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Key Points:
- In Corn Belt, El Niño (La Niña) has positive (negative) impact on corn yield
- Crop models can capture the regional impacts of ENSO on yield
- The study highlights the advantage of simpler crop models and gridded data sets

Supporting Information:
- Figures S1–S4 and Tables S1 and S2

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Crop models capture the impacts of climate variability on corn yield

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Abstract We investigate the ability of three different crop models of varying complexity for capturing El Niño–Southern Oscillation-based climate variability impacts on the U.S. Corn Belt (1981–2010). Results indicate that crop models, irrespective of their complexity, are able to capture the impacts of climate variability on yield. Multiple-model ensemble analysis provides best results. There was no significant difference between using on-site and gridded meteorological data sets to drive the models. These results highlight the ability of using simpler crop models and gridded regional data sets for crop-climate assessments.

1. Introduction

The U.S. Corn Belt produces nearly a third of the global corn supply. Weather and climate variability across the Corn Belt influences crop progress during the crop-growing season. The El Niño–Southern Oscillation (ENSO) is one of the notable drivers of climate variability and influences weather globally. In the Corn Belt, compared to neutral years, La Niña years can be warmer and drier in summer and El Niño years can be cooler and wetter [*Phillips et al.*, 1999]. However, year by year and regional variability exists.

Studies indicate that ENSO impacts on crop yield globally. *Ray et al.* [2015] showed that at the global scale, nearly a third of global crop yield variability results from climatic variability. *Hansen et al.* [1998] indicate that the mean corn yield across the southeastern U.S. during La Niña years is 13.9% higher than the mean yield in neutral and El Niño years. While *Cadson et al.* [1996] conclude that corn yields averaged across the Corn Belt can be higher in El Niño and lower in La Niña years, *Phillips et al.* [1999] show that while subregional anomalies emerge, typically, ENSO explains 15% of the variability of corn yields in the Corn Belt, with positive (negative) corn yield anomalies being associated with El Niño (La Niña) years.

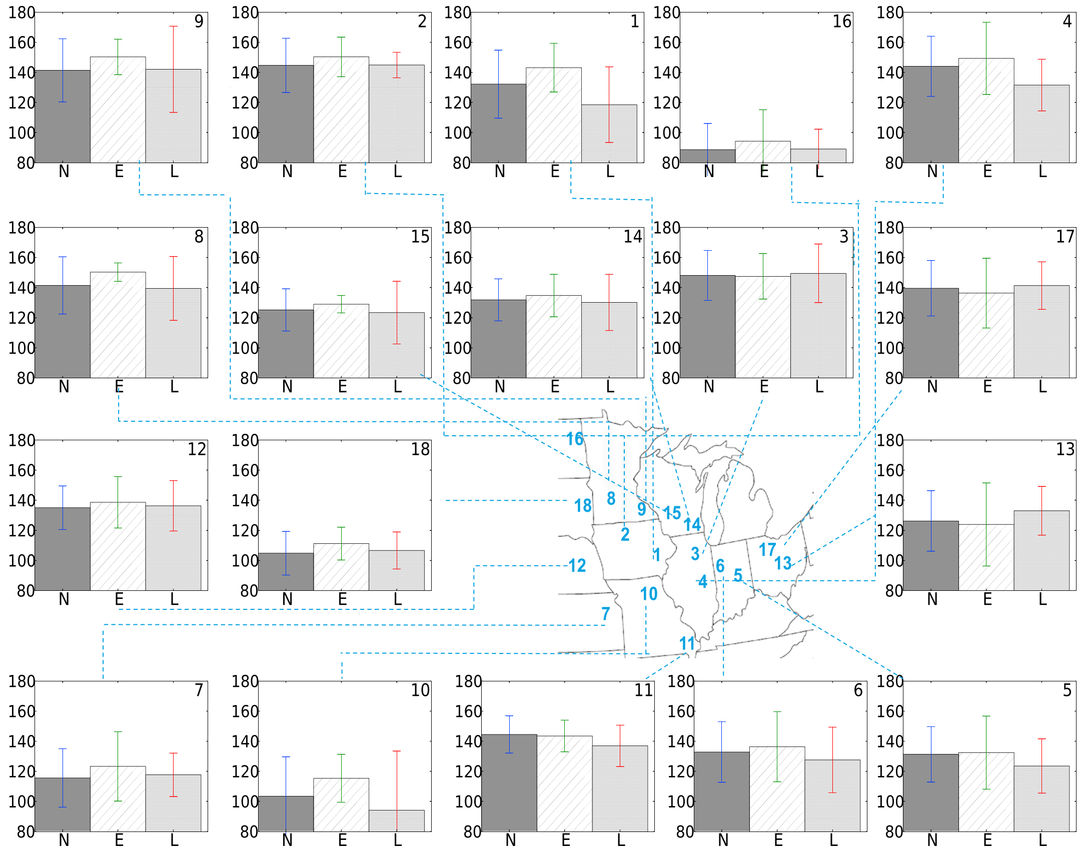
There is a growing interest in incorporating climate projections with crop models to assess climatic impacts on crop yield [*Rosenzweig et al.*, 2013]. This interest also highlights the question whether the crop models can capture the impacts of climate variability on crop yield. Therefore, there is a need to evaluate crop model predictions of the variability of past yields before they can be used for future yield projections and food security assessment. ENSO events provide a unique opportunity to evaluate the ability of crop models to simulate known yield responses to known climate variability.

