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D. Menefee

Russell L. Scott

M. Abraha

J. G. Alfieri

J. Baker

See next page for additional authors

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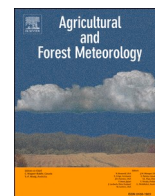
Authors

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Unraveling the effects of management and climate on carbon fluxes of U.S. croplands using the USDA Long-Term Agroecosystem (LTAR) network

D. Menefee^{a,*}, Russell L. Scott^b, M. Abraha^c, J.G. Alfieri^d, J. Baker^e, Dawn M. Browning^f, Jiquan Chen^c, Jeff Gonet^g, J.M.F. Johnson^h, G.R. Millerⁱ, Rachel Nifong^j, Phil Robertson^c, E.S. Russell^k, N. Saliendra^l, Adam P. Schreiner-Mcgraw^m, A. Suykerⁿ, P. Wagle^o, Chris Wente^h, P.M. White^p, Doug Smith^a

^a Grassland Soil and Water Laboratory, USDA-ARS, Temple, TX, United States

^b Southwest Watershed Research Center, USDA-ARS, Tucson, AZ, United States

^c W.K. Kellogg Biological Station, Michigan State University, Hickory Corners, MI, United States

^d Beltsville Agricultural Research Center, USDA-ARS, Beltsville, MD, United States

^e Soil and Water Management Research Unit, USDA-ARS, St. Paul, MN, United States

^f Range Management Research, USDA-ARS, Las Cruces, NM, United States

^g Pasture Systems & Watershed Management Research, USDA-ARS, University Park, PA, United States

^h Soil Management Unit, USDA-ARS, Morris, MN, United States

ⁱ Department of Civil & Environmental Engineering, Texas A&M University, College Station, TX, United States

^j Coastal Plain Experiment Station, USDA-ARS, Tifton, GA, United States

^k Laboratory for Atmospheric Research, Washington State University, Pullman, WA, United States

^l Northern Great Plains Research Laboratory, USDA-ARS, Mandan, ND, United States

^m Cropping Systems and Water Quality Research, USDA-ARS, Colombia, MO, United States

ⁿ School of Natural Resources, University of Nebraska-Lincoln, Lincoln, NE, United States

^o Grazinglands Research Laboratory, USDA-ARS, El-Reno, OK, United States

^p Sugarcane Research Unit, USDA-ARS, Houma, LA, United States

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ABSTRACT

Understanding the carbon fluxes and dynamics from a broad range of agricultural systems has the potential to improve our ability to increase carbon sequestration while maintaining crop yields. Short-term, single-location studies have limited applicability, but long-term data from a network of many locations can provide a broader understanding across gradients of climate and management choices. Here we examine eddy covariance measured carbon dioxide (CO₂) fluxes from cropland sites across the United States Department of Agriculture's Long-Term Agroecosystem Research (LTAR) network. The dataset was collected between 2001 and 2020, spanning 13 sites for a total of 182 site-years. Average seasonal patterns of net ecosystem CO₂ exchange (NEE), gross primary productivity (GPP), and ecosystem respiration (R_{eco}) were determined, and subsequent regression analysis on these "flux climatologies" was used to identify relationships to mean annual temperature (MAT), mean annual precipitation (MAP), cropping systems, and management practices. At rainfed sites, carbon fluxes were better correlated with MAP ($r^2 \leq 0.5$) than MAT ($r^2 \leq 0.22$). Net carbon balance was different among cropping systems ($p < 0.001$), with the greatest net carbon uptake occurring in sugarcane (*Saccharum spp.* hybrids) and the least in soybean (*Glycine max*) fields. Crop type had a greater effect on carbon balance than irrigation management at a Nebraska site. Across cropping systems, grain crops often had higher GPP and were more likely to have net uptake when compared to legume crops. This multi-site analysis highlights the potential of the LTAR network to further carbon flux research using eddy covariance measurements.

* Corresponding author.

E-mail address: dorothy.menefee@usda.gov (D. Menefee).

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1. Introduction

Identifying strategies to increase carbon dioxide (CO₂) uptake and subsequently net ecosystem exchange (NEE) from agricultural systems is currently a major priority of agroecological research as a means to mitigate climate change. Maintaining high yields while simultaneously reducing greenhouse gas emissions (GHG) is essential to meet the food, fiber, and fuel needs of the 21st century while meeting greenhouse gas reduction targets (Burney et al., 2010; Frank et al., 2017). In the United States, agricultural production accounts for approximately 10% of GHG emissions, most of which are in the form of CO₂, methane (CH₄), and nitrous oxide (N₂O) (Baum et al., 2014; Desai and Camobreco, eds, 2019; Smith et al., 2014). However, management practices that allow net carbon sequestration via soil storage have the potential to offset emissions from other sources (Pellerin et al., 2017; Smith et al., 2014).

Ecosystem-atmosphere carbon flux measurement networks using eddy covariance (EC) have the potential to expand our knowledge of how management and the environment contribute to agricultural emissions and sequestration potential (Hermes et al., 2021). Land management decisions and climatic factors both contribute to the carbon source/sink status of an agricultural system, often interacting with each other (Fan et al., 2019; Vleeshouwers and Verhagen, 2002). Thus, it is important to understand cropland carbon dynamics across a range of climates and management practices (Browning et al. 2021).

The implementation of best cropland management practices, such as high-yielding crop varieties, improved irrigation scheduling, and reduced tillage need to provide multiple benefits including soil protection, improved climate resilience, increased soil carbon sequestration (Pellerin et al., 2017), as well as improved productivity. Increasing crop productivity (e.g., grain yield) typically also increases overall carbon uptake by the crop, and thus produces more crop residue and root biomass, thereby increasing carbon inputs to the soil (Burney et al., 2010; Fan et al., 2019; Frank et al., 2017).

Year-to-year weather and climate variations can affect crop productivity, management decisions, and GHG emissions, masking the effects of treatments in short-term studies (Büchi et al., 2017; Pittelkow et al., 2015; Rasmussen et al., 1998). Therefore, to gain a full understanding of the effects of management practices on land productivity and ecosystem services requires multiple years of study across different climate, soil, and crop types. Because the demands of managing an agricultural site can conflict with other research needs, such as changes in management to control pests and mitigate the effects of adverse weather events, long-term studies of agricultural carbon dynamics are still uncommon.

In the past decade, the United States Department of Agriculture (USDA)'s Agricultural Research Service (ARS) established the Long-Term Agroecosystem Research (LTAR) network to collaboratively address agricultural sustainability and productivity across a variety of soil types, climates, and agricultural systems within the United States (Boughton et al., 2021; Goodrich et al., 2020; Kleinman et al., 2018). The LTAR network was officially established in 2012 to leverage the historic time series of established individual research sites spanning diverse agroecosystems. The network currently consists of 18 sites with different climatic regimes, of which eight are croplands, five grazing/pasture sites, and five mixed systems (both cropland and grazing land). Thirteen of the cropland and mixed sites (cropland portion) were used in this study. Across the network 77 eddy covariance (EC) towers have so far been deployed. The network has established a set of common experiments and methods to study sustainable intensification (Spiegel et al., 2018). EC measurements are now widely used across the network to examine CO₂ fluxes and evapotranspiration (ET) to better understand the vertical exchanges of carbon and water between the land and the atmosphere (Baldocchi, 2003).

Eddy covariance towers provide real-time, continuous observations of carbon and water vapor fluxes from ecosystems. This method utilizes a sonic anemometer and infrared gas analyzer (IRGA) to calculate fluxes

as the covariance between vertical wind speed and gas concentration of interest (typically CO₂, CH₄, N₂O, or H₂O) and allows for gas fluxes to be determined at very fine temporal resolution (i.e., data collected typically at 10 or 20 Hz with fluxes computed every half-hour) (Aubinet et al., 2012; Baldocchi, 2014; Burba, 2013; Sharma et al., 2017). While the half-hourly CO₂ flux is the net ecosystem exchange (NEE) between the ecosystem and atmosphere, it can be partitioned into gross primary productivity (GPP) and ecosystem respiration (R_{eco}) using standardized methods to describe the seasonal interplay between CO₂ uptake and losses by the ecosystem (Menefee et al., 2020; Rajan et al., 2013; Wharton et al., 2012). The EC method is suitable for field-scale agricultural systems and works best in flat, uniform environments. By utilizing EC across the common experiments of the LTAR network, there is potential to look at both climate and management effects on carbon dynamics in agricultural systems (Hermes et al., 2021).

There is a growing wealth of carbon flux data from EC studies of croplands as this method has been used to study impacts of management practices on annual carbon fluxes. Suyker and Verma (2012) provided an overview of ecosystem carbon fluxes at a Nebraska LTAR site (included in this study), finding that soybean had approximately half the GPP of maize but 78% of the R_{eco} , leading to a stronger C sink with maize than with soybean. Zeri et al. (2011) and Abraha et al. (2018a) also reported differences in carbon dynamics between crop species when comparing potential biofuel crops. Abraha et al. (2018) further demonstrated higher carbon emissions from candidate bioenergy crops grown on former Conservation Reserve Program grasslands compared to the same crops grown on former croplands. Wagle et al. (2019) documented a greater uptake and emissions for wheat compared to canola at an LTAR site in Oklahoma.

Differences in growth habits of crops have been found to frequently influence crop GPP using EC systems (Anapalli, et al., 2019; Hernandez-Ramirez et al., 2011; Gelybó et al., 2022). Year-to-year weather or climate variations impact annual C fluxes within a system. For example, Chi et al. (2017) found links between precipitation and C fluxes in the Pacific Northwest of the United States. In Iowa, Dold et al. (2017) identified precipitation, air temperature, and soil water availability as key drivers of C fluxes from maize and soybean. Many more studies have found that year-to-year differences in precipitation and water availability contribute to variations in GPP and R_{eco} within individual sites (Hunt et al., 2014; Menefee et al., 2020; Prueger et al., 2004; Qun and Huizhi, 2013; Sharma et al., 2017). Variation in light availability and air temperature have also been shown to drive agricultural C fluxes (Dold et al., 2017; Gebremedhin et al., 2012; Hernandez-Ramirez et al., 2011; Wagle et al., 2019). However, similar studies across larger networks, rather than at individual sites, are still less common (see Browning et al. 2021). Do the same trends of impacts of weather, climate, and management on C fluxes at individual sites hold true across larger networks?

The objectives of this study are to perform an exploratory data analysis of the EC datasets to characterize the annual carbon fluxes and their seasonality across a range of agricultural cropland sites within the LTAR network and to determine how climate and crop management influence NEE, GPP, and R_{eco} over a 19-year study period and across 13 climatic regimes. Our goal is to develop a benchmark for future work on EC measurements in the LTAR network by providing an inventory of available data and a brief summary of the typical pattern of carbon dynamics at each site. Differences in carbon fluxes among sites are likely large due to differences in climate (e.g., temperature and precipitation) and management practices, including tillage and crop selection. However, within sites, management practices may drive differences in carbon dynamics, which we explore by examining management practices employed by groupings of sites. This includes comparisons of the productivity of grain versus legume with maize/soybean rotations and wheat/garbanzo rotations, a comparison of potential bioenergy crops, and a comparison of irrigated versus rainfed maize/soybean crops. This is a first look at a budding agroecology network within the United States. This initial site and data summary explores tradeoffs between cropping

Table 1
Description of the 13 cropland eddy covariance (EC) sites and data within the Long-Term Agricultural Research (LTAR) network.

