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Responses of gross primary production of grasslands and croplands under drought, pluvial, and irrigation conditions during 2010–2016, Oklahoma, USA

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ABSTRACT

To accurately estimate the terrestrial carbon cycle and food production, it is essential to understand how gross primary production (GPP) of irrigated and non-irrigated grasslands and croplands respond to drought and pluvial events. This study analyzed annual GPP of irrigation-permitted and non-permitted grasslands, winter wheat (*Triticum aestivum* L.), other C3 croplands, and C4 croplands in Caddo County of western Oklahoma from 2010 through 2016, a period which consisted of extreme drought (2011) and pluvial events (2015). First, we compared GPP from the Vegetation Photosynthesis Model (GPP_{VPM}) and GPP data from the Moderate Resolution Imaging Spectroradiometer (GPP_{MOD17}) with GPP estimates from three eddy covariance towers (GPP_{EC}) in Oklahoma. GPP_{VPM} more accurately estimated mean daily GPP_{EC} at each of the three sites than GPP_{MOD17}. Second, we analyzed the seasonal and interannual dynamics of GPP_{VPM} for eight pixels, one each for the four irrigation-permitted and non-permitted land types. The interannual variation of GPP_{VPM} was due to the complexity of decision making and practice for irrigation, cropping intensity, and crop types. Finally, at the county scale, annual GPP_{VPM} from the 2011 drought and pluvial 2015 were compared with mean annual GPP_{VPM} from the other 5 years of the study period. The results show that for the 2011 drought: 1) non-permitted C4 croplands had the largest percentage decrease in GPP, but permitted C4 croplands had the smallest decrease; 2) regardless of water rights, GPP was significantly lower than the 5-year reference mean for grasslands, winter wheat, and other C3 crops; and 3) non-permitted lands were more affected by drought than irrigation-permitted lands, except for grasslands, which had similar percentage reductions in GPP. Results for the pluvial year 2015 show that: 1) GPP was significantly higher for grasslands, winter wheat, and non-permitted C3 croplands than the 5-year reference mean, but there was no significant difference in GPP for irrigation-permitted C3 croplands or non-permitted C4 croplands; and 2) GPP for C4 irrigation-permitted croplands was lower than the 5-year reference mean. Crop-specific responses to drought and pluvial events largely depend on a landowner's ability to irrigate, and caution should be used when assessing or generalizing how crops respond to climate variability, drought, and pluvial conditions in the absence of irrigation-related data.

1. Introduction

Drought can severely reduce forage, hay, crop, and livestock production, resulting in economic losses, reduced employment, and increased commodity prices that have spillover effects into other non-agricultural markets (Ziolkowska, 2016). Similarly, flooding and heavy precipitation events can cause crop damage and reduce yields (Rosenzweig et al., 2002). However, sustainable food production needs more knowledge about landscape-scale, crop-specific responses to drought and pluvial events and the role of irrigation in those responses to changes in climate. Recent studies have used MODIS and Landsat data products to estimate crop yield at large spatial scales (Doraiswamy et al., 2004; Xin et al., 2013), but they did not consider a water management component because it is largely unknown how crops respond to irrigation at the landscape scale (Yuan et al., 2015). More

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specifically, He et al. (2018) expected that more specific model calibrations for irrigated and non-irrigated crops would increase the precision of their crop yield estimates.

Although national agricultural survey and economic data can give us insight into how extreme weather events and changes in climate have affected crop-specific yields and market prices, such data does not provide wisdom on the physiological responses of vegetation to drought and pluvial events at high temporal or spatial resolution. Similarly, meteorological drought indices, such as the Palmer Drought Severity Index (PDSI) (Palmer, 1965) and the Standardized Precipitation Index (SPI) (McKee et al., 1993), are widely used as indicators of drought, but they do not measure plant productivity. Agricultural drought indices, such as the Crop Moisture Index (CMI) (Palmer, 2010), often use soil moisture to indicate drought, but they are not an explicit indicator of vegetation stress and fail to capture variances in soil moisture due to irrigation at the field scale. Satellite-based remote sensing vegetation indices (VIs), such as the greenness-related Enhanced Vegetation Index (EVI) (Huete et al., 1997; Justice et al., 1998; Huete et al., 2002), and water-related VIs such as Normalized Difference Water Index (NDWI) (Gao, 1996) and Land Surface Water Index (LSWI) (Xiao et al., 2004; Zhou et al., 2017b), have been used as proxies for several biophysical and biochemical variables such as plant response to drought (Wagle et al., 2014; Bajgain et al., 2015; Bajgain et al., 2016) and rainfall (Chandrasekar et al., 2010), leaf area index (Boegh et al., 2002), canopy chlorophyll content (Blackburn, 1998; Gitelson et al., 2005), and gross primary production (the total amount of carbon fixed by plants) (Wagle et al., 2015). However, satellite-based remote sensing techniques have not yet been developed to capture landscape-scale irrigation activities with high accuracy at interannual timescales (Masoner et al., 2003; Ozdogan et al., 2010). Thus, irrigated and non-irrigated crop-specific responses to drought and pluvial events remain unknown at large spatial scales.

