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Climate data induced uncertainties in simulated carbon fluxes under corn and soybean systems

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Abstract (400 words)

Net carbon balance on croplands depends on numerous factors (e.g., crop type, soil, climate and management practices) and their interactions. Agroecosystem models are generally used to assess cropland carbon fluxes under various agricultural land use and land management practices because of their ability to capture the complex interactive effects of factors influencing carbon balance. For regional carbon flux simulations, generally gridded climate data sets are used because they offer data for each grid cell of the region of interest. However, studies consistently report large uncertainties in gridded climate datasets, which will affect the accuracy of carbon flux simulations.

This study investigates the uncertainties in daily weather variables of commonly used high resolution gridded climate datasets in the U.S (NARR, NLDAS, Prism and Daymet), and their impact on the accuracy of simulated Net Ecosystem Exchange (NEE) under irrigated and non-irrigated corn and soybeans using the Environmental Policy Integrated Climate (EPIC) agroecosystem model and observational data at four flux tower cropland sites in the U.S Midwest region. Further, the relative significance of each weather variable in influencing the uncertainty in flux estimates was evaluated.

Results suggest that daily weather variables in all gridded climate datasets display some degree of bias, leading to considerable uncertainty in simulated NEE. The gridded climate datasets produced based on interpolation techniques (i.e. Daymet and Prism) were shown to have less uncertainties, and resulted in NEE estimates with relatively higher accuracy, likely due to their higher spatial resolution and higher dependency on meteorological station observations. The Mean Absolute Percentage Errors (MAPE) values of average growing season NEE estimates for Dayment, Prism, NLDAS and NARR include 22.53%, 23.45%, 62.52% and 66.18%, respectively. The NEE under irrigation management (MAPE= 53.15%) tends to be more sensitive to uncertainties compared to the fluxes under non-irrigation (MAPE= 34.19%).

Further, this study highlights that NEE respond differently to the individual climate variables, and responses vary with management practices. Under irrigation management, NEE are more sensitive to shortwave radiation and temperature. Conversely, under non-irrigation management, precipitation is the most dominant climate factor influencing uncertainty in simulated NEE. These findings demonstrate that careful consideration is necessary when selecting climate data to mitigate uncertainties in simulated NEE. Further, alternative approaches such as integration of remote sensing data products may help reduce the models' dependency on climate datasets and improve the accuracy in the simulated CO_2 fluxes.

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1. Introduction

There has been renewed interest in tracking carbon on croplands because of their potential to offset atmospheric CO_2 through sequestering carbon in crop vegetation and soil, and also soil carbon indicates the status of soil quality affecting long term crop production. Croplands act either as a source or sink for atmospheric CO_2 depending on numerous factors (e.g. crop type, soil characteristics, climatic conditions and management practices), and their interactions. For instance, studies of continuous long-term flux tower measurements of CO_2 exchange on agricultural sites have demonstrated that conservation practices (e.g., no tillage) promote significant amounts of carbon sequestration; thus, making such agricultural systems behave as a strong net carbon sink (Hollinger et al., 2005; Bernacchi et al., 2005). Sustainable agricultural management practices are estimated to result in approximately 45-98 Tg C year^{-1} soil carbon sequestration on US croplands (Lal et al., 1998; Chambers et al., 2016). On the other hand, intensive land use and land management practices (e.g., conventional tillage, residue burning) in agriculture often lead to negative carbon balance, leaving these systems as a source for atmospheric CO_2 (Anderson-Teixeira et al., 2009). These intensive practices not only contribute to climate change, but also lead to deterioration of soil fertility through losing soil organic carbon, subsequently affecting long term agriculture production. The magnitude of impact on carbon balance with different agricultural land use and management practices is highly variable in space and time, and depends on environmental conditions and geographic characteristics (Hernandez-Ramirez et al., 2011). As such, there exists a need for understanding the impact of various agronomic practices and their interactions under various soil and management regimes on regional scale carbon dynamics. Such a knowledge base will help in developing effective policies and management strategies targeting carbon friendly agriculture at local to regional scale.

Agroecosystem models are tools widely used for analyses integrating the effects of climate, crop, soil, and land-use (Jones et al., 2017). Such models employ biophysical and biogeochemical principles coupled with crop management, climate and soils to simulate detailed carbon balance (Izaurralde et al, 2006; Bandaru et al., 2013). Climate variables are dominant factors influencing model simulations substantially (Agarwal, 1995). Models rely on weather inputs to simulate critical crop parameters (crop phenology, leaf area index [LAI] and evapotranspiration [ET]) that determine crop growth and development, subsequently impacting the net primary productivity (NPP), a primary carbon input. In addition, weather variables (e.g. temperature and precipitation) drive the simulation of soil respiration, which impacts NEE. Therefore, errors in weather variables will introduce uncertainty in the model estimates of carbon dynamics, and the magnitude of uncertainty depends not only on the level of error but also on an indefinite weather variable. For instance, soil respiration is

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relatively more sensitive to temperature inconsistencies than other weather variables (Jones et al., 2003). As such, a small margin of error in temperature irregularities may have substantial impacts on soil respiration estimates.

Models use either point scale in-situ observational data collected at meteorological stations or gridded climate databases that include geographically distributed weather estimates produced using either 1) interpolating observational climate data and other ancillary datasets (e.g. topographic characteristics) or (2) data modeling and assimilation techniques that model regional changes in weather based on satellite observations, land cover, local geographical characteristics and other attributes (Eum et al., 2014). For regional scale carbon flux simulations, generally gridded climate data sets are used because they offer data for each grid cell of the region of interest, while insufficient density of meteorological stations restricted the accurate representation of inherent spatial weather patterns over large regions (Bandaru et al., 2017). However, studies have been consistently reporting large uncertainties in gridded climate datasets (Van Wart et al., 2013; Bandaru et al., 2017). For instance, recently Bandaru et al. (2017) found higher biases in monthly weather variables (e.g. up to 3°C in minimum temperature) of high-resolution climate datasets generally used in the U.S, which were found to result in percent errors up to 45% in biomass of hybrid poplar, a short rotation woody cropping system, simulated using 3-PG forest growth model. Similarly, other studies reported uncertainties ranging 10-50% in carbon fluxes under forest systems (Ito and Sasai, 2006; Poulter et al., 2011; Wu et al., 2017). However, there are no or very limited studies on understanding uncertainties in modeled cropland carbon fluxes. Crop models are typically run on daily time steps so biases in daily climate variables are expected to be different from those in monthly variables. As such, currently, there is a knowledge gap on the level of uncertainty in the estimated daily carbon fluxes with the use of gridded climate datasets in the agroecosystem models, and the relative importance of each of the weather variables (e.g. precipitation) affecting accuracy of carbon flux estimates. As such, this study was conducted to 1) quantify the degree of uncertainty in daily weather variables of four gridded climate data sets commonly used in regional scale agroecological modeling studies in the U.S: the NARR (North American Regional Reanalysis), NLDAS (North American Land Data Assimilation System), Prism (Parameter-elevation Relationships on Independent Slopes Model), and Daymet; 2) evaluate their impact on simulated net ecosystem exchange (NEE), defined as a measure of net exchange of carbon between atmosphere and land surface per unit ground area (Kramer et al., 2002), under both irrigated and non-irrigated corn and soybeans using the Environmental Policy Integrated Climate (EPIC) agroecosystem model, and 3)

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understand the relative significance of each weather variable in influencing the uncertainty in flux estimates.