Site and Tower*	Years	Latitude and Longitude	Crop / Rotation	Cover Crops / Other Practices	Tillage**	Irrigation	Typical Growing Season
CMRB ¹	5 (2016 -2020)	39.2293, -92.1170	Maize / Soy / Wheat	Yes	No-Till	None	May – October
CMRB ¹	4 (2017 – 2020)	39.2322, -92.1494	Maize / Soy	None	Conventional Till	None	May - October
CAF - Cook East ² (US-CF2)	2 (2018 – 2019)	46.7815, -117.0821	Wheat / Garbanzo	None	No-Till	None	May - September
CAF - Cook West ² (US-CF3)	2 (2018 – 2019)	46.7840, -117.091	Wheat / Garbanzo	None	Reduced Till	None	May - September
CAF – Boyd South ⁵	2 (2018 – 2019)	46.7518, -117.1285	Wheat / Garbanzo	None	Conventional Till	None	May - September
CAF – Boyd North ² (US-CF1)	2 (2018 – 2019)	46.7551, -117.1261	Wheat / Garbanzo	None	Conventional Till	None	May - September
GACP ³	1 (2020)	31.5109, -83.6179	Peanut	None	Conventional Till	Irrigated	May – October
KBS – CRP-Pr ⁴	9 (2010 – 2018)	42.4427, -85.3236	Restored prairie (Biofuel)	None	No-till	None	Perennial
KBS – CRP-Sw ⁴	9 (2010 – 2018)	42.4427, -85.3236	Switchgrass (Biofuel)	None	No-till	None	Perennial
KBS – CRP-C ⁴ (US-KM1)	9 (2010 – 2018)	42.4427, -85.3236	Maize	Partial Residue Removal	No-till	None	Early May – Early October
KBS – CRP-Ref ⁴	9 (2010 – 2018)	42.4427, -85.3236	Smooth bromegrass	None	No-till	None	Perennial
KBS – AGR-Pr ⁴	9 (2010 – 2018)	42.4805, -85.4481	Restored prairie (Biofuel)	None	No-till	None	Perennial
KBS – AGR Sw ⁴	9 (2010 – 2018)	42.4805, -85.4481	Switchgrass (Biofuel)	None	No-till	None	Perennial
KBS – AGR – C ⁴	9 (2010 – 2018)	42.4805, -85.4481	Maize	Partial Residue Removal	No-till	None	Early May – Early October
LCB – Chop ⁵	5 (2014 – 2018)	39.0587, -75.8513	Maize / Soy	None	Conventional	Central Pivot	Mid May - September
LCB – OP3 ⁵	1 (2019)	39.0587, -75.8513	Maize	None	Conservation	None	Mid May - September
LMRB ⁶	3 (2017 – 2019)	29.6340, -90.8350	Sugarcane	None	Conventional/ Reduced	None	May - October
NP (h5) ⁷ (US-NP1)	8 (2009 -2018)	46.7754, -100.9511	Alfalfa (5 yr), Wheat / Maize / Soy (3 year)	None	No-Till	None	Alfalfa: Apr – Oct Wheat: Jun – Jul Maize: Jun - Oct Soy: Jun – Sept
NP (i2) ⁷ (US-NP2)	3 (2016 -2018)	46.7614, -100.9257	Wheat / Maize / Soy	None	No-Till	None	
PRHPA – Ne1 ⁸ (US-Ne1)*	19 (2001-2019)	41.1651, -96.4766	Maize	None	Conservation	Center-Pivot	May - October
PRHPA – Ne2 ⁸ (US-Ne2)	19 (2001-2019)	41.1649, -96.4701	Maize / Soy	None	No-Till	Center-Pivot	May - October
PRHPA – Ne3 ⁸ (US-Ne3)	19 (2001-2019)	41.1797, -96.4397	Maize / Soy	None	No-Till	None	May - October
SP ⁹	1	35.5753, -98.0550	Alfalfa	None	No-till	None	Perennial
SP ⁹	2 (2017, 2019)	35.5644, -98.0615	Wheat	Stover Grazing	No-till	None	October – June
SP ⁹	2 (2017, 2019)	35.5598, -98.0615	Wheat	Stover Grazing	Conventional	None	October - June
TG – TA ¹⁰ (US-Tx4)	2 (2019 -2020)	31.4693, -96.8865	Maize	None	Conventional	None	March – August
TG – AA ¹⁰ (US-Tx3)	2 (2019 -2020)	31.4777, -96.8883	Maize	Winter Pea	No-Till	None	March – August
UCB ¹¹	1 (2017)	40.7559, -77.9998	Maize	None	No-Till	None	May - September
UMRB – Ro1 ¹² (US-Ro1)	17 (2004 – 2016)	44.7143, -93.0898	Maize / Soy	None	Conventional	None	May - October
UMRB – Ro2 ¹² (US-Ro2)	3 (2008, 2012, 2016)	44.7288, -93.0888	Maize / Soy / Clover	Clover cover crop	Conventional	None	May - October
UMRB – Ro3 ¹² (US-Ro3)	3 (2005 – 2007)	44.7217, -93.0893	Maize / Soy	None	Conventional	None	May - October
UMRB – Ro5 ¹² (US-Ro5)	3 (2017 – 2019)	44.6910, -93.0576	Maize / Soy	None	Conventional	None	May - October
UMRB – Ro6 ¹² (US-Ro6)	3 (2017 – 2019)	44.6946, -93.0578	Maize / Soy / Clover	Clover cover crop	Conventional	None	May - October
UMRB - Morris ¹³	2 (2018 – 2019)	45.627, -96.127	Corn / Wheat	Oats / Radish	Strip Till	None	May - October

Footnotes:

*Ameriflux designations given in parentheses when available.

**Tillage Footnote: Conventional tillage referred to standard regional tillage practices for the site, as defined by site managers and included a wide range of practices, particularly disc tillage. Reduced tillage refers to practices that reduce tillage intensity and frequency, such as Strip Till.

¹ Central Mississippi River Basin Site; PI: Adam Schreiner-Mcgraw. Data obtained directly from PI.

² Cook Agronomy Farm Site; PI: Dave Huggins and Eric Russell. Data obtained directly from PI.

³ Gulf Coast Atlantic Plain Site; PI: Rachel Nifong. Data obtained directly from PI.

⁴ Kellogg Biological Station; Michael Abraha. Data obtained directly from PI.

⁵ Lower Chesapeake Bay Site; PI: Joe Alfieri. Data obtained directly from PI.

⁶ Lower Mississippi River Basin; PI: Paul White. Data obtained directly from PI.

⁷ Northern Plains Site; PI: Nicanor Saliendra. Data obtained directly from PI.

⁸ Platte River High Plains Aquifer Site; PI: Andy Suyker. Data obtained from Ameriflux network (Suyker, 2021a, Suyker 2021b; Suyker, 2021c).

⁹ Southern Plains Site; PI: Pradeep Wagle. Data obtained directly from PI.

¹⁰ Texas Gulf Site; PI: Gretchen Miller. Data obtained from the site directly with permission from PI.

¹¹ Upper Chesapeake Bay Site; PI: Sarah Goslee and Jeff Gonet. Data obtained directly from PI.

¹² Upper Mississippi River Basin (Rosemount Site); PI: John Baker. Data obtained from Ameriflux Network (Baker et al., 2018; Baker and Griffis, 2018; Baker and Griffis, 2019; Baker and Griffis, 2021a; Baker and Griffis 2021b).

¹³ Upper Mississippi River Basin (Morris Site); PI: Jane Johnson. Data obtained directly from PI.

system and sustainability, and establishes a framework for solving national food system issues related to carbon flux and sustainability.

2. Materials and methods

2.1 Data collection

Eddy covariance data was collected for LTAR cropland and mixed sites with at least one full calendar year (Jan – Dec) of measurements. A summary (location, years, and crop management) of all collected data is shown in Table 1, and a map of all LTAR sites is shown in Fig. 1. The participating sites were as follows with abbreviations that will be used for the rest of the paper: Central Mississippi River Basin (CMRB), Cook Agronomy Farm (CAF), Gulf Atlantic Coastal Plain (GACP), Kellogg Biological Station (KBS), Lower Chesapeake Bay (LCB), Lower

Mississippi River Basin (LMRB), Northern Plains (NP), Platte River High Plains Aquifer (PRHPA), Southern Plains (SP), Texas Gulf (TG), Upper Chesapeake Bay (UCB), and Upper Mississippi River Basin (UMRB). The oldest EC towers are at PRHPA, established in 2001, and the newest at TG, in 2017 (although data for an annual cycle was not available until 2019). While differences in the amounts of available data likely adds bias in favor of trends seen at sites with longer histories, however, as this network matures, and the sites accumulate more data this problem will be less prominent. This is a common situation in cross-site eddy covariance analysis work, as most larger-scale studies require utilizing data from sites with a variety of histories and record lengths (Chen et al., 2018; Chu et al., 2021; Pastorello et al., 2020). The following crops were grown in sites included in the analysis, but not all crops were grown at all sites: maize (*Zea mays* L. - 8 sites), soybean (*Glycine max* L. - 5 sites), alfalfa (*Medicago sativa* L. - 2 sites), garbanzo (*Cicer arietinum* L. - 1 site),

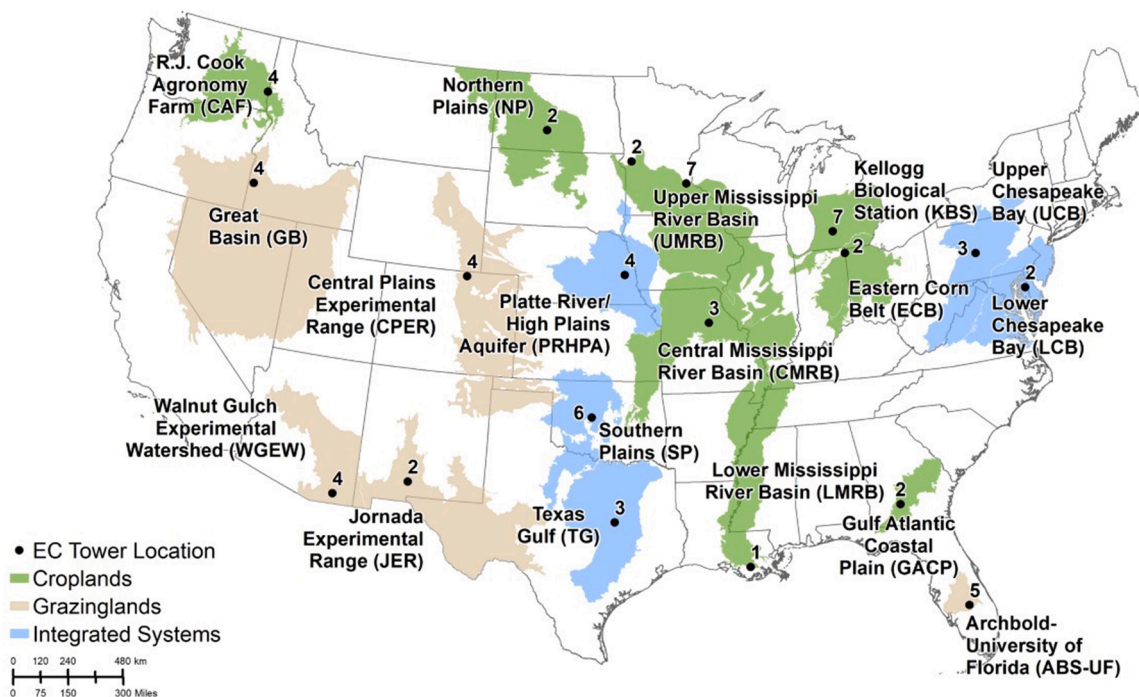


Fig. 1. Map of all LTAR locations by agricultural system type (Croplands, Grazinglands, and Integrated Systems) with the number of EC towers at each site indicated. Cropland sites consist solely of crop production, both row crops, and perennial biofuel crops. Grazinglands consist solely of livestock grazing, both rangeland and pasture. Integrated Systems sites contain both cropland and grazing lands at the same site. Cropland sites and cropland portions of Integrated Systems sites were considered for this analysis.

