Quantification of Resilience Metrics as Affected by a Conservation Agricultural Practice at a Watershed Scale

Rasu Eeswaran [a], A. Pouyan Nejadhashemi [a, b, *], Josué Kpodo [b, c], Zachary K. Curtis [d], Umesh Adhikari [d], Huasheng Liao [d], Shu-Guang Li [d,e], J. Sebastian Hernandez-Suarez [b], Filipe Couto Alves [f], Anna Raschke [b], Prakash Kumar Jha [g]

[a] Department of Plant, Soil and Microbial Sciences Michigan State University, East Lansing, MI 48824 USA

[b] Department of Biosystems and Agricultural Engineering, Michigan State University, East Lansing, MI 48824 USA

[c] Department of Computer Science and Engineering, Michigan State University, East Lansing, MI 48824 USA

[d] Hydrosimulatics inc., 721 N Ste. 2Captial Ave., Lansing, MI 48906 USA

[e] Department of Civil and Environmental Engineering, Michigan State University, East Lansing, MI 48824 USA

[f] Department of Epidemiology and Biostatistics, Michigan State University, East Lansing, MI 48824 USA

[g] Feed the Future Innovation Lab for Collaborative Research on Sustainable Intensification, Kansas State University, Manhattan, KS, 66506 USA

* Corresponding author: Tel.: +1 (517) 432-7653 Fax: +1 (517) 432-2892. Email address: pouyan@msu.edu

Abstract: It is suggested that conventional tillage operations exacerbate global environmental changes and affect the sustainability of our food production systems. Therefore, no-till has been introduced as one of the conservation practices to counteract these challenges. No-till has been adopted by a substantial number of farmers in major cropping regions; however, its resilience from large scale implementation has been overlooked. The majority of the studies have reported only a few aspects of the no-till practice (e.g., yield, soil properties, etc.), often with contradicting observations. To fill this gap, we present an approach that integrates long-term field experimental data and modeling to quantify resilience at a watershed scale. The study was conducted in the Kalamazoo River watershed located in Michigan, USA. Recharge, groundwater table, soil moisture, yield, and net return were used as resilience metrics. The DSSAT sequence crop model was developed for a corn-soybean-wheat rotation and calibrated using the yield and soil moisture data from a long-term (1993-2019) experiment for the conventional and the no-till treatment conducted within the study area. Soil moisture, recharge and yield were simulated, and the recharge was fed into a calibrated groundwater model to analyze changes in groundwater heads. The results showed clear evidence of higher recharge and net return under the no-till treatment, which were statistically significant for all crops at the watershed scale. Moreover, the no-till treatment consistently retained greater soil moisture than the conventional treatment, thereby helping to mitigate the impacts of droughts. The rise in groundwater table as affected by the adoption of no-till practices in this watershed has ranged between 0.1-0.5 m, depending on the underlying groundwater system, and has the potential to beneficially affect the aquifers and groundwater-dependent ecosystems. Therefore, the no-till treatment could improve the overall resilience of the row crop system.

Keywords: Crop Modeling; Drought; Groundwater Modeling; No-till; Recharge; Soil Moisture

1. Introduction

Similarly 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.

2. Materials and Methods

2.1. Overview of Methodology

The modeling framework of this study is presented in Figure 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).

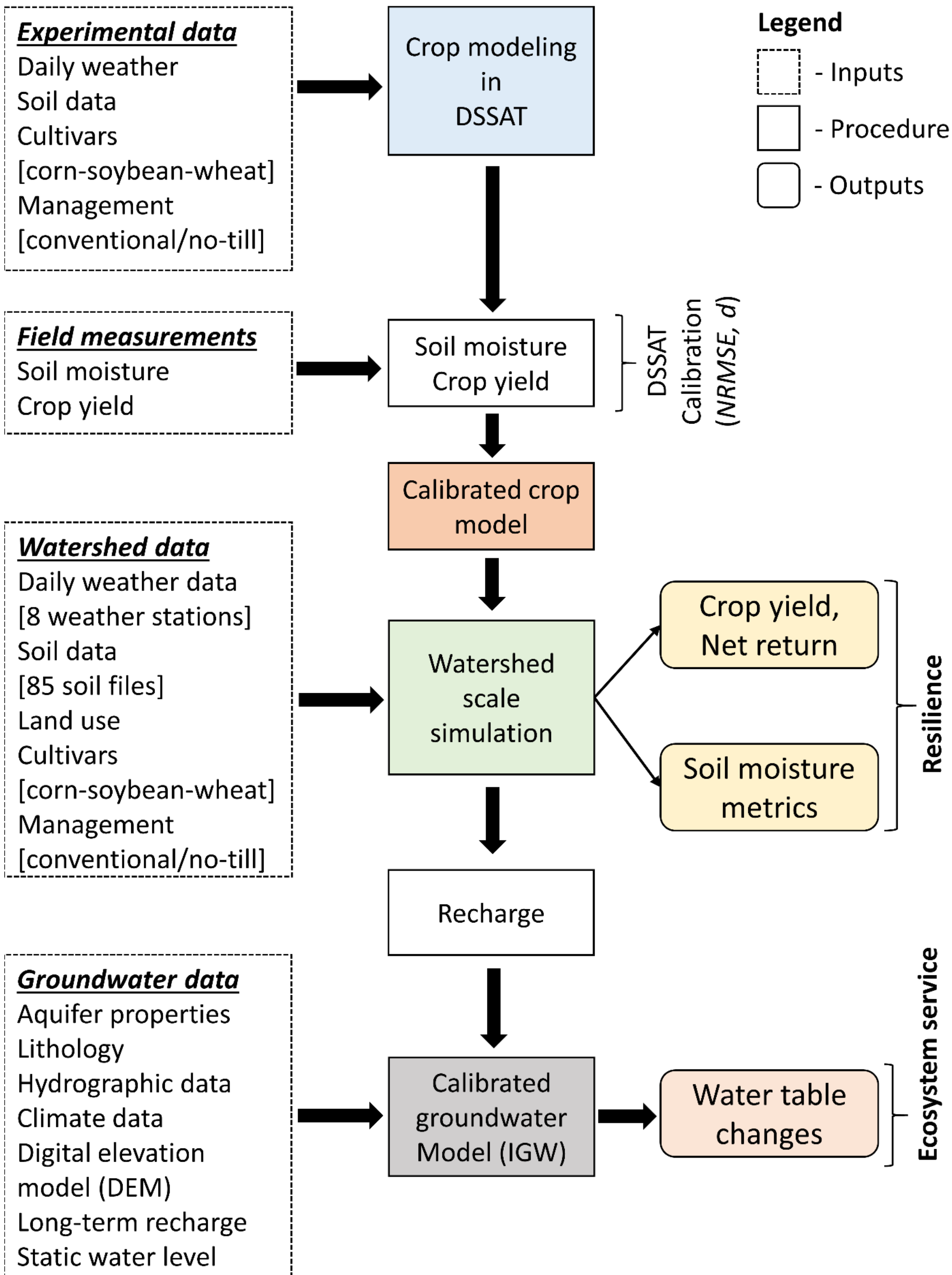
Experimental data
Daily weather
Soil data
Cultivars
[corn-soybean-wheat]
Management
[conventional/no-till]
Crop modeling in DSSAT
Legend
- Inputs
- Procedure
- Outputs
Field measurements
Soil moisture
Crop yield
Soil moisture
Crop yield
DSSAT Calibration (NRMSE, d)
Calibrated crop model
Watershed data
Daily weather data
[8 weather stations]
Soil data
[85 soil files]
Land use
Cultivars
[corn-soybean-wheat]
Management
[conventional/no-till]
Watershed scale simulation
Crop yield, Net return
Soil moisture metrics
Resilience
Recharge
Groundwater data
Aquifer properties
Lithology
Hydrographic data
Climate data
Digital elevation model (DEM)
Long-term recharge
Static water level
Calibrated groundwater Model (IGW)
Water table changes
Ecosystem service

Figure 1. An overview of the modeling process

2.2. 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.

2.2.1. 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 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.

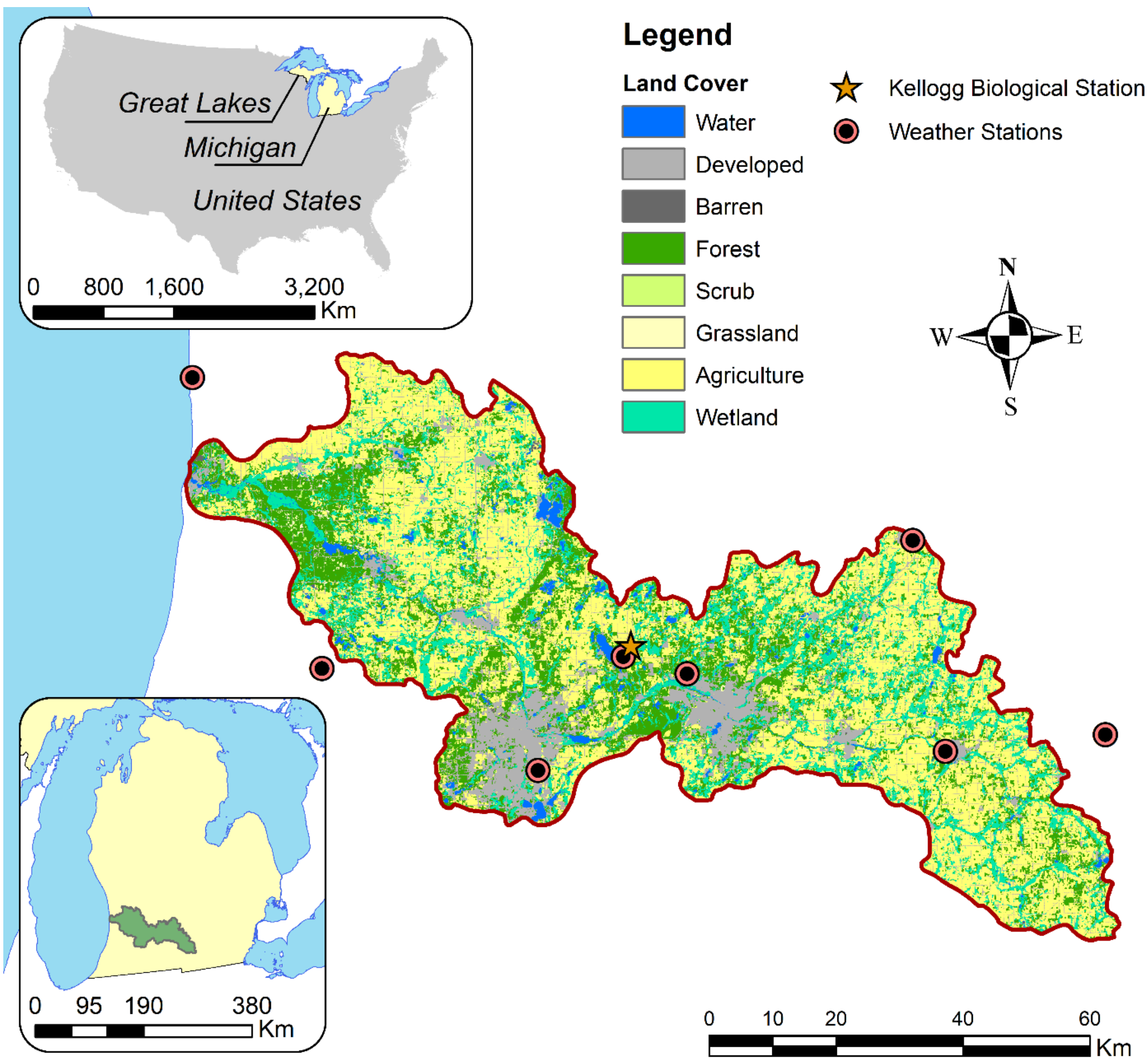

Figure 2. Location of the experimental site and the Kalamazoo River Watershed in Michigan, USA

2.1.2. Description of the Study Watershed

The study was conducted in the Kalamazoo River watershed, which is in the southwest part of Michigan, USA (Figure 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 defined 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 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 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 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.

