during dry years (Figure 5.3).

The pattern of net returns for the study period as affected by climate variability in corn, soybean, and wheat production system is presented as boxplot in Figures 5.4, S5.1, and S5.2, respectively. Overall, variations in net returns are largest in corn while smallest in soybean. This may be due to higher interannual yield variability in corn compared to other crops, as observed by Kravchenko et al. (2005) and Porter et al. (1998). Net returns were positive (gain) for corn and wheat for all scenarios except for the conventional treatment during dry years. In contrast, the net returns were negative (loss) in all scenarios in soybean except for the organic and the no-till treatments during wet years.

Despite lower yields in the organic treatment (Table S5.5), organic offered higher net returns mainly because of premium prices and lower production costs compared to other treatments, as highlighted by Nemes (2009). Our findings also support those of Toliver (2010), who demonstrates no-till treatment is profitable than the conventional system. This is mainly due to the higher yields in the no-till treatment in comparison to the conventional treatment (Table S5.5). No-till also has lower production cost from reduced tillage operations, which for chisel/moldboard plowing, can be cost intensive.

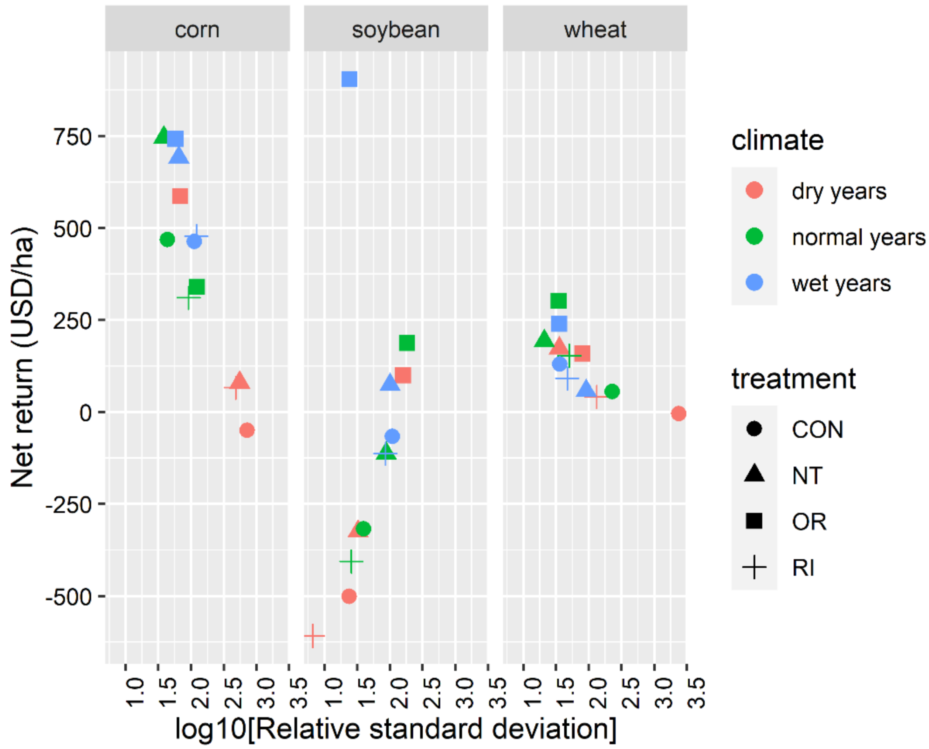

Figure 5.3. Scatter plot between the expected net return and the relative standard deviation for different treatments as affected by climate variability in different production systems.

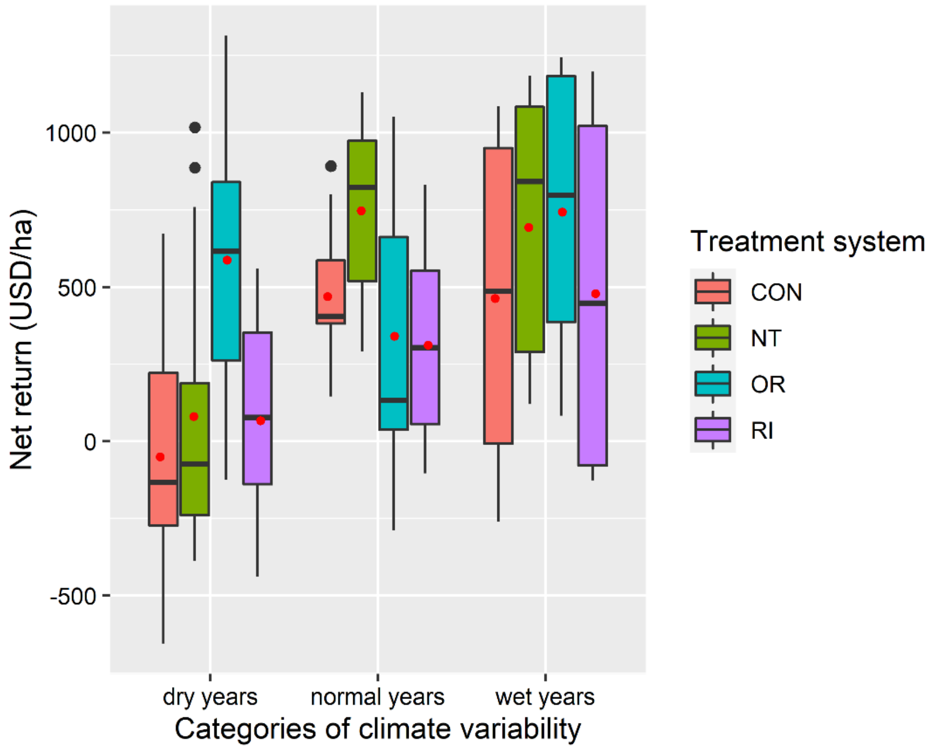

Figure 5.4. Box plot of net return of corn production system under different treatments as affected by climate variability. *Note: The thick black line represents the median of the distribution; the red dot is the mean, the edges of the box are 25% and 75% quantiles, whiskers denote the range of the data, and the black dots are the outliers.*

5.3.3 Producer Risk Levels for the Adaptation of Different Production and Treatments Systems

The payoff matrix for the corn, soybean, and wheat production systems are presented in Tables 5.4. According to the decision, rules explained in section 2.5, a risk-averse farmer who does not consider the uncertainty of climate variability, would prefer to select the organic treatment. In contrast, a risk-loving farmer would prefer to select the no-till treatment to produce corn. However, for a corn producer who considers the uncertainty of climate variability, risk-neutral action would be the selection of the organic treatment, while the risk-averse action could be the selection of either the no-till or the organic treatment (Table 5.4). Regardless of the consideration of the uncertainty in climate variability, the organic treatment is shown to be the selective action for the soybean and wheat producers with risk-averse, risk-loving, and risk-neutral preferences (Table 5.4). No-till and organic treatments generally posit higher returns over most climatic conditions, though organic returns outperform others in adverse climate years, while no-till exhibits the highest returns for normal climate years. However, expected profits is only one consideration when selecting production practices. Risks, which generally relate to the minimum lower bound of outcomes, is also a factor. Those seeking strictly to minimize risk would select the same combination as those solely considering expected profits. That is, no-till provides the best downside, or risk, during normal years, while organic provides the best downside risk during adverse climatic years.

Profitability is often positively related to risk (Tobin, 1958); however, this study shows that the organic treatment achieved higher profits with lower volatility, and showed appropriateness to cater to a range of farmers with different risk preferences. This is followed by the no-till treatment. According to the findings of this study, the conventional and the reduced input treatments are poor substitutes to organic and no-till agriculture in terms of both expected net earnings and annual variations of those net earnings.

Table 5.4. Payoff matrix of production systems under different treatment systems as affected by climate variability.

Production system	Climate variability	Probability	Net Return (USD ha^{-1})			
			CON*	NT	RI	OR
Corn	Dry year	0.3	**(50.30)**	**80.10**	**66.30**	586.60
	Normal year	0.3	*468.40*	*746.40*	310.70	**340.60**
	Wet year	0.4	463.00	692.00	*478.00*	*742.00*
	Expected Monetary Value (EMV)		310.60	524.70	304.30	***575.00***
	*EMV_{CON} = (0.3)(50.3)+(0.3)(468.4)+(0.4)(463)					
Soybean	Dry year	0.3	**(500.80)**	**(324.60)**	**(608.10)**	**99.60**
	Normal year	0.3	(318.10)	(112.60)	(405.90)	187.40
	Wet year	0.4	*(66.30)*	*74.40*	*(112.70)*	*904.70*
	Expected Monetary Value (EMV)		(272.10)	(101.4)	(349.30)	***448.00***
	*EMV_{CON} = (0.3)(-500.8)+(0.3)(-318.1)+(0.4)(-66.3)					
Wheat	Dry year	0.3	**(4.40)**	173.10	**41.20**	**158.80**
	Normal year	0.3	55.50	*193.60*	*152.90*	*302.30*
	Wet year	0.4	*130.10*	**58.20**	91.70	239.40
	Expected Monetary Value (EMV)		67.40	133.30	95.00	***234.10***
	*EMV_{CON} = (0.3)(-4.4)+(0.3)(55.5)+(0.4)(130.1)					

Note: The worst outcome from each production and treatment system is in **bold** format. The best outcome from each production and treatment system is in *italic* format. The maximum EMV for each production system is in ***bold-italic*** format. *shows how EMV is calculated under the conventional treatment, and the equation was used to calculate EMV in other treatments.

The organic treatment commends a higher expected net revenue as a result of the current market value proposition afforded to the organic crops. The organic crop production practices, which consist of the use of non-genetically modified crops and avoidance of any synthetic agrochemicals, have comparably lower costs and higher revenues. Thus, more farmers can enter into the organic agriculture and increase the supply of organic produces. Of course, the law of supply dictates that as entrants increase the supply of organic produce, the price will fall until all excess profits that can be gleaned from organics are exhausted. However, there are barriers to entry that may protect profits to the organic sector. Such barriers include the initial transition period and associated costs of three years to transition to certified organic production, where farmers face declining transitional yields and revenues (Bravo-Monroy et al., 2016; Bowman and Zilberman, 2013). Other barriers include surmounting the learning curve for managing a profitable organic operation. Though not a barrier to entry to organic, farmers are often unwilling to change current practices despite the potential for gains (Fleming and Vanclay, 2010; Takahashi et al., 2016). In addition, as organic operations become more common, abiotic stressors such as pests and diseases will likely increase production costs (Röös et al., 2018), thereby reducing the net earnings advantage afforded by organics. Finally, there is the threat that widespread organic production has on aggregate food supply. If widespread organic production reduces aggregate farm productivity, the conventional market will shrink, giving rise to the price of non-organic foods, and thereby eroding the organic food price advantage. That is, in the long run, many factors will be at play, impacting the future direction of the agri-food economy.

5.4 Conclusions

Identifying alternative agricultural practices to improve climate resilience in current crop production systems is an urgent requirement to face the challenges of increasing climate extremes. Profitability and associated risks are the key determinants of climate resilience as they affect the decision of farmers for transition and adaptation. In this study, we evaluated the climate resilience of three alternative treatments, namely, no-till, reduced input, and organic treatments in comparison to the conventional treatment in the long-term (26-years) corn-soybean-wheat rotational production system in Southwest Michigan, US. Historical seasonal precipitation data was used to categorize the climate variability during the study period, and an appropriate enterprise budget analysis was conducted to derive expected annual net returns using the crop management and production data collected from the experimental station. A statistical mixed model was used to evaluate the effects of different treatments and climate variability on the expected net returns. Mean and volatility of the expected net returns were used to define climate-resilient treatments. Additionally, the payoff matrix approach was used to identify the suitability of alternative treatments for farmers with different risk preferences.

According to the findings of this study, the organic treatment showed the highest resilience, followed by the no-till treatment. The conventional and the reduced input treatments showed lower levels of resilience to climate change. The findings are significant in showing that no-till practices dominate conventional and reduced input practices in both expected annual net revenues with relatively lower risk to those revenues in light of climate change. It also shows that while organic production revenues are largely expected to exceed net revenues of conventional food crops, for many commodities, organic systems may exert greater annual stability in revenues. However, market conditions assert that such an advantage is likely to wane over time as growers migrate to this more profitable option. Related to this is the question of why migration to organic has not occurred faster than experienced. Part of the reason may be the high transition costs going to organic, while another component likely arises from market structures that favor conventional practices and psychological barriers to significant disruptions of existing production practices. Overcoming these constraints will require policy and industry buy-in to alternative agricultural practices, including an expansion of crop insurance offerings, favorable Natural Resources Conservation Service (USDA-NRCS) – Environmental Quality Incentives Programs, and industry support for sustainably-produced food crops.

5.5 Acknowledgment

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6. QUANTIFICATION OF RESILIENCE METRICS AS AFFECTED BY A CONSERVATION AGRICULTURAL PRACTICE AT A WATERSHED SCALE

6.1 Introduction

In similarity to other regions in the world, the Midwestern United States has already been adversely impacted by climate change and variability (Andresen et al., 2012; Fuchs et al., 2015; Hatfield et al., 2018), and the increasing climate extremes, such as droughts, are projected to increase in the future (Jin et al., 2018). These extreme events have lead to substantial crop yield losses (Hatfield et al., 2018; Wang et al., 2016), affecting both producers and consumers. To counteract these drought extremes, groundwater based irrigation systems are widely used in the U.S. (Siebert et al., 2010). However, extraction of groundwater for irrigation above the rate of recharge has significantly reduced groundwater levels, affecting the baseflow to streams, groundwater-fed wetlands, and other groundwater dependent habitats and species (Dalin et al., 2017; Scanlon et al., 2012; Wada et al., 2010). Therefore, there is an increasing consensus among researchers that the resilience and ecosystem services provided by agricultural production systems should be improved.

Ecosystem services denote all the benefits humans obtain from different natural systems for their physical and socio-economic prosperity (Costanza et al., 1997; Mengist et al., 2020). Agricultural practices are responsible for the primary production of food and fiber, while providing numerous ecosystem services at different scales (Dale and Polasky, 2007; Power, 2010; Swinton et al., 2007; Tancoigne et al., 2014; Wood et al., 2015). Comprehensive documentation of ecosystem services has been conducted within the framework of the Millennium Ecosystem Assessment (MEA); accordingly, ecosystem services can be broadly categorized based on provisioning, regulating, supporting, and cultural roles of the ecosystem (Fisher et al., 2009; MEA, 2005).

Supporting services are fundamental in nature; without them, other types of services cannot occur. Nevertheless, the current trend of agricultural intensification deliberately focuses on a few provisioning services (e.g., food, water, energy), through agricultural landscape simplification, rather than harnessing a range of ecosystem services (Bommarco et al., 2013; Gaba et al., 2015; Robertson and Swinton, 2005) which in turn affects the resilience and sustainability of the agricultural systems. This phenomenon is very common in the Midwestern United States (Landis, 2017), which is one of the industrialized large-scale agricultural regions in the world, and contributes significantly to global food security and the economy as it produces the majority of the U.S. row crops and several other food, feed, and fuel crops (Hatfield, 2012; Oppedahl, 2018).

Ecosystem services and resilience are interconnected, where the ecosystems with lower resilience are vulnerable to disturbances (e.g., climate perturbations) and higher resilience ensures a stable supply and/or recovery of ecosystem services (Biggs et al., 2012; Fedele et al., 2017; Montoya and Raffaelli, 2010). In other words, the loss of ecosystem resilience could compromise ecosystem services that are indispensable for sustainable agricultural production systems (DeClerck et al., 2016; El Chami et al., 2020; Swift et al., 2004). Therefore, increased resilience and ecosystem services can be seen as an opportunity for climate change adaptation and disaster risk reduction (Munang et al., 2013).

Improving agroecosystem services and resilience is not only confined to the farm scale, but can be expanded across the landscape (Bailey and Buck, 2016; Scherr et al., 2012). For example, agricultural recharge, which is the water leaving the vadose zone from agricultural farms, may contribute to groundwater-dependent wetlands, streams, and dependent species (Gordon et al., 2010; Sampath et al., 2015) beyond those farms. These groundwater-dependent systems deliver services such as microclimate regulation, water for irrigation, flood mitigation, and control of pests and diseases (Griebler and Avramov, 2015; McLaughlin and Cohen, 2013), which in turn enhance the resilience of agro-ecosystems. Although groundwater recharge is broadly considered as a provisioning service (Prudencio and Null, 2018; Serna-Chavez et al., 2014), it is also indirectly linked to regulatory and support services. Therefore, recharge can be considered as a major water-related ecosystem service and can be used as a metric to evaluate resilience in agro-ecosystems (Coates et al., 2013; Serna-Chavez et al., 2014).

Resilience signifies the ability of an agricultural ecosystem to maintain its structure and function in the face of disturbances (Walker et al., 2004). The initial step of improving resilience is the assessment of resilience at appropriate scales. Resilience metrics are used to quantify resilience and can be used individually or in combination (Douxchamps et al., 2017; Serfilippi and Ramnath, 2018). Commonly used resilience metrics are means and variance of agricultural production/yields (Di Falco and Chavas, 2008; Eeswaran et al., 2021; Martin and Magne, 2015), profit/revenue (Browne et al., 2013; Kandulu et al., 2012; Komarek et al., 2015; Rigolot et al., 2017), soil moisture (Eeswaran et al., 2021), crop failure (Jones and Thornton, 2009), and farming risks (Komarek et al., 2015).