Table 2

Summary of average (\pm standard error) annual NEE , GPP , and R_{eco} ($g\ C\ m^{-2}\ year^{-1}$) across all sites and separated by crop type.

Site	Crop	Site - Years	MAT (deg C)	MAP (mm)	Average Annual NEE	Average Annual GPP	Average Annual R_{eco}	Years Net $-NEE$	Months Net $-NEE$ / Year
CMRB	Maize	3	13.8 \pm 0.1	770 \pm 81	-514 \pm 55	1612 \pm 99	1097 \pm 136	3/3	3.67
CMRB	Wheat	2	12.9	837	-493	1997	1504	2/2	8.00
CMRB	Soy	4	13.0 \pm 0.6	1010 \pm 82	-257 \pm 80	1543 \pm 111	1286 \pm 143	3/3	3.75
CAF	Wheat	4	8.0 \pm 0.4	290 \pm 29	-365 \pm 40	811 \pm 48	446 \pm 33	4/4	3.75
CAF	Garbanzo	4	9.6 \pm 0.3	233 \pm 51	-113 \pm 48	612 \pm 71	499 \pm 43	3/4	3.25
GACP	Peanut	1	20.9	1245	411	2918	3329	0/1	3.00
KBS	Maize	18	9.2 \pm 0.3	1016 \pm 49	-208 \pm 33	1462 \pm 47	1270 \pm 50	17/18	3.44
KBS	Switchgrass	18	9.2 \pm 0.3	1016 \pm 49	-304 \pm 40	1492 \pm 82	1185 \pm 49	17/18	4.83
KBS	Bromegrass	9	9.2 \pm 0.3	1016 \pm 49	18 \pm 21	1450 \pm 52	1466 \pm 48	4/9	3.22
KBS	Prairie	18	9.2 \pm 0.3	1016 \pm 49	-185 \pm 35	1347 \pm 61	1163 \pm 38	16/18	4.44
LCB	Maize	4	13.6 \pm 0.5	938 \pm 134	-205 \pm 104	1006 \pm 280	801 \pm 236	4/4	4.50
LCB	Soybean	2	13.6	957	-240	1249	1008	2/2	5.00
LMRB	Sugarcane	4	20.9 \pm 0.1	1644 \pm 121	-785 \pm 108	2648 \pm 100	1862 \pm 163	4/4	8.25
NP	Alfalfa	5	5.3 \pm 0.5	519 \pm 51	-295 \pm 53	1185 \pm 150	890 \pm 97	5/5	5.60
NP	Wheat	2	7.4	499	32.3	616.0	648	0/2	2.00
NP	Maize	2	6.2	358	-121	900	778	2/2	3.00
NP	Soybean	2	5.1	496	-7	601	595	1/2	2.00
PRHPA	Maize	8	10.4 \pm 0.3	600 \pm 41	-488 \pm 42	1543 \pm 42	1055 \pm 31	8/8	3.63
PRHPA	Maize (Irrigated)	27	10.5 \pm 0.2	883 \pm 21	-436 \pm 33	1722 \pm 29	1286 \pm 23	27/27	3.67
PRHPA	Soybean	9	10.8 \pm 0.4	685 \pm 59	-59 \pm 30	1024 \pm 80	965 \pm 64	5/9	2.56
PRHPA	Soybean (Irrigated)	8	10.6 \pm 0.5	882 \pm 32	-73 \pm 69	1150 \pm 111	1077 \pm 66	3/8	2.63
SP	Alfalfa	1	15.5	1109	-454	2417	1963	1/1	7.00
SP	Wheat	4	15.1 \pm 0.3	1097 \pm 7	-127 \pm 71	1872 \pm 55	1745 \pm 78	3/4	5.50
TG	Maize	4	19.5 \pm 0.1	772 \pm 69	-156 \pm 25	1362 \pm 127	1206 \pm 151	4/4	5.75
UCB	Maize	1	11.0	1130	-281	893	612	1/1	4.00
UMRB	Wheat	1	5.8	650	-83	809	725	1/1	4.00
M									
UMRB	Maize	1	5.9	650	-714	1544	829	1/1	6.00
M									
UMRB R	Clover	3	7.0 \pm 0.9	991 \pm 49	-220 \pm 99	1269 \pm 287	1050 \pm 253	3/3	5.00
UMRB R	Maize	9	7.5 \pm 0.5	772 \pm 75	-366 \pm 61	1426 \pm 102	1060 \pm 80	9/9	5.00
UMRB R	Soybean	9	7.9 \pm 0.4	812 \pm 50	11 \pm 17	762 \pm 36	768 \pm 28	3/9	3.00
UMRB R	Maize / Clover	1	6.4	627	-597	1598	1001	1/1	7.00
UMRB R	Soybean / Clover	1	9.3	823	-102	957	855	1/1	5.00
UMRB R	Wheat	1	7.8	861	-23	717	698	1/1	2.00

Footnote: Acronyms used include: GPP – gross primary productivity, NEE – net ecosystem exchange, R_{eco} – ecosystem exchange, MAT – mean annual temperature, MAP – mean annual precipitation, LCB – Lower Chesapeake Bay, SP – Southern Plains, KBS – Kellogg Biological Station, CAF – Cook Agronomy Farm, $LMRB$ – Lower Mississippi River Basin, $PRHPA$ – Platte River High Plains Aquifer, $UMRB$ – Upper Mississippi River Basin (R - Rosemount; M - Morris), TG – Texas Gulf, NP – Northern Plains.

wheat (*Triticum aestivum* - 5 sites), sugarcane (*Saccharum* spp. hybrids – 1 site), switchgrass (*Panicum virgatum* L. – 1 site), smooth bromegrass (*Bromus inermis* L. – 1 site), restored mixed-grass prairie (1 site), peanut (*Arachis hypogaea* - 1 site) and clover (*Trifolium incarnatum* L. – 1 site). Center-pivot irrigation occurred at the GACP, LCB, and PRHPA sites; the rest were rainfed. All sites were fertilized as required to maintain crop yields. No two sites had the same exact cropping system and management practices, which may make analysis more challenging, but also better reflects the reality of agriculture in the United States.

Eddy covariance instrumentation varied among sites. Infrared gas absorption (IRGA) analyzers included LI-COR's LI-7500 (LCB, SP, KBS, UMRB, and NP), LI-COR's LI-7200 (PRHPA), Campbell Scientific's EC150 (CAF), and Campbell Scientific's combined IRGASON system (LMRB, GACP, CMRB, and TG). Sonic anemometers included Gill's (Gill Instruments, Hampshire, UK) R3-100 (PRHPA), Campbell Scientific's CSAT3 (LCB, SP, KBS, CAF, UMRB, and NP), and Campbell Scientific's combined IRGASON system (CMRB, LMRB, GACP, TG, and UCB). Flux processing was completed at each site using LI-COR's EddyPro (SP, CAF, GACP, UCB, and NP), EdiRe from the University of Edinburgh, Edinburgh, UK (KBS), Campbell Scientific's EasyFlux (LMRB and TG), or custom codes (CMRB, LCB, PRHPA, and UMRB). The differing types of

equipment and internal software between sites likely introduces biases – however this is a common systemic error in network-scale eddy covariance analysis (Curtis et al., 2002; Lu et al., 2016; Novick et al., 2018; Restrepo-Coupe et al., 2013), especially with grassroots-style networks like Ameriflux and LTAR. Schmidt et al., (2012) investigated sources of error in eddy covariance studies and found that while instrument selection variation does contribute to error, that it was a relatively small source compared to other sources of errors. Gap filling via REddyProc's online tool (Max Plank Institute for Biogeochemistry) was used to fill gaps in available data, usually due to loss of instrument power or low-quality data as indicated by QC flags in the flux processing software. REddyProc's nighttime partitioning method was used to separate assimilatory fluxes (GPP) from respiratory fluxes (R_{eco}) (Wutzler et al., 2018). More in-depth summaries of this method can be found in Menefee et al. (2020) and Reichstein et al. (2005).

2.2: Data analysis

All tower sites with at least one full year of data were included in this analysis. Daily, monthly, and annual summaries of total GPP , NEE , R_{eco} , air temperature (T or T_{air}), and precipitation (P) were compiled across

Table 3

Results of stepwise regression on annual carbon flux sums versus climate and management practices. Significant results to $p < 0.05$ are in bold.

Forward Stepwise						
Independent Variable	NEE		GPP		R _{eco}	
	P-value	F value	P value	F value	P value	F value
Annual Temperature (°C)	0.154	2.046	<0.001	33.095	<0.001	64.897
Annual Precipitation (mm)	0.025	8.022	<0.001	47.762	<0.001	35.398
Irrigation Practice	0.147	2.123	0.054	3.773	0.112	2.548
Tillage Practice	0.096	2.789	0.695	0.154	0.044	4.124
Crop Selection	<0.001	10.695	0.069	3.339	0.728	0.121
Backward Stepwise						
Independent Variable	NEE		GPP		R _{eco}	
	P-value	T test	P value	T test	P value	T test
Annual Temperature (°C)	0.154	2.046	<0.001	33.095	<0.001	64.897
Annual Precipitation (mm)	0.025	8.022	<0.001	47.762	<0.001	35.398
Irrigation Practice	0.147	2.123	0.054	3.773	0.112	2.548
Tillage Practice	0.096	2.789	0.695	0.154	0.044	4.124
Crop Type	<0.001	10.695	0.069	3.339	0.728	0.121

Table 4

Net ecosystem exchange (NEE, gC m⁻² yr⁻¹) by crop type for all crops with at least three years of data. Letters indicate significant differences ($p < 0.05$).

Crop	Average NEE	NEE Range
Sugarcane	-785 ± 108 ^A	-1061 — -580
Maize	-353 ± 22 ^B	-776 — 66
Alfalfa	-322 ± 51 ^{BC}	-454 — -92
Switchgrass	-304 ± 40 ^B	-558 — 166
Clover	-219 ± 99 ^{BCDEF}	-401 — -61
Wheat	-214 ± 56 ^{BCD}	-645 — 79
Prairie	-185 ± 35 ^{CD}	-424 — 166
Garbanzo	-113 ± 48 ^{DEF}	-202 — 23
Soy	-75 ± 24 ^E	-431 — 114
Brome grass	18 ± 21 ^F	-71 — 127

LTAR sites. Annual cumulative GPP, NEE, and R_{eco} were all compared to mean annual temperature (MAT) and to mean annual precipitation (MAP) using linear regressions. Subsequently, the sites were then analyzed by crop type, management practices (e.g., tillage and irrigation), and locations to further isolate trends in carbon fluxes. Stepwise regression (both forward and backward) was performed on annual timestamp data using the following as potential predictors: location (LTAR site - categorical variable), average annual air temperature, cumulative annual precipitation, crop, tillage practice (no-till or tilled), and irrigation practice. Forward stepwise regression adds variables to a linear model until a best fit is found, while backward stepwise regression starts with all variables in the model and removes until a best fit is found. All regression analyses were performed using SigmaPlot (Version 14.0, Systat Software Inc, Berkshire, U.K.). Multiple linear regression was also performed, and the results are provided in supplementary materials.

