Evaluating Sensitivities of Economic Factors through Coupled Economics-ALMANAC Model System

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ABSTRACT

Using crop models to simulate crop growth and productivity at a regional scale is a complex process designed to represent the observed impact of individual farmer decision-making on the agricultural landscape. Typically, during agricultural simulation efforts, the planting acreages have largely been based on a set of predetermined, static scenarios. In this study, we developed a system to dynamically enhance the Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC) crop simulation model through a two-way linkage with an economics land-use model. This coupled model approach integrated farmers' land-use choices based on relative economic returns and produced dynamic land-use probabilities for ALMANAC simulations through a feedback loop. The coupled model approach was intercompared with static crop modeling through a historic acreage approach, and comparable accuracies were found from both modeling efforts for the 2014 growing season. Furthermore, as a proof-of-concept effort, the method was applied to evaluate the impact of two scenarios on crop simulations: major crops (maize, soybean, and wheat) intensification through price increases (e.g., market change) and incentivized grassland conservation (e.g., policy change). The results of this sensitivity study suggest that the coupled system has the capability to integrate economic factors into traditional crop simulation, allowing for insight into the impacts of changes in markets and policies on agricultural landscapes and crop yields.

Core Ideas

- A linked Economics land-use model with the ALMANAC model has been constructed for crop simulation.
- The linked crop and economics modeling system can be used for estimating dynamic crop acreages.
- The impacts of policy and market changes on crop simulations can be studied with the linked system.

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To accurately estimate crop yields at regional scales for economic analysis and prediction, crop models have been developed and used in simulating crop yields and soil health over selected regions (Hertel and Rosch, 2010; Williams et al., 1983). Some crop models commonly used for this simulation include the Environmental Policy Integrated Climate (EPIC) model (Williams et al., 1983), the Agricultural Land Management Alternative with Numerical Assessment Criteria (ALMANAC) model (Kiniry et al., 1992), the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003), the Agricultural Production Systems sIMulator (APSIM) (Keating et al., 2003), and Crop Environment REsource Synthesis (CERES) (Ritchie and Otter, 1985).

Although these crop simulation models take into account both weather and soil changes, one factor lacking in the crop models is the dynamic impact of land-use changes due to economic factors, such as market fluctuations and changes in policy. These factors can influence landowners' decision-making on land uses and management practices and thus further affect crop yields. The inherent agricultural productivity of land is determined by its biophysical characteristics and the surrounding climate, making inputs in these areas near static at annual time scales. However, decisions on land-use and management practices are dynamically driven by the individual landowner and can change at an annual time scale based on the economic return from each available alternative. Studies at the regional scales often simulate crop yields with a set of fixed assumptions on land uses and management practices throughout the analyses. However, this process ignores the impact of landowners' dynamic decision-making at a local scale with multiple soil profiles as responses to changes in local economic conditions, such as changes in market and policy conditions, reflected by crop prices and policy incentives. Furthermore, over decadal time scales, the policy-induced changes in land allocation and in farming practices for crop production will affect soil health and its agricultural productivity at longer time scales, which feeds back into the decision-making process.

Although coupling crop models with economic models to adjust for this impact has been the topic of several studies, these

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Abbreviations: ALMANAC, Agricultural Land Management Alternative with Numerical Assessment Criteria; CDL, Cropland Data Layer; LCC, Land Capability Class; NARR, North American Regional Reanalysis; NASS, National Agricultural Statistics Service; SSURGO, Soil Survey Geographic.

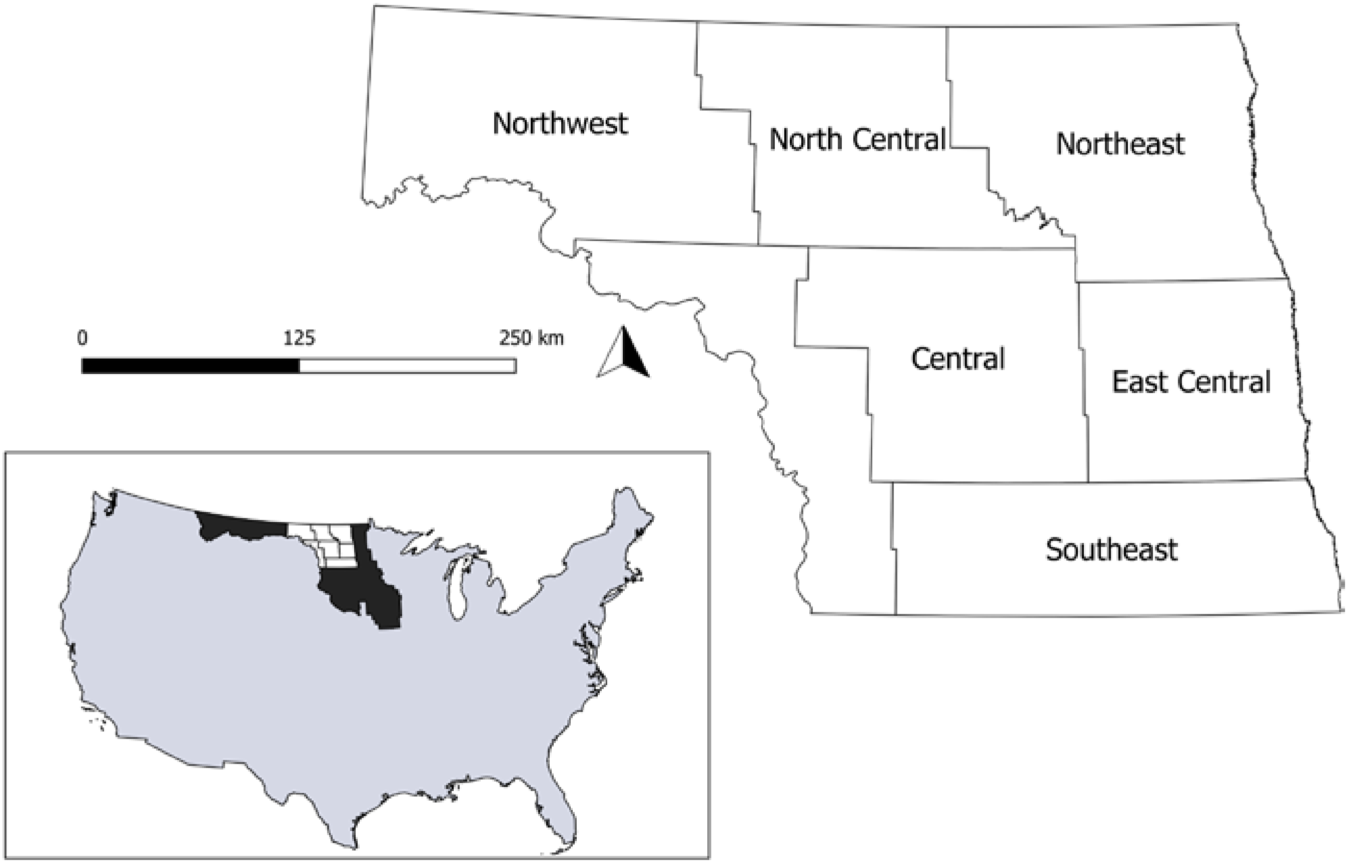

Fig. 1. Locations included in this study and their relative positioning inside the United States Prairie Pothole Region.

studies are typically set up in a one-directional fashion, with results from the economic model feeding the crop simulation model (e.g., Briner et al., 2012; Robertson et al., 2012) or with the crop simulation model results feeding the economic model (e.g., García-Vila and Fereres 2012) without a two-way interaction, as attempted in this study. Additionally, while looking at long-term changes, crop production simulations of responses to future scenarios often use gridded data, include few locations, or use a single soil profile per location (White et al., 2011). Therefore, without taking into account the feedback loop between soil health and economic decision-making at a finite, individual soil-based resolution, the simulation results from the traditional crop modeling approaches can ignore the two-way interaction between annual yields and profits and the resulting land-use changes. This shortcoming likely leads to a tendency to move toward unrealistic depictions during these longer-term simulations.

In this paper, we expand on the standard crop simulation model paradigm by generating dynamic agricultural land-use choices and implementing them into large-scale crop simulations. We accomplish this through a two-way linked economics land-use model and a crop model at an annual time step looking at seven crops common to the study area: maize (*Zea mays* L.), soybean [*Glycine max* (L.) Merr.], spring wheat (*Triticum aestivum* L.), oats (*Avena sativa* L.), alfalfa (*Medicago sativa* L.), canola (*Brassica napus* L.), and sunflower (*Helianthus annuus* L.). In this proof-of-concept paper, we focus our preliminary studies on the following questions: (i) Can a linked system be developed to incorporate economic factors in modeling land-use at soil-based resolution and offer advantages in crop simulations? and (ii) Can we use the linked economics–crop modeling system to further evaluate the sensitivity of economic factors, such as policy and market changes, on crop yields and soil health prediction?

Data and Models

The selected area for the study is the Prairie Pothole region of North Dakota (Fig. 1), a region spanning east and north of the Missouri River with extensive grassland and wetland coverages for providing crucial habitats for endangered species and other ecosystem services. This region was selected for its well-known high soil productivity as well as the recent significant grassland conversion to corn and soybean cultivation (Ojima et al., 2002; Wright and Wimberly, 2013).

For the simulations, three primary environmental datasets were used. The structure and properties of the soils in the study region were obtained by using the 2015 version of the Soil Survey Geographic (SSURGO) database (Soil Survey Staff, 2016) covering the state of North Dakota. Meteorological variables were acquired through the North American Regional Reanalysis (NARR) (Mesinger et al., 2006) dataset from the National Center for Environmental Prediction. Finally, the Cropland Data Layer (CDL) (USDA–NASS, 2016) was used to determine the historic crop locations and total area. In addition to these datasets, an economics framework (Kharel et al., 2016) and the ALMANAC crop model (Kiniry et al., 1992) were linked together (heretofore referred to as ALM-EC) and are applied in this study.