No-till has been endorsed for enhancing ecosystem services such as carbon sequestration, greenhouse gas mitigation, microclimate regulation, control of nutrient leaching, soil erosion control and improving species richness (Lal, 2013; Robertson and Swinton, 2005; Syswerda and Robertson, 2014; Zhang et al., 2016), often at the field scale. Considering all of the aforementioned benefits, there is an increasing trend in the adoption of no-till agriculture around the world (Kassam et al., 2019). However, there is a dearth of knowledge on how no-till affects the overall resilience at a larger scale. To fill this gap, we present an approach that integrates long-term field experimental data and modeling to evaluate an ecosystem service (i.e., groundwater recharge and water table) and resiliency (i.e., soil moisture, drought mitigation, yield, and net return) of convetinal and no-till practices in a large, diverse watershed. The objectives of this study are: 1) assess recharge, groundwater table, and soil moisture variabilities for the long-term corn-soybean-wheat rotation under conventional and no-till practices at a watershed scale; 2) estimate yields and net returns under conventional and no-till practices within a large, diverse watershed; and 3) evaluate the overall changes in resiliency as affected by the adaptation of no-till as conservation agriculture.

6.2 Materials and Methods

The modeling framework of this study is presented in Figure 6.1. Initially, observed data from a long-term (1993-2019) corn-soybean-winter wheat rotation experiment of both conventional tillage and no-till treatments were used to parameterize a crop model (i.e., the Decision Support System for Agrotechnology Transfer-DSSAT) (Jones et al., 2003). Next, the DSSAT model was calibrated using the measured volumetric soil moisture and crop yield from the long-term field experiment. The calibrated DSSAT model was applied to individual fields within a large and diverse watershed. The results from the large-scale crop model were used to calculate the annual recharge and resilience measures for individual fields.

The simulated drainage from the crop model, i.e., the deep percolation from the bottom of the soil profile, was assumed to reach the water table instantaneously and act as recharge from the agricultural land use (Xiang et al., 2020). This assumption can be supported by the existence of permeable soils and strong connection between the surface and groundwater within the study watershed (Grannemann et al., 2008). Groundwater flow in the watershed was modeled using a process-based groundwater model called Interactive Groundwater (IGW) (Li and Liu, 2006; Liao et al., 2015a) and calibrated using static water level data. Finally, changes in the water table as ecosystem service and metrics of resilience were evaluated as affected by the adaptation of a no-till treatment and compared to the base scenario (a conventional tillage treatment).

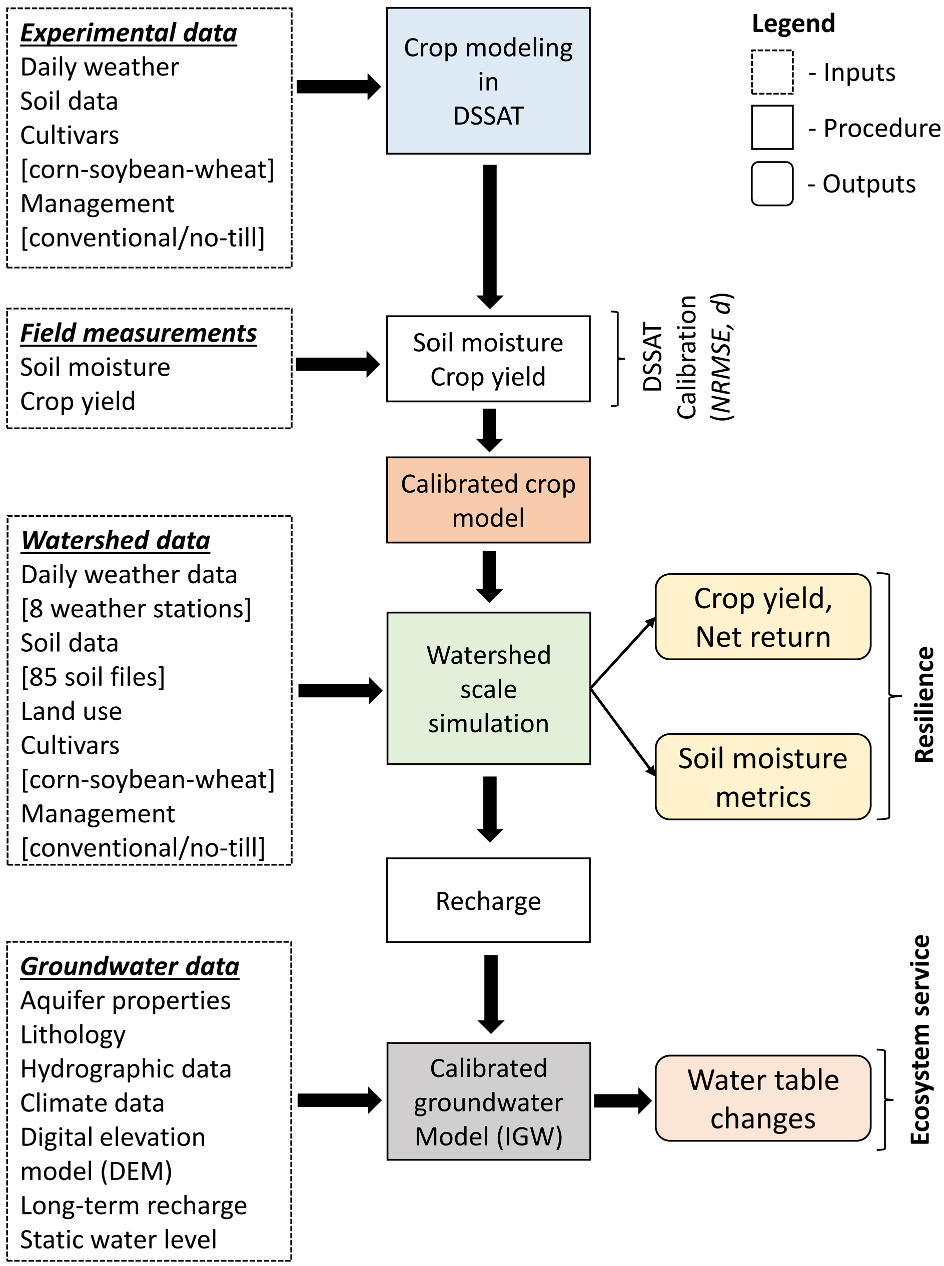

Figure 6.1. An overview of the modeling process.

6.2.1 Study Area

Our research project comprises of both field experiments and modeling efforts. The following sections describe the study area for each of these efforts.

6.2.2 Description of Long-Term Field Experiment

The DSSAT cropping system model (Jones et al., 2003) for the watershed scale evaluation was developed using the long-term experimental data collected from the Main Cropping System Experiment (MCSE) of the Kellogg Biological Station (KBS). KBS is located within the Kalamazoo River watershed in Michigan, U.S. at the coordinates of 42.41˚ N, 85.37˚ W and the altitude of 288m AMSL (Figure 6.2). The annual precipitation at the KBS is about 1,027 mm, while the annual mean temperature is 10.1 ˚C, ranging from the lowest monthly mean of -9.4 ˚C to the highest of 28.9 ˚C in January and July, respectively (Cusser et al., 2020). This experimental site has fine loamy, well-drained, mesic Typic Hapludalf (Kalamazoo loam series) soils formed from the glacial till and outwash (Syswerda and Robertson, 2014).

The MCSE, established in 1989, consists of several experimental treatments of annual and perennial cropping systems. To meet the objectives of this study, only conventional and no-till treatments were considered of a corn (*Zea mays*), soybean (*Glycine max*), and winter wheat (*Triticum aestivum*) annual rotation. Both treatments have been under rainfed management. Further, each of these experimental treatments consisted of six replicants (blocks) in a randomized complete block design, and each block has a dimension of 87 × 105 m. In the conventional treatment, crops were planted following the primary tillage using moldboard plough until 1998 and thereafter using chisel plough. Primary tillage was followed by soil finishing each year. Disking was practiced as secondary tillage before planting a wheat crop in the rotation while inter-row cultivation was performed for corn and soybean. Nitrogen fertilizer was applied as per the soil-test recommendations for each crop. Appropriate herbicides were broadcasted to control weeds depending on the weed intensity. Crops were not applied with any manure or insecticides. The same management was used for the no-till treatment, except crops were planted without tillage using a no-till drill (Robertson and Hamilton, 2015). Even though the MCSE was established in the late 1980s, an appropriate experimental design was adopted from 1993. Therefore, our study was designed for the experimental period of 1993-2019. The crop rotation begins with corn in 1993 and ends with wheat harvest in 2019, covering nine complete rotations (27 years). The following data were used to parameterize the crop model developed for this experiment.

The daily weather data (precipitation, maximum temperature, minimum temperature, and solar radiation) for the experimental period were obtained from the automated weather station located within the MCSE site. The soil analysis data of bulk density, organic carbon, total nitrogen, soil pH, extractable phosphorous, and exchangeable potassium at different depths were collected from previously published data (Crum and Collins, 1995). Crop management data such as cultivar, planting (date of planting, planting method, planting distribution, planting density, row spacing, row direction, and planting depth), nitrogen fertilizer application (date of application, type of nitrogen fertilizer, method of application, depth of application and quantity of application), tillage (date of tillage, tillage implement and tillage depth), and harvesting date were collected from the MCSE agronomic log. The gravimetric soil moisture was measured typically in biweekly intervals at a depth of 0-25 cm from each replicate of the treatment during the study period. Periodically, updated soil bulk density data for the same depth (0-25 cm) was used to transform gravimetric soil moisture into volumetric soil moisture. The detailed procedure for sampling gravimetric soil moisture and the conversion into volumetric soil moisture can be found in Eeswaran et al. (2021). Crop yields were measured at harvest using combine harvesters for the entire block. The seed yield was calculated based on the standard seed moisture level of 15.5% for corn and 12.5% for wheat and soybean.

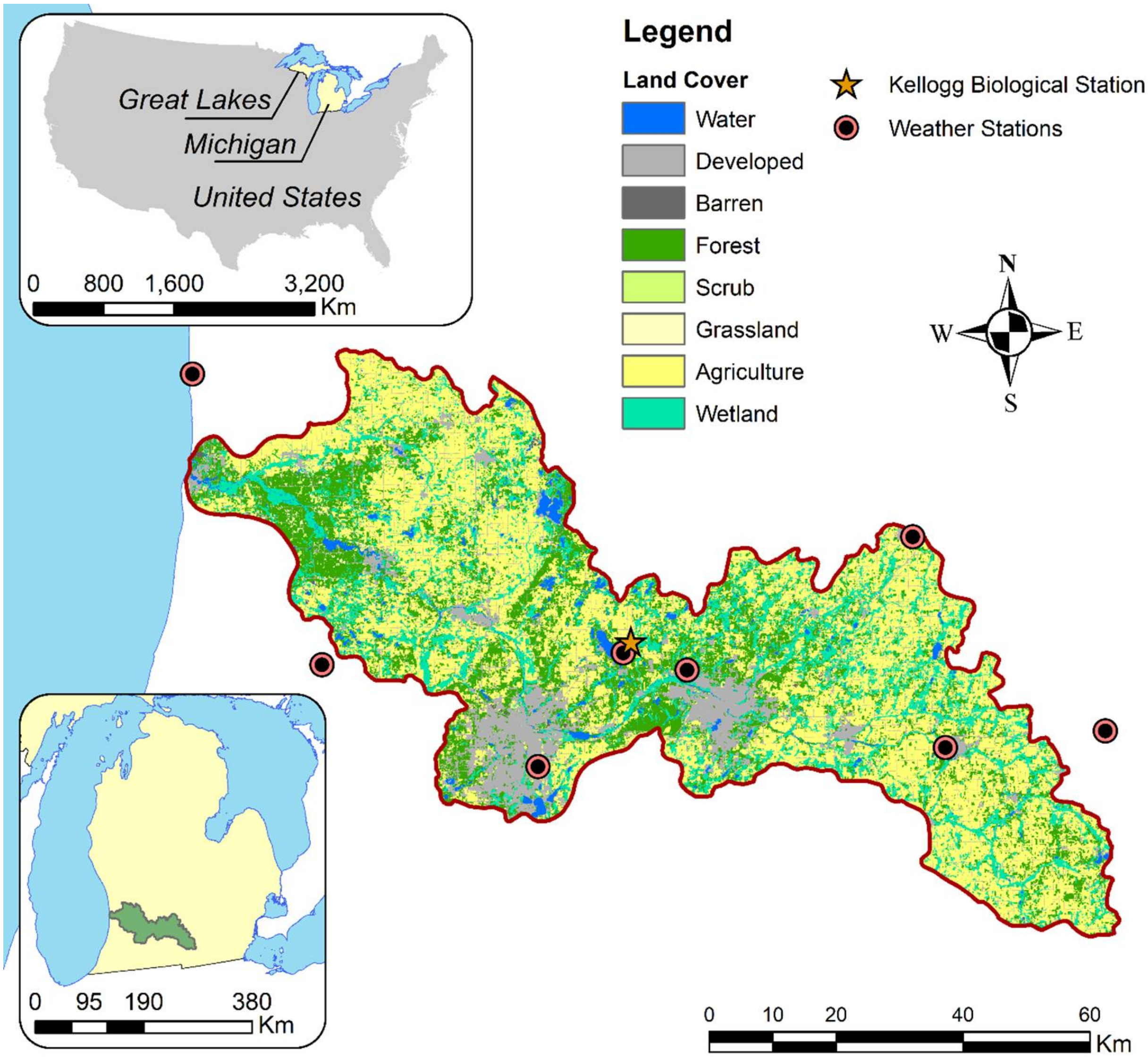

Figure 6.2. Location of the experimental site and the Kalamazoo River Watershed in Michigan, USA.

6.2.3 Description of the Study Watershed

The study was conducted in the Kalamazoo River watershed, which is in the Southwest part of Michigan, USA (Figure 6.2). The watershed drains an extent of 5,232 km^2 from the counties of Allegan, Barry, Calhoun, Eaton, Hillsdale, Jackson, Kalamazoo, Kent, Ottawa, and Van Buren into Lake Michigan near the towns of Saugatuck and Douglas (KRWC, 2011). The hydrogeology of this watershed is determined by thick glacial deposits of sand and gravel that contribute to permeable soils and stable groundwater inflows (Wesley, 2005). Generally, there is a high degree of connection between surface and groundwater in the basin (Grannemann et al., 2008). Soil groups which make up the watershed are 40% of sandy loam, 30% of loamy sand, 25% of clay loam, and 5% of organic soils (Wesley, 2005). The watershed has a gentle to moderate slope, and the drainage class is moderate to well-drained (Schaetzl et al., 2009).

The Kalamazoo River Watershed is historically well known for its richness in biodiversity, ecosystem services, and recreational opportunities as it consists of several lakes, headwater streams, wetlands, and flood plains that are heavily contributed by its groundwater system (Alexander et al., 2014; KRWC, 2011). A stable baseflow to streams and other habitats is essential to attenuate temperature extremes and to sustain aquatic life (KRWC, 2011). In contrast, growing pressures from development, urbanization, and agricultural operations have significantly altered the hydrology and water quality within the watershed (Wesley, 2005). Moreover, groundwater is extracted for industries, public water supply, domestic wells, irrigation, livestock, mining, and other commercial purposes; thus, groundwater withdrawal in this watershed is rated highest in the State of Michigan (Wesley, 2005). The high groundwater withdrawal within the Kalamazoo River Watershed warranted its use for this study.

Agriculture is the primary land use within the watershed (47%) followed by forest cover and successional vegetation (30%), lakes, wetlands, and flood plains (15%), and urban areas (8%) (Figure 6.2; KRWC, 2011). Row crops such as corn, soybean, and wheat dominate agricultural lands while pasture, alfalfa, fruit crops, and livestock are also produced in the region.

The climate varies across the watershed depending on location, distance from Lake Michigan (lake effect), the formation of air masses, and atmospheric disturbances. The mean annual temperature of the basin is about 8.8 ˚C, and the annual precipitation ranges between 810-865 mm, of which about half is snowfall (Wesley, 2005).

Watershed scale crop modeling was performed for the period 1993-2019 and the following data were collected for this task. The daily weather data (precipitation, maximum temperature, and minimum temperature) for the study period were obtained from eight meteorological stations in the Kalamazoo River Watershed (Figure 6.2) using NOAA's National Centers for Environmental Information. To fill in the missing weather data, the Soil Water Assessment Tool (SWAT) weather generator, i.e., WXGEN, was used (Sharpley and Williams, 1990). The soil data for the watershed were downloaded from a global soil profile database for crop modeling applications available at Harvard Dataverse (Han et al., 2015). This soil data is available as compatible to the DSSAT crop model (.SOL format) at 10 km resolution and recommended for large scale crop modeling (Han et al., 2019). A total of 85 grids were found in the Kalamazoo River Watershed. The land use data were collected from National Land Cover Database (NLCD) 2013 (Homer et al., 2020) and the agricultural land use (legend 82: cultivated crops) in the watershed was extracted using ArcGIS 10.6 (Esri, Redlands, California, USA). Finally, the soil grids were assigned to respective weather stations using geoprocessing tools (Thiessen method) in ArcGIS (Thiessen, 1911). Therefore, a total of 85 modeling domains were used for crop modeling in the watershed.