In this study we seek to answer the following research questions: how accurately do crop models capture the ENSO-based climate variability impacts on corn yield and how does model complexity influence the results? Inherent to this assessment is the question whether there is a significant difference in using local agronomically representative on-site meteorological data versus regional representative gridded data such as from reanalysis for crop models in capturing the impacts of climate variability.

2. Methodology

2.1. Agronomic and Meteorological Data Source

To address the first question of this study, we analyze the available county-level crop yield data for 12 states across the Corn Belt for 30 years (938 counties, 1981–2010) (Figure 1). The data are collected from the



1. Johnson, IA 2. Winnebago, IA 3. DeKalb, IL 4. Douglass, IL 5. Huntington, IN 6. Jasper, IN
7. Shawnee, KS 8. Olmsted, MN 9. Renville, MN 10. Adair, MO 11. New Madrid, MO 12. Platte, NE
13. Union, OH 14. Rock, WI 15. Sauk, WI 16. Grand Forks, ND 17. Lucas, OH 18. Brookings, SD

Figure 1. Research domain (the U.S. Corn Belt) and bar charts with error bars of corn yield under ENSO events for selected 18 counties used in model assessment. (N: normal, E: El Niño, and L: La Niña. *Y* axis represents corn yield in bu/acre.)

National Agricultural Statistics Service annual surveys. Eighteen counties across the U.S. Corn Belt (Figure 1) are selected for crop model evaluation based on the geographical representation and data availability. Because this study focuses on the impacts of climate variability, the yield data are restricted to and detrended from the 30 year averaged yield of each county to decrease the influence of technological changes. The on-site station daily meteorological data for these 18 counties are obtained from the National Climatic Data Center. The 30 year subdaily reanalysis meteorological data from North American Land Data Assimilation System (NLDAS-2) [*Mitchell et al.*, 2004] and the National Centers for Environmental Prediction North American Regional Reanalysis (NARR) corresponding to the grids covering the stations location are processed into daily fields.

2.2. ENSO Years Classification

The Ocean Niño Index (ONI) of the growing season (defined as April–October) is analyzed to classify ENSO years in this study [*Ocean Niño Index (ONI)*, 2014]. This index is based on the 3 month running mean of sea surface temperature anomalies which are spatially averaged across the “Niño 3.4” region (5°N–5°S, 120°W–170°W). When the anomaly is equal to or larger than 0.5°C for three consecutive periods, it is classified as an El Niño year. If the anomaly is equal to or less than −0.5°C for three consecutive periods, the year is classified as a La Niña year. Those indexed years not fitting either criteria are classified as neutral years. Accordingly, seven growing seasons (1982, 1987, 1991, 1997, 2002, 2004, and 2009) are classified as El Niño impacted, while six growing seasons are affected by La Niña (1985, 1988, 1998, 1999, 2000, and 2010). Supporting information Figure S1 shows the intensity and occurrence of the anomalies and the corresponding classification as El Niño or La Niña status.

