Field Crops Research 284 (2022) 108563

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Assessing the impacts of pre-growing-season weather conditions on soil nitrogen dynamics and corn productivity in the U.S. Midwest

Ziyi Li [a,b,*], Kaiyu Guan [a,b,c,*], Wang Zhou [a,b], Bin Peng [a,b,c], Zhenong Jin [d], Jinyun Tang [e], Robert F. Grant [f], Emerson D. Nafziger [b], Andrew J. Margenot [a,b], Lowell E. Gentry [b], Evan H. DeLucia [a,g,h,i], Wendy H. Yang [a,h,j], Yaping Cai [a,b], Ziqi Qin [a,b], Sotirios V. Archontoulis [k], Fabián G. Fernández [l], Zhongjie Yu [b], DoKyoung Lee [a,b], Yufeng Yang [d]

[a] Agroecosystem Sustainability Center, Institute for Sustainability, Energy, and Environment, University of Illinois at Urbana Champaign, Urbana, IL 61801, USA
[b] College of Agricultural, Consumer and Environmental Sciences, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
[c] National Center for Supercomputing Applications, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
[d] Department of Bioproducts and Biosystems Engineering, University of Minnesota-Twin Cities, Saint Paul, MN 55108, USA
[e] Climate Sciences Department, Climate and Ecosystem Sciences Division, Lawrence Berkeley National Laboratory, Berkeley, CA 94720, USA
[f] Department of Renewable Resources, University of Alberta, Edmonton, AB T6G 2R3, Canada
[g] Carl R. Woese Institute for Genomic Biology, University of Illinois at Urbana-Champaign, Urbana, IL, USA
[h] Department of Plant Biology, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
[i] Center for Advanced Bioenergy and Bioproducts Innovation, University of Illinois at Urbana-Champaign, Urbana, IL, USA
[j] Department of Geology, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
[k] Department of Agronomy, Iowa State University, Ames, IA 50011, USA
[l] Department of Soil, Water and Climate, University of Minnesota-Twin Cities, Saint Paul, MN 55108, USA

A R T I C L E I N F O

Keywords:
Corn agroecosystem nitrogen cycle
Process-based modeling
Ecosys

A B S T R A C T

Improving nitrogen (N) use efficiency is urgently needed to achieve co-sustainability of agricultural productivity and environmental quality. Environmental conditions and farming management practices affect the N cycle in agroecosystems. Particularly, weather conditions during the pre-growing-season (e.g. winter and early spring for the U.S. Corn Belt) can influence the dynamics of soil inorganic N (SIN) content and have implications for the end-of-season crop yield. Here, we used an advanced agroecosystem model, *ecosys*, to assess the consequences of different pre-growing-season weather scenarios in terms of both SIN dynamics and crop productivity. We first benchmarked *ecosys* using extensive N trial data collected across the U.S. Midwest, and found that *ecosys* captured the N fertilizer-yield responses and field-scale N cycle dynamics. We then used *ecosys* to conduct multiple experiments by changing the pre-growing-season precipitation and temperature, and assessed how these changes affected soil N dynamics and crop yield. We found that: (1) wetter pre-growing-seasons reduced SIN content through increasing leaching, leading to a reduction in corn grain yield of 0.54–0.86 Mg/ha (5–14%) under no fertilizer and of 0.21–0.33 Mg/ha (1–3%) under the normal N fertilizer rate (167 kg N/ha; Illinois average N fertilizer rate in 2018); yield loss induced by higher pre-growing-season precipitation can be eliminated by applying more N fertilizer in spring; and (2) colder pre-growing-seasons can reduce SIN content through decreased N mineralization and enhanced leaching. Both factors further contribute to corn yield loss of 0.10–0.68 Mg/ha (2–8%) under no fertilizer and of 0.12–0.48 Mg/ha (1–4%) under the normal fertilizer rate; however, in this case adding more fertilizer does not necessarily eliminate the yield loss caused by the colder pre-growing-season, because the lower temperature not only causes SIN deficiency but also reduces early-growing-season active root nutrients uptake and crop N demand by cooling soil temperature. These findings expand our understanding of the impact of weather conditions on crop yield and can inform improvements in N fertilizer use efficiency in the U.S. Midwest agroecosystems.

* Corresponding authors at: Agroecosystem Sustainability Center, Institute for Sustainability, Energy, and Environment, University of Illinois at Urbana Champaign, Urbana, IL 61801, USA.
E-mail addresses: ziyili5@illinois.edu (Z. Li), kaiyug@illinois.edu (K. Guan).

https://doi.org/10.1016/j.fcr.2022.108563
Received 31 October 2021; Received in revised form 30 April 2022; Accepted 7 May 2022
Available online 24 May 2022
0378-4290/

1. Introduction

Nitrogen (N) inputs are required to sustain crop production, especially for non-legume crops (Robertson and Vitousek, 2009; Scharf, 2015). The U.S. Midwest produces about 30% of the global corn grain and has become the world largest N fertilizer consumption region (Frink et al., 1999). Farmers in the U.S. Midwest usually apply N fertilizer at high rates to ensure high yields, but only about half of the applied fertilizer is removed from the agroecosystem through harvest (Cassman et al., 2002; Stevens et al., 2005). A significant amount of applied N is retained in the soil or degrades the environment as it is lost into the atmosphere, surface, or groundwater (Bianchi et al., 2010; David et al., 1997, 2010; Rabalais et al., 2002). Considering both the soil N supply including the initial soil inorganic N (SIN) content before planting, and demand of crops could be ways to improve N fertilizer use efficiency (NUE; Cassman et al., 2002).

Weather conditions between the previous harvest and the following spring planting (the pre-growing-season) can significantly affect the initial SIN content before planting (Wagner-Riddle and Thurtell, 1998; DeLuca et al., 1992; Joseph, 2008). This period usually spans from November to April in the U.S. Midwest (Mishra and Cherkauer, 2010; Struffert et al., 2016; Fig. 1a). Laboratory and field experiments have found the impacts of pre-growing-season weather on soil N dynamics to be mediated through processes such as leaching and mineralization; however, such studies only focused on the impact of one single environmental variable on some specific N processes, rather than the integrated impact on agroecosystem N cycling and crop yield (DeLuca et al., 1992; Goolsby et al., 2000; Kalkhoff et al., 2016; Turner and Henry, 2010). Although an increasing number of studies have indicated that incorporating weather information is a feasible approach to improve NUE (Bean et al., 2018; Clark et al., 2020; Ransom et al., 2021), pre-growing-season weather information is still not explicitly utilized by prevailing N recommendation methods in the U.S. Midwest (e.g. yield goal (YG) and maximum return to nitrogen (MRTN)). Additionally, the U.S. Midwest is projected to have higher mean precipitation and temperature with increased climate variability during the pre-growing-season (Feng et al., 2016; Pryor et al., 2014; Sinha et al., 2010; Wuebbles and Hayhoe, 2004). The lack of understanding and quantification of weather impacts on soil N status during pre-growing-seasons restricts the development of more informed N fertilizer management strategies for current and changing climate conditions.

The inability to control weather and challenges of measuring spatially and temporally variable N fluxes and underlying processes at field scales are major obstacles to evaluating the holistic impact of weather conditions on soil N cycling and crop yield (Basso et al., 2012; Batchelor et al., 2002; Fountas et al., 2006; Puntel et al., 2016). Process-based agroecosystem models such as APSIM (Holzworth et al., 2014), DNDC (Giltrap et al., 2010; Li et al., 1992), and EPIC (Williams, 1995), which simulate the carbon-water-nutrient balance in the soil-plant systems can be a viable approach to overcome the measurement challenge (Bassu et al., 2014; Chen et al., 2010; Dietzel et al., 2016;

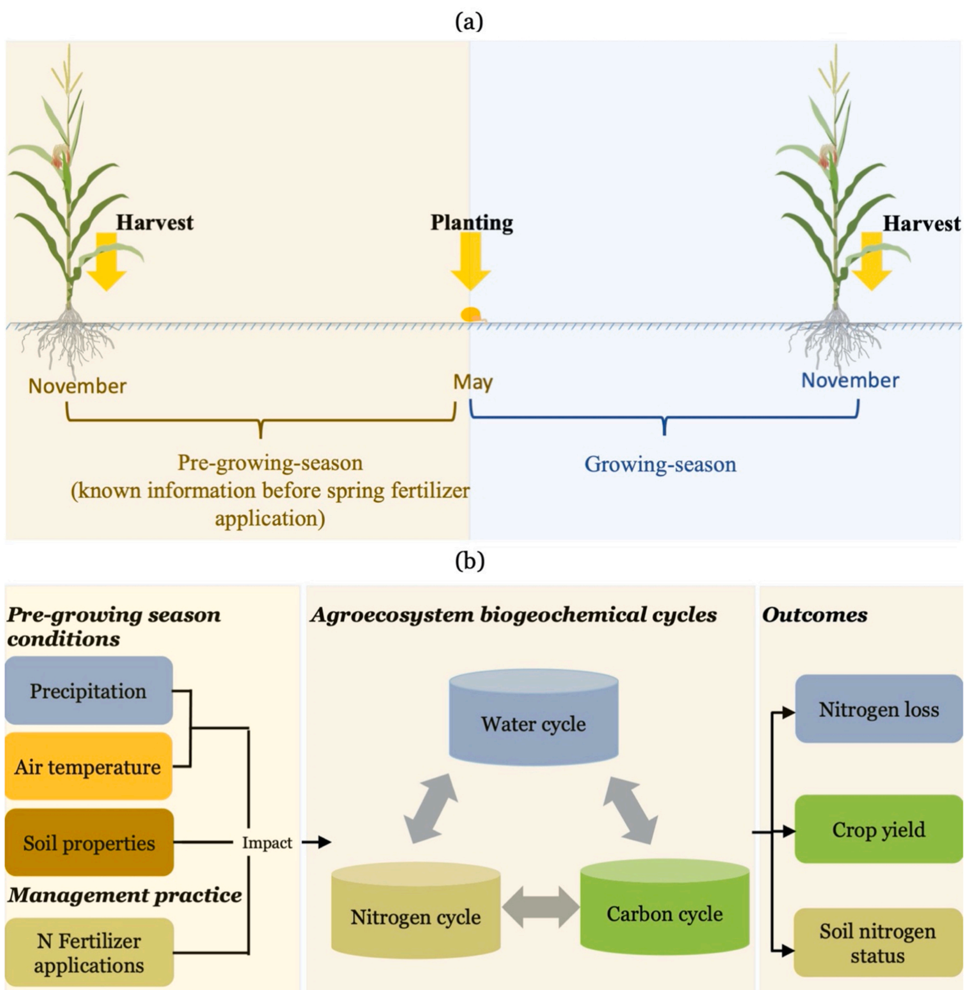

Fig. 1. (a) A schematic diagram illustrating the time span of pre-growing-seasons, and (b) the framework of this study to investigate the impact of pre-growing-season weather conditions on soil nitrogen status and crop production.

Peng et al., 2020; Tubiello and Ewert, 2002). Process-based models have been widely used to study the impact of crop development (Chen et al., 2012; He et al., 2018; Lobell et al., 2013; Riha et al., 1996; Waha et al., 2013; Wang et al., 2016). While previous modeling studies indicated early-growing-season weather conditions are important factors affecting crop available N (Sogbedji et al., 2001; Banger et al., 2019; Malone et al., 2010), more comprehensive studies focusing on impact of pre-growing-seasons on soil N dynamics and crop yield are needed.