3. Results and discussion

3.1: Annual carbon flux overview

Average cumulative annual NEE ranged from -785 to 32 g C m⁻²

year⁻¹ for the 13 sites (Table 2). Of sites with data for more than three years, the greatest net uptake (i.e., negative NEE) was seen at LMRB with sugarcane (-785 ± 108 g C m⁻² year⁻¹), while the lowest net uptake (net emission) was seen at the UMRB Rosemont site with soybean (11 ± 17 g C m⁻² year⁻¹). Wheat at the NP site and peanut at GACP had lower net uptake than soybean at UMRB albeit there was not enough data to estimate annual variability, making it difficult to compare the value to others. The highest annual GPP occurred with sugarcane at LMRB (2648 ± 100 g C m⁻² year⁻¹) and the lowest annual GPP (612 ± g C m⁻² year⁻¹) occurred with garbanzo at CAF. Greatest R_{eco} occurred with alfalfa at SP (1963 g C m⁻² year⁻¹), although only one year of data was available; the greatest R_{eco} with an uncertainty estimate (4 years data - Table 2) was with wheat at SP (1745 ± 78 g C m⁻² year⁻¹). The lowest R_{eco} (446 ± 33 g C m⁻² year⁻¹) occurred with wheat at CAF. A negative annual NEE was most common in grass (both grain and biofuel) crops (i.e., maize, wheat, sugarcane) and less common in legumes (soybean, garbanzo). Alfalfa, a perennial legume, had a carbon uptake magnitude similar to maize instead of other legumes, as seen at the NP site. Clover, another perennial legume, overlapped with both alfalfa and the annual legumes, likely an artifact of low sample size.

Forward and backward stepwise linear regressions were performed on annual carbon flux sums against climate (temperature and precipitation), crop selection, irrigation practice, and tillage practice (Table 3). The best predictor for NEE was crop type ($p < 0.001$), with annual precipitation also being significantly correlated with NEE ($p < 0.025$). Annual temperature, tillage practice, and irrigation practice were found to have no significant correlation with NEE. The strongest predictor of GPP was annual precipitation ($p < 0.001$) followed by average annual temperature ($p < 0.001$). The best predictor of R_{eco} was annual precipitation ($p < 0.001$) with average annual temperature being a close second ($p < 0.001$) and tillage practice being a weaker predictor ($p < 0.044$).

3.2 Annual carbon fluxes with tillage and crop type

Tillage practice was found to be a weak predictor of R_{eco} through stepwise regression. Greater respiration was seen in no-till (1217 ± 29 gC m⁻² yr⁻¹) compared to tilled (1069 ± 43 gC m⁻² yr⁻¹), with all tilled sites grouped together for simplicity. Since this is not a paired experiment, the outcome here is possibly a result of site bias, however a literature review shows that greater R_{eco} has been documented in paired no-till experiments designed to look at this specifically. Given the tendency of no-till to promote increased soil carbon (Follett et al., 2012; Ogle et al., 2019; Sun et al., 2020), this is possibly a result of greater microbial activity from more available soil carbon and soil moisture. In a literature review, Young and Ritz (2000) found that no-till soils tended to have greater microbial populations and activity. Others have come to similar conclusions with both total microbial population and fungi specifically (Doran, 1980; Helgason et al., 2010; Menefee et al., 2022; Sharma-Poudyal et al., 2017; Zuber and Villamil, 2016). Some studies have found that soil compaction (i.e., with tillage) can decrease microbial activity (Beylich et al., 2010; Torbert and Wood, 1992; Whalley et al., 1995). Other studies have found that no-till systems can have higher overall respiration when annual trends are studied as tillage often creates short-term pulses of respiration during the growing season (Gelybó et al., 2022; Hendrix et al., 1988; Shi et al., 2012). This increased microbial activity and population is possibly the driver of greater respiration under no-till seen across the LTAR study sites. The nature of the LTAR network could allow for further insight into the exact drivers of the changing carbon flux pattern seen in no-till sites compared to tilled sites. It may be possible to use the LTAR network to explore soil properties (organic matter, bulk density, etc.) and residue dynamics at these network sites. In future work, separating sites by more precise methods (i.e., disc tillage vs. moldboard plow) may also yield more insight into the patterns seen here.

Crop type was found to be the best predictor of NEE in the regression

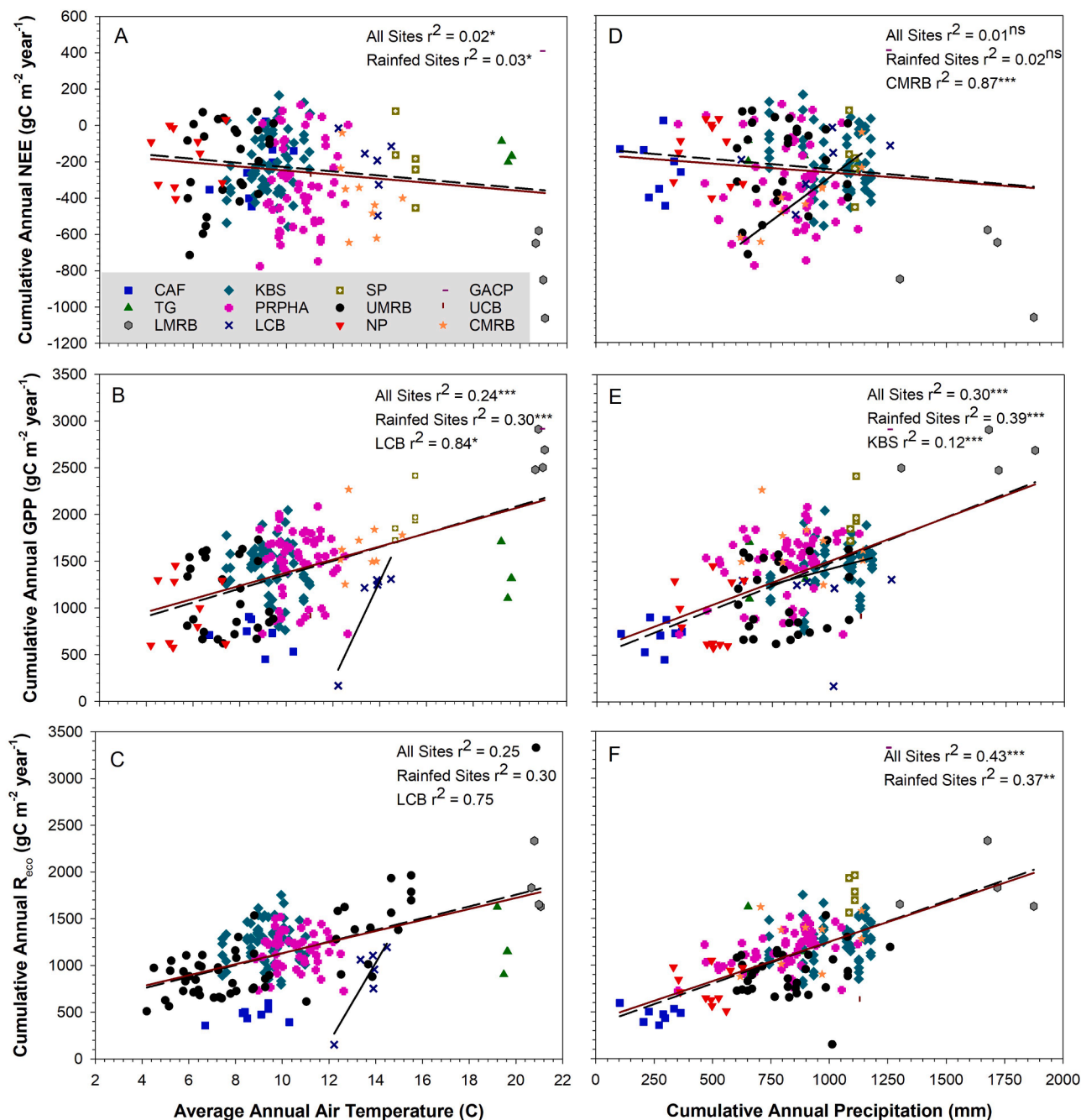


Fig. 2. Net ecosystem exchange (*NEE*), gross primary productivity (*GPP*), and ecosystem respiration (R_{eco}) compared to average annual temperature (Images A, B, and C, respectively). *NEE*, *GPP*, and R_{eco} compared to cumulative annual precipitation (D, E, and F, respectively). Results from simple linear regression are indicated with lines, dark red for rainfed sites, black for all sites, and short dark blue for individual sites as indicated with r^2 values. The legend shown in image A is the same for all graphs. Significant relationships are indicated with asterisks: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Site abbreviations: Cook Agronomy Farm (CAF), Texas Gulf (TG), Lower Mississippi River Basin (LMRB), Kellogg Biological Station (KBS), Platte River High Plains Aquifer (PRHPA), Upper Mississippi River Basin (UMRB), Southern Plains (SP), Northern Plains (NP), Gulf Coast Atlantic Plain (GACP), Upper Chesapeake Bay (UCB), and Central Mississippi River Basin (CMRB).

analysis (Table 4). Sugarcane stood out amongst the crops grown in the network as having higher net carbon uptake ($-785 \pm 108 \text{ gC m}^{-2} \text{ yr}^{-1}$) than any other crops. Sugarcane is a highly productive C_4 grass that grows in humid subtropical and tropical climates. Given the relationship of carbon fluxes to climate, it is possible that part of the reason that higher carbon uptake is seen in sugarcane compared to other LTAR crops is that sugarcane is grown in the warmest and wettest site (20.9°C MAT and 1644 mm yr^{-1} MAP). Sugarcane is also a highly productive crop with high C uptake and high biomass accumulation (Cabral-Netto et al., 2013; Carvalho-Netto et al., 2014; Inman-Bamber et al., 2011). Comparisons of

biofuel production systems have found that sugarcane’s high biomass production frequently leads to greater net carbon uptake than other C_4 grasses grown for biofuel feedstock (de Vries et al., 2010; Knoll et al., 2012).

