



1 **Ensemble Agroecosystem Modeling Enhances Predictions of Crop Yields and Soil Carbon**
2 **Across the United States**

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1 **Abstract.** Accurately estimating crop yields and soil organic carbon (SOC) dynamics is essential
2 for agricultural planning, carbon accounting, and sustainable land management. However,
3 process-based agroecosystem models often produce divergent estimates due to variations in
4 model structure, parameterization, and underlying assumptions. In this study, we developed a
5 multi-model ensemble framework that integrates three widely used process-based models-Daily
6 Century (DAYCENT), DeNitrification DeComposition (DNDC), and Ecosystem model
7 (ECOSYS)-to simulate crop yields and SOC stock changes (0-30 cm) across cultivated lands of
8 the continental United States (CONUS) at 4 km² spatial resolution. Each model was
9 parameterized using harmonized environmental, soil, and management datasets and evaluated
10 using observed crop yields from the National Agricultural Statistics Service and measured SOC
11 data from the Rapid Carbon Assessment. For the baseline period (2014-2023) under
12 conventional corn-soybean rotation, the ensemble mean showed strong agreement with
13 observations (corn: 7.7 vs. 8.5 Mg ha⁻¹, RMSE = 3.0; soybean: 2.5 vs. 3.0 Mg ha⁻¹, RMSE = 1.0),
14 while simulated SOC stocks (5.5 vs. 4.8 kg C m⁻², RMSE = 2.5) closely matched measured data.
15 Spatially, the ensemble model projected SOC gains in the Midwest and Southeastern regions and
16 losses in the Great Plains and Western United States, underscoring the importance of region-
17 specific management practices. Overall, the ensemble approach improved predictive accuracy
18 and reduced uncertainty relative to individual models, providing a scalable pathway for robust,
19 data driven assessments of soil carbon and crop productivity across U.S. agroecosystems.
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1 **1 Introduction**

2 Agroecosystems occupy a substantial portion of the global landscape, with agricultural land
3 covering about 47.7 million km² (36.9%) of the global land area in 2022 (FAO, 2025). These
4 system provide food, feed, fiber, and fuel, and also deliver ecosystem services (ESs) such as soil
5 carbon (C) sequestration, water retention, and nutrient cycling (Robertson et al., 2014). As
6 anthropogenic pressures intensify through consumption patterns, resource demand and weather
7 variability, management of agroecosystems has become essential to maintain productivity and
8 ecological balance. Enhancing soil organic carbon (SOC) sequestration is one of the key benefits
9 of improved management, contributing to climate solutions and long-term soil health
10 maintenance (Paustian et al., 2016).

11 Among agricultural practices, crop rotation particularly the inclusion of legumes such as soybean
12 (*Glycine max* (L.) Merr.) is widely recognized for its positive effects on SOC accumulation
13 (King & Blesh, 2018; Kumar et al., 2018). Legume-based rotations improve soil fertility through
14 biological nitrogen fixation (BNF), reduce reliance on synthetic fertilizers, and enhancing carbon
15 inputs from crop residues and root exudates (Drinkwater et al., 1998; Meena & Lal, 2018). They
16 also stimulate microbial activity and stabilize SOC stocks compared to monocultures or less
17 diverse crop rotations (Davis et al., 2012; Xiao et al., 2017). These benefits highlight the
18 importance of understanding how site-specific management strategies and crop rotation influence
19 SOC dynamics across diverse ecoregions and soil conditions.

20 Several process-based agroecosystem models have been developed to simulate the long-term
21 effects of agricultural practices on SOC dynamics and crop productivity. Among the widely used
22 models are the Daily Century (DAYCENT) model, DeNitrification-DeComposition (DNDC)
23 model, and the Ecosystem Simulation Model (ECOSYS) (Grant, 1998; C. Li et al., 1992; Parton
24 et al., 1994). Each of these models provides unique structural features and strengths representing
25 plant-soil-atmosphere interactions. DAYCENT a daily time-step version of the CENTURY
26 model simulates C and N fluxes with-in plant-soil systems, incorporating processes such as plant
27 growth, organic matter (OM) decomposition, and soil emissions. It is extensively used for
28 evaluating SOC dynamics and nitrous oxide (N₂O) emissions under different land uses and
29 climate conditions (SJ Del Grosso et al., 2005). DNDC, focuses on coupled C and N
30 biogeochemistry, simulate key emissions including methane (CH₄), carbon dioxide (CO₂), and
31 N₂O (C. Li et al., 1992). ECOSYS is a more mechanistic model that offers detailed
32 representations of plant physiology, root growth, soil physics, microbial dynamics, and
33 management practices, making it well-suited for capturing complex feedbacks in high-resolution
34 agroecosystem analyses (Grant et al., 2001).

35 Given the strengths of individual models, there remains substantial variability in predicted crop
36 yields and SOC dynamics due to differences in model structure, parameterization, and
37 underlying assumptions (Smith et al., 1997; Tao et al., 2018). Consequently, recent studies
38 increasingly employ multi-model ensemble approaches to represent uncertainty and enhance
39 predictive reliability. Ensemble modeling leverages the complementary strengths of individual
40 models to capture a range of plausible system responses under diverse climate and management
41 conditions, thereby improving the robustness of land management and environmental
42 assessments (Basso et al., 2025; Martre et al., 2015). The Agricultural Model Intercomparison
43 and Improvement Project (AgMIP) exemplifies this progress, using ensemble to evaluate model
44 sensitivities and parameter uncertainties in crop yield projections (Rosenzweig et al., 2014).