2.3. 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. 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 basis (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 S1. Performance of the soil moisture and yield calibration was evaluated using coefficient of determination (R^2) (Equation 1), normalized root mean square error (*NRMSE*) (Equation 2), and index of agreement (*d*) (Equation 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).

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

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

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{O}| + |O_i - \bar{O}|)^2} \tag{3}$$

where, S_i is the simulated ith value, O_i is the observed ith 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.

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 4) to solve confined and unconfined flow conditions:

$$S_s \frac{\partial h}{\partial t} = \nabla(K \cdot \nabla H) + q \tag{4}$$

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. 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 aquifertests, 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 period 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 USGS NED (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 USGS NHD (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.

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. 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).

2.6. Simulation of Crop Yields and Recharge at the 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.

2.7. Assessment of Ecosystem Services and 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:

$$MRD = \frac{1}{N}\sum_{j=1}^{N}\{(\Theta_v - \overline{\Theta})/\overline{\Theta}\} \tag{5}$$

$$\overline{\Theta} = \frac{1}{n}\sum_{i=1}^{n}\Theta_v \tag{6}$$

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;

$$SWDI = \left(\frac{\Theta_v - \Theta_{fc}}{\Theta_{fc} - \Theta_{wp}}\right) \times 10 \quad (7)$$

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 8) to evaluate the significance of fixed and random effects on these response variables for each evaluated crop (i.e., corn, soybean and wheat).

$$Y_{ijk} = \mu + a_k + t_i + s_j + (ta)_{ik} + (sa)_{jk} + (ts)_{ij} + \varepsilon_{ijk} \quad (8)$$

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).

3. Results and Discussion

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 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 1).

Table 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

3.2. Calibration of Groundwater Model

The steady-state simulation results are shown in Figure S1. 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 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. Calibration results show that the model performance was good, as indicated by a strong Nash-Sutcliffe model efficiency coefficient of 0.90. Even though there was 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). 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).

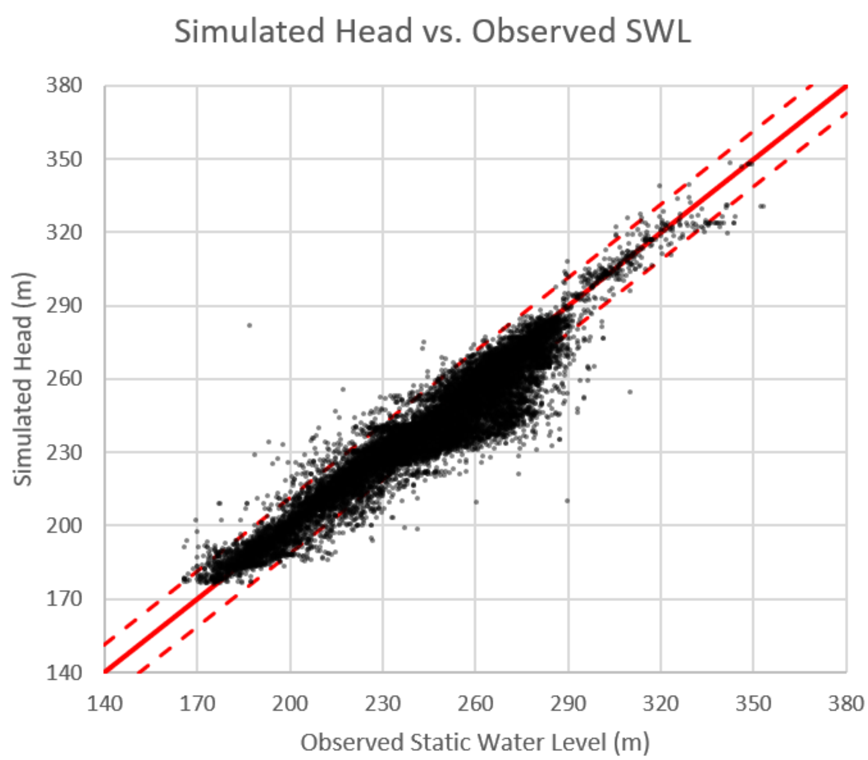

Figure 3. Comparison between simulated groundwater heads and observed groundwater heads. The solid red line in the calibration indicates a 1:1 perfect agreement. The dashed lines represent a confidence interval of one standard deviation

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.

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 S2). The means of the annual recharge across different soils and years from each crop can be seen in Figure 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 S2), the comparisons between treatments for each crop during the period of study is presented in Figure S2. 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 S2).

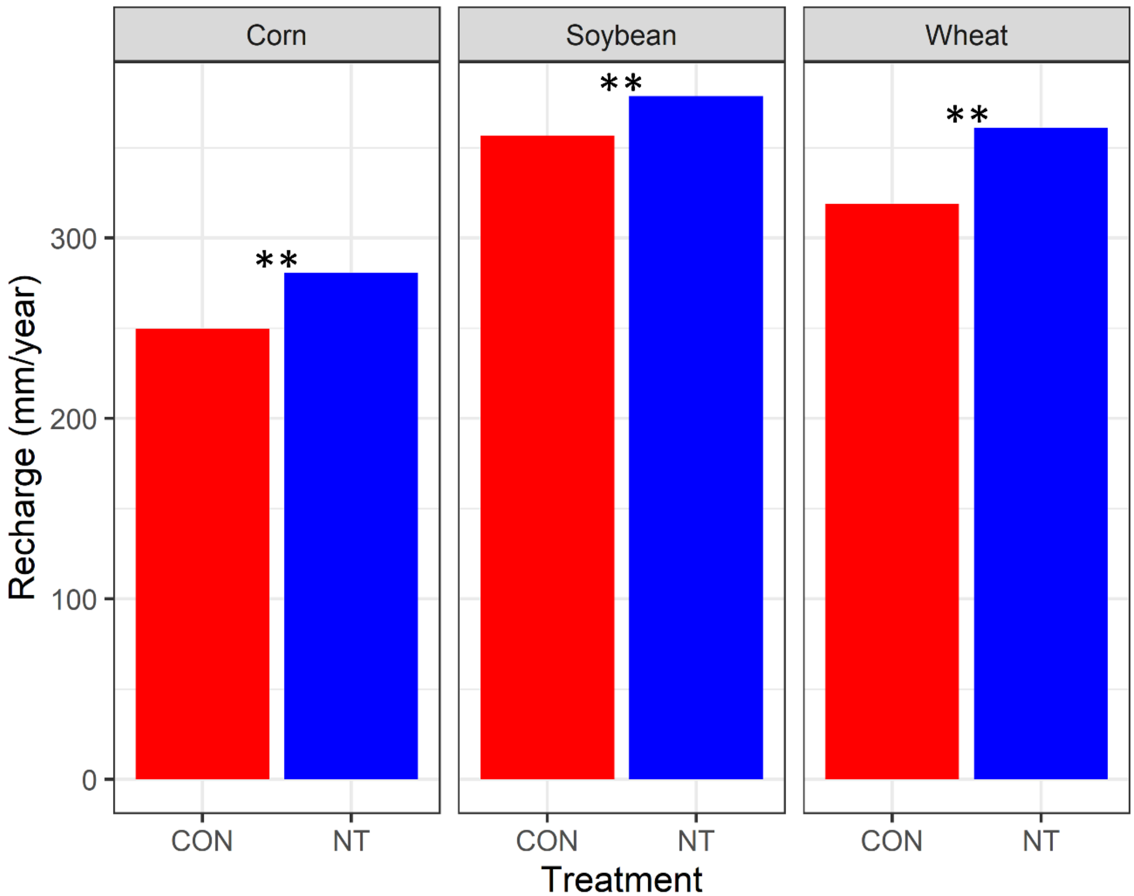

Figure 4. The mean annual recharge from different crops under two treatments in the Kalamazoo River watershed. ** indicates strongly significant means at $p<0.0001$

The results from the transient groundwater flow simulation for the conventional and no-till treatments are presented in Figures 5 and 6. Figure 5 shows the 2019 hydraulic head distribution under the conventional treatment, and the location of the six ('virtual') monitoring wells where transient head results were reported. 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). 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: 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).