2. Materials and methods:

To understand the uncertainty in the four gridded datasets, observed weather data from four flux tower sites located in U.S. Midwest were used as reference data while quantifying the level of uncertainty in five weather variables typically required for agroecosystem models. These weather variables include (1) minimum air temperature (Tmin), (2) maximum air temperature (Tmax), (3) shortwave radiation (SR), (4) precipitation (Precip), and (5) relative humidity (RH). Further, we used the Environmental Policy Integrated Climate (EPIC) model to understand the influence of biases in gridded datasets on daily NEE under irrigated and non-irrigated corn and soybeans. First, we calibrated the EPIC model for corn and soybean crops using measured weather at flux tower sites, management and observed NEE data. Then 5 different site-level simulations were carried out using weather variables from four different gridded weather data sources, along with measured weather at the tower sites (Table-1). Later, NEE simulated by the measured weather data was used as a reference and assessed uncertainty in the NEE estimated using NARR, NLDAS, Daymet and Prism gridded datasets. Finally, to evaluate the relative contribution of each weather variable to the uncertainty in the NEE estimates, simulations were run using a single weather variable from the gridded datasets, and the rest of the weather variables were measured at sites for each simulation. For instance, to understand the impact of biases in shortwave radiation, simulations were run using shortwave radiation data from all four gridded data sources and the remaining weather variables (i.e. Tmax, Tmin, precipitation and relative humidity) from measured data at the flux tower sites.

2.1 Study sites

For this study, three AmeriFlux field experimental sites (US-NE1, US-NE2 and US-NE3) located at the University of Nebraska–Lincoln (UNL) Agricultural Research and Development Center near Mead, Nebraska were selected, as well as one AmeriFlux field site (US-BO1) at Bondville, Illinois (Meyers, 2016) (Table 1). These four sites are characterized by diverse crop management practices. US-NE1 (41°09′54.2″N, -96°28′35.9″W) and US-NE2 (41°09′53.6″N, -96°28′07.5″W) are irrigated sites equipped with center-pivot irrigation systems while US-NE3 (41°10′46.8″N, -96°26′22.7″W) and US-BO1 (40°00′61.3″, -88°29′04.4″W) are non-irrigated agriculture sites. US-NE1 has been continuously planted with corn since 2001 while US-NE2, US-NE3 and US-BO1 are generally planted with corn and soybeans in rotation. Weather variables, energy, water and carbon fluxes have been measured on an hourly basis at these sites, which were averaged to produce daily measured values for this study.

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2.2 Gridded Weather Databases

Agroecosystem models prefer high resolution climate data, when available, to capture heterogeneity present in agricultural landscapes. As such, we evaluated four commonly used gridded datasets characterized by spatial resolution finer than 0.5° and covering the spatial extent of the U.S. The details of the selected gridded data are listed in Table 2. These datasets are classified into two groups. The data sets in the first group include NARR and NLDAS, which are determined based on atmospheric models and assimilation techniques, while the second group datasets (i.e. Daymet and Prism) are produced by spatially interpolating weather observations collected from various weather monitoring networks.

2.2.1. NARR (North American Regional Reanalysis):

The NARR gridded dataset (approximately 32 km spatial resolution) is produced at three-hour intervals using the National Centers for Environmental Prediction (NCEP) Eta model, a mesoscale weather forecasting atmospheric model, along with the Regional Data Assimilation System (RDAS) (DiMegoet al., 1992). RDAS integrates data variables from various sources (e.g. outputs from the NCAR/NCEP Global reanalysis) (Mesinger et al., 2006) using a three-dimensional variational analysis scheme (3DVAR) and statistical interpolation (Kalnay et al., 1996), and produces fine spatial and temporal resolution estimates of various weather variables.

2.2.2. NLDAS (North American Land Data Assimilation System)

NLDAS produces high spatial (1/8°, approximately 12 km) and temporal (1-h) resolution weather variables through downscaling, and adjusts weather variables to account for the vertical difference between the NARR and NLDAS fields (Cosgrove et al., 2003). In addition, it corrects biases in shortwave radiation using Geostationary Operational Environmental Satellite (GOES) data (Pinkeret al., 2003). NLDAS precipitation data are constructed by taking daily gauge-based precipitation data and disaggregating to hourly resolution using radar data (Xia et al., 2012).

2.2.3. PRISM (Parameter-elevation Relationships on Independent Slopes Model)

Prism generates gridded weather data at two spatial resolutions (800 m and 4 km) and two temporal resolutions (daily and monthly) by interpolating observed weather at weather station networks (Abatzoglou, 2013). Prism uses gridded elevation data and computes a climate-elevation regression for each grid cell using observed data of nearby stations. Each station included in the regression is weighted based on similarity in physiographic characteristics (Daly et al., 2008).

2.2.4. Daymet:

Daymet interpolates daily weather station observations including T_{min}, T_{max}, and Precipitation based on gridded elevation data using a spatial convolution of a truncated Gaussian filter

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interpolation method (Thornton and Running, 1999) and produces gridded data at 1 km spatial resolution on daily time intervals. Daymet produces downward shortwave radiation by using the MTclim algorithm (Thornton and Running, 1999).

2.3 Estimation of uncertainties in gridded weather

To estimate the uncertainties in weather variables of gridded datasets, measured climate data at flux tower sites were acquired from the Ameriflux website (http://ameriflux.lbl.gov/). Flux tower data was selected as opposed to observational data at meteorological weather stations because stations' data are generally used as an input for producing some of the gridded datasets (i.e. Prism and Daymet) and therefore do not constitute as an independent source for comparison. Weather variables of each gridded dataset corresponding to each flux tower site were obtained. The Prism and Daymet datasets provide daily weather variables whereas NARR and NLDAS produce data at 3-hour and 1-hour temporal resolution, respectively. As such, NARR and NLDAS variables were aggregated to produce daily data and compared with daily flux tower data. Two metrics were used to assess the accuracy in the gridded datasets: 1) bias and 2) Mean Absolute Percentage Error (MAPE). The bias denotes the deviation in the values of gridded weather variables from the corresponding measured values at flux tower sites, and is used to compute the direction (i.e. under- or over-estimation) of the uncertainty. A negative bias indicates underestimation compared to the flux tower observed data, while a positive bias indicates overestimation of the values. The MAPE values represent average error and can be used to assess the uncertainties in the gridded datasets. The bias and MAPE for precipitation, T_{max}, T_{min}, shortwave radiation and relative humidity of four gridded datasets were estimated using the equations below (Eq. (1&2)).

$$Bias = \frac{1}{n}\sum_{i=1}^{n}(W_g - W_o) \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|(W_g - W_o)|}{W_g}\% \tag{2}$$

where bias = mean bias (units)
MAPE = mean absolute percentage error
n = available daily data for all stations
i = index for a unique station, year, and day combination
W_g = gridded data products
W_o = flux tower observed value

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In the U.S. Midwest, major crops such as corn and soybeans are cultivated during the summer growing season, typically from spring (April) through late fall (November). Therefore, we included weather data for the time period covering the summer growing season in our analysis. Prism does not include shortwave radiation; therefore, biases and MAPE were computed for Daymet, NARR and NLDAS.