6.2.4 Crop Modeling

Crop modeling for conventional and no-till treatments of the long-term experiment was performed in DSSAT. DSSAT is one of the most highly cited crop modeling platforms in global agricultural research and currently consists of process-based simulation models for more than 42 crops (Hoogenboom et al., 2019; Jones et al., 2003, 2017). DSSAT has been successfully implemented in the evaluation of interactions among genetics, environment, and management at scales ranging from field to landscape (Adnan et al., 2019; Eitzinger et al., 2017). This includes the assessment of genetic improvement (Boote et al., 1996), evaluation of the impacts of climate change (Fodor et al., 2017; Rosenzweig et al., 2014), optimization of management practices such as tillage, water, and nutrients (Iocola et al., 2017; Kropp et al., 2019; Liu et al., 2013; Malik and Dechmi, 2019; Roy et al., 2019), and yield gap analysis (Teixeira et al., 2019). Moreover, DSSAT was applied for yield forecasting, precision farming, decision support, and policy analysis in agriculture (Boote et al., 1996; Shelia et al., 2015; Thorp et al., 2008). Crop modeling can also offer valuable opportunities to evaluate resilience against climate extremes when integrated with long-term research experiments (Rötter et al., 2018).

In this study, the SEQUENCE modeling procedure (Bowen et al., 1998; Liu et al., 2013; Salmerón et al., 2014) in DSSAT-CSM was used to simulate the corn-soybean-winter wheat rotation for the conventional and the no-till treatments. The DSSAT version 4.7.5 (Hoogenboom et al., 2019) was used to simulate corn, soybean, and winter wheat by applying crop models of CERES-maize, CROPGRO-soybean, and CERES-wheat for the respective crops (Jones et al., 2003). Weatherman application within the DSSAT (Pickering et al., 1994) was used to create DSSAT format (.WTH) weather files for the experimental period (1993-2019) using collected daily precipitation, maximum temperature, minimum temperature, and solar radiation from the MCSE site. The soil information (Kalamazoo Loam soil-MSKB 890006) was obtained from the DSSAT soil database and the Web Soil Survey (NRCS, 2020), and the relevant model parameters, such as the saturated hydraulic conductivity (SSKS), were updated accordingly. The soil analysis data collected from Crum and Collins, (1995) were used as the initial soil analysis values.

The best cultivar options suggested by Grace and Robertson for MCSE at KBS were available in DSSAT sequence models (MSKB8902.SQX) and were used to initialize the simulation (Hoogenboom et al., 2019). Accordingly, four crop cultivars (two corn cultivars and one cultivar each for soybean and winter wheat) were used for crop modeling. The identification codes of the corn cultivars used are IB0090 and IB0093, both belong to the ecotype IB0001. The identification code of the soybean cultivar is 990002 (ecotype: SB0201) while the identification code for the wheat cultivar is IB0488 (ecotype: USWH01). Planting information, nitrogen fertilizer applications, and harvesting information were incorporated for both treatments. The period between crops in the rotation was modeled as fallows. Irrigation information was not required as both treatments were managed as rainfed. Tillage operation for the conventional treatment was set as moldboard plow until 1998 and then as chisel plow. For the no-till treatment, tillage was set to be a no-till drill. Treatments were appropriately assigned in separate files (.SQX), and simulation was initiated using the following methods: The Priestly-Taylor/Ritchie method was used to estimate evapotranspiration (Priestley and Taylor, 1972), Suleiman-Ritchie method (Suleiman and Ritchie, 2003) was used to estimate soil evaporation, infiltration rate was estimated using the Soil Conservation Service method (SCS, 1985), Century method (Parton, 1996) was used to simulate soil organic matter, and soil layer distribution was set to the modified soil profile. The soil water balance was simulated in DSSAT as a function of daily precipitation, irrigation (if any), transpiration, soil evaporation, runoff, and drainage on a daily time step (Ritchie, 1998).

Daily volumetric soil moisture was simulated for the depths of 0-5 cm, 5-15 cm, 15-22 cm, and 22-31 cm using the DSSAT model. Then, weighted average soil moistures were calculated for the comparison with the observed soil moisture at 0-25 cm depth. The root growth factor (SRGF), lower limit/wilting point (SLLL), drained upper limit/field capacity (SDUL) were manually adjusted to match the simulated and observed soil moisture to calibrate the DSSAT soil water balance module (Calmon et al., 1999; Fang et al., 2008). The final soil properties generated from soil data calibration is presented in Table S6.1. Performance of the soil moisture and yield calibration was evaluated using coefficient of determination (R^2) (Equation 6.1), normalized root mean square error (*NRMSE*) (Equation 6.2), and index of agreement (*d*) (Equation 6.3). *NRMSE* and *d* are commonly used to statistically evaluate the goodness of fit between observed and simulated soil moisture and yield (Araya et al., 2017; Dokoohaki et al., 2016; Liu et al., 2013; Yang et al., 2014). The model performance according to *NRMSE* goodness of fit can be classified as 0-15% (good), 15-30% (moderate), and >30% (poor). Goodness of fit based on *d* (Willmott, 1982) can be categorized as <0.7 (poor), 0.7-0.8 (moderate), 0.8-0.9 (good), and 0.9-1.0 (excellent) as proposed by Liu et al. (2013).

$$R^2 = \frac{[\sum_{i=1}^{n}(S_i - \bar{S})(O_i - \bar{O})]^2}{\sum_{i=1}^{n}(S_i - \bar{S})^2 \sum_{i=1}^{n}(O_i - \bar{O})^2} \tag{6.1}$$

$$NRMSE = \frac{\sqrt{\sum_{i=1}^{n}(S_i - O_i)^2 / n}}{\bar{O}} \times 100 \tag{6.2}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \tag{6.3}$$

where, S_i is the simulated *i*th value, O_i is the observed *i*th value, $\bar{S}$ is the mean of the simulated values, $\bar{O}$ is the mean of the observed values, and *n* is the number of values.

6.2.5 Groundwater Modeling

Groundwater flow in the shallow unconsolidated glacial deposits was modeled using Interactive Groundwater (IGW), a groundwater modeling software introduced by Li and Liu (2006), which uses the finite difference approximation of the governing partial differential equation (Equation 6.4) to solve confined and unconfined flow conditions:

$$S_s \frac{\partial h}{\partial t} = \nabla(K \cdot \nabla H) + q \tag{6.4}$$

where, S_s is the specific storage coefficient, h is the hydraulic head [L], t is time [T], K is the saturated hydraulic conductivity, ∇ is the mathematical gradient operator, q is the net source (positive) or sink (negative) flux term, including recharge, and surface seepage [LT^{-1}].

IGW is periodically updated (see, e.g., Liao et al., 2015a, 2015b, 2020); for this study, the IGW model was developed, calibrated, and visualized using the new web-based version of IGW called MAGNET – Multi-scale Adaptive Global Network – 4 Water, accessible on the magnet4water website: https://www.magnet4water.com/magnet.

The IGW modeling software is live linked to a database comprising terabytes of raw and derived data useful for the groundwater modeling. A high-resolution (10 m) digital elevation model (DEM) (NED USGS 2006) was used to map topographic variations (i.e., the aquifer top) and to simulate groundwater-surface seeps in the watershed (see more below). The bottom boundary is represented by a spatially variable surface based on the top of the bedrock underneath the unconsolidated sediments. For this project, the bedrock was assumed to be impermeable, however it is known that the lower portion of this watershed has a bedrock that is very transmissive. The reason for assuming an impermeable bedrock is to better compare the impacts of different scenarios of agricultural management on restoring the unconfined aquifer, which is impossible to quantify if the bedrock is transmissive. The bedrock top elevation raster

(500 m resolution) was interpolated from borehole records found in the statewide water well database called Wellogic (MDEQ, 2020). Hydraulic conductivity (K) of the aquifer was represented by a spatially-variable, two-dimensional (2D) raster of horizontal hydraulic conductivity. This was generated by interpolating estimated K values from records in the Wellogic database, public water supply, and U.S. Geological Society aquifer-tests, and aquifer properties reported in the literature (State of Michigan, 2006). Given that the horizontal extent of the model was much larger than the vertical extent, it was hypothesized that flow was predominantly two-dimensional (2D) and that a 2D model could capture the dominant flow processes. The model extent was divided into 418 cells in the x- (west-east) direction and 258 cells in the y- (north-south) direction.

The model was executed for the time period between 1993-2019 using a one-year time step. The initial condition was generated by running the model in steady-state mode to represent long-term mean conditions, since no data was available to prescribe the initial head distribution. Annual recharge distributions from the calibrated DSSAT SEQUENCE model were included in the source/sink term at each time step. In non-cropland areas, the long-term mean recharge applied in the steady-state model was used. Natural, long-term mean recharge to the aquifer was input to the steady-state model and was created following empirical methods presented by Holtschlag (1997) involving observed streamflow hydrographs and information related to land use, soil conditions, and watershed characteristics (State of Michigan, 2006).

For both the ‘initial condition’ steady-state model and the subsequent transient model, groundwater discharge into lakes, streams, and wetlands/springs - the major control of the long-term prevailing groundwater flow patterns – was captured through the critical use of high-resolution Digital Elevation Models (DEMs). Specifically, the entire land surface, modeled using the 10 m DEM from NED USGS (2006), was treated as a one-way head-dependent boundary condition (seepage). This allowed groundwater to discharge to the surface where the groundwater level intercepted the land surface. The flux per unit area leaving the aquifer was the product of the leakance (hydraulic conductivity per unit thickness) of the land surface with the difference between the land surface elevation and the head in the aquifer. Leakance is a calibration parameter that is manually calibrated. For example, if the leakance was too low the flooded area would be too large and vice versa (note: a final calibrated value of 1 day^{-1} was used for transient simulation). Surface seepage maps at different time-steps were compared to the surface water features obtained from NHD USGS (2010) to ensure that this approach effectively captured the spatial patterns of groundwater discharge to the surface water bodies. Groundwater pumping was not represented in the initial condition model nor the transient simulation. A 'no-flow' condition (i.e., zero groundwater flux) was applied along the lateral and bottom boundaries of both steady state and transient models. In short, recharge in the watershed was balanced by surface seepage to surface water bodies in the simulations presented here.

The initial head distribution was obtained from the steady-state solution, and the simulation was advanced in time by solving Eq. (4) with annual time-steps. Annual recharge distributions from the calibrated DSSAT SEQUENCE model for the conventional and no-till treatments were included in the source/sink term at each time step in sperate runs. In non-cropland areas, the long-term mean recharge applied in the steady-state model was used (State of Michigan, 2006). All other aquifer properties / attributes from the steady-state model were applied during the transient simulation. In addition, a specific yield of 0.1 was assigned based on the aforementioned distribution of soil types in the watershed (detailed specific yield data was not available).

6.2.6 Simulation of Crop Yields and Recharge at a Watershed Scale

Calibrated DSSAT SEQUENCE model for the conventional and no-till treatments were used to simulate crop yields and agricultural recharge for the period of 1993-2019. The watershed was clustered according to climate and soil types. It was assumed that the corn-soybean-wheat rotation was planted on all agricultural land within the watershed. The crop model was later run for each unique set of climate and soil type under the conventional and no-till treatment scenarios.

6.2.7 Assessment of Resilience as Affected by the Adoption of No-Till Agriculture

A rising groundwater table from increased recharge is beneficial since many natural habitats, such as wetlands, depend on year-round groundwater availability (McLaughlin and Cohen, 2013; Sampath et al., 2015, 2016). In addition, increases in soil moisture within the root zone can improve the resilience of rainfed agricultural productions (Eeswaran et al., 2021). Yield, net return, and soil moisture metrics, namely mean relative difference (MRD) and soil water deficit index (SWDI), were used as metrics of resilience. MRD and SWDI were shown to be suitable metrics to evaluate resilience in agricultural systems (Eeswaran et al., 2021). MRD was presented by (Vachaud et al., 1985) to evaluate the temporal stability of spatially distributed soil moisture measurements. Additionally, treatment with a higher MRD was considered resilient to climate extremes, such as droughts (Eeswaran et al., 2021). The MRD during a particular growing season was computed as follows:

$$MRD = \frac{1}{N}\sum_{j=1}^{N}\{(\Theta_v - \overline{\Theta})/\overline{\Theta}\} \qquad (6.5)$$

$$\overline{\Theta} = \frac{1}{n}\sum_{i=1}^{n}\Theta_v \qquad (6.6)$$

where, Θ_v is the simulated daily volumetric soil moisture for *i*th treatment on *j*th day. This soil moisture was derived as a weighted average for 0-25 cm depth from the simulation outputs. The number of treatments denoted by n. $\overline{\Theta}$ is the average volumetric soil moisture of all treatments and N is the total number of days in the growing season. In this study, the growing season was considered to start on April 1st and end October 31st, since it covered the critical stages of each crop and the MRD values were calculated in percentages. Probability analysis (Alizadeh, 2013) was conducted for the annual MRD values, and probability curves were compared between treatments to assess the resilience as affected by the adoption of the no-till treatment.

SWDI is an agricultural drought index proposed by Martínez-Fernández et al. (2015) and can be implemented to assess droughts when continuous soil moisture data is available. The SWDI is calculated using the following formula:

$$SWDI = \left(\frac{\Theta_v - \Theta_{fc}}{\Theta_{fc} - \Theta_{wp}}\right) \times 10 \tag{6.7}$$

where, Θ_v is the simulated daily volumetric soil moisture during the growing season as above. Θ_{fc} is the field capacity/drain upper limit, and Θ_{wp} is the wilting point/lower limit. Θ_{fc} and Θ_{wp} values were obtained from each selected soil file (Han et al., 2015) as weighted averages for the 0-25 cm soil depth. A particular soil will have excess water when SWDI is positive, soil will be at the field capacity when SWDI equals zero, and be in a drought phase when SWDI is negative. Moreover, drought severity categories can be classified based on SWDI as "no drought" if SWDI > 0, as "mild" if 0 > SWDI > -2, as "moderate" if -2 > SWDI > -5, as "severe" if -5 > SWDI > -10, and as "extreme" if -10 > SWDI (Martínez-Fernández et al., 2015). Calculated SWDI for the entire growing season (April-October) for each year during the study period (1993-2019) was used to calculate the median, mean, maximum, and minimum across all soils, and these values were later arranged in descending order to perform probability analysis for each treatment (Alizadeh, 2013). Probability curves were compared between treatments to assess the resilience of the no-till agriculture to drought.

The net return was estimated through cost-benefit analysis using the annual crop yields and the price received for crops in November 2018 in Michigan (USDA, 2019). In 2018, the price of corn, soybean, and winter wheat was 131.50, 307.50, and 180.76 US dollars per ton, respectively. The cost was calculated using the variable cost involved in all agricultural operations for both treatments during the year 2018 in the long-term research experiment. This cost was estimated based on a detailed 2018 enterprise budget from Clemson University Cooperative Extension for the respective crops (Clemson, 2020). The pricing of cost and benefit components were considered as static over the years of simulation and the fixed cost was excluded due to lack of information for reliable estimates.

The yield, net return, and annual recharge were statistically analyzed in a mixed model (Equation 6.8) to evaluate the significance of fixed and random effects on these response variables for each evaluated crop (i.e., corn, soybean and wheat).

$$Y_{ijk} = \mu + a_k + t_i + s_j + (ta)_{ik} + (sa)_{jk} + (ts)_{ij} + \varepsilon_{ijk} \tag{6.8}$$

where, Y_{ijk} is the response (grain yield/net return/annual recharge) simulated for the ith treatment, within jth soil type on the kth cropping year; μ is the intercept; a_k is the fixed effect of the cropping year k; t_i is the fixed effect of the treatment i; s_j represents the random effects of the jth soil type, with $s \sim N(0, \sigma_s^2)$; $(ta)_{ik}$ denotes the fixed interaction between the ith treatment and kth cropping year; $(sa)_{jk}$ is the random effect of the interaction between jth soil type and kth cropping year, with $(sa) \sim N(0, \sigma_{sa}^2)$; $(ts)_{ij}$ is the random effect of the interaction between the ith treatment and jth soil type, $(ts) \sim N(0, \sigma_{ts}^2)$; and ε_{ijk} is the error associated with each observation, with $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. To ensure the normality of the residuals and the homogeneity of variances, the grain yield and annual recharge data were log-transformed. Transformations were not needed for net return. There were varying extents of acreage of agricultural land use for each soil in the watershed. Hence, the area of each soil was used as a weighting factor in the model. The comparison between the means was performed using the Tukey-Kramer test, assuming $\alpha = 0.05$ (Herberich et al., 2010). All analyses were performed using the GLIMMIX procedure (Milliken and Johnson, 2009) in the SAS software version 9.4 (SAS Institute Inc. Cary, North Carolina, USA).