2.3. Crop Models

Three crop models are used: the Hybrid-Maize [*Yang et al.*, 2004], Decision Support System for Agrotechnology Transfer (DSSAT) [*Jones et al.*, 2003], and Integrated Science Assessment Model (ISAM) [*Song et al.*, 2013]. Hybrid-Maize and DSSAT are site-specific crop models driven primarily by temperature and solar radiation. ISAM is an interactive coupled biogeochemical and biogeophysical model that uses CO_2 assimilation calculation and dynamic phenology in computing the crop yield. The three models are of different complexity ranging from simple to interactive biosphere-atmosphere models and also have different requirements for input data. These models also form the suite of models being used in a much larger synthesis study termed U2U: making climate data useful to usable (http://www.Agclimate4U.org) [*Niyogi and Andresen*, 2011]. The purpose of selecting the three models is to assess the impact of model complexity on simulated corn yields in response to ENSO/climate variability.

2.3.1. The Hybrid-Maize Model

The Hybrid-Maize model combines the attributes related to vegetation phenology from the Clouds and the Earths Radiant Energy System (CERES)-Maize model and the features related to plant growth from models considering carbon assimilation. This is a relatively simple model that simulates the potential corn yield and sensitivity to climatic conditions [*Yang et al.*, 2004]. Despite its simplicity, the Hybrid-Maize model has demonstrated reliable performance in previous studies and shows considerable responsiveness to environmental conditions [*Yang et al.*, 2004; *Grassini et al.*, 2009]. The model is also used by agricultural extension community in making seasonal yield guidance.

The Hybrid-Maize model was run with daily solar radiation, maximum air temperature, minimum air temperature, and precipitation. The crop parameters are set as model default values. Field management parameters are set uniformly for all the simulation sites: planting date was set as 1 May, default plant population as 7.8 plants/m^2, and the model is run under optimal water condition and nitrogen condition. To estimate actual yields, the simulated potential yields are multiplied by 0.6 following *Liu and Niyogi* [2012]. The model is run with both on-site and gridded reanalysis meteorological data sets.

2.3.2. DSSAT

The CERES-Maize crop model (v4.5) from the Decision Support for Agrotechnology Transfer (DSSAT) model system [*Jones et al.*, 2003] is the second model used. Most agronomic management variables are held constant at values representative of current technology so as to isolate the climatic effects. The effects of insects, disease, and weed stress are not considered. A continuous maize crop rotation is assumed, with a model default plant population of 8.1 plants/m^2 and a row spacing of 0.75 m. Nitrogen applications are set at 200 kg/ha each year at planting. A single, constant set of crop cultivar characteristics representative of the region is selected based on the discussions with agronomists and the results of a previous study [*Andresen et al.*, 2001]. These input variables are based on thermal time requirements of commercial full-season cultivars currently grown in the vicinity of each location across the region. Planting dates at each location are determined automatically by the model for each growing season based on user-specified soil temperature and moisture criteria. Representative soil data in the study are chosen based on profile data typical of agricultural soils in the vicinity of each location and are obtained from the National Web Soil Survey (U.S. Department of Agriculture (USDA)/National Resources Conservation Service, 2009). The DSSAT model was also driven by both on-site meteorological data and reanalysis data.

2.3.3. ISAM

ISAM is a land surface model, which couples biogeophysical (energy and hydrology) and biogeochemical (carbon and nitrogen) processes [*Barman et al.*, 2014]. It calculates carbon, nitrogen, energy, and water fluxes at 0.5° spatial resolution and at multiple temporal resolutions ranging from half hour to yearly time scales. Recently, two row crops (corn and soybean) and three energy crops and their dynamic growth processes are further implemented in the model [*Song et al.*, 2013]. The model is able to calculate the land surface processes for natural vegetation and crop functional types at a local, regional, and global scales [*Song et al.*, 2013].

ISAM accounts for crop-specific phenology and dynamic carbon allocation schemes. These schemes account for light, water, and nutrient stresses while allocating the assimilated carbon to leaf, root, stem, and grain pools. The dynamic vegetation structure captures the seasonal variability in leaf area index, canopy height, and root depth. Moreover, the coupled dynamic carbon allocation and root distribution parameterizations highlight the ability of ISAM to capture the feedbacks between root growth and availability of soil water in each soil layer, particularly under dry conditions.