2.3 Model simulations

The EPIC agroecosystem model was used to simulate the NEE under irrigated and non-irrigated corn and soybeans cultivated at flux tower sites and for the periods NEE measurements are available at flux tower sites (Table 1).

2.3.2. Model description:

The EPIC model simulates biophysical and biogeochemical ecosystem processes as influenced by climate, landscape, soil and management conditions (Williams et al., 1989; 2008). The carbon cycling module in EPIC was developed based on the Century model (Parton et al., 1994), and it includes detailed carbon routines that consider coupled carbon and nitrogen cycling to simulate carbon stocks and fluxes (both vertical and lateral fluxes) in managed and unmanaged lands. The EPIC carbon model has been well-tested and widely used for studying carbon dynamics under different cropping systems, management regimes, locations and at various scales (Apezteguía et al., 2009; Bandaru et al., 2013; Izaurralde et al., 2007; Wang et al., 2005).

2.3.3. Model calibration:

To calibrate the model, we have used collected and measured data at flux tower sites on soil, weather, management practices and NEE, and implemented simulations at these sites for all available data and available years as listed in Table 1. The parameters were adjusted to optimize NEE estimates against measured flux data utilizing multi-objective genetic algorithm NSGA-II (Deb et al., 2002). This method aims to provide near-optimal parameter sets for simulating each model output as well as a compromise between desired outcomes in order to identify parameter sets which provide more balanced model outcomes than single objective approaches. The calibrated results suggested that model was able to explain the variability present in the measured fluxes reasonably well, indicated by higher R^2 and low RMSE values for all the sites (Figure 2). The R^2 and RMSE (in bracket) values were 0.80 (29.11), 0.76 (30.34), 0.62 (34.05) and 0.61 (48.67) for US-NE1, US-NE2, US-NE3 and US-BO1, respectively. We used these calibration settings to simulate NEE using various gridded climate datasets.

2.3.4. Model Simulations:

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To estimate the impact of gridded datasets, simulations were implemented at flux tower sites using weather data from various data sources, and other inputs and parameters for the simulations were kept fixed. For soil information, we obtained input from the Soil Survey Geographic (SSURGO) database (http://websoilsurvey.nrcs.usda.gov/). The simulations were implemented for 12 years (i.e. 2002 to 2012) for the US-NE1, US-NE2 and US-NE3 sites, while for US-BO1 site, runs were performed for 11 years from 1997-2007. Before actual simulations were initialized, spin-up runs were implemented for 20 historical years for all the sites using historical crop and management information to set the right initial conditions.

Additional simulations were conducted to quantify the relative influence of each weather variable on the uncertainty in the NEE estimation. For each simulation, one weather variable from each of the gridded datasets was used, along the rest of the variables from site weather data. To use all weather variables from all gridded data sources, a total of 16 simulations were run.

2.3.5. Assessment of uncertainty in the simulated NEE:

To understand the uncertainty in the simulated fluxes due to errors in the gridded weather data sources, we used NEE simulations conducted using measured weather data at flux tower sites (hereafter, referred to as reference fluxes) and compared them with estimated NEE using gridded weather datasets. Similar metrics (i.e. bias and MAPE) for evaluating uncertainty in the weather variables were used for assessing the uncertainty in NEE estimates based on various gridded datasets.

3. Results

3.1 Uncertainty in the gridded climate datasets

The bias and Mean Absolute Percentage Error (MAPE) in the daily weather variables of various gridded datasets averaged over the years and sites are presented in Fig 1. Bias in T_{max} and T_{min} ranges from -3.94°C to 6.67°C depending on climate data source and the day of the growing season. Results showed that NARR and NLDAS overestimated T_{min} while Daymet and Prism did not exhibit any consistent pattern showing both negative and positive bias values across the growing season. All data sources were shown to overestimate T_{max} for most of the days in the growing season. The MAPE values range from 3.48% to 100.05%. Overall, the MAPE in both T_{max} and T_{min} tends to be higher at the beginning and end of the growing season irrespective of the data source. Among the climate datasets, Prism was found to have the lowest MAPE in T_{max} and T_{min} with an average growing season MAPE of 17.31% and 32.16%, respectively, followed by Daymet with 17.75% and 38.86% MAPE for T_{max} and T_{min}, respectively (Table 3), but there is no significant difference between the two datasets. The NLDAS's T_{max} and T_{min}, on average, have 18.93% and 76.59% MAPE, respectively, while NARR variables have MAPE of 18.53% and 75.01%, respectively (Table

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3). These trends in MAPE were consistent across the study sites indicating the NLDAS and NARR have higher uncertainty in temperature variables compared to Prism and Daymet variables (Figure 3). Prism does not provide shortwave radiation; therefore, biases and MAPE were reported for other data sources (i.e. Daymet, NARR and NLDAS). All data sources were shown to overestimate shortwave radiation with bias ranging from 0.44 to 14.89 MJ m^{-2}. Similar to the temperature variables, MAPE in shortwave radiation was found to be higher at the beginning and end of the growing season, more so at the end of the season, irrespective of the data source, with values ranging from 19.89 to 354.12%. At all locations, patterns in average growing season MAPE in shortwave radiation are similar to NARR, exhibiting the highest MAPE (average over locations =146.28%), followed by NLDAS (average over locations=107.38%) and Daymet (average over locations=107.27%) (Table 3). Unlike temperature and radiation variables, the daily uncertainty in precipitation data did not exhibit any specific behavior and showed inconsistency across the growing season. Bias in precipitation is either negative or positive with values spreading from -8.54 to 7.20 mm depending on the data source and date of the growing season. Further, all data sources have a high level of uncertainty in precipitation as shown by MAPE ranging 2.5 to 253.89%. The Daymet and Prism data were found to have relatively less uncertainty with growing season average MAPE values of 107.51% and 117.87%, respectively, compared to NLDAS (MAPE=157.13%) and NARR (MAPE=180.08%) (Table 3). Results showed that all data sources underestimated relative humidity for most of the days with bias values ranging from -21.13 to 4.23. Among all weather variables, relative humidity was shown to have the lowest uncertainty as indicated by MAPE values ranging between 6.88 to 30.30%. The uncertainty in relative humidity was found to be insignificant among the data sources. The average growing season MAPE values for NLDAS, NARR, Daymet and Prism are 14.22%, 15.71%, 16.06% and 14.46%, respectively (Table 3).

3.2 Impact of gridded datasets on NEE estimates

Figure 4 shows simulated daily NEE for corn and soybeans averaged over the years and grouped by irrigated and non-irrigated sites. Overall, daily trends in NEE estimated using gridded datasets were consistent with fluxes simulated using observed climate at flux tower sites. All flux estimates, irrespective of gridded data source, crop type and irrigation management, showed strong net carbon gain during the growing season. However, the results showed that the level of agreement among the estimated fluxes varies with the climate data source and irrigation management. The Daymet and Prism-based estimates showed better alignment with reference flux estimates compared to that of NLDAS and NARR. Further, simulated fluxes at irrigated sites, irrespective of climate data

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source and crop type, were shown to deviate more from reference fluxes relative to the fluxes at non-irrigated sites.