6.3 Results and Discussion

6.3.1 Calibration of the Crop Model

The sequential DSSAT crop model was calibrated and validated for yield and soil moisture during the period of 1993-2019, which included nine complete rotations of corn-soybean-wheat crops. The performance of the model to simulate crop yields under both treatments was measured by the goodness of fit indicators shown in Table 6.1. According to the R^2 and *d-index*, the model performance was considered excellent, whereas the *NRMSE* indicated moderate performance (Liu et al., 2013; Willmott, 1982). However, relatively large *NRMSE* values are expected when modeling long-term crop performance for multiple growing seasons as a result of interannual variations. It is also important to note that the performance of the no-till model was slightly better than the conventional model. A similar performance was observed for the simulation of soil moisture. However, performance indicators show that the crop model was reasonably calibrated for the corn-soybean-wheat rotation (Table 6.1).

Table 6.1. The goodness of fit parameters of the calibrated crop model to simulate yield and soil moisture under the conventional and no-till treatments.

Treatment	Crop yield			Soil moisture		
	R^2	*NRMSE (%)*	*d-index*	R^2	*NRMSE (%)*	*d-index*
Conventional	0.73	27.6	0.92	0.74	29.0	0.8
No-till	0.75	26.6	0.93	0.74	19.3	0.9

6.3.2 Calibration of the Groundwater Model

The steady-state simulation results are shown in Figure S6.1. The comparison between the simulated results (heads) of the steady-state model and Static Water Level (SWL) measurements from water well records in the Wellogic database can be seen in Figure 6.3. SWL observations from 23,757 glacial wells were used to calibrate the model. The solid 45-degree line represents “perfect agreement” between simulated and actual observations while the dashed lines represent confidence intervals of one standard deviation (Figure 6.3). Calibration results show that the model performance was good, as indicated by a strong Nash-Sutcliffe model efficiency coefficient (NSE) of 0.90. Even though there was slightly large spread of the data points, all data was centered around the line of perfect agreement. The center-focused distribution demonstrates that the model was able to capture the dominant spatial structure of the groundwater system (i.e., the distribution of groundwater recharge and discharge areas). Slightly large spread in the data, as indicated by the root-mean-square error of 7.91 m, primarily reflects the significant noise embedded in the SWL observations (Curtis et al., 2018).

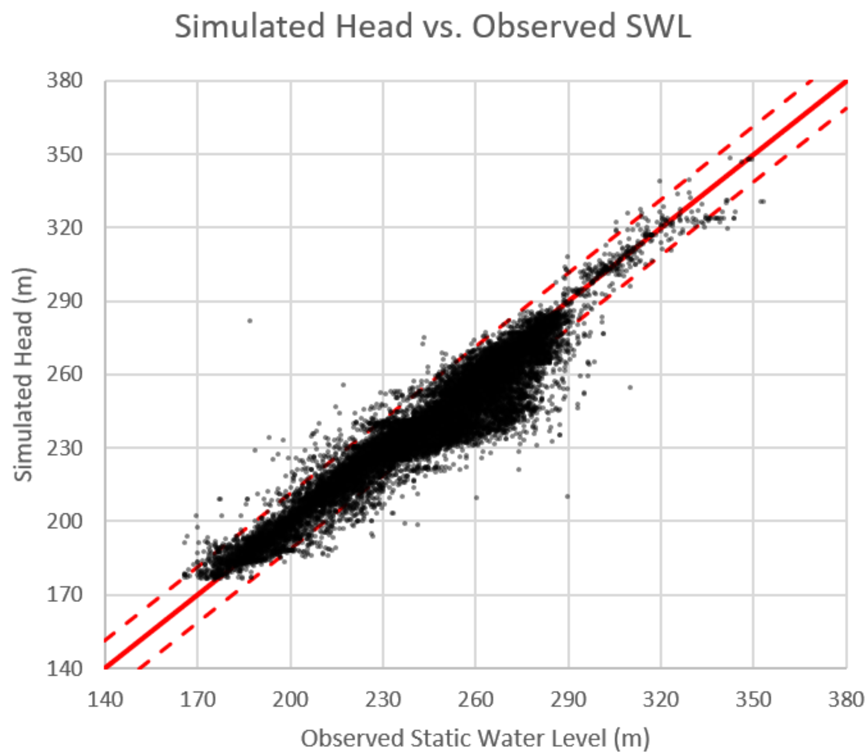

Figure 6.3. Comparison between simulated groundwater heads and observed groundwater heads. *The solid red line in the calibration indicates a 1:1 perfect agreement. The dashed lines represent a confidence interval of one standard deviation.*

6.3.3 Resilience as Affected by the Adoption of No-Till Agriculture

In this study, we quantified resilience in terms of recharge, groundwater table, soil moisture metrics, crop yield, and net return for both the conventional and the no-till treatments. Treatments with higher recharge, groundwater table, soil moisture retention, ability to mitigate drought, larger crop yields, and higher net revenues were considered as resilient over the long-term (1993-2019) evaluation.

6.3.3.1 Recharge and Groundwater Table as Affected by the Adoption of No-Till Agriculture

The statistical analysis for the annual recharge showed that the effects of treatment, year, and the interaction between treatment and year were strongly significant (see the supplementary material Table S6.2). The means of the annual recharge across different soils and years from each crop can be seen in Figure 6.4. Results showed that the no-till treatment significantly increased the annual recharge from all crops in comparison to the conventional treatment. The annual recharge from the no-till treatment for corn, soybean, and wheat were 12.4%, 6.2%, and 13.2% greater than the annual recharge from the conventional treatment, respectively. The soybean had the highest recharge followed by wheat and corn. Because the interaction effect between treatment and year was also significant for the annual recharge (Table S6.2), the comparisons between treatments for each crop during the period of study is presented in Figure S6.2. In most years, the no-till treatment had significantly higher recharge than the conventional treatment. The changes in recharge across the years can be attributed to the changes in precipitation and crop growth, which affect other water balance components (Figure S6.2).

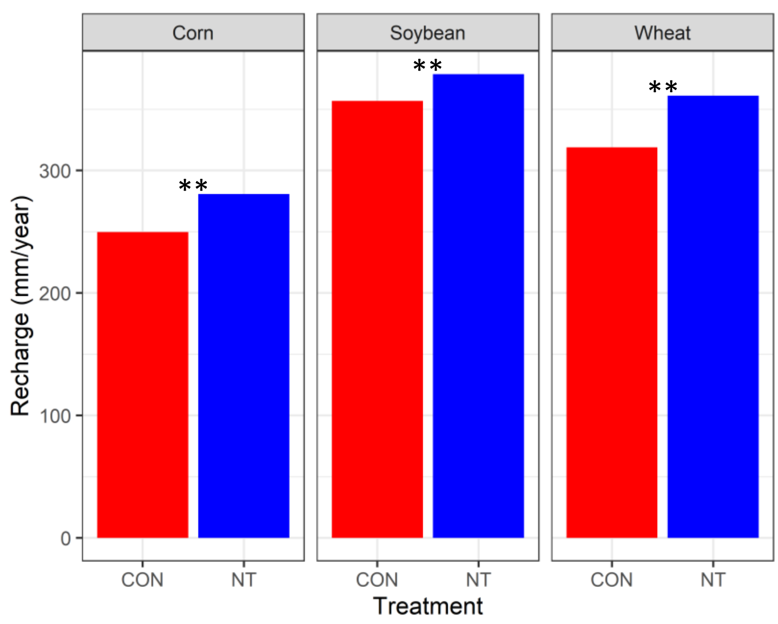

Figure 6.4. The mean annual recharge from different crops under two treatments in the Kalamazoo River watershed. *** indicates strongly significant means at p<0.0001.*

The results from the transient simulation for the conventional and no-till treatments are presented in Figures 6.5 and 6.6. Figure 6.5 shows the 2019 head distribution under the conventional treatment, and the location of the six monitoring wells where transient head results were reported. It is important to note that the changes in the water table at the watershed scale over time were difficult to distinguish, therefore no comparison of plan-view model results under each agricultural scenario was presented. Therefore, temporal changes of groundwater levels were presented at each monitoring wells (Figure 6.6). The time-series comparisons show that the no-till treatment resulted in higher water tables compared to the conventional treatment. The differences were typically small, with about 0.3-0.5 m at Monitoring Well 1, 0.1-0.3 m at Monitoring Well 4, and 0.1 m or less at the other locations. However, even a relatively small improvement in the groundwater table can have beneficial effects on streams and aquatic ecosystems in the Kalamazoo River Watershed, due to the large contribution of groundwater to streamflow in this region (Cooper and Merritt, 2012; Sampath et al., 2016).

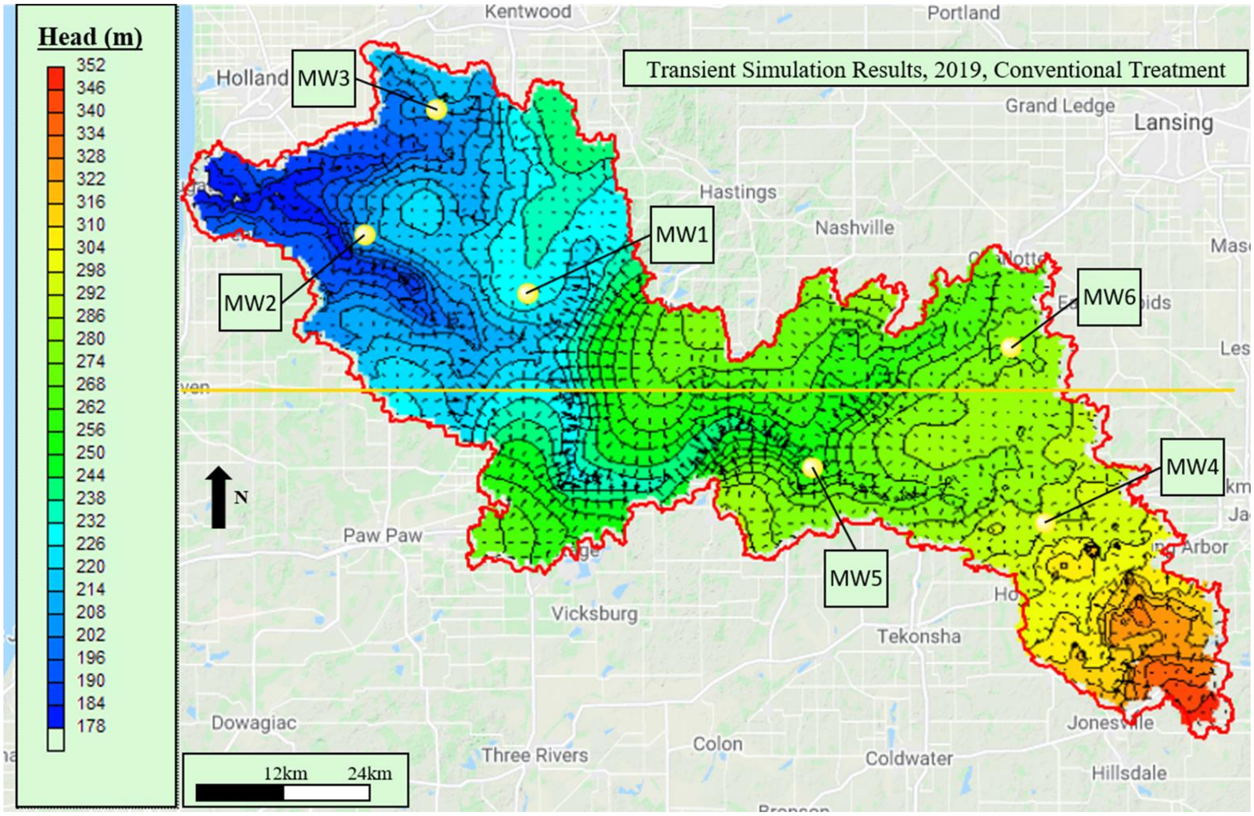

Figure 6.5. Monitoring well (MW) locations superimposed over the 2019 head distribution under conventional treatment.

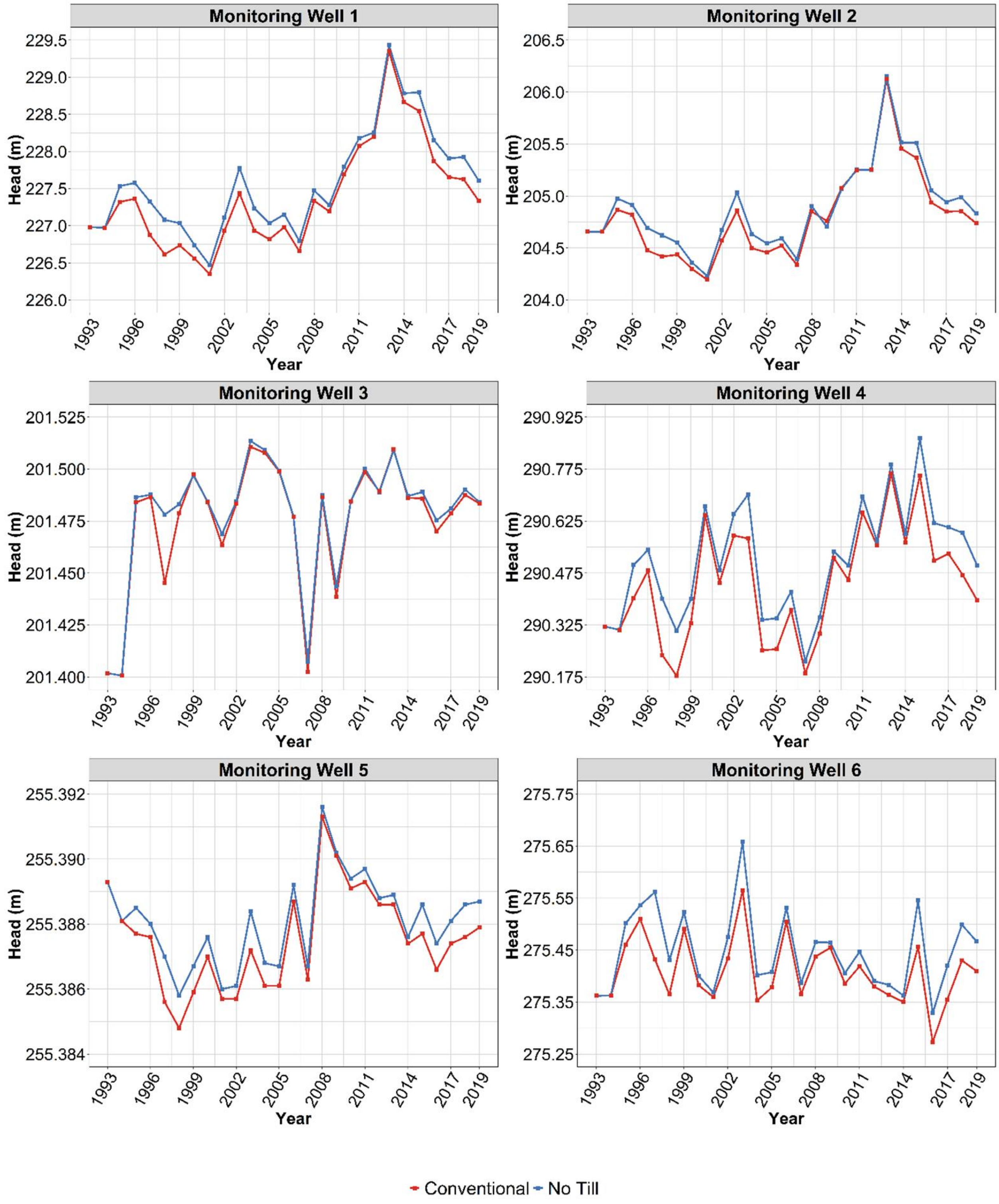

Figure 6.6. Simulated water table heads under the conventional and no-till treatments for the six monitoring wells.

As observed in our study, higher recharge in the no-till treatment simultaneously increased the groundwater table; however, the magnitude of change was dependent upon the characteristics of the underlying groundwater system (Figure 6.6). The higher recharge observed under the no-till treatment in this study may have been caused by the greater infiltration of rainwater (Nunes et al., 2018). According to Kravchenko et al. (2011), the no-till system establishes large pores associated with the undisturbed root channels created by the previous crops. The macropores in a no-till system may contribute to greater infiltration and thus recharge. In agreement with the findings reported here, Syswerda and Robertson (2014) also found higher downward drainage under the no-till treatment compared to the conventional treatment.

In many regions of the world, groundwater is being tapped at rates greater than the local recharge, leading to the depletion of aquifers (Dalin et al., 2017; Reitz et al., 2017). Furthermore, increasing climate variability has already posed additional challenges to water resources and accelerated stresses to the water-energy-food nexus (Smidt et al., 2016). Therefore, an improved recharge and water table under the no-till practice can increase the resilience of the food systems, while also supporting the sustainability of groundwater-dependent ecosystems.