The SSURGO Data

The SSURGO database is a spatially referenced database containing soil profile and general characteristics information for the majority of the United States land area at a scale varying from 1:12,000 to 1:63,360. This dataset was chosen due to its extensive scope and high spatial resolution as the proper fit to simulate the prairie pothole area at a fine spatial scale. Internally the ALMANAC model uses the SSURGO information to generate soil profiles based on water holding capacity, soil depth, and chemical components (Kiniry et al., 1992). The database contains a collection of uniquely identified soil types covering the whole of North Dakota, with each soil characterized by the depth of each layer of the profile as well as the overall properties of the soil, expressed in means and ranges, for each independent layer of soil. Typically, these soil files are divided into separate databases for each county or distinct geographic region. For the Prairie Pothole Region included this study, there are a total of 6995 unique soil profiles (median area, 328 ha) broken into 39 unique databases with a scale of 1:12,000. The SSURGO dataset was acquired from the NRCS data gateway website (https://datagateway.nrcs.usda.gov/) (Soil Survey Staff, 2016).

The nonirrigated Land Capability Class (LCC) in the SSURGO database, which defines a soil's potential for crop production during standard rain-fed farming practices, is used to determine soil productivity in this study. Soils in North Dakota fall into the range of LCC 2 to LCC 8 classifications; these groups have increasing levels of limitations on crop growth, with LCC 2 containing the least and LCC 8 containing the most; these limitations reduce overall potential productivity to varying degrees (USDA Soil Conservation Service, 1961). The LCC database is used in this study to identify the potential impacts of migration patterns in land uses as demands for crops increase or decrease total acreages over finite resources.

The North American Regional Reanalysis Data

The NARR database is generated by combining research weather models with past observations to complete a gridded summary of the local atmospheric conditions at resolutions up to 32 km per grid. These data are provided in eight-times-daily and daily summary formats at defined model pressure levels. For the Prairie Pothole study region, the grid spacing is on average 32.40 ± 0.05 km. Although this resolution is coarser than other available datasets, such as the 4-km PRISM dataset (Daly et al., 1997), this system was chosen due to the similar lineage to data generated from current generation climate models. This allows for past, present, and future climate simulations to be run without recalibration of the crop models when using the same assumptions. The NARR dataset provides a wide variety of meteorological variables, such as wind speed and temperature. For this study, temperature at the 3-h time step scale was used. Precipitation, wind speed, relative humidity, and solar energy inputs were derived from the daily summaries. The ALMANAC model uses solar radiation, temperature, and precipitation values to calculate growth rates and stresses; wind speed, relative humidity, and solar radiation are used to determine potential evaporation. The NARR dataset was acquired from the Earth Systems Research Laboratory (https://www.esrl.noaa.gov/psd/data/gridded/data.narr.html) (Mesinger et al., 2006).

The Cropland Data Layer Data

The CDL is an annually produced georeferenced raster file that defines surface crop types for the majority of the United States at a resolution of 30 to 56 m. Crop types are determined through analysis of satellite imagery (Boryan et al., 2011). The data are then processed and verified against the National Agricultural Statistics Service (NASS) and Farm Service Agency farmer records to increase the accuracy of the detection algorithm (Boryan et al., 2011). A total of 132 land-use types are included in the CDL data, of which 47 are found within the study region. In this study we used the CDL to map the seven major crop types (spring wheat, maize, soybean, oats, sunflower, canola, and alfalfa) but accounted for other crops and land uses given by the CDL in our final land-use area estimates. Within the study area, a total of 9.98×10^6 ha or 74.7% is in land cover accounted for in this study, leaving 25.2% of the area consisting of wetlands, other nonfarmable, and nonstudy crops, which are held static. The CDL dataset was obtained from the Cropscape website (https://nassgeodata.gmu.edu/CropScape/) (USDA–NASS, 2016).

The ALMANAC Model

In this study, the USDA's ALMANAC model is selected for use in crop simulation for its inherent connections with the Soil Survey Geographic (SSURGO) database (Soil Survey Staff, 2016), its ability to accurately simulate a wide range of crops, the depth of its field management options (Xie et al., 2001), and the extensive reviews on the input sensitivities that have been completed (e.g., Xie et al., 2003). The ALMANAC model is a daily time step crop simulation model originally based on the EPIC model (Mearns et al., 1999). The ALMANAC model produces a point-based, soil-specific simulation of the growth, health, and yield of a variety of crops, including the seven selected crops mentioned previously. Additionally, the ALMANAC model was chosen due to its ability to simulate at a per-soil basis, directly matching the input of the economics model, allowing for the investigation of land-use migration at this same level.

The ALMANAC model requires three main inputs: management protocols, soil characteristics, and local meteorological conditions. For management, planting and harvesting dates from statewide climatological averages are used for each study crop, fertilizer applications are static and set to once at planting if required by the crop, and no irrigation or other in-season intervention is included. Soil characteristics and components are handled internally through the ALMANAC model using the SSURGO soil dataset dated 2015. Meteorological information were derived from the NCEP NARR dataset. Each SSURGO soil area in the study region is geometrically subsected by the native NARR grid spacing of 32 km using geometric intersection and treated independently, resulting in 18,136 individual simulations for each crop with a median area of 119.7 ha. For this study, each simulation was run for the specified year after a 1-yr spin-up; longer time-frame spin-ups were tested for this study, but no major changes in results were found.

Before the study, the ALMANAC model was calibrated for the study region by adjusting the built-in crop parameters within the model to match local crop varieties. This calibration step is needed because varieties of commonly grown crops differ from region to region due to the specific needs or limitations of each area. To compensate for this impact on the overall growth and eventual yield, each crop requires separate calibration to the ALMANAC parameters.

Calibration was completed for the study crops using annual yield as the primary factor for a single year. A randomized set of

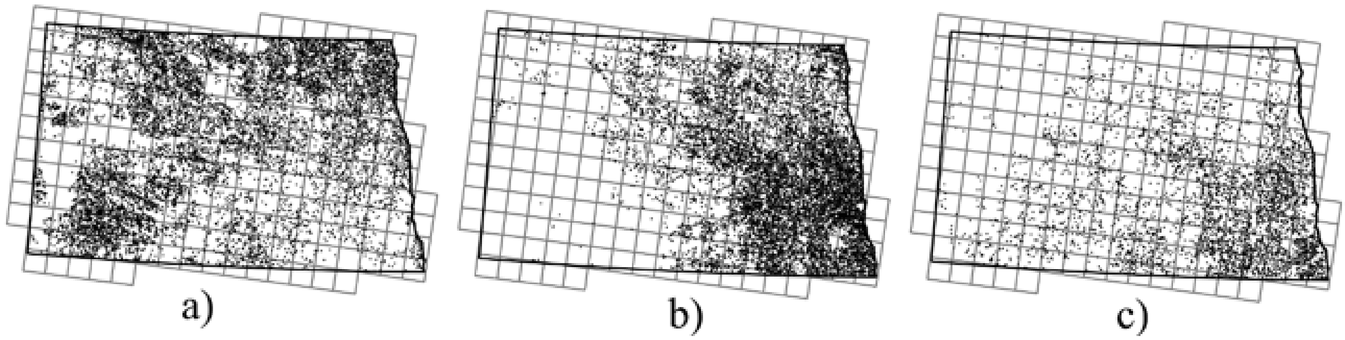

Fig. 2. Locations used to simulate spring wheat (a), soybean (b), and maize (c) during model calibration over North Dakota with the native North American Regional Reanalysis weather data grid superimposed

points (set as $n > 1000$ per crop) was generated within the state of North Dakota based on the estimated crop grown within that year at that location as reported by the CDL (Fig. 2). These points were then repeated for each year through the 2001–2013 growing seasons using a similar technique, each year individually simulated, with spin-up period, but with a shared point selection filtered to only include locations with a frequent reoccurrence of the selected crop. The county-by-county yield aggregates were tabulated and compared with the NASS given statistics for that county in that year. As an example, Fig. 2 shows the validation points selected to compare model-simulated yields with the reference county reported yields for spring wheat, maize, and soybean, respectively. The primary parameters adjusted included total growing degree days to account for the shorter growing season as well as increased water stress tolerance to compensate for both the climate of the area and the diffuse nature of the precipitation in the weather model data used in this study; additional minor growth parameters for each crop were adjusted as needed. The parameters were calibrated until the resulting simulation annual county level means were within 10% of NASS-reported annual mean yields at the county level.

The Economics Land Use Model

The individual-based economics land-use model focuses on the agricultural profitability of producing different crops under policy and market assumptions (Kharel et al., 2016). The spatially explicit land-use model calculates the net return of each crop and determines the crop composition for a given unit using crop yields simulated by the ALMANAC model. The net return of a soil unit s ($s = 1...S$) in year t, to be assigned for a certain use or to grow a particular crop c ($c = 1...C$), is calculated as $\pi_{s,c,t} = P_{c,t}Y_{s,ct-1} - C_{c,t}$, where $Y_{s,ct-1}$ is the crop yield simulated by the ALMANAC model for a particular soil type and productivity in year t–1, $C_{c,t}$ is the crop production cost, and $P_{c,t}$ is the expected price for a crop c in year t. We assume that an individual landowner estimates the expected economic return to grow a certain crop based on previous observations, knowledge of the soil type, productivity of the land, and the current price information of future market movements. Therefore, the likelihood of growing a certain crop in a given unit is determined by the relative profitability of that crop compared with other competing land-use alternatives by assuming that each landowner makes optimal choices to maximize the total economic return.