Maize and alfalfa had more net carbon uptake than soybean, bromegrass, and the restored prairie. Additionally, switchgrass had more net carbon uptake than soybean or bromegrass. Of the crops grown across LTAR, all three C_4 plants (sugarcane, maize, and switchgrass) tended to be more productive than the C_3 plants with the exception of alfalfa. The C_4 photosynthesis pathway is a more recently evolved

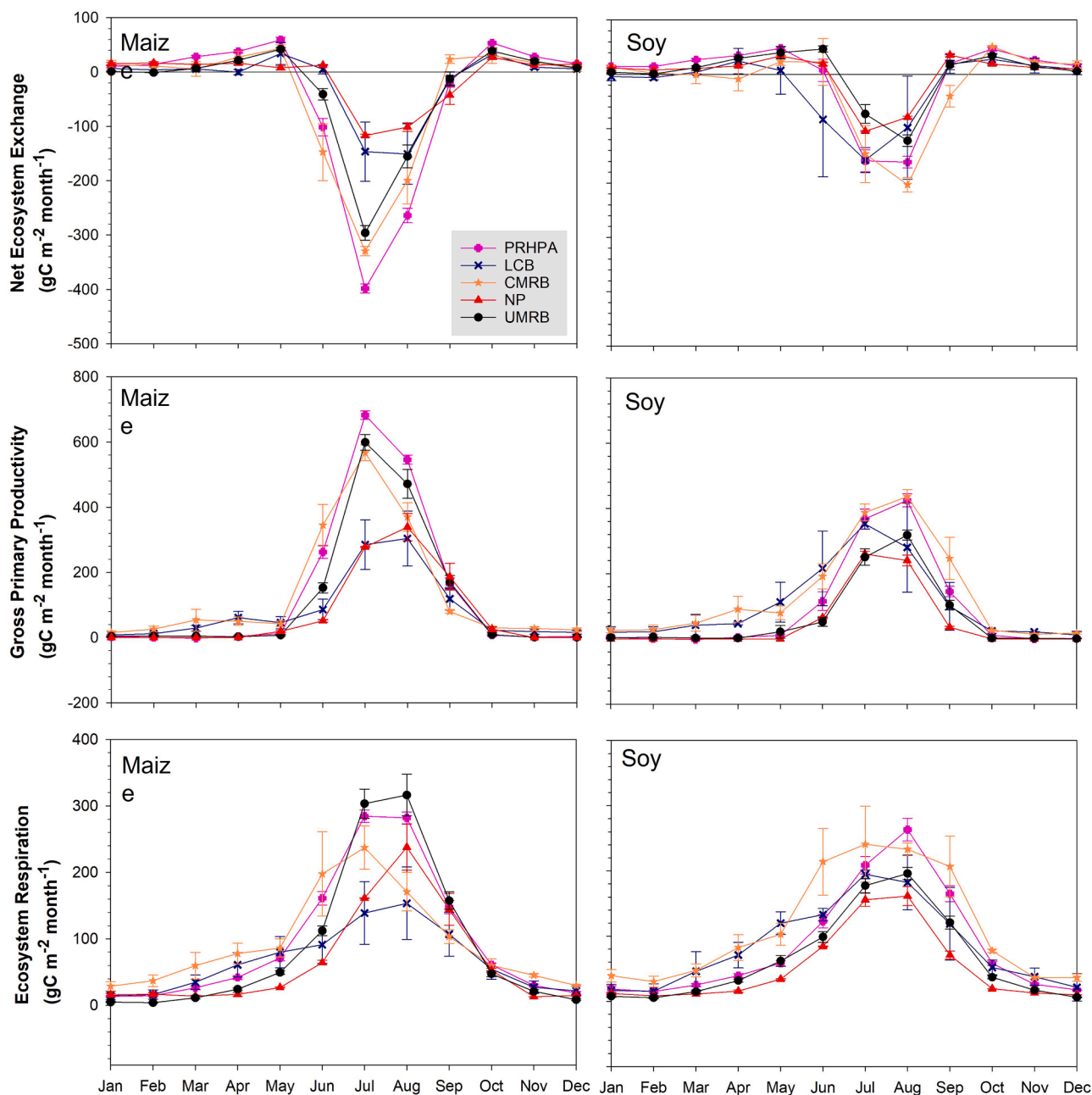


Fig. 3. Monthly Net Ecosystem Exchange, Gross Primary Productivity, and Ecosystem Respiration for rotated maize (left) and soybean (right) across LTAR sites. Sites with maize / soybean rotation were Lower Chesapeake Bay (LCB), Platte River High Plains Aquifer (PRHPA), Upper Mississippi River Basin (UMRB), Central Mississippi River Basin (CMRB), Upper Chesapeake Bay (UCB) and Northern Plains (NP). Legend symbols shown in the top left apply to all images. Error bars show the standard error of the mean.

alternate photosynthesis biochemical pathway that reduces photorespiration losses and increases carbon use efficiency compared to the older C_3 pathway (Sage et al., 2012; Way et al., 2014). C_4 photosynthesis has been shown to take up more carbon per unit of water and light, particularly in warm climates (Anapalli et al., 2019; Ehleringer and Pearcy, 1983; Jansson et al., 2010). The differences between C_3 and C_4 photosynthesis may also partially explain the lower net uptake seen in the bromegrass (C_3) and restored prairie (mixed C_3/C_4) at KBS site; however, the cooler climate at the site and lack of bromegrass biomass harvest, likely also contribute (Abraha et al., 2018, 2019). While alfalfa is a C_3 legume, it is also a perennial and has been selectively bred to produce large amounts of biomass, particularly through a large taproot system. Additionally, other studies have found that alfalfa can produce biomass and uptake C on a similar scale to maize and switchgrass in

ideal conditions, although a much higher portion of biomass is typically harvested multiple times in a year (Alberti et al., 2010; Hallam et al., 2001; Zhang et al., 2011). It is also possible that low sample size (6 years) may be biasing our results in this overview.

The low NEE seen in soybean crops is likely a combined effect of previous crop residue (increasing R_{eco}) and reduced growing season GPP. All soybean crops in the LTAR EC network were grown in rotation with either maize, wheat, or both. Grasses, like maize and wheat, tend to produce more recalcitrant residue (i.e., higher C:N ratio) and larger amounts of residue biomass that takes longer to break down (Cookson et al., 1998; Johnson et al., 2007; Stewart et al., 2015; Vachon and Oelbermann, 2011), meaning that during the soybean years there was likely still residue from the previous maize crop decomposing and contributing to R_{eco} in addition to the residue of the soybean crop itself.

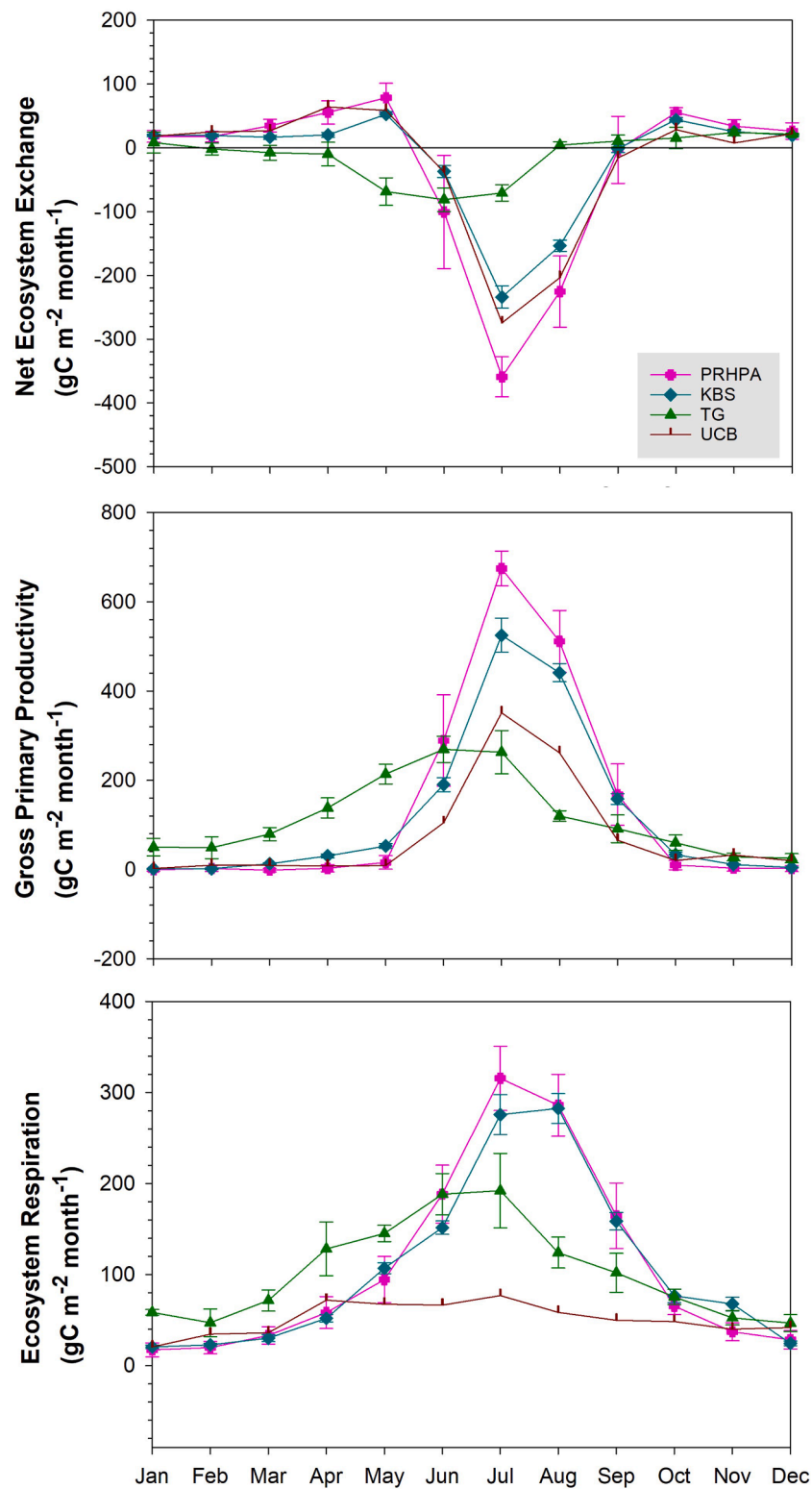


Fig. 4. Monthly Net Ecosystem Exchange, Gross Primary Productivity, and Ecosystem Respiration for continuous maize. Continuous maize was grown at Platte River High Plains Aquifer (PRHPA), Texas Gulf (TG), Kellogg Biological Station (KBS), and Upper Chesapeake Bay (UCB). Legend shown in the top graph applies to all images. Error bars show the standard error of the mean.

The same would be true during garbanzo years of the wheat/garbanzo rotation with wheat having recalcitrant residue like maize. Soybean residue is much more readily available for microbial breakdown due to a low C:N ratio and lower levels of recalcitrant compounds (Broder and Wagner, 1988; Stewart et al., 2015; Vachon and Oelbermann, 2011).

