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Field scale SWAT+ modeling of corn and soybean yields for the contiguous United States: National Agroecosystem Model Development

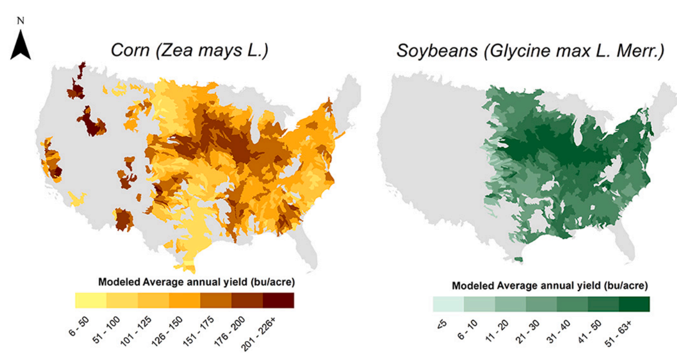
Natalja Čerkasova [a,f,*], Michael White [b], Jeffrey Arnold [b], Katrin Bieger [c], Peter Allen [d], Jungang Gao [a], Marilyn Gambone [b], Manyowa Meki [a], James Kiniry [b], Philip W. Gassman [e]

[a] Texas A&M AgriLife Research, Blackland Research and Extension Center, 720 E. Blackland Road, Temple, TX 76502, United States
[b] USDA-ARS Grassland Soil and Water Research Laboratory, 808 E. Blackland Road, Temple, TX 76502, United States
[c] Aarhus University, Department of Ecoscience, C.F. Møllers Allé 3, 8000 Aarhus C, Denmark
[d] Baylor University, Department of Geosciences, Baylor Sciences Building D409, 101 Bagby Ave., Waco, TX 76706, United States
[e] Center for Agricultural and Rural Development, Iowa State University, 578 Heady Hall, Ames, IA 50011, United States
[f] Klaipeda University Marine Research Institute, Universiteto ave. 17, LT-92294 Klaipeda, Lithuania

HIGHLIGHTS

- SWAT+: a high-resolution national-scale model for crop growth and yield estimation
- National scale model with over 2.5 M individual corn and soybeans fields simulated.
- Crop yield calibration procedure incorporated into the new SWAT+ model.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Despite a steady increase in staple crop yields over the past ten years, current agricultural production must escalate even more to keep pace with the expected world population growth, which in turn will require improved agricultural methods that are adapted to many environmental pressures. Comprehensive models that can simulate crop production systems and the impact of management and conservation practices on natural resources and the environment, including water quality at large scale present important contributions to this challenge.
OBJECTIVE: To this end we developed the National Agroecosystem Model (NAM): a comprehensive model that uses the updated Soil and Water Assessment Tool (SWAT+) to accurately simulate staple crop yields across the contiguous United States (CONUS), with an initial focus on Corn (*Zea mays L.*) and Soybean (*Glycine* max L. *Merr.*) yields.
METHODS: Available open-access data was used to setup this high-resolution modeling system, where every 8-digit hydrologic unit (HUC8) is represented as an individual SWAT+ simulation. A total of 2201 HUC8

* Corresponding author at: Texas A&M AgriLife Research, Blackland Research and Extension Center, 720 E. Blackland Road, Temple, TX 76502, United States.
E-mail address: natalja.cerkasova@brc.tamus.edu (N. Čerkasova).

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simulations across the CONUS were interconnected from upstream to downstream to make the NAM. Field boundary data was used to setup the NAM in such a way that every identified cultivated field is modeled as a unique Hydrologic Response Unit (HRU). Simulated corn and soybean yield from over 2.5 million field-type HRUs were compared to reported average annual corn and soybean yields for the respective area for the 2015–2020 period.

RESULTS AND CONCLUSIONS: Results show a good agreement between simulated and reported yields ($R^2 = 0.90$ for corn and $R^2 = 0.70$ for soybeans), with a very good model performance in the high corn and soybean production region of the US Corn Belt (Relative Error $< \pm 5\%$).

SIGNIFICANCE: Apart from assessing the capability of the updated SWAT+ model, we also demonstrate the new crop yield calibration module embedded in SWAT+, highlight changes to the plant growth module, and model parameterization. Results of an analysis of possible crop production differences for corn and soybeans in irrigated, tiled, and non-irrigated-non-tiled fields are also discussed. The versatility of the NAM provides the possibility to analyze information on impacts of changing conservation practices and enables identification of conservation gains and remaining conservation needs at the national scale.

1. Introduction

In February 2020, the United States Department of Agriculture (USDA) announced the Agriculture Innovation Agenda, with a goal of increasing U.S. agricultural production by 40% while cutting the environmental footprint of U.S. agriculture in half by 2050 (USDA, 2021). National models that simulate the impact of land management and climate on crop production and environmental quality can assist in policy making to achieve this ambitious goal. National models have been developed by the USDA and university partners for conservation and environmental assessment. The Conservation Effects Assessment Project (CEAP) was developed to determine the impact of USDA conservation practices on agriculture and the environment (Mausbach and Dedrick, 2004; Duriancik et al., 2008). The Hydrologic and Water Quality System (HAWQS) was developed for the U.S. Environmental Protection Agency (USEPA) for national and local environmental policy development (Yen et al., 2016). The Long Term Agroecosystem Research (LTAR) project, led by the USDA Agricultural Research Service (ARS), also applies national modeling and monitoring efforts to determine "aspirational" practices to achieve USDA policy goals (USDA, 2019a, 2019b; White et al., 2022).

Crop yield estimates have broad impacts on economic sectors, such as food production monitoring, global trade, food security, and environmental externalities including hydrologic processes, pollutant transport and production sustainability. According to the Agriculture Census (USDA/NASS, 2021), there has been a steady increase in corn and soybean yields in the U.S. over the past ten years (Fig. 1). Nevertheless, to keep pace with the expected world population growth, current agricultural production must increase by about 70% by 2050 (FAO, 2018). Addressing this food production challenge will require improved agricultural methods that are adapted to many environmental pressures. Comprehensive ecohydrological models that can simulate crop production systems and the impact of management and conservation practices on natural resources and the environment, including water quality at large scale can make a very important contribution to this challenge (Chen et al., 2021).

The U.S. Corn Belt is an example of a region that could benefit from the application of ecohydrological modeling tools, due to the pervasive export of nutrients and other pollutants from cropland landscapes and other source areas (Jones and Schilling, 2011; Jones et al., 2018a, 2018b; Sprague et al., 2011; USEPA, 2008). The application of such models can provide vital insights regarding the need for alternative cropping systems and best management practices (BMPs) to reduce nonpoint source pollution losses, relative to dominant row crop systems in intensive crop production areas. Several ecohydrological models have been developed that can assess soil cycling processes and subsequent transport of sediment, nutrients, pesticides and/or other pollutants as documented in previous review studies (e.g., Mottes et al., 2014; Collender et al., 2016; Habibiandehkordi et al., 2020; Arnillas et al., 2021; Borrelli et al., 2021, Fu et al., 2019). A number of these ecohydrological

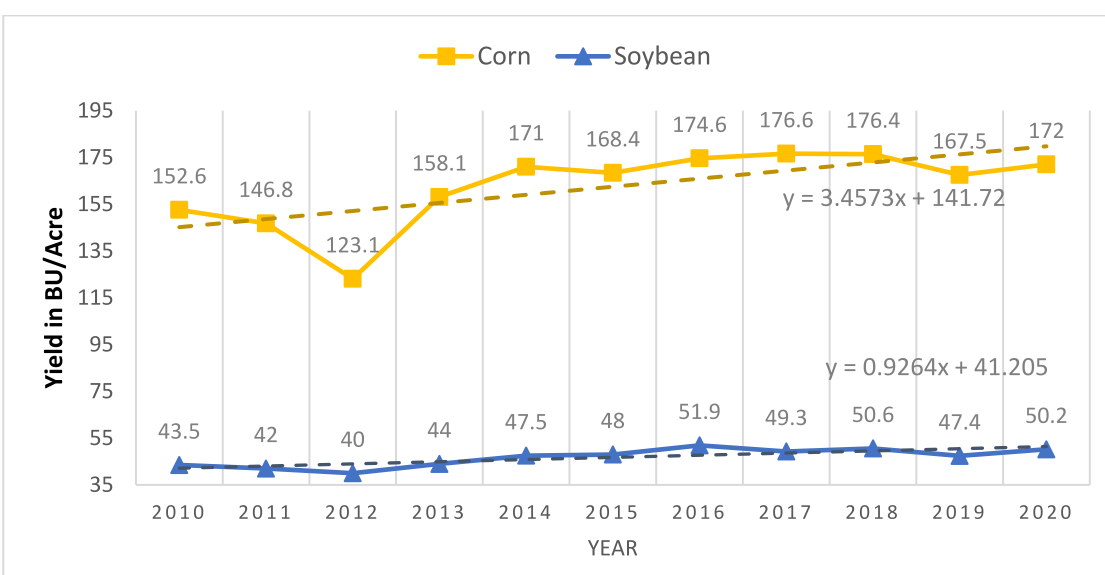

Fig. 1. Reported national yields for corn (*Zea mays* L.) and soybeans (*Glycine* max L. Merr.) during the period 2010 to 2020 (USDA/NASS, 2021). The dotted lines show the yield trends.

models (e.g., APEX, AnnAGNPS, COLI, GIBSI, GWLF, HSPF, IHACRES, SWAT, WATFLOOD, WAMVIEW, WEPPI) can be used to simulate the effects of in-field or structural agricultural BMPs (Xie et al., 2015; Arnillas et al., 2021), irrigation-related BMPs (Uniyal and Dietrich, 2021) and/or urban landscape BMPs (Kaykhosravi et al., 2018; Lisenbee et al., 2021).