The response of vegetation to drought and pluvial events are not only determined by external factors such as temperature, precipitation, and sunlight, but also by the species' photosynthetic pathways. Generally, plants with the C3 photosynthetic pathway are less drought-resistant than plants that perform C4 photosynthesis (Tilman and Downing, 1994; Nayyar and Gupta, 2006). Previous studies have shown that C4 plants (1) have a higher quantum yield (Ehleringer et al., 1997), or light use efficiency (LUE) (Haxeltine and Prentice, 1996; Xiao, 2006; Chen et al., 2011), in that they can fix more CO_2 per photon absorbed by chlorophyll than C3 plants; and (2) have a higher water use efficiency (WUE) (Hsiao and Acevedo, 1974; O'Leary, 1988), in that they can fix more CO_2 per molecule of water than C3 plants. Thus, the response of a monoculture to drought and pluvial events are expected to differ for C3 or C4 crop species (Chaves et al., 2003), and the response of grasslands depends upon the ratio of C3 to C4 species in the grassland community (Tilman and Downing, 1994).

In this study, we hypothesized that the responses of grassland, winter wheat (*Triticum aestivum* L.), other C3 cropland, and C4 cropland to drought and pluvial events are largely determined by their respective photosynthetic pathway and landowners' ability or inability to irrigate. The specific objective of this study was to analyze the response of gross primary production (GPP) for irrigated and non-irrigated grasslands, winter wheat, other C3 croplands, and C4 croplands in Caddo County, Oklahoma (Fig. 1) to the 2011 drought and pluvial 2015.

2. Materials and methods

For our analysis, we used four datasets each year from 2010 to 2016: (1) satellite-based GPP data from the Vegetation Photosynthesis Model (GPP_{VPM}) (Jin et al., 2015; Zhang et al., 2017); (2) the MODIS GPP product (GPP_{MOD17}) (Running and Zhao, 2015); (3) the Cropland Data Layer (CDL); and (4) irrigation permit data from the Oklahoma Water Resources Board (OWRB). Our analysis included three main steps: (1) we compared GPP estimates at three eddy flux towers (GPP_{EC}) placed in sites with native grassland, old world bluestem pasture (*Bothriochloa caucasica* C.E. Hubb.), and winter wheat in El Reno, Oklahoma, with GPP_{VPM} and GPP_{MOD17}; (2) we compared 8 day, intra-annual GPP_{VPM} estimates in 2011, 2013, and 2015 for eight 500 m pixels, one each for irrigation-permitted and non-permitted grasslands, winter wheat, other C3 croplands, and C4 croplands in Caddo County; and (3) we analyzed the responses of each land cover type at the county scale to the 2011 drought and pluvial 2015. For steps 2 and 3, we determined which 500 m GPP_{VPM} pixels were suitable for study in each year 2010–2016 using the workflow illustrated in Fig. 2.

2.1. Study area

The state of Oklahoma, located in the Southern Great Plains of the United States (US), has been characterized as being in a region with reoccurring periods of drought (Basara et al., 2013; Christian et al., 2015), heavy rainfall events (McCorkle et al., 2016), high variability in precipitation (Weaver et al., 2016), and increased climate variability (Flanagan et al., 2017b). For Oklahoma, a period of prolonged drought began in 2011 (Fernando et al., 2016; Flanagan et al., 2017a) and persisted for most of the state until May 2015 when it was broken by record amounts of precipitation (Oklahoma Climatological Survey, 2015). Thus, these dipolar climate events in Oklahoma provided a suitable region in which we were able to conduct our study.