The bias and MAPE in the daily NEE averaged over the years and grouped by irrigation management are presented in Figure 5. Bias values in NEE range from -96.01 kg ha^{-1} day^{-1} to 104.11 kg ha^{-1} day^{-1} while MAPE in estimated fluxes spans from 0.01% to 391.09%. The magnitude of bias and MAPE depends on the source of the gridded data, day of the growing season, irrigation management and crop type. Bias in simulated fluxes early in the growing season was observed to be negative, indicating either overestimation of carbon gain or underestimation of carbon loss, while later in the growing season, bias values were positive, suggesting either underestimation of carbon gain or overestimation of carbon loss. Similar to the observed trends in the temperature and shortwave radiation data, MAPE values in the estimated fluxes were higher at the beginning and end of the growing season. Daymet based fluxes were found to have the lowest average growing season uncertainty with the lowest average MAPE and RMSE values of 22.53% and 10.82 kg ha^{-1} day^{-1}, respectively followed by Prism (MAPE=23.45% and RMSE=13.59 kg ha^{-1} day^{-1}), NLDAS (MAPE=62.52% and RMSE=24.47 kg ha^{-1} day^{-1}) and NARR (MAPE=66.18% and RMSE=25.02 kg ha^{-1} day^{-1}) (Table 4). Irrespective of the source of the climate data and crop type, simulated fluxes at irrigated sites showed higher uncertainty indicated by higher average growing season MAPE (53.15%) and RMSE values (23.98 kg ha^{-1} day^{-1}) compared to that of the simulated NEE at non-irrigated sites (MAPE=34.19% and RMSE=13.07 kg ha^{-1} day^{-1}). The MAPE values for corn NEE were slightly less than soybeans NEE values. However, RMSE values for soybeans were lower compared to that of corn. This could be attributed to higher values of NEE for corn resulting in higher RMSE values, which may not necessarily indicate higher uncertainty.

3.3 Influence of individual climate variables on NEE estimates

The MAPE values in average NEE estimates that resulted from errors in the individual climate variables of different gridded datasets were grouped by irrigation management and crop type (Figure 6). These results suggest that dominant climate factors influencing uncertainty in NEE vary with irrigation management irrespective of crop type and the source of gridded data. Under non-irrigation management, precipitation was found to be the most influential factor followed resulting in higher uncertainty in NEE relative to other factors. The MAPE values in simulated NEE under non-irrigation management range from 76.53% to 185.57% due to bias in precipitation, while bias in shortwave radiation resulted in MAPE values ranging from 72.92% to 119.11% depending on the source of climate data. Bias in other variables was found to induce less than 50% MAPE in simulated NEE. Uncertainty patterns in NEE estimates of different climate data sources were similar to the

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findings in section 2.1. The Daymet and Prism climate variables performed better compared to NLDAS and NARR variables in terms of accuracy in estimated fluxes. Influence of precipitation biases appears to be less in soybeans simulations than in corn NEE estimates indicated by less MAPE values for soybeans fluxes. In contrast to the results observed under non-irrigated management, precipitation was shown to be the least influential factor under irrigation management, and shortwave radiation and temperature variables were dominant factors inducing higher uncertainty in NEE. The shortwave radiation bias resulted in MAPE values ranging from 90.79% to 148.36% in estimated NEE under irrigation management while bias in temperature variables induced MAPE values ranging from 28.71% to 91.90%.

4. Discussion

Given the high dependency of agroecosystem models on gridded climate datasets for simulating carbon fluxes, in this study four commonly used gridded data sets in the U.S were evaluated to understand uncertainty in their daily weather variables using observed meteorological data at four flux towers located on agricultural sites in the U.S Midwest region. In addition, we further studied the impact of uncertainties in climate datasets on estimated NEE.

4.1 Uncertainties in climate datasets

Our analysis suggests that all gridded climate datasets have some degree of uncertainty in their daily weather variables. The degree of uncertainty varies largely among the datasets depending on numerous factors (e.g., quality of inputs used in the climate and geo-statistical models, scale of the models, representation of land-atmosphere interactions) (Newman et al., 2015; Strachan and Daly, 2017). Similar to earlier findings (Bandaru et al., 2017), daily weather variables of Daymet and Prism datasets were shown to have less uncertainty as indicated by MAPE values compared to that of NLDAS and NARR datasets. The better performance of Daymet and Prism datasets could be mainly attributed to the use of meteorological station observations as part of model input and a finer model scale. In contrast, the NLDAS and NARR data sets primarily rely on atmospheric models run at coarse spatial scale, which often fails to capture local fine scale land use, or topographic and atmospheric interactions. Among Daymet and Prism, the Daymet daily weather variables exhibited less uncertainty, and this finding is in contrast to the earlier study where Prism variables showed higher accuracy when monthly weather variables were compared (Bandaru et al., 2017). This could be attributed to differences in topographic, physical, and atmospheric factors affecting daily and monthly weather variables and model scale. The Daymet model apparently has a better representation of daily local land-atmosphere interactions compared to the Prism model. The Prism uses historical climatology to establish local relationships whereas Daymet develops independent

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regression of weather variables against elevation (Thornton et al., 1997; Daly et al., 2008; Mourtzinis et al., 2018). Further, the use of finer resolution elevation maps as input in the Daymet model also contribute to superior accuracy (Ruiz-Arias et al., 2009; Bishop and Beier, 2013). Previous studies noted that a change in the model scale to a coarser spatial scale led to greater uncertainty in the output for interpolation models (Bishop & Beier, 2013).

Irrespective of the dataset, temperature and shortwave radiation variables exhibited a high level of uncertainty during the beginning and end of the growing season which represent early spring and late fall, respectively. The high uncertainty during early spring and late fall could be due to many factors. During winter months, seasonal variance in temperature and radiation is high due to constant strife between subtropical warm air and polar cold air interacting each other. Also, the storm track is more powerful because of a much stronger equator-to-pole temperature gradient. These factors could create a lower signal-to-noise ratio in reanalysis datasets due to model scale and an inadequate representation of these complex processes. Additionally, the cloud cover mask used in the models may have a lot of uncertainty during winter months affecting simulation of cloud radiative effects leading to errors in shortwave radiation (Zhang et al., 2016). Interpolation models used in the Daymet and Prism primarily rely on the relationship between climate and topographic features and do not have representation for complex climate dynamics that exist during winter months. Also measurement errors were found to be high during the winter months which could introduce uncertainty in interpolated datasets.

4.1 Trends and uncertainties in NEE estimates

Croplands are generally regarded as a carbon sink in all growing seasons since the carbon assimilation rate is higher than the total respiration rate during most of the growing season. At the start of the growing season, NEE tends to be positive indicating carbon loss due to negligible rates of photosynthesis and relatively higher respiration rates but as the growing season progresses, the carbon assimilation rate increases and NEE becomes negative, making croplands act as a carbon sink. NEE increases until the onset of senescence (Hernandez-Ramirez et al., 2011; Gilmanov et al., 2013) and tends to become positive again at the end of the growing season due to the decline in the rate of carbon sequestration (Gilmanov et al., 2013). In both corn and soybeans NEE estimates, this pattern was evident even though there were differences in magnitude of daily NEE estimates depending on the climate data sources, crop type, growth stage and irrigation management. Corn has a higher net CO_2 uptake potential compared to that of soybeans as corn is a C4 plant, which has a more efficient in CO_2 sequestration mechanism. Earlier studies found that corn's peak CO_2 uptake rate is approximately 1.7 times higher than that of soybeans. Further, corn has ~15 days more CO_2

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sink periods (Dold et al., 2019). Irrigated croplands generally have higher net carbon gain compared to non-irrigated croplands. Suyker & Verma (2012) reported approximately 20% higher net carbon gain in irrigated corn systems compared to the gain under non-irrigated corn. These trends in daily NEE differences between corn and soybeans and irrigated and non-irrigated management found in our NEE estimates, which suggests that the model structure is adequate to capture seasonal complex dynamics in carbon exchange under various cropping systems and management practices.