This study aims to improve our understanding of the pre-growing-season weather impact on soil N status and the subsequent crop yield, and assess possible mitigation strategies through N fertilizer management (Fig. 1b). This investigation is motivated by two questions: (1) How do pre-growing-season precipitation and temperature affect soil N dynamics and corn productivity? (2) How do different annual N fertilizer application rates influence the impact of pre-growing-season precipitation and temperature on crop productivity? To answer these questions, we adopted an advanced process-based agroecosystem model, *ecosys*, to first ensure its ability to reproduce the key processes through rigorous validation with a large amount of field-measured data collected from the U.S. Midwest. We then used the validated model to assess impacts of different pre-growing-season weather scenarios on soil N status and crop yield at seven sites in Illinois. Finally, we teased out major pathways of these impacts and provided corresponding implications for N fertilizer management.

2. Data and methods

2.1. Ecosys model

Ecosys is an advanced process-based mathematical model that couples water, energy, carbon (C), and nutrient cycles in the soil-vegetation-atmosphere continuum based on foundational biophysical and biochemical principles (Fig. S1, Grant, 2001). *Ecosys* has been extensively validated in many ecosystems, especially for agroecosystems (Grant et al., 2007, 2011a, 2011b; Mezbahuddin et al., 2020), and can simulate impacts of major agriculture practices, including tillage (Grant, 1997), fertilization (Grant et al., 2001), cover crop (Qin et al., 2021), crop rotation (Grant, 1997; Grant et al., 2020) and irrigation (Grant et al., 2007). The performance of *ecosys* in the Midwestern croplands C cycle simulations have been validated by a previous study (Zhou et al., 2021). In this study, we incorporated more field-level N and C measurements in the U.S. Midwest to further test *ecosys* in simulating the agroecosystem N cycle and nitrogen-carbon interactions.

Below we describe how *ecosys* simulates the major N cycling processes in agroecosystems by describing each individual term in N balance equations (Eqs. (1) and (2)).

$$\Delta SIN = \text{Mineralization} + \text{Fertilizer} - \text{Leach}_{SIN} - \text{Uptake}_{SIN} - \text{Gaseous loss} \quad (1)$$

$$\Delta DON = \text{Fixation} + \text{Litter} - \text{Mineralization} - \text{Leach}_{DON} - \text{Uptake}_{DON} \quad (2)$$

where ΔSIN and ΔDON represent the change of SIN and soil dissolved organic N (DON), respectively; Mineralization is the net N mineralization representing the difference between gross microbial N mineralization and N immobilization; Fertilizer is the fertilizer amount, Leach_{SIN} and Leach_{DON} are the total SIN and SON leaching through surface runoff and subsurface discharge, respectively; Uptake_{SIN} and Uptake_{DON} are the root SIN and DON uptake, but Uptake_{DON} only exists when SIN is sparingly available; Gaseous loss is the N gas emission (e.g. NH_3, N_2O, and N_2) through processes including nitrification, denitrification and volatilization; Fixation includes both non-symbiotic diazotrophic N fixation and symbiotic fixation by legumes; and Litter represents plant litter N. More detailed information for other processes in *ecosys* can be found in the supplement of Grant et al. (2020).

2.1.1. N uptake and transformation within the plants

N uptake in *ecosys* is iteratively solved by considering both mass flow and diffusion of N ions from soil water solutions, and the respiration-driven active uptake at root and mycorrhizal surfaces (Grant, 1991). The N taken up is then transported into different organs (i.e. grain, stalk, sheath, leaf, and root) based on concentrations of their soluble carbohydrate and N pools (Grant, 1989). Organ growth respirations drive the combination of soluble C and N from these pools to form new biomass (Grant, 1998). Litter N from senescent leaves and harvest residues (Eq. (2)) decomposes into the SON pool, and finally transforms into SIN through mineralization (Grant et al., 1993). SIN can be absorbed again by crops through uptake, or leached through runoff and discharge, or transformed into gas emissions by microbes (Grant, 1991, 1995b; Grant and Pattey, 1999) (Eq. (1)).

2.1.2. N mineralization

N mineralization or immobilization in *ecosys* is coupled with growth of microbial populations (M) in each of five parallel microbe-substrate complexes (woody and fine plant residue, manure, particulate organic matter, and humus) (Grant, 2013; Grant et al., 1993). The growth of M is induced by heterotrophic respiration through consuming dissolved organic matter (DOM), which is then transformed into microbial biomass. The microbial C:N ratio of one M determines whether the microbe population experiences mineralization (negative values; Eq. (3a)) or immobilization (positive values; Eq. (3b)), which is constrained by active uptake kinetics of SIN (Grant, 2013; Grant et al., 1993).

$$\text{Gross mineralization} = M_C \times C_N - M_N \quad (3a)$$

$$\text{Gross immobilization} = \min\left\{M_C \times C_N - M_N,\ U' \times a \times \frac{([SIN] - [SIN_0])}{([SIN] - [SIN_0] + K_{SIN})} \times f_{Tw}\right\} \quad (3b)$$

where M_C is the microbial C content; C_N is the maximum N:C ratio maintained by M_C; M_N is microbial N content; U' is the maximum microbial SIN (i.e. NH_4^+ and NO_3^-) uptake at 25 °C under non-limiting SIN conditions; a is the microbial surface area; [SIN] and [SIN_0] are the SIN concentration at microbial surfaces and SIN concentration where there is no microbial SIN uptake; K_{SIN} is the Michaelis-Menten constant for SIN uptake; f_{Tw} represents the microbial constraint from soil water stress and soil temperature stress (Grant et al., 2010; Welegedara et al., 2020).

2.1.3. N leaching

N Leaching is tightly connected to the soil water cycle in *ecosys* (Eq. (4)), where plant hydraulics is represented through the soil-plant-atmosphere pathway (Grant et al., 2011). Soil evaporation and transpiration are calculated from energy balances at the ground and canopy surfaces (Grant, 1995a), and plant water uptake is calculated from the difference between canopy water potential and soil water potential and from soil and root hydraulic resistances (Grant, 1995a, 1998). Surface runoff is modeled using the Manning equation, and subsurface transport driving discharge is calculated by the Richards equation or the Green-Ampt equation based on the degree of saturation of source and destination cells (Grant, 2004). N loss through surface runoff and subsurface leaching are calculated based on the simulated runoff and discharge together with the N concentration in the top and each bottom soil water layers (Grant, 1991).

$$\Delta SWC = \text{Precipitation} - \text{Evaporation} - (\text{Runoff} + \text{Discharge}) - \text{Uptake}_{Water} \quad (4)$$

where Precipitation is the precipitation to ground; ΔSWC is the change of soil water content; Evaporation is the soil evaporation; and Uptake_{Water} is the plant water uptake.

2.1.4. N gas emission and N fixation

In *ecosys*, nitrification and denitrification are both microbially driven and modeled as a function of soil oxygen availability. Heterotrophic denitrifiers first assimilate organic matter by consuming oxygen as

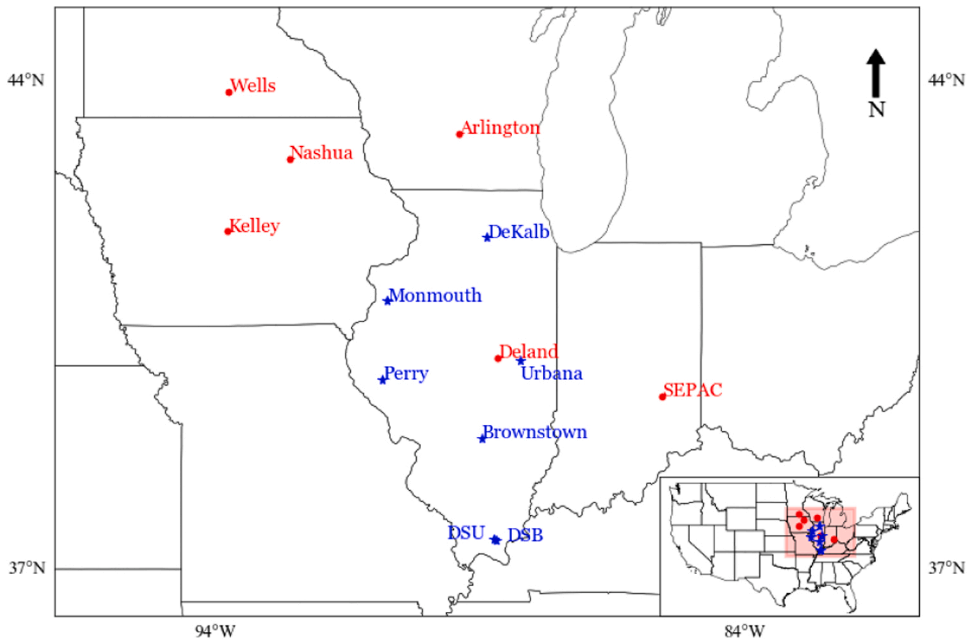

Fig. 2. The locations of field experiments used in this study. Sites listed in blue are where 10-year field trials were run to measure N-yield responses. Sites listed in red have N cycle related measurements. DSU (DS-upland), DSB (DS-bottomland) and SEPAC (Southeastern Indiana Purdue Ag Center) are abbreviations of the three corresponding sites.

electron acceptors, and when oxygen availability is limited, other acceptors can also be used following the order of NO_3-, NO_2-, and N_2O (Grant and Pattey, 1999). During nitrification, NH_3 is oxidized by ammonia oxidizers into NO_2-, and NO_2- is oxidized by nitrite oxidizers using oxygen as the electron acceptor. When oxygen supply is insufficient, NO_2- is used as an alternative electron acceptor to produce N_2O (i.e. nitrifier denitrification) (Grant and Pattey, 1999, 2003, 2008). In addition, key processes of mineralization, nitrification, and denitrification are coupled with exchange and transport of gasses (volatilization-dissolution) in aqueous and gaseous states (Grant et al., 1993; Grant and Pattey, 1999, 2003; Grant and Roulet, 2002). N fixation in *ecosys* can be classified by two categories: (1) heterotrophic non-symbiotic diazotrophs (Eq. (2)), and (2) autotrophic symbiotic legumes (e.g. soybean), for which detailed information can be found in the related references (Grant et al., 2007; Postgate, 1998).

2.2. Data and model validation

2.2.1. Field trial data

We validated *ecosys* based on two field trial datasets from 13 sites across the U.S. Midwest regarding the N fertilizer-yield (N-yield) response together with C and N related measurements (Fig. 2). Specifically, N-yield data from seven sites throughout Illinois were collected from 70 field-year trials during 1999–2008 under six fertilizer rates with the same increment (0, 50.45, 100.90, 151.34, 201.79, 252.24 kg N/ha), and was used to test the model performance in simulating the response to N fertilizer of soil available N and crop productivity. Data from six more sites across the Midwest were collected to validate the model performance in simulating both C and N dynamics within soil and plants. The whole-plant biomass and grain biomass data were used to validate the performance of *ecosys* in simulating C fixation and allocation. The soil and plant N related data were used to validate *ecosys* in terms of transfer and transformation of N in agroecosystems, including plant N uptake and soil nitrate concentration (direct measurements), net mineralization (in-situ incubations), and denitrification (laboratory-incubations). Soil temperature and water content data were also used to validate the model in simulating soil thermal and hydrological conditions. Detailed information including management practices, measured variables and corresponding measuring methods for each site are given in Table S1 (Fernández et al., 2017; Kucharik and Brye, 2003; Martinez-Feria et al., 2018; Negm et al., 2014; Woli et al., 2010).

2.2.2. Model calibration and validation

Inputs in *ecosys* included field-specific soil, weather, and management practice data. Specifically, the North American Land Data Assimilation System (NLDAS-2) hourly meteorological data with 0.125° spatial resolution was used as the weather input, including precipitation, temperature, solar radiation, humidity, and wind speed (Xia et al.,

Table 1
Average soil organic carbon concentration, available water-holding capacity (i.e. differences between field capacity and permanent wilting point; 0-2.52 m depth), and pre-growing-season weather information during the simulation period (2000–2008) at seven Illinois trial sites. std_p and std_t are the precipitation and temperature variation metrics calculated based on 37-years (1980–2016) climate information from NLDAS-2 used for the scenarios design in Table 2.