1 However, most model ensemble studies have focused primarily on crop productivity or provided
2 limited evaluation of SOC dynamics, often constrained by small spatial scales (Basso et al.,
3 2025; Rosenzweig et al., 2014). Furthermore, few studies have combined mechanistic models
4 such as ECOSYS with semi-empirical models like DAYCENT and DNDC, despite their
5 widespread use in soil carbon measurement, reporting, and verification (MRV) and carbon credit
6 calculation. This gap limits comprehensive evaluations of how integrated management strategies
7 influence both agronomic outcomes and ecosystem services (ESs).

8 In this work, we develop and benchmark an ensemble agroecosystem modeling framework
9 integrating DAYCENT, DNDC and ECOSYS to predict crop yields (corn and soybean) and SOC
10 dynamics across the continental United States (CONUS). This framework bridges agronomic,
11 environmental, and computational disciplines, enabling improved carbon accounting and
12 sustainability assessments at continental scales. By combining models with distinct process
13 representations, we assess both consistency and divergence of predictions and identify areas of
14 model convergence that inform robust management strategies. Unlike previous efforts, this study
15 emphasizes the spatial variability in multi modal agreement across U.S. croplands, providing
16 valuable insights into the design of resilient agroecosystems under weather variability.
17 Furthermore, the results provide actionable information for policymakers, startups, and
18 stakeholders engaged in carbon MRV and market-based sustainability initiatives.

19 The specific objectives of this study were to: (a) develop an ensemble agroecosystem modeling
20 framework for CONUS croplands; (b) simulate crop yields and SOC stock changes under
21 baseline conditions from 2014 to 2023; and (c) compare model outputs from DAYCENT,
22 DNDC, and ECOSYS to characterize variability and uncertainty in predicted yields and SOC
23 stocks. We hypothesized that: 1) the ensemble of DAYCENT, DNDC, and ECOSYS would
24 capture the uncertainty of SOC stock change projections; and 2) ensemble mean corn and
25 soybean yields would align more closely with observations while exhibiting spatially
26 heterogeneous responses linked to geographic and environmental gradients.

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29 **2 Methods**

30 **2.1 Study area and model input**

31 This study encompassed three primary land cover types (croplands, pastures, and grasslands)
32 identified using National Land Cover Database (NLCD) (USGS, 2023). The daily precipitation
33 and minimum and maximum air temperature data for the 30-year period (1994–2023) were
34 obtained from Daily Surface Weather and Climatological Summaries (DAYMET) (Thornton et
35 al., 2016). The key soil parameters for model initialization included multilayer soil texture, bulk
36 density, soil moisture retention characteristics, hydraulic conductivity, soil organic carbon
37 (SOC), and pH, derived from the Soil Survey Geographic Database (SSURGO) (Staff, 2023).
38 The study simulated a corn-soybean rotation spanning 2014 to 2023 to evaluate crop
39 management impacts on soil biogeochemical processes. Nitrogen (N) fertilizer was applied at a
40 rate of 185 kg N/ha during the corn year following planting. Tillage operations included a spring
41 chisel plow of 30 cm and a fall field cultivator to 20 cm, representing conventional management
42 practices. In contrast, soybean cultivation followed a no-till (NT) approach with minimal soil
43 disturbance during the growing season. This rotation setup reflects typical Midwestern U.S.



1 agricultural practices and provides a consistent framework for evaluating long-term SOC
2 dynamics and crop productivity across multiple models. The schematic overview of the
3 modeling framework and workflow is presented in Figure. 1.

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5 **2.2 Process model description and setup:**

6 DAYCENT is a daily time step, process-based agroecosystem model developed to simulate the
7 biogeochemical cycles at a point scale (S Del Grosso et al., 2002). It is daily version of the
8 CENTURY model (Parton et al., 1998). It can simulate exchange of carbon and soil nutrients [N,
9 phosphorus (P), and sulfur (S)] between the atmosphere and terrestrial ecosystems, along with
10 soil water and temperature dynamics (Schimel et al., 2001). In the DAYCENT model, SOC is
11 predicted based on OM decomposition and C cycling among multiple soil pools, including
12 surface litter (structural and metabolic), and fast, slow and passive C pools (S Del Grosso et al.,
13 2002; Parton et al., 1998). Carbon inputs arise from plant residues and organic amendments,
14 while decomposition is driven by soil temperature, moisture, and texture. DAYCENT simulates
15 daily C fluxes between soil pools, accounting for mineralization, immobilization, and
16 heterotrophic respiration losses (Parton et al., 1994). Additionally, DAYCENT also represent
17 various management practices including tillage, crop rotation, residue retention, and fertilization.
18 Crop yield is simulated through net primary production (NPP) as a function of sunlight,
19 temperature, soil water, and nutrients. The assimilated carbon is partitioned among plant
20 components including grain, roots and shoots based on their C:N ratios. The final yield is
21 determined using the harvest index (HI), which defines the proportion of aboveground biomass
22 converted into harvestable product, such as grain. This HI is crop specific and sensitive to
23 environmental and stress conditions, enabling DAYCENT to represent realistic interactions
24 among biophysical processes and management practices. The model was initialized with a long-
25 term spin-up (1000 to 4,000 years) to achieve the steady-conditions for soil nutrient pools,
26 representing pre-disturbance natural land conditions prior to human intervention. For the
27 equilibrium simulations, ecoregion-specific native grass were grown, based on data from the
28 US Environmental Protection Agency Inventory of US GHG emissions and sinks (USEPA,
29 2015). Historical land use and land cover data were compiled from historical datasets (Ogle et
30 al., 2010). Historical management practices from initial tillage to the modern agricultural period
31 was compiled at the Major Land Resource Area (MLRA) level from multiple historical data
32 sources (Ogle et al., 2010). Contemporary agricultural management was represented based on the
33 multiyear analysis of the National Land Cover Database. Additionally, historical database was
34 used to estimate the average annual nitrogen fertilizer rates for each agricultural crop across
35 different ecoregion (USEPA, 2005).