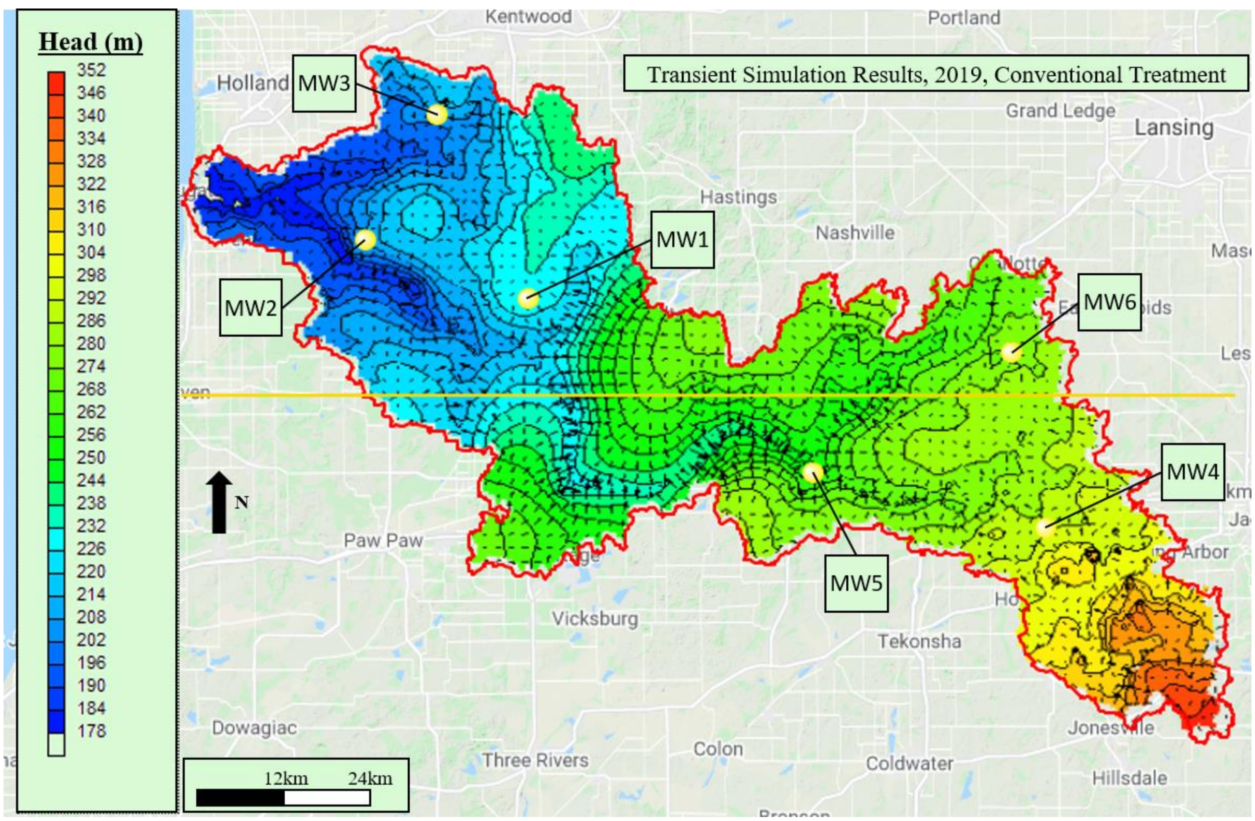

Figure 5. Monitoring well (MW) locations superimposed over the 2019 head distribution under conventional treatment

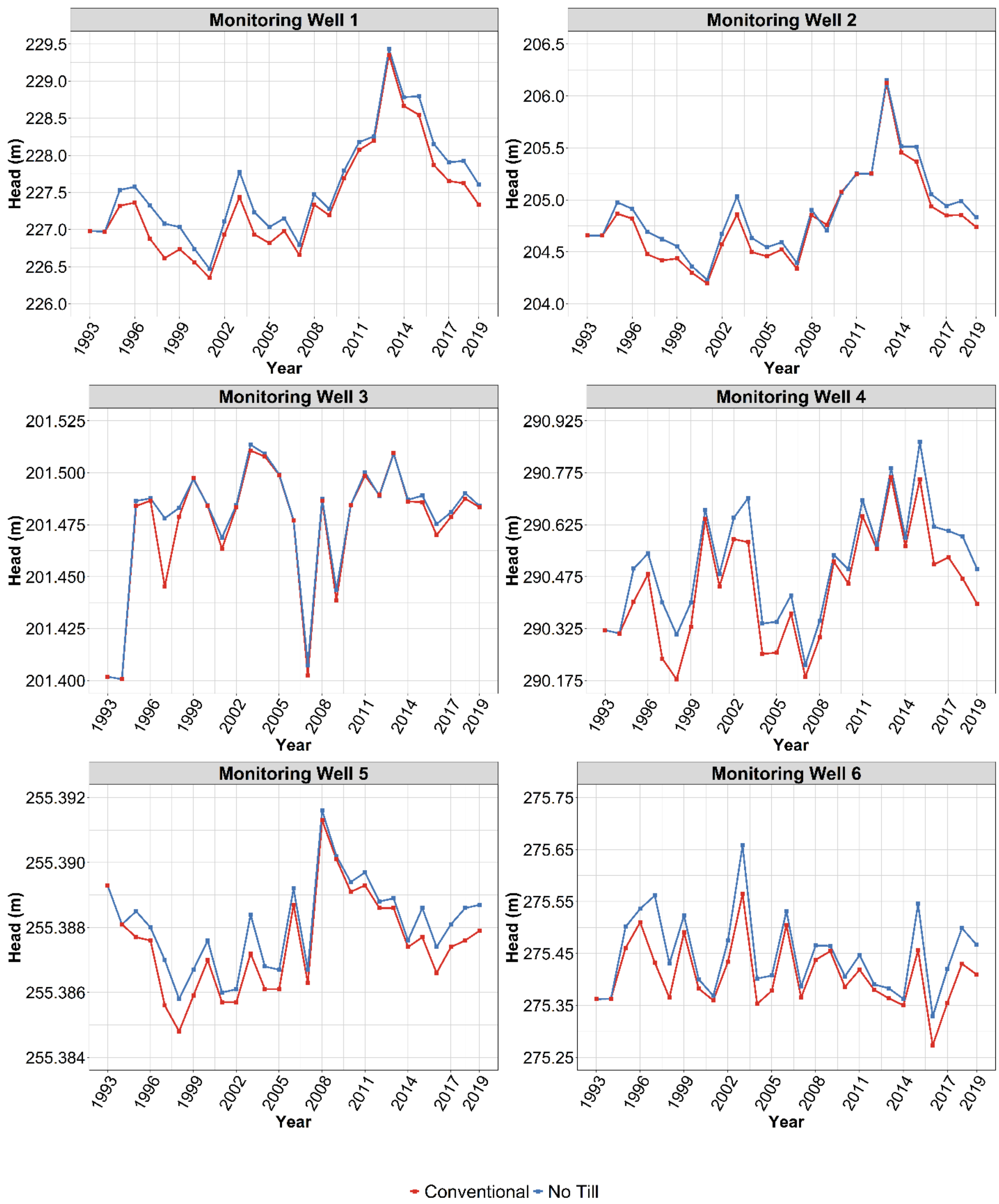

Figure 6. Simulated water table heads under the conventional and no-till treatments for the six monitoring wells

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). 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 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 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.

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 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 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 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 8. As shown in Figure 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.

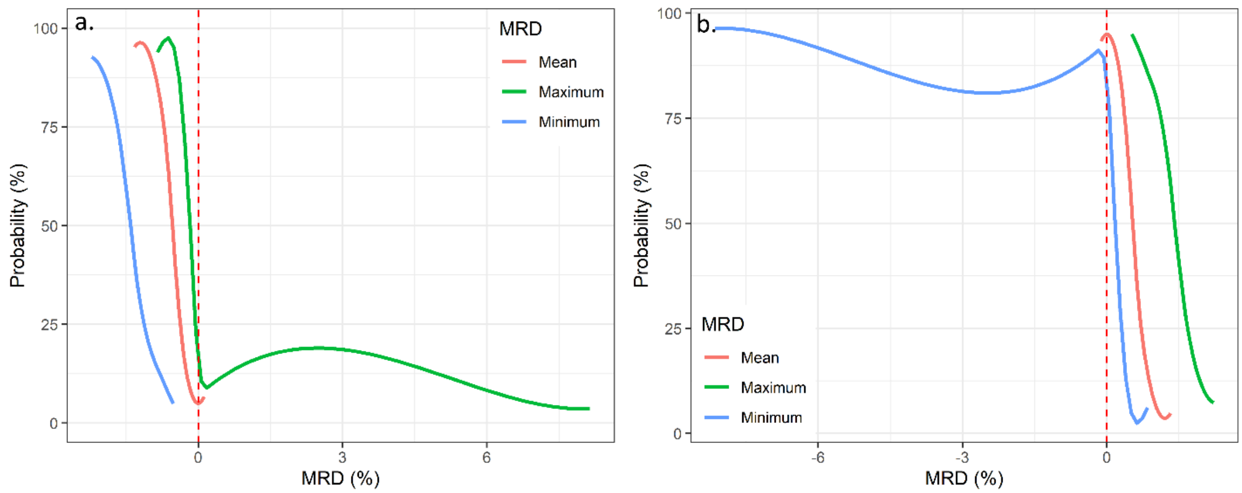

Figure 7. The probability distribution for the mean, maximum, and minimum of MRD across different soils in the Kalamazoo River watershed for the period of 1993-2019 as affected by the conventional (a) and the no-till (b) treatments. Note: Red dashed line at zero MRD indicates the demarcation, where the positive MRD values signify *wetter* treatment while the negative MRD values signify *drier* treatment

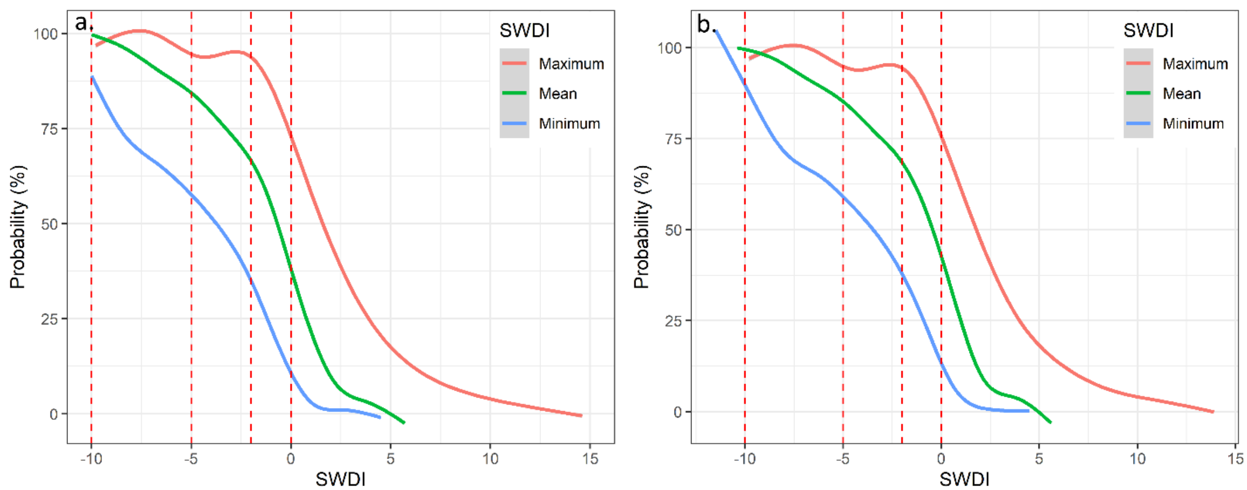

Figure 8. The probability distribution for the mean, maximum, and minimum of SWDI across different soils in the Kalamazoo River watershed for the period of 1993-2019 as affected by the conventional (a) and the no-till (b) treatments (b). Note: Red dashed lines are to demarcate different drought severity 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 is in agreement 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.

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 S2. 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 S2).

The means of crop yield and net return as separated by treatments across the years and soils are presented in Table 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 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 S3 (yield) and Figure S4 (net return). In summary, the no-till outperformed the conventional treatment in the majority of the years.

Table 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).

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.

5. Acknowledgments

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. We also thank principal investigators and staff at the KBS-LTER for their assistance in this research. This work was also supported by the USDA National Institute of Food and Agriculture, Hatch project 1019654.