Site name	SOC (g C/kg)	Available water-holding capacity (m^3/m^3)	Pre-growing-season cumulative precipitation (mm)	std_p	Pre-growing-season mean temperature (°C)	std_t (°C)
DeKalb	4.27	0.14	330.10	0.26	0.45	1.54
Monmouth	5.18	0.15	350.78	0.24	1.50	1.68
Urbana	6.04	0.10	424.25	0.20	2.70	1.70
Perry	2.35	0.14	383.89	0.23	3.14	1.55
Brownstown	1.92	0.14	480.90	0.22	4.35	1.43
DSU	1.69	0.14	611.88	0.23	6.00	1.22
DSB	1.40	0.11	611.88	0.23	6.00	1.22

Table 2
Design of the scenario experiments in this study. P and T respectively represent the pre-growing-season precipitation and temperature, std_p represents the standard deviation of the 37-years (1980–2016) division between P in each year and the multi-year average P. std_t represents the standard deviation of the 37-years T.

Scenarios		Name	Setting
Baseline scenarios (actual historical weather)		P, T	P and T
Precipitation scenarios	Low precipitation	P↓↓	P × (1 – $2std_p$) and T
		P↓	P × (1 – std_p) and T
	High precipitation	P↑	P × (1 + std_p) and T
		P↑↑	P × (1 + $2std_p$) and T
Temperature scenarios	Low temperature	T↓↓	P and T – $2std_t$
		T↓	P and T – std_t
	High temperature	T↑	P and T + std_t
		T↑↑	P and T + $2std_t$

2012). The Gridded Soil Survey Geographic Database (gSSURGO) data, a detailed soil geographic dataset developed by the USDA National Cooperative Soil Survey, was used to provide soil inputs in *ecosys* (e.g. SOC, bulk density, soil texture, pH, and CEC). Management practices for each site were shown in Table 1. We ran *ecosys* in each of the 13 sites during their experimental period (Table 1), with 30 years before each experimental period as spin-up period to ensure the model reached equilibrium. Most corn cultivar parameters were *ecosys* default values, and only one phenology related parameter (i.e. maturity group) was calibrated based on yield data according to the different time of each site to reach physiological maturity (Neild, 1986; Ransom et al., 2019). We compared the *ecosys* simulated yield and observed yield by using the coefficient of determination (R^2) and root mean square error (RMSE) to assess the model performance. The other field data related to C and N dynamics within soil and plants were directly used as validation to compare with the corresponding model simulations.

2.3. Model experiment design

The validated *ecosys* was then used to simulate the N cycling and crop yield under different pre-growing-season weather scenarios at seven University of Illinois Urbana-Champaign (UIUC) trials across Illinois with different soil and weather conditions during 2000–2008 (from the November of 1999 to the end of growing-season in 2008). Basic information about each trial is listed in Table 2, including SOC and available water-holding capacity (0–2.52 m), pre-growing-season average precipitation and temperature. NLDAS-2 and gSSURGO were used as the meteorological and soil inputs for scenario simulation with the adjusted corn cultivar parameters. In our simulation, we considered the predominant timing strategies of N fertilizer application in the U.S. Midwest, in which N fertilizer is applied in spring around the corn planting time (Bierman et al., 2012; Cao et al., 2018; Paustian et al., 2004). Thus, May 5th was selected as the planting date with May 20th as the spring N fertilizer application date in the form of banded urea ammonium nitrate (UAN 28–0–0, N-P-K). The timing of planting and fertilization were kept constant for all model scenarios. For each site-year, we followed the trial experiment setup to use five fertilizer rates with the same increment (0, 75.60, …, 302.40 kg N/ha) to represent low to high rates. Other management practices for these seven sites are as shown in Table 1.

In our simulation, pre-growing-season was defined from the November 1st of the previous year to the April 30th of the current year for all years during 2000–2008 (Mishra and Cherkauer, 2010; Struffert et al., 2016). For each year, we designed nine scenarios by changing the pre-growing-season weather conditions (precipitation and temperature; Table 2). These nine scenarios are classified into one baseline scenario with actual precipitation and temperature and eight other scenarios based on the variation of pre-growing-season precipitation and temperature during the past 37 years (1980–2016). The standard deviation of the past 37-year ratios between the annual pre-growing-season precipitation to the 37-year average pre-growing-season precipitation (std_p) was used to generate the variation in precipitation used in the model simulations. Similarly, the standard deviation of the past 37-years pre-growing-season temperature (std_t) was used to generate the variation in temperature. Specifically, P↓↓, P↓, P↑ and P↑↑ respectively represented the lowest, lower, higher and highest pre-growing-season precipitation, which were respectively calculated by P × (1 – $2std_p$), P × (1 – std_p), P × (1 + std_p) and P × (1 + $2std_p$). T↓↓, T↓, T↑ and T↑↑ respectively represented the lowest, lower, higher and highest pre-growing-season temperature, which were respectively calculated by T – $2std_t$, T – std_t, T + std_t and T + $2std_t$. Values of std_p and std_t for each seven UIUC trials can be referred to Table 1.

3. Results

3.1. Model performance evaluation with the field experiments

We found *ecosys* adequately simulated the crop yield for both the set of seven sites across Illinois (R^2 =0.81 and RMSE=1.72 Mg/ha; Fig. 3a) by reproducing the N-yield responses (Fig. 4), and for the other six sites in the U.S. Midwest (R^2 =0.64 and RMSE=2.01 Mg/ha; Fig. 3b). *Ecosys* captured the dynamics of C fixation and allocation processes (i.e. biomass and grain formulation collected from the Nashua and Kelley sites; Fig. S2a-d), the N cycling processes between crop and soil (i.e.

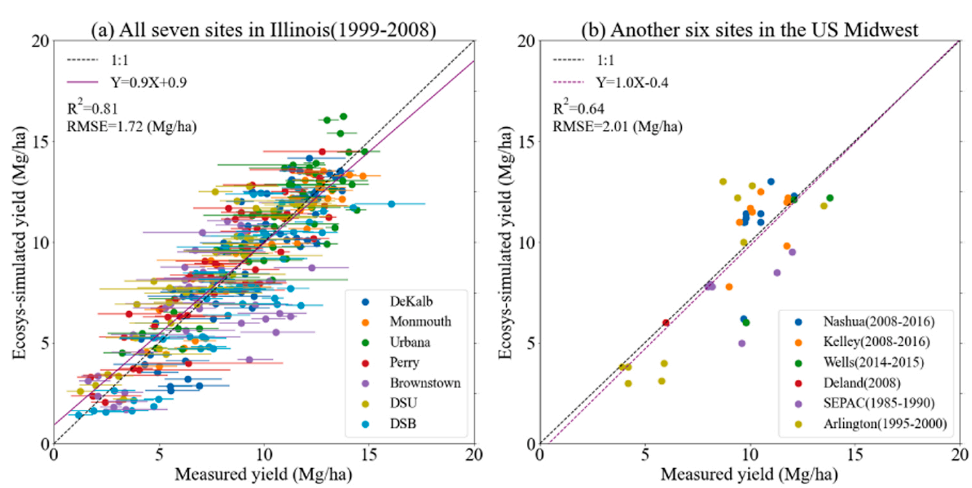

Fig. 3. Comparison of *ecosys* simulated and measured corn grain yield (15% moisture) at seven sites in Illinois (a; ranges and mean values of measured yield are respectively represented as lines and points) and six additional sites across the US Midwest (b).

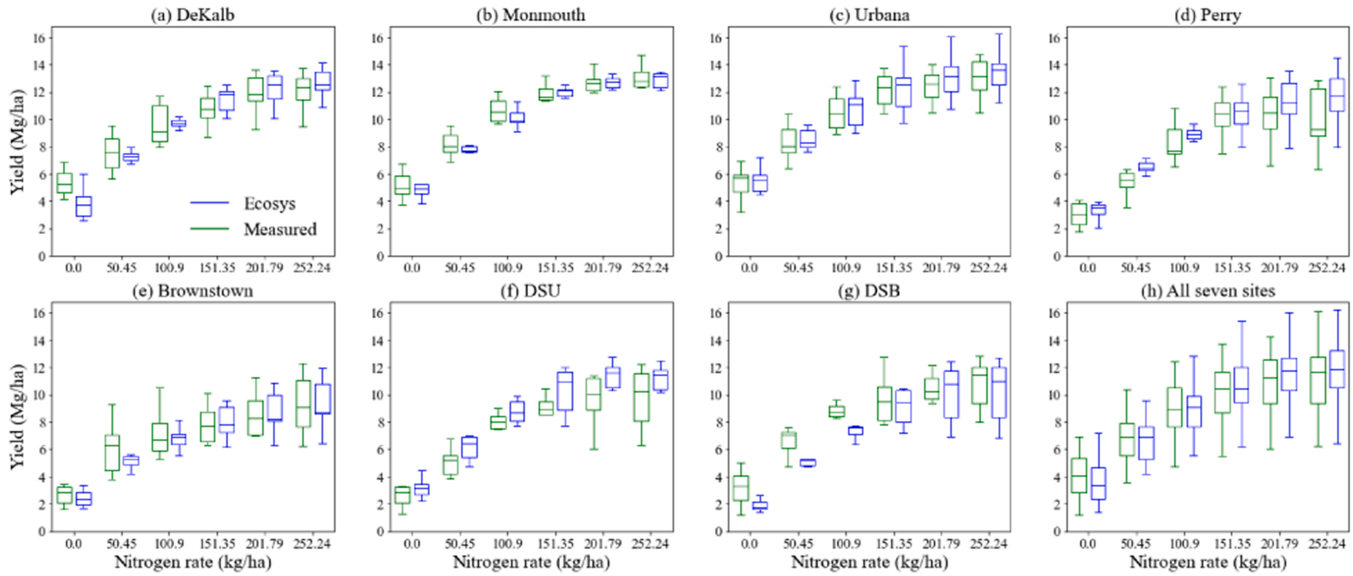

Fig. 4. Comparison of *ecosys* simulated and measured multi-year average N-yield responses during 1999–2008 at each (a-g) and all (h) seven sites in Illinois.