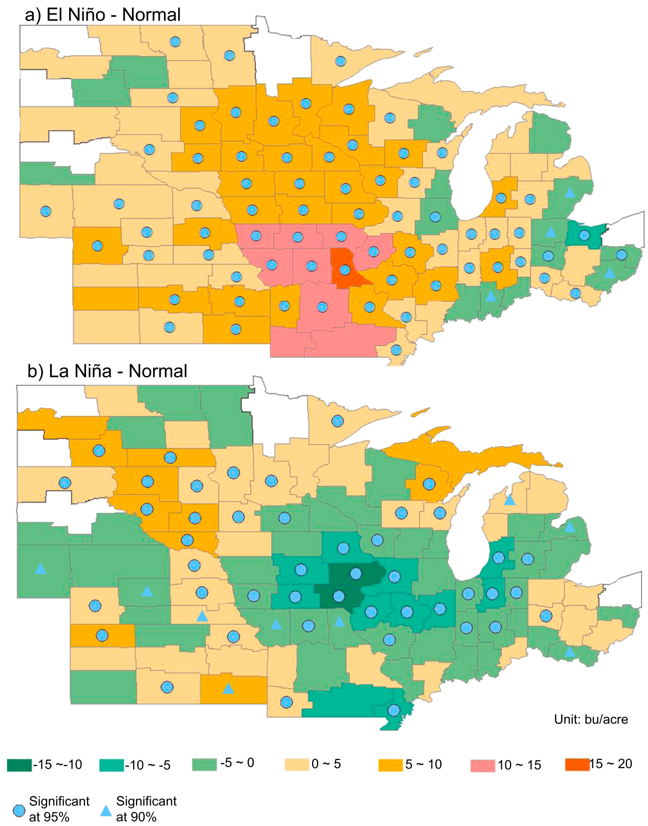


Figure 2. ENSO impacts on corn yield for the crop reporting districts (CRDs) in the U.S. Corn Belt. The difference between average yield during (a) El Niño years and (b) La Niña years corresponding to the normal yield (normal yield: the average yield for 30 years (1981–2010)). The difference between yield in individual ENSO event year and the 30 year averaged yield is shown in the supporting information Figures S2 and S3.

ISAM simulations require both soil texture and climate forcing data. In this study, the climate data for each site are extracted from NLDAS-2, while the soil texture data follow the State Soil Geographic Database (STATSGO2).

The model is spin-up by prescribing vegetation distribution prior to crop planting. The spin-up run takes about 20,000 years until the soil carbon and nitrogen, temperature, and moisture are stabilized. Then crops are "planted" using 8.6 seeds/m^2 of seeding rate. Unlike the prescribed phenological development in the other two models, both planting and harvest dates are dynamically simulated based on specific environmental conditions at each site.

2.4. Data Analysis

The mean absolute error (MAE), which is the averaged absolute value between simulated and observed yields, is used for model comparisons. To evaluate the ENSO impacts on corn yield for both surveyed ("observed" or "measured") and simulated data, the yield ratio (El Niño/normal and La Niña/normal) and bias are used as a simple indicator following *Phillips et al.* [1999]. The variability in the data sets was analyzed using spatial plots for different episodes as well as by computing the coefficient of variance. To ascertain the significance of the ENSO impacts, the Mann-Whitney-Wilcoxon (MWW) RankSum test is applied to surveyed yield data of 12 states at crop reporting district (CRD) scale. To compare model results using different meteorological input data set (e.g., on-site versus reanalysis), the MWW test is also applied.

3. Results

3.1. The Impacts of ENSO on Corn Yield

The results of ENSO group classification of the 30 year detrended county-scale yields are shown in Figure 2. The majority of CRDs in the Corn Belt has higher yield during El Niño periods, while La Niña years show a negative impact. Comparing to the 30 year averaged yield (which serves as the "normal" or "baseline" yield), El Niño years are associated with up to 20 bu/acre(16%) higher yields in most parts of Illinois, Iowa, Missouri, and Minnesota, while La Niña years show up to 15 bu/acre(11%) lower yield in most part of Illinois, Iowa, Missouri, and Indiana. The difference between yield in individual ENSO event year and the 30 year averaged yield is shown in the supporting information Figures S2 and S3. (Note that we use bu/acre for comparison with other field studies, and 1 bu/acre = 62.77 kg/ha.)