Even though NEE estimates captured general seasonal trends, a considerable amount of uncertainty was introduced by climate datasets. The differences in uncertainty in the NEE estimates match with bias patterns in climate datasets. Lower biases in Daymet and Prism climate variables yielded better NEE estimates with less uncertainty compared to the estimates from NLDAS and NARR datasets. Similar findings were reported in the earlier studies, which found that interpolated climate datasets produced based on observational data are characterized by less bias, and result in flux estimates with better accuracy (Poulter et al., 2011).

Our results indicated that biases in individual climate variables won't translate linearly to the uncertainties in NEE estimates, even though biases in certain climate variables have strong impact under specific conditions. For instance, irrespective of the source of climate data, shortwave radiation and maximum temperature were overestimated for all days during the growing season while precipitation exhibited random seasonal bias. However, the biases in daily NEE did not reflect a bias pattern in any of these variables. Similar trends were found in the earlier studies on forest fluxes (Barman et al., 2014). The processes determining various carbon components (e.g. net primary production and soil respiration) are influenced by various individual climate factors and their interactions among themselves and with other factors (e.g., soil characteristics) (Schelenkar and roberts, 2009; Hernandez-Ramirez et al., 2011). Their relationship is generally non-linear. For instance, in widely distant vapor pressure deficit conditions at different locations, similar temperature and moisture conditions can lead to entirely different carbon uptake responses (Siebert et al., 2017). Further, water and heat stress during the reproductive stage impacts the CO_2 assimilation rate significantly higher than stress during some vegetative growth stages. Therefore, bias in NEE is a cumulative effect of biases in climate variables and their interactions with other factors such as crop type, phenology, soil and management practices.

Results suggest that NEE are more sensitive to the biases in precipitation and shortwave radiation compared to other climate variables under non-irrigated conditions, whereas under irrigated conditions, biases in shortwave radiation and temperature variables impact the NEE uncertainty maximum. The temperature and precipitation variables are used in models to determine plant growth

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limiting factors (i.e. heat stress, water stress, and number of frost days) influencing net primary production. Additionally, these variables influence other plant and soil processes (e.g., soil respiration, evapotranspiration). Under non-irrigated conditions, precipitation becomes the most limiting factor, particularly in sub-tropical and temperate climatic conditions such as in our study region (Kukal & Irmak, 2018). Further, daily biomass (primary carbon input) simulated by models is highly sensitive to the duration and timing of dry/wet spells (Dubrovsk´y et al., 2000), which also impacts respiration rates through affecting litter decomposition rates. Therefore, uncertainty in the precipitation amounts, especially during critical growth stages, has a substantial impact on the NEE estimates (Irmak et al., 2000). Our results showed that precipitation biases are characterized by a random pattern with both under- and over-estimation of precipitation amounts throughout the growing season which substantially impact simulation of duration and timing of wet/dry spells and lead to high uncertainty in NEE. Under irrigation management, precipitation is not a limiting factor. So, heat stress acts as a primary growth limiting factor and leads to a pronounced impact on plant growth and carbon exchange (Sippel, 2018). Uncertainty in the temperature variables also influence growing season length and crop maturity period since it influences crop development (Warrington and Kanemasu, 1983; Ritichi et al., 1998). Shortwave radiation was found to be a major climatic variable in models affecting NEE under both non-irrigated and irrigated conditions. Shortwave radiation determines total potential biomass (a primary carbon input), which contributes to a major fraction in the total NEE values. Therefore, a small degree of uncertainty in shortwave radiation may result in high level of uncertainty in total net primary production.

Our results showed that NEE uncertainties are larger under irrigated conditions compared to those under non-irrigated conditions, particularly towards the end of the growing season. Relative to the reference NEE at irrigated sites, NEE estimates based on gridded datasets, particularly NARR and NLDAS were found to reach peak earlier (Figure 2) and showed large deviation in the daily NEE trends after the peak. This could be because model simulated earlier development of the crop due to uncertainties in short wave radiation and temperature variables which primarily influence crop growth and development patterns under irrigated conditions.

5. Conclusions

This study demonstrates that commonly used high resolution gridded climate datasets, irrespective of data source, are characterized with some degree of uncertainty and these uncertainties have a large influence on simulated NEE. However, the level of uncertainty in NEE estimates vary with gridded data source and management practices. The gridded climate datasets produced based on interpolation techniques (i.e. Daymet and Prism) were shown to have less uncertainties and resulted in better NEE estimates with relatively higher accuracy. Simulations of NEE under irrigation management were shown to be more sensitive to errors in climate data compared to fluxes under non-irrigation. Further, this study highlights that NEE respond differently to individual climate variables, and responses vary with management practices. Under irrigation management, NEE are more sensitive to shortwave radiation and temperature, and biases in these variables substantially influence uncertainty in NEE estimates. Conversely, under non-irrigation management, precipitation is a dominant climate factor influencing uncertainty in simulated NEE at the most.

Considering the biases in gridded data sources and their impact on NEE estimates, it is important that careful consideration is taken when selecting climate data so that uncertainties in simulated NEE can be mitigated. Also, when reporting NEE or other carbon elements (e.g. NPP) or used in other models (e.g. integrated assessment models), uncertainties should be accounted. Further, alternative approaches such as integration of remote sensing data products should be considered to reduce the model's dependency on climate datasets. Advances in remote sensing facilitate the development of crop type land surface products (i.e. leaf area index (LAI), evapotranspiration and soil moisture), which are determined in the models as intermediate state variables using climate data. These variables play an important role in determining NEE by influencing various processes (e.g. CO_2 uptake rate and soil respiration). Forcing agroecosystem models to use remote sensing retrieved crop variables instead of estimating using climate variables is expected to decrease the uncertainty in the NEE estimates.