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38 DNDC is a process based soil biogeochemical model developed to simulate C and N cycling in
39 agricultural ecosystems (C. Li et al., 1992; C. Li et al., 1994). It integrates key soil physical and
40 chemical properties (e.g., soil texture, bulk density and soil pH) to represent soil biogeochemical
41 processes. DNDC also includes a detailed plant growth module that simulates the entire crop life
42 cycle, linking plant development with soil C and N dynamics. The model partitions the net
43 assimilated C among leaves, stems, roots, and grain according to the crop's phenological stage.
44 Final crop yield is determined at the end of the simulation as the total biomass allocated to the
45 grain at physiological maturity. Due to its explicit representation of plant growth and
46 decomposition processes, DNDC is widely used to evaluate the effects of agricultural



1 management practices on crop yields, SOC dynamics and soil emissions (Ding et al., 2023; Jiang
2 et al., 2021).

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4 ECOSYS is a process-based ecosystem model grounded in biophysical and biochemical
5 principles that integrates water, energy, C and nutrient cycles (Grant et al., 2001). It explicitly
6 represents interactions among soil, plant, and atmospheric components with high mechanistic
7 details. Due to its comprehensive process representation, including plant photosynthesis and
8 hydraulics, dynamic C and nutrient allocations in plants and microbes, soil biogeochemistry, and
9 agricultural management practices, ECOSYS is a robust tool for simulating agroecosystem
10 responses to diverse environmental and management conditions (Grant et al., 2006; Shekoofa et
11 al., 2021; Zhou et al., 2021). The model incorporates detailed physical, chemical and biological
12 processes to simulate plant-microbe-soil-atmosphere interactions across diverse soil types,
13 climatic regimes, and land-use practices. It explicitly models nutrient exchange between
14 microbes and plants, allowing nutrient-based evaluation of management effects on crop
15 productivity and SOC dynamics. Crop yield is calculated based on dynamic plant C allocation,
16 which balances photosynthetic C gain and respiratory losses, and partitions assimilated biomass.
17 Grain filling is regulated by canopy temperature, available carbon and nutrient reserves, and
18 physiological constraints, allowing ECOSYS to capture crop yield responses to environmental
19 stress and management variability.

22 **2.3 Model Evaluation**

23 Each of the three models was validated using county level crop yield data from the National
24 Agricultural Statistics Service (NASS) (NASS, 2025) and site-level SOC data from the Rapid
25 Carbon Assessment (RaCA) dataset (Wills et al., 2014) across CONUS. Model parameterization
26 was conducted to minimize the root mean square error (RMSE) between observed and predicted
27 values, as defined by Equation (i):

$$28 \quad RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \quad (\text{Eq.i})$$

29 where, P_i and O_i are the predicted and observed values, respectively, and n is the total number of
30 observations. After model evaluation, each model was updated using a calibrated parameter set,
31 and large-scale simulations were executed on the Sandia National Laboratories high performance
32 computing (HPC) system in a parallel environment.

33 **3 Results**

34 **3.1 Model Evaluation of crop yield and SOC**

35 A comparison of simulated corn yields across the CONUS croplands from three agroecosystem
36 models and their ensemble median against observed yields from the NASS dataset showed that
37 the ensemble model provided the closest agreement with observations (Figure. 2a). The
38 ensemble exhibited the lowest variability and achieved the smallest root mean square error
39 (RMSE = 3.0 Mg ha⁻¹) (Figure. 2a). Its median corn yield of (7.7 Mg ha⁻¹) closely matched the
40 observed median of 8.5 Mg ha⁻¹. Among individual models, DAYCENT and DNDC performed
41 moderately well, producing RMSEs of 3.8 Mg ha⁻¹ and 5.0 Mg ha⁻¹, and median yields of 9.4 Mg
42 ha⁻¹ and 8.7 Mg ha⁻¹, respectively. In contrast, ECOSYS exhibited the greatest deviation, with an
43 RMSE of 4.1 Mg ha⁻¹ and a median yield of only 4.4 Mg. ha⁻¹, reflecting a consistent tendency to
44 underpredict yields and higher variability across the CONUS region (Figure. 2a).



1 For soybean yields, the ensemble model again demonstrated the best performance, yielding the
2 lowest root mean square error (1.0 Mg ha^{-1}) and most accurate representation of the observed
3 yield distribution (Figure. 2b). The ensemble median soybean yield (2.5 Mg ha^{-1}) was in close
4 agreement with the observed median (3.0 Mg ha^{-1}). Among the individual models, DAYCENT
5 and DNDC yielded RMSEs of 1.3 Mg ha^{-1} and 2.1 Mg ha^{-1} with median yields of 3.2 Mg ha^{-1}
6 and 2.7 Mg ha^{-1} , respectively (Figure. 2b). ECOSYS again underpredicted soybean yields, with
7 an RMSE and a median yield of 1.3 Mg ha^{-1} . Overall, the ensemble approach minimized
8 prediction errors and more accurately represented the central tendency of observed yields
9 compared with individual models. These results highlight the advantage of multi-model
10 ensemble frameworks in enhancing prediction accuracy and reducing uncertainty in large-scale
11 crop yield simulations.