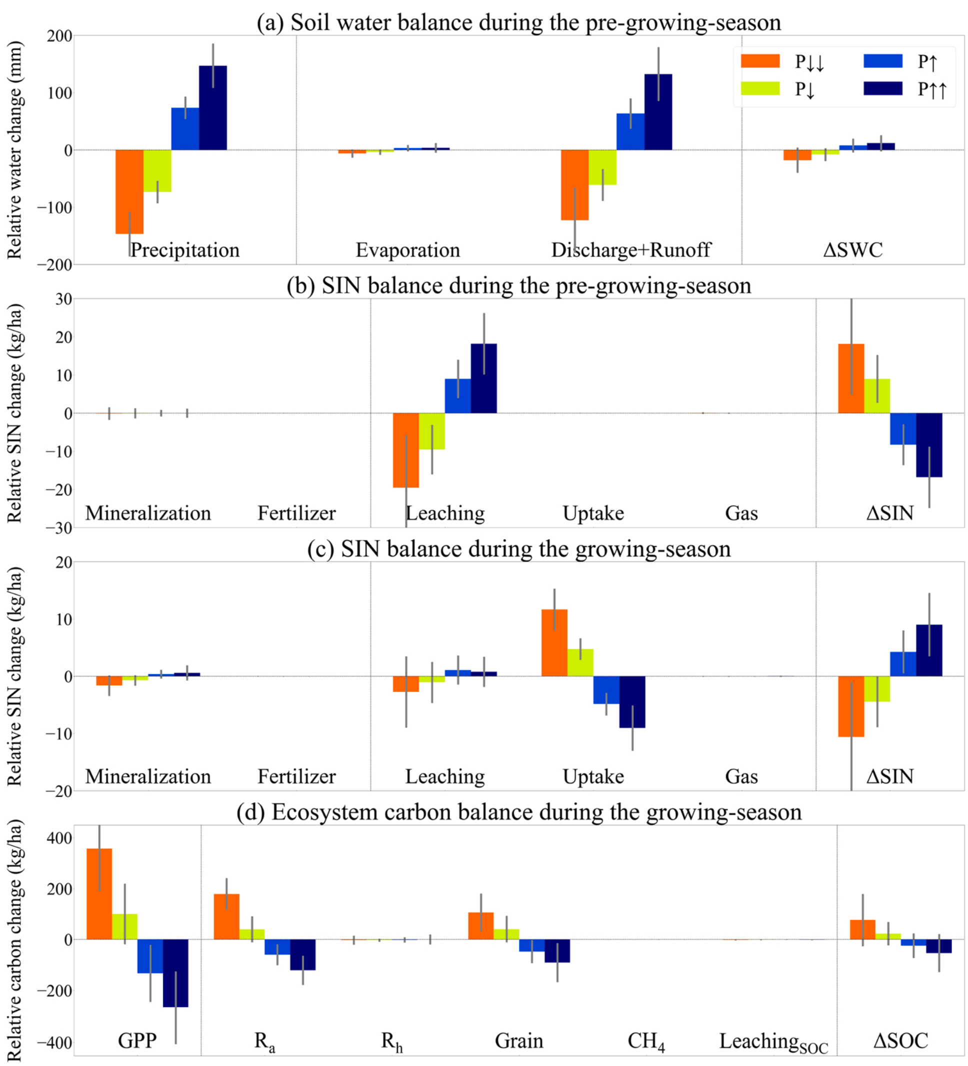

Fig. 5. Effects of pre-growing-season precipitation on soil water balance (a) and SIN balance (b) during pre-growing-season, and SIN balance (c) together with ecosystem carbon balance (d; $\Delta SOC = GPP - (R_a + R_h + Grain + CH_4 + Leaching_{SOC})$ during the growing season for the Urbana site with the fertilizer rate at 151.20 kg N/ha. Here, ΔSOC is SOC change; R_a and R_h are respectively ecosystem autotrophic and heterotrophic respirations; Grain is grain carbon, and $Leaching_{SOC}$ is SOC leaching. Each bar represents the average result during 2000–2008 under one scenario compared with the baseline scenarios (P). Four precipitation scenarios are calculated based on the standard deviation of the 37-years (1980–2016) ratios between annual pre-growing-season precipitation and 37-year average precipitation (std_p=0.20). Specifically, P↓↓, P↓, P↑, and P↑↑ respectively represent the lowest, lower, higher, and highest precipitation, and the detailed description can be found in Table 2.

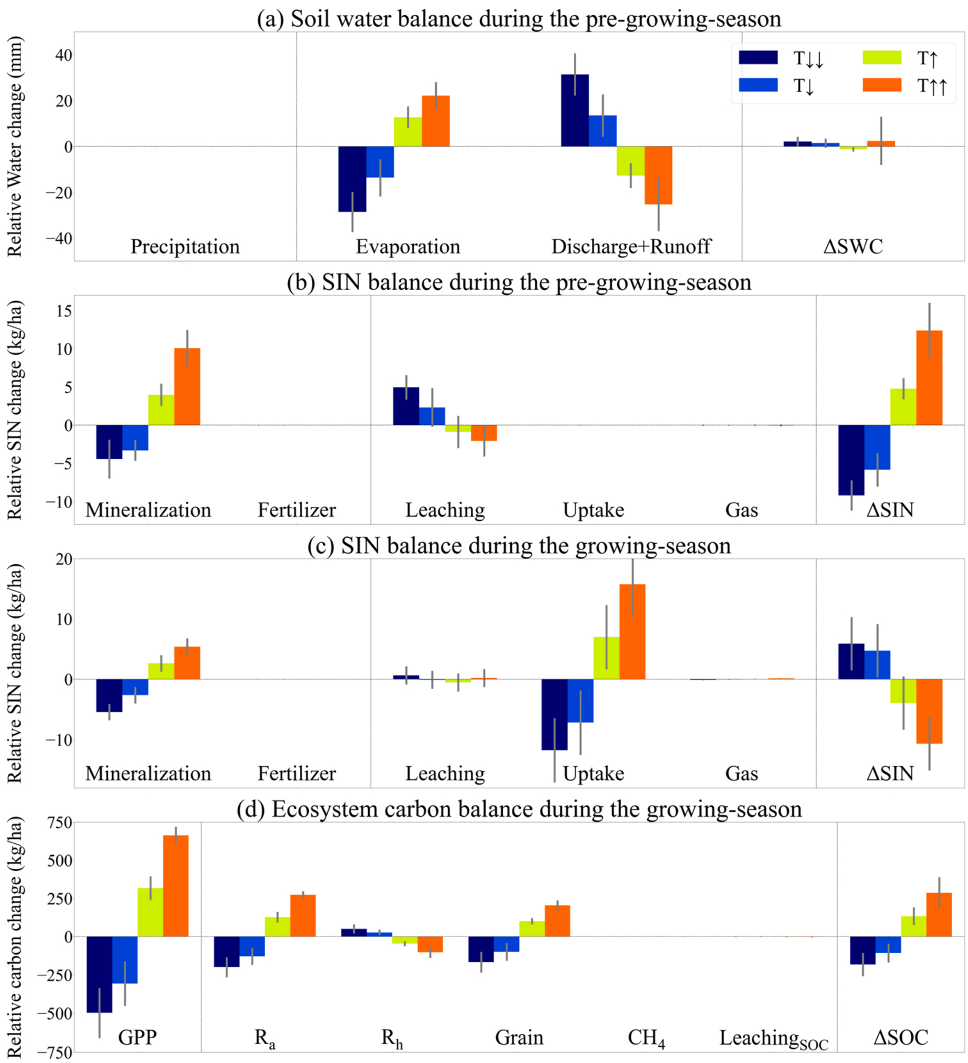

Fig. 6. Effects of pre-growing-season temperature on ecosystem water balance (a) and SIN balance (b) during pre-growing-season, and SIN balance (c) together with ecosystem carbon balance (d) during growing-season for the Urbana site under one fertilizer rate (151.2 kg N/ha). Each bar represents the average result during 2000–2008 under one scenario compared with the original scenarios (T). Four temperature scenarios are calculated based on the standard deviation of the 37-years (1980–2016) pre-growing-season temperature (std_t=1.70 °C). Specifically, T↓↓, T↓, T↑, and T↑↑ respectively represent the lowest, lower, higher, and highest temperature, and the detailed description can be found in Table 2.

plant N uptake from the Nashua and Kelley sites; Fig. S2e-f), the soil nitrate dynamics (0–30 cm; the Nashua and Kelley sites; Fig. S2g-h). *Ecosys* also accurately simulated cumulative growing-season N mineralization and daily denitrification. The R^2 and RMSE of simulated cumulative growing-season N mineralization are 0.93 and 12.53 Mg/ha respectively for soil within 0–15 cm at the Wells site (Fig. S3a), and the R^2 and RMSE of simulated daily denitrification are 0.99 and 0.02 Mg/ha respectively at the Deland site (Fig. S3b). In addition, we found *ecosys* can capture the dynamics of other two soil variables including soil temperature and soil water content as well (0–60 cm; the Nashua and Kelley sites, Fig. S2i-l). The performance of *ecosys* in simulating processes related to the agroecosystem N cycle and crop productivity in many sites across the U.S. Midwest demonstrated that this model can predict soil N dynamics and crop yield across different soil and weather conditions with acceptable accuracy.

3.2. Model-simulated effect of pre-growing-season precipitation on soil N cycles and crop yield

We found that simulated higher pre-growing-season precipitation led to less corn N uptake and crop yield across all seven Illinois sites. For example, compared with the baseline scenario (P), the highest precipitation scenario (P↑↑) with 147 mm more precipitation induced 132 mm more runoff and discharge combined at the Urbana site (Fig. 5a). This caused 18.15 kg N/ha more pre-growing-season SIN leaching and 16.80 kg N/ha less SIN content with the average baseline fertilizer rate at the Urbana site during 2000–2008, 151.20 N kg/ha (Fig. 5b). Accordingly, the scenario P↑↑ resulted in 9.04 kg N/ha less crop N uptake (Fig. 5c) and as a result 90.75 kg C/ha less grain carbon (Fig. 5d) compared with the baseline scenario. The other sites shared similar qualitative trends.

3.3. Model-simulated effect of pre-growing-season temperature on soil N cycles and crop yield

Although the multi-year average pre-growing-season temperature varied from 0.45 °C to 6.00 °C for seven Illinois sites, the *ecosys* simulation showed that higher pre-growing-season temperature increased SIN content and crop yield in all these sites. For example, compared with the baseline scenario (T) at the Urbana site, the highest temperature scenario (T↑↑) caused 10.06 kg N/ha more mineralization and 2.07 kg N/ha less SIN leaching (Fig. 6b) accompanied by decreased discharge and runoff (25 mm; Fig. 6a). This contributed to an increase of SIN content (12.37 kg N/ha), and finally more N uptake (15.74 kg N/ha; Fig. 6c) and more grain carbon accumulation (205.47 kg C/ha; Fig. 6d) under T↑↑ compared with T. The other six sites exhibited similar qualitative trends.