In this modeling exercise, we simplified the management details and used static managements in ALMANAC by assuming that farmers grow a certain crop under a general fixed management scheme. However, the choices of management practices as well as their costs likely affect farmers' decision-making on land-use and crop type selections. The profit maximization, therefore, can be further achieved by modeling a farmer's management choices based on physical conditions related to soil and climate as well as economic factors such as the fluctuations of input prices.

For this study, we treated prices as exogenously determined outside of the system based on the fact that the study region is relatively small and has played a moderate role as a "price-taker" in the domestic commodity markets. We collected crop price information for small crops (oats, sunflowers, canola, and alfalfa/hay) and production cost data, shown in Table 1, for all seven crops in the study region from the Farm Financial Database (http://www.finbin.umn.edu) hosted by the Center for Farm Financial Management at the University of Minnesota. We chose this dataset to use the real-world farmers' budgetary information by considering farming itself as a systematic decision-making process wherein each management choice is made in conjunction with the others. We imported annual 2014 market year prices from the USDA National Agricultural Statistics Services (NASS) (USDA–NASS, 2018) for the major crops to reflect the general fluctuations across domestic markets. For scenario analyses, we used a different set of prices to demonstrate the potential increases in market demand for the major crops. We used FINBIN price information for the small crops because these prices are likely determined by the regional/local market. To focus on modeling land productivity for crop production, we simplified the modeling of grassland and forestland by using a static average net return reported by Lubowski et al. (2006, 2008) based on the spatial association of an individual soil unit with each North Dakota county and adjusted for inflation. The final estimated net return of each land-use alternative was transformed to a probabilistic surface using logistic distribution to represent the likelihood of the land-use transition (Lewis and Plantinga, 2007; Lubowski et al., 2006, 2008).

Methods and Experimental Design

In this study, we developed a linked crop–economics model and intercompared the performance of the linked crop–economics model with crop simulations from a static crop modeling approach. After completion of this initial stage, the linked crop–economics model is used, as a concept-proofing effort, to investigate the sensitivity of crop simulations with respect to major crops intensification as well as grassland conservation

Table 1. Direct production costs and economic net returns of crops.

	Corn	Soybeans	Wheat	Oats	Sunflowers	Canola	Alfalfa	Grass	Forest
Direct cost,† $ acre^{-1}									
Seed	87.63	68.64	19.09	12.75	39.06	54.34	2.93		
Fertilizer	111.95	15.35	67.96	37.81	57.73	72.00	5.80		
Crop chemicals	22.79	22.48	34.73	14.97	43.47	30.30	0.93		
Crop insurance	22.08	17.84	15.61	14.55	12.88	12.97	5.17		
Fuel and oil	27.26	19.21	17.62	15.46	18.87	22.11	12.50		
Repairs	31.07	19.98	18.76	19.22	20.45	21.67	17.20		
Custom hire	5.05	4.24	7.58	14.28	11.88	5.32	2.15		
Land rent	49.34	53.91	34.62	17.59	34.22	28.99	20.31		
Operating interest	6.89	4.34	4.13	3.29	5.02	4.23	3.11		
Miscellaneous	1.78	0.95	1.58		0.93	0.29	0.60		
Drying expense	9.84								
Storage	0.76								
Crop prices,‡ $ unit^{-1}									
Baseline	3.70	10.10	5.99	2.58	20.10	16.73	74.04		
Crop intensive	4.44	12.12	7.19	2.58	20.10	16.73	74.04		
Net returns,§ $ acre^{-1}									
Baseline	45.32	55.97	28.79	2.33	20.10	16.73	12.59	4.76	3.03
Crop intensive	56.65	66.04	34.61	2.33	20.10	16.73	12.59	4.76	3.03
Grassland incentive	45.32	55.97	28.79	2.33	20.10	16.73	12.59	44.76	3.03

† The direct costs of crop productions were collected from FINBIN at the FINPACK financial database (https://finbin.umn.edu/Home/AboutFinbin) for North Dakota in 2014.

‡ The crop prices are in $ per bushel for corn, soybeans, wheat, and oats; in $ per hundredweight for sunflowers and canola, and in $ per ton for alfalfa/hay. The same crop prices were used in the baseline and grassland incentive scenarios.

§ The economic net returns of grassland and forestland were adopted from Lubowski et al. (2006, 2008).

scenarios as a proxy for perturbations in market and policy conditions, respectively.

Description of the Economics and Crop Model Feedback Loop

A primary goal of this study is to develop a linked economics land-use and crop model system that integrates economic-based land-use changes into the crop simulation modeling process. To facilitate this, we established the looped-feedback pattern as described in Fig. 3, interconnecting the models directly. At the beginning of the process, weather, soil, and crop datasets for the previous year are used as inputs to the ALMANAC model for estimating yield performance for all crop and soil combinations within the study area for the previous year. The yields are used as inputs, along with policy and markets information, to the economics model. The economics component calculates the economic return of each land-use alternative and the relative likelihood of each crop being grown in a specific location with a unique combination of soil and weather for the current year. In other words, the land-use probabilities from the economics land-use model can further prescribe the allocation of land within a particular unit. This structure demonstrates that a farmer's decision-making process uses simulated crop yields from the previous year as a reflection of the farmer's knowledge or observation of land productivity as well as the current prices as a proxy of market and policy changes. With the detailed information of crop allocations within each individual soil unit, the ALMANAC model produces the final yields over those areas and soil information for the study region for the current year. Each subsequent (annual) time step repeats the entire process, save for the calibration stage, using the soil state from the previous year's simulation. As an example of this connection, Fig. 3 shows this study's concept proof design, focused on simulating land-use probabilities for the year 2014 (Fig. 4). In this practice, yields from 2013 are used for predicting agricultural land-use and land change for 2014, using price and policy as control variables. This provides a potential forecasting capability for future studies.

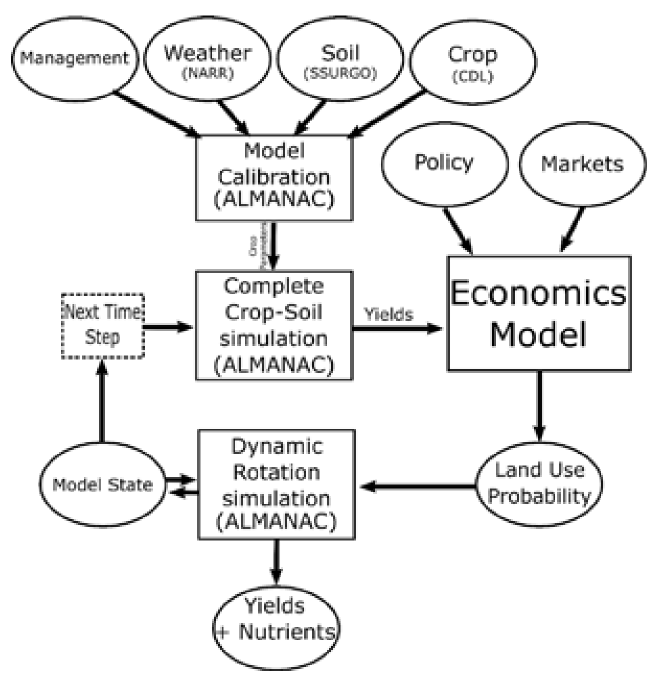

Fig. 3. Study workflow for crop simulation using land use probability from the economics model.

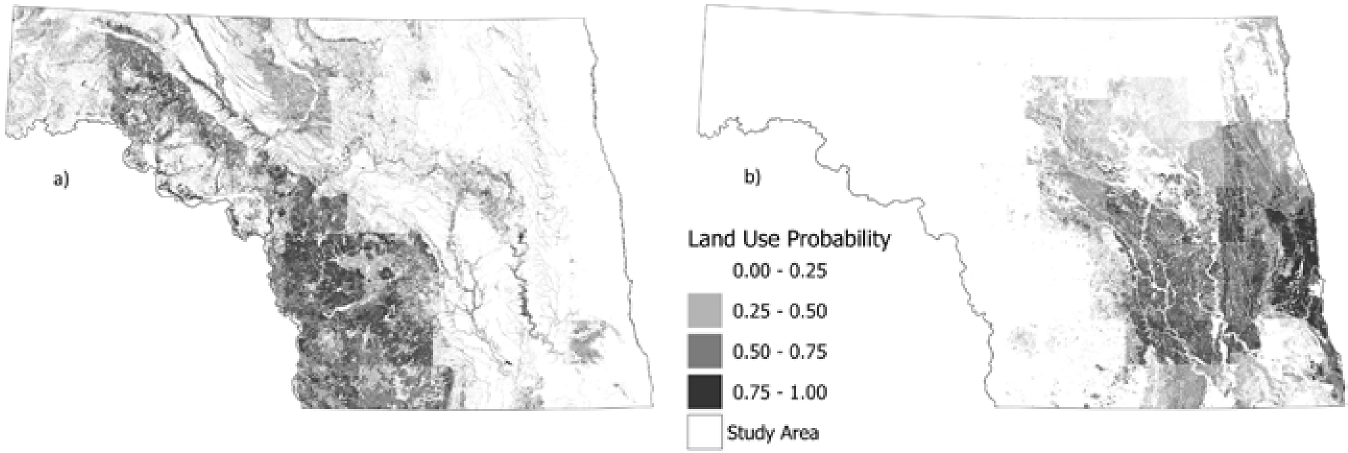

Fig. 4. Resulting land-use probabilities for (a) grassland and (b) soybean generated by the economics model for the 2014 season.