It is important to highlight that the ENSO impacts occur at heterogeneous spatiotemporal scales. As noted from Figure 2, the spatial pattern of ENSO impacts is not homogeneous across the Corn Belt. Each ENSO event lasts differently. Although instances of anomalous seasonal temperatures are evident during spring and summer of El Niño years, the impact can persist or amplify during the winter. There is also an inherent uncertainty of ENSO patterns and hydroclimatology impacting the subsequent years weather patterns [*Pathak et al.*, 2012]. Despite these uncertainties, some consistent features have been reported in prior studies and also emerge from this analysis.

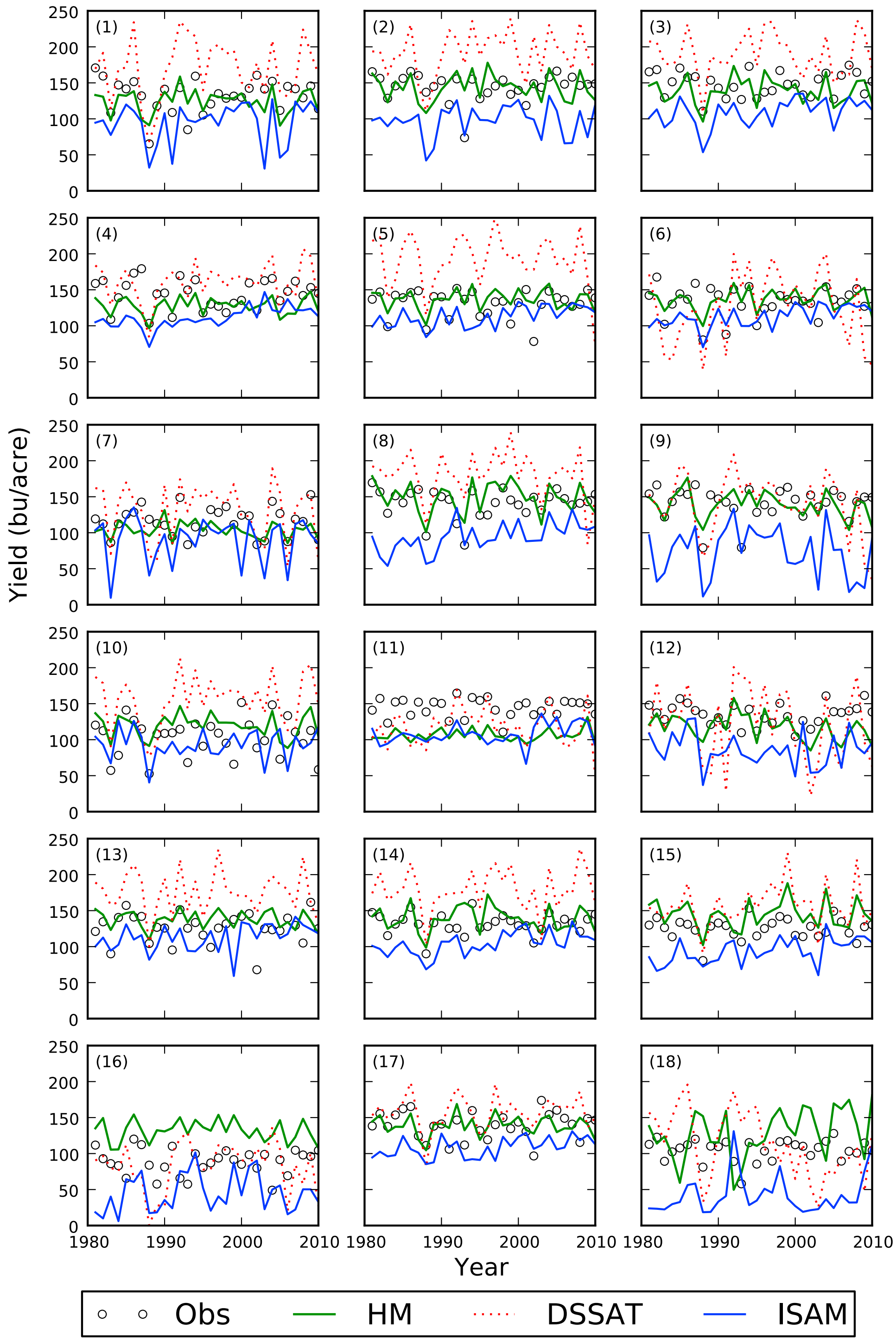


Figure 3. Comparisons of three models (Hybrid-Maize, DSSAT, and ISAM) using the gridded reanalysis meteorological data sets. Numbers (1–18) indicate locations as shown in Figure 1.

The yield ratios—El Niño years yield to 30 year averaged (normal) yield—indicate that 14 of the 18 (78%) counties obtained a higher yield during El Niño years. For La Niña years the yield ratios decrease in 11 (61%) counties (Figure 1 and supporting information Table S1). The averaged summary of these 18 counties also shows that El Niño events have a positive influence (ratio = 1.04) on corn yield while La Niña events have a negative impact (ratio = 0.98). The reason for lower yields during La Niña years could be that La Niña summers tend to be warmer and drier than neutral years in the Corn Belt [*Phillips et al.*, 1999]. Additionally, cooler

Table 1. Simulated Average Corn Yield (1981–2013) of 18 Counties Grouped Into ENSO Phases[a]

		Yield Ratio									
		HM_S		HM_R		$DSSAT_S$		$DSSAT_R$		$ISAM_R$	