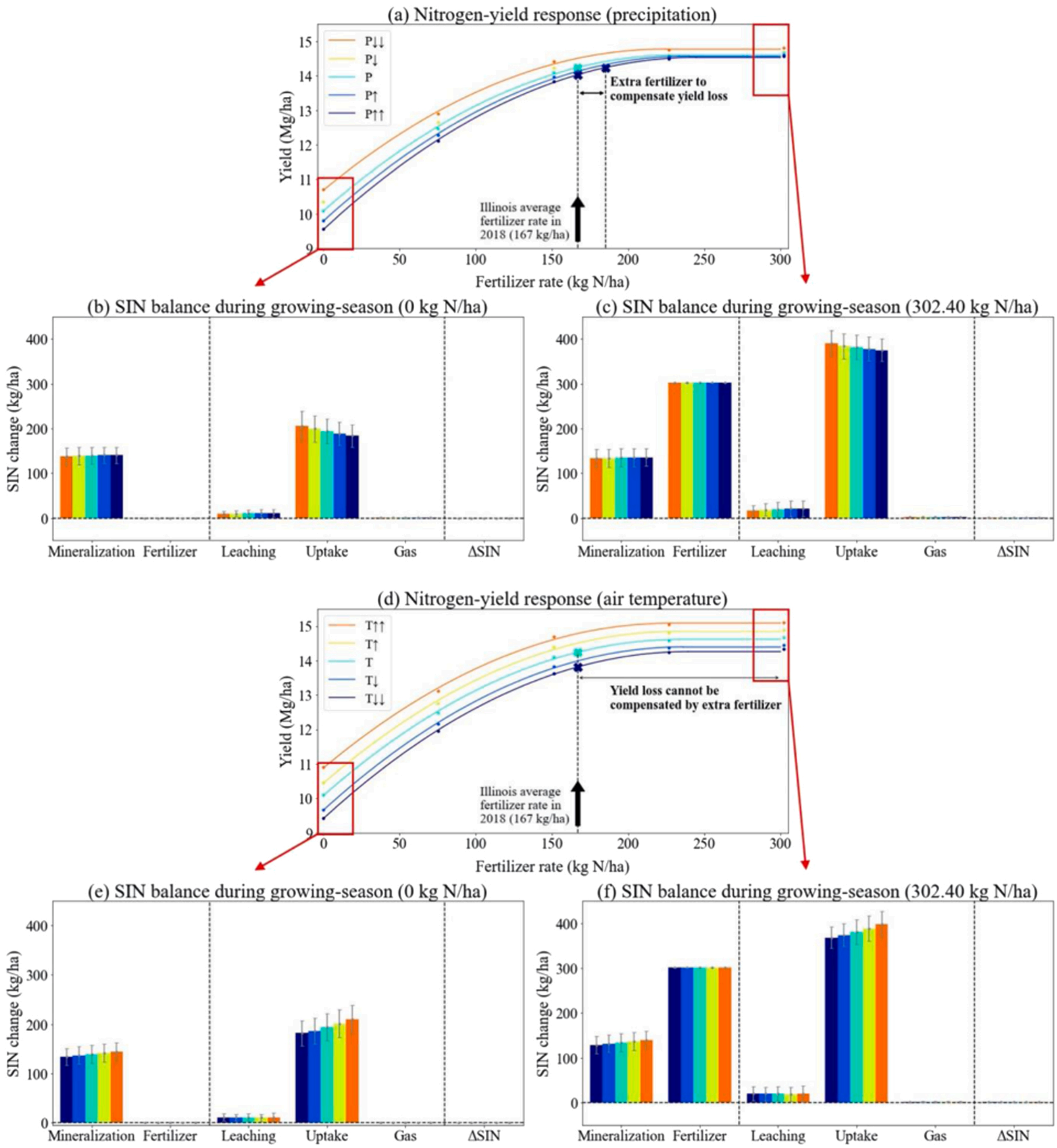

Fig. 7. Effects of fertilizer rate on the relationship between pre-growing-season weather and crop yield for the Urbana site. (a) is the fertilizer-yield response simulated under different precipitation scenarios, in which points represent the crop yield under different fertilizer rates with curves being fitted based on "quadratic-plateau" model (Ransom et al., 2020). (b) and (c) are respectively the growing-season SIN balance under no (0 kg N/ha) and high fertilizer rates (302.40 kg N/ha) for all pre-growing-season precipitation scenarios. (d) is the fertilizer-yield response simulated under different temperature scenarios with similar definitions of points and curves as (a), (e), and (f) are respectively the growing-season SIN balance under no and high fertilizer rates for all pre-growing-season temperature scenarios.

3.4. Model-simulated response between pre-growing-season weather conditions and yield under different N fertilizer rates

The yield loss caused by increased pre-growing-season precipitation (i.e. the yield difference between P and P↑↑) was mitigated by applying more N fertilizer. Taking average results during 2000–2008 of the Urbana site as an example (Fig. 7a), its yield loss changed from 0.54 Mg/ha (0.54–0.86 Mg/ha across seven sites) and to just above 0 Mg/ha with fertilizer rates increasing from none to 302.40 kg N/ha. The diminishing yield loss at higher fertilizer rates suggested that the SIN loss through leaching induced by the increased pre-growing-season precipitation was compensated by applying more N fertilizer, which further minimized the impact on crop growth (Fig. 7a, b, and c). However, the N uptake differences between scenarios still existed under the high fertilizer rates (302.40 kg N/ha; Fig. 7c), which were transferred into vegetative N biomass but not reflected in grain N content (Fig. S6). This indicates the same grain N demand for different pre-growing-season precipitation scenarios under the high fertilizer rate.

Decreased pre-growing-season temperature also caused a yield loss (i.e. the yield difference between T and T↓↓) based on averaged yield simulations during 2000–2008. However, applying more N fertilizer did not eliminate the yield loss, as these losses persisted even under high fertilizer rates. For example, the yield loss in the Urbana site decreased only slightly, from 0.68 (0.10–0.68 Mg/ha across the seven sites) to 0.33 Mg/ha (0.08–0.51 Mg/ha) with fertilization increasing from 0 to 302.40 kg N/ha (Fig. 7d). This lack of sensitivity of the simulated yield loss to fertilizer rates indicated there were other factors aside from SIN content that limited the crop growth, which will be further discussed in

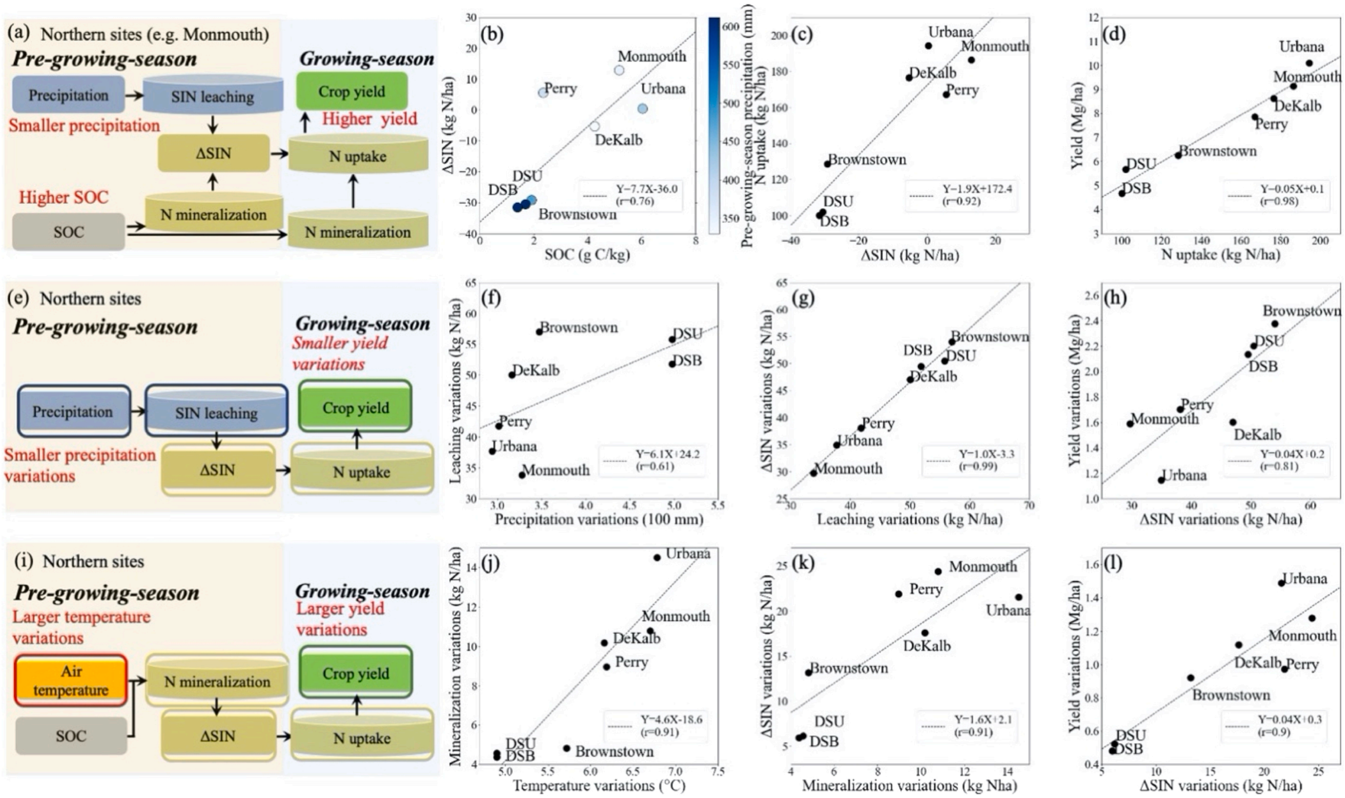

Fig. 8. The impacts of soil and pre-growing-season weather conditions on soil N dynamics among seven sites across Illinois, where all values are average results during 2000–2008. (a), (e), and (i) are the diagrams to illuminates the pathway of how soil and pre-growing-season weather conditions affect the spatial distribution of SIN change during the pre-growing-season (ΔSIN), ΔSIN variations under precipitation scenarios and ΔSIN variations under temperature scenarios. (b) is the relationship between site SOC concentration, multi-year average pre-growing-season precipitation and pre-growing-season SIN change under baseline scenario (ΔSIN); (c) and (d) shows the linear relationship between ΔSIN, N uptake, and unfertilized yield. (f), (g), and (h) shows the linear relationship between variations in pre-growing-season precipitation, leaching, ΔSIN, and unfertilized yield among precipitation scenarios. (j), (k), and (l) show the linear relationship between variations in pre-growing-season temperature, mineralization, ΔSIN, and unfertilized yield among temperature scenarios.

Section 4.2.

3.5. Explanations of soil and pre-growing-season weather conditions to the difference of soil N dynamics and yield among sites

We observed a spatial pattern of the multi-year average SIN change during the pre-growing-season (ΔSIN) in the baseline simulations of the seven Illinois sites during 2000–2008 (Fig. 8a). The northern sites (e.g. Monmouth) had a more marked ΔSIN compared with the southern sites (e.g. DSB), and thus greater crop yield with no fertilizer application (Fig. 8c and d). Further analysis suggested that the larger ΔSIN in the northern sites was caused by higher N mineralization and lower SIN leaching, because of their higher SOC concentration and lower pre-growing-season precipitation (Fig. 8b).

We also found spatial patterns for the multi-year average ΔSIN variations under precipitation scenarios (i.e. ΔSIN differences between P↓↓ and P↑↑; Fig. 8e) and temperature scenarios (i.e. ΔSIN differences between T↓↓ and T↑↑; Fig. 8i) of the seven Illinois sites during 2000–2008. Specifically, ΔSIN variations under precipitation scenarios were smaller in the northern sites than the southern sites (Fig. 8g), because the northern sites had smaller variations in precipitation, which resulted in smaller variations of the corresponding nutrient leaching (Fig. 8f-h), and thus smaller variations of unfertilized yield (Fig. 8h). In contrast, ΔSIN variations among temperature scenarios were larger in the northern sites than the southern sites (Fig. 8k). This was caused by the higher SOC and the larger temperature variations in the northern sites (Fig. 8j). These two factors together contributed to larger mineralization variations (Fig. 8k), and finally caused larger variations of unfertilized yield (Fig. 8l) among temperature scenarios in the northern sites.

4. Discussion

We used 70 field-years of N-yield data and high-resolution soil and plant measurements across the U.S. Midwest to first calibrate and validate *ecosys*, and then used it to assess the impact of pre-growing-season weather conditions on corn-based cropping systems in Illinois. Below, we summarized our results to answer the two questions raised in the introduction.

4.1. How do pre-growing-season precipitation and temperature affect soil N dynamics and crop productivity?

Increased pre-growing-season precipitation reduced SIN content and crop yield, mainly due to increased SIN leaching through discharge and runoff (Fig. 9a). Our simulation also showed decreased soil O_2 content caused by increased soil water content. However, this decreased O_2 still persisted in soil due to inactive microbial activity during the pre-growing-season and was insufficient to significantly affect SIN content through denitrification, which is consistent with other field and laboratory experiments (Krichels and Yang, 2019).