Evaluation of Land-Use Area and Yield Simulated Using the Linked Economics-Crop Model System

Crop simulations without and with the use of the economics land-use model are performed and intercompared for year 2014, setting the basis for evaluating the influence of crop and market changes on crop simulations.

The standalone crop simulation approach follows a simplified process that determines the composition of land uses for 2014 based solely on historical records of crop patterns observed over the period of 2010 to 2013 at the coarsest resolution (30 m) the CDL supplies during that timeframe. The linked crop–economic model approach uses a paired crop simulation and economics land-use model to determine the most likely cropping patterns in the 2014 season, emphasizing the two-way linkage as a more systematic method. The results from each of these two approaches were used in the simulations of the 2014 growing season for comparison. Crop yields and land-use simulations from both approaches were then compared with both the estimated land uses as described by the 2014 CDL as well as actual yields reported by NASS.

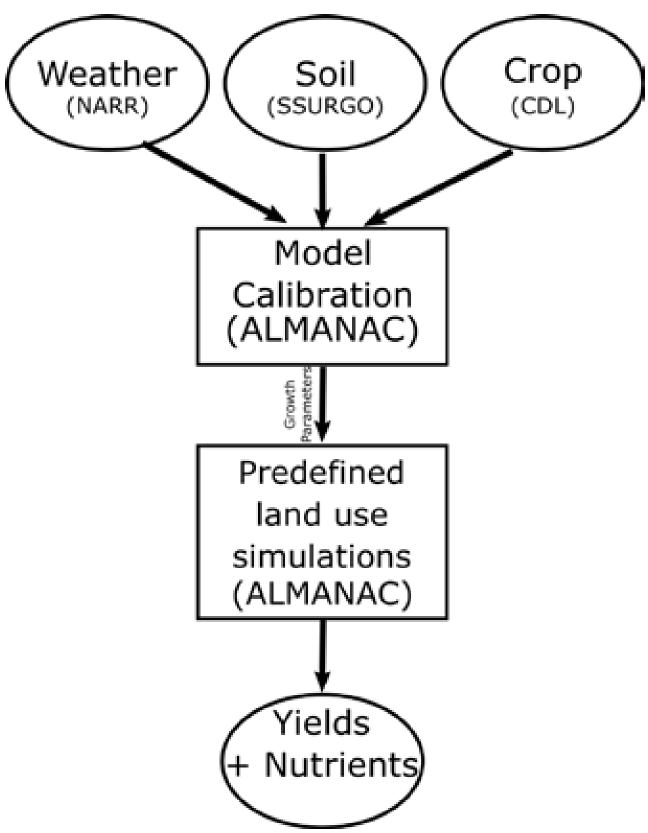

Fig. 5. Study workflow for the noncoupled, stand-alone crop simulations using historical acreages

Crop Simulation with Historical Crop Patterns

The standalone model approach used the ALMANAC model to simulate crop yields for the 2014 season using the fixed historical crop percentages (Fig. 5). To determine the historic crop planting percentage used in each soil type, the CDL from 2010 to 2013 was geospatially intersected with the individual SSURGO soil types to determine the most commonly seen crops for each soil area. These were then applied to determine the soil and crop combinations for the ALMANAC model and run for the 2014 growing season. The resulting yields were tabulated at an individual SSURGO soil type using the CDL's historic area percentage. This process enables a direct comparison to the yields generated by the economics land-use model.

Crop Simulation with Land-Use Probability from the Economics Model

As a comparison, the second approach simulates crop yields using land-use probability prescribed by the ALM-EC model. Data from CDL, SSURGO, and NARR from 2013 are used as inputs for the ALMANAC model, which simulates soybean, maize, spring wheat, sunflower, canola, oats, and alfalfa yields for all soil map units over North Dakota for 2013 (Fig. 3). These simulated crop yields for 2013, along with crop prices and management costs determined by a specific scenario, are used as inputs for the economics model. The land-use probability (Fig. 4), as the outcome from the economics model, is used to generate possible soil–crop combinations for ALMANAC to simulate for the 2014 season, with the resulting total land area and production for each soil–crop simulation weighted by the economic probability per soil.

To test the integrated approach via coupling the two models, the simulated land-use composition was compared with the estimated acreage derived from the previous years' CDL as well as the CDL-estimated 2014 crop acreages.

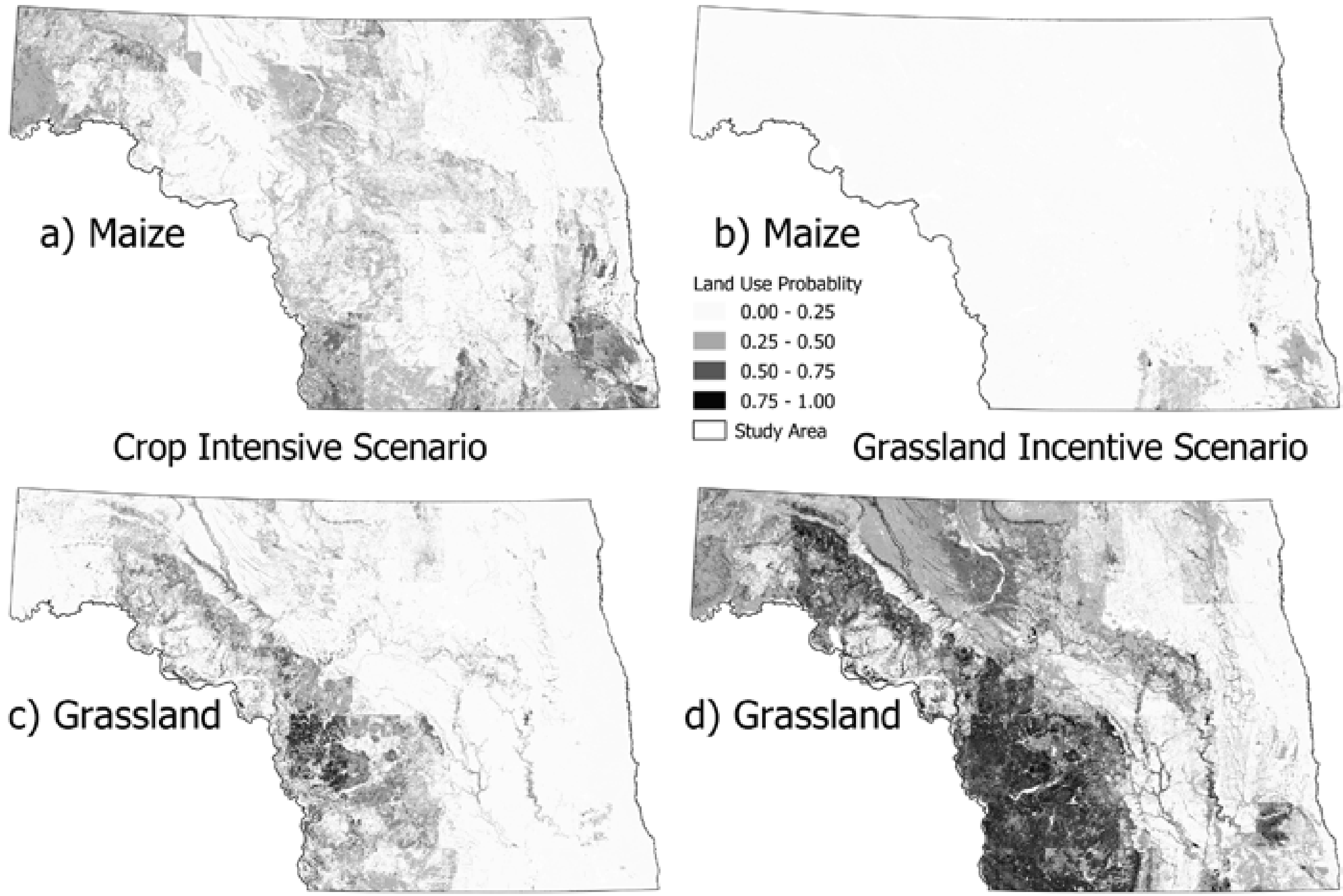

Fig. 6. Probability of planting for each SSURGO soil type for maize (a and b) and grassland (c and d) using the ALM-EC model for two scenarios: crop intensive, representing the increased market prices for maize, soybean, and wheat (a and c) and grassland incentive, representing the policy change of enacting a flat per acre payment for grassland acreage (b and d). Darker gray indicates a higher probability of planting.

Evaluation of the Impacts of Market Price and Policy Changes on Crop Simulations

Upon evaluation of the linked crop and economics modeling system, we extended crop simulation from a nonperturbed setting to two alternative scenarios to quantify the impact of changes in market prices and policy incentives on crop yields, soil health, and nutrients for the year 2014. The first scenario is based on historic occurrences where the market prices of the major crops (maize, soybeans, and wheat) are increased, resulting in higher net returns to major crop productions. In contrast, the second scenario evaluates the impact of incentivizing grassland with a subsidy, as an illustration of the US Conservation Reserve Program, with all prices and costs remaining the same as in the nonperturbed.

Major Crops Intensification Scenario (Market Price Change)

The first alternative scenario corresponds to an intensive crop production related to either agricultural market shocks or energy policies to expand biofuel production. The scenario assumes a 20% increase compared with the nonperturbed in maize, soybean, and wheat market prices likely resulting from higher demands for these major crops in the region. The prices under the intensive cropping scenario fall well within the range of the most recent price surge during 2012 and 2013 (USDA–NASS, 2018) (Table 1). Similarly, the economics land-use model used the 2013 simulated yields for all study crops in the prairie pothole region of North Dakota to calculate the net return of each potential land-use alternative under the scenario prices and transformed to the land-use probability for each crop. We then implemented the ALMANAC simulations for the 2014 growing season with the scenario land-use probabilities (Fig. 6) under all soil and weather combinations.