6.3.3.2 Soil Moisture Metrics as Affected by the Adoption of No-Till Agriculture

The probability distribution of the of mean, maximum, and minimum of MRD for both treatments across 85 soils over the period of the study is presented in Figure 6.7. MRD measures soil moisture deviations from the average soil moisture of agricultural treatments, and a positive MRD signifies a *wetter* treatment while a negative MRD signified a *drier* treatment (Eeswaran et al., 2021). The mean of the MRD clearly shows that the conventional treatment mostly (>93% probability) generated a negative MRD while the no-till treatment generated a positive MRD. Therefore, the no-till treatment consistently retained higher soil moisture than the conventional treatment. Based on the maximum line for the conventional treatment (Figure 6.7a), it also had a small probability (<14%) to be *wetter* than the no-till treatment. Similarly, the minimum line of the no-till treatment (Figure 6.7b) shows that it also had the chance to be *drier* than the conventional treatment by the same magnitude of probability as above.

The probability distribution of SWDI across all soils over the study period is shown in Figure 6.8. As shown in Figure 6.8, the probability of having different drought severity levels can be analyzed based on respective SWDI values (Martínez-Fernández et al., 2015). Based on the mean SWDI, the no-till treatment had a 43% probability of having no drought events, which was substantially higher than the conventional treatment (38%). Moreover, the no-till treatment had a lower probability of having mild, moderate, severe, and extreme droughts in comparison to the conventional treatment. According to the maximum SWDI, the no-till treatment had 78% probability to have drought free days while the probability for the conventional treatment was 75%. The minimum SWDI also showed that the no-till treatment (13%) had higher drought free days than the conventional treatment (10%). Thus, the no-till treatment was superior in mitigating drought compared to the conventional treatment in this watershed.

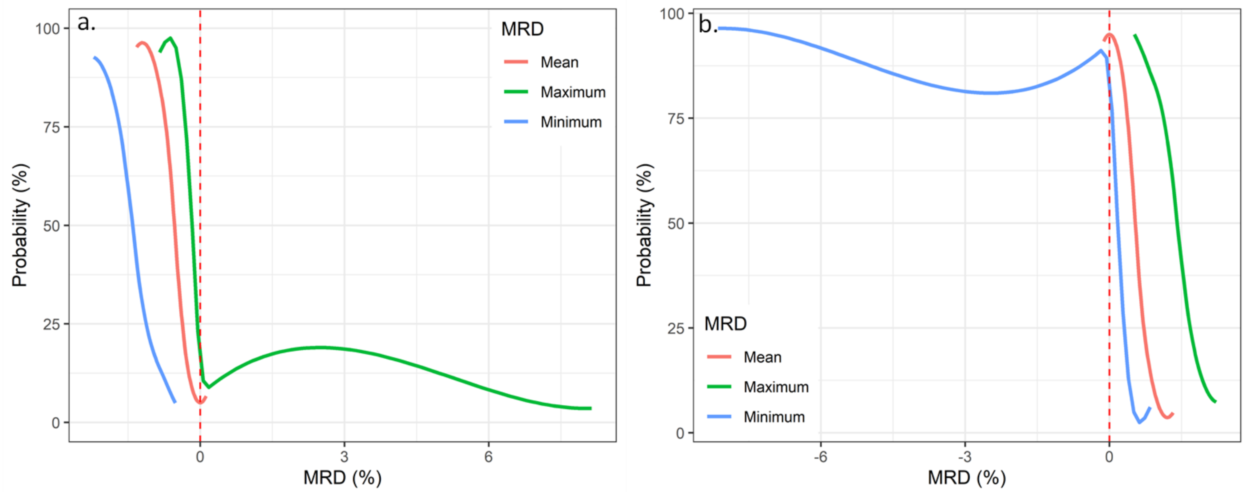

Figure 6.7. The probability distribution for the mean, maximum, and minimum of MRD across different soils in the Kalamazoo River watershed for the period of 1993-2019 as affected by the conventional (a) and the no-till (b) treatments.*Note: Red dashed line at zero MRD indicates the demarcation, where the positive MRD values signify wetter treatment while the negative MRD values signify drier treatment.*

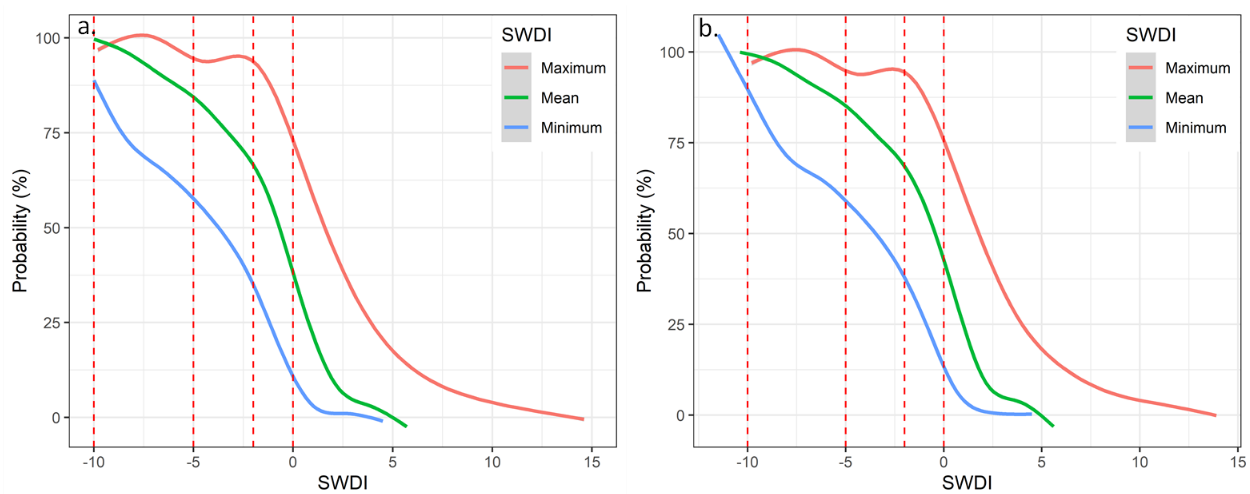

Figure 6.8. The probability distribution for the mean, maximum, and minimum of SWDI across different soils in the Kalamazoo River watershed for the period of 1993-2019 as affected by the conventional (a) and the no-till (b) treatments. *Note: Red dashed lines are to demarcate different drought severity levels.*

Consistently higher soil moisture retention by the no-till treatment was due to the beneficial improvement of soil physical properties, such as water holding capacity (Moebius-Clune et al., 2008). Furthermore, the no-till treatment has been found to increase rainwater infiltration, decrease runoff, and to reduce soil evaporation thereby increasing the proportion of available water in the root zone (Lal et al., 2012; Lampurlanés et al., 2016; Verhulst et al., 2011). The ability of the no-till treatment to store more soil moisture could help to mitigate the impacts of droughts on the crops, as evident in this study. This agreed with the findings of Thierfelder and Wall (2010) where the no-till system performed better for soil water dynamics in a drought-prone region of Africa. Based on the above findings, the no-till treatment was more resilient than the conventional treatment and adaptation of the no-till management in the Kalamazoo River Watershed would enhance its resilience to extreme drought events, which are detrimental to rainfed systems.

6.3.3.3 Crop Yield and Net Return as Affected by the Adoption of the No-Till Agriculture

The probabilities for the statistical significance of the effects evaluated for crop yield and net return is presented in Table S6.2. To perform this statistical analysis, the extent of each soil in the agricultural land use was used as a weighting factor, since it is critical to consider production area when comparing management effects at larger scales (Leng et al., 2019). As a result, we evaluated the effects of treatments in the watershed over the entire study period with high confidence. The statistical analysis showed that the effect of treatments was strongly significant on the yield of corn and soybean, but not in wheat. Nonetheless, treatment effect was strongly significant for the net return from all crops. Furthermore, the effect of year and interaction between the treatment and year were significant for both yield and net return of all crops (Table S6.2).

The means of crop yield and net return as separated by treatments across the years and soils are presented in Table 6.2. Accordingly, the yield increased under the no-till treatment by 1.23%, 0.61%, and 0.24% for corn, soybean, and wheat, respectively. Deines et al. (2019)

reported a 3.3% and 0.74% yield improvement, respectively, for corn and soybean as a result of conservation tillage adoption in the US corn belt region. However, it is important to note that conservation tillage is a mixture of different intensities of reduced tillage and not necessarily entirely no-tillage. In this study, the net return was 20%, 23.4%, and 48.3% higher under the no-till treatment for corn, soybean, and wheat, respectively (Table 6.2). The higher margin of net revenues for the no-till treatment was mainly because of its lower production costs compared to the conventional treatment. The no-till treatment was cheaper due to absence of tillage operations, even though the herbicide application rates were higher than the conventional tillage. The costs to produce corn, soybean, and wheat conventionally were 918.84, 705.03, 586.56 USD/ha, respectively. On the other hand, no-till treatment costs were 867.36, 632.12, and 508.58 USD/ha, for corn, soybean, and wheat productions, respectively. As the interaction effects between treatment and year were significant for both yield and net return in all the crops, the strength of significance may vary across different years. This differential performance, as affected by treatment and years, is shown in Figure S6.3 (yield) and Figure S6.4 (net return). In summary, the no-till outperformed the conventional treatment in the majority of the years.

Table 6.2. The mean yield and net return for different crops under two treatments in the Kalamazoo River watershed*.

Treatment	Corn		Soybean		Wheat	
	Yield (Mg/ha)	Net return (USD/ha)	Yield (Mg/ha)	Net return (USD/ha)	Yield (Mg/ha)	Net return (USD/ha)
Conventional	8.91[b]	315.31[b]	3.27[b]	345.87[b]	4.09[a]	165.77[b]
No-till	9.02[a]	378.47[a]	3.29[a]	426.78[a]	4.10[a]	245.88[a]

**Means with the same letter in each column are not significantly different at $p<0.05$.*

The no-till treatment increased crop yields in most studies around the world (Corbeels et al., 2014; Pittelkow et al., 2015; Rusinamhodzi et al., 2011). However, some studies have found no significant effects on yield under the no-till systems (e.g., Daigh et al., 2018), while a few other studies reported reductions in crop yield (e.g., Powlson et al., 2014). In contrast, to see the consistently outperforming trends under the adoption of the no-till agriculture the evaluation must be longer than a decade (Cusser et al., 2020). This study was built on this need and successfully captured the long-term impacts of the no-till treatment. The results showed that the adoption of the no-till treatment could significantly improve the resilience of agricultural systems by increasing crop yields and net return. The increment in crop yields under the no-till management can be attributed to the enhancement of soil physical, chemical, and biological properties (Nunes et al., 2018).

6.4 Conclusions

In this long-term study, we found that the adoption of no-till treatment for a corn-soybean-wheat rotation has potential to increase the resilience in the Kalamazoo River Watershed. This improvement of resilience was demonstrated using the following metrics: recharge, water table, soil moisture, drought vulnerability, yield, and net return. The no-till treatment had significantly higher annual recharge, for corn, soybean, and wheat which were 12.4%, 6.2%, and 13.2% greater than the annual recharge from the conventional treatment, respectively. The highest recharge was observed for soybean followed by wheat then corn. The rise in the water table resulting from the adoption of the no-till treatment in the watershed ranged between 0.1-0.5 m, which could substantially contribute to replenishing the aquifers and groundwater-dependent ecosystems. MRD of soil moisture clearly showed that the no-till treatment consistently maintained higher soil moisture compared to the conventional treatment, thus remained as a relatively *wetter* treatment. Therefore, the no-till treatment had a higher resilience against drought compared to the conventional treatment as quantified by the drought index (SWDI). Yields and net returns were also improved under the no-till treatment for all crops in the rotation. When averaged across the years and soils, the no-till treatment produced 1.23%, 0.61%, and 0.24% higher grain yields for corn, soybean, and wheat, respectively. Moreover, the no-till generated 20.0%, 23.4%, and 48.3% higher net returns for corn, soybean, and wheat, respectively.

There were two major assumptions in this study. First, all agricultural land use in the Kalamazoo River Watershed was assumed to be planted with a corn-soybean-wheat rotation. However, farmers plant a variety of crops throughout the watershed; therefore, the findings are mostly applicable to the row crop rotations in this region. Secondly, we assumed that the deep percolation simulated by the crop model instantly reached the water table. This assumption is only valid in regions where there is a greater connection between the surface and groundwater, similar to our study area. To expand our approach to different landscapes with varying climate, soil, groundwater, and cropping systems, we recommend modifying both the crop and groundwater modeling procedures adhering to site-specific parameters and requirements.

6.5 Acknowledgment

This research project was financially supported by the Dissertation Completion Fellowship from the College of Agricultural and Natural Resources at Michigan State University. The KBS Long-Term Ecological Research (KBS-LTER) experiment was funded by the National Science Foundation Long-term Ecological Research Program (DEB 1832042) at the Kellogg Biological Station and by Michigan State University AgBioResearch.

7. CONCLUSIONS

In this dissertation, several innovative approaches were introduced within three studies to quantify the resilience of rainfed agricultural systems at both the field and watershed scales. The robustness of these approaches was tested using data from a long-term cropping system experiment at KBS and then scaled up to the Kalamazoo River Watershed located in the Southwestern portion of Michigan, USA.

In the first study, the applicability of soil moisture metrics to gauge resiliency of differently managed rainfed agricultural treatments were evaluated at the field scale. In addition, the robustness of soil moisture metrics was examined over a long-term period (1993-2018) by monitoring the impacts of climate variabilities on crop growth and yield for a corn-soybean-wheat rotation. The major takeaways from this study are as follows:

- Soil moisture-based metrics can be used to measure the resilience in rainfed agricultural systems.
- The no-till treatment significantly improved the resiliency of a corn-soybean-wheat rotation than the conventional treatment in terms of higher soil moisture retention, higher effectiveness for drought mitigation, greater crop yields, and increased stability of yields.
- The organic treatment had substantially higher resiliency in terms of greater soil moisture retention and drought mitigation than the conventional treatment; however, nitrogen limitation significantly reduced yields, especially for cereal crops (i.e., corn and wheat).
- The reduced input treatment was the least resilient as it had limited capacity to recover from the impacts of climate extremes (i.e., drought).

In the second study, climate resilience of alternative treatments for a long-term (1993-2018) corn-soybean-wheat rotation was evaluated in terms of profitability and farm risks for adaptation using enterprise budgeting and risk analysis. Means and volatility of expected net revenues and risk preferences were used as evaluation metrics. The key take-home messages from this study are as follows:

- The organic treatment was expected to exceed the conventional treatment's net revenues and stability making it more resilient.
- The no-till treatment was superior to the conventional and the reduced input treatments in expected annual net revenues with lower risk under climate extremes.
- Due to higher resilience and lower risk levels, the organic and no-till treatments were suitable to cater to a large group of farmers with different risk preferences for adaptation.
- The conventional and reduced input treatments were vulnerable to climate extremes and should not be promoted in areas with a high-level of climate variabilities.

In the third study, the overall resilience of a conservation agricultural practice (i.e., no-till) was compared to the conventional tillage for the corn-soybean-wheat rotation at the watershed scale using an integrated framework of crop and groundwater models. Recharge, groundwater head, soil moisture, yield, and net return were used as resilience metrics. The key conclusions of this study are as follows:

- The adoption of the no-till treatment increased the annual recharge and groundwater heads in the watershed over the long-term study (1993-2019), and the highest recharge was observed for soybean followed by wheat and corn.
- The rise in the groundwater table under the no-till treatment ranged from 0.1m to 0.5 m, depending on the underlying groundwater system in the watershed, and had the potential to beneficially impact the groundwater-dependent ecosystems.
- Shifting from the conventional tillage to the no-till treatment significantly increased the yield of corn and soybean and the expected net returns from all crops.
- The no-till treatment consistently retained higher soil moisture than the conventional treatment and thereby helped to mitigate the impacts of droughts.
- The overall resilience of the corn-soybean-wheat rotation was substantially improved by the adoption of the no-till treatment.

8. RECOMMENDATIONS FOR FUTURE RESEARCH

This dissertation presented innovative approaches to quantify the resilience of rainfed agricultural systems at the field and watershed scales. The possible areas to further strengthen these approaches are as follows:

- Soil moisture-based metrics can be further improved with more frequently measured soil moisture at different depths within the root zone. This can be achieved through installing automated soil moisture sensors in the treatment plots at sufficient densities.
- Remote sensing-based soil moisture measurements (e.g., Soil Moisture Active Passive-SMAP, Soil Moisture Ocean Salinity-SMOS) can be applied to develop soil moisture-based resilience metrics if their spatial resolutions are reasonably improved at the field scale.
- The approaches presented here can also be extended to the irrigated cropping systems if the frequency and amount of irrigation are periodically recorded.
- The current version of the DSSAT model does not allow intercropping. Therefore, developing the intercropping module for DSSAT can assist in the evaluation of different cover crop species on the resilience of cropping systems. In addition, simulation of crop responses to nutrients can be improved by developing potassium and phosphorus (e.g., wheat) uptake models.
- Seamless integration of crop and groundwater models can give us better insights to study the impacts of different agricultural practices on recharge and groundwater restoration.