Thus, soybean residue is likely decomposing within the soybean year, in addition to the previous crop residue. The impacts of residue quantity and composition on C fluxes is a question for further research within the LTAR EC network. Additionally, soybean (and related crops, i.e., garbanzo) tends to produce less biomass and uptake C at a lower rate than

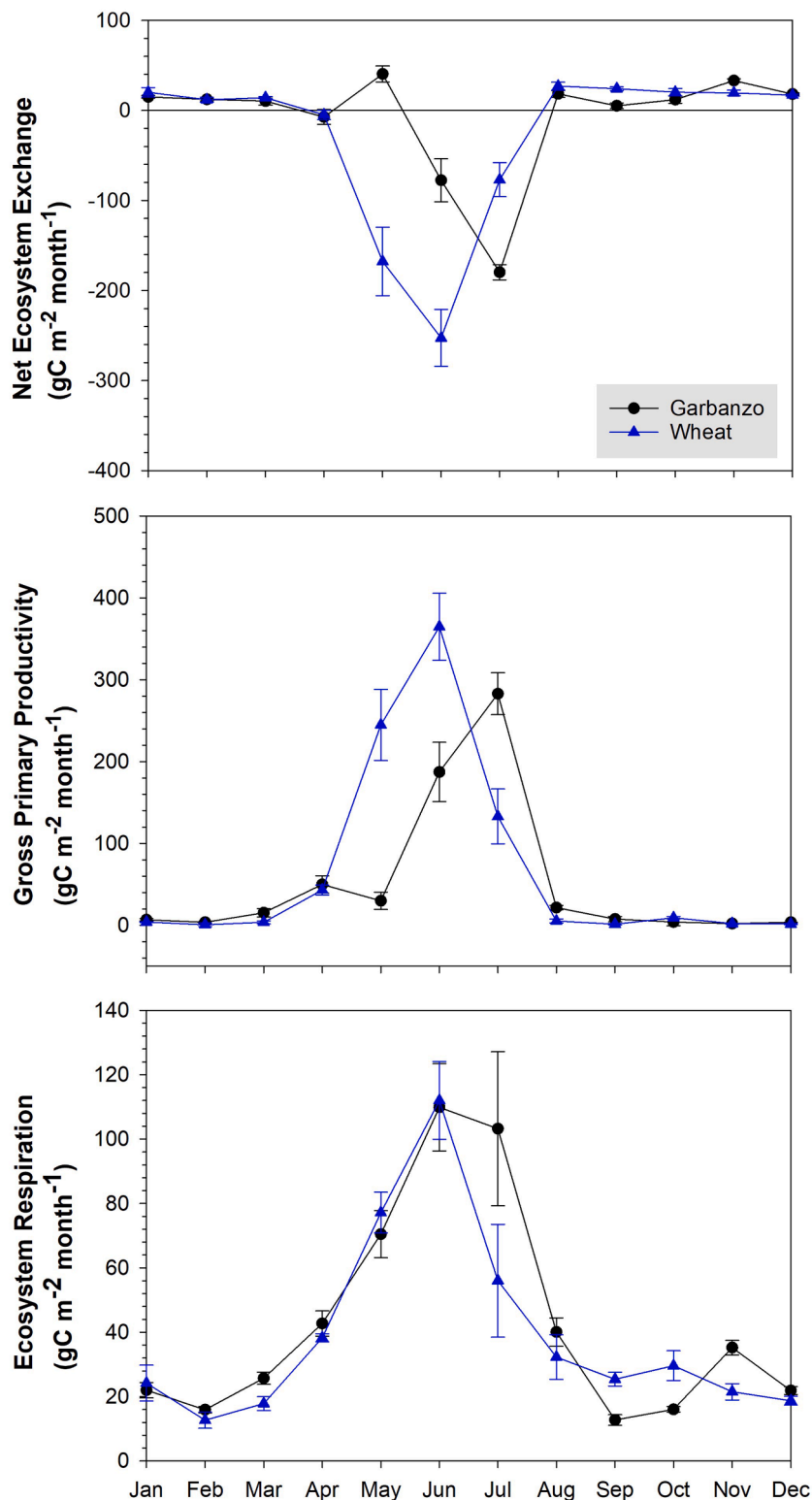


Fig. 5. Monthly carbon fluxes (Top: Net Ecosystem Exchange, Middle: Gross Primary Productivity, Bottom: Ecosystem Respiration) for a wheat/garbanzo system at the Cook Agronomy Farm site in Pullman, Washington. Legend in top graph applies to all three graphs. Error bars show the standard error of the mean.

crops like maize, leading to relatively low GPP (Bybee-Finley et al., 2017; Dold et al., 2017; Suyker and Verma, 2010). While years with soybean have less net carbon uptake when compared to maize years in a rotation cycle, soybean crops contribute to the sustainability of agroecosystems by fixing nitrogen and improving soil fertility for the next grain crop, breaking up pest cycles, and providing a higher protein

product than possible with grain crops (Barthès et al., 2004; Hazra et al., 2019; Hutchinson et al., 2007; Kumar et al., 2019).

3.3 Carbon fluxes and climate

A comparison of annual carbon fluxes with MAT and MAP across all

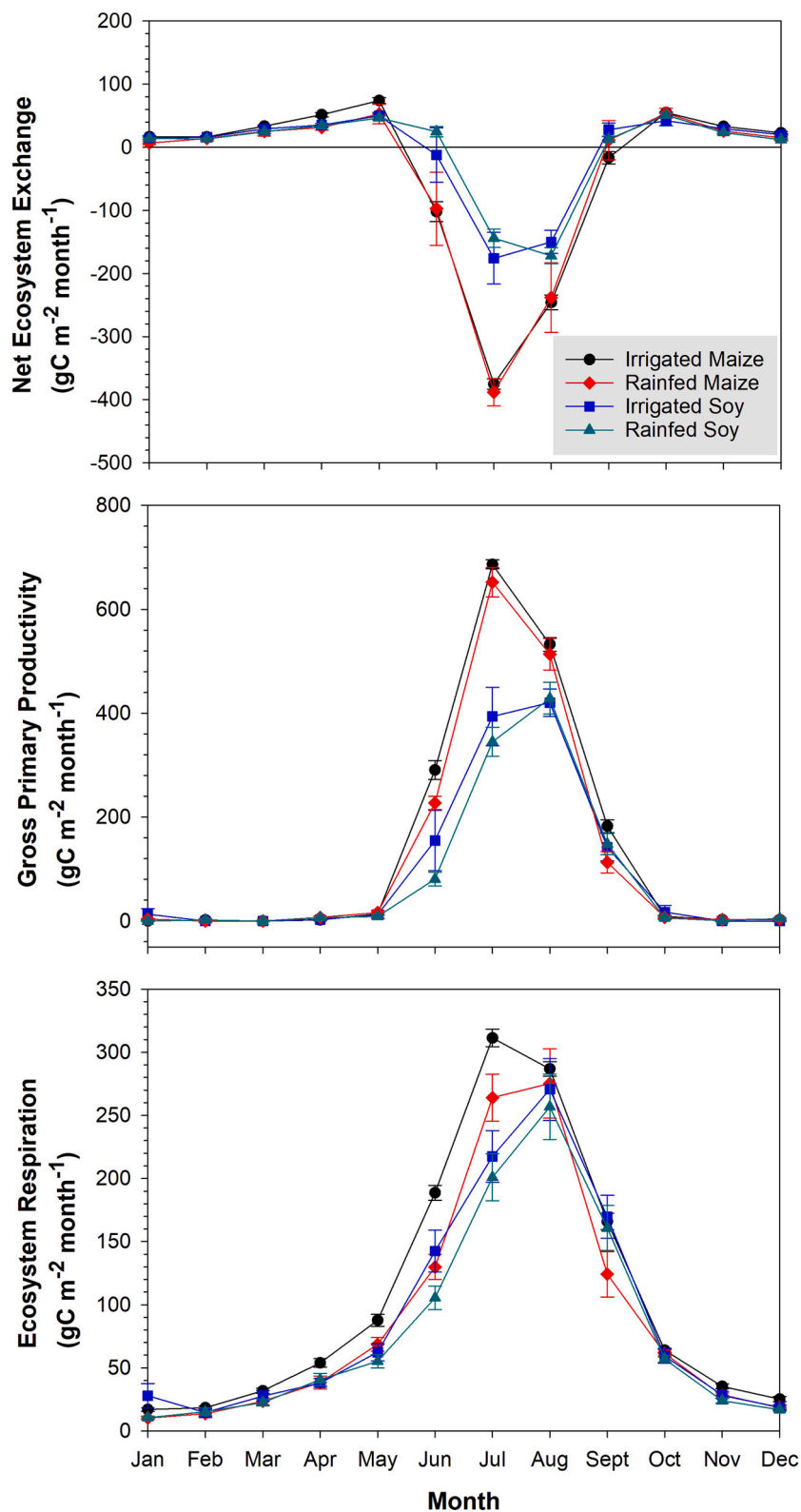


Fig. 6. Monthly Net Ecosystem Exchange, Gross Primary Productivity, and Ecosystem Respiration for irrigated and rainfed maize and soybean at the Platte River High Plains Aquifer LTAR site (A, B, and C, respectively) in Mead, Nebraska. Legend symbols shown in the top image apply to all three images. Error bars represent the standard error of the mean.

sites is shown in Fig. 2. Stepwise regression analysis found strong relationships between MAT and MAP with GPP and R_{eco} , and weaker relationships with NEE . There was a strong positive relationship ($p < 0.001$) between GPP and both MAP and MAT. The relationships between

GPP and climate were stronger when only rainfed sites were included in the analysis and were stronger with MAP (r^2 of 0.30 and 0.39 for all sites and rainfed sites, respectively) than with MAT (r^2 of 0.24 and 0.30 for all sites and rainfed sites, respectively). The analysis with rainfed sites

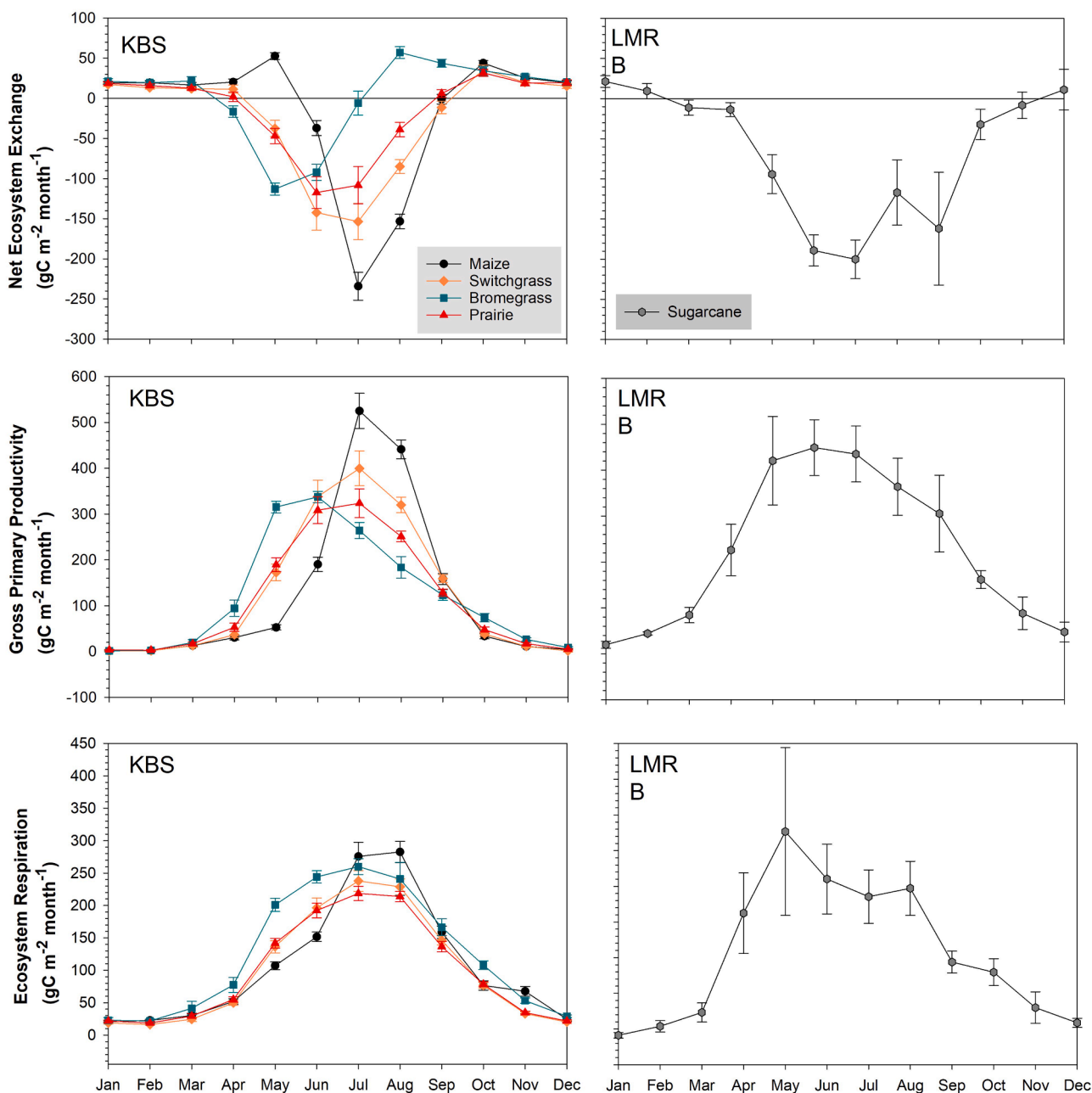


Fig. 7. Monthly Net Ecosystem Exchange, Gross Primary Productivity, and Ecosystem Respiration for biofuel crops at Kellogg Biological Station (KBS) and Lower Mississippi River Basin (LMRB). Legends in top graphs apply to all graphs. Error bars show standard error of the mean.

alone better highlights the significant impact of water availability on crop growth. This finding is not unique, particularly for temperate agroecosystems where water availability is often a limiting factor for crop growth and production (Chi et al., 2017; Dold et al., 2017; Xie et al., 2020; Xu et al., 2019; Zhang et al., 2018). Given the relationship between optimal temperature and plant growth, it is anticipated that MAT is also correlated well with GPP, a finding which is fairly common among ecosystem C flux analysis (Chen et al., 2013; Lu et al., 2017; Xu et al., 2019).