We selected a Caddo County, Oklahoma as our pilot study area because it has a high concentration of both irrigation-permitted and non-permitted land (Fig. 3(a)) and the county experienced the extreme climate events of 2011 and 2015. Apart from a brief break in the drought in the spring of 2012, no less than 60% of Caddo County was in climatological drought for 4.5 years, from January 2011 to May 2015 (Fig. 4). Entering 2015, 100% of the county was in drought. However, 2015 became the wettest year on record for Caddo County with precipitation of 1285 mm as recorded by the Fort Cobb Mesonet station in Caddo County, beating the old record set in 1923 by 61 mm (Oklahoma Climatological Survey, 2017a).

The predominant geologic formation in the study area is the Permian-age Rush Springs formation, which is composed of cross-bedded, fine-grained sandstone with some dolomite and gypsum beds ranging from 57 to 91 m in thickness (Becker and Runkle, 1998). Soils in Caddo County are characterized as dark and loamy with clayey to loamy subsoils developed on Permian shales, mudstones, sandstones and/or alluvial deposits under tall grasses (Carter and Gregory, 2008).

Caddo County largely overlies the Rush Springs Aquifer, a bedrock aquifer that has provided adequate flow for irrigation in the northern portion of the county. The Rush Springs Aquifer is the second most developed aquifer in the state after the Ogallala Aquifer (Oklahoma Water Resources Board, 2012). Some irrigation wells have been reported to produce over 3785 L of water a minute, and daily crop irrigation water use (159 million liters) accounts for 77.8% of daily water withdrawals on average (Becker and Runkle, 1998). Due to the accessibility of groundwater from the Rush Springs Aquifer and the high density of irrigation-permitted lands, Caddo County ranked third in the state of Oklahoma for area of land permitted for irrigation (438 km^2) as a proportion of the county's total land area (13.1%) in 2016. There were 1062 active permits in the county for irrigation during the 2016 planting season. The total area of land in the county dedicated to active irrigation permits was 43.5% of the county's total cropland area (1006 km^2) (Oklahoma Water Resources Board, 2017).

Natural vegetation types in Caddo County are primarily tallgrass prairie dominated by little bluestem (*Schizachyrium scoparium*) and post oak-blackjack forest (Hoagland, 2000; Johnson and Luza, 2008). The grasslands classification used in our study includes native prairies, improved pastures, hay fields, and open herbaceous spaces as classified by the Cropland Data Layer (CDL). Average annual temperature and precipitation for Caddo County are 16 °C and 816 mm, respectively (Oklahoma Climatological Survey, 2017a). Most of the precipitation falls in late spring and early summer, with May and June being the wettest months, and the average growing season is 208 days in length (Oklahoma Climatological Survey, 2017b).

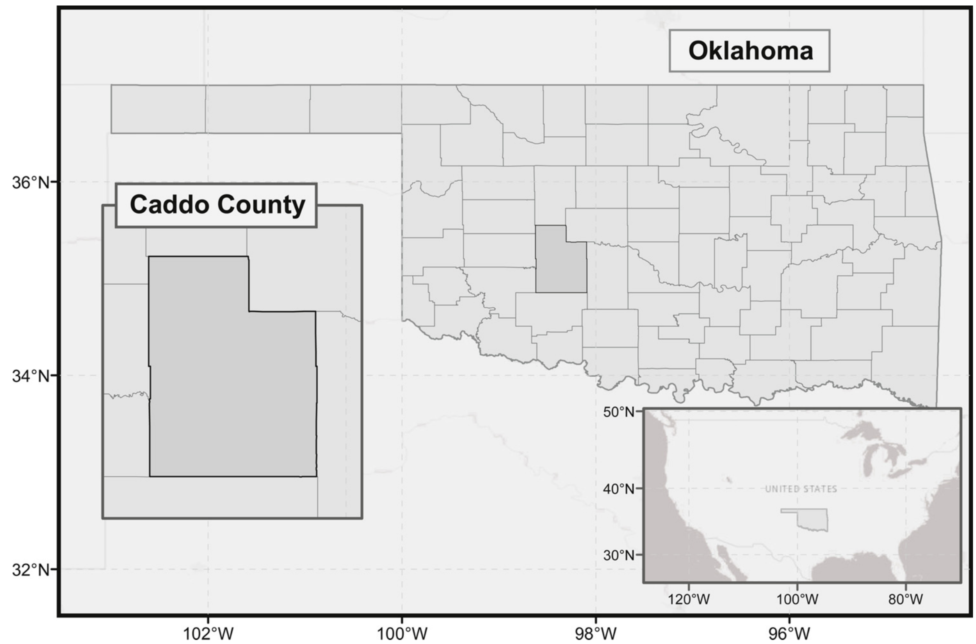

Fig. 1. Location of Caddo County, Oklahoma, United States.