- In this study the annual recharge and groundwater average head were reported to gauge the resiliency as related to ecosystem services. However, it is recommended to report these metrics during the dry season to better represent the impacts of groundwater restoration on ecosystem services.
- Studying different pathways to motivate producers to adopt climate-resilient practices considering market and policy implications.

APPENDIX

APPENDIX

Table S4.1. Details of the four annual row crop treatments of MCSE investigated in this study.

Treatment	Description of Management
Conventional (CON)	Crops were planted in corn-soybean-winter wheat rotation. Primary tillage was practiced using moldboard plow until 1998 and chisel plowing was used from 1999 onward. Disks were used for secondary tillage before wheat planting, while the field was conditioned with a soil finisher prior to soybean and maize planting. Moreover, inter-row cultivation was practiced for soybean and maize. Fertilizers were applied at the rates based on soil-test recommendations for each crop. Herbicides were broadcasted within and between rows to control weeds. There were no applications of manure/compost or insecticides.
No-till (NT)	Crops were planted in corn-soybean-winter wheat rotation. These crops were established under zero tillage. Fertilizers were applied at rates based on soil-test recommendations for each crop. Herbicides were broadcasted within and between rows to control weeds. There were no applications of manure/compost or insecticides.
Reduced input (RI)	Crops were planted in corn-soybean-winter wheat rotation. Primary tillage was practiced using moldboard plow until 1998 and chisel plowing was used from 1999 onward. Disks were used for secondary tillage before wheat planting, while the field was conditioned with a soil finisher prior to soybean and maize planting. Moreover, inter-row cultivation was practiced for soybean and maize. Nitrogen (N) fertilizer and herbicide inputs were applied as one-third of N and herbicides applied to the conventional system (Reduced input). These herbicides were banded within rows. Winter cover crop was established following the corn and wheat crops within the rotation with the intention of supplementing nitrogen to the following crop. Generally, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted after wheat. There were no applications of manure/compost or insecticides.
Organically managed (USDA certified organic) (OR)	Crops were planted in corn-soybean-winter wheat rotation. Primary tillage was practiced using moldboard plow until 1998 and chisel plowing was performed from 1999 onward. Disks were used for secondary tillage before wheat planting, while the field was conditioned with a soil finisher prior to soybean and maize planting. Moreover, inter-row cultivation was practiced for soybean and maize. Winter cover crop was established following the corn and wheat crops within the rotation with the intention of supplementing nitrogen to the following crop. Generally, cereal rye (*Secale cereal*) was planted following corn, while red clover (*Trifolium pratense*) was planted after wheat. This certified organic treatment was not applied with any chemical fertilizers/herbicides/insecticides.

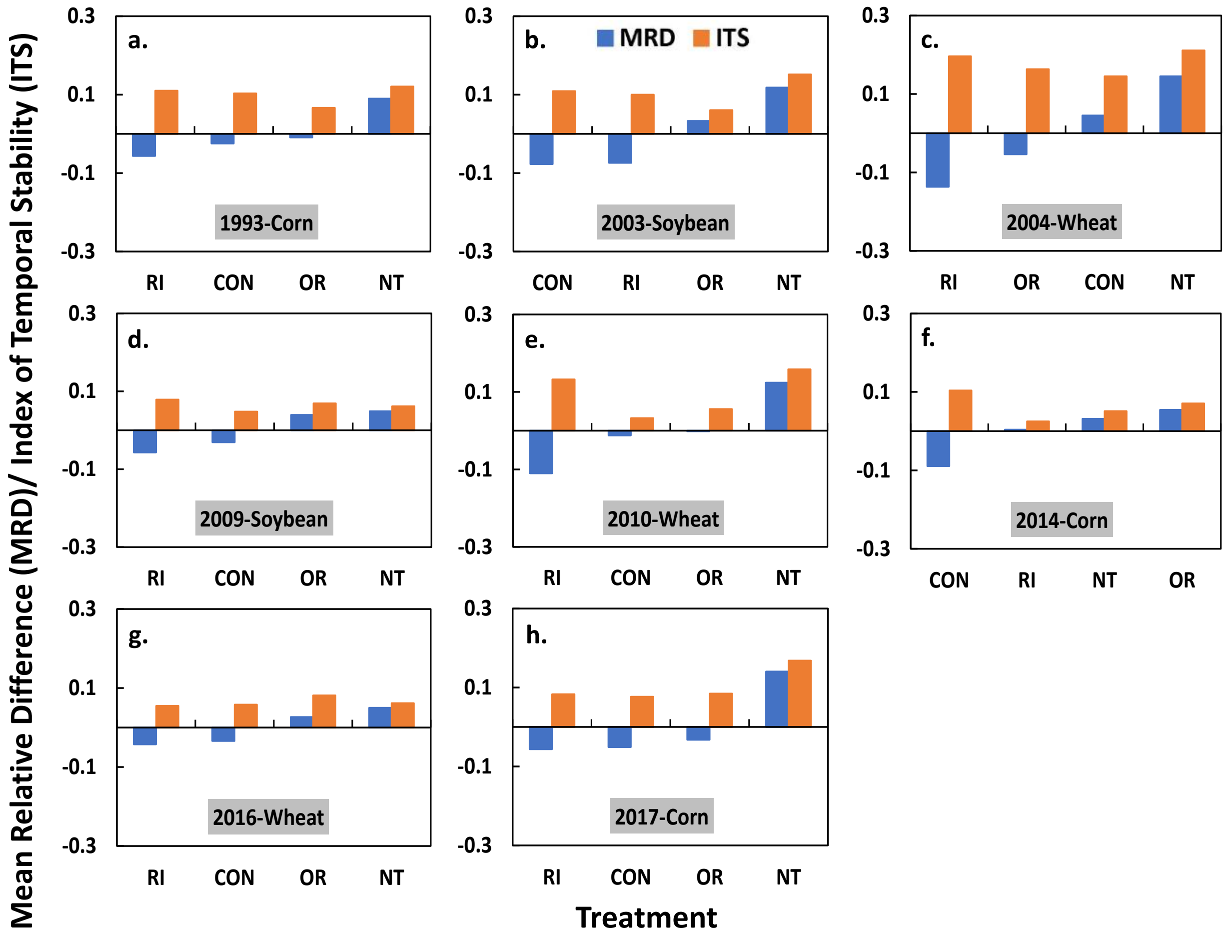

Figure S4.1. Ranked MRD of volumetric soil moisture and ITS for each treatment during the normal years.*Note: Crop grown is given next to the respective year for each plot. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

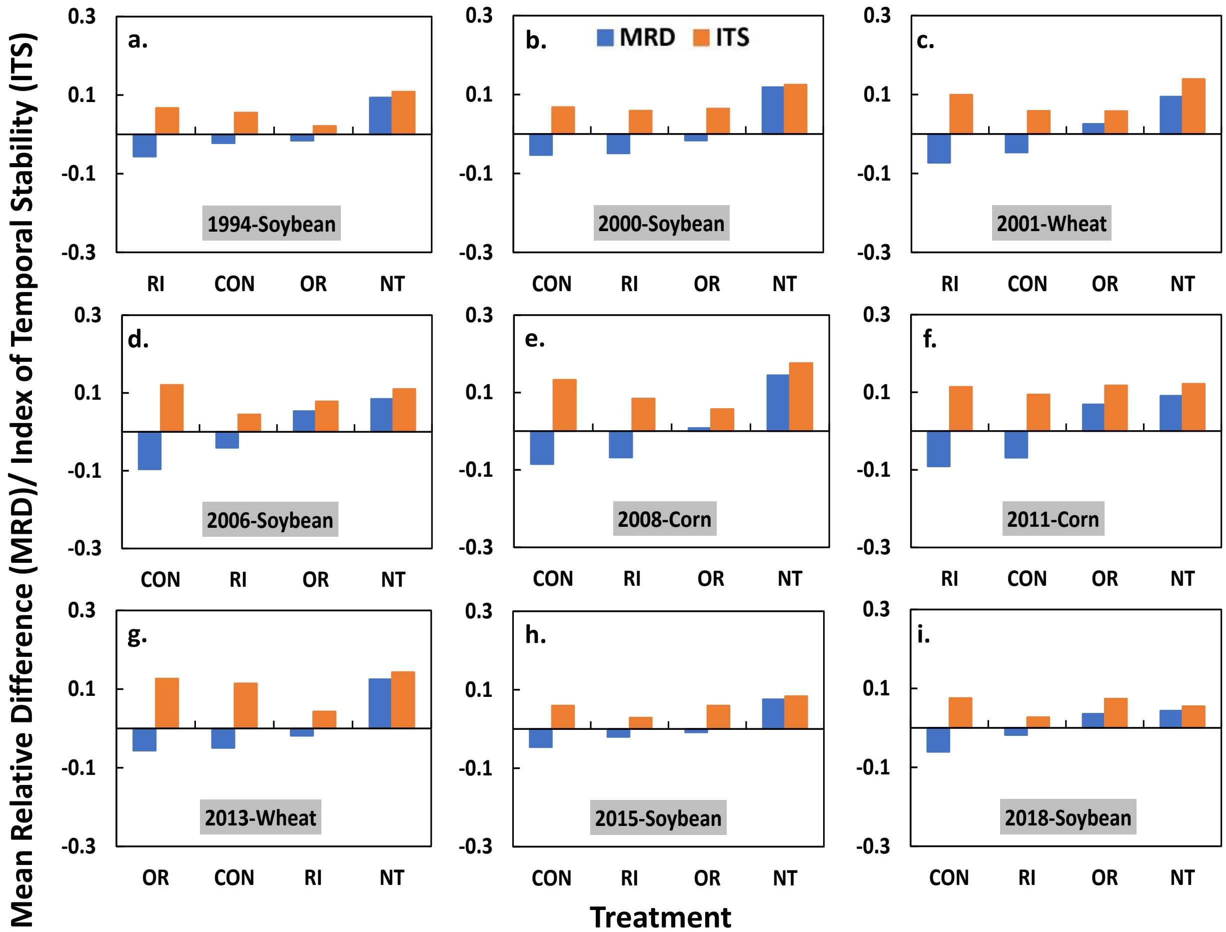

Figure S4.2. Ranked MRD of volumetric soil moisture and ITS for each treatment during the wet years. *Note: Crop grown is given next to the respective year for each plot. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

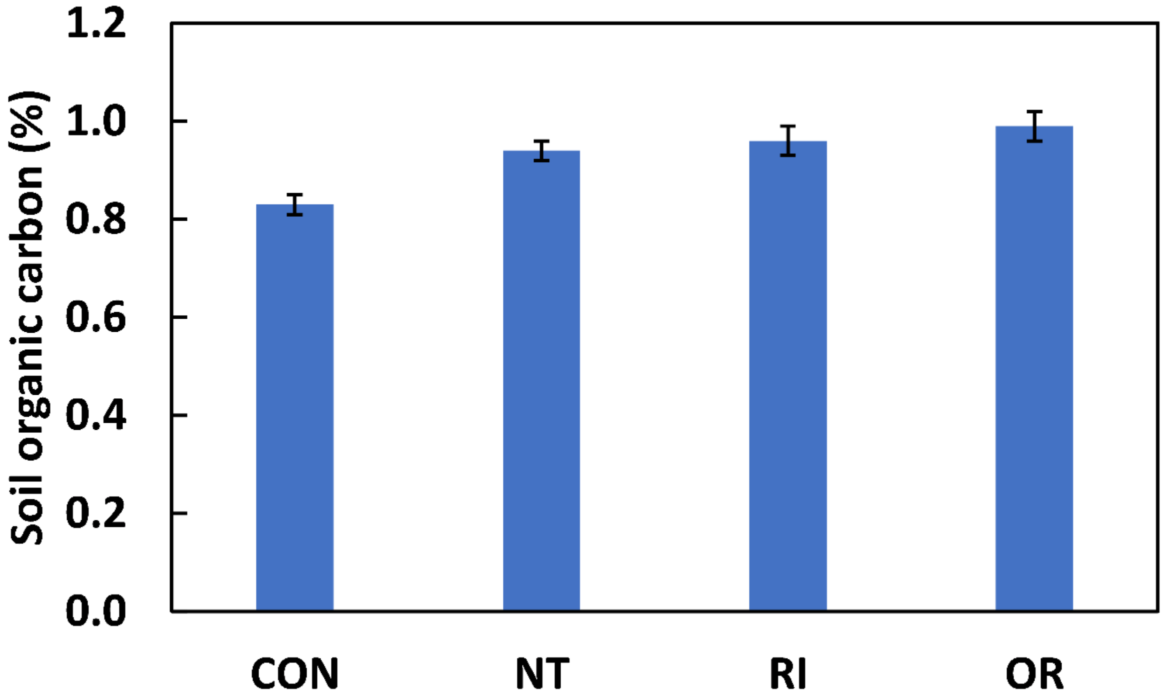

Figure S4.3. Means of soil organic carbon content in different treatments during the period of 1989-2001 in this experiment.*The error bars represent the standard error. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

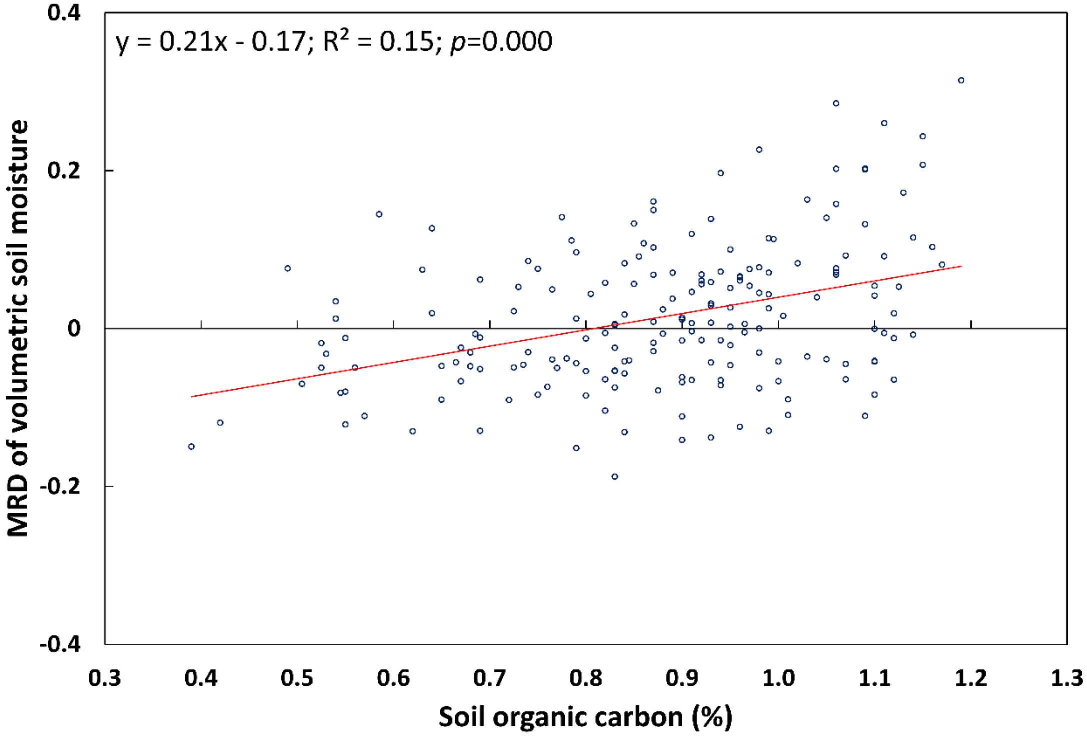

Figure S4.4. Association between mean relative difference (MRD) of volumetric soil moisture and soil organic carbon content in the treatments investigated in this study.