Conversely, an increase of pre-growing-season temperature raised SIN content through enhanced N mineralization, which finally contributed to increased crop yield (Fig. 9b). Higher temperature also increased SIN content via increased evaporation to decrease SIN leaching through discharge and runoff. The warming-induced increase in soil N mineralization agrees well with previous soil warming experiments regarding soil N dynamics (Contosta et al., 2011; Guntiñas et al., 2012; Rustad et al., 2001), but the contribution from reduced SIN leaching to increased SIN content caused by increased temperature has yet to be

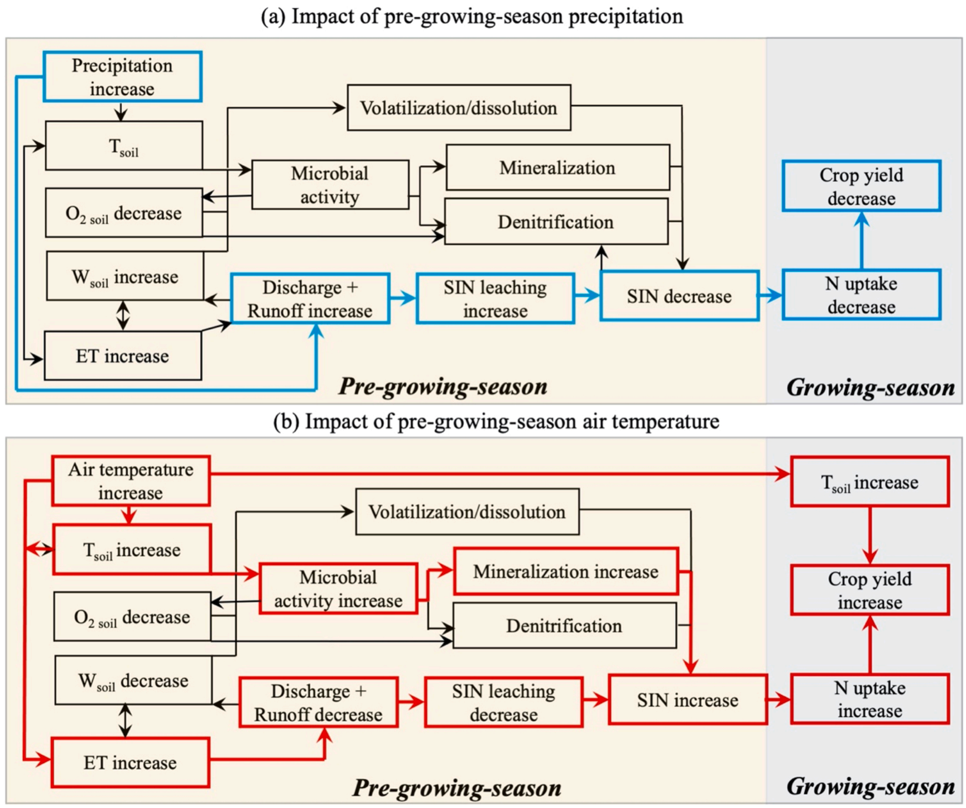

Fig. 9. Schematic diagram of the main processes by which pre-growing-season precipitation (a; the main pathway is represented in blue color) and temperature (b; the main pathway is represented in red color) affect soil nitrogen dynamics, and crop yield. SWC, $O_{2\ soil}$ and T_{soil} are respectively soil water content, soil O_2 content, and soil temperature.

empirically assessed. Besides, increased pre-growing-season temperature stimulated root respiration during the beginning of the growing-season by elevating soil temperature in the same period, which contributed to yield increase (see Section 4.3; Fig. 9b). Our findings that higher precipitation and lower temperature during pre-growing-seasons reduced SIN content were consistent with previous studies focusing on early-growing-season weather (Sogbedji et al., 2001; Malone et al., 2010; and Banger et al., 2019), indicating the similar mechanism of the weather during these two periods affecting crop available soil N before rapid uptake.

4.2. How do different annual fertilizer rates influence the impact of pre-growing-season precipitation and temperature on crop productivity?

Based on results in Section 3.4, we found that applying more fertilizer can mitigate and even eliminate the yield loss induced by increased pre-growing-season precipitation (Fig. 7a). According to NASS's latest survey (2019), the Illinois average N fertilizer rate is 167 kg/ha. Taking average results (2000–2008) of the Urbana site under this fertilizer rate as an example, the 0.21 Mg/ha (0.21–0.33 Mg/ha or 1–3% across seven sites) yield loss induced by increased pre-growing-season precipitation can be mitigated by adding 18.18 kg/ha (11.37–29.37 kg/ha across seven sites) N fertilizer (Fig. 7a), because this yield loss was caused by lower SIN (Fig. S4; soil NO_3^- concentration dynamics in different soil layers are also shown in Fig. S8). Although crop yield increased by adding more fertilizer, the yield reduction of 0.43 Mg/ha (0.12–0.48 kg/ha or 1–4% across seven sites) caused by low pre-growing season temperatures cannot be completely overcome by the addition of N fertilizer (Fig. 7d). The persistent yield loss under high fertilizer rates indicated that the yield loss was caused by factors other than low SIN.

Our simulation predicted that the decreased pre-growing-season temperature can reduce soil temperature in the early-growing-season (Fig. S5). This decrease in soil temperature reduced root respiration and active N uptake during germination as well as early crop growth stages, and ultimately reduced corn grain yield potential (Fig. S5). Others have observed similar results (Allmaras et al., 1964; Bollero et al., 1996; Cooper and Law, 1978; Stone et al., 1999). Therefore, our simulation revealed that the pre-growing-season temperature not only changed the soil N status temporally, but also indirectly affected crop development, growing-season grain N demand (Fig. S7), and ultimately grain yield potential (Fig. 7d).

4.3. Implications to fertilizer management

The impact from pre-growing-season weather conditions on in-field crop yield variability is relatively smaller than impact from many other factors including growing-season climate variability, topography, and soil variability (Ray et al., 2015; Grisso et al., 2002). However, our results shed light on why year-to-year fertilizer applications may still need to be adjusted for different pre-growing-season weather conditions in the rainfed part of the U.S. Midwest. Warmer and/or drier pre-growing-seasons are generally favorable for corn growth in the U.S. Midwest, due to more mineralization and less nutrient leaching. In contrast, colder and/or wetter pre-growing-seasons can cause yield loss in the U.S. Midwest. Although the yield loss can be compensated by applying more N fertilizer, the marginal economic benefits of adding more fertilizer decreased as the fertilizer rate increased, and fertilization in excess of what is required by the crop also increases the risk of negative environmental impacts. Effectively managing N fertilizer for both productivity and environmental sustainability is beyond the scope of the current study, but both should be considered in tandem when providing farmers guidance on fertilizer management (Sawyer et al., 2006; Vanotti and Bundy, 1994; Zhang et al., 2015).

The U.S. Midwest agroecosystem is projected to have warmer and wetter pre-growing-seasons under climate change (Feng et al., 2016). The average winter and spring precipitation could increase up to 30% and 40% by 2071–2099 compared with 1961–1990 by global climate model projections (Wuebbles and Hayhoe, 2004). Meanwhile, the average winter and spring temperature are respectively projected to increase 1–9 °C and 3–8 °C. Since these two conditions have opposite effects on crop yield and the large uncertainty in future climate projections, the overall impact of future weather conditions during pre-growing-seasons will depend on the magnitudes of both precipitation and temperature.

5. Conclusion

This study investigated the impact of pre-growing-season weather conditions on soil N status and crop yield in the U.S. Midwest by using scenario simulations based on a well-validated agroecosystem model *ecosys* at seven sites in Illinois. For model validations, we found *ecosys* had a strong capability to capture the C fixation and allocation processes (i.e. biomass and grain mass), soil variables (i.e. soil temperature, nitrate content and water content), N fluxes (i.e. N uptake, mineralization and denitrification), and N-yield responses collected from a number of U.S. Midwest sites. For scenario simulations, we predicted wetter pre-growing-seasons can cause a reduction of SIN content through increasing leaching, and cause yield loss of 0.54–0.86 Mg/ha (5–14%) under no fertilizer and of 0.21–0.33 Mg/ha (1–3%) under the normally used N fertilizer rate (167 kg N/ha). This precipitation-induced yield loss can be mitigated by adding more N fertilizer. In contrast, we predicted colder pre-growing-seasons can also reduce SIN content, but through different pathways including decreased mineralization and increased leaching enhanced by decreased evapotranspiration. This decreased SIN content caused by lower pre-growing-season temperature can contribute to corn yield loss of 0.10–0.68 Mg/ha (2–8%) under no fertilizer and of 0.12–0.48 Mg/ha (1–4%) under the normal fertilizer rate. This yield decrease can be mitigated but cannot be eliminated by N fertilizer because the decreased pre-growing-season temperature also reduces growing-season crop N demand by cooling the early-growing-season soils and ultimately reducing crop yield potential. This study provides useful insights to improve fertilizer management for crop productivity in the U.S. Midwest.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Science Foundation (NSF) Career Award (1847334), USDA NIFA Program (2017-67013-26253, 2018-68002-27961 and Hatch), Illinois Nutrient Research and Education Council (NREC) and NSF Signal-in-soil program.

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fcr.2022.108563.

References

Allmaras, R.R., Burrows, W.C., Larson, W.E., 1964. Early growth of corn as affected by soil temperature. Soil Sci. Soc. Am. J. 28 (2), 271–275. https://doi.org/10.2136/sssaj1964.03615995002800020041x.

Banger, K., Nafziger, E.D., Wang, J., Pittelkow, C.M., 2019. Modeling inorganic soil nitrogen status in maize agroecosystems. Soil Sci. Soc. Am. J. 83 (5), 1564–1574. https://doi.org/10.2136/sssaj2019.05.0140.

Basso, B., Sartori, L., Cammarano, D., Fiorentino, C., Grace, P.R., Fountas, S., Sorensen, C.A., 2012. Environmental and economic evaluation of N fertilizer rates in a maize crop in Italy: a spatial and temporal analysis using crop models. Biosyst. Eng. 113 (2), 103–111. https://doi.org/10.1016/j.biosystemseng.2012.06.012.

Bassu, S., Brisson, N., Durand, J.L., Boote, K., Lizaso, J., Jones, J.W., Rosenzweig, C., Ruane, A.C., Adam, M., Baron, C., Basso, B., 2014. How do various maize crop models vary in their responses to climate change factors? Glob. Chang. Biol. 20 (7), 2301–2320. https://doi.org/10.1111/gcb.12520.

Batchelor, W.D., Basso, B., Paz, J.O., 2002. Examples of strategies to analyze spatial and temporal yield variability using crop models. Eur. J. Agron. 18 (1–2), 141–158. https://doi.org/10.1016/S1161-0301(02)00101-6.

Bean, G.M., Kitchen, N.R., Camberato, J.J., Ferguson, R.B., Fernández, F.G., Franzen, D. W., Laboski, C.A.M., Nafziger, E.D., Sawyer, J.E., Scharf, P.C., Schepers, J., 2018. Improving an active-optical reflectance sensor algorithm using soil and weather information. Agron. J. 110 (6), 1. https://doi.org/10.2134/agronj2017.12.0733.

Bianchi, T.S., DiMarco, S.F., Cowan Jr., J.H., Hetland, R.D., Chapman, P., Day, J.W., Allison, M.A., 2010. The science of hypoxia in the Northern Gulf of Mexico: a review. Sci. Total Environ. 408 (7), 1471–1484. https://doi.org/10.1016/j.scitotenv.2009.11.047.

Bierman, P.M., Rosen, C.J., Venterea, R.T., Lamb, J.A., 2012. Survey of nitrogen fertilizer use on corn in Minnesota. Agric. Syst. 109, 43–52. https://doi.org/10.1016/j.agsy.2012.02.004.

Bollero, G.A., Bullock, D.G., Hollinger, S.E., 1996. Soil temperature and planting date effects on corn yield, leaf area, and plant development. Agron. J. 88 (3), 385–390. https://doi.org/10.2134/agronj1996.00021962008800030005x.

Cao, P., Lu, C., Yu, Z., 2018. Historical nitrogen fertilizer use in agricultural ecosystems of the contiguous United States during 1850–2015: application rate, timing, and fertilizer types. Earth Syst. Sci. Data 10 (2), 969–984. https://doi.org/10.5194/essd-10-969-2018.

Cassman, K.G., Dobermann, A., Walters, D.T., 2002. Agroecosystems, nitrogen-use efficiency, and nitrogen management. AMBIO J. Hum. Environ. 31 (2), 132–140. https://doi.org/10.1579/0044-7447-31.2.132.

Chen, C., Wang, E., Yu, Q., 2010. Modelling the effects of climate variability and water management on crop water productivity and water balance in the North China Plain. Agric. Water Manag. 97 (8), 1175–1184. https://doi.org/10.1016/j.agwat.2008.11.012.