The strongest correlation seen between a climate variable and carbon fluxes was with R_{eco} and MAP in rainfed sites. Like with GPP, the relationship between climate variables and R_{eco} was a highly significant ($p < 0.001$) positive where MAP (r^2 of 0.43 and 0.37 for all sites and rainfed sites, respectively), and was stronger than that with MAT (r^2 of 0.25 and 0.30 for all sites and rainfed sites, respectively). With R_{eco} , separating out rainfed versus all sites had less of an effect. A positive relationship

between R_{eco} and precipitation was reported in other studies as water availability drives microbial activity and plant root respiration (Chimner and Welker, 2005; Jenerette et al., 2008; Wu et al., 2011). In addition to water availability, temperature is a key driver of microbial activity as it sets the rate of cellular respiration, and thus R_{eco} is often well correlated with air and soil temperature across ecosystems (Chi et al., 2017; Li et al., 2020; Chen, 2021; Zhang et al., 2021).

Annual NEE had a weak positive correlation with MAT (all sites r^2 : 0.02, rainfed sites r^2 : 0.03) under individual regression ($p < 0.05$), but no relationship under stepwise regression. While stepwise regression found a weak relationship ($p < 0.05$) between NEE and MAP, this relationship was not significant under individual regression. The weak significance and low correlation between annual NEE and climate variables indicate that, at least within the LTAR network (of mostly temperate and subtropical sites), climate is not the best predictor of NEE . This finding was similar to the findings of Dold et al. (2017) and Chen et al. (2013)

Appendix Table 1

Results of stepwise regression on annual carbon flux sums versus location, climate, and management practices. Significant results to $p < 0.05$ are in bold.

Forward Stepwise						
Independent Variable	NEE		GPP		R _{eco}	
	P-value	F value	P value	F value	P value	F value
Annual Temperature (°C)	0.250	1.332	<0.001	29.853	<0.001	34.616
Annual Precipitation (mm)	0.020	5.551	<0.001	50.146	<0.001	64.281
Irrigation Practice	0.220	1.518	0.087	2.968	0.113	2.531
Tillage Practice	0.259	1.281	0.932	0.007	0.043	4.152
Crop Selection	<0.001	12.278	0.117	2.473	0.803	0.062
Location	0.099	2.755	0.050	3.886	0.283	1.16
Backward Stepwise						
Independent Variable	NEE		GPP		R _{eco}	
	P-value	T test	P value	T test	P value	T test
Annual Temperature (°C)	0.250	1.332	<0.001	29.853	<0.001	34.616
Annual Precipitation (mm)	0.020	5.551	<0.001	50.146	<0.001	64.281
Irrigation Practice	0.220	1.518	0.087	2.968	0.113	2.531
Tillage Practice	0.259	1.281	0.932	0.007	0.043	4.152
Location	<0.001	12.278	0.117	2.473	0.803	0.062
Crop Type	0.099	2.755	0.050	3.886	0.283	1.16

Appendix Table 2

Gross primary productivity (GPP, $\text{g C m}^{-2} \text{ yr}^{-1}$) by location for all locations with at least three years of data. Letters indicate significant differences ($p < 0.05$).

Location	Average GPP	GPP Range
LMRB	2647 ± 101 ^A	2480 — 2914
SP	1981 ± 117 ^B	1726 — 2417
CMRB	1667 ± 96 ^{BC}	1253 — 2269
PRHPA	1485 ± 48 ^{CD}	722 — 2086
KBS	1436 ± 33 ^D	762 — 2048
TG	1362 ± 127 ^{CDE}	1105 — 1712
UMRB	1120 ± 75 ^{EF}	620 — 1730
LCB	1087 ± 184 ^{DEFG}	167 — 1309
NP	924 ± 105 ^{FG}	576 — 1453
CAF	711 ± 55 ^G	452 — 904

that *NEE* was more weakly related to climate variables than other components of carbon fluxes. However, this result is not universal and other authors have found *NEE* to be well correlated with air temperature and precipitation (Yi et al., 2010; Wu et al., 2011; Zhang et al., 2018).

When looking at individual sites, for the most part, climate variables were not well correlated, with a few exceptions. At CMRB, annual precipitation was highly positively correlated (r^2 : 0.87) with *NEE*. At LCB, GPP and R_{eco} were both strongly positively correlated with MAT (r^2 : 0.84 and r^2 : 0.75, respectively). Lastly, at KBS, GPP showed a weak positive correlation with MAP (r^2 : 0.12). The variation in annual carbon fluxes with climate contributes to the overall picture of cropland carbon fluxes within the LTAR network, paving the way for further work.

3.4.1: Maize and soybean in rotation

Maize and soybean are the most commonly grown crops in the LTAR network with maize at eight and soybean at five sites. Maize was sometimes grown continuously (PRHPA, KBS, TG, UCB), as a rotation with soybean (PRHPA, UMRB, LCB, CMRB), or in more complex rotations (CMRB, UMRB, NP). Soybean was always grown as a rotation with maize at all sites (PRHPA, LCB, CMRB, NP, UMRB). Monthly carbon

fluxes of maize and soybean in rotation are shown in Fig. 3, with complex rotations being included where maize and soybean were adjacent on the cycle. Monthly carbon fluxes of continuous maize are shown in Fig. 4.

Across maize sites (both rotated and continuous), maximum GPP occurred in June (TG), July (PRHPA, CMRB, UMRB, KBS, UCB), or August (LCB, NP). Across all maize sites 69 - 99% of the uptake occurred between May and September, with TG being a bit of an outlier with high April uptake as expected since maize is typically planted in March at this site. Excluding TG (79% of GPP occurred between April and September), 83 - 99% of GPP occurred between May and September. At PRHPA, where both continuous and rotated maize were studied, maximum monthly GPP was slightly higher in rotated maize compared to continuous ($683 \pm 13 \text{ g C m}^{-2} \text{ mo}^{-1}$ and $675 \pm 39 \text{ g C m}^{-2} \text{ mo}^{-1}$, respectively), although the error estimates overlapped, indicating that the difference is not significant. Maximum R_{eco} occurred in July (PRHPA, CMRB, TG, UCB) or August (LCB, NP, UMRB, KBS). At PRHPA, R_{eco} was greater with continuous maize, although error estimates overlapped, indicating insignificance. Across all sites, 52 - 89% of R_{eco} occurred between May and September. Maximum net uptake (negative *NEE*) occurred in June (TG), July (PRHPA, KBS, UCB, CMRB, NP, UMRB), or August (LCB), depending on the site. At PRHPA, maximum uptake was greater at the rotated sites ($-398 \pm 8 \text{ g C m}^{-2} \text{ mo}^{-1}$) compared to continuous ($-351 \pm 31 \text{ g C m}^{-2} \text{ mo}^{-1}$). Soybean crops can improve subsequent maize crop yield and growth by fixing nitrogen and breaking up pest cycles (Carsky et al., 2000; Crookston et al., 1991; Ennin and Clegg, 2001; Omay et al., 1998), which appears to be reflected in the trend seen at PRHPA.

With soybean, maximum GPP occurred in July (LCB, NP) and August (PRHPA, CMRB, UMRB). Most (84 - 100%) of the GPP occurred between May and September. Maximum R_{eco} occurred in July (LCB, CMRB) and August (PRHPA, NP, UMRB). The majority (82 - 89%) of R_{eco} occurred between the months of April and September. High R_{eco} often occurred before planting, likely a continuation of microbial breakdown from the previous year's maize residue. Maximum net uptake occurred in July (LCB, NP) and August (PRHPA, CMRB, UMRB). Net uptake was seen in all sites in July and August, in September at CMRB, and in June at LCB.

For the PRHPA, UMRB, and NP sites, soybean years had lower maximum monthly GPP than maize years at the same site, which was also reported in other studies (Dold et al., 2017; Verma et al., 2005). In contrast, soybean at the LCB site had similar GPP to maize at the same site, with error estimates overlapping. Soybean R_{eco} was only slightly less than that of maize, and typically increased earlier in the growing season, both likely due to carry over effects of crop residue where maize residue was still decomposing during the soybean year as previously discussed. Several authors have found that a substantial amount (20 - 50%) of maize residue was still in the field after one year (Grandy et al., 2013; Vachon and Oelbermann, 2011; Verma et al., 2005; Xu et al., 2017; Abraha et al. 2021). The net result of the differences in GPP and R_{eco} between the crops was a smaller net annual carbon uptake in soybean years compared to maize years at all sites except LCB.

3.4.2: Wheat and garbanzo at Cook Agronomy Farm

Monthly *NEE*, GPP, and R_{eco} of a wheat/garbanzo rotation system at Cook Agronomy Farm (CAF) followed similar trends to that seen in maize/soybean systems (Fig. 5). Cumulative *NEE* was greater for wheat ($-365 \pm 40 \text{ g C m}^{-2} \text{ yr}^{-1}$) than for garbanzo ($-113 \pm 48 \text{ g C m}^{-2} \text{ yr}^{-1}$). Net carbon uptake occurred between April and July for wheat and garbanzo, with maximum net uptake occurring in the month of June for wheat ($-252 \pm 32 \text{ g C m}^{-2} \text{ mo}^{-1}$) and July for garbanzo ($-179 \pm 8 \text{ g C m}^{-2} \text{ mo}^{-1}$). The maximum monthly cumulative GPP occurred in June for wheat and was greater than that of garbanzo, which occurred in July. Wheat GPP exceeded that of garbanzo in May ($245 \pm 87 \text{ g C m}^{-2} \text{ mo}^{-1}$ versus $30 \pm 21 \text{ g C m}^{-2} \text{ mo}^{-1}$) and June ($365 \pm 82 \text{ g C m}^{-2} \text{ mo}^{-1}$ versus $187 \pm 73 \text{ g C m}^{-2} \text{ mo}^{-1}$), with the reverse occurring in July ($133 \pm 67 \text{ g C m}^{-2} \text{ mo}^{-1}$ for wheat versus $283 \pm 51 \text{ g C m}^{-2} \text{ mo}^{-1}$ for garbanzo), and all other months had similar GPP between the two crops. Maximum R_{eco}

occurred in June for both crops ($103 \pm 48 \text{ g C m}^{-2} \text{ mo}^{-1}$ for garbanzo and $112 \pm 24 \text{ g C m}^{-2} \text{ mo}^{-1}$ for wheat) and remained high in July for garbanzo ($110 \pm 27 \text{ g C m}^{-2} \text{ mo}^{-1}$), but rapidly declined for wheat ($56 \pm 35 \text{ g C m}^{-2} \text{ mo}^{-1}$). However, it is important to keep in mind that this analysis was performed for a single site with specific climate and soil conditions; these trends in carbon flux with crop rotation might not apply to a similar system in a different setting.