No.	County	E/N	L/N	E/N	L/N	E/N	L/N	E/N	L/N	E/N	L/N
1	Johnson, IA	1.03	0.96	1.04	0.97	1.08	0.96	1.11	0.92	1.03	1.07
2	Winnebago, IA	1.02	0.97	1.04	0.94	1.05	1.14	1.07	0.95	1.04	1.05
3	DeKalb, IL	1.05	0.94	1.06	0.95	1.05	1.05	1.09	0.92	1.01	1.03
4	Douglass, IL	1.00	0.96	1.01	0.98	1.06	0.92	1.05	0.92	0.98	0.96
5	Huntington, IN	1.04	0.93	1.04	0.95	1.02	0.94	1.09	0.87	0.98	1.03
6	Jasper, IN	1.05	0.94	1.03	0.95	0.91	0.77	0.99	0.84	0.98	1.00
7	Shawnee, KS	1.03	0.93	0.98	0.97	1.06	0.91	1.06	0.94	1.09	0.93
8	Olmsted, MN	1.02	1.02	1.05	0.98	1.16	1.00	0.99	0.98	1.00	1.03
9	Renville, MN	1.00	0.97	1.07	0.94	1.20	0.98	1.07	0.84	1.13	0.96
10	Adair, MO	1.08	0.94	1.04	0.96	1.20	0.94	1.08	0.92	1.09	0.97
11	New Madrid, MO	0.99	0.94	1.01	0.95	1.03	0.99	1.04	0.88	1.01	0.94
12	Platte, NE	1.04	1.00	0.98	0.97	0.97	0.91	0.93	0.92	1.04	0.86
13	Union, OH	1.04	0.96	1.02	0.95	1.04	0.94	1.05	0.91	1.00	0.96
14	Rock, WI	1.02	0.94	1.05	0.94	1.07	0.95	1.11	0.95	0.99	1.04
15	Sauk, WI	1.01	1.01	1.06	1.02	1.05	1.07	1.03	1.01	1.03	1.10
16	Grand Forks, ND	0.91	1.01	1.06	0.98	1.24	1.01	1.20	0.90	1.10	1.00
17	Lucas, OH	1.03	0.96	1.03	0.95	0.98	0.90	1.05	0.93	1.00	1.04
18	Brookings, SD	1.01	1.06	1.01	1.06	0.93	0.73	1.00	0.90	1.05	1.21
	Average	1.02	0.97	1.03	0.97	1.06	0.95	1.06	0.92	1.03	1.01(0.99[b])

[a] *S*: model running with on-site meteorological data; *R*: model running with reanalysis meteorological data; E: El Niño; L: La Niña; and N: normal. Event to event variability is available in the supporting information Figure S4.
[b] Average without using Brookings, SD.

temperatures and higher rainfall rates in El Niño years may lead to yield improvement in some counties [*Phillips et al.*, 1999].