Chen, G., Tian, H., Zhang, C., Liu, M., Ren, W., Zhu, W., Chappelka, A.H., Prior, S.A., Lockaby, G.B., 2012. Drought in the Southern United States over the 20th century: variability and its impacts on terrestrial ecosystem productivity and carbon storage. Clim. Chang. 114 (2), 379–397. https://doi.org/10.1007/s10584-012-0410-z.

Clark, J.D., Fernández, F.G, Camberato, J.J., Carter, P.R., Ferguson, R.B., Franzen, D.W, Kitchen, N.R., Laboski, C.A., Nafziger, E.D., Sawyer, J.E., Shanahan, J.F., 2020. Weather and Soil in the US Midwest Influence the Effectiveness of Single-and Split-nitrogen Applications in Corn Production. Agron. J. 112, 5288–5299. https://doi.org/10.1002/agj2.20446.

Contosta, A.R., Frey, S.D., Cooper, A.B., 2011. Seasonal dynamics of soil respiration and N mineralization in chronically warmed and fertilized soils. Ecosphere 2 (3), 1–21. https://doi.org/10.1890/ES10-00133.1.

Cooper, P.J.M., Law, R., 1978. Enhanced soil temperature during very early growth and its association with maize development and yield in the Highlands of Kenya. J. Agric. Sci. 91 (3), 569–577. https://doi.org/10.1017/S0021859600059955.

David, M.B., Drinkwater, L.E., McIsaac, G.F., 2010. Sources of nitrate yields in the Mississippi River Basin. J. Environ. Qual. 39 (5), 1657–1667. https://doi.org/10.2134/jeq2010.0115.

David, M.B., Gentry, L.E., Kovacic, D.A., Smith, K.M, 1997. Nitrogen Balance in andExport from an Agricultural Watershed. J. Environ. Qual. 26 (4), 1038–1048. https://doi.org/10.2134/jeq1997.00472425002600040015x.

DeLuca, T.H., Keeney, D.R., McCarty, G.W., 1992. Effect of freeze-thaw events on mineralization of soil nitrogen. Biol. Fertil. Soils 14 (2), 116–120. https://doi.org/10.1007/BF00336260.

Dietzel, R., Liebman, M., Ewing, R., Helmers, M., Horton, R., Jarchow, M., Archontoulis, S., 2016. How efficiently do corn-and soybean-based cropping systems use water? A systems modeling analysis. Glob. Chang. Biol. 22 (2), 666–681. https://doi.org/10.1111/gcb.13101.

Feng, Z., Leung, L.R., Hagos, S., Houze, R.A., Burleyson, C.D., Balaguru, K., 2016. More frequent intense and long-lived storms dominate the springtime trend in central US rainfall. Nat. Commun. 7 (1), 1–8. https://doi.org/10.1038/ncomms13429.

Fernández, F.G., Fabrizzi, K.P., Naeve, S.L., 2017. Corn and soybean's season-long in-situ nitrogen mineralization in drained and undrained soils. Nutr. Cycl. Agroecosyst. 107 (1), 33–47. https://doi.org/10.1007/s10705-016-9810-1.

Fountas, S., Wulfsohn, D., Blackmore, B.S., Jacobsen, H.L., Pedersen, S.M., 2006. A model of decision-making and information flows for information-intensive agriculture. Agric. Syst. 87 (2), 192–210. https://doi.org/10.1016/j.agsy.2004.12.003.

Frink, C.R., Waggoner, P.E., Ausubel, J.H., 1999. Nitrogen fertilizer: retrospect and prospect. Proc. Natl. Acad. Sci. 96 (4), 1175–1180. https://doi.org/10.1073/pnas.96.4.1175.

Giltrap, D.L., Li, C., Saggar, S., 2010. DNDC: A process-based model of greenhouse gas fluxes from agricultural soils. Agric. Ecosyst. Environ. 136 (3–4), 292–300. https://doi.org/10.1016/j.agee.2009.06.014.

Goolsby, D.A., Battaglin, W.A., Aulenbach, B.T., Hooper, R.P., 2000. Nitrogen flux and sources in the Mississippi River Basin. Sci. Total Environ. 248 (2–3), 75–86. https://doi.org/10.1016/S0048-9697(99)00532-X.

Grant, R.F., 1989. Simulation of carbon assimilation and partitioning in maize. Agron. J. 81 (4), 563–571. https://doi.org/10.2134/agronj1989.00021962008100040004x.

Grant, R.F., 1991. The distribution of water and nitrogen in the soil-crop system: a simulation study with validation from a winter wheat field trial. Fertil. Res. 27 (2), 199–213. https://doi.org/10.1007/BF01051128.
Grant, R.F., 1995a. Salinity, water use and yield of maize: testing of the mathematical model ecosys. Plant Soil 172 (2), 309–322. https://doi.org/10.1007/BF00011333.
Grant, R.F., 1995b. Mathematical modelling of nitrous oxide evolution during nitrification. Soil Biol. Biochem. 27 (9), 1117–1125. https://doi.org/10.1016/0038-0717(95)00038-G.
Grant, R.F., 1997. Changes in soil organic matter under different tillage and rotation: mathematical modeling in ecosys. Soil Sci. Soc. Am. J. 61 (4), 1159–1175. https://doi.org/10.2136/sssaj1997.03615995006100040023x.
Grant, R.F., 1998. Simulation in ecosys of root growth response to contrasting soil water and nitrogen. Ecol. Model. 107 (2–3), 237–264. https://doi.org/10.1016/S0304-3800(97)00221-4.
Grant, R.F., 2001. A review of the Canadian ecosystem model ecosys. Model. Carbon Nitrogen Dyn. Soil Manage.
Grant, R.F., 2004. Modeling topographic effects on net ecosystem productivity of boreal black spruce forests. Tree Physiol. 24 (1), 1–18. https://doi.org/10.1093/treephys/24.1.1.
Grant, R.F., 2013. Modelling changes in nitrogen cycling to sustain increases in forest productivity under elevated atmospheric CO_2 and contrasting site conditions. Biogeosciences 10 (11), 7703–7721. https://doi.org/10.5194/bg-10-7703-2013.
Grant, R.F., Pattey, E., 1999. Mathematical modeling of nitrous oxide emissions from an agricultural field during spring thaw. Glob. Biogeochem. Cycles 13 (2), 679–694. https://doi.org/10.1029/1998GB900018.
Grant, R.F., Pattey, E., 2003. Modelling variability in N_2O emissions from fertilized agricultural fields. Soil Biol. Biochem. 35 (2), 225–243. https://doi.org/10.1016/S0038-0717(02)00256-0.
Grant, R.F., Pattey, E., 2008. Temperature sensitivity of N_2O emissions from fertilized agricultural soils: mathematical modeling in ecosys. Glob. Biogeochem. Cycles 22 (4). https://doi.org/10.1029/2008GB003273.
Grant, R.F., Roulet, N.T., 2002. Methane efflux from boreal wetlands: theory and testing of the ecosystem model Ecosys with chamber and tower flux measurements. Glob. Biogeochem. Cycles 16 (4). https://doi.org/10.1029/2001GB001702, 2-1.
Grant, R.F., Juma, N.G., McGill, W.B., 1993. Simulation of carbon and nitrogen transformations in soil: Mineralization. Soil Biol. Biochem. 25 (10), 1317–1329. https://doi.org/10.1016/0038-0717(93)90046-E.
Grant, R.F., Juma, N.G., Robertson, J.A., Izaurralde, R.C., McGill, W.B., 2001. Long-term changes in soil carbon under different fertilizer, manure, and rotation: Testing the mathematical model ecosys with data from the Breton plots. Soil Sci. Soc. Am. J. 65 (1), 205–214. https://doi.org/10.2136/sssaj2001.651205x.
Grant, R.F., Arkebauer, T.J., Dobermann, A., Hubbard, K.G., Schimelfenig, T.T., Suyker, A.E., Verma, S.B., Walters, D.T., 2007. Net biome productivity of irrigated and rainfed maize–soybean rotations: modeling vs. measurements. Agron. J. 99 (6), 1404–1423. https://doi.org/10.2134/agronj2006.0308.
Grant, R.F., Barr, A.G., Black, T.A., Margolis, H.A., McCaughey, J.H., Trofymow, J.A., 2010. Net ecosystem productivity of temperate and boreal forests after clearcutting—a Fluxnet-Canada measurement and modelling synthesis. Tellus B Chem. Phys. Meteorol. 62 (5), 475–496. https://doi.org/10.1111/j.1600-0889.2010.00500.x.
Grant, R.F., Kimball, B.A., Conley, M.M., White, J.W., Wall, G.W., Ottman, M.J., 2011b. Controlled warming effects on wheat growth and yield: field measurements and modeling. Agron. J. 103 (6), 1742–1754. https://doi.org/10.2134/agronj2011.0158.
Grant, R.F., Dyck, M., Puurveen, D., 2020. Nitrogen and phosphorus control carbon sequestration in agricultural ecosystems: modelling carbon, nitrogen, and phosphorus balances at the Breton Plots with ecosys under historical and future climates. Can. J. Soil Sci. 100 (4), 408–429. https://doi.org/10.1139/cjss-2019-0132.
Grisso, R.D., Jasa, P.J., Schroeder, M.A., Wilcox, J.C., 2002. Yield monitor accuracy: successful farming magazine case study. Appl. Eng. Agric. 18 (2), 147. https://doi.org/10.13031/2013.7775.
Guntiñas, M.E., Leirós, M.C., Trasar-Cepeda, C., Gil-Sotres, F., 2012. Effects of moisture and temperature on net soil nitrogen mineralization: a laboratory study. Eur. J. Soil Biol. 48, 73–80. https://doi.org/10.1016/j.ejsobi.2011.07.015.
He, W., Yang, J.Y., Drury, C.F., Smith, W.N., Grant, B.B., He, P., Qian, B., Zhou, W., Hoogenboom, G., 2018. Estimating the impacts of climate change on crop yields and N_2O emissions for conventional and no-tillage in Southwestern Ontario, Canada. Agric. Syst. 159, 187–198. https://doi.org/10.1016/j.agsy.2017.01.025.
Holzworth, D.P., Huth, N.I., deVoil, P.G., Zurcher, E.J., Herrmann, N.I., McLean, G., Chenu, K., van Oosterom, E.J., Snow, V., Murphy, C., Moore, A.D., 2014. APSIM–evolution towards a new generation of agricultural systems simulation. Environ. Model. Softw. 62, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009.
Joseph, G., Henry, H.A., 2008. Soil nitrogen leaching losses in response to freeze–thaw cycles and pulsed warming in a temperate old field. Soil Biol. Biochem. 40 (7), 1947–1953. https://doi.org/10.1016/j.soilbio.2008.04.007.
Kalkhoff, S.J., Hubbard, L.E., Tomer, M.D., James, D.E., 2016. Effect of variable annual precipitation and nutrient input on nitrogen and phosphorus transport from two Midwestern agricultural watersheds. Sci. Total Environ. 559, 53–62. https://doi.org/10.1016/j.scitotenv.2016.03.127.
Krichels, A.H., Yang, W.H., 2019. Dynamic controls on field-scale soil nitrous oxide hot spots and hot moments across a microtopographic gradient. J. Geophys. Res. Biogeosci. 124 (11), 3618–3634. https://doi.org/10.1029/2019JG005224.
Kucharik, C.J., Brye, K.R., 2003. Integrated BIosphere Simulator (IBIS) yield and nitrate loss predictions for Wisconsin maize receiving varied amounts of nitrogen fertilizer. J. Environ. Qual. 32 (1), 247–268. https://doi.org/10.2134/jeq2003.2470.
Li, C., Frolking, S., Frolking, T.A., 1992. A model of nitrous oxide evolution from soil driven by rainfall events: 1. Model structure and sensitivity. J. Geophys. Res. Atmos. 97 (D9), 9759–9776. https://doi.org/10.1029/92JD00509.
Lobell, D.B., Hammer, G.L., McLean, G., Messina, C., Roberts, M.J., Schlenker, W., 2013. The critical role of extreme heat for maize production in the United States. Nat. Clim. 3 (5), 497–501. https://doi.org/10.1038/nclimate1832.
Malone, R.W., Jaynes, D.B., Ma, L., Nolan, B.T., Meek, D.W., Karlen, D.L., 2010. Soil-test N recommendations augmented with PEST-optimized RZWQM simulations. J. Environ. Qual. 39 (5), 1711–1723. https://doi.org/10.2134/jeq2009.0425.
Martinez-Feria, R.A., Castellano, M.J., Dietzel, R.N., Helmers, M.J., Liebman, M., Huber, I., Archontoulis, S.V., 2018. Linking crop-and soil-based approaches to evaluate system nitrogen-use efficiency and tradeoffs. Agric. Ecosyst. Environ. 256, 131–143. https://doi.org/10.1016/j.agee.2018.01.002.
Mezbahuddin, S., Spiess, D., Hildebrand, D., Kryzanowski, L., Itenfisu, D., Goddard, T., Iqbal, J., Grant, R., 2020. Assessing effects of agronomic nitrogen management on crop nitrogen use and nitrogen losses in the Western Canadian prairies. Front. Sustain. Food Syst. 149. https://doi.org/10.3389/fsufs.2020.512292.
Mishra, V., Cherkauer, K.A., 2010. Retrospective droughts in the crop growing season: Implications to corn and soybean yield in the Midwestern United States. Agric. For. Meteorol. 150 (7–8), 1030–1045. https://doi.org/10.1016/j.agrformet.2010.04.002.
Negm, L.M., Youssef, M.A., Skaggs, R.W., Chescheir, G.M., Kladivko, E.J., 2014. DRAINMOD-DSSAT simulation of the hydrology, nitrogen dynamics, and plant growth of a drained corn field in Indiana. J. Irrig. Drain. Eng. 140 (8), 04014026 https://doi.org/10.1061/(ASCE)IR.1943-4774.0000738.
Neild, R.E., Newman, J.E., 1986. Growing season characteristics and requirements in the corn Belt. National Corn Handbook NCH-40. Purdue University.
Paustian, K., Babcock, B., Kling, C., Hatfield, J.L., Lal, R., Mccarl, B., Mclaughlin, S., Schlesinger, W.H., Zilberman, D., 2004. Climate change and greenhouse gas mitigation: challenges and opportunities for agriculture. CAST Task Force Rep. 141.
Peng, B., Guan, K., Tang, J., Ainsworth, E.A., Asseng, S., Bernacchi, C.J., Cooper, M., Delucia, E.H., Elliott, J.W., Ewert, F., Grant, R.F., Gustafson, D.I., Hammer, G.L., Jin, Z., Jones, J.W., Kimm, H., Lawrence, D.M., Li, Y., Lombardozzi, D.L., Marshall-Colon, A., Messina, C., Ort, D., Schnable, J., Vallejos, C.E., Wu, A., Yin, X., Zhou, W., Zhou, W., 2020. Towards a multiscale crop modelling framework for climate change adaptation assessment. Nat. Plants 6 (4), 338–348. https://doi.org/10.1038/s41477-020-0625-3.
Postgate, J.R., 1998. Nitrogen Fixation, 3rd ed. Cambridge University Press, Cambridge, UK.
Pryor, S.C., Scavia, D., Downer, C., Gaden, M., Iverson, L., Nordstrom, R., Patz, J., Robertson, G.P., 2014. Midwest. Climate Change Impacts in the United States: The third national climate assessment. National Climate Assessment Report, pp. 418–440.
Puntel, L.A., Sawyer, J.E., Barker, D.W., Dietzel, R., Poffenbarger, H., Castellano, M.J., Moore, K.J., Thorburn, P., Archontoulis, S.V., 2016. Modeling long-term corn yield response to nitrogen rate and crop rotation. Front. Plant Sci. 7, 1630. https://doi.org/10.3389/fpls.2016.01630.
Qin, Z., Guan, K., Zhou, W., Peng, B., Villamil, M.B., Jin, Z., Tang, J., Grant, R., Gentry, L., Margenot, A.J., Bollero, G., Li, Z., 2021. Assessing the impacts of cover crops on maize and soybean yield in the U.S. Midwestern agroecosystems. Field Crop. Res. 273, 108264 https://doi.org/10.1016/j.fcr.2021.108264.
Rabalais, N.N., Turner, R.E., Wiseman Jr., W.J., 2002. Gulf of Mexico hypoxia, aka "The dead zone". Annu. Rev. Ecol. Evol. Syst. 33 (1), 235–263. https://doi.org/10.1146/annurev.ecolsys.33.010802.150513.
Ransom, J.K., Calles-Torrez, V., Daigh, A., Franzen, D., Friskop, A., Hellevang, K.J., Ikley, J., Knodel, J.J., 2019. Basics of Corn Production in North Dakota. NDSU Extension.
Ransom, C.J., Kitchen, N.R., Camberato, J.J., Carter, P.R., Ferguson, R.B., Fernández, F. G., Franzen, D.W., Laboski, C.A., Nafziger, E.D., Sawyer, J.E., Scharf, P.C., 2020. Corn nitrogen rate recommendation tools' performance across eight US midwest corn belt states. Agron. J. https://doi.org/10.1002/agj2.20035.
Ransom, C.J., Kitchen, N.R., Sawyer, J.E., Camberato, J.J., Carter, P.R., Ferguson, R.B., Fernández, F.G., Franzen, D.W., Laboski, C.A., Myers, D.B., Nafziger, E.D., Shanahan, J.F., 2021. Improving publicly available corn nitrogen rate recommendation tools with soil and weather measurements. Agron. J. https://doi.org/10.1002/agj2.20627.
Ray, D.K., Gerber, J.S., MacDonald, G.K., West, P.C., 2015. Climate variation explains a third of global crop yield variability. Nat. Commun. 6 (1), 1–9. https://doi.org/10.1038/ncomms6989.
Riha, S.J., Wilks, D.S., Simoens, P., 1996. Impact of temperature and precipitation variability on crop model predictions. Clim. Chang. 32 (3), 293–311. https://doi.org/10.1007/BF00142466.
Robertson, G.P., Vitousek, P.M., 2009. Nitrogen in agriculture: balancing the cost of an essential resource. Annu. Rev. Environ. 34, 97–125. https://doi.org/10.1146/annurev.environ.032108.105046.
Rustad, L.E.J.L., Campbell, J., Marion, G., Norby, R., Mitchell, M., Hartley, A., Cornelissen, J., Gurevitch, J., GCTE-NEWS, 2001. A meta-analysis of the response of soil respiration, net nitrogen mineralization, and aboveground plant growth to experimental ecosystem warming. Oecologia 126 (4), 543–562. https://doi.org/10.1007/s004420000544.
Sawyer, J., Nafziger, E.D., Randall, G., Bundy, L., Rehm, G., Joern, B., 2006. Concepts and rationale for regional nitrogen rate guidelines for corn. Iowa State University-University Extension.