The Soil and Water Assessment Tool (SWAT) has been developed over three decades (Arnold et al., 1998, Arnold et al., 2012a; Arnold et al., 2012b; Williams et al., 2008a, 2008b; Bieger et al., 2017) and is one of the most widely used ecohydrological models in the world used for various hydrological and environmental applications (Heistermann et al., 2014; Mannschatz et al., 2016; Hossard and Chopin, 2019). The model features climate, weather, crop growth, hydrologic, pollutant (e.g., nutrients, sediment, pathogens) cycling and transport, and other key components that support considerable application flexibility (Arnold et al., 2012b; Neitsch et al., 2011). SWAT simulates many types of agricultural, irrigation and urban BMPs (Arnillas et al., 2021; Uniyal and Dietrich, 2019; Lisenbee et al., 2021), and is adaptable and robust for assessing a suite of water resource problems for a range of environmental conditions (Gassman et al., 2014, 2022; Krysanova and White, 2015; Tan et al., 2020; Tan et al., 2021; Wang et al., 2019; Samimi et al., 2020; Ghimire et al., 2020; Wang and Chen, 2021; Akoko et al., 2021; CARD, 2018). Accurate simulation of corn, soybean and other crops is critical for applying SWAT to the Corn Belt and other intensive U.S. agricultural production regions. Errors in prediction of crop biomass and yields can result in incorrect depictions of hydrologic balance, crop residues on the soil surface, nutrient cycling and simulation of pollutant transport (Nair et al., 2011; Ilampooranan et al., 2021). Improved predictions of crop yields and biomass in SWAT have resulted in more accurate overall simulation of hydrology and/or pollutant export for watersheds that represent a considerable spectrum of climate, vegetation and other conditions (Strauch and Volk, 2013; Guo et al., 2019; Ma et al., 2019; Rajib et al., 2018; Lai et al., 2020; Čerkasova et al., 2021; Fernandez-Palomino et al., 2021; Nkwasa et al., 2020, 2022).

The primary objective of this study is to evaluate crop growth processes predicted with the updated SWAT+ model (Bieger et al., 2017) as implemented in the National Agroecosystem Model (NAM), developed by the USDA Agricultural Research Service (ARS) and Texas A&M AgriLife Research and Extension (Arnold et al., 2021; White et al., 2022). The National Agroecosystem Model was designed to cover the CONUS and selected drainages of Canada and Mexico and provides a fine-resolution national-scale model to address the needs of the USDA and many other projects and studies. A key aspect of ongoing NAM testing is focused on assessing the capability of SWAT+ to accurately represent crop growth processes. Thus, the specific objective of this research is to describe: (1) the development and functioning of the SWAT+ crop growth module, and (2) assess the capability of SWAT+ to simulate corn and soybean yields in the Corn Belt and other U.S. production regions.

2. Data and methods

2.1. SWAT+ description

SWAT simulates the full spectrum of hydrological processes, sediment and nutrient cycles, as well as vegetation growth including crop production. Over the years, the SWAT source code has undergone major modifications as documented by Gassman and Wang (2015) through SWAT version 2012. The model has evolved to the present SWAT+ code, which is a restructured version of the model as described by Bieger et al. (2017). Many core functions, described in the extensive SWAT theoretical and I/O documentation (Arnold et al., 2011; Arnold et al., 2012a, 2012b; Neitsch et al., 2011) are present and relevant for the current version of SWAT+. Changes in SWAT+ include more realistic simulation of water areas, different levels of complexity for simulating land phase and channel routing processes, the possibility to maintain management schedules and operations as databases, flexibility in defining variables affecting the timing of management operations and simulation of plant communities. Bieger et al. (2017) and documentation available at the SWAT webpage (SWAT Development Team, 2022a) give comprehensive descriptions of the revised model. In this study we describe changes in SWAT+ related to the simulation of crop growth processes.

Revised crop growth module of SWAT+.

The original SWAT plant growth submodel (Neitsch et al., 2011) is a simplified version of the corresponding module incorporated in the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1989). However, several plant growth improvements and additions have been incorporated into SWAT+ as described here. In the context of this section of the paper, we define an "object" as a plain structure that contains attributes and methods in the code of SWAT+. The term is common within an object-oriented programming dictionary. The SWAT+ is programmed using object-oriented programming language (Fortran). The code for the revised crop growth module is provided in Supplementary Material A. The full and the most up-to date SWAT+ code, revision history, and used databases are located at the SWAT+ source code repository: https://bitbucket.org/blacklandgrasslandmodels/modular_swatplus/src/master/.

SWAT+ uses a plant specific radiation use efficiency (RUE), intercepted photosynthetically active radiation and leaf area index (LAI), to calculate potential daily biomass increase (Neitsch et al., 2011). Simulated plant growth is reduced by extreme temperature, insufficient water, and insufficient available nitrogen or phosphorus as in previous SWAT versions (Neitsch et al., 2011). In addition, an algorithm used in the Agricultural Policy/Environmental eXtender (APEX) model (Williams et al., 2008a, 2008b; Gassman et al., 2010) which calculates aeration stress from excess water as a function of soil water content and a plant specific aeration factor, has been included in SWAT+.

SWAT+ partitions plant parts between leaf, stem, roots, and seeds (as shown in the code objects in the Supplemental Material A). By partitioning the plant into separate objects, the code is more transparent and easier to maintain while the harvest operations have physical meaning to the user. SWAT+ uses harvest index (HI), which is specified in the harvest management operations. The user may choose to harvest grain, root, or biomass. The root harvest operation specifies the ratio of root yield to total root biomass. The biomass harvest specifies the ratio of biomass yield to total above ground biomass. For the grain harvest operation, users input an optimum and minimum harvest index (ratio of grain harvested to the total above ground biomass). The actual HI is computed as a function of actual and potential water uptake as described in Neitsch et al. (2011) and is bounded by the optimum and minimum HI.

A major improvement to the SWAT+ code is the use of an organic object containing total carbon, nitrogen, and phosphorus. This object is used for each part of the plant including roots, leaves, stalk, seeds, above ground, and total biomass. Using an organic object for storing each component and partitioning daily allows the model to move nutrients from one plant component to another (i.e., above ground to roots).

Another plant growth addition to SWAT+ is plant competition taken from the Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC) model (Kiniry et al., 1992). Although not implemented in this study, multiple plants can grow at the same time and compete for light, water, and nutrients. Light competition is a function of LAI and height of competing plants. Water and nutrient competition are functions of plant demand and root depth and distribution.

2.2. PHU program incorporation into SWAT+

Heat unit systems quantify the thermal environment of plants and are commonly used in phenology models that relate plant growth and development to local climate conditions. Plant heat units are defined using the Eq. (1):

$$hu_i = sum(t_{mean_i} - t_{base}), \text{when } t_{mean_i} > t_{base} \quad (1)$$

where hu_i is the current sum of heat units on the day (i) of simulation from start of seasonal growth in degrees Celsius, t_{mean_i} is the average daily temperature, and t_{base} is the base temperature of the plant. A heat unit index is calculated by dividing hu by the heat units to maturity. This index is used to determine phenological stages of growth including leaf development, root growth, grain development, and maturity.

SWAT model users can access an external potential heat unit (PHU) program (SWAT Development Team, 2022b) that calculates the total number of heat units required to bring a plant to maturity using 1) long-term maximum and minimum temperature data, 2) the base or minimum temperature required by the plant for growth, 3) and the average number of days for the plant to reach maturity. A slightly modified version of the PHU program (Potential Heat Unit Program, (accessed 10.5.21)) is now incorporated directly into SWAT+. The main difference is that it uses days to maturity as an input instead of heat units to maturity. The concept of heat units to maturity was developed for annual crops but heat units are now used in SWAT+ for the entire growing season for both native perennials and annual crops. By inputting days to maturity, different crop varieties can be included as defined by length of growing season (for example, corn varieties for 120-, 110-, 100- and 90-day maturities). The heat units to maturity calculation in the model first computes base zero heat units (the above equation with $t_{base} = 0$) for the entire year and assumes a planting date when heat units exceed *0.15*base zero*, which starts the growing season. Then, the model calculates heat units from the planting date through the days to maturity, using the crop's base temperature as input. If the maximum days for a crop are input (for example, 120 days for corn) and the growing season is less than the inputted value, the model essentially sums heat units for the entire growing season which represents (and estimates) the maximum days to maturity. The algorithm uses maximum and minimum air temperature weather generator parameters, specifically the long-term average daily temperature values for each month. The SWAT+ model provides heat unit estimates in both the northern and southern hemispheres.