12 A comparison of simulated SOC stocks (0-30 cm) from three agroecosystem models
13 (DAYCENT, ECOSYS, and DNDC) and their ensemble against observations from the RaCA
14 dataset revealed distinct differences in model performance (Figure. 3). The RaCA observations
15 indicated a median SOC stock of 4.8 kg C m^{-2} across CONUS for 0-30 cm layer. Among the
16 individual models, DAYCENT performed most consistently with observations, producing a
17 median SOC of 5.5 kg C m^{-2} and an RMSE of 2.7 kg C m^{-2} . ECOSYS underestimated SOC,
18 yielding a median of 3.2 kg C m^{-2} and an RMSE of 3.0 kg C m^{-2} , suggesting limitations in its
19 representation of SOC accumulation processes. In contrast, DNDC consistently overestimated
20 SOC, with median of 7.7 kg C m^{-2} and the largest RMSE (4.9 kg C m^{-2}) among the three models
21 (Figure. 3). The ensemble approach effectively reduced model-specific biases, producing a
22 median SOC estimate of 5.5 kg C m^{-2} with the lowest RMSE (2.5 kg C m^{-2}) across CONUS
23 (Figure. 3). Collectively, these results demonstrate that the ensemble modeling enhances
24 agreement with observed data and improves the reliability of SOC stock estimates at regional
25 and national scales.

27 **3.2 Model prediction of corn yield**

28 During the 10-year simulation period (2014-2023), DAYCENT estimated annual corn yields
29 ranging from 1.0 to 15.3 Mg ha^{-1} , with a mean of 8.8 Mg ha^{-1} . DNDC projected yields between 1
30 and 15 Mg ha^{-1} (mean = 8.7 Mg ha^{-1}), whereas ECOSYS computed a similar range but a
31 substantially lower mean of 5.95 Mg ha^{-1} (Figure. 4). All three models captured the broad spatial
32 pattern of high corn productivity across the U.S. Midwest Corn Belt, particularly in central Iowa,
33 Illinois, and Indiana. Regional difference among models reflected contrasts in structure
34 representation and parameterizations. DNDC projected relatively higher yields in the Mississippi
35 River Basin and the Southeast U.S., while DAYCENT simulated more moderate yields in the
36 same regions (Figure. 4). By contrast, ECOSYS estimated comparatively higher productivity
37 across parts of the Northern Plains and Northwestern U.S. The ensemble yield map effectively
38 moderated these model-specific extremes, generating a spatially coherent pattern that preserved
39 agreement within high-yield zones while diminishing the influence of outlier projections.
40 Overall, the ensemble framework produced robust regional yield estimates by integrating model
41 variability, leveraging complementary strengths, and redacting individual model biases.

43 **3.3 Model prediction of soybean yield**

44 From 2014 to 2023, DAYCENT simulated annual soybean yields ranging from 0.1 to 5 Mg ha^{-1}
45 with a mean of 2.8 Mg ha^{-1} . DNDC projected yields within a similar range (0.1 - 5 Mg ha^{-1}) and a
46 mean of 2.7 Mg ha^{-1} , while ECOSYS estimated a slightly broader range (0.01 to 6 Mg ha^{-1}) with



1 a mean of 2.5 Mg ha⁻¹ (Figure. 5). All three models reproduced the general spatial pattern of
2 highest soybean productivity across the Midwestern and central U.S., particularly in major
3 soybean producing regions such as Iowa, Illinois, and Indiana. Model-specific variability
4 emerged in both the spatial extent and magnitude of yield predictions. DNDC projected high
5 yields concentrated in central Iowa and surrounding areas, whereas DAYCENT and ECOSYS
6 predicted more spatially uniform yield distributions across the Corn Belt (Figure. 5).
7 Additionally, DAYCENT simulated comparatively higher yields across parts of the Southeast
8 U.S.
9 The ensemble yield map integrated outputs from all three models, producing a harmonized
10 spatial distribution characterized by a concentrated high-yield zone in the central Midwest and a
11 gradual decline in productivity toward coastal and arid western regions. This ensemble approach
12 provided a more coherent and robust estimate of soybean productivity across diverse
13 agroclimatic zones, effectively smoothing local extremes and reducing model-specific outliers.
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17 **3.4 Model prediction of soil organic carbon change**

18 Figure 6 illustrates the spatial distribution of projected annual SOC change (kg C m⁻² yr⁻¹) under
19 a 10-year (2014-2023) conventional-till corn-soybean rotation across CONUS, based on
20 simulations from the three agroecosystem models and their ensemble mean. Positive values
21 represent SOC sequestration, whereas negative values indicate net C emissions. DAYCENT
22 consistently projected widespread SOC sequestration across the Midwest and eastern U.S., with
23 rates often exceeding 0.02 kg C m⁻² yr⁻¹ in many areas (Figure. 6). In contrast, DNDC and
24 ECOSYS exhibited greater spatial heterogeneity, including notable zones of SOC decline in the
25 Northern Great Plains and parts of the Midwest. DNDC simulated SOC losses surpassing 0.01 kg
26 C m⁻² yr⁻¹, particularly within high-yielding zones (Figure. 6). The ensemble map integrated
27 these model-specific responses, capturing the broad sequestration trends indicated by
28 DAYCENT while incorporating SOC-loss zones highlighted by DNDC and ECOSYS. Overall,
29 the ensemble projection suggested a modest net increase in SOC across much of the Corn Belt,
30 underscoring the capacity of conventional corn-soybean systems to enhance carbon sequestration
31 under region-specific environmental and management conditions.
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34 **4 Discussion**