6. Disclaimer

Any opinions, findings, conclusions, and recommendations reported in this paper are those of the authors and do not necessarily reflect the views of the National Science Foundation and the USDA National Institute of Food and Agriculture.

7. References

Adnan, A.A., Diels, J., Jibrin, J.M., Kamara, A.Y., Craufurd, P., Shaibu, A.S., Mohammed, I.B., Tonnang, Z.E.H., 2019. Options for calibrating CERES-maize genotype specific parameters under data-scarce environments. PLoS One 14, e0200118. https://doi.org/10.1371/journal.pone.0200118

Alexander, K., Jackson, J., Kikuyama, F., Sasamoto, B., Stevens, A., 2014. Kalamazoo River Watershed Land Conservation Plan. University of Michigan, School of Natural Resources and Environment, Ann Arbor, MI, USA.

Alizadeh, A., 2013. The Principles of Applied Hydrology, 36th Editi. ed. University of Mashhad.

Andresen, J., Hilberg, S., Kunkel, K., 2012. Historical Climate and Climate Trends in the Midwestern USA, U.S. National Climate Assessment Midwest Technical Input Report.

Araya, A., Kisekka, I., Gowda, P.H., Prasad, P.V.V., 2017. Evaluation of water-limited cropping systems in a semi-arid climate using DSSAT-CSM. Agric. Syst. 150, 86–98. https://doi.org/10.1016/j.agsy.2016.10.007

Bailey, I., Buck, L.E., 2016. Managing for resilience: a landscape framework for food and livelihood security and ecosystem services. Food Secur. 8, 477–490. https://doi.org/10.1007/s12571-016-0575-9

Biggs, R., Schlüter, M., Biggs, D., Bohensky, E.L., BurnSilver, S., Cundill, G., Dakos, V., Daw, T.M., Evans, L.S., Kotschy, K., Leitch, A.M., Meek, C., Quinlan, A., Raudsepp-Hearne, C., Robards, M.D., Schoon, M.L., Schultz, L., West, P.C., 2012. Toward Principles for Enhancing the Resilience of Ecosystem Services. Annu. Rev. Environ. Resour. 37, 421–448. https://doi.org/10.1146/annurev-environ-051211-123836

Bommarco, R., Kleijn, D., Potts, S.G., 2013. Ecological intensification: harnessing ecosystem services for food security. Trends Ecol. Evol. 28, 230–238. https://doi.org/10.1016/j.tree.2012.10.012

Boote, K.J., Jones, J.W., Pickering, N.B., 1996. Potential Uses and Limitations of Crop Models I. Model Use as a Research Tool. Agron. J. 716, 704–716.

Bowen, W.T., Thornton, P.K., Hoogenboom, G., 1998. The simulation of cropping sequences using DSSAT, in: Tsuji, G.Y., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, pp. 313–327. https://doi.org/10.1007/978-94-017-3624-4_15

Browne, N., Kingwell, R., Behrendt, R., Eckard, R., 2013. The relative profitability of dairy, sheep, beef and grain farm enterprises in southeast Australia under selected rainfall and price scenarios. Agric. Syst. 117, 35–44. https://doi.org/10.1016/j.agsy.2013.01.002

Calmon, M.A., Batchelor, W.D., Jones, J.W., Ritchie, J.T., Boote, K.J., Hammond, L.C., 1999. Simulating Soybean Root Growth and Soil Water Extraction Using a Functional Crop Model. Trans. ASAE 42, 1867–1878. https://doi.org/10.13031/2013.13352

Clemson, 2020. Agronomic Crops Enterprise Budgets [WWW Document]. Enterp. Budgets. URL https://www.clemson.edu/extension/agribusiness/enterprise-budget/index.html (accessed 6.1.20).

Coates, D., Pert, P.L., Barron, J., Muthuri, C., Nguyen-Khoa, S., Boelee, E., Jarvis, D.I., 2013. Water-related ecosystem services and food security., in: Managing Water and Agroecosystems for Food Security. CABI, Wallingford, pp. 29–41. https://doi.org/10.1079/9781780640884.0029

Cooper, D.J., Merritt, D.M., 2012. Assessing the water needs of riparian and wetland vegetation in the western United States. USDA For. Serv. - Gen. Tech. Rep. RMRS-GTR-282 1–125. https://doi.org/10.2737/RMRS-GTR-282

Corbeels, M., Sakyi, R.K., Kühne, R.F., Whitbread, A., Kühne, R.F., Whitbread, A., 2014. Meta-analysis of crop responses to conservation agriculture in sub-Saharan Africa. Copenhagen: CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS).

Costanza, R., D’Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O’Neill, R. V., Paruelo, J., Raskin, R.G., Sutton, P., van den Belt, M., 1997. The value of the world’s ecosystem services and natural capital. Nature 387, 253–260. https://doi.org/10.1038/387253a0

Crum, J.R., Collins, H.P., 1995. KBS Soils. KBS LTER Special Publication. Zenodo 1–2.

Curtis, Z.K., Li, S.-G., Liao, H.-S., Lusch, D., 2018. Data-Driven Approach for Analyzing Hydrogeology and Groundwater Quality Across Multiple Scales. Groundwater 56, 377–398. https://doi.org/10.1111/gwat.12584

Cusser, S., Bahlai, C., Swinton, S.M., Robertson, G.P., Haddad, N.M., 2020. Long-term research avoids spurious and misleading trends in sustainability attributes of no-till. Glob. Chang. Biol. 26, 3715–3725. https://doi.org/10.1111/gcb.15080

Daigh, A.L.M., Dick, W.A., Helmers, M.J., Lal, R., Lauer, J.G., Nafziger, E., Pederson, C.H., Strock, J., Villamil, M., Mukherjee, A., Cruse, R., 2018. Yields and yield stability of no-till and chisel-plow fields in the Midwestern US Corn Belt. F. Crop. Res. 218, 243–253. https://doi.org/10.1016/j.fcr.2017.04.002

Dale, V.H., Polasky, S., 2007. Measures of the effects of agricultural practices on ecosystem services. Ecol. Econ. 64, 286–296. https://doi.org/10.1016/j.ecolecon.2007.05.009

Dalin, C., Wada, Y., Kastner, T., Puma, M.J., 2017. Groundwater depletion embedded in international food trade. Nature 543, 700–704. https://doi.org/10.1038/nature21403

DeClerck, F., Jones, S., Attwood, S., Bossio, D., Girvetz, E., Chaplin-Kramer, B., Enfors, E., Fremier, A., Gordon, L., Kizito, F., Lopez Noriega, I., Matthews, N., McCartney, M., Meacham, M., Noble, A., Quintero, M., Remans, R., Soppe, R., Willemen, L., Wood, S., Zhang, W., 2016. Agricultural ecosystems and their services: the vanguard of sustainability? Curr. Opin. Environ. Sustain. 23, 92–99. https://doi.org/10.1016/j.cosust.2016.11.016

Deines, J.M., Wang, S., Lobell, D.B., 2019. Satellites reveal a small positive yield effect from conservation tillage across the US Corn Belt. Environ. Res. Lett. 14, 124038. https://doi.org/10.1088/1748-9326/ab503b

Di Falco, S., Chavas, J.P., 2008. Rainfall shocks, resilience, and the effects of crop biodiversity on agroecosystem productivity. Land Econ. 84, 83–96. https://doi.org/10.3368/le.84.1.83

Dokoohaki, H., Gheysari, M., Mousavi, S.-F., Zand-Parsa, S., Miguez, F.E., Archontoulis, S. V., Hoogenboom, G., 2016. Coupling and testing a new soil water module in DSSAT CERES-Maize model for maize production under semi-arid condition. Agric. Water Manag. 163, 90–99. https://doi.org/10.1016/j.agwat.2015.09.002

Douxchamps, S., Debevec, L., Giordano, M., Barron, J., 2017. Monitoring and evaluation of climate resilience for agricultural development – A review of currently available tools. World Dev. Perspect. 5, 10–23. https://doi.org/10.1016/j.wdp.2017.02.001

Eeswaran, R., Nejadhashemi, A.P., Alves, F.C., Saravi, B., 2021. Evaluating the applicability of soil moisture-based metrics for gauging the resiliency of rainfed agricultural systems in the midwestern United States. Soil Tillage Res. 205, 104818. https://doi.org/10.1016/j.still.2020.104818

Eitzinger, A., Läderach, P., Rodriguez, B., Fisher, M., Beebe, S., Sonder, K., Schmidt, A., 2017. Assessing high-impact spots of climate change: spatial yield simulations with Decision Support System for Agrotechnology Transfer (DSSAT) model. Mitig. Adapt. Strateg. Glob. Chang. 22, 743–760. https://doi.org/10.1007/s11027-015-9696-2

El Chami, D., Daccache, A., El Moujabber, M., 2020. How Can Sustainable Agriculture Increase Climate Resilience? A Systematic Review. Sustainability 12, 3119.

https://doi.org/10.3390/su12083119

Fang, Q., Ma, L., Yu, Q., Malone, R.W., Saseendran, S.A., Ahuja, L.R., 2008. Modeling Nitrogen and Water Management Effects in a Wheat-Maize Double-Cropping System. J. Environ. Qual. 37, 2232–2242. https://doi.org/10.2134/jeq2007.0601

Fedele, G., Locatelli, B., Djoudi, H., 2017. Mechanisms mediating the contribution of ecosystem services to human well-being and resilience. Ecosyst. Serv. 28, 43–54. https://doi.org/10.1016/j.ecoser.2017.09.011

Fisher, B., Turner, R.K., Morling, P., 2009. Defining and classifying ecosystem services for decision making. Ecol. Econ. 68, 643–653. https://doi.org/10.1016/j.ecolecon.2008.09.014

Fodor, N., Challinor, A., Droutsas, I., Ramirez-Villegas, J., Zabel, F., Koehler, A.-K., Foyer, C.H., 2017. Integrating Plant Science and Crop Modeling: Assessment of the Impact of Climate Change on Soybean and Maize Production. Plant Cell Physiol. 58, 1833–1847. https://doi.org/10.1093/pcp/pcx141

Fuchs, B.A., Wood, D.A., Ebbeka, D., 2015. From too much to too little: How the central US drought of 2012 evolved out of one of the most devastating floods on record in 2011. National Drought Mitigation Center (NDMC), University of Nebraska–Lincoln, USA.

Gaba, S., Lescourret, F., Boudsocq, S., Enjalbert, J., Hinsinger, P., Journet, E.-P., Navas, M.-L., Wery, J., Louarn, G., Malézieux, E., Pelzer, E., Prudent, M., Ozier-Lafontaine, H., 2015. Multiple cropping systems as drivers for providing multiple ecosystem services: from concepts to design. Agron. Sustain. Dev. 35, 607–623. https://doi.org/10.1007/s13593-014-0272-z

Gordon, L.J., Finlayson, C.M., Falkenmark, M., 2010. Managing water in agriculture for food production and other ecosystem services. Agric. Water Manag. 97, 512–519. https://doi.org/10.1016/j.agwat.2009.03.017

Grannemann, N.G., Hunt, R.J., Nicholas, J.., Reilly, T.E., Winter, T.., 2008. The importance of ground water in the Great Lakes Region, Water-Resources Investigations Report 00–4008, U.S. Geological Survey.