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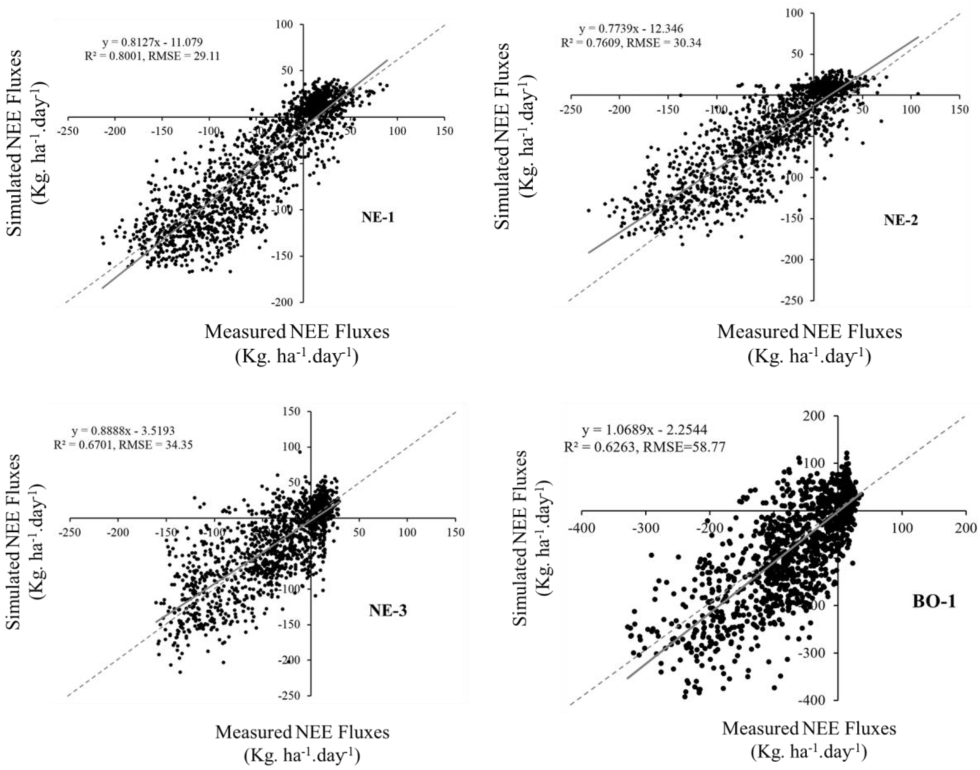

Fig.1. Comparison of simulated NEE estimated with best calibration settings, with measured fluxes at four Ameriflux tower sites located in the U.S Midwest.

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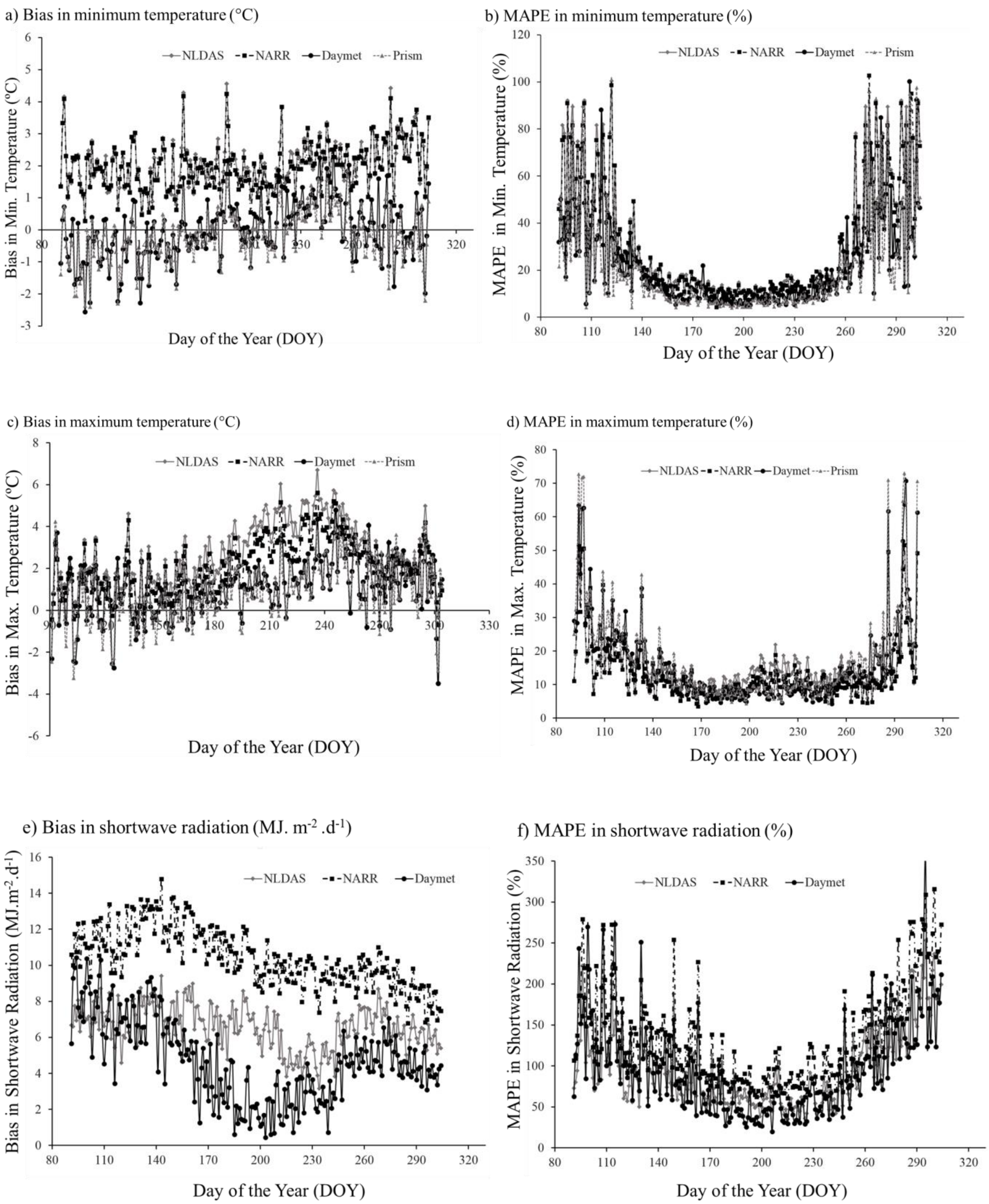