Scharf, P.C., 2015. Understanding nitrogen. Managing Nitrogen in Crop Production, pp. 1–24.
Sinha, T., Cherkauer, K.A., Mishra, V., 2010. Impacts of historic climate variability on seasonal soil frost in the Midwestern United States. J. Hydrometeorol. 11 (2), 229–252. https://doi.org/10.1175/2009JHM1141.1.
Sogbedji, J.M., Van Es, H.M., Klausner, S.D., Bouldin, D.R., Cox, W.J., 2001. Spatial and temporal processes affecting nitrogen availability at the landscape scale. Soil Tillage Res. 58 (3–4), 233–244. https://doi.org/10.1016/S0167-1987(00)00171-9.
Stevens, W.B., Hoeft, R.G., Mulvaney, R.L., 2005. Fate of nitrogen-15 in a long-term nitrogen rate study: II. Nitrogen uptake efficiency. Agron. J. 97 (4), 1046–1053. https://doi.org/10.2134/agronj2003.0313.
Stone, P.J., Sorensen, I.B., Jamieson, P.D., 1999. Effect of soil temperature on phenology, canopy development, biomass and yield of maize in a cool-temperate climate. Field Crop. Res. 63 (2), 169–178. https://doi.org/10.1016/S0378-4290(99)00033-7.
Struffert, A.M., Rubin, J.C., Fernández, F.G., Lamb, J.A., 2016. Nitrogen management for corn and groundwater quality in Upper Midwest irrigated sands. J. Environ. Qual. 45 (5), 1557–1564. https://doi.org/10.2134/jeq2016.03.0105.
Tubiello, F.N., Ewert, F., 2002. Simulating the effects of elevated CO_2 on crops: approaches and applications for climate change. Eur. J. Agron. 18 (1–2), 57–74. https://doi.org/10.1016/S1161-0301(02)00097-7.
Turner, M.M., Henry, H.A., 2010. Net nitrogen mineralization and leaching in response to warming and nitrogen deposition in a temperate old field: the importance of winter temperature. Oecologia 162 (1), 227–236. https://doi.org/10.1007/s00442-009-1435-5.
Vanotti, M.B., Bundy, L.G., 1994. An alternative rationale for corn nitrogen fertilizer recommendations. J. Prod. Agric. 7 (2), 243–249. https://doi.org/10.2134/jpa1994.0243.
Wagner-Riddle, C., Thurtell, G.W., 1998. Nitrous oxide emissions from agricultural fields during winter and spring thaw as affected by management practices. Nutr. Cycl. Agroecosyst. 52 (2), 151–163. https://doi.org/10.1023/A:1009788411566.
Waha, K., Müller, C., Rolinski, S., 2013. Separate and combined effects of temperature and precipitation change on maize yields in sub-Saharan Africa for mid-to late-21st century. Glob. Planet. Chang. 106, 1–12. https://doi.org/10.1016/j.gloplacha.2013.02.009.
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.
Welegedara, N.P., Grant, R.F., Quideau, S.A., Das Gupta, S., 2020. Modelling nitrogen mineralization and plant nitrogen uptake as affected by reclamation cover depth in reclaimed upland forestlands of Northern Alberta. Biogeochemistry 149, 293–315. https://doi.org/10.1007/s10533-020-00676-5.
Williams, J.R., 1995. The EPIC model. Comput. Models Watershed Hydrol. 909–1000.
Woli, K.P., David, M.B., Cooke, R.A., McIsaac, G.F., Mitchell, C.A., 2010. Nitrogen balance in and export from agricultural fields associated with controlled drainage systems and denitrifying bioreactors. Ecol. Eng. 36 (11), 1558–1566. https://doi.org/10.1016/j.ecoleng.2010.04.024.
Wuebbles, D.J., Hayhoe, K., 2004. Climate change projections for the United States Midwest. Mitig. Adapt. Strateg. Glob. Chang. 9 (4), 335–363. https://doi.org/10.1023/B:MITI.0000038843.73424.de.
Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., 2012. Continental-scale water and energy flux analysis and validation for the North American Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products. J. Geophys. Res. Atmos. 117 (D3) https://doi.org/10.1029/2011JD016048.
Zhang, X., Davidson, E.A., Mauzerall, D.L., Searchinger, T.D., Dumas, P., Shen, Y., 2015. Managing nitrogen for sustainable development. Nature 528 (7580), 51–59. https://doi.org/10.1038/nature15743.
Zhou, W., Guan, K., Peng, B., Tang, J., Jin, Z., Jiang, C., Grant, R., Mezbahuddin, S., 2021. Quantifying carbon budget, crop yields and their responses to environmental variability using the ecosys model for US Midwestern agroecosystems. Agric. For. Meteorol. 307, 108521 https://doi.org/10.1016/j.agrformet.2021.108521.