Griebler, C., Avramov, M., 2015. Groundwater ecosystem services: a review. Freshw. Sci. 34, 355–367. https://doi.org/10.1086/679903

Han, E., Ines, A., Koo, J., 2015. Global high-resolution soil profile database for crop modeling applications. Harvard Dataverse. https://doi.org/10.7910/DVN/1PEEY0

Han, E., Ines, A.V.M., Koo, J., 2019. Development of a 10-km resolution global soil profile dataset for crop modeling applications. Environ. Model. Softw. 119, 70–83. https://doi.org/10.1016/j.envsoft.2019.05.012

Hatfield, J.L., Antle, J., Garrett, K.A., Izaurralde, R.C., Mader, T., Marshall, E., Nearing, M., Philip Robertson, G., Ziska, L., 2018. Indicators of climate change in agricultural systems. Clim. Change 1–14. https://doi.org/10.1007/s10584-018-2222-2

Hatfield, Jerry, 2012. Agriculture in the Midwest, in: Winkler, J., Andresen, J., Hatfield, J, Bidwell, D., Brown, D. (Eds.), U.S. National Climate Assessment Midwest Technical Input Report. pp. 1–8.

Herberich, E., Sikorski, J., Hothorn, T., 2010. A Robust Procedure for Comparing Multiple Means under Heteroscedasticity in Unbalanced Designs. PLoS One 5, e9788.

https://doi.org/10.1371/journal.pone.0009788

Holtschlag, D.., 1997. A generalized estimate of ground-water-recharge rates in the Lower Peninsula of Michigan. Department of the Interior, US Geological Survey, Washington, DC.

Homer, C., Dewitz, J., Jin, S., Xian, G., Costello, C., Danielson, P., Gass, L., Funk, M., Wickham, J., Stehman, S., Auch, R., Riitters, K., 2020. Conterminous United States land cover change patterns 2001–2016 from the 2016 National Land Cover Database. ISPRS J. Photogramm. Remote Sens. 162, 184–199. https://doi.org/10.1016/j.isprsjprs.2020.02.019

Hoogenboom, G., Porter, C.H., Shelia, V., Boote, K.J., Singh, U., White, J.W., Hunt, L.A., Ogoshi, R., Lizaso, J.I., Koo, J., Asseng, S., Singels, A., Moreno, L.P., Jones, J.W., 2019. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7.5 (https://DSSAT.net), DSSAT Foundation, Gainesville, Florida, USA.

Iocola, I., Bassu, S., Farina, R., Antichi, D., Basso, B., Bindi, M., Dalla Marta, A., Danuso, F., Doro, L., Ferrise, R., Giglio, L., Ginaldi, F., Mazzoncini, M., Mula, L., Orsini, R., Corti, G., Pasqui, M., Seddaiu, G., Tomozeiu, R., Ventrella, D., Villani, G., Roggero, P.P., 2017. Can conservation tillage mitigate climate change impacts in Mediterranean cereal systems? A soil organic carbon assessment using long term experiments. Eur. J. Agron. 90, 96–107. https://doi.org/10.1016/j.eja.2017.07.011

Jin, Z., Ainsworth, E.A., Leakey, A.D.B., Lobell, D.B., 2018. Increasing drought and diminishing benefits of elevated carbon dioxide for soybean yields across the US Midwest. Glob. Chang. Biol. 24, e522–e533. https://doi.org/10.1111/gcb.13946

Jones, J.W., Antle, J.M., Basso, B., Boote, K.J., Conant, R.T., Foster, I., Godfray, H.C.J., Herrero, M., Howitt, R.E., Janssen, S., Keating, B.A., Munoz-Carpena, R., Porter, C.H., Rosenzweig, C., Wheeler, T.R., 2017. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. Agric. Syst. 155, 269–288. https://doi.org/10.1016/j.agsy.2016.09.021

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Jones, P.G., Thornton, P.K., 2009. Croppers to livestock keepers: livelihood transitions to 2050 in Africa due to climate change. Environ. Sci. Policy 12, 427–437. https://doi.org/10.1016/j.envsci.2008.08.006

Kandulu, J.M., Bryan, B.A., King, D., Connor, J.D., 2012. Mitigating economic risk from climate variability in rain-fed agriculture through enterprise mix diversification. Ecol. Econ. 79, 105–112. https://doi.org/10.1016/j.ecolecon.2012.04.025

Kassam, A., Friedrich, T., Derpsch, R., 2019. Global spread of Conservation Agriculture. Int. J. Environ. Stud. 76, 29–51. https://doi.org/10.1080/00207233.2018.1494927

Komarek, A.M., Bell, L.W., Whish, J.P.M., Robertson, M.J., Bellotti, W.D., 2015. Whole-farm economic, risk and resource-use trade-offs associated with integrating forages into crop-livestock systems in western China. Agric. Syst. 133, 63–72. https://doi.org/10.1016/j.agsy.2014.10.008

Kravchenko, A.N., Wang, A.N.W., Smucker, A.J.M., Rivers, M.L., 2011. Long-term Differences in Tillage and Land Use Affect Intra-aggregate Pore Heterogeneity. Soil Sci. Soc. Am. J. 75, 1658–1666. https://doi.org/10.2136/sssaj2011.0096

Kropp, I., Nejadhashemi, A.P., Deb, K., Abouali, M., Roy, P.C., Adhikari, U., Hoogenboom, G., 2019. A multi-objective approach to water and nutrient efficiency for sustainable agricultural intensification. Agric. Syst. 173, 289–302. https://doi.org/10.1016/j.agsy.2019.03.014

KRWC, 2011. Kalamazoo River Watershed Management Plan. Kalamazoo River Watershed Council, Prepared for the Michigan Nonpoint Source Program (Michigan Department of Environmental Quality and the United States Environmental Protection Agency).

Lal, R., 2013. Enhancing ecosystem services with no-till. Renew. Agric. Food Syst. 28, 102–114. https://doi.org/10.1017/S1742170512000452

Lal, R., Delgado, J.A., Gulliford, J., Nielsen, D., Rice, C.W., Pelt, R.S. Van, 2012. Adapting agriculture to drought and extreme events. J. Soil Water Conserv. 67, 162–166. https://doi.org/10.2489/jswc.67.6.162A

Lampurlanés, J., Plaza-Bonilla, D., Álvaro-Fuentes, J., Cantero-Martínez, C., 2016. Long-term analysis of soil water conservation and crop yield under different tillage systems in Mediterranean rainfed conditions. F. Crop. Res. 189, 59–67. https://doi.org/10.1016/j.fcr.2016.02.010

Landis, D.A., 2017. Designing agricultural landscapes for biodiversity-based ecosystem services. Basic Appl. Ecol. 18, 1–12. https://doi.org/10.1016/j.baae.2016.07.005

Leng, G., Peng, J., Huang, S., 2019. Recent changes in county-level maize production in the United States: Spatial-temporal patterns, climatic drivers and the implications for crop modelling. Sci. Total Environ. 686, 819–827. https://doi.org/10.1016/j.scitotenv.2019.06.026

Li, S.G., Liu, Q., 2006. A Real-Time, Interactive Steering Environment for Integrated Ground Water Modeling. Ground Water 44, 758–763. https://doi.org/10.1111/j.1745-6584.2006.00225.x

Liao, H.S., Curtis, Z.K., Sampath, P.V., Li, S.G., 2020. Simulation of Flow in a Complex Aquifer System Subjected to Long-Term Well Network Growth. Groundwater 58, 301–322. https://doi.org/10.1111/gwat.12918

Liao, H.S., Sampath, P. V., Curtis, Z.K., Li, S.G., 2015a. Hierarchical modeling of a groundwater remediation capture system. J. Hydrol. 527, 196–211. https://doi.org/10.1016/j.jhydrol.2015.04.057

Liao, H.S., Sampath, P. V., Curtis, Z.K., Li, S.G., 2015b. Hierarchical Modeling and Parameter Estimation for a Coupled Groundwater–Lake System. J. Hydrol. Eng. 20, 04015027. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001219

Liu, S., Yang, J.Y., Zhang, X.Y., Drury, C.F., Reynolds, W.D., Hoogenboom, G., 2013. Modelling crop yield, soil water content and soil temperature for a soybean–maize rotation under conventional and conservation tillage systems in Northeast China. Agric. Water Manag. 123, 32–44. https://doi.org/10.1016/j.agwat.2013.03.001

Malik, W., Dechmi, F., 2019. DSSAT modelling for best irrigation management practices assessment under Mediterranean conditions. Agric. Water Manag. 216, 27–43. https://doi.org/10.1016/j.agwat.2019.01.017

Martin, G., Magne, M.A., 2015. Agricultural diversity to increase adaptive capacity and reduce vulnerability of livestock systems against weather variability - A farm-scale simulation study. Agric. Ecosyst. Environ. 199, 301–311. https://doi.org/10.1016/j.agee.2014.10.006

Martínez-Fernández, J., González-Zamora, A., Sánchez, N., Gumuzzio, A., 2015. A soil water based index as a suitable agricultural drought indicator. J. Hydrol. 522, 265–273. https://doi.org/10.1016/j.jhydrol.2014.12.051

McLaughlin, D.L., Cohen, M.J., 2013. Realizing ecosystem services: wetland hydrologic function along a gradient of ecosystem condition. Ecol. Appl. 23, 1619–1631. https://doi.org/10.1890/12-1489.1

MDEQ, 2020. Wellogic System (periodically updated) [WWW Document]. Michigan Dep. Environ. Qual. URL https://secure1.state.mi.us/wellogic/ (accessed 9.20.20).

MEA, 2005. Millennium Ecosystem Assessment-Ecosystems and Human Well-being: Synthesis. Island Press, Washington, DC. https://doi.org/10.5822/978-1-61091-484-0_1

Mengist, W., Soromessa, T., Feyisa, G.L., 2020. A global view of regulatory ecosystem services: existed knowledge, trends, and research gaps. Ecol. Process. 9, 40. https://doi.org/10.1186/s13717-020-00241-w

Milliken, G.., Johnson, D.., 2009. Analysis of messy data, Volume I: Designed Experiments, 2nd editio. ed. Chapman and Hall/CRC.