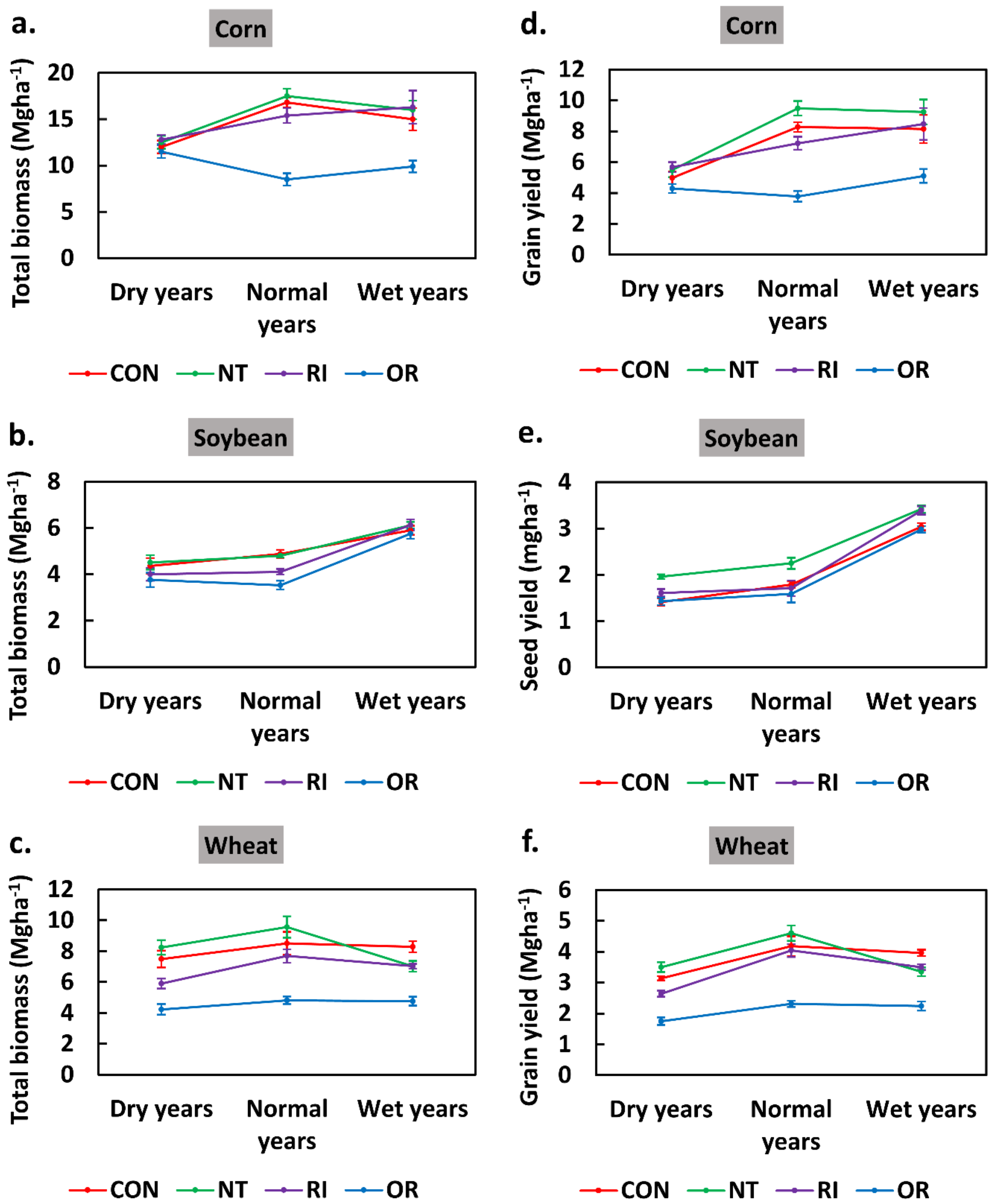

Figure S4.5. Total biomass (a-c) and yield (d-f) of crops as affected by the interaction between treatment and climate variability. *The error bars represent the standard error. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; OR: Organic treatment.*

Table S4.2. *P*-values for the effects evaluated in the statistical mixed model for MRD, total biomass and yield.

Crop	Effects in the statistical model	Probability (*p*-value)		
		MRD	Total biomass	Yield
Corn	Treatment (*trt*)	<0.0001**	<0.0001**	<0.0001**
	Climate variability (*clim*)	0.9250	0.5154	0.2641
	Year (*yr*)	>0.05	0.0563	0.0948
	Interaction between treatment and climate variability (*trt* × *clim*)	0.1733	0.0002**	0.0003**
	Interaction between treatment and year (*trt* × *yr*)	0.2497	0.0171*	0.0043*
Soybean	Treatment (*trt*)	<0.0001**	0.0020*	0.0198*
	Climate variability (*clim*)	0.9998	0.0024*	<0.0001**
	Year (*yr*)	>0.05	0.0845	0.0867
	Interaction between treatment and climate variability (*trt* × *clim*)	0.1442	0.0071*	0.0031*
	Interaction between treatment and year (*trt* × *yr*)	0.4661	0.6700	0.8306
Wheat	Treatment (*trt*)	<0.0001**	<0.0001**	<0.0001**
	Climate variability (*clim*)	0.9805	0.7511	0.2335
	Year (*yr*)	>0.05	0.0698	0.0729
	Interaction between treatment and climate variability (*trt* × *clim*)	0.8305	0.3534	0.1965
	Interaction between treatment and year (*trt* × *yr*)	0.8107	0.0700	0.0640

***Strongly significant at p<0.001; *significant at p<0.05.*

Table S4.3. Coefficient of variation of total crop biomass and yield of crops under different treatments as affected by climate extremes.

Crop parameter	Category of climate extreme	Treatment	Coefficient of variation (%)		
			Corn	Soybean	Wheat
Total crop biomass	Dry year	CON	28.1	26.3	30.9
		NT	19.0*	22.6*	21.0*
		RI	25.1	24.0	22.7
		OR	31.9	28.1	35.4
	Wet year	CON	27.9	18.6	15.1
		NT	20.0*	11.6*	16.6
		RI	38.1	21.2	7.4*
		OR	22.1	20.2	21.0
Crop yield	Dry year	CON	38.4	19.0	17.7
		NT	27.7*	7.8*	10.0*
		RI	39.3	16.9	16.2
		OR	33.2	18.3	28.4
	Wet year	CON	38.6	13.6	8.9
		NT	28.9*	12.3*	13.4
		RI	42.2	15.0	8.5*
		OR	30.7	13.0	23.5

**Lowest coefficient of variation for the total crop biomass and yield within each climate extreme.*

Table S5.1. Details and timing of management operations for corn-soybean-wheat rotation under the conventional treatment (CON).

Month	Week of the month	Management operation	Year
April	2	0-0-60 potassium fertilizer application	1
May	1	Chisel plowing (moldboard plow until 1998)	1
May	1	Soil finishing	1
May	2	Corn planting	1
May	2	19-17-0 liquid fertilizer application	1
May	3	Herbicide Application	1
June	2	28-0-0 liquid nitrogen fertilizer application	1
October	3	Corn harvesting	1
November	1	Mowing	1
April	3	0-0-60 potassium fertilizer application	2
April	4	11-52-0 monoammonium phosphate fertilizer application	2
May	1	Chisel plowing (moldboard plow until 1998)	2
May	2	Soil finishing	2
May	3	Soybean planting	2
May	4	Herbicide application	2
July	3	Herbicide application	2
August	1	Miticide application (if required)	2
October	1-2	Soybean harvesting	2
October	2	Chisel plowing (moldboard plow until 1998)	2
October	2	Soil finishing	2
October	4	Wheat planting	2
March	4	19-19-19 N-P-K fertilizer application	3
April	2	Herbicide application	3
April	3	28-0-0 liquid nitrogen fertilizer application	3
July	2	Wheat harvesting	3
August	4	Mowing	3
September	2-3	Glyphosate application to kill	3

Table S5.2. Details and timing of management operations for corn-soybean-wheat rotation under the no-till treatment (NT).

Month	Week of the month	Management operation	Year
April	2	0-0-60 potassium fertilizer application	1
May	2	Corn planting (no-till drill)	1
May	2	19-17-0 liquid fertilizer application	1
May	3	Herbicide Application	1
June	2	28-0-0 liquid nitrogen fertilizer application	1
October	3	Corn harvesting	1
November	1	Mowing	1
April	3	0-0-60 potassium fertilizer application	2
April	4	11-52-0 monoammonium phosphate fertilizer application	2
May	3	Soybean planting (no-till drill)	2
May	4	Herbicide application	2
July	3	Herbicide application	2
August	1	Miticide application (if required)	2
October	1-2	Soybean harvesting	2
October	4	Wheat planting (no-till drill)	2
March	4	19-19-19 N-P-K fertilizer application	3
April	2	Herbicide application	3
April	3	28-0-0 liquid nitrogen fertilizer application	3
July	2	Wheat harvesting	3
August	4	Mowing	3
September	2-3	Glyphosate application to kill	3

Table S5.3. Details and timing of management operations for corn-soybean-wheat rotation under the reduced input treatment (RI).

Month	Week of the month	Management operation	Year
April	2	0-0-60 potassium fertilizer application	1
May	1	Chisel plowing (moldboard plow until 1998)	1
May	1	Soil finishing	1
May	2	Corn planting	1
May	2	19-17-0 liquid fertilizer application	1
May	3	Herbicide Application	1
June	3	Row cultivation (inter row cultivator)	1
October	3	Corn harvesting	1
November	1	Mowing	1
November	2	Planting cereal rye cover crop	1
April	3	0-0-60 potassium fertilizer application	2
April	3	0-48-0 phosphate fertilizer application	2
May	1	Chisel plowing (moldboard plow until 1998)	2
May	2	Soil finishing	2
May	3	Soybean planting	2
June	3	Row cultivation (inter row cultivator)	2
July	3	Herbicide application	2
August	1	Miticide application (if required)	2
October	1-2	Soybean harvesting	2
October	2	Chisel plowing (moldboard plow until 1998)	2
October	2	Soil finishing	2
October	4	Wheat planting	2
April	2	Herbicide application	3
April	3	28-0-0 liquid nitrogen fertilizer application	3
July	2	Wheat harvesting	3
August	1-2	Planting red clover cover crop	3

Table S5.4. Details and timing of management operations for corn-soybean-wheat rotation under the organic treatment (OR).

Month	Week of the month	Management operation	Year
May	1	Chisel plowing (moldboard plow until 1998)	1
May	1	Soil finishing	1
May	2	Corn planting	1
June	1	Row cultivation (rotary hoe)	1
June	2	Row cultivation (rotary hoe)	1
June	4	Row cultivation (inter row cultivator)	1
July	1	Row cultivation (inter row cultivator)	1
October	3	Corn harvesting	1
November	1	Mowing	1
November	2	Planting cereal rye cover crop	1
May	1	Chisel plowing (moldboard plow until 1998)	2
May	2	Soil finishing	2
May	3	Soybean planting	2
June	2	Row cultivation (rotary hoe)	2
June	3	Row cultivation (rotary hoe)	2
July	1	Row cultivation (inter row cultivator)	2
July	3	Row cultivation (inter row cultivator)	2
October	1-2	Soybean harvesting	2
October	2	Chisel plowing (moldboard plow until 1998)	2
October	2	Soil finishing	2
October	4	Wheat planting	2
July	2	Wheat harvesting	3
August	1-2	Planting red clover cover crop	3

Table S5.5. Means of yield under different production and treatment systems as affected by climate variability*.

Production systems	Treatment systems	Crop Yield ($Mgha^{-1}$)		
		Dry years	Normal years	Wet years
Corn	CON	4.98[a]	8.27[b]	8.14[a]
	NT	5.50[a]	**9.48**[a]	9.25[a]
	RI	5.67[a]	7.22[c]	8.47[a]
	OR	4.29[b]	3.78[d]	5.10[b]
Soybean	CON	1.41[b]	1.79[b]	3.04[b]
	NT	**1.96**[a]	**2.25**[a]	**3.42**[a]
	RI	1.61[b]	1.71[bc]	**3.39**[a]
	OR	1.43[b]	1.59[c]	2.98[b]
Wheat	CON	3.14[b]	4.18[ab]	3.96[a]
	NT	**3.50**[a]	4.60[a]	3.35[b]
	RI	2.64[c]	4.04[b]	3.50[b]
	OR	1.75[d]	2.31[c]	2.24[c]

** Means with the same letter in a single column for each crop are not significantly different at $p<0.05$. CON: Conventional treatment; NT: No-till treatment; RI: Reduced input treatment; and OR: Organic treatment. Means of yield, which are significantly higher in comparison to the conventional treatment, are presented in bold letters.*

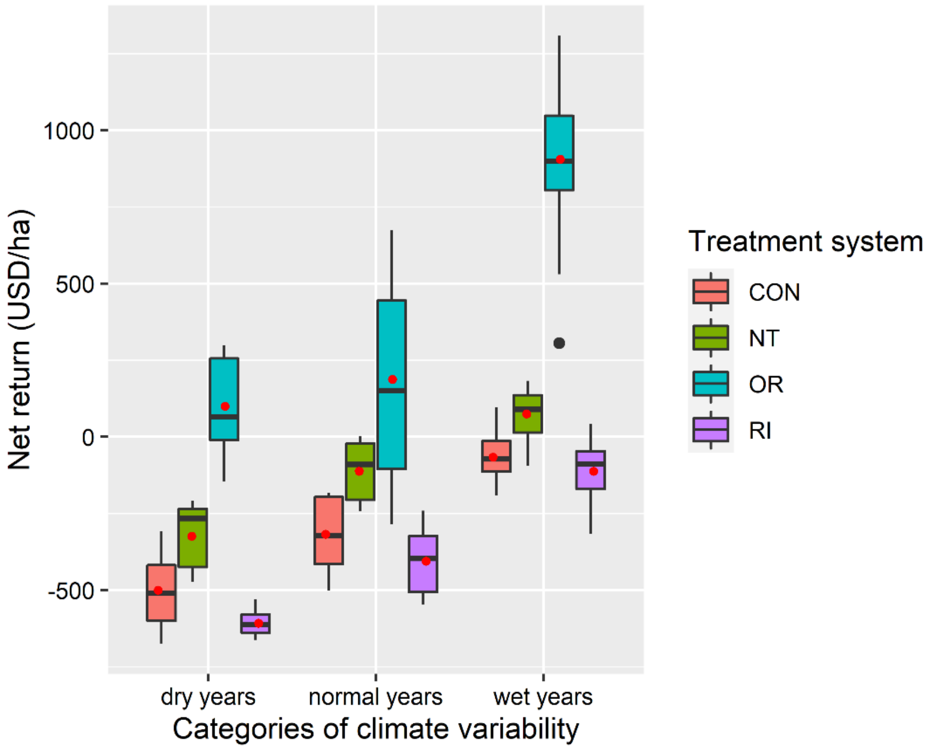

Figure S5.1. Box plot of net return of soybean production system under different treatments as affected by climate variability. *Note: The thick black line represents the median of the distribution, the red dot is the mean, the edges of the box are 25% and 75% quantiles, whiskers denote the range of the data and the black dots are the outliers.*

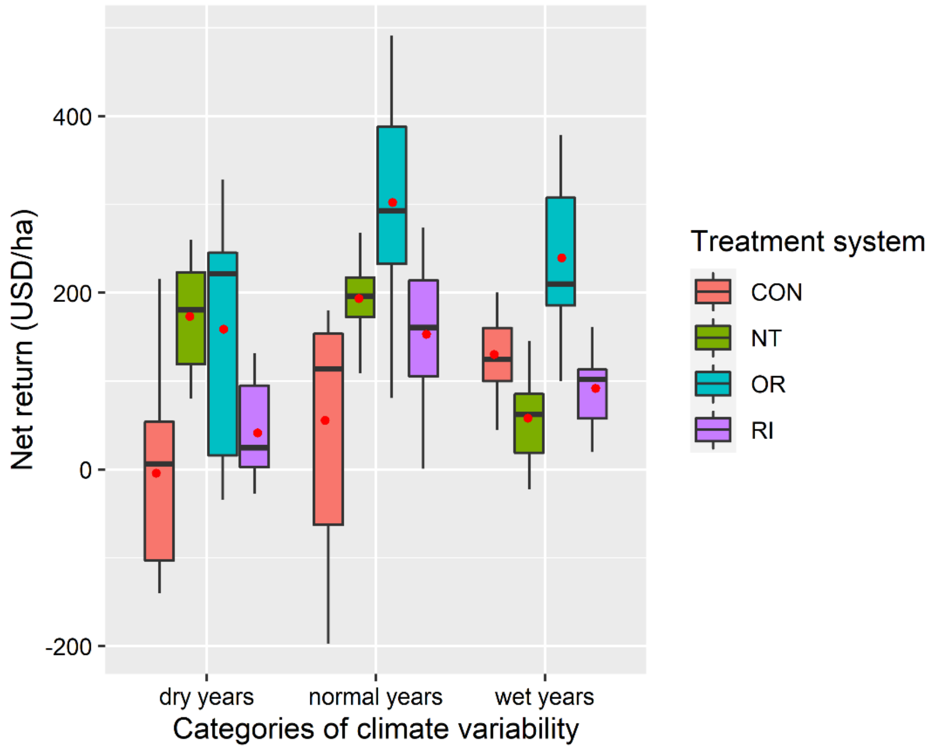

Figure S5.2. Box plot of net return of wheat production system under different treatments as affected by climate variability. *Note: The thick black line represents the median of the distribution, the red dot is the mean, the edges of the box are 25% and 75% quantiles, whiskers denote the range of the data and the black dots are the outliers.*

Table S6.1. Soil properties at the KBS Main Cropping System Experiment site used to develop the sequential DSSAT model.