2.3. Built-in calibration procedure

Two types of data that can be used for model calibration: "soft" and "hard" data. Measured time series data (i.e., streamflow, water quality parameters, etc.) are defined as "hard" data, whereas information on the processes that cannot be directly measured or compared, or aggregated statistical information (i.e., average annual estimates of water balance components) are defined as "soft" data. Model calibration using soft data is called soft calibration, or mass-balance calibration, whereas using directly measured data – hard calibration. Such an approach was suggested by Seibert and McDonnell (2002) and Arnold et al. (2015) for multi-criteria model calibration. Both studies emphasize that the use of soft data in model calibration could provide realistic parameter ranges and ensure a formal check on the rationality and consistency of internal model structures and simulations. The new SWAT+ model has built-in soft calibration modules to perform model parameter adjustments for water budget and crop yield calibration in a semi-automated way. This procedure is further described in the "Model calibration" section of this paper.

2.4. Study site and model setup description

The NAM covers the entire contiguous U.S. and selected drainages of Canada and Mexico, which have contributing (in terms of flow) areas. The region is extremely varied in terms of climate, geology, topography, agriculture and management practices, which make it an excellent application platform for the enhanced flexibility of SWAT+. The NAM setup procedure and model structure are different than the majority of SWAT/SWAT+ applications due to their complexity and size. Like in the earlier versions of SWAT, SWAT+ estimates land processes at HRU level, which is a fundamental spatial unit of the model represented by the combination of unique land use, soil, and slope characteristics, while the water processes are handled at the channel level. The United States Watershed Boundary Dataset (WBD) maps the extent of surface water drainage for the U.S. using a hierarchical system of nesting hydrologic units at various scales, each with an assigned hydrologic unit code (HUC). HUC8 maps the subbasin level, analogous to medium-sized river basins. A total of 2201 HUC8 models across the CONUS make up the NAM. An advanced field-HRU definition and a multi-model routing structure are distinctive features of the NAM.

2.5. Data

A SWAT+ model requires many datasets to be incorporated in the model setup. Standard data includes the topographical information of the modeled area, soil types and properties, land use and land management data. To accurately describe the crop growth related processes, modelers need to include data for crop management, tile drainage and irrigation, tillage and fertilization, and other related datasets (Table 1). The latest reported field crop yields at county-level for the 2015–2020 period (USDA, 2020) were used for model calibration and performance assessment.

2.6. HRU definition

Agricultural fields delineated by Yan and Roy (2016) are represented as separate HRUs, each with its assigned crop or crop rotation and management template. These field HRUs in the NAM no longer correspond to a distinct combination of land use, soil, and slope, unlike in a typical setup of the SWAT model. Instead, field HRUs are parameterized based on the dominant soil type and the average slope of the field. Although this method is considered suitable for analysis, it may result in some loss of information, particularly when the HRU field covers significantly different soil/slope conditions. There are 2,457,063 HRUs representing corn and 2,638,348 HRUs representing soybean production at any point within the simulation period (example of a simulated agriculture dominant HUC8 is presented in Fig. 2). Many of these HRUs (fields) produce corn and soybeans in two- or more year rotations. The average HRU size which represents a field is 24 ha, whereas non-field HRUs average 323 ha.

We used a set of custom tools, programs, and scripts to pre-process the data stored in SQL (Structured Query Language) tables and to set up the model in a semi-automatic way. These tools use the tabulated data and a set of rules to produce a complete SWAT+ model setup with parameterized HRUs, management tables, routing information, and weather data. Each HUC8 is represented by a separate SWAT+ simulation, which, if relevant, receives hydrological and water quality information from the upstream model and transfers its output to the downstream model. We use a model executor program for executing each of the SWAT+ simulations in the correct order from upstream HUC8s to downstream areas, until the entire CONUS area has been simulated. For an in-depth description of the setup and tools, we refer the reader to White et al. (2022).

2.7. Management operations and field categories

SWAT+ management templates were prepared from existing data sources at the national management database using semi-automated procedures described in White et al. (2016). The national management database uses the existing U.S. Department of Agriculture data sources and covers operation scheduling and fertilization application rates for all major cultivated crops in the U.S. These templates were used to assign management operations, such as planting, tillage, fertilization, etc., to each HRU based on field category and other factors. An automatic procedure compared land-cover data of each field-type HRU for

Table 1
Summary of datasets used for National Agroecosystem Model (NAM) model setup.

Data	Description and source	Reference
Base model setup		
Topography	10 m Digital Elevation Model (DEM) from the USGS National Elevation Dataset	(USGS, 2017)
Land use	Cropland Data Layer (CDL) 2014 CDL land use	(Han et al., 2012)
Soil	10 m Gridded Soil Survey Geographic (gSSURGO) U.S. General Soil Map (STATSGO2)	(Soil Survey Staff, 2020, Soil Survey Staff, 2020b)
Channel/Stream network	National Hydrography Dataset Plus Version 2 (NHD+)	(Moore and Dewald, 2016)
Waterbodies: Reservoirs, ponds, wetlands, etc.	2011 National Land Cover Database (NLCD) National Hydrography Dataset (NHD)	(Homer et al., 2012; USGS, 2015)
Hydrologic Unit boundaries	Watershed Boundary Dataset (WBD)	(USGS, 2015)
Cropland field boundaries	Combination of weekly 30 m Web Enabled Landsat, (WELD), Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhance Thematic Mapper Plus (ETM+) imagery.	(Yan and Roy, 2016)
Irrigation	Summary of irrigated and non-irrigated planted acres for years 2010 to 2018	(USDA, 2020)
Observations		
Weather	Observed daily weather data and data derived from Parameter-elevation Regressions on Independent Slopes Model (PRISM)	(Gao et al., 2020; GeoPlatform Curator, 2019)
Upland water balance components	Precipitation, surface runoff, ET, total water yield, baseflow, reassigned by HUC8 used for the soft calibration of the water balance	(Baffaut et al., 2020), (Reitz et al., 2017)
Water management	Estimated surface and ground agricultural irrigation withdrawals by county, total surface and groundwater withdrawals for municipal usage by county	(Dieter et al., 2018)
Land management (planting, fertilization, etc.)	Expert panel and USDA Natural Resources Conservation Service personnel at the HUC8 level and derived management template	(White et al., 2016)
Tillage	Tillage intensity by crop type and HUC8	(Baker, 2011)
Tile drains	Summarized data on county level estimates of cropland under tile drainage	(Schwartz, 2015)
Point sources	Measured pollutant concentrations from permitted wastewater discharge facilities, derived from the National Permit Discharge Elimination System (NPDES); Estimated pollutant loads per capita using the U.S. Census population data (Urban).	(Maupin and Ivahnenko, 2011; Skinner and Maupin, 2019; US Census Bureau, 2019)
Crop yields	NASS Census of Agriculture County level yields for major field crops	(US Census Bureau, 2019)
Commercial Fertilizer ApplicaitIon	NASS Census of Agriculture fertilizer application data	(USDA, 2019a, 2019b)
Structural Conservation Practices	Conservation data for terraces, waterways, filter strips, riparian buffers, contour farming, and strip cropping	(White et al., 2017)

multiple years. If changes in crop type were detected, then the HRU was classified as having multi-crop rotations and assigned the corresponding management. Other HRUs were classified as single-crop HRUs. Similar to crop rotation, we used an automatic procedure to apply tillage, tiles, and irrigation parameters, based on statistics and probability functions. Although such a probabilistic approach may result in under- or over-estimation of certain processes at a small scale, when averaged over large areas these discrepancies do not have a noticeable influence on the annual crop yield estimations. The NAM development team members are constantly integrating new open-access data into the NAM to improve the process representation and the predictive capabilities of the model. Future versions of NAM may include products of other studies, such as the crop frequency map produced by (Zhang et al., 2020) based on Google Earth Engine, which can provide information regarding the potential geospatial distribution of crop planting in the future, or the irrigated land map generated from MODerate Resolution Imaging Spectroradiometer ("Irrigated Lands from Remote Sensing," 2001).

We sorted all fields into four categories based on the water sources and management: 1) irrigated – fields that have irrigation systems in place, and are not tiled; 2) tiled – fields that are rainfed and have tile drainage systems implemented, 3) no irrigation no tile – fields that are naturally rainfed and have no irrigation or tile drainage systems, and 4) irrigated and tiled fields. Subsequently, we analyzed the average annual yields for each category in each state in the Corn Belt region (US Midwest region) which traditionally reports the highest yields for both corn and soybeans. The irrigated-tiled field type was excluded from the analysis, as there are very few fields in this category, and they therefore do not provide any statistical or analytical insight.