3.2. Model Validations

Corn yield simulations using the three crop models are conducted for 18 counties for the 30 year period (1981–2010). The MAE (supporting information Table S2) indicates that the overall performance of the simplest model (Hybrid-Maize) is surprisingly slightly better than the other two models. For 14 (78%) counties, the Hybrid-Maize results also indicate that there is no significant difference between running the model with on-site meteorological data and running it with gridded regional data such as from NLDAS-2 reanalysis data ($p > 0.05$). DSSAT results in 10 (56%) counties indicate no significant difference between running the model with on-site meteorological data and running it with the gridded data ($p > 0.05$). These results provide confidence in using crop models at larger spatial scales using gridded reanalysis data sets or climate model outputs as from the past and in future studies. Figure 3 shows that gridded reanalysis-based simulated results from the three different models have the similar trends. It is worth noting that the interactive ISAM model shows good ability in simulating the lower range of the yields and the simulated results from DSSAT have higher variability compared to the other models. ISAM has a detailed soil structure representation that may be contributing to increased infiltration and rock bed variability/rooting depth. Each of these factors can have a feedback on the simulated yield.

3.3. Model Performance in Capturing the ENSO/Climate Variability Impacts

To evaluate the ability of how crop models simulate known yield responses to known climate variability, we grouped model results by different ENSO phases. Each of the three models provided generally similar results for the regional corn yield across the Corn Belt.