3.4.3: Irrigated and rainfed crops at Platte River High Plains Aquifer

Monthly *NEE*, *GPP*, and *R_{eco}* for maize and soybean at the PRHPA LTAR site varied with both irrigation practice and crop species (Fig. 6). In both crops, C fluxes followed the same seasonal trend regardless of irrigation status, with maximum carbon uptake occurring in July for maize and August for soybean. Maximum monthly *GPP* was higher for irrigated maize ($687 \pm 9 \text{ g C m}^{-2}$) than for rainfed ($652 \pm 15 \text{ g C m}^{-2}$), as was maximum monthly *R_{eco}* (311 ± 7 and $275 \pm 18 \text{ g C m}^{-2}$, respectively). Monthly *NEE* was similar between the rainfed and irrigated maize. With soybean, maximum monthly *GPP* (August) was not different between irrigated and rainfed, however, July *GPP* was higher in the irrigated treatment ($394 \pm 56 \text{ g C m}^{-2}$) compared to the rainfed treatment ($345 \pm 28 \text{ g C m}^{-2}$). Minimal differences for *NEE* and *R_{eco}* between irrigated and rainfed soybean were noted. When comparing soybean and maize years at this site, the same trend as discussed earlier was apparent. Average soybean *GPP* was 66% of maize *GPP* in both irrigated and dryland treatments. Soybean crops maintained net carbon uptake for a shorter period of time (2.6 months) compared to maize (3.7 months). Meanwhile, average *R_{eco}* was 84% and 91% of maize *R_{eco}*, in irrigated and rainfed soybean, respectively. Given that increased water availability through precipitation enhances *GPP* due to increased plant growth (Chi et al., 2017; Dold et al., 2017; Xie et al., 2020) and increases *R_{eco}* through enhanced microbial activity (Chimner and Welker, 2005; Jenerette et al., 2008; Wu et al., 2011), it is unsurprising that irrigation has a similar impact. The effect of increased *GPP* with irrigation has also been well documented (e.g., Doughty et al., 2018; Patnaik and Biswal, 2020; Ryan et al., 2017). However, this analysis was performed for a single location with specific climate and soil conditions, meaning that this pattern of carbon flux with irrigation differ in other agroecosystems.

3.4.4. Production of biofuel feedstocks

Crops often linked to biofuel production were grown at the KBS and LMRB sites, and maize, a common biofuel feedstock, was grown at many sites. At KBS, two lignocellulosic feedstock crops, switchgrass and restored prairie, were grown alongside maize with the intention of comparing them as biofuel feedstocks, and a CRP non-harvested bromegrass as a reference. At LMRB, sugarcane, a high-biomass feedstock, was grown. Monthly carbon fluxes of the KBS and LMRB crops (including maize) are shown in Fig. 7. At KBS, given that all fields are in close proximity, the differences observed are primarily due to site management, with maize an annual crop and the others perennial. The greatest difference in *NEE* among the four systems occurred in May, when there was a net carbon uptake in bromegrass, switchgrass, and restored prairie (-113 ± 7 , -37 ± 10 , and $-47 \pm 10 \text{ g C m}^{-2}$, respectively) and *R_{eco}* in maize ($53 \pm 4 \text{ g C m}^{-2}$). Maximum *GPP* occurred in July for maize, switchgrass, and restored prairie and in June for bromegrass. Maximum monthly *GPP* was greatest in maize ($525 \pm 38 \text{ g C m}^{-2}$), followed by switchgrass ($400 \pm 38 \text{ g C m}^{-2}$) and bromegrass ($337 \pm 12 \text{ g C m}^{-2}$), and lowest in restored prairie ($324 \pm 32 \text{ g C m}^{-2}$). Maximum *R_{eco}* occurred in July for bromegrass, switchgrass, and restored prairie and in August for maize with the greatest monthly respiration in maize ($283 \pm 16 \text{ g C m}^{-2}$) and lower, but equivalent respiration among switchgrass ($238 \pm 16 \text{ g C m}^{-2}$) and bromegrass ($260 \pm 12 \text{ g C m}^{-2}$), and restored prairie ($219 \pm 11 \text{ g C m}^{-2}$). At LMRB with sugarcane, greatest net uptake occurred in July ($-200 \pm 24 \text{ g C m}^{-2}$), greatest *GPP* occurred in June ($449 \pm 61 \text{ g C m}^{-2}$), and greatest *R_{eco}* occurred in May ($327 \pm 118 \text{ g C m}^{-2}$). *GPP* exceeded *R_{eco}* from March through November, with *R_{eco}* dominating *GPP* in December, January, and

February.

Many of these biofuel feedstocks exhibited net negative *NEE* annually. However, the net carbon balance (and thus source/sink status) of the system depends on the amount of biomass removed as well (Qin et al., 2018). As long as harvested biomass carbon is less than net uptake, the biomass systems can operate as net carbon sinks, which is likely in the perennial systems (Abraha et al., 2018, 2019). While this analysis only includes two biofuel sites with widely differing climates, limiting its utility alone, this result is commonly found in the literature. Studies of full life cycle analysis of biomass crop production have found that these systems can be net carbon sinks (Abraha et al., 2019; Adkins et al., 2019; McGowan et al., 2019; Qin et al., 2014; Sprunger and Robertson, 2018) or net carbon sources (Abraha et al., 2019; DeCicco et al., 2016; Liska et al., 2014; Zhao et al., 2020). Qin et al. (2018) found that while standard biomass or feedstock production was a net source, the addition of cover crops changed the system to a net sink. The impact of biomass production on soil carbon balance has also been shown to depend on previous land use and land conversion (e.g., Abraha et al., 2019; Mello et al., 2014) and in temperate perennial grasses (Harris et al., 2015). Monitoring of carbon through EC can guide management decisions regarding the amount of biomass to harvest versus the amount to return to the soil (De Kleine et al., 2017; Lindorfer et al., 2014; Qin et al., 2014).

4: Limitations and potential for future study

This initial characterization of cropland carbon flux data within the LTAR network has produced an overview that will be useful for future studies. The large quantity of data available via LTAR and other data sharing networks like LTER, AmeriFlux, EuroFlux, ChinaFlux, USCCC, NEON, and OzFlux provide many opportunities for expanding our understanding of terrestrial carbon fluxes. While this study focused solely on the cropland portion of the LTAR network, the grazinglands portion of the network represents an additional avenue for understanding carbon fluxes in food production systems. The LTAR data are also potentially useful as inputs or as training data for modeling efforts, including both process-based models like DSSAT or APSIM and empirical models using newer methods, like machine learning. Networks such as LTAR allow for a better understanding of carbon fluxes over broader regions than possible with single-site studies, making them invaluable for our continued effort in studying agricultural carbon dynamics.

Observed carbon fluxes result from the complex processes of climate on plant photosynthesis, plant respiration, and microbial respiration, which depend on many environmental and management factors (Chen, 2021). Soil quality and inputs of water, nitrogen and carbon in particular can affect carbon fluxes (Abraha et al., 2018b; Azeem et al., 2019; Guttières et al., 2021; Jiang et al., 2012); Guttières et al. (2021) found that *R_{eco}* was related to the chemistry of carbon residue in addition to the quantity of available soil carbon. We observed moderate effects of climate on residue decomposition, which contributes to the carbon balance of agroecosystems. Including soil-based climatic drivers of residue fate in future studies, such as soil temperature and soil moisture, might provide further insight. Incoming plant-available radiation has also been shown to affect crop carbon fluxes (Oliveira et al., 2018; Wagle et al., 2019; Yan et al., 2009). Additional potential drivers that were not included in this analysis include soil water content, soil carbon and nitrogen content, and incoming solar radiation (Guo et al., 2021; Guttières et al., 2021; Jiang et al., 2012; Klumpp et al., 2011; Skinner, 2013). Also, differences in vegetation metrics (e.g., leaf area index, vegetation indices, biomass) and crop yield were also not considered. Future studies with these sites will explore these drivers.

5: Conclusion

Across the LTAR network, both management and weather patterns had substantial impacts on carbon fluxes. Precipitation had a greater influence on *GPP* and *R_{eco}* than did air temperature, but both were

positively correlated with carbon fluxes. However, these climatic variables were less correlated with *NEE*. For cropping systems in the conterminous U.S., crop selection was more correlated than climate with carbon source/sink status. High biomass grass crops, including sugarcane and maize, were more frequently carbon sinks than were low biomass legume crops such as soybean and garbanzo. Despite being a legume, alfalfa fluxes followed a pattern more like that seen in maize than in other legumes studied (soybean, garbanzo, clover). At most sites, maize had greater carbon uptake and was more frequently a carbon sink when compared to soybean; the LCB site was an exception to this, with minimal difference seen between maize and soybean. At the KBS biofuel production site, all biofuel crops were frequently net carbon sinks while uncultivated conservation land remained near-neutral. At the PRHPA site, crop type (maize or soybean) was more correlated to carbon fluxes than the precipitation regime. The garbanzo-wheat rotation at the CAF site followed a similar trend in carbon fluxes to the maize-soybean rotation at other sites. However, some of the sites had more data than others, biasing results in favor of those sites. This along with differing management and instrumentation between sites creates some potential for error, but it is a common issue for network-scale eddy covariance studies. Although these results should be interpreted cautiously, the long-term sites in the LTAR network should continue to provide insights into the effects of management and climate on ecosystem carbon fluxes and source/sink status.

Data Availability Statement

Data for non-Ameriflux sites are available on request to the lead author.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2022.109154.

Appendix A. Impact of Location on Carbon Fluxes

A stepwise regression with location as predictor was also run (Appendix Table 1), however due to concerns over a potential correlation with climate variables and crop selection, this analysis was

not included in the primary manuscript. However, it does show the potential for site-related variability, so it was included as an appendix.

There was a weak correlation between annual GPP and LTAR site (Appendix Table 2). Given that both climate and crop type were also correlated with carbon fluxes, it is possible that the relationship of carbon fluxes to location is partially related to the variation in climate and cropping systems across sites. The LMRB site (sugarcane) stood out for high gross and net C uptake compared to other sites. As previously discussed, this is the warmest and wettest site and was planted to a highly productive crop. Following LMRB, CMRB and SP also had fairly high GPP and were warmer sites with sufficient precipitation. The lowest GPP occurred at LCB, NP, and CAF. CAF and NP were relatively cool dry sites, while LCB had a large degree of year-to-year variability, overlapping with both low and moderate uptake sites. Given the way that climate and typical management practices vary across the United States, the significant impact of location on fluxes may be a partial artifact of local climate and typical management practices.

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