2.8. Decision tables

In the previous version of SWAT (SWAT2012), planting, tillage, fertilization, irrigation, harvesting, and other agricultural management activities had to be specified via management operations for each HRU in the input files (.mgt). Only irrigation and fertilization could be initiated automatically when certain conditions were met, i.e., when the plant was under a user-defined water stress (i.e., soil water content or plant water demand) or nitrogen stress. However, without having an in-depth knowledge of farm-level management practices in the simulated area, it is challenging to set up an accurate representation of crop production and to calibrate and validate the model. Many studies rely on statistical data, averaged over large areas like administrative units, agricultural, or soil zones, to get a representation of farm practices, amounts of applied fertilizers, and crop production (Lai et al., 2020; Masud et al., 2019; Pagliero et al., 2019; Panagopoulos et al., 2011; Psomas et al., 2016; Udias et al., 2018). SWAT+ facilitates the definition of management operations by use of decision tables (DT) as described by Arnold et al. (2018). We used a unified decision table (full DT setup is given in the Supplementary Material B) to describe some of the land use management operations, triggered by pre-defined conditions for the typical crops:

- fert_rot_1 – defines the fertilization (Nitrogen), based on the growing stage and plant nitrogen stress

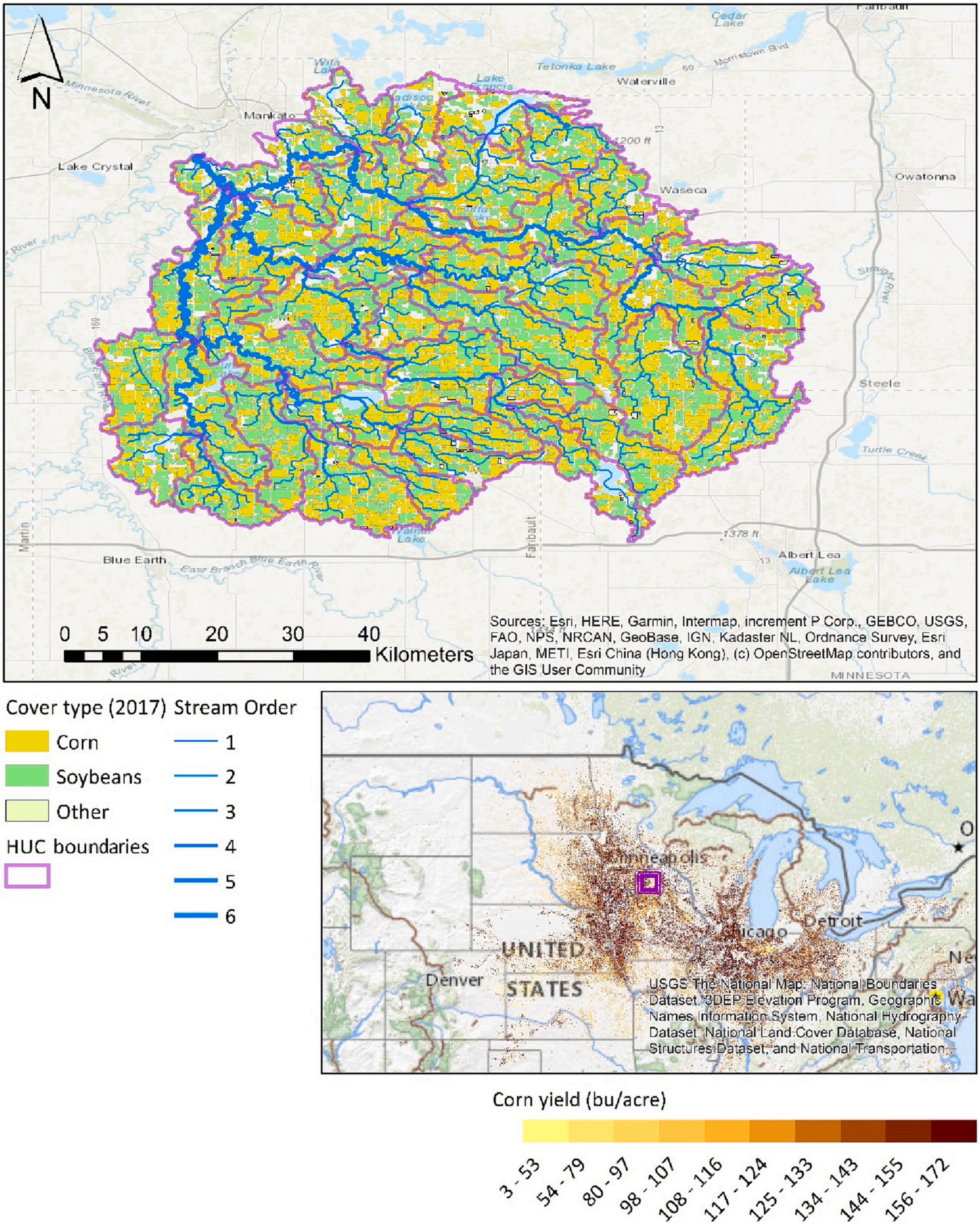

Fig. 2. Example of a HUC8 model and its location in the U.S., with identified corn and soybean fields for the year 2017, in the Corn Belt represented as unique Hydrologic Response Units.

- fert_sprg_side defines the fertilization (Phosphorus), based on the growing stage and plant phosphorus stress
- irr_str8 and irr_str8_unlim – define drip irrigation initiation triggered by plant water stress
- irr_sw75 and irr_sw75_unlim – define sprinkler irrigation initiation triggered by plant water stress
- pl_hv_ccsws – defines the plant and harvest operations of corn, soybeans, and winter wheat in rotation, based on the year
- pl_hv_corn – defines the planting and harvesting of corn based on soil moisture and air temperature (accumulation of PHU)
- pl_hv_corn_sb – defines the planting and harvesting of corn and soybeans in rotation, based on soil moisture, air temperature (accumulation of PHU), and year

- pl_hv_soyb – defines the planting and harvesting of soybeans based on soil moisture and air temperature (accumulation of PHU).

The water and nitrogen stress calculations are provided in Chapter 5:3.1. of the Theoretical Documentation (Neitsch et al., 2011).

2.9. Model calibration

As an initial step we performed the water balance calibration using soft data (see Table 1. Upland water balance components) to verify that the processes associated with the hydrological cycle are represented adequately by reducing the percent difference of the simulated average annual water balance components (precipitation, surface runoff, ET, total water yield, baseflow) compared to the ones derived from Baffaut et al. (2020), supplemented by Reitz et al. (2017), and reassigned by HUC8. For a detailed description of the water balance calibration, the reader is referred to White et al. (2022). After several calibration iterations we obtained satisfactory results for water yield ($R^2 = 0.932$ and average annual relative error for total flow fell below 1%) and proceeded with the second step, the calibration of crop parameters.

2.10. Crop and crop yield associated parameters

There are several parameters in SWAT+ that impact plant growth and crop yields. The parameters used for the calibration of crop yields in the NAM are: 1) plant uptake compensation factor (epco), 2) pest stress (pest_stress), 3) maximum potential leaf area index (lai_pot), and 4) HI for optimal growing conditions (hi_pot) (Table 2). These four parameters were selected based on their significant impact on crop yield simulation, as reported in previous studies (see Kiniry et al., 1997, 2004, Kiniry and Bockholt, 1998, Xie et al., 2001, Yuan et al., 2017, Setiyono et al., 2008, Xiong et al., 2016, Kenichi, 2006; Choruma et al., 2019), and our insights into the model sensitivity. The calibration procedure is a heuristic, one variable at a time approach similar in concept to the procedure developed by Kannan et al. (2008) for soft calibration of a national water balance by HUC8. Observed average county-level yields from the Census of Agriculture recalculated for each HUC8 are input to the model. The initial simulation is performed with default input values. Each HUC8 model is executed in the correct order from upstream to downstream areas and the routing information is transferred between the HUCs. The model then calculates the difference between simulated and observed yields, adjusts calibration variables based on the percent difference, and reruns the model with the updated variables. The procedure is coded in SWAT+ so no other interface or software is needed. It is simple and efficient, requiring a maximum of 13 simulations to minimize the difference between simulated and observed yields.

SWAT+ uses a plant water uptake compensation factor (epco) to allow water uptake from deeper soil layers to occur. As epco approaches 1.0, water uptake from deeper layers is allowed to compensate if water is unavailable in the upper layers. As epco approaches 0.0, the original uptake distribution is followed without allowing lower layers to compensate.

The parameter pest_stress is applied directly to the HI at harvest to account for the impact of insects, disease, and weeds on yields. The APEX model uses soil cover by plant biomass, temperature, and 30-day accumulated rainfall in an algorithm that increases stress in warm, moist periods with adequate ground cover and decreases in cold temperatures. This approach is realistic, but difficult to parameterize and validate, so we chose to input a stress factor instead. The pest_stress is allowed to vary from 0 to 10%.

The default values for parameter lai_pot in the plant growth database are based on average plant densities in dryland (rainfed) agriculture. The parameter may need to be adjusted for drought-prone regions where planting densities are smaller or irrigated conditions where densities are greater. We define the allowable variation of lai_pot to range by ±1 from the value in the plant database.

For corn and soybeans the value of HI defines the fraction of grain that is removed from the plant during harvest. Two harvest indices are provided in the database, the HI for optimal growing conditions (hi_pot) and the HI under highly stressed growing conditions (hi_min). The value of hi_pot is allowed to vary to account for differences in conditions, uncertainty in field measurements, and different crop varieties.

Table 2
Crop yield calibration parameters and their initial values and ranges for corn and soybeans (soyb).