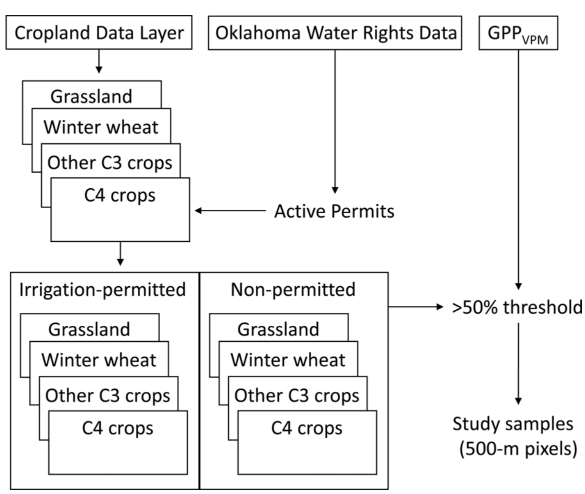

Fig. 2. The workflow used to determine which 500 m pixels were a majority irrigation-permitted and non-permitted grasslands or croplands for each year 2010–2016.

Caddo County has been an important contributor to Oklahoma's agricultural industry. In 2016, Caddo County ranked second among all counties in sheep inventory (2000 head) and third in beef cattle (49,000 head) and hog inventories (60,000 head). The county ranked sixth in acres of cotton (12,600) and sorghum (9900) planted, eighth in acres of alfalfa harvested (4300), twelfth in acres of other harvested hay (50,000), and thirteenth in the number of acres planted for wheat (173,500) (United States Department of Agriculture National Agricultural Statistics Service Oklahoma Field Office, 2017).

2.2. Data and preprocessing methods

2.2.1. Cropland Data Layer (CDL) 2010–2016

The Cropland Data Layer (CDL) is produced annually by the United States Department of Agriculture (USDA) to provide acreage estimates to the Agricultural Statistics Board for the state's major commodities. The first CDL dataset became available for Oklahoma in 2007. The spatial resolution of the data layer was 56 m from 2007 to 2009, but beginning in 2010 the resolution was 30 m. Thus, this study uses CDL data from 2010 to 2016 so that interannual comparisons can be made at the same spatial resolution. The overall accuracy of the CDL dataset for Oklahoma ranges from 80.3% in 2014–92.2% in 2012, and annual crop-specific accuracies are reported for the dominant crops in Caddo County in Table 1 as published in the CDL metadata (https://www.nass.usda.gov/Research_and_Science/Cropland/metadata/meta.php). For a complete list of crop type classifications, see Table S1.

The CDL dataset incorporates non-agricultural land cover types (e.g., grasslands) from the National Land Cover Database (NLCD), which is updated every 5 years. In 2014, all CDL datasets were recoded by combining Pasture/Grass, Grassland Herbaceous, and Pasture/Hay categories into a single category named Grass/Pasture (United States Department of Agriculture National Agricultural Statistics Service, 2017) due to inconsistencies and large margins in error when attempting to break grasslands into different categories (Wickham et al., 2013; Wickham et al., 2017). The CDL Grass/Pasture category for 2010–2013 was derived from the 2006 NLCD, and the Grass/Pasture category for 2014–2016 was derived from the 2011 NLCD (United States Department of Agriculture National Agricultural Statistics Service, 2017).

For this study, we grouped the multitude of vegetative land cover types (Table S1) into four categories: grasslands, winter wheat, other C3 croplands, and C4 croplands. Pixels in which double-cropping occurred in a year were excluded from the study. Winter wheat was considered separately from the other C3 crops because winter wheat is the dominant cropland type in the region and the crop has a different growing season and irrigation regime relative to other C3 crops. More specifically, winter wheat was expected to respond differently to drought than crops planted in the spring and summer months, which are characterized by high temperatures and low amounts of precipitation. Crops with the C3 photosynthetic pathway were expected to respond differently to water and temperature stress than C4 crops given the greater LUE and WUE of C4 plants (Ehleringer et al., 1997; Epstein et al., 1997).