Grassland Conservation Scenario (Policy Change)

In contrast to the nonperturbed scenario, where a constant net return to grassland was assigned for each land unit, the second scenario considers policies that increase subsidies or payments for ecosystems services or land rents for conservation easements such as USDA Conservation Reserve Program land and wetland. It is assumed that an incentive of \$40 acre^{-1} was added to the net return of grassland for encouraging cropland conversion to grass/pasture land with forestland remaining constant. The \$40 acre^{-1} rate of compensation was a midpoint of Conservation Reserve Program rental payment, which ranged from \$30 to \$50 acre^{-1} as reported by the USDA–NASS database over the past 10 yr among all North Dakota counties. With the additional \$40 acre^{-1} added to the net return of grass/pasture land, it is expected that less-productive lands are more likely to remain or convert to grass/pasture use due to increased grassland profitability. To highlight the effect of this conservation effort, all other crop prices stayed at the baseline level. This generated a unique probability of planting dataset, which was then fed back into the ALMANAC model to simulate the resulting yields and soil health in the 2014 growing season.

Table 2. Table of 2014 land-use area for each agricultural district as calculated by the ALM-EC model, the CDL-derived 2010–2013 mean planted area, and the estimated planting percentages for 2014 as reported by the CDL.

Crop	Agricultural district	Land-use area			Error	
		ALM-EC	2010–2013 CDL	2014 CDL	ALM-EC	2010–2013 CDL
		ha			%	
Maize	Central	113,948	126,410	164,308	–31	–23
	East central	115,262	266,064	227,441	–49	17
	North central	151,309	50,575	65,966	129	–23
	Northeast	87,690	89,282	84,987	3	5
	Northwest	145,919	11,980	17,402	739	–31
	Southeast	317,059	341,253	341,567	–7	0
	Other	65,407	75,676	88,571	–26	–15
Total		996,594	961,239	990,243	1	–3
Soybean	Central	460,482	336,395	443,551	4	–24
	East central	805,314	536,348	577,507	39	–7
	North central	170,726	115,360	224,204	–24	–49
	Northeast	400,553	273,257	390,536	3	–30
	Northwest	56,628	14,489	75,679	–25	–81
	Southeast	497,438	440,948	564,152	–12	–22
	Other	20,807	31,077	79,692	–74	–61
Total		2,411,948	1,747,875	2,355,320	2	–26
Wheat	Central	74,443	199,669	192,233	–61	4
	East central	27,599	158,064	137,598	–80	15
	North central	250,607	271,498	271,554	–8	0
	Northeast	591,991	517,693	534,204	11	–3
	Northwest	603,268	230,651	418,865	44	–45
	Southeast	40,801	110,151	111,293	–63	–1
	Other	242,915	192,209	194,135	25	–1
Total		1,831,624	1,679,935	1,859,880	–2	–10

RESULTS AND DISCUSSIONS

Comparison of Historically Based and Economics Model–Based Crop Acreages

We compared the projected land-use through the ALM-EC model to both the CDL-derived land-use probabilities and the NASS statistics. Land-use areas are aggregated to the agricultural districts, the results of which are shown in Table 2 for each of the three major crop types in the area. Yields for the seven crop types were simulated for all soil types and are used as inputs for the economics model. However, a total of 47 land types are found through the CDL layer over the study region. We assume the land cover that is not modeled by this study, such as nonagricultural land cover and minor crops, stays constant over the study time frame, and their acreages are removed from the analysis. However, this does not include noncrop land uses that are accounted for by the economics model, such as grassland and forest.

The historic crop hectares were derived from the historical dataset given by the CDL for the years 2010 to 2013 to determine the probability of each crop within each soil type within that time frame. Finally, the 2014 data were derived from the 2014 version of the same CDL dataset to compare directly with the projected hectares from both the historical and the economics land-use model. The CDL measures area for each crop independently, which accounts for the impacts of both noncropland and crops not covered in this study; therefore, the CDL areas do not need an adjustment to account for nonstudy land uses.

Maize was closely predicted by the ALM-EC model as well as the historic mean (Table 2). However, although the ALM-EC model produced a more accurate estimation of the total 2014 planted area, the 2010–2013 CDL mean was able to more accurately project within most agricultural districts based on goodness of fit (estimated using R Project for Statistical Computing). Overall the ALM-EC model performs well for the region but does not factor in some of the limitations of planting such a high–resource demanding crop in regions not historically seen. Land-use dedicated to soybean for the whole area is well projected by the ALM-EC model, surpassing the accuracy of the 2010–2013 CDL means overall and within the majority of agricultural districts. In contrast to maize, the ALM-EC model's expansion of crops into regions not historically planted contributed to an increase in accuracy, judged by goodness of fit, within these divisions. Finally, ALM-EC's projection of spring wheat land-use area is a noticeable improvement over the 2010 to 2013 CDL means for the whole area but, similar to maize, does poorer than the 2010–2013 CDL means within most of the individual agricultural districts. Unlike maize, this inaccuracy appears to be centered around the regions that experienced little to no change in planted area from the past three years. As illustrated, by configuring economic factors to current market and policy conditions, the ALM-EC model can reproduce the landscape of a specified year with similar, and in some cases better (e.g., soybean), accuracy compared with using a historic mean approach.

Impacts of the Economics Model-Based Simulation to Crop Yields

With the use of agricultural land-use probability from the economics model as inputs and with the methodology described previously, crop yields were simulated based on the

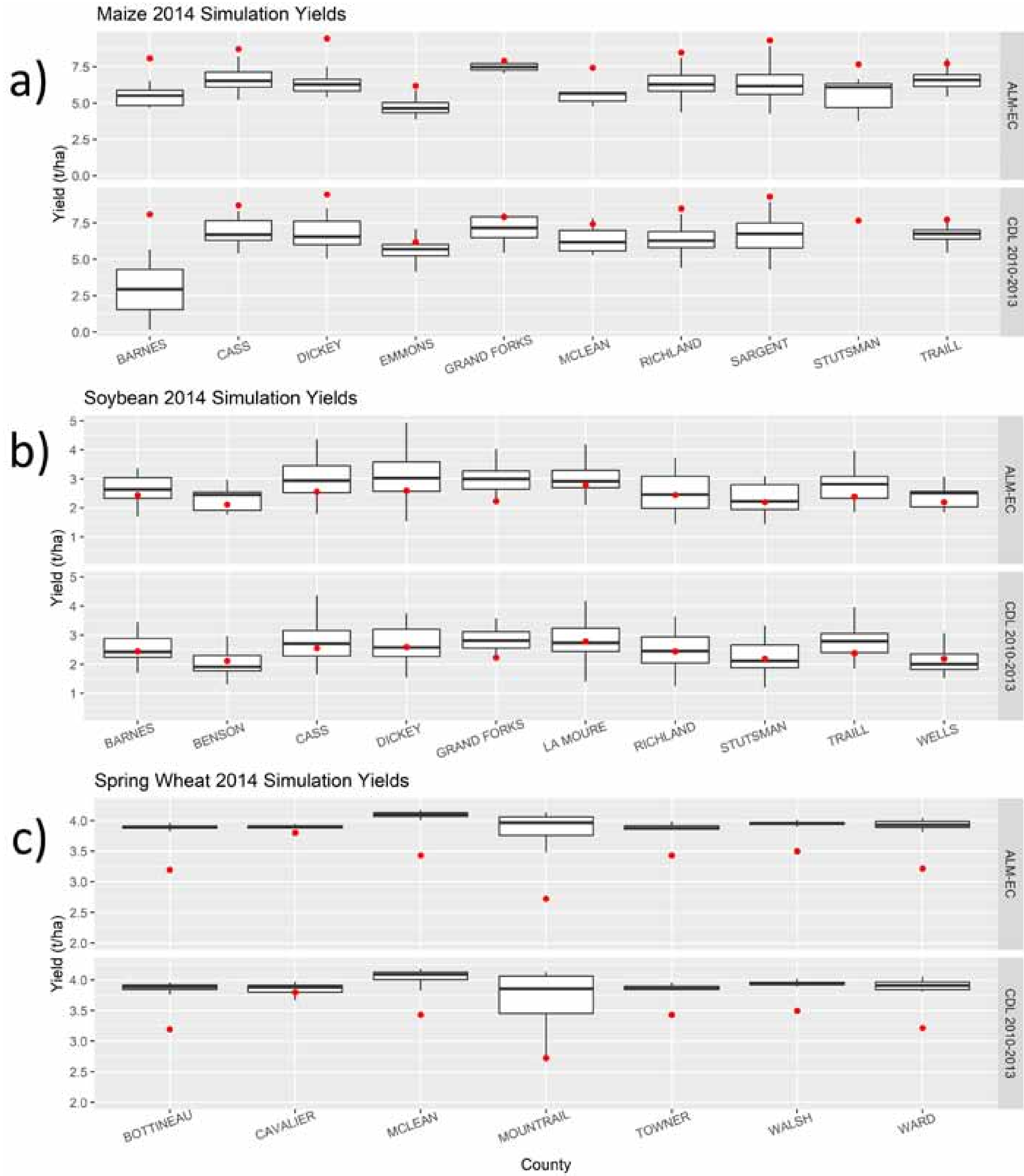

Fig. 7. Simulated yields for simulations including the ALM-EC model or the ALM-EC scenario (upper) and the static area CDL scenario (lower) scenarios of maize (a), soybean (b), and spring wheat (c) using box whisker for simulated yields. Mean yields for each county as reported by NASS are represented as a red dot. Simulation medians represented by the solid line.