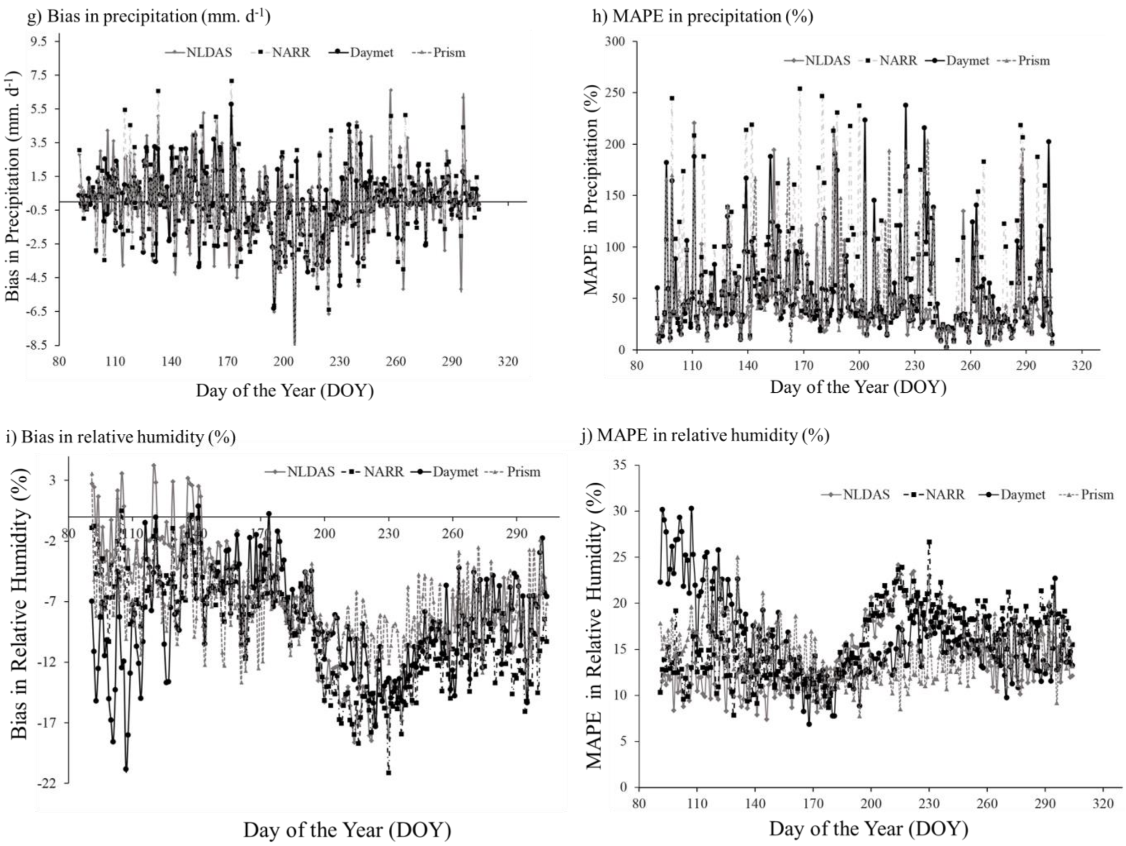

Fig.2. Comparison of bias and Mean Absolute Percentage Error (MAPE) in weather variables over the growing season (April–October) from gridded climate datasets. Bias and MAPE values shown in this figure calculated using equation 1&2.

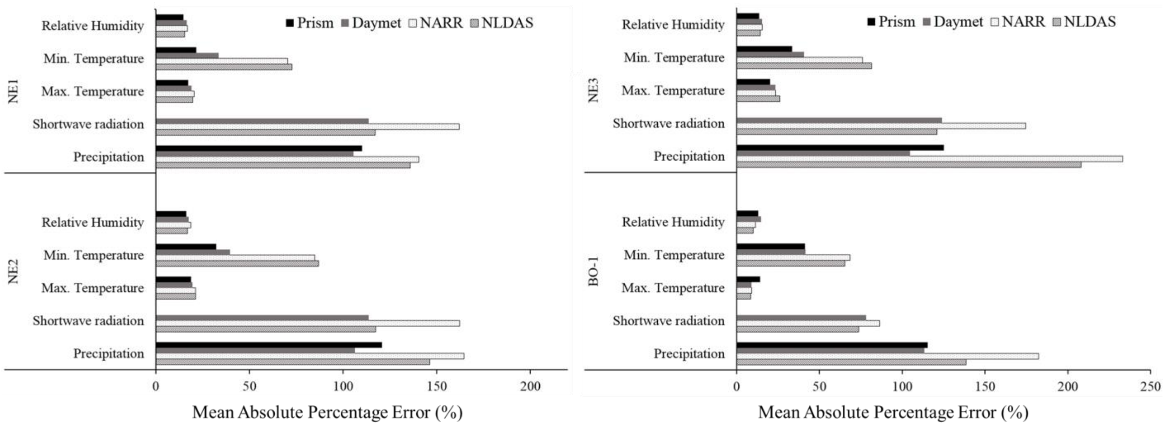

Fig.3. Comparison of Mean Absolute Percentage Error (MAPE) (averaged over the growing season and years) in weather variables of gridded datasets for different flux tower locations.

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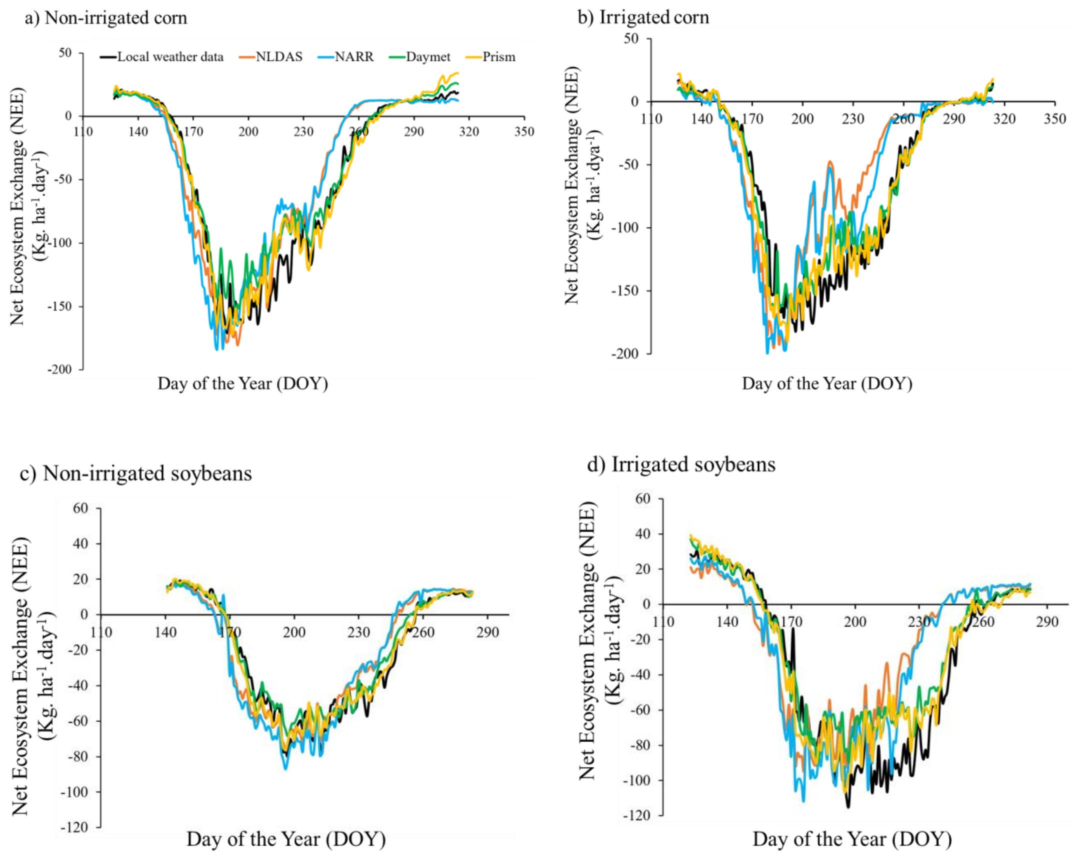

Fig.4. Average daily Net Ecosystem Exchange (NEE) estimates (averaged over sites and years) for irrigated corn and soybeans systems, simulated using various gridded datasets and measured weather data at flux tower sites.