Moebius-Clune, B.N., van Es, H.M., Idowu, O.J., Schindelbeck, R.R., Moebius-Clune, D.J., Wolfe, D.W., Abawi, G.S., Thies, J.E., Gugino, B.K., Lucey, R., 2008. Long-Term Effects of Harvesting Maize Stover and Tillage on Soil Quality. Soil Sci. Soc. Am. J. 72, 960–969. https://doi.org/10.2136/sssaj2007.0248

Montoya, J.M., Raffaelli, D., 2010. Climate change, biotic interactions and ecosystem services. Philos. Trans. R. Soc. B Biol. Sci. 365, 2013–2018. https://doi.org/10.1098/rstb.2010.0114

Munang, R., Thiaw, I., Alverson, K., Liu, J., Han, Z., 2013. The role of ecosystem services in climate change adaptation and disaster risk reduction. Curr. Opin. Environ. Sustain. 5, 47–52. https://doi.org/10.1016/j.cosust.2013.02.002

NED USGS. 2006. National Elevation Dataset. Reston, Virginia: U.S. Geological Survey. http://ned.usgs.gov/Ned/about.asp

NHD USGS. 2010. USGS: National Hydrography Dataset.Reston, Virginia: U.S. Geological Survey. http://nhd.usgs.gov/index.html

NRCS, 2020. Web Soil Survey [WWW Document]. United States Dep. Agric. URL http://websoilsurvey.sc.egov.usda.gov/ (accessed 8.28.20).

Nunes, M.R., van Es, H.M., Schindelbeck, R., Ristow, A.J., Ryan, M., 2018. No-till and cropping system diversification improve soil health and crop yield. Geoderma 328, 30–43. https://doi.org/10.1016/j.geoderma.2018.04.031

Oppedahl, D.B., 2018. Midwest agriculture’s ties to the global economy. Chicago Fed Lett.

Parton, W.J., 1996. The CENTURY model, in: Powlson, D.S., Smith, P., Smith, J.. (Eds.), Evaluation of Soil Organic Matter Models. Springer-Verlag Berlin Heidelherg, pp. 283–291. https://doi.org/10.1007/978-3-642-61094-3_23

Pickering, N.B., Hansen, J.W., Jones, J.W., Wells, C.M., Chan, V.K., Godwin, D.C., 1994. WeatherMan: A Utility for Managing and Generating Daily Weather Data. Agron. J. 86, 332–337. https://doi.org/10.2134/agronj1994.00021962008600020023x

Pittelkow, C.M., Linquist, B.A., Lundy, M.E., Liang, X., Van Groenigen, K.., Lee, J., Van Gestel, N., Six, J., Venterea, R.T., Van Kessel, C., 2015. When does no-till yield more ? A global meta-analysis. F. Crop. Res. 183, 156–168. https://doi.org/10.1016/j.fcr.2015.07.020

Power, A.G., 2010. Ecosystem services and agriculture: tradeoffs and synergies. Philos. Trans. R. Soc. B Biol. Sci. 365, 2959–2971. https://doi.org/10.1098/rstb.2010.0143

Powlson, D.S., Stirling, C.M., Jat, M.L., Gerard, B.G., Palm, C.A., Sanchez, P.A., Cassman, K.G., 2014. Limited potential of no-till agriculture for climate change mitigation. Nat. Clim. Chang. 4, 678–683. https://doi.org/10.1038/nclimate2292

Priestley, C.H.B., Taylor, R.J., 1972. On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. Mon. Weather Rev. 100, 81–92. https://doi.org/10.1175/1520-0493(1972)100<0081:otaosh>2.3.co;2

Prudencio, L., Null, S.E., 2018. Stormwater management and ecosystem services: a review. Environ. Res. Lett. 13, 033002. https://doi.org/10.1088/1748-9326/aaa81a

Reitz, M., Sanford, W.E., Senay, G.B., Cazenas, J., 2017. Annual Estimates of Recharge, Quick-Flow Runoff, and Evapotranspiration for the Contiguous U.S. Using Empirical Regression Equations. JAWRA J. Am. Water Resour. Assoc. 53, 961–983. https://doi.org/10.1111/1752-1688.12546

Rigolot, C., de Voil, P., Douxchamps, S., Prestwidge, D., Van Wijk, M., Thornton, P.K., Rodriguez, D., Henderson, B., Medina, D., Herrero, M., 2017. Interactions between intervention packages, climatic risk, climate change and food security in mixed crop–livestock systems in Burkina Faso. Agric. Syst. 151, 217–224. https://doi.org/10.1016/j.agsy.2015.12.017

Ritchie, J.T., 1998. Soil water balance and plant water stress, in: Tsuji, G.Y., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, pp. 41–54. https://doi.org/10.1007/978-94-017-3624-4_3

Robertson, G.P;, Hamilton, S.., 2015. Long-Term Ecological Research at the Kellogg Biological Station LTER Site, in: Hamilton, S.., Doll, J.., Robertson, G.P (Eds.), The Ecology of Agricultural Landscapes: Long-Term Research on the Path to Sustainability. Oxford University Press, New York, USA, pp. 1–32.

Robertson, G.P., Swinton, S.M., 2005. Reconciling Agricultural Productivity and Environmental Integrity: A Grand Challenge for Agriculture. Front. Ecol. Environ. 3, 38. https://doi.org/10.2307/3868443

Rosenzweig, C., Elliott, J., Deryng, D., Ruane, A.C., Müller, C., Arneth, A., Boote, K.J., Folberth, C., Glotter, M., Khabarov, N., Neumann, K., Piontek, F., Pugh, T.A.M., Schmid, E., Stehfest, E., Yang, H., Jones, J.W., 2014. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proc. Natl. Acad. Sci. 111, 3268–3273. https://doi.org/10.1073/pnas.1222463110

Rötter, R.P., Appiah, M., Fichtler, E., Kersebaum, K.C., Trnka, M., Hoffmann, M.., 2018. Linking modelling and experimentation to better capture crop impacts of agroclimatic extremes—A review. F. Crop. Res. 221, 142–156. https://doi.org/10.1016/j.fcr.2018.02.023

Roy, P.C., Guber, A., Abouali, M., Nejadhashemi, A.P., Deb, K., Smucker, A.J.M., 2019. Crop yield simulation optimization using precision irrigation and subsurface water retention technology. Environ. Model. Softw. 119, 433–444. https://doi.org/10.1016/j.envsoft.2019.07.006

Rusinamhodzi, L., Corbeels, M., Van Wijk, M.., Rufino, M.., Nyamangara, J., Giller, K.., 2011.

A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions. Agron. Sustain. Dev. 31, 657–673. https://doi.org/10.1007/s13593-011-0040-2

Salmerón, M., Cavero, J., Isla, R., Porter, C.H., Jones, J.W., Boote, K.J., 2014. DSSAT Nitrogen Cycle Simulation of Cover Crop-Maize Rotations under Irrigated Mediterranean Conditions. Agron. J. 106, 1283–1296. https://doi.org/10.2134/agronj13.0560

Sampath, P.V., Liao, H.S., Curtis, Z.K., Doran, P.J., Herbert, M.E., May, C.A., Li, S.G., 2015. Understanding the Groundwater Hydrology of a Geographically-Isolated Prairie Fen: Implications for Conservation. PLoS One 10, e0140430. https://doi.org/10.1371/journal.pone.0140430

Sampath, P.V., Liao, H.S., Curtis, Z.K., Herbert, M.E., Doran, P.J., May, C.A., Landis, D.A., Li, S.G., 2016. Understanding fen hydrology across multiple scales. Hydrol. Process. 30, 3390–3407. https://doi.org/10.1002/hyp.10865

Scanlon, B.R., Faunt, C.C., Longuevergne, L., Reedy, R.C., Alley, W.M., McGuire, V.L., McMahon, P.B., 2012. Groundwater depletion and sustainability of irrigation in the US High Plains and Central Valley. Proc. Natl. Acad. Sci. 109, 9320–9325. https://doi.org/10.1073/pnas.1200311109

Schaetzl, R.J., Darden, J.T., Brandt, D, S., 2009. Michigan Geography and Geology. Pearson Custom Publishing, New York.

Scherr, S.J., Shames, S., Friedman, R., 2012. From climate-smart agriculture to climate-smart landscapes. Agric. Food Secur. 1, 12. https://doi.org/10.1186/2048-7010-1-12

SCS, 1985. National Engineering Handbook Section 4: Hydrology. Soil Conservation Service, United States Department of Agriculture, Washington, DC.

Serfilippi, E., Ramnath, G., 2018. Resilience Measurement and Conceptual Frameworks: a Review of the Literature. Ann. Public Coop. Econ. 89, 645–664. https://doi.org/10.1111/apce.12202

Serna-Chavez, H.M., Schulp, C.J.E., van Bodegom, P.M., Bouten, W., Verburg, P.H., Davidson, M.D., 2014. A quantitative framework for assessing spatial flows of ecosystem services. Ecol. Indic. 39, 24–33. https://doi.org/10.1016/j.ecolind.2013.11.024

Sharpley, A.N., Williams, J.R., 1990. EPIC-The erosion/productivity impact calculator: 1. Model Documentation. U.S. Dep. Agric. Tech. Bull. 235.

Shelia, V., Sharda, V., Hansen, J., Porter, C., Zhang, M., Aggarwal, P., Hoogenboom, G., 2015. CCAFS Regional Agricultural Forecasting Toolbox (CRAFT): software for forecasting of crop production, risk analysis and climate change impact studies, in: 2015 ASABE International Meeting. American Society of Agricultural and Biological Engineers, pp. 1094–1116. https://doi.org/10.13031/aim.20152182505

Siebert, S., Burke, J., Faures, J.M., Frenken, K., Hoogeveen, J., Döll, P., Portmann, F.T., 2010. Groundwater use for irrigation – a global inventory. Hydrol. Earth Syst. Sci. 14, 1863–1880. https://doi.org/10.5194/hess-14-1863-2010

Smidt, S.J., Haacker, E.M.K., Kendall, A.D., Deines, J.M., Pei, L., Cotterman, K.A., Li, H., Liu, X., Basso, B., Hyndman, D.W., 2016. Complex water management in modern agriculture: Trends in the water-energy-food nexus over the High Plains Aquifer. Sci. Total Environ. 566–567, 988–1001. https://doi.org/10.1016/j.scitotenv.2016.05.127

State of Michigan, 2006. Public Act 148—Groundwater inventory and map project (GWIM): Executive Summary. Michigan State University, East Lansing, MI, USA.