35 The ensemble modeling approach produced corn yield estimates across the CONUS that closely
36 aligned with the observed data, underscoring the value of multi-model ensembles in reducing
37 individual model biases and improving prediction accuracy (Asseng et al., 2013; Basso et al.,
38 2025; Martre et al., 2015). The ensemble model benefited from complementary model structures,
39 error compensation and statistical averaging, resulting in enhanced stability and performance
40 across diverse environmental gradients. The moderate accuracy of DAYCENT and DNDC was
41 consistent with prior evaluations demonstrating their strengths in simulating corn productivity
42 under temperate conditions, particularly in the U.S. Midwest (Campbell et al., 2014; S Del
43 Grosso et al., 2002; Ingraham & Salas, 2019). In contrast, ECOSYS substantially underpredicted
44 corn yield, likely due to its complex coupling root and canopy processes, which are highly
45 sensitive to input uncertainty and parameterization constraints in large-scale applications (Liu et
46 al., 2024). Regional anomalies, such as DNDC's higher corn yield projections in the Southeast,



1 likely influenced by how it simulated water stress and nutrient availability under less favorable
2 climatic conditions, as well as the linear response of crop yield to precipitation (Kaur et al.,
3 2023). Collectively, these results supported the hypothesis that ensemble predictions provide
4 more reliable and robust estimation of corn yield across diverse agroecological zones in CONUS.
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6 Similarly, the ensemble model demonstrated superior performance in predicting soybean yield,
7 achieving the lowest RMSE (1.0 Mg ha^{-1}) and reproducing the observed median yield (2.5 Mg
8 ha^{-1}). This finding aligns with previous research highlighting the advantages of ensemble
9 modeling in stabilizing projections across variable cropping systems (Battisti et al., 2017). The
10 relatively strong performance of DAYCENT and DNDC reflected their ability to simulate
11 soybean physiology and biological nitrogen fixation (BNF) processes in temperate regions.
12 However, DNDC's spatial overestimation in Iowa is likely resulted from its limited
13 representation of soil drainage and water balance (Helmets et al., 2012). ECOSYS
14 underpredicted soybean yields, possibly due to its sensitivity to soil moisture dynamics and
15 restricted calibration in drier regions. These model specific biases highlight the persistent
16 challenges of representing complex interactions among soil texture, weather variability, and
17 cultivar adaptability further reinforcing the utility of an ensemble approaches for yield
18 estimation.
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20 Ensemble projections for SOC stock changes (0-30 cm) across CONUS under a 10-year corn-
21 soybean rotation indicated a modest net sequestration, consistent with previous finding
22 identifying the Corn Belt as a region with high SOC sequestration potential (Grace & Robertson,
23 2021; Wu et al., 2025). Strong performance of DAYCENT in capturing SOC accumulation
24 within the Midwest aligns with its established capacity to simulate long-term C cycling and
25 residue turnover in U.S. cropping systems (Basso et al., 2025). In contrast, DNDC and ECOSYS
26 underpredicted SOC stocks, likely due to model sensitivities to decomposition rates, soil
27 moisture retention, and microbial activity, which are critical determinants of SOC turnover. The
28 greater variability observed with DNDC was consistent with prior reports attributing its coarser
29 parameterization of SOC pools and limited regional calibration, as its original design emphasis
30 on CH_4 and N_2O emissions rather than SOC dynamics (Zhang et al., 2014). The ensemble's
31 intermediate median SOC and reduced RMSE illustrate its effectiveness in mitigating structural
32 uncertainty and reproducing the SOC patterns captured in the RaCA database. These results
33 underscore the promise of ensemble-based approaches for improving national scale carbon
34 accounting and guiding sustainable land management strategies.
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36 This study uses a uniform set of crop phenotypic and parameter values for corn and soybean
37 across the entire spatial domain. While this standardization enabled large-scale simulations and
38 computational efficiency, it inherently omitted genotype-environment interactions and region-
39 specific cultivar adaptations. In ECOSYS, for example, crop phenology is highly sensitive to
40 thermal time and maturity group parameters, both of which are vary significantly across U.S.
41 regions. Using a single maturity group for corn and soybean may therefore have misrepresented
42 region-specific growth dynamics and yield responses. Previous work have demonstrated that
43 regional calibration of maturity group is essential for accurately reproducing phenological
44 development (Z. Li et al., 2022). Although this approach supports continental scale consistency,
45 it introduces limitations in representing localized cultivar adaptation and environmental
46 responses, highlighting an important direction for future ensemble model refinement.