Variable	Initial Value	Min Lower Limit	Max Upper Limit
epco	1.0	0.0	1.0
pest_stress	0.05	0.0	0.1
lai_pot	corn = 5.0	corn = 4.0	corn = 6.0
	soyb = 4.0	soyb = 3.0	soyb = 5.0
hi_pot	corn = 0.50	corn = 0.425	corn = 0.575
	soyb = 0.33	soyb = 0.235	soyb = 0.385

2.11. Crop yield calibration procedure

The crop yield calibration algorithm uses one variable at a time in the following order: 1) epco, 2) pest_stress, 3) lai_pot, and 4) hi_pot (Fig. 3). SWAT+ will run several simulations, called iterations in the context of the procedure, and adjust parameter values based on the difference between observed and simulated yields. After each iteration, the procedure will loop and repeat the process. There is a different number of iterations for each variable (defined as *MAX iterations* in Fig. 3). The model will stop iterating when the mean yields are within 3% difference with the observed. The code for the crop yield calibration subroutine in SWAT+, called calsoft_plant, is provided in Supplementary Material A.

The first iteration uses the initial default values shown in Table 2. The initial change applied to each parameter is a function of the difference between the simulated and observed yields (Table 3). After the initial change, the algorithm uses linear interpolation in subsequent iterations (simulations). Four additional simulations are needed for epco because it is highly non-linear as it approaches zero. No additional simulations were needed for pest_stress since it has a direct linear relationship with HI and thus with yield. Only two additional simulations were needed for both lai_pot and hi_pot.

2.12. Model evaluation

To quantify the difference between the simulated and reported annual average crop yields and to assess model calibration performance, we used coefficient of determination (R^2), relative error (RE) and Normalized Root Mean Square Error (NRMSE). We recalculate the reported by the Census of Agriculture corn and soybean county-wise yields to the HUC8 level to harmonize the comparison and to display it on the same spatial unit. The modeled crop yield output was recalculated to bushels per acre and adjusted for the moisture content to match the units used by the Census of Agriculture (US Census Bureau, 2019).

3. Results and discussion

3.1. Spatial variability of model parameters

Assigned epco, lai_pot, hi_pot, and pest_stress values for corn and soybeans after calibration varied spatially (Fig. 4). For a more focused analysis, specific SWAT+ models (executed at the HUC8 level) were excluded where the cultivated field areas for corn or soybean crops were <500 acres (2 km^2). This threshold was defined to deal with uncertainty in areas where total crop areas are very small and could have resulted from the misclassification of land use or other errors, which are difficult, if not impossible, to trace on a national scale.

The crop yield calibration procedure returned higher potential LAI and HI values in irrigated areas and areas with reported higher corn

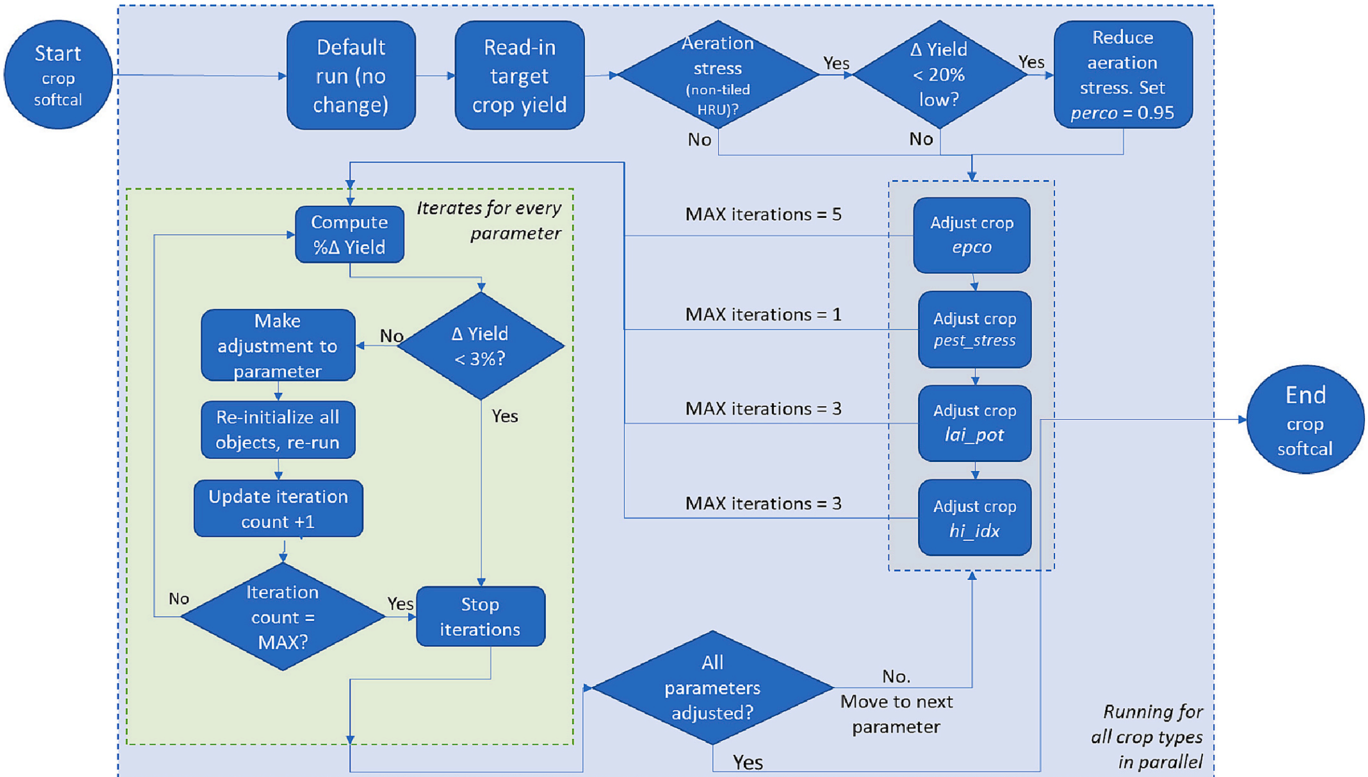

Fig. 3. Built-in crop yield calibration procedure – simplified flowchart.

Table 3
Crop yield calibration parameter sequence and adjustment to the NAM.

Sequence	Parameter	Change Type	Initial change	Number of linear interpolations
1	epco	absolute value	if ($diff_{pct} \geq 10\%$) $chg\_init = -0.01 * diff_{frac} + 0.06$ if ($diff_{pct} < 10\%$) $chg\_init = 1.0$	4
2	pest_stress	absolute value	$diff_{frac}$	0
3	lai_pot	absolute change	$0.5 * diff_{frac}$	2
4	hi_pot	absolute change	$0.005 * diff_{frac}$	2

yields (Fig. 4). Kiniry et al. (1997) reports potential LAI values for corn ranging from 2.8 to 4.1 in nine U.S. Locations and HI values ranging from 0.46 in New York to 0.58 in Nebraska and Georgia. In later studies (Kiniry et al., 2004; Kiniry and Bockholt, 1998), areas with higher corn yields (>10 t/ha or > 147 bu./ac) were reported to have LAI values of 6.0 or higher. In the same studies the minimum HI was set to 0.30 and the maximum to 0.54. The authors report that in some cases the parameter maximum values for HI resulted in overestimation of crop yields (Kiniry and Bockholt, 1998; Xie et al., 2001). Considering that crop yields increased substantially over the last decade (Fig. 1), we expect the HI to have increased as well. The crop yield calibration procedure in SWAT+ was able to correctly identify the increase in corn yield and assigned higher HI values, ranging from 0.42 to 0.57. In particular, the maps show the irrigated plains, irrigated Mississippi delta, and parts of Iowa with highest HI values, where crop yields are near yield potential.

The SWAT+ crop yield calibration procedure returned lai_pot values for soybeans between 4.6 and 6.0 (Fig. 4), which falls within the reported ranges of studies focused on soybean LAI estimation and modeling. Yuan et al. (2017) reported a mean LAI value of 4.9 from 46 varieties of soybeans produced in a case study site located in the North China Plain with conventional agricultural management practices. Setiyono et al. (2008) analyzed LAI dynamics and used a sink-driven approach (driven by the recursive algorithm) to evaluate LAI simulation of soybean under near-optimal environments. Their data from irrigated field experiments at two locations in Nebraska report an average maximum LAI value of 6.4 (Setiyono et al., 2008).

Assigned soybean HI ranges from 0.23 to 0.39, and the highest yielding HUC8 areas fall within 0.33–0.36, which is close to the reported values by Krisnawati and Adie (2015), where the average HI of 29 soybean genotypes was 0.38. Descriptive statistics of traits over 32 soybean families from high yielding varieties, drought tolerant varieties, and diverse ancestry classes show HI values between 0.2 and 0.5 (Lopez et al., 2021), which is in line with the SWAT+ parameterization results of the CONUS.

SWAT+ model functionality does not support any plant rooting depth restrictions and uses the epco parameter to allow the plant to compensate for the water uptake distribution with depth. The parameter is non-linear, so that the water uptake is not restricted until the value of epco falls below 0.2. This behavior explains the almost binary assignment of epco values (0 or 1) through the HUC8s for both corn and soybeans, meaning that, in most cases, the water uptake from deeper layers is either fully allowed or fully restricted.

The calibration procedure pushes the pest_stress parameter in high yielding areas closer to zero and low yielding areas closer to 1 and is applied directly to the HI. The assigned values for pest_stress through the modeled region range between 0.01 and 0.1 (Fig. 4) for both corn and soybeans. The pest_stress values of 0.04–0.05 were assigned to mostly high-yielding areas.