Suleiman, A.A., Ritchie, J.T., 2003. Modeling Soil Water Redistribution during Second-Stage Evaporation. Soil Sci. Soc. Am. J. 67, 377–386. https://doi.org/10.2136/sssaj2003.3770

Swift, M.J., Izac, A.-M.N., van Noordwijk, M., 2004. Biodiversity and ecosystem services in agricultural landscapes—are we asking the right questions? Agric. Ecosyst. Environ. 104, 113–134. https://doi.org/10.1016/j.agee.2004.01.013

Swinton, S.M., Lupi, F., Robertson, G.P., Hamilton, S.K., 2007. Ecosystem services and agriculture: Cultivating agricultural ecosystems for diverse benefits. Ecol. Econ. 64, 245–252. https://doi.org/10.1016/j.ecolecon.2007.09.020

Syswerda, S.P., Robertson, G.P., 2014. Ecosystem services along a management gradient in Michigan (USA) cropping systems. Agric. Ecosyst. Environ. 189, 28–35. https://doi.org/10.1016/j.agee.2014.03.006

Tancoigne, E., Barbier, M., Cointet, J.-P., Richard, G., 2014. The place of agricultural sciences in the literature on ecosystem services. Ecosyst. Serv. 10, 35–48. https://doi.org/10.1016/j.ecoser.2014.07.004

Teixeira, W.W.R., Battisti, R., Sentelhas, P.C., Moraes, M.F., Oliveira Junior, A., 2019. Uncertainty assessment of soya bean yield gaps using DSSAT-CSM-CROPGRO-Soybean calibrated by cultivar maturity groups. J. Agron. Crop Sci. 205, 533–544. https://doi.org/10.1111/jac.12343

Thierfelder, C., Wall, P.C., 2010. Investigating Conservation Agriculture (CA) Systems in

Zambia and Zimbabwe to Mitigate Future Effects of Climate Change. J. Crop Improv. 24, 113–121. https://doi.org/10.1080/15427520903558484

Thiessen, A.H., 1911. Precipitation avarages for large areas. Mon. Weather Rev. 39, 1082–1084. https://doi.org/10.1175/1520-0493(1911)39<1082b:PAFLA>2.0.CO;2

Thorp, K.R., DeJonge, K.C., Kaleita, A.L., Batchelor, W.D., Paz, J.O., 2008. Methodology for the use of DSSAT models for precision agriculture decision support. Comput. Electron. Agric. 64, 276–285. https://doi.org/10.1016/j.compag.2008.05.022

USDA, 2019. Agricultural Prices. National Agricultural Statistics Service (NASS), United States Department of Agriculture, Washington, DC.

Vachaud, G., Passerat de Silans, A. Balabanis, P., Vauclin, M., 1985. Temporal Stability of Spatially Measured Soil Water Probability Density Function. Soil Sci. Soc. Am. J. 49, 822–828.

Verhulst, N., Nelissen, V., Jespers, N., Haven, H., Sayre, K.D., Raes, D., Deckers, J., Govaerts, B., 2011. Soil water content, maize yield and its stability as affected by tillage and crop residue management in rainfed semi-arid highlands. Plant Soil 344, 73–85. https://doi.org/10.1007/s11104-011-0728-8

Wada, Y., van Beek, L.P.H., van Kempen, C.M., Reckman, J.W.T.M., Vasak, S., Bierkens, M.F.P., 2010. Global depletion of groundwater resources. Geophys. Res. Lett. 37, n/a-n/a. https://doi.org/10.1029/2010GL044571

Walker, B., Holling, C.S., Carpenter, S.R., Kinzig, A., 2004. Resilience , Adaptability and Transformability in Social – ecological Systems. Ecol. Soc. 9, 5.

Wang, R., Bowling, L.C., Cherkauer, K.A., 2016. Estimation of the effects of climate variability on crop yield in the Midwest USA. Agric. For. Meteorol. 216, 141–156. https://doi.org/10.1016/j.agrformet.2015.10.001

Wesley, J., 2005. Kalamazoo River Assessment. Michigan Department of Natural Resources, Fisheries Division, Special Report 35, Ann Arbor, MI, USA.

Willmott, C.J., 1982. Some Comments on the Evaluation of Model Performance. Bull. Am. Meteorol. Soc. 63, 1309–1313. https://doi.org/10.1175/1520-0477(1982)063<1309:SCOTEO>2.0.CO;2

Wood, S.A., Karp, D.S., DeClerck, F., Kremen, C., Naeem, S., Palm, C.A., 2015. Functional traits in agriculture: agrobiodiversity and ecosystem services. Trends Ecol. Evol. 30, 531–539. https://doi.org/10.1016/j.tree.2015.06.013

Xiang, Z., Bailey, R.T., Nozari, S., Husain, Z., Kisekka, I., Sharda, V., Gowda, P., 2020. DSSAT-MODFLOW: A new modeling framework for exploring groundwater conservation strategies in irrigated areas. Agric. Water Manag. 232, 106033. https://doi.org/10.1016/j.agwat.2020.106033

Yang, J.M., Yang, J.Y., Liu, S., Hoogenboom, G., 2014. An evaluation of the statistical methods for testing the performance of crop models with observed data. Agric. Syst. 127, 81–89. https://doi.org/10.1016/j.agsy.2014.01.008

Zhang, X.Q., Pu, C., Zhao, X., Xue, J.-F., Zhang, R., Nie, Z.-J., Chen, F., Lal, R., Zhang, H.-L., 2016. Tillage effects on carbon footprint and ecosystem services of climate regulation in a winter wheat–summer maize cropping system of the North China Plain. Ecol. Indic. 67, 821–829. https://doi.org/10.1016/j.ecolind.2016.03.046

Supplementary Material

Quantification of Resilience Metrics as Affected by a Conservation Agricultural Practice at a Watershed Scale

Rasu Eeswaran [a], A. Pouyan Nejadhashemi [a, b, *], Josué Kpodo [b, c], Zachary K. Curtis [d], Umesh Adhikari [d], Huasheng Liao [d], Shu-Guang Li [d,e], J. Sebastian Hernandez-Suarez [b], Filipe Couto Alves [f], Anna Raschke [b], Prakash Kumar Jha [g]

[a] Department of Plant, Soil and Microbial Sciences Michigan State University, East Lansing, MI 48824 USA

[b] Department of Biosystems and Agricultural Engineering, Michigan State University, East Lansing, MI 48824 USA

[c] Department of Computer Science and Engineering, Michigan State University, East Lansing, MI 48824 USA

[d]Hydrosimulatics inc., 721 N Captial Ave. Ste. 2, Lansing, MI 48906 USA

[e] Department of Civil and Environmental Engineering, Michigan State University, East Lansing, MI 48824 USA

[f] Department of Epidemiology and Biostatistics, Michigan State University, East Lansing, MI 48824 USA

[g] Feed the Future Innovation Lab for Collaborative Research on Sustainable Intensification, Kansas State University, Manhattan, KS, 66506 USA

* Corresponding author: Tel.: +1 (517) 432-7653 Fax: +1 (517) 432-2892. Email address: pouyan@msu.edu

Table S1. 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 S2. 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

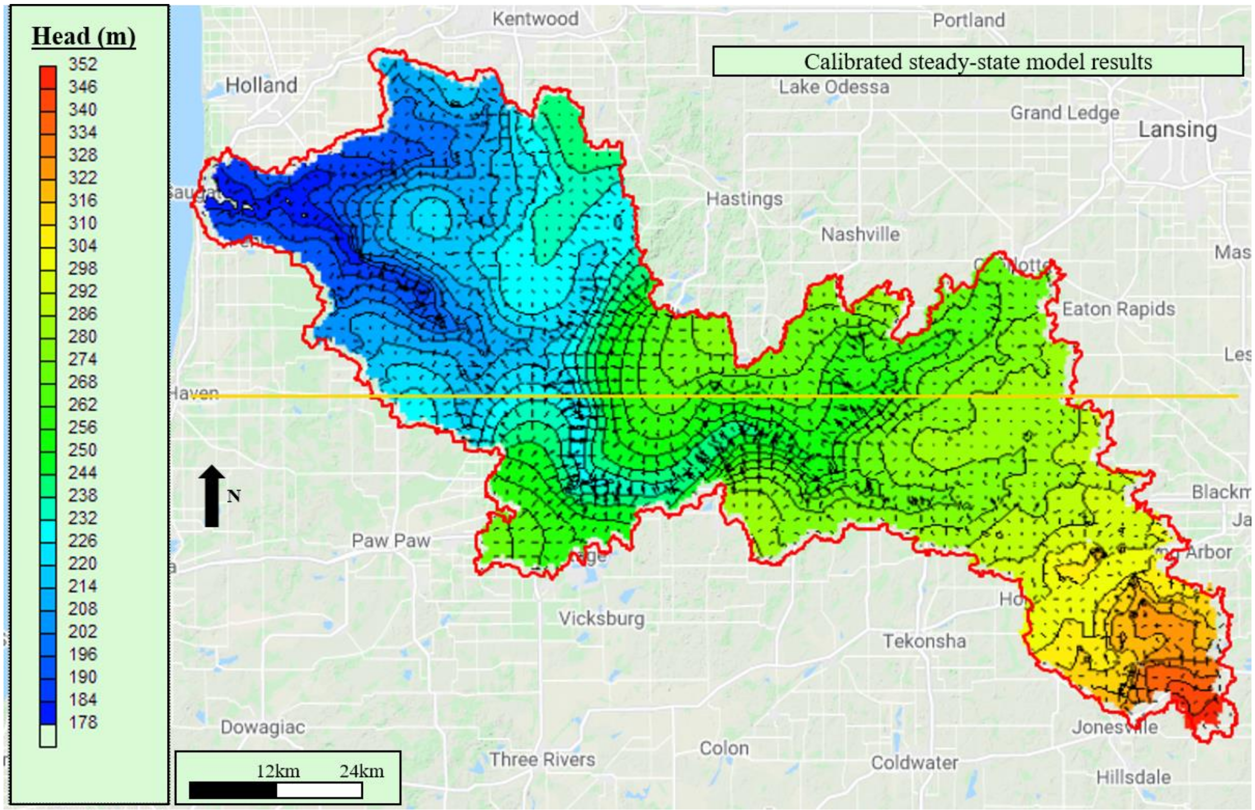

Figure S1. Results of the calibrated steady-state groundwater model including head contours, color map for head, and velocity vectors.