1 **5 Conclusions**

2 This study advances multi-model integration in agroecosystem science by developing and
3 benchmarking an ensemble framework that combines three process-based models, DAYCENT,
4 DNDC, and ECOSYS, to improve large scale predictions of crop yields and soil carbon
5 dynamics across the continental United States. The ensemble approach outperformed individual
6 models, producing lower root mean square errors (RMSEs) and stronger agreement with
7 observed corn and soybean yields and SOC stocks in terms of both mean values and variability.
8 Ensemble results captured the central tendency of observed data more effectively, while
9 generating spatially coherent yield patterns. For SOC dynamics, ensemble projections
10 represented both sequestration potential and emission hotspots, capturing net carbon gains in the
11 Midwest while reducing over and under estimation patterns from DNDC and ECOSYS,
12 respectively. Overall, this study highlights the need of ensemble modeling framework for
13 accurate regional to national scale assessment of crop productivity and soil carbon dynamics. By
14 reducing structural uncertainty and bias, this approach strengthens the scientific basis for carbon
15 measurement, reporting, and verification, carbon credit quantification, and regenerative
16 agriculture initiatives. Ensemble agroecosystem modeling provides a critical foundation for
17 advancing evidence-based land management and sustainable agricultural policy in a changing
18 weather pattern.

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20 **Data Availability**

21 All data supporting the findings of this study are contained within the article.

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44 **Author Contributions:** Conceptualization: S.G. and U.M.; methodology and investigation:
45 S.G., and C.G.J.; formal analysis, visualization, and writing original draft: S.G., and C.G.J.; data



1 curation: S.G., and C.G.J.; resources: S.G., and C.G.J.; writing-review and editing: S.G., C.G.J.,
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3

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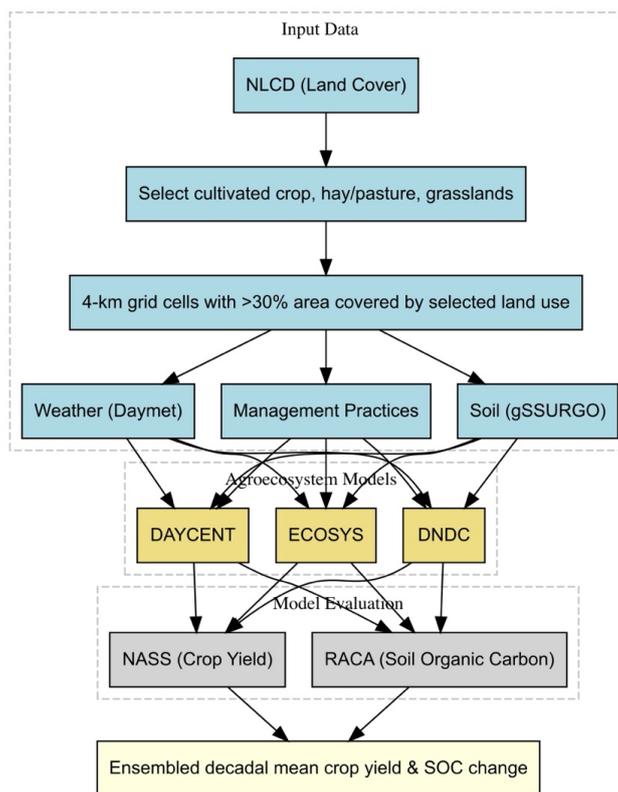
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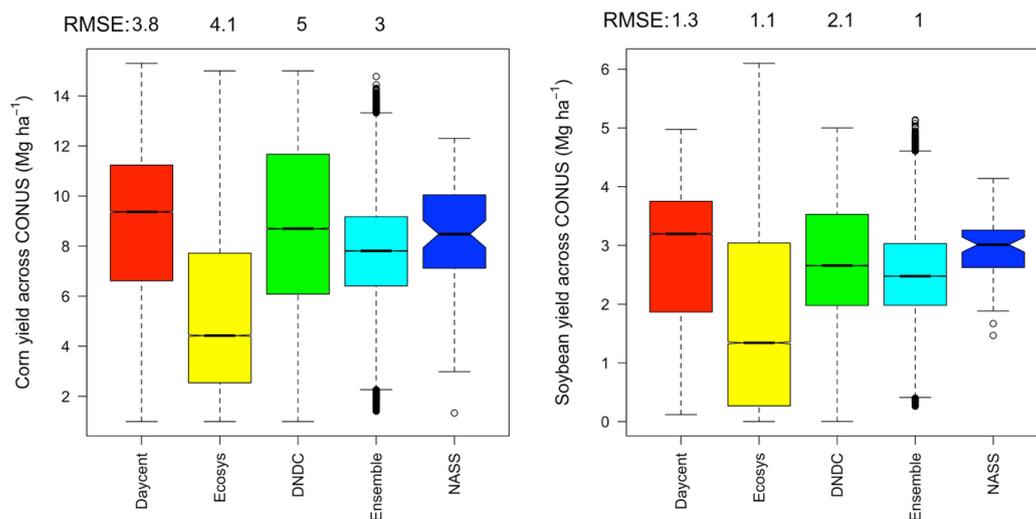


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Figure 1 Schematic representation of the workflow for large-scale application of the ensemble agroecosystem model (DAYCENT, DNDC, ECOSYS). Environmental and management inputs were derived from multiple datasets, including Daymet (daily surface weather data), SSURGO (Soil Survey Geographic Database), NASS (National Agricultural Statistics Service crop yield surveys), RaCA (Rapid Carbon Assessment soil carbon database), and NLCD (National Land Cover Database).