In the default or initial setup, we used the same corn and soybean database entry across the entire U.S. We then adapted the management operations, such as planting dates and potential heat units required to reach maturity, as well as the above-mentioned parameters: epco, lai_pot, hi_pot, pest_stress, for each HUC8 to represent the growing

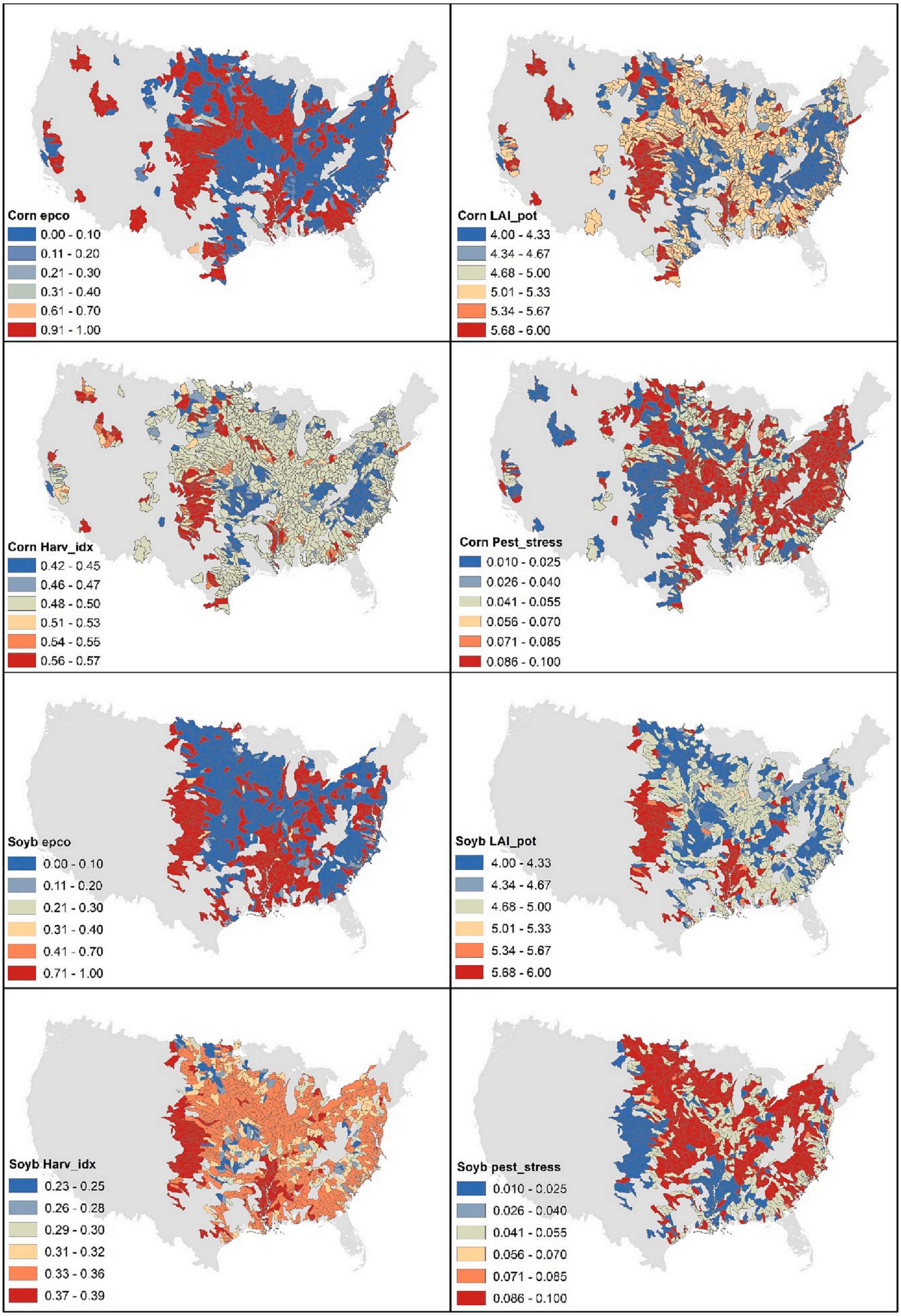

Fig. 4. Spatial variability of the calibrated parameters (epco, lai_pot, hi_pot, pest_stress) values for corn and soybeans (Soyb) in HUC8s with a cultivated field area of >500 acres (2 km^2).

conditions and the differences in plant growth across the U.S. Studies have indicated that the maximum corn yields differ among crop hybrids, and for the same hybrid across environments, i.e., across locations or across seasons at the same location (Tokatlidis, 2013). Without knowing the exact planting areas, hybrids, and their characteristics, it is impossible to reach a particular parameterization for fitting plant populations on the national scale. Hence, we adopted the abovementioned approach to account for different climatic conditions, pest stress, generic plant growing, and HI parametrization in the model, which demonstrates the ability to provide satisfactory crop yield results for the CONUS.

3.2. Model calibration and simulation results

After the crop yield calibration procedure, the simulated average annual corn and soybean yields show good agreement with the reported yields for the 2010–2015 period for crop areas >500 acres (200 ha) (Fig. 5). Several simulated soybean production outliers (HUC8 models) can be recognized on the graph (Fig. 5 right). We detected an overestimation of cropland areas for soybeans in some of the HUC8 simulations. Other outliers may have resulted from misclassification of fields.

We did not assess the quality of the yield data reported by USDA/NASS (2021). Grassini et al. (2015) compared the Agricultural Census corn yields of Nebraska to average actual farm yield data independently collected through the Nebraska Natural Resources Districts. Their analysis reports only 6% difference between the average yields calculated based on the two data sources.

Corn and soybeans are grown in varying environmental conditions under irrigated, rainfed and tiled farming systems. Thus, Genotype-by-Environment-by-Management (G x E x M) interactions affect production stability of both crops. Ultimately, the model should demonstrate the ability to reproduce G x E x M interactions across a relevant range of potential yields (Grassini et al., 2015). With high coefficient of determination for both corn ($R^2 = 0.99$ for total yields, $R^2 = 0.9$ for yields per unit area) and soybean ($R^2 = 0.99$ for total yields, $R^2 = 0.7$ for yields per unit area) production across the CONUS, we conclude that the SWAT+ implementation in the NAM is well suited to reproduce the corn and soybean production processes at national level.

The model can simulate average annual corn and soybean yields in most of the high-yielding regions in the mid-west with low relative error (RE) (Fig. 6). The RE in the high yielding areas fall within the ±5% interval. Highest RE is detected in the Great Plains area, where the model tends to underpredict the average annual yield per unit area by 15% for corn, and >30% for soybeans. Semi-arid regions, such as the U. S. Great Plains area experience limited and inconsistent rainfall, which makes it challenging to accurately predict water availability for crops, moreover, to model the irrigation demand. Large temperature fluctuations between day and night, as well as seasonally, impact crop development and yield potential, making it difficult to accurately model crop growth within the region. There is also limited data available on crop performance in this region as the cropland area is smaller, where some agricultural fields/countries might not get reported but included in the model. With less calibration data we have more uncertainty in our results and performance statistics. The combination of all these factors is the reason for RE being higher in this region.

3.3. Yield distribution by field category

The analysis of the field categories indicates that most of the high-yielding fields have no irrigation or tile drainage systems (Fig. 7). The Corn Belt region is characterized by fertile soils and favorable meteorological conditions for optimal crop growth, therefore rainfed fields in this area naturally provide high yields. Tile drainage or irrigation systems can provide a boost in production in areas where conditions are not optimal. Some studies show an increase and more stable yields when irrigation or tile drainage systems have been implemented, controlling the shallow water table or minimizing nutrient leaching (Helmers et al.,