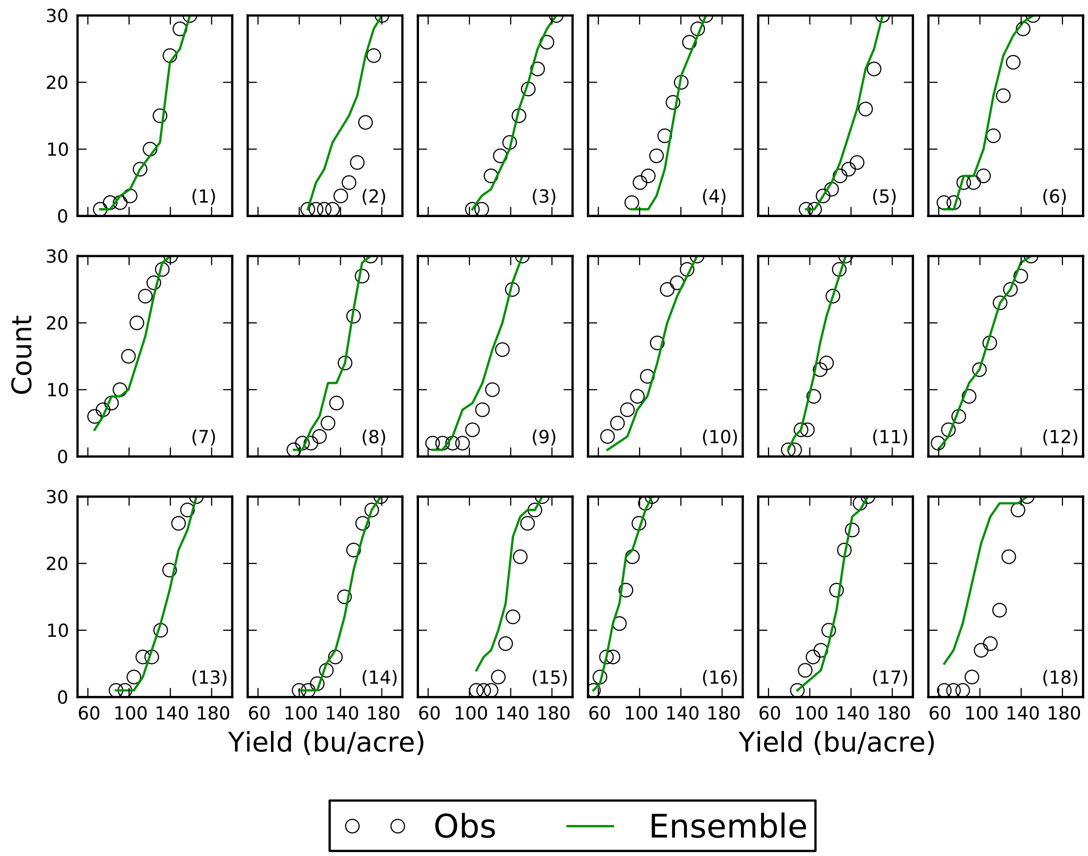


Figure 4. Cumulative distribution function (CDF) of the multicrop model ensemble. The numbers in parentheses indicate locations shown in Figure 1.

Results from the Hybrid-Maize model for the 18 counties driven by on-site meteorological data show that El Niño events have a positive influence (ratio = 1.02) on corn yield while La Niña events have a negative impact (ratio = 0.97) (Table 1). Similarly, when the model is driven by a gridded reanalysis meteorological data set (NLDAS-2), the El Niño events have a positive influence (ratio = 1.03) on corn yield while La Niña events have a negative impact (ratio = 0.97).

DSSAT yield ratios also show a negative impact on yield from La Niña events and a positive influence on yields from an El Niño event, when the model is driven by either on-site meteorology or the gridded data set (NARR) (Table 1). ISAM shows the similar results and broadly captures a positive impact on corn yield of El Niño and the regional negative impact of La Niña (Table 1). Comparing with the site-specific models, the agronomic factors (e.g., planting date, harvest date, and nitrogen application) in ISAM are dynamically simulated instead of prescribed as in Hybrid-Maize and DSSAT. The simulations of dynamic landscape evolution and dynamic interactions between vegetation cover and canopy temperature/soil moisture in ISAM make it a useful tool for studying different processes but also can introduce uncertainties in site-specific corn yield simulating. For example, at one northern high plains site (Brookings, SD), ISAM-simulated anomalously high yield during La Niña year and results from this site were eliminated in computing the average.

For a fully interactive model, ISAM does have a highly credible performance and could show improvements with more site-specific inputs. The simpler, diagnostic models also follow the observations well.

3.4. The Multicrop Model Ensemble

The variability of simulations and parameter uncertainties in the three models lead us to explore the multicrop model ensemble approach. Although different methods are available to create an ensemble, we simply weigh each model equally and compute the average. The results indicate that the ensemble has lower MAE (19.80 bu/acre) and lower standard deviation of MAE (standard deviation = 5.09 bu/acre) than each model we assessed individually (Figure 4). Further, the ensemble output also can capture the impacts of climate variability well (El Niño event: yield ratio = 1.04; La Niña events: yield ratio = 0.96). The cumulative distribution function (CDF) of corn yield (Figure 4) shows good agreement between observations and model ensemble results. Supporting information Figure S4 shows that the coefficient of variation of the ensemble output is also closer to the observations than each individual model.

4. Conclusions

We use ENSO events to evaluate the ability of crop models to simulate known yield responses to known climate variability. During El Niño years, corn yields are found to be up to 20 bu/acre (16%) higher than the 30 year averaged yield in majority of the U.S. Corn Belt, while the yields are up to 15 bu/acre (11%) lower than the 30 year averaged yield during La Niña years. Significant event to event variability, however, exists.

Results analyzing whether the crop models can capture ENSO impacts on corn yields indicate that both the site-specific crop models (Hybrid-Maize and DSSAT) and interactive model (ISAM) are able to capture the regional impacts well. The interactive model ISAM has better performance in capturing the low- to middle-range yield, while the site-specific crop models show better performance in capturing middle- to high-range yield. These results should not be interpreted as indicating one model being better than the others but that there are distinct advantages of using models with different complexity in conducting large spatial-scale simulations. These results also highlight the challenge in capturing the crop-climate impacts for assessment studies. While this study does not explore the many interactions of crop-climate impact analysis [e.g., *Mera et al.*, 2006], it does provide a defensible advantage of simpler crop models and gridded meteorological data sets for assessing yield. Also, the multicrop model ensemble approach has the potential to be the best indicator of crop response to climate variability.

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