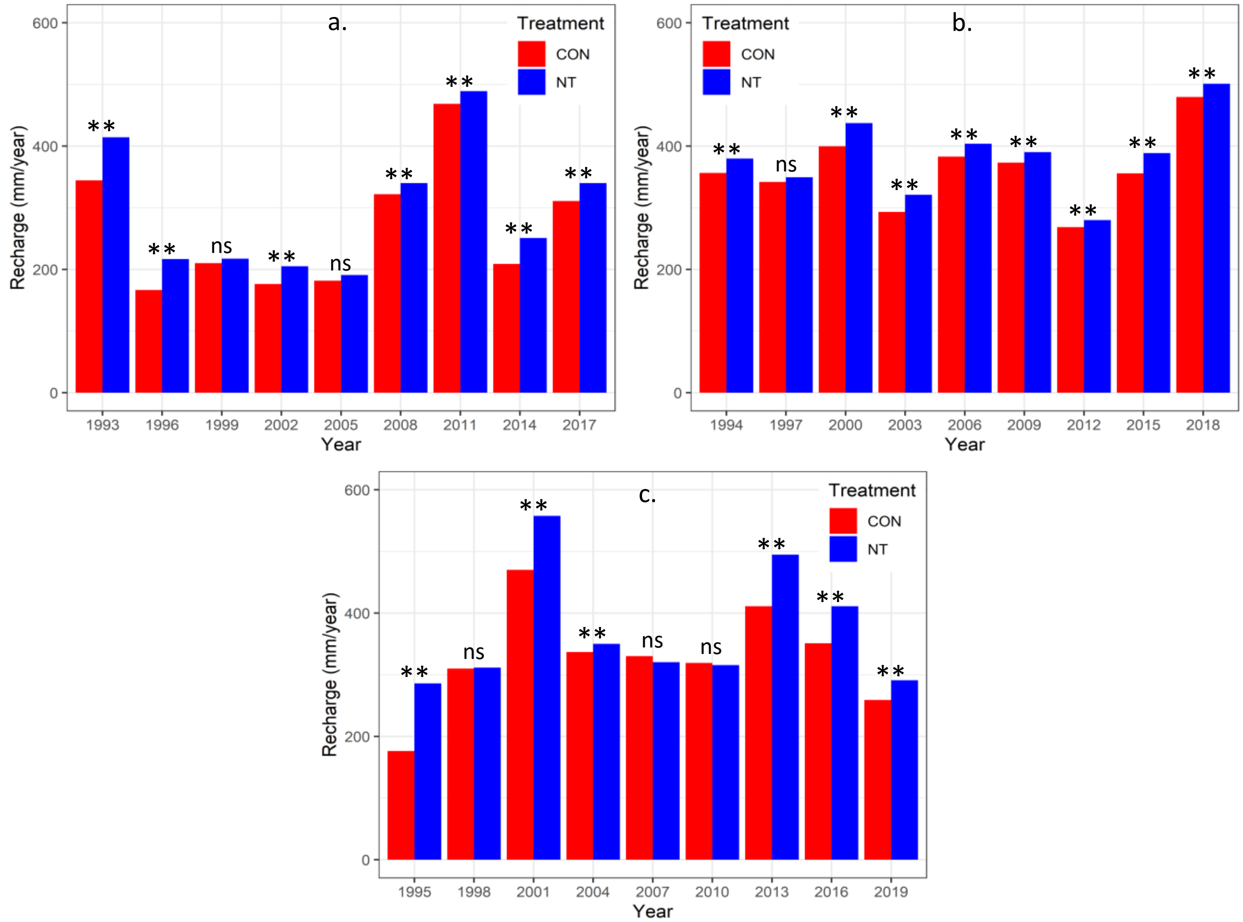

Figure S2. Mean annual recharge from corn (a), soybean (b), and wheat (c) across different soils in the Kalamazoo River watershed for the period between 1993-2019 as affected by the conventional and the no-till treatments. Strongly significant means (p<0.0001) are indicated by ** , and non-significance cases are denoted by “ns”.

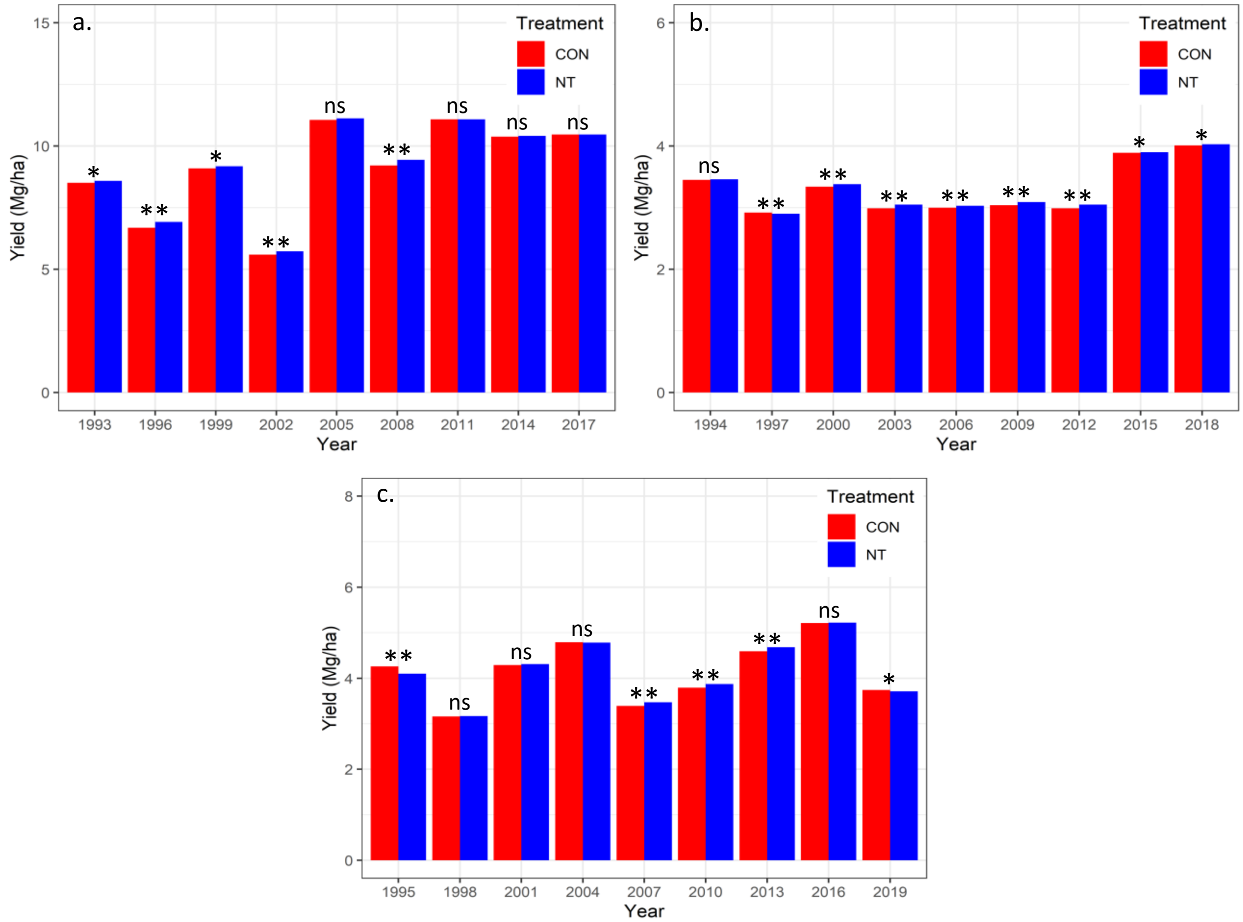

Figure S3. Mean yield of corn (a), soybean (b), and wheat (c) across different soils in the Kalamazoo River watershed for the period between 1993-2019 as affected by the conventional and the no-till treatments. Strongly significant means (p<0.0001) are indicated by **, significant means (p<0.05) are indicated by *, and non-significance cases are denoted by “ns”.

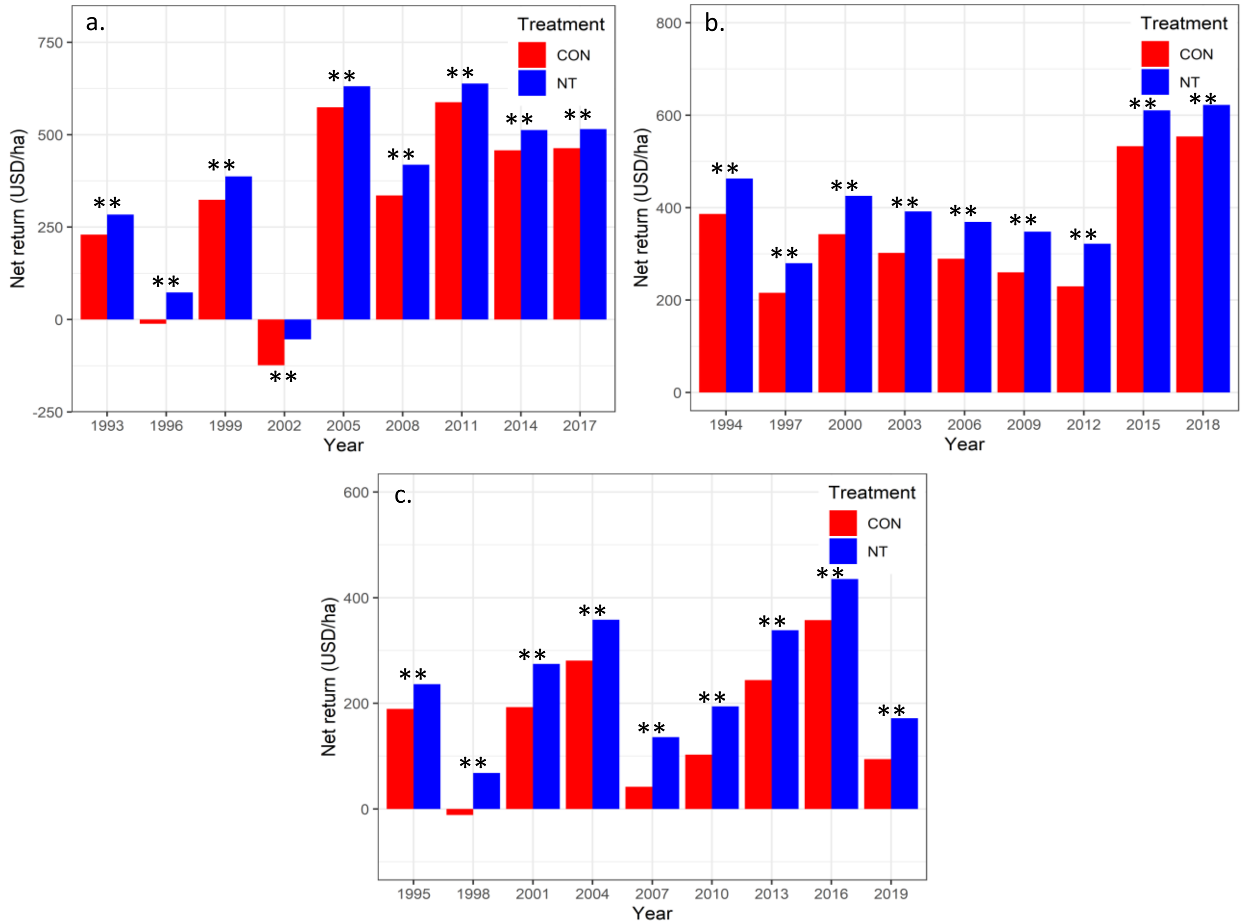

Figure S4. Average net return of corn (a), soybean (b), and wheat (c) across different soils in the Kalamazoo River watershed for the period between 1993-2019 as affected by the conventional and the no-till treatments. Strongly significant means (p<0.0001) are indicated by **, significant means (p<0.05) are indicated by *, and non-significance cases are denoted by "ns".