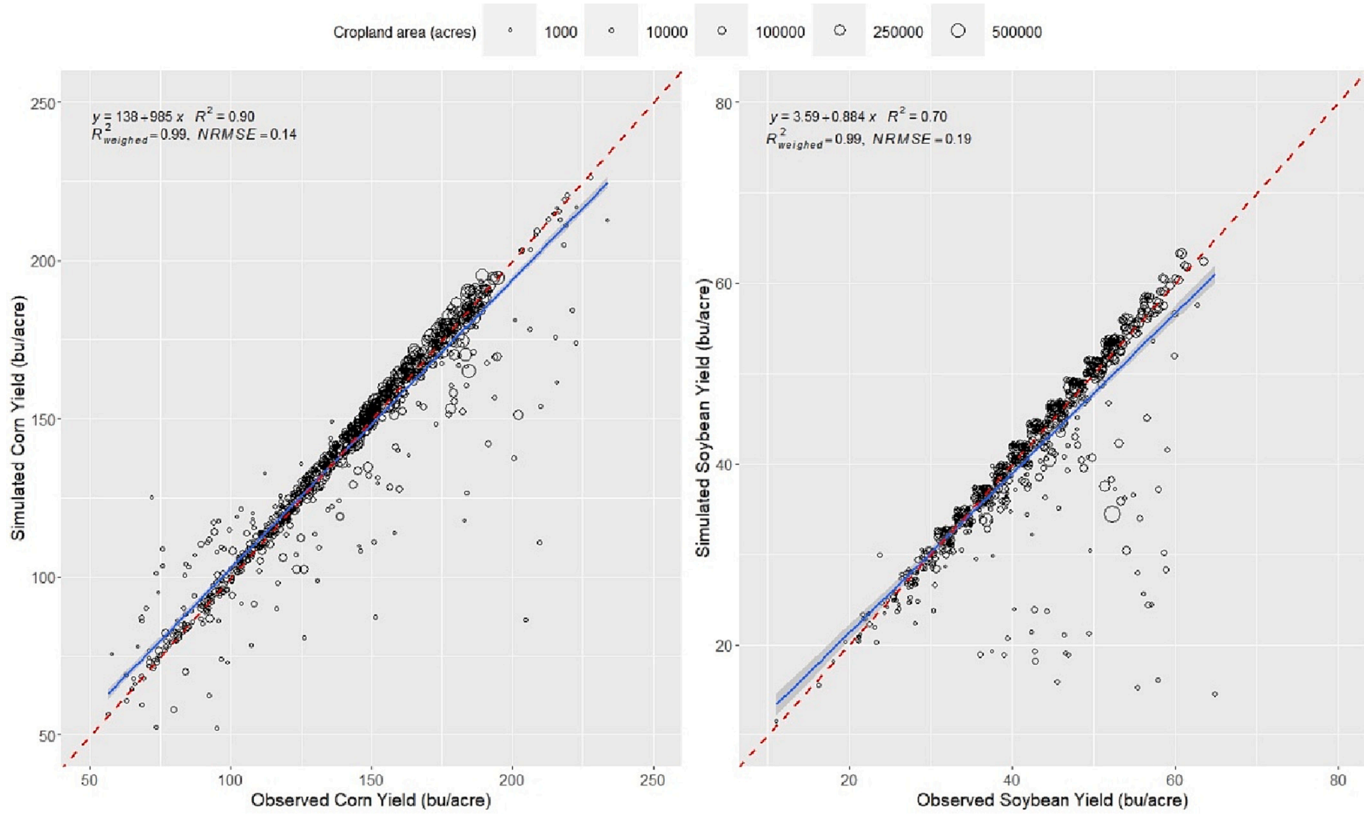

Fig. 5. Average annual observed (as reported by the Census of Agriculture for 2010–2015) and simulated corn (left) and soybean (right) production at HUC8 level. Size of the circles indicates the total area of the corn and soybean within each HUC8.

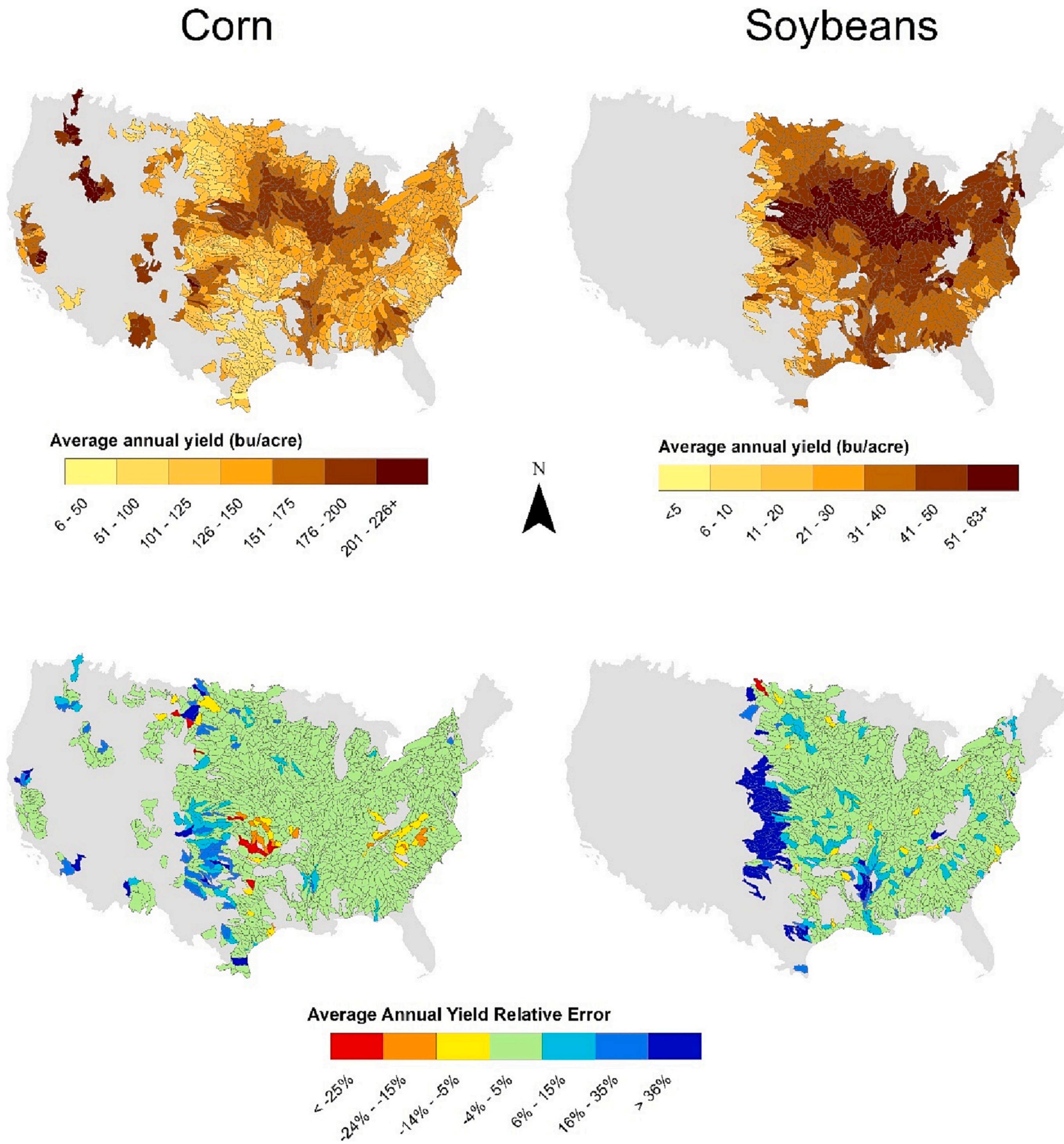

Fig. 6. Modeled average annual corn and soybean yields in bushels per acre and relative error at HUC8 level.

2012; Rizzo et al., 2018; Wayne Skaggs et al., 2012). Similar results can be seen in Kansas, Nebraska, North and South Dakota, where the average corn and soybean yields of irrigated fields skew toward higher yields (Fig. 7). Corn and soybean production under tile-drained fields tend to be slightly lower than that of the irrigated fields and similar to corn and soybean production in the "no irrigation or tile" areas. It is reasonable to assume that without tile drainage corn or soybean production might not be optimal or even not feasible in those areas. Due to the large number of modeled fields represented in Fig. 7, it is difficult to draw firm conclusions on the productivity of specific systems. Hence more detailed analysis is needed to determine the effectiveness of each system on corn or soybean crop productivity.

We further analyzed the distribution of field categories and compared the modeled yields with observations. The information on field location, field areas, observed and simulated yields were overlaid and summarized in Fig. 8. Fig. 8 shows the percentages of fields by the defined category ("no irrigation no tile", irrigated, or tiled) in each state in the Corn Belt and their simulated and observed corn and soybean yields. Each dot represents all field areas in the same category ("no irrigation no tile", irrigated or tiled) in the models (HUC8) located

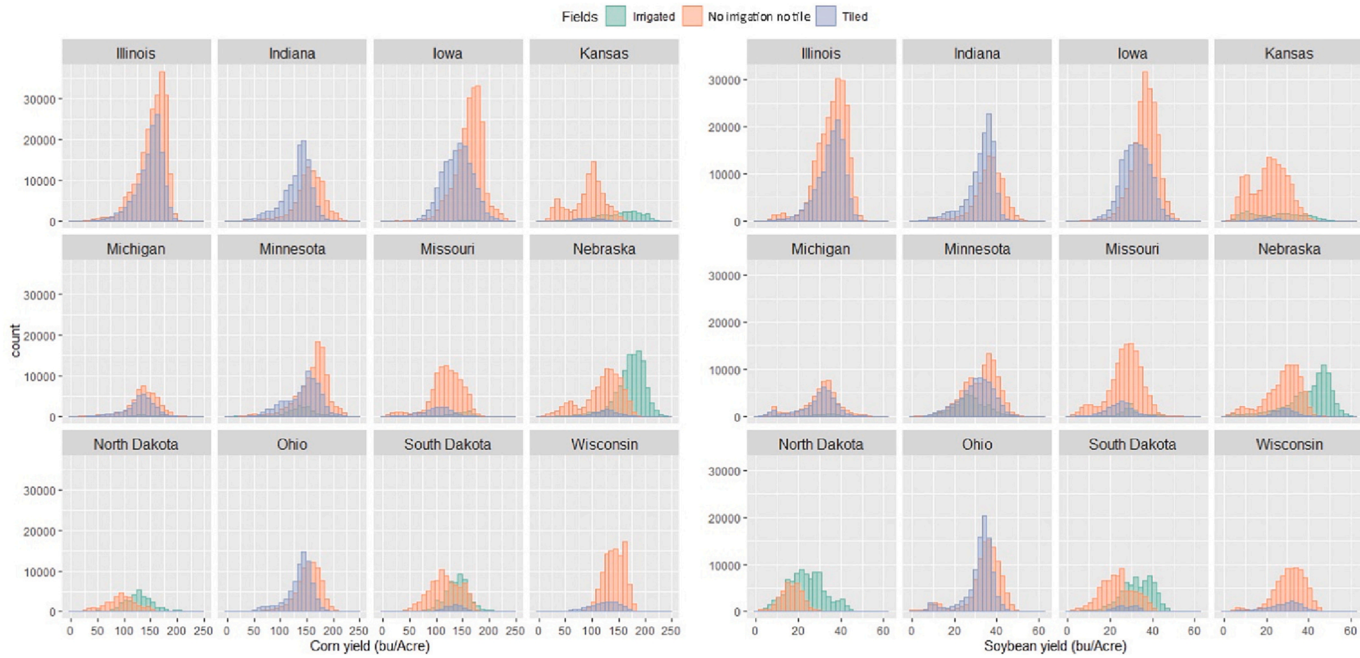

Fig. 7. Distribution of field categories (irrigated, no irrigation no tile, tiled) and yields for corn and soybeans.