The spatial distribution of grasslands, winter wheat, other C3 croplands, and C4 croplands for 2016 in Caddo County are illustrated in Fig. 3(b,c). According to the 2016 CDL, Caddo County was approximately 49% grassland, 31% cropland, 11% forest and shrubland, 6% developed, 2% fallow and barren, 1% open water, and 0.02% wetland. The county's croplands were dominated by winter wheat, which constituted 85% of the total single-cropland area, with other C3 and C4

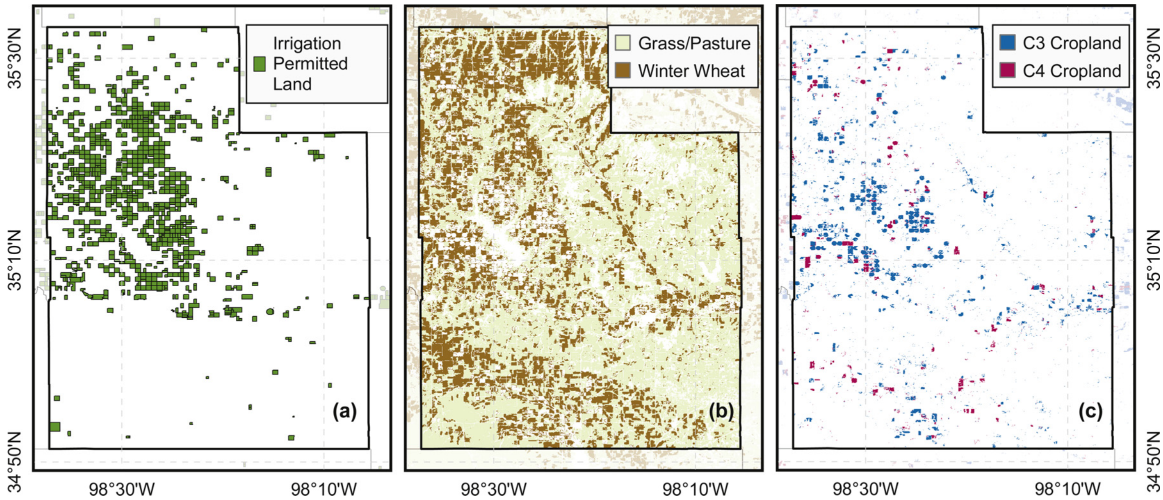

Fig. 3. Spatial distribution of (a) irrigation-permitted land, (b) grass/pasture and winter wheat, and (c) C3 and C4 croplands in Caddo County.

crops comprising 11% and 3.5% of the cropland area, respectively. Double-crop systems were 3.4% of the total cropland area. The predominant C3 crops among those classified by the CDL were cotton, canola, alfalfa, and rye. Corn and sorghum were the only C4 crops.

2.2.2. Water rights data during 2010–2016

The Oklahoma Water Resource Board (OWRB) provided a geospatial vector dataset that is updated monthly and documents all statewide groundwater and surface water rights permits. Applicants for any type of water right must declare whether water will be used for public water supply, recreation, livestock, irrigation, or some other use. Groundwater right applicants must dedicate one acre to their water rights permit for each two acre-feet they wish to utilize each year but are not required to report where the water will be used. For groundwater irrigation permits issued after 1973, the well supplying the groundwater must be located on the dedicated land. Thus, it is generally assumed that the water will be used on the land dedicated to the water rights permit due to the added cost of transporting water from its source.

Applicants seeking surface water rights for irrigation, on the other hand, must report the land boundaries in which the water will be used, and they cannot apply for more than 2 acre-feet/year (0.25 ha-m/year) of water for each acre they intend to irrigate. Given these rules, we assume that the lands dedicated to a groundwater permit or lands reported as the area of use on a surface water permit accurately reflect the boundary in which irrigation is expected to occur. The OWRB does not actively monitor each permit in the field to assess whether a permit holder is exercising their right to withdraw water, nor do they meter water use due to the extensive cost of obtaining such data. Thus, there is no comprehensive information on who used water or how much water they used in a year.

The OWRB's geospatial vector (polygon) dataset was used to create annual datasets of all active irrigation permits for 2010–2016. For a permit to be listed in an annual dataset, it must meet the following conditions: 1) for new permits, the permit must be granted by the end of the planting season for all non-winter wheat crops (August 1st each year); 2) for existing permits, the permit must not have become inactive or have an expiration date prior to the end of the planting season for all non-winter wheat crops; 3) permits must have a valid issue date (not null); 4) inactive or expired permits must have a valid date of deactivation or expiration (not null); and 5) permits must not be temporary or special. Temporary permits are only valid for 90 days, and special permits are valid for 6 months and cannot be renewed for the same water-use purpose. Thus, these two permit types were not considered to be reliable, consistent sources of irrigation at large spatial scales and were excluded from the study.