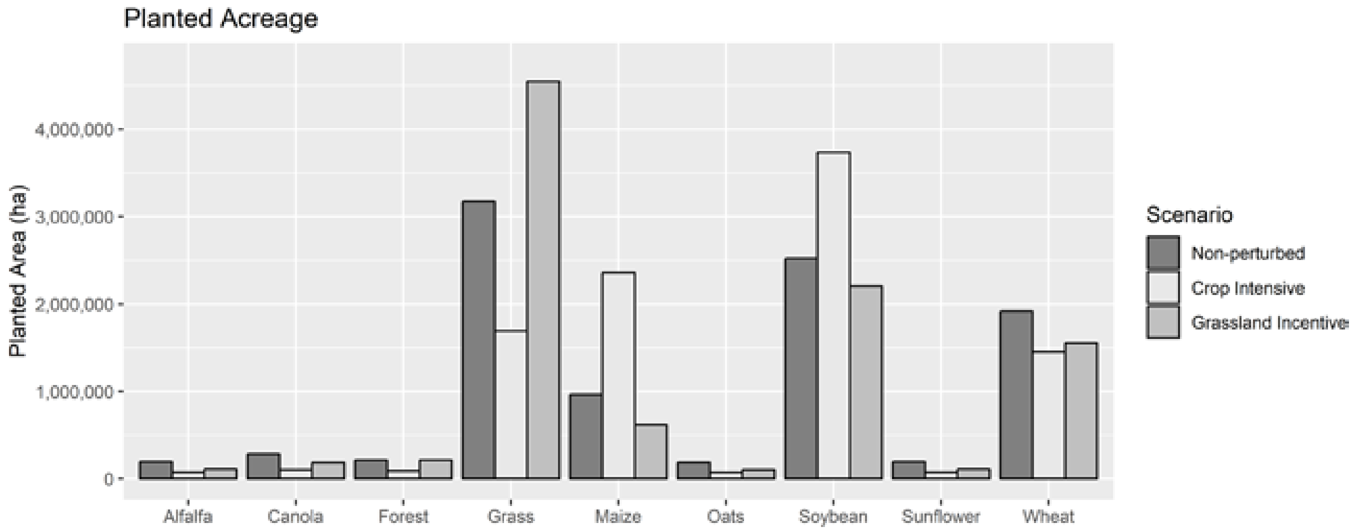

Fig. 8. Total planted area of each crop under the nonperturbed scenario, the crop intensification scenario, and the grassland incentive scenarios.

ALMANAC model for 2014 for maize, soybean, and spring wheat. Figure 7 shows the range of simulated yields in counties where the crops were commonly seen to be grown, derived from NASS quickstats total planted area for 2014 (USDA–NASS, 2018). The box whisker chart is used to compare simulated crop yields, contrasted with NASS records for the mean, county-wide yield for the same year represented by the red dot.

Here the ALM-EC scenario refers to the ALM-EC model configured to replicate conditions as found in 2014, whereas the CDL scenario refers to the static area–based stand-alone ALMANAC simulations based on land-use mean from 2010 to 2013 as determined from the CDL. Simulated yields of spring wheat and soybean under the ALM-EC system remain relatively unchanged compared with the results of the static CDL-based scenario.

In contrast, maize yields under the ALM-EC overall declined compared with the NASS-reported yields. This yield underperformance is likely caused by simulated expansion of maize acreage into suboptimal productivity soils within individual LCCs and migration to poorer productivity LCCs, resulting in lower overall yields. This expansion to poorer-productivity soils is due to limited quantities of the higher-quality soils; once saturation of these higher productivity soils is reached, lower-quality soils are used to fulfill the remaining demand. A factor of the overall low range seen in both scenarios' maize yields may be a result of the crop moving outside of the calibration soils because only frequently planted sites between 2001 and 2013 were included in calibration. This greatly limited the amount of soils used during calibration, with only the highest-quality soils seeing frequent maize planting during that period, relative to soybeans and wheat. Still, other factors, such as soil profile inaccuracies, calibration method, and model processes, could add to this yield discrepancy.

Using the ALM-EC model resulted in soybean yields of 2.84 t ha^{-1}, which is 22% higher than NASS-reported yields for the region (2.33 t ha^{-1}), and wheat yields of 3.88 t ha^{-1}, which is 17% higher than NASS-reported yields (3.29 t ha^{-1}). Similarly, simulated yields were found to be 21 and 20% higher than NASS-reported yields for soybean and wheat, respectively, for crop simulations with the use of historic area. The estimated maize yields are 6.02 and 6.88 t ha^{-1}, which are 25 and 14% lower than NASS reported average (7.97 t ha^{-1}) for crop simulations with the nonperturbed and the historic scenario, respectively.

Although a yield underperformance is found for maize, the overall performance of crop simulations, through the use of land-use probabilities generated from the economics land-use model, compare reasonably well with the crop simulations using CDL-based land-use acreage. Distinct from the standalone crop simulations, the ALM-EC modeling system treats economic factors, such as policy and market changes, as fully incorporated variables, which enables the feasibility of studying the influence/sensitivity of market and policy on crop simulations.

Proof-of-Concept Study of the Impact of Market and Policy on Crop Simulations

Using the developed ALM-EC system, as a proof-of-concept study, we have perturbed the market and policy conditions for the major crops intensification scenario and the grassland conservation scenario, for a total of three competing simulations: (i) a nonperturbed simulation with a "business-as-usual" assumption to represent the conditions of the 2014 growing season with no changes (nonperturbed); (ii) a perturbation in market forces where the price of maize, soybean, and wheat are increased (crop intensive); and (iii) a perturbation in policy changes where grassland is incentivized through a flat per acre payment (grass incentive). The corresponding changes to crop acreage, crop yields, and soil conditions from the three simulations are described below.

Impacts on Crop Planted Areas

With the increase in demand for major crops (maize, soybean, and spring wheat), the crop intensification scenario found a significant increase in simulated planted area of two of the crops. Maize experienced the largest impact, experiencing a 157% increase in planting area, whereas soybean experienced a 49% increase in planting area compared with the nonperturbed case (Fig. 8). The other two major land uses decreased in area, with a 47% decrease in grasslands and a 24% decrease in wheat over the nonperturbed planted area. Although the price of spring wheat was increased in this scenario and spring wheat expanded area in the western half of the study area, it lost ground to maize

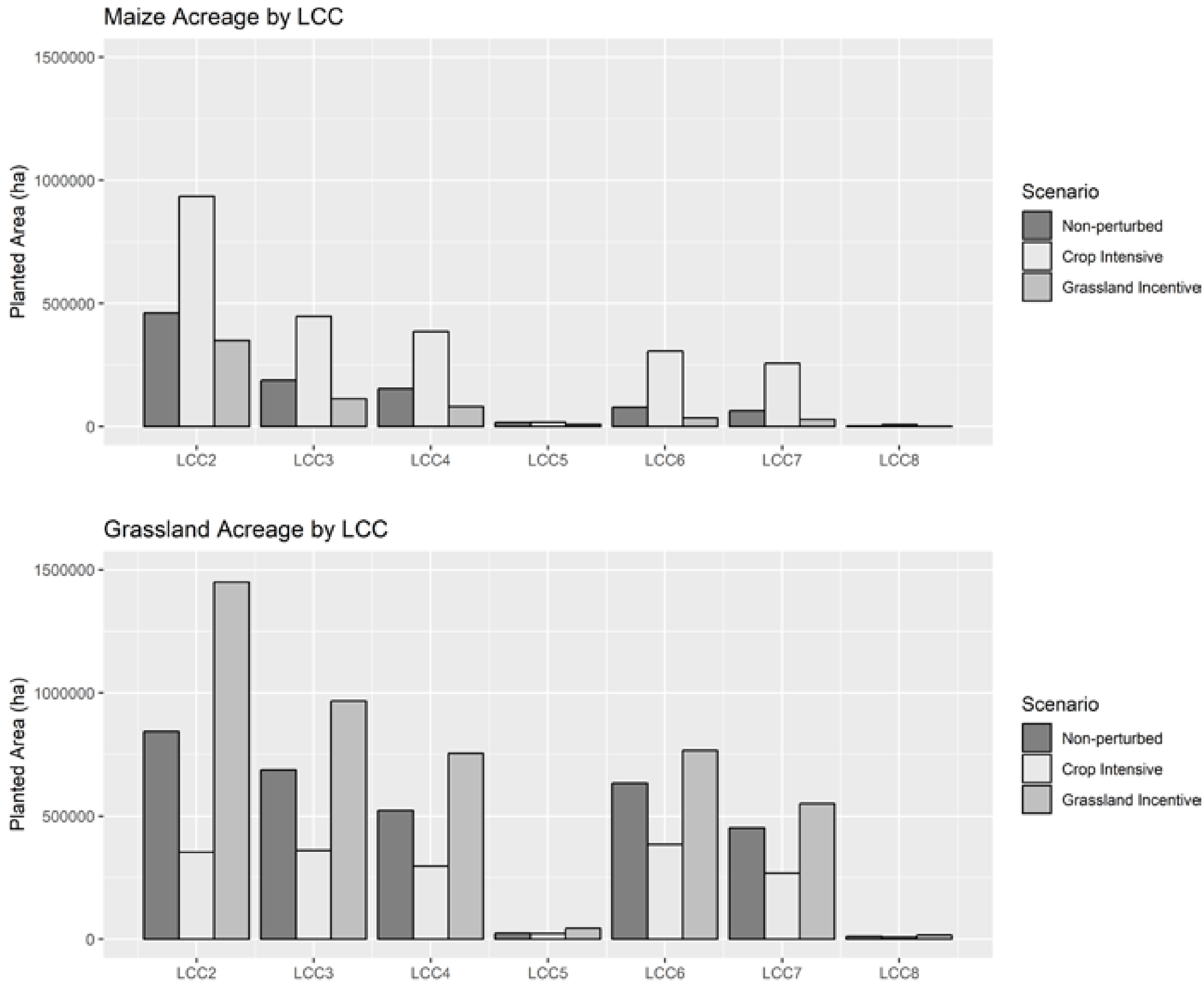

Fig. 9. Total study-wide planted hectares of (a) maize and (b) grasslands by nonirrigated land capability class for the nonperturbed as well as the crop intensification and grassland incentive scenarios in hectares. LCC, Land Capability Class.

and soybeans in the eastern half, where the profits (and thereby increased acreage) from those crops were greater than the potential spring wheat acreage gains.