Soil depth	Bulk density	Organic carbon	Sand	Silt	Clay	Root growth factor in soil*	Saturated hydraulic conductivity	Field capacity water content at 33kPa*	Wilting point water content at 1,500kPa*
(cm)	(g/cm ^{3})	---------------(%)---------------				unitless	cm/h	cm ^{3}/cm ^{3}	cm ^{3}/cm ^{3}
0-10	1.60	1.10	43	38	19	1.0	0.36	0.267	0.125
10-22	1.60	0.90	43	38	19	0.8	0.36	0.267	0.137
22-31	1.60	0.70	31	47	22	0.5	0.25	0.267	0.137
31-41	1.60	0.30	33	44	23	0.4	0.20	0.295	0.165
41-51	1.60	0.22	56	19	25	0.3	0.20	0.297	0.165
51-61	1.60	0.10	62	17	21	0.3	0.20	0.267	0.137
61-75	1.60	0.05	69	12	19	0.2	0.96	0.267	0.137
75-89	1.60	0.02	89	4	7	0.2	1.98	0.160	0.060
89-102	1.60	0.02	88	5	7	0.1	20.0	0.160	0.060
102-120	1.60	0.02	88	5	7	0.1	20.0	0.160	0.060

**parameters used to calibrate the soil water module of the DSSAT.*

Table S6.2. Probability values for the significance of the effects evaluated in the statistical mixed model for crop yields and net return.

Crop	Fixed effect	Probability (*p*-value) of the parameters		
		Yield	Net return	Recharge
Corn	Treatment (*trt*)	<0.0001	<0.0001	<0.0001
	Year (*yr*)	<0.0001	<0.0001	<0.0001
	Interaction between treatment and year (*trt* × *yr*)	<0.0001	<0.0001	<0.0001
Soybean	Treatment (*trt*)	<0.0001	<0.0001	<0.0001
	Year (*yr*)	<0.0001	<0.0001	<0.0001
	Interaction between treatment and year (*trt* × *yr*)	<0.0001	<0.0001	<0.0001
Wheat	Treatment (*trt*)	0.0856	<0.0001	<0.0001
	Year (*yr*)	<0.0001	<0.0001	<0.0001
	Interaction between treatment and year (*trt* × *yr*)	<0.0001	<0.0001	<0.0001

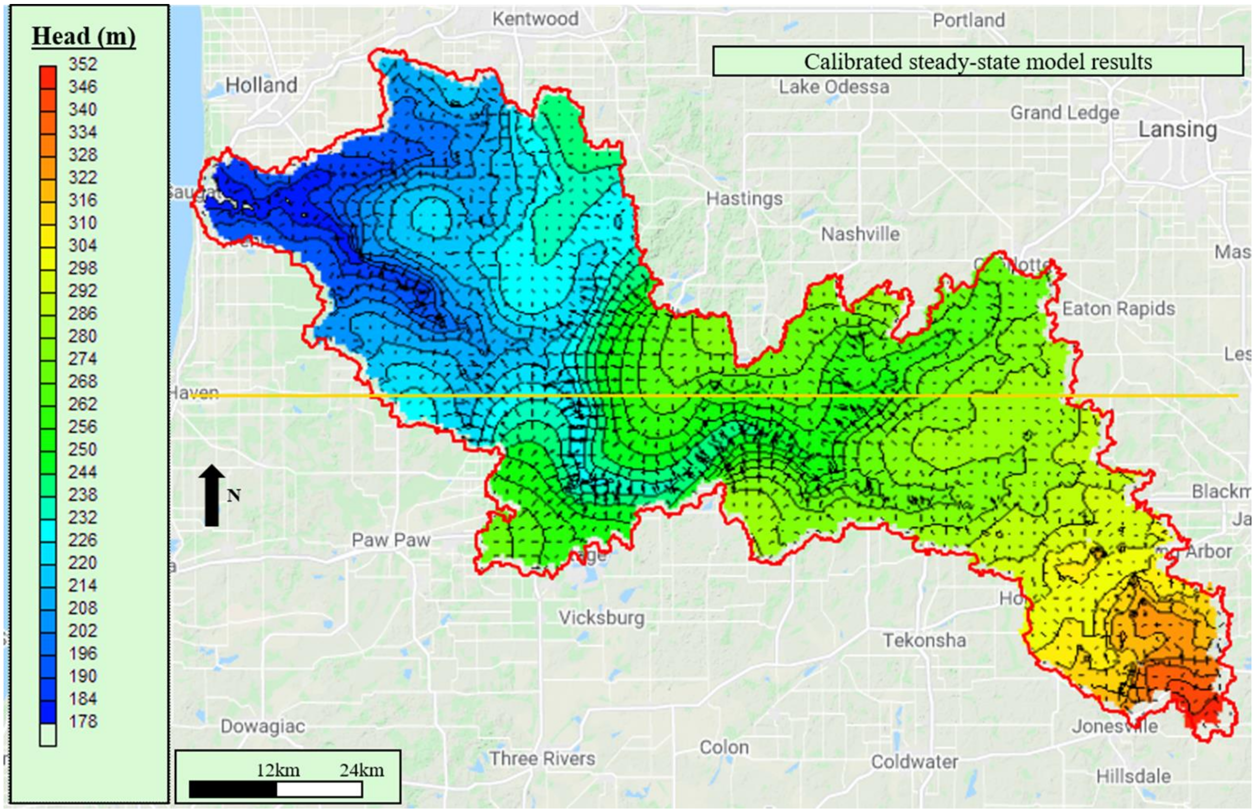

Figure S6.1. Results of the calibrated steady-state groundwater model including head contours, color map for head, and velocity vectors.

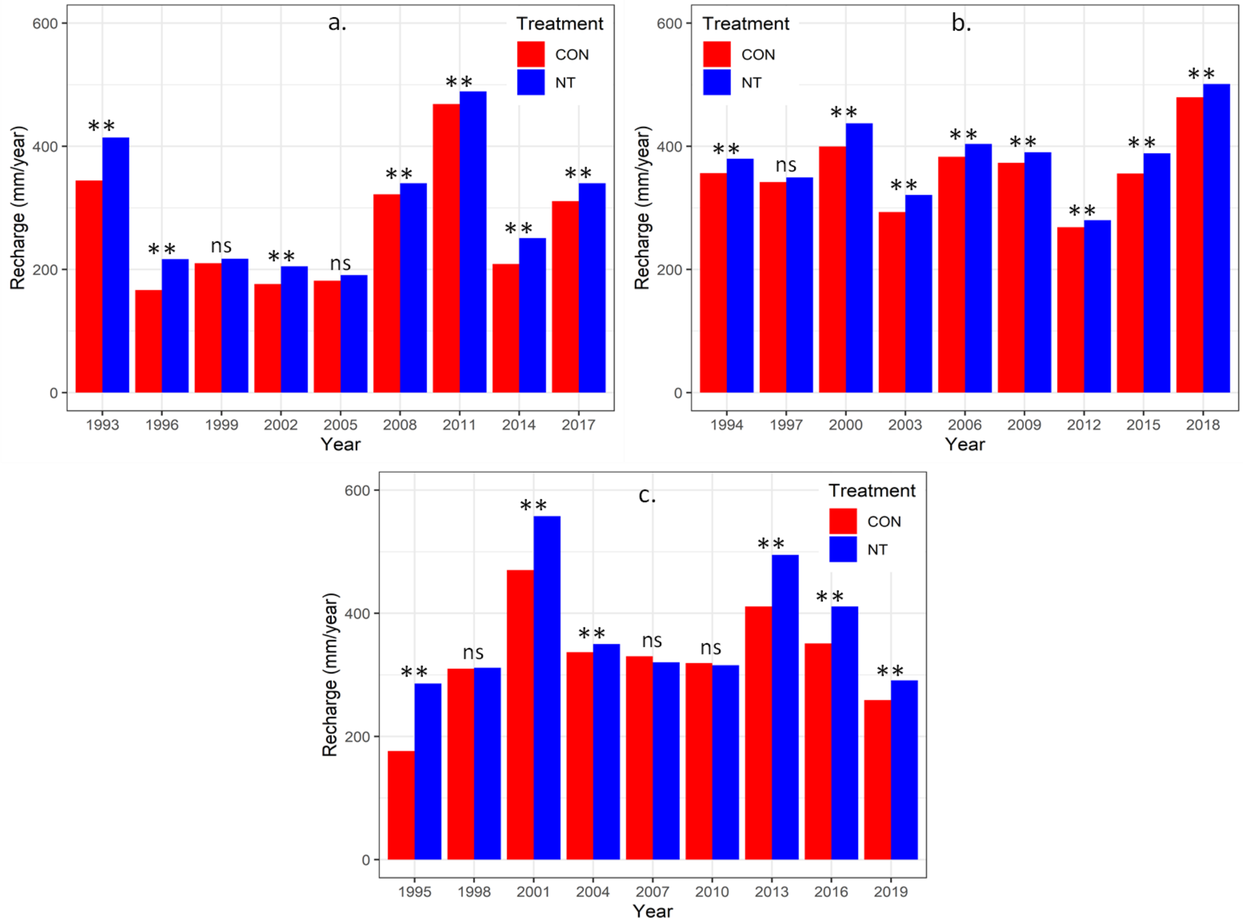

Figure S6.2. Mean annual recharge from corn (a), soybean (b), and wheat (c) across different soils in the Kalamazoo River watershed for the period between 1993-2019 as affected by the conventional and the no-till treatments. *Note: Strongly significant means (p<0.0001) are indicated by **, and non-significance cases are denoted by "ns".*

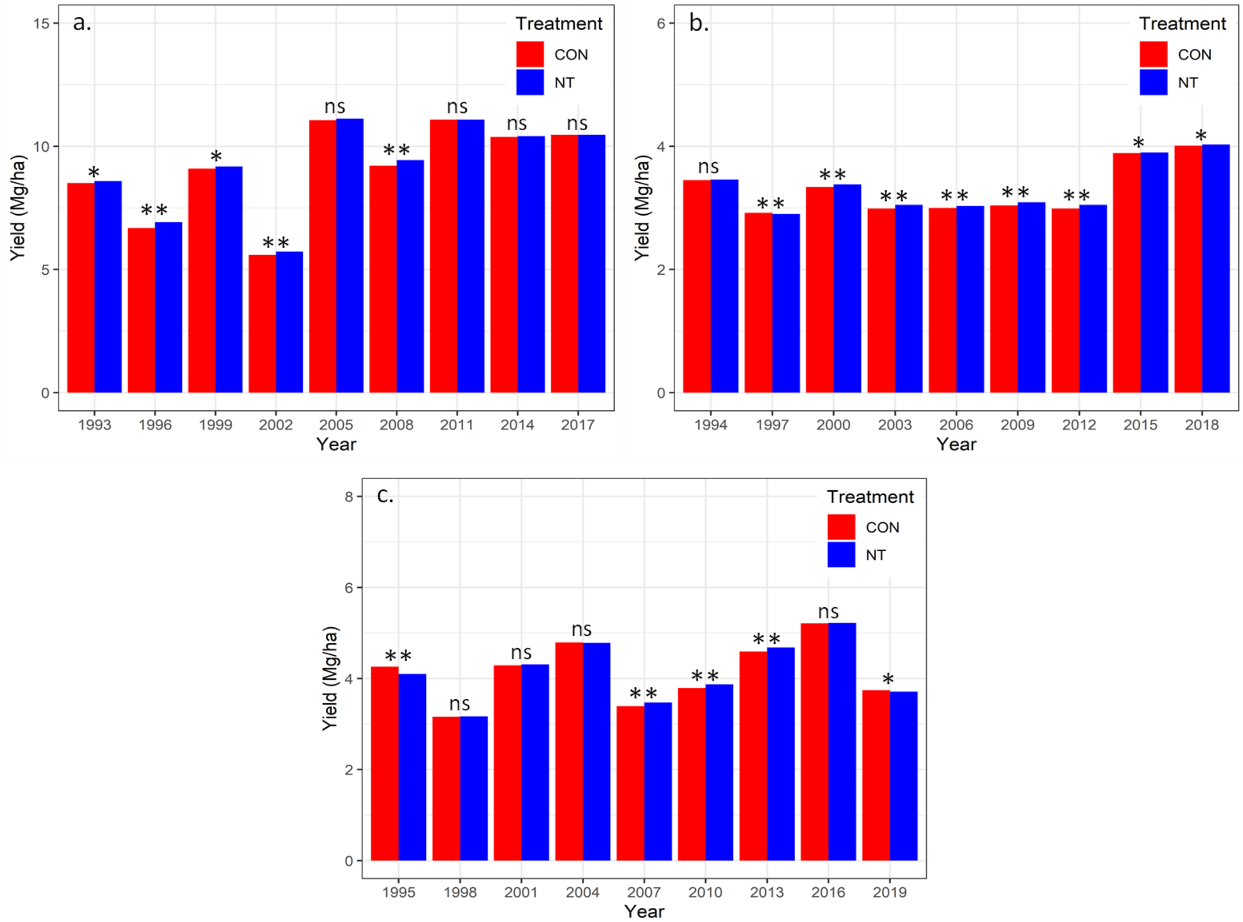

Figure S6.3. Mean yield of corn (a), soybean (b), and wheat (c) across different soils in the Kalamazoo River watershed for the period between 1993-2019 as affected by the conventional and the no-till treatments. *Note: Strongly significant means (p<0.0001) are indicated by **, significant means (p<0.05) are indicated by *, and non-significance cases are denoted by "ns".*

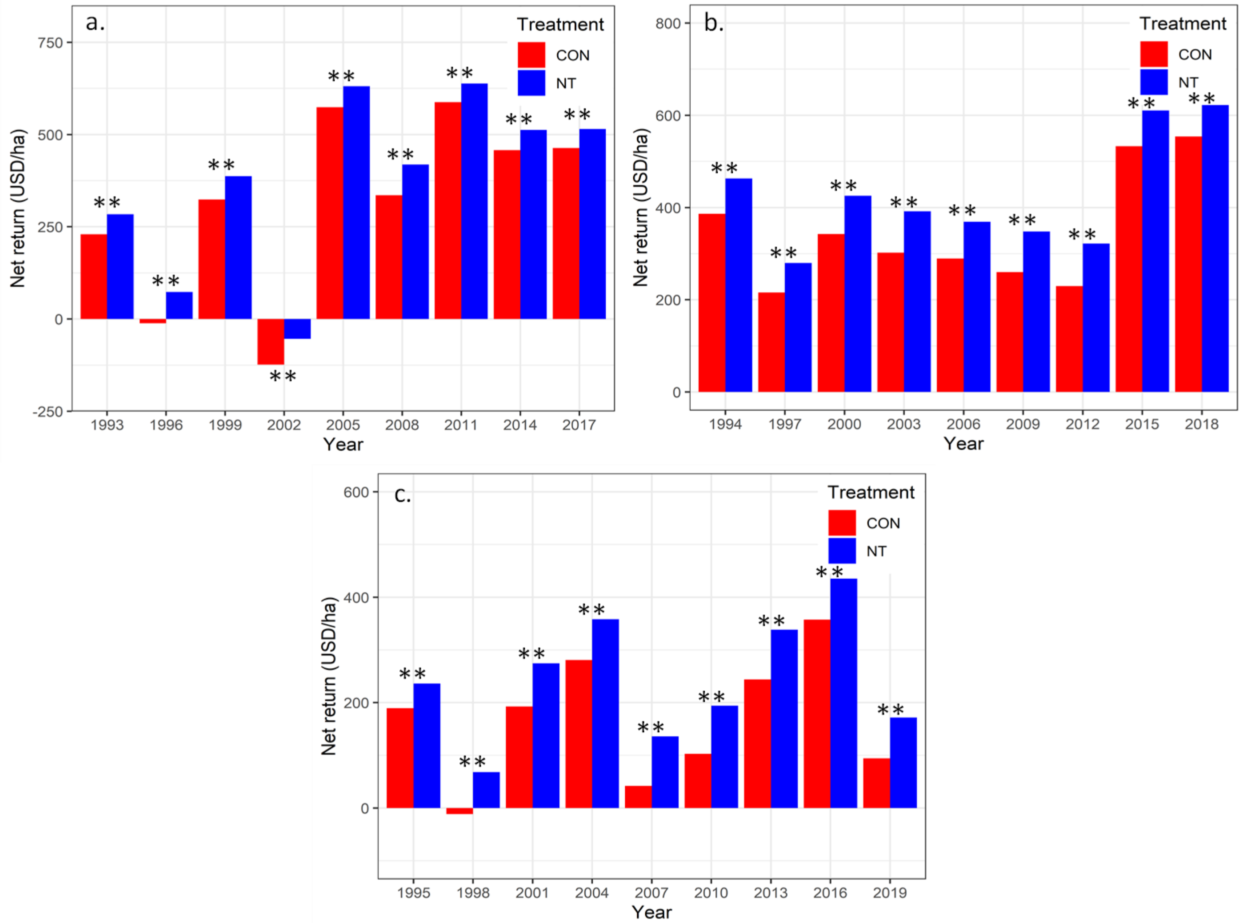

Figure S6.4. Average net return of corn (a), soybean (b), and wheat (c) across different soils in the Kalamazoo River watershed for the period between 1993-2019 as affected by the conventional and the no-till treatments. *Note: Strongly significant means (p<0.0001) are indicated by **, significant means (p<0.05) are indicated by *, and non-significance cases are denoted by "ns".*

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