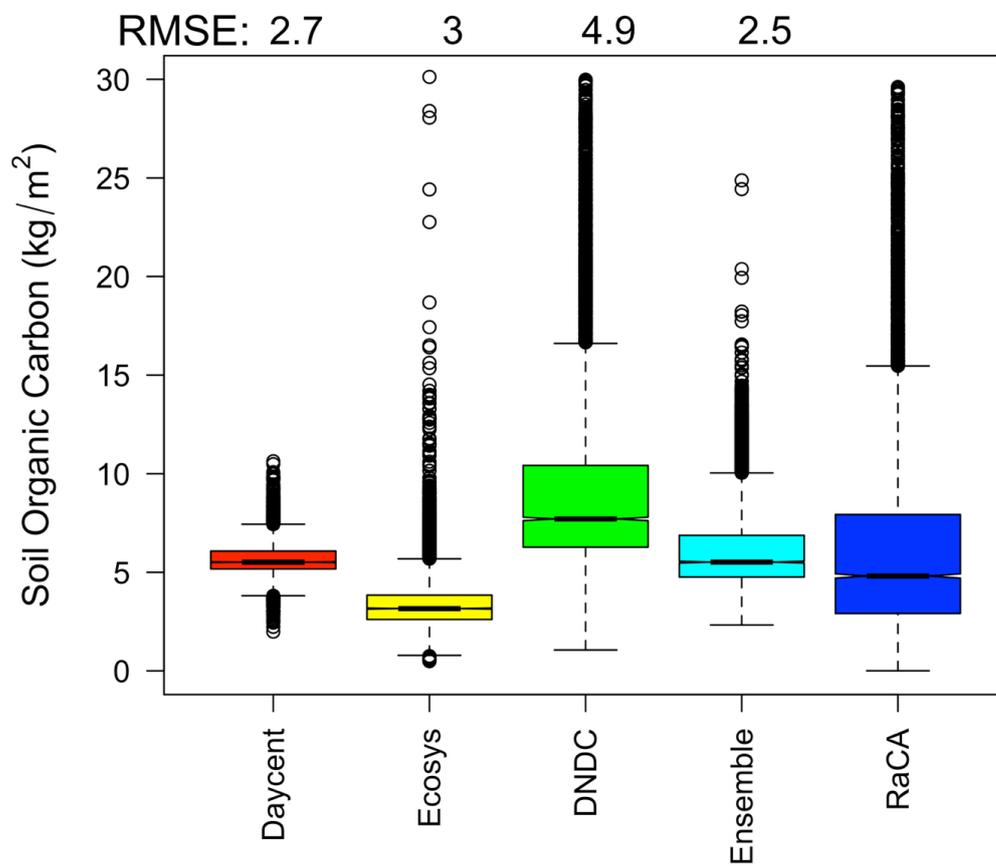


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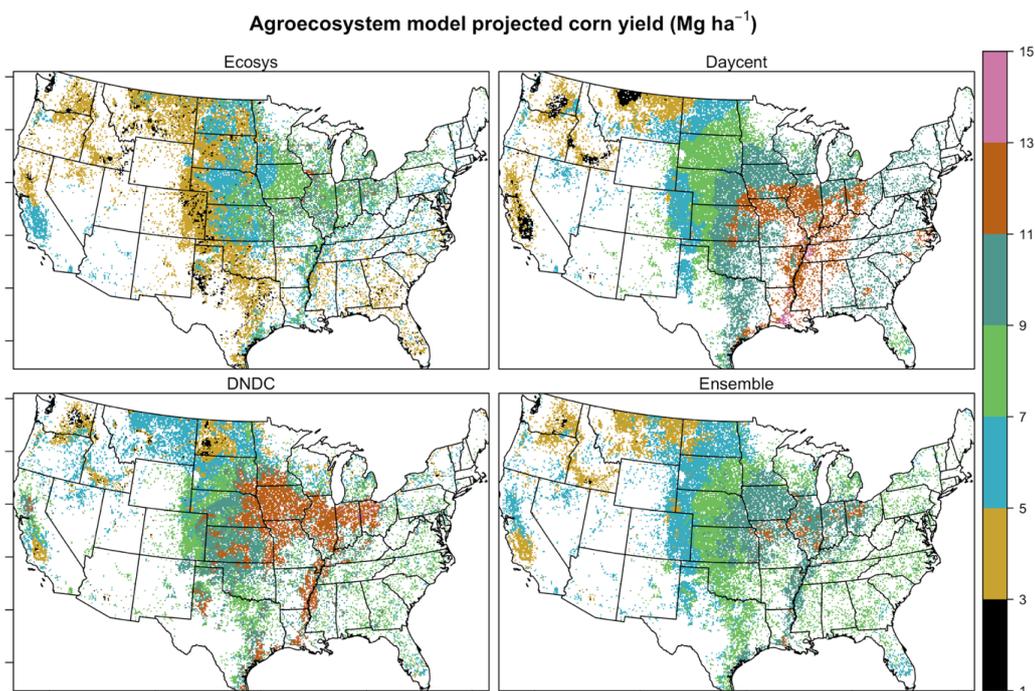