Conversely, with the incentivized grassland production the planted area of the major crops maize, soybean, and wheat fell by 35, 12, and 19%, respectively, whereas grasslands increased planting by 43% with respect to nonperturbed grassland area. In all scenarios the minor crops sunflowers and oats decreased in planting area by 34 to 71%, depending on the crop and scenario, because both the major crops and grasslands used areas previously containing these crops during their respective scenarios.

As planting incentives were modified, crops began migrating from their original state to cover LCCs not seen in the nonperturbed study. This is demonstrated in Fig. 9 where, during the crop price–intensive scenario, a majority of the additional maize acreage went onto the higher potential productivity soils in LCC 2 (Fig. 9) but also increased acreage on the less-favorable LCCs. Similarly, when grassland is incentivized, the majority of the acreage growth can be found at more productive LCCs, albeit at the simulated lower-yielding soils within this class, whereas the less-productive LCCs saw a smaller overall acreage growth.

Impacts on Yields and Production

Due to the expansion of acreages and the prioritization of more productive soils for the more profitable crops, a similar change in yields based on the scenarios is observed (Fig. 10). In the crop-intensive scenario, maize, soybean, and wheat are given priority over the other four crops, resulting in expansion of those crops into less-productive soils and subsequently to an overall drop in yields for maize as maize is moved into the lower-potential LCC (Fig. 11), but not as large of an impact as found on the higher-productive LCC2, where its largest increase in area is seen. Minimal impacts, leading to nonsignificant differences in total mean yield, are found on the soybean yield because the yield drop-off from LCC2 to lower LCCs is less severe than maize during this study year and because its increased area on higher-productivity soil helps offset these already smaller losses. Similarly, no major change is found for spring wheat yield. Mean yield drops are found in all four of the remaining crops as those crops are forced to more marginal lands by the encroaching maize and soybean, suppressing their yields.

However, in the grassland incentivized scenario, a grassland conversion on less-productive lands limiting crop expansion is

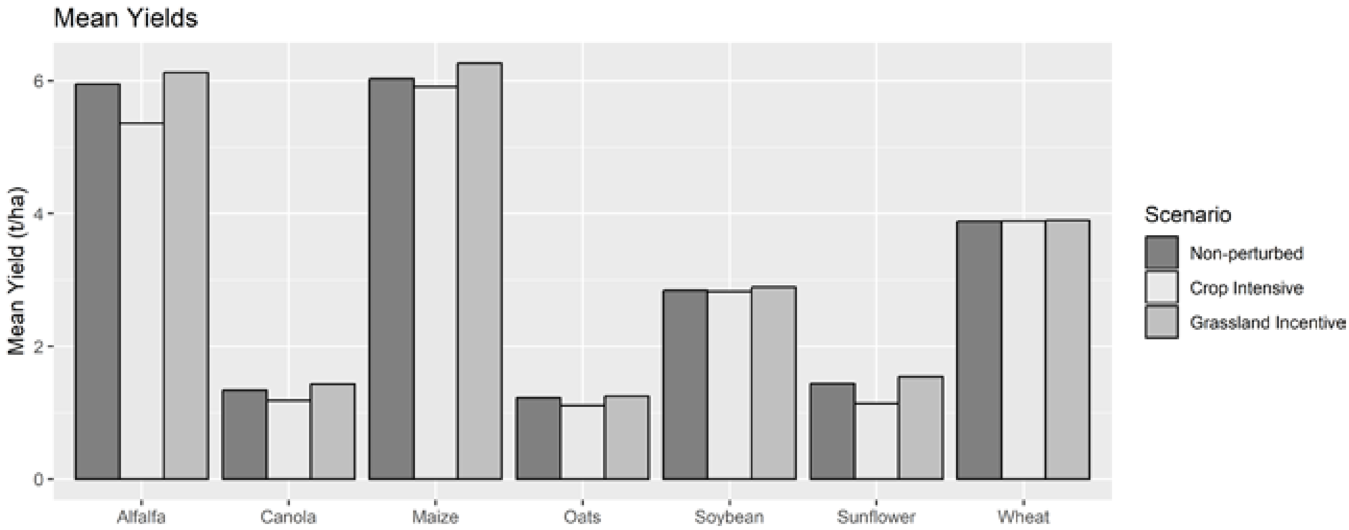

Fig. 10. Mean study-wide yields for the study crops under nonperturbed, crop-intensive, and grass incentive scenarios.

observed. As a result of this land-use change, a slight boost in mean yields are found for all crops because, although decreases in acreage relative to nonperturbed are observed for those crops, the poorly producing lands are removed from farming, which ultimately achieves the typical conservation goal for this type of environmental policies.

Additionally, we combine the changes in acreage with the changes in yields to calculate the total production change of each study crop in the study (Fig. 12). In the crop intensification study, in the study region total production increases of 152 and 48% total are found for maize and soybean, respectively. This is slightly less of than the amount expected from the overall increase in acreage due to the yield impacts of planting on lower-productivity soils. In contrast, the decreased in yields of alfalfa, canola, oats, and sunflowers amplifies the impact of the decrease in acreage, which causes the total production of each to drop more significantly than otherwise expected when looking at each impact individually. However, for the grassland incentivized scenario, the increase in yields of the nonpriority crops caused a weakening of the impacts of the acreage decrease, where, although overall production is down, the increased yields help to mitigate the loss of production relative to acreage losses. The end result is production of each crop falling relative to nonperturbed but not to the extent we would expect if the new grassland acreage were equally distributed on all soils regardless of productivity.

Additional Details of Future Scientific Potential for the Coupled Model

The ALMANAC model also provides outputs from each soil layer about changes in soil carbon, nitrogen, and other key components in soil health. However, due to the short-term nature of this study, these results for the combined ALM-EC model were generated but not formally included in this study. Given a longer-term study and the sufficient calibration data, the impacts of the annually changing land-use could be measured with this system, which could provide valuable insight into long-term changes and their subsequent impact on overall soil health. Furthermore, due to the single-year status of the simulations, impacts from rotations were not analyzed within this study. These effects can be handled by the ALM-EC model via an assumption that all crop movement will follow standardized

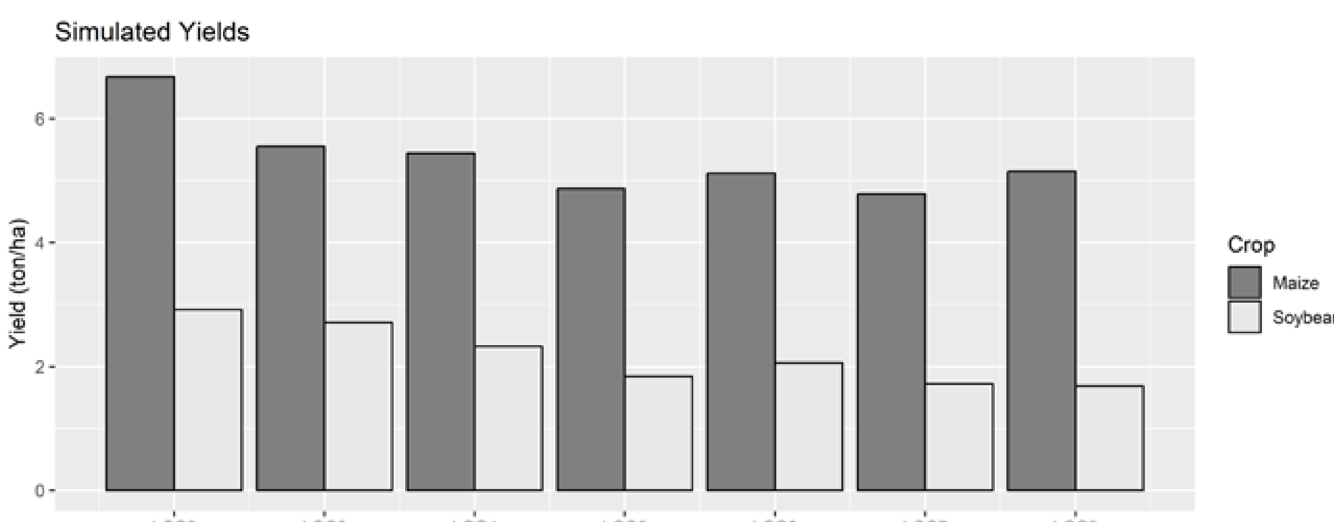

Fig. 11. Mean study-wide yields for maize and soybeans crops under nonperturbed scenario grouped by Land Capability Class (LCC).