within the states in the Corn Belt. The entire corn or soybean producing area in a single simulation (HUC8) is considered as 100%, hence the percentage of a field category in a single HUC8 may fall within 0–100%.

The trendlines indicate a good agreement between the observed and simulated yield distributions within the Corn Belt. In most cases the "no irrigation no tile" fields produce stable yields per field, except in Kansas, Nebraska, North and South Dakota, where irrigated fields tend to outperform the rainfed-only fields. We observed one issue with the model estimates: the trend for irrigated soybean fields in Kansas predicted by NAM is different from the observed (Fig. 8). This is the outcome of the earlier recognized outliers (Fig. 5), where we detected an overestimation of cropland areas in some of the modeled areas for the soybean fields.

The yield trendlines in Fig. 8 for corn and soybeans of the tile-drained fields show stable yields, with positive slopes in many states i. e., Illinois, Indiana, Iowa, Michigan, Minnesota, South Dakota, Wisconsin, meaning that the tile-drainage installation might boost corn or soybean production in these areas. In Ohio tile-drained fields perform on par with areas where such systems are not installed. Nevertheless, these findings need further analysis and robustness testing.

3.4. The improvements of SWAT+

The application of SWAT+ is extremely evident when modeling large-scale areas. It allows for greater flexibility and customization of the setup to tailor the model to specific needs, locations, and research questions. In case of this study, we want to particularly highlight the benefits of model input file restructuring: where in previous version of SWAT, each individual HRU would have several setup files associated with it. In SWAT+ there is a single HRU data file with all the necessary information and key pointers to databases. Such a complex model as the NAM would require hundreds of millions of input files, if modeled using SWAT2012 or earlier versions, which would render the entire application as infeasible. The additional benefit of using SWAT+ is provided by the flexible setup using decision tables to manage processes, i.e., irrigation or fertilization. The added benefit of decision tables makes the model highly re-usable and simulations with adjusted parameters easily repeatable.

The novelty of large-scale SWAT+ crop modeling study with a field-HRU setup lies in the ability to capture the heterogeneity and variability of the crop environment, and to account for the complex interactions between different factors. By integrating data from various sources, the NAM can provide a detailed picture of the current state of crop systems and predict their future behavior under different scenarios.

4. Conclusions

This study used the SWAT+ model to simulate corn and soybean yields across the Contiguous United States. The National Agroecosystem Model was set up with each HUC8 region represented by an individual SWAT+ model, and over 2.5 million individual fields were included in the comprehensive modeling setup. SWAT+ provided the needed flexibility and functionality to implement such a modeling endeavor. Modifications to the plant growth module in SWAT+ allowed for potential daily biomass increase calculation, aeration stress from excess water estimation, scheduling independent operations across the vast area, and more. The semi-automated soft-calibration module proved to be a powerful and fast tool for crop production parameter calibration. The NAM was tested against average annual corn and soybean yields for the 2005–2015 period, with good agreement between the reported and simulated yields.

The implementation of SWAT+ within NAM was able to reliably capture the spatial trend of corn and soybean production over different regions, land management, and climatic conditions in the U.S. A field-type analysis was performed, providing further insight into spatial distribution of corn or soybean yields and trends. Most of the high-yielding fields are rainfed, while tile drainage or irrigation systems provide a boost in production in areas where conditions are not optimal.

The model accuracy is reliant on the accuracy of input and calibration data. Better methods are needed to estimate inputs where observation information is not available. Overall, this study demonstrates the usefulness of SWAT+ for simulating crop yields at a large scale, and the unique setup approach and crop yield calibration strategy, with some modification, can be applied to other areas worldwide.

Software availability

SWAT+ is an open access software, programmed in Fortran. The

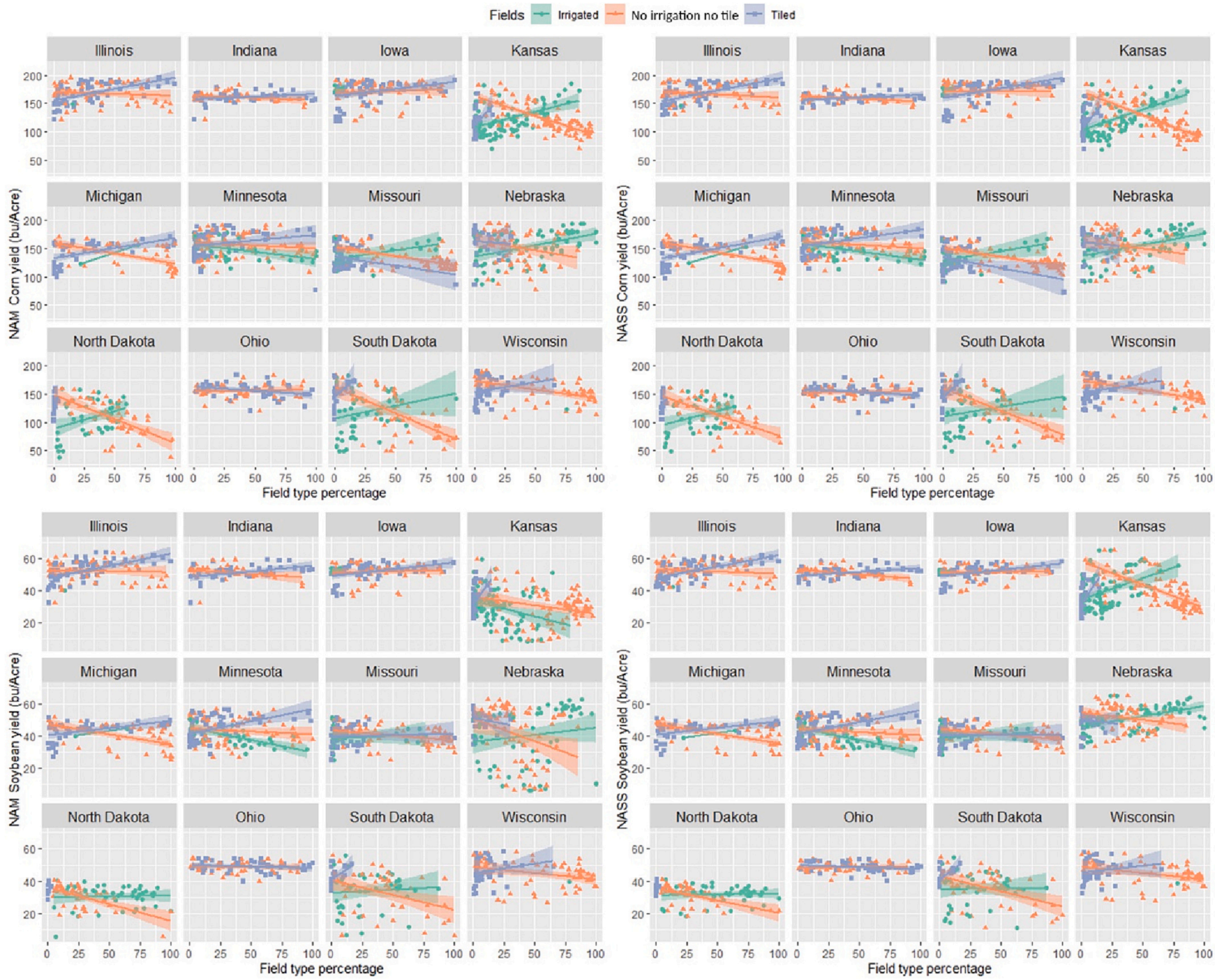

Fig. 8. Field category (irrigated, no irrigation no tile, tiled) percentage per HUC8 within each state in the Corn Belt and their simulated (left) and observed (right) corn (top) and soybean (bottom) yields in bushels per acre with trendlines.

source code is constantly maintained and can be found at: https://bitbucket.org/blacklandgrasslandmodels/modular_swatplus/src/master/. A user support group open for questions and discussions related to the model can be accessed here: https://groups.google.com/d/forum/swatplus.

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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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2023.103695.

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