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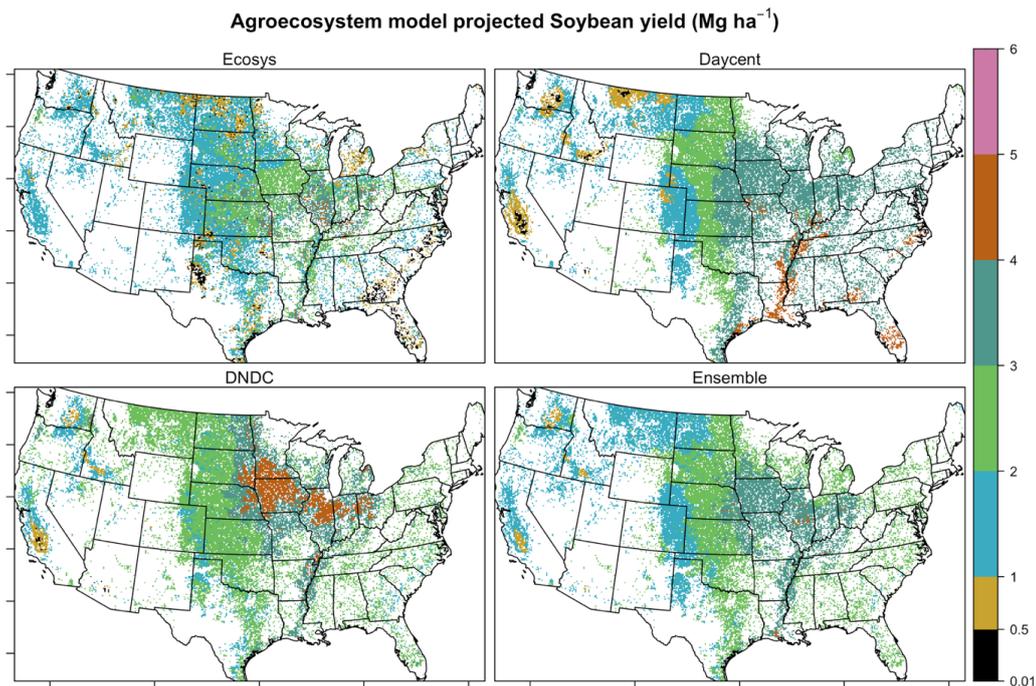
Figure 2 Comparison of observed crop yields (Mg/ha; NASS, 2014-2023) with simulated yields and root mean square error (Mg/ha) from individual agroecosystem models and the ensemble approach for (a) corn and (b) soybean.



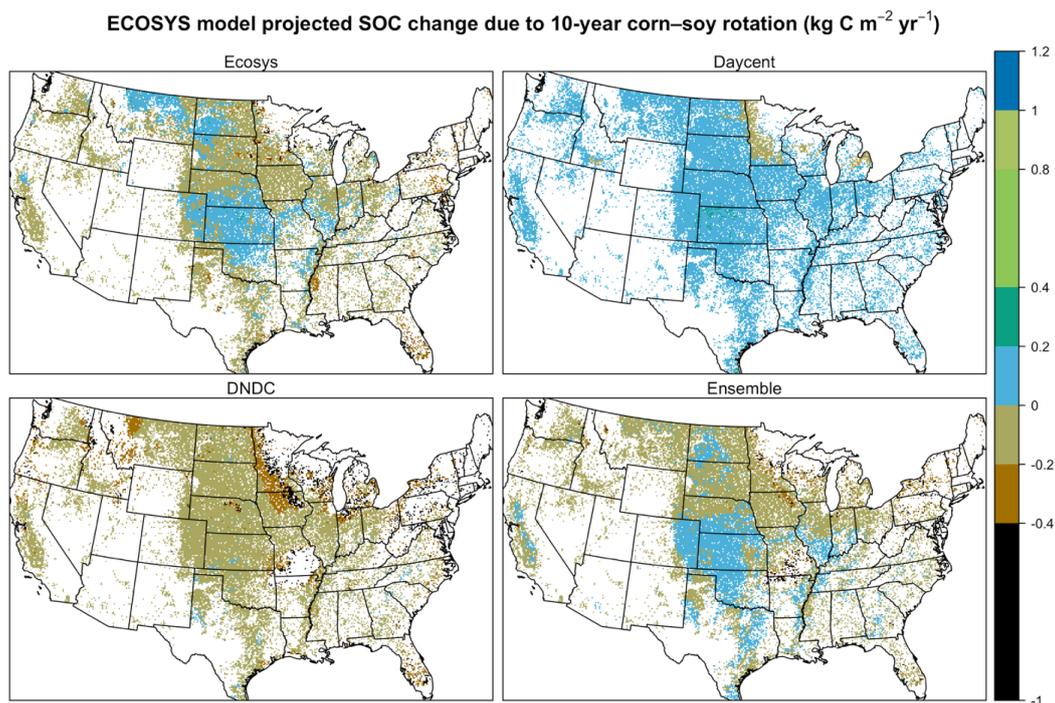
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2 **Figure 3** Comparison of observed soil organic carbon (SOC) stocks (0-30 cm) (kg C m²) from
3 the RaCA dataset with SOC simulated and root mean square error (kg C m²) by individual
4 agroecosystem models and the ensemble approach.
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2 **Figure 4** Spatial distribution of annual corn yield (Mg ha^{-1}) across the CONUS simulated by the
3 ensemble and individual agroecosystem models (DAYCENT, DNDC, and ECOSYS) for the
4 2014–2023 period.
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2 **Figure 5** Spatial distribution of annual soybean yield (Mg ha^{-1}) across the CONUS simulated by
3 the ensemble and individual agroecosystem models (DAYCENT, DNDC, and ECOSYS) for the
4 2014–2023 period.
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Figure 6 Spatial distribution of simulated soil organic carbon (SOC) stock changes ($\text{kg C/m}^2 \cdot \text{yr}$) over a 10-year period (2014–2023) using individual agroecosystem models and the ensemble approach.