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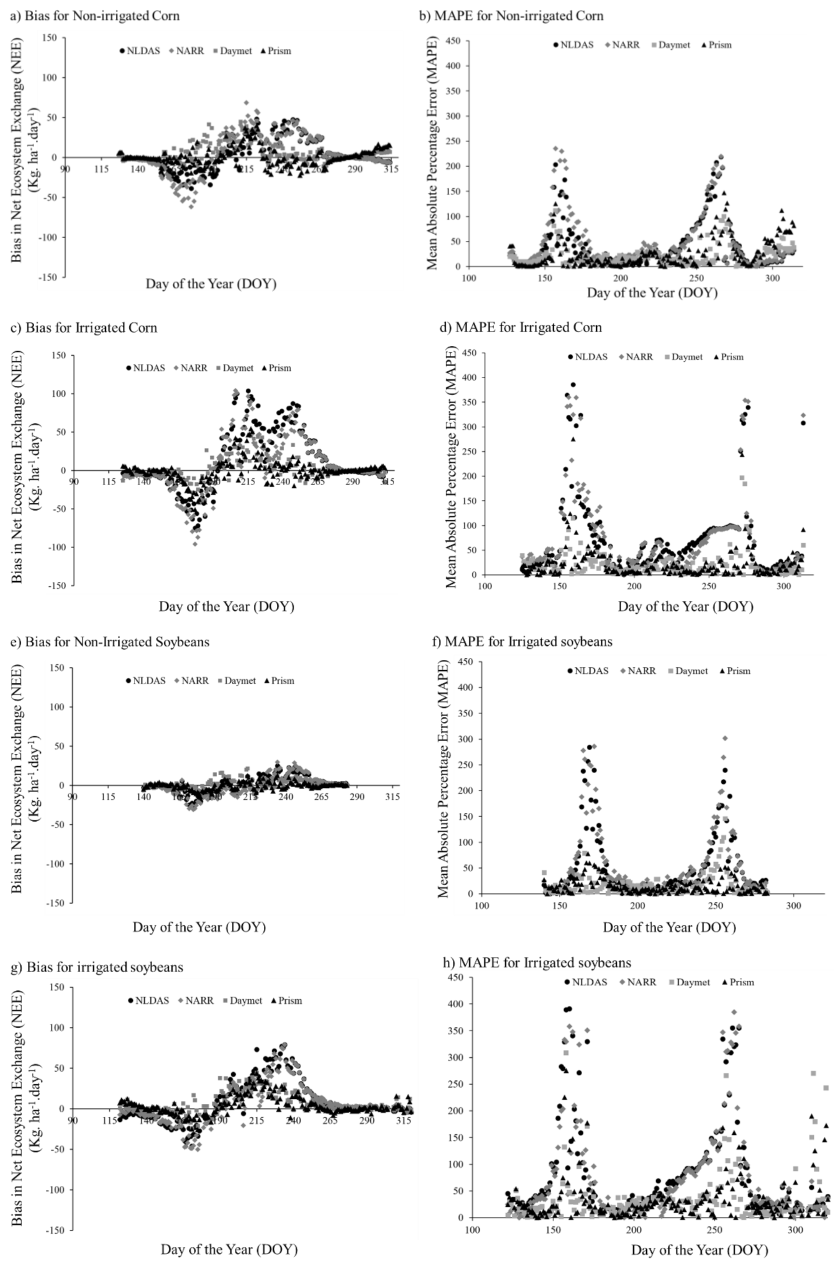

Fig.5. Comparison of bias and Mean Absolute Percentage Error (MAPE) in daily Net Ecosystem Exchange (NEE) estimates for irrigated and non-irrigated corn and soybeans, simulated using gridded climate datasets.

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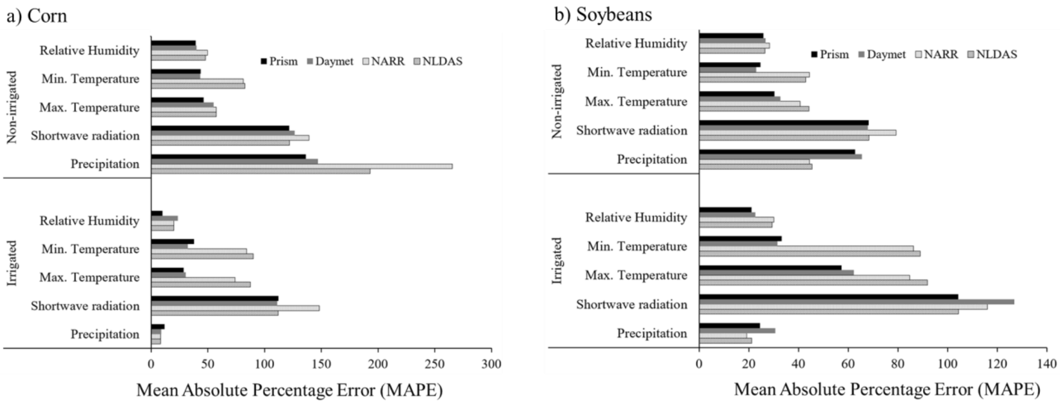

Fig.6. Mean Absolute Percentage Error (MAPE) (averaged over growing season and years) in Net Ecosystem Exchanges (NEE) estimates for irrigated and non-irrigated corn and soybeans from 16 simulations conducted to understand the impact of individual weather variables. For each simulation, one weather variable from a one of the gridded datasets was used along the rest of the variables from site weather data.

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Table 1. Details of flux tower sites providing reference observational climate and CO_2 flux data.

Station	**Abbrev.**	**Latitude**	**Longitude**	**Crop rotation**	**data length (y)**	**Elevation (m)**
Mead Irrigated, NE	Ne1	41.16	-96.47	Continuous Corn	2001 to 2012	361
Mead Irrigated, NE	Ne2	41.16	-96.47	Corn-Soybeans	2001 to 2012	362
Mead Non-irrigated, NE	Ne3	41.18	-96.43	Corn-Soybeans	2001 to 2012	363
Bondville, IL	Bo1	40.00	-88.29	Corn-Soybeans	1996 to 2007	219

Table 2. Details of gridded weather datasets evaluated in this study.

Gridded data	**Spatial resolution**	**Temporal resolution**	**Data length**	**Download Source**
NARR	32 km	3-hourly	1979-present	ftp://ftp.cdc.noaa.gov/Datasets/NARR/
NLDAS	12 km	1-hourly	1979-present	http://disc.sci.gsfc.nasa.gov/hydrology
Prism	800 m	daily	1981-present	http://www.prism.oregonstate.edu/
Daymet	1 km	daily	1980-present	https://Daymet.ornl.gov/

Table 3. MAPE (%) of climate variables (averaged over growing season and years) of various climate datasets.

	Max. Temperature	Min. Temperature	Shortwave radiation	Precipitation	Relative humidity
NLDAS	18.93	76.59	107.38	157.13	14.22
NARR	18.53	75.01	146.28	180.08	15.71
Daymet	17.75	38.86	107.27	107.51	16.06
Prism	17.31	32.16	-	117.87	14.46

Table 4. MAPE and RMSE of Net Ecosystem Exchange (NEE) estimates (averaged over growing season and years) for irrigated and non-irrigated corn and soybeans.

	Non-Irrigated Corn		Irrigated Corn		Non-Irrigated Soybeans		Irrigated Soybeans	
	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE	MAPE (%)	RMSE
NLDAS	41.36	19.76	76.39	40.46	51.96	10.61	80.37	27.06
NARR	49.83	25.02	77.96	37.89	57.93	12.94	79.04	24.88
Daymet	18.91	11.54	20.77	15.00	16.85	4.66	33.60	12.11
Prism	21.89	13.89	22.97	19.99	14.83	6.12	34.12	14.43