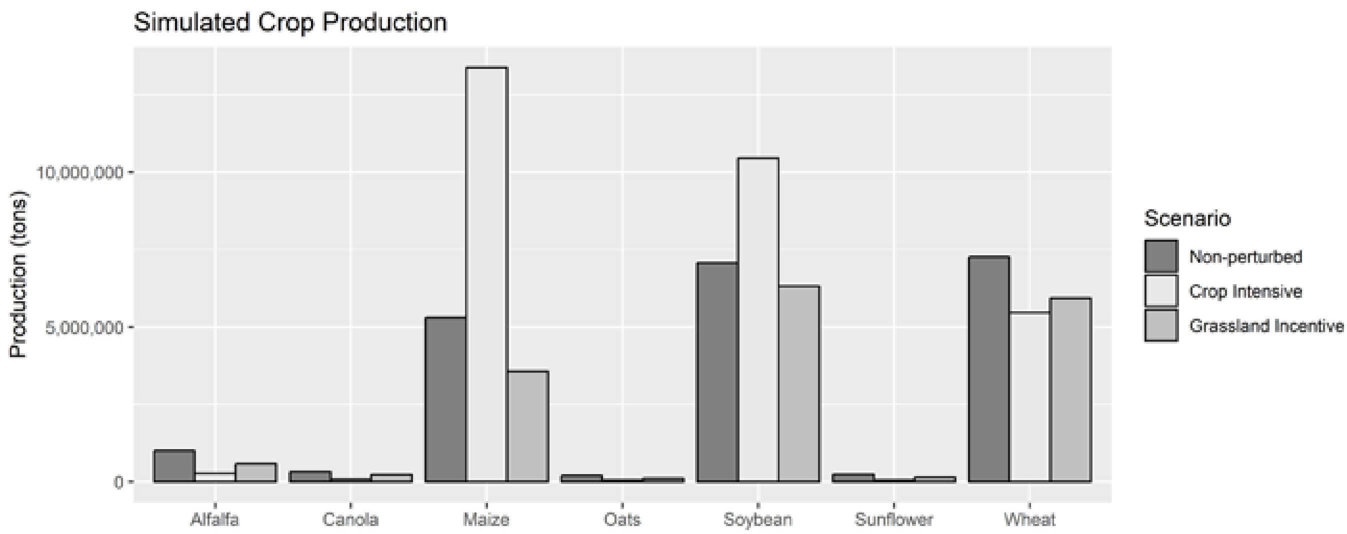

Fig. 12. Total study-wide production under nonperturbed and each scenario.

rotations predefined prior to the simulations, creating best-fits for each possible combination, or through a statistical likelihood approach using historic records of representative acreage within the area to project future probabilities.

CONCLUSIONS AND DISCUSSIONS

In this concept demonstration paper, a crop and economics modeling system is developed through a two-way linkage of an economics land-use model with the ALMANAC model for crop simulation. The designed goal for this system is to include economic factors as fully incorporated variables in crop simulations, allowing the study of the sensitivity of crop simulations with respect to market and policy changes. We have demonstrated and tested the concept for the 2013–2014 season over North Dakota and intercompared the new crop simulation concept with a static approach that uses historical acreage data to simulate seven crops common to North Dakota. This study has several important findings. (i) For the 2014 study period, dynamic crop acreages can be generated using the ALM-EC system while producing similar performances in acreage and yields in comparison to a static, standalone crop simulation. (ii) Compared with the nonperturbed case in market and policy conditions, crop simulations under a crop-intensified scenario where market prices for major crops are increased, the model introduces increases in acreages for the in-demand crops on the remaining higher productivity soils; both of these factors affect other competing crops, leading to decreases in both acreage and yields. (iii) Repeating this study with a policy change that favored grasslands, we observed a grassland expansion due to an increase in its net return. However, unlike the market price study, we found that the grassland conversion was mainly focused on the lower-productivity soils. As a result of the removal of these lower-productivity soils from the available planting pool for the minor crops, yields increased and slightly offset the overall loss of acreage for these crops.

In the newly developed ALM-EC, land-use probabilities are derived from the economics land-use model. This allows us to examine the impacts of likely crop locations and the effect of specific soil types on yields even when lacking accurate land-use information, which may enable a more realistic long-term crop simulation and forecast.

This study suggests that, with the use of a two-way linkage between an economics land-use model and a crop model, economic factors can be included as control variables and can be further used to study the sensitivity of market drivers on crop simulations. This study serves as a foundational step toward the goal of reducing the impact of unrealistic depictions of static agricultural land-use in both short- and long-term simulations by incorporating high-resolution dynamic land-use, through a coupled economics model, into crop simulations. The developed system, in theory, may be used to gain an insight into the changes in agricultural practice due to policy and market changes for potential policy and decision-making.

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REFERENCES

Boryan, C., Z. Yang, R. Mueller, and M. Craig. 2011. Monitoring US agriculture: The US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. Geocarto Int. 26:341–358. doi:10.1080/10106049.2011.562309

Briner, S., C. Elkin, R. Huber, and A. Grêt-Regamey. 2012. Assessing the impacts of economic and climate changes on land-use in mountain. Agric. Ecosyst. Environ. 149:50–63. doi:10.1016/j.agee.2011.12.011

Daly, C., G. Taylor, and W. Gibson. 1997. The Prism approach to mapping precipitation and temperature. 10th AMS Conference on Applied Climatology, Reno, NV.

García-Vila, M., and E. Fereres. 2012. Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. Eur. J. Agron. 36:21–31. doi:10.1016/j.eja.2011.08.003

Hertel, T.W., and S.D. Rosch. 2010. Climate change, agriculture and poverty. World Bank Group, Washington, DC. doi:10.1596/1813-9450-5468

Jones, J.W., G. Hoogenboom, C.H. Porter, K.J. Boote, W.D. Batchelor, L.A. Hunt, et al. 2003. The DSSAT cropping system model. Eur. J. Agron. 18:235–265. doi:10.1016/S1161-0301(02)00107-7

Keating, B.A., P.S. Carberry, G.L. Hammer, M.E. Probert, M.J. Robertson, D. Holzworth, et al. 2003. An overview of APSIM, a model designed for farming systems simulation. Eur. J. Agron. 18:267–288. doi:10.1016/S1161-0301(02)00108-9

Kharel, G., H. Zheng, and A. Kirilenko. 2016. Can land-use change mitigate long-term flood risks in the Prairie Pothole region? The case of Devils Lake, North Dakota, USA. Reg. Environ. Change 16:2443–2456. doi:10.1007/s10113-016-0970-y

Kiniry, J.R., J.R. Williams, P.W. Gassman, and P. Debaeke. 1992. A general, process-oriented model for two competing plant species. Trans. ASAE 35:801–810. doi:10.13031/2013.28665

Lewis, D.J., and A.J. Plantinga. 2007. Policies for habitat fragmentation: Combining econometrics with GIS-based landscape simulations. Land Econ. 83:109–127. doi:10.3368/le.83.2.109

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2006. Land-use change and carbon sinks: Econometric estimation of the carbon sequestration supply function. J. Environ. Econ. Manage. 51:135–152. doi:10.1016/j.jeem.2005.08.001

Lubowski, R.N., A.J. Plantinga, and R.N. Stavins. 2008. What drives land-use change in the United States? A national analysis of landowner decisions. Land Econ. 84:529–550. doi:10.3368/le.84.4.529

Mearns, L.O., T. Mavromatis, and E. Tsvetsinska. 1999. Comparative responses of EPIC and CERES crop models to high and low spatial resolution climate change scenarios. J. Geophys. Res. 104:6623–6646. doi:10.1029/1998JD200061

Mesinger, F., G. DiMego, E. Kalnay, K. Mitchell, P.C. Shafran, W. Ebisuzaki, et al. 2006. North American regional reanalysis. Bull. Am. Meteorol. Soc. 3:343–360 [erratum: 88(6):vi]. doi:10.1175/BAMS-87-3-343

Ojima, D.S., and J.M. Lackett, and the Central Great Plains Steering Committee and Assessment Team. 2002. Preparing for a changing climate: The potential consequences of climate variability and change-central Great Plains: A report for the US global Change Research Program. Colorado State Univ., Fort Collins.

Ritchie, J., and S. Otter. 1985. Description and performance of CERES-wheat: A user-oriented wheat yield model. USDA–ARS, Washington, DC.

Robertson, R., G. Nelson, T. Thomas, and M. Rosegrant. 2012. Incorporating process-based crop simulation models into global economic analyses. Am. J. Agric. Econ. 95:228–235.

Soil Survey Staff. 2016. USDA–NRCS Soil Survey Geographic (SSURGO) database. https://sdmdataaccess.sc.egov.usda.gov (accessed 19 Sept. 2016).

USDA–NASS. 2016. Cropland data layer. https://nassgeodata.gmu.edu/CropScape/ (accessed Jan. 2015).

USDA–NASS. 2018. NASS QuickStats. https://quickstats.nass.usda.gov (accessed 20 Nov. 2018).

USDA Soil Conservation Service. 1961. Land-capability classification. U.S. Gov. Print. Office, Washington, DC.

White, J.W., G. Hoogenboom, B.A. Kimball, and G.W. Wall. 2011. Methodologies for simulating impacts of climate change on crop production. Field Crops Res. 124:357–368.

Williams, J.R., K.G. Renard, and P.T. Dyke. 1983. Viewpoint: EPIC: A new method for assessing erosion's effect on soil productivity. J. Soil Water Conserv. 38:381–383.

Wright, C.K., and M.C. Wimberly. 2013. Recent land use change in the Western Corn Belt threatens grasslands and wetlands. Proc. Natl. Acad. Sci. USA 110(10):4134–4139. doi:10.1073/pnas.1215404110

Xie, Y., J.R. Kiniry, and J.R. Williams. 2003. The ALMANAC model's sensitivity to input variables. Agric. Syst. 78:1–16. doi:10.1016/S0308-521X(03)00002-7

Xie, Y., J.R. Kiniry, V. Nedbalek, and W.D. Rosenthal. 2001. Maize and sorghum simulations with CERES-maize, SORKAM, and ALMANAC under water-limiting conditions. Agron. J. 93:1148–1155. doi:10.2134/agronj2001.9351148x