After preprocessing, the annual active irrigation permit database was used to select 500 m pixels that were a majority (> 50%) irrigation-permitted grassland, winter wheat, other C3 cropland, or C4 cropland. Pixels representing non-permitted lands were defined as pixels that did not contain any irrigation-permitted land but were a majority (> 50%) of one of the four land cover types. These two thresholds ensured that the 500 m pixels were mutually exclusive, and that the same pixel wasn't representative of both irrigation-permitted and non-permitted land. The total number of pixels for each irrigation-permitted and non-permitted land cover type 2010–2016 used in our analyses is reported in Table 2.

2.2.3. Climate data during 2010–2016

The climate data used in this study originated from the Oklahoma Mesonet (https://www.mesonet.org), which is a world-class network of 121 automated environmental monitoring stations. There is at least one Mesonet observation tower in each of Oklahoma's 77 counties, three of which are in Caddo County. We calculated the aridity index (AI) for each year from 1979 to 2016 using data gathered at the Fort Cobb Mesonet station (Brock et al., 1995; McPherson et al., 2007), which is near the geographic center of

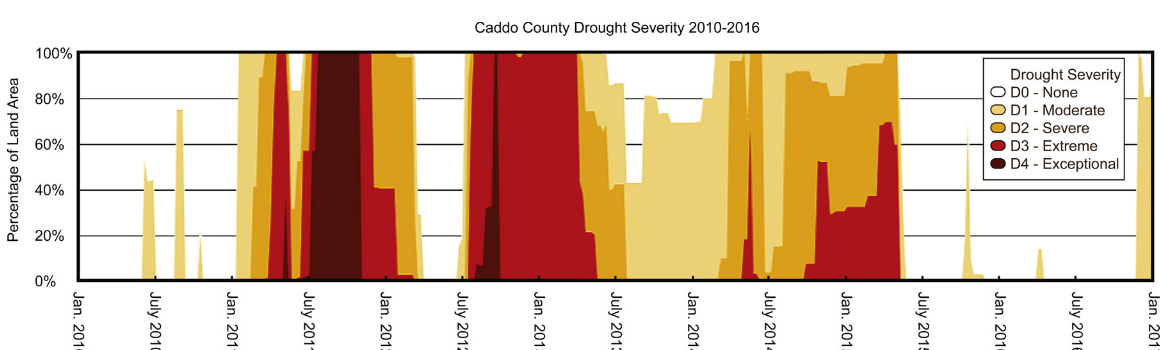

Fig. 4. Drought severity for Caddo County and the Upper Washita River Watershed 2010–2016. Adapted from United States Drought Monitor (2017).

Table 1
Overall and crop-specific accuracies of the Oklahoma Cropland Data Layer (CDL) 2010–2016 as reported in the CDL metadata. PA is producer's accuracy, and UA is user's accuracy rounded to the nearest 1%.

	C3 Crops										C4 Croplands				
Year	Winter Wheat		Cotton		Canola		Alfalfa		Rye		Corn		Sorghum		Overall
	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA	UA	
2010	92	95	89	85	71	96	78	84	67	59	89	90	68	73	84
2011	92	93	79	78	68	91	68	83	57	64	89	90	51	64	83
2012	95	97	92	90	97	94	92	94	80	77	93	97	82	86	92
2013	94	93	80	78	71	84	83	85	64	65	90	85	72	71	83
2014	90	93	93	78	80	71	79	76	69	54	89	89	75	71	80
2015	96	92	86	81	71	92	80	87	48	73	89	91	82	82	86
2016	96	90	87	82	77	98	82	88	54	76	93	92	79	81	85

Table 2
The total number of 500 m pixels (samples) used in our study for each irrigation-permitted and non-permitted land cover type 2010–2016.

Cover Type	2010		2011		2012		2013		2014		2015		2016		Total Obs.
	Perm.	Non.	Perm.	Non.	Perm.	Non.	Perm.	Non.	Perm.	Non.	Perm.	Non.	Perm.	Non.	
Grassland	396	6862	359	6516	350	6663	359	6762	356	6862	298	6428	292	6399	48,902
Winter Wheat	471	1840	504	2148	417	2277	528	2269	509	1908	585	2302	570	2261	18,589
C3 Cropland	124	154	167	123	196	158	126	115	133	134	135	91	138	89	1883
C4 Cropland	4	18	12	29	5	32	54	90	15	56	16	48	18	50	447
Total	995	8874	1042	8816	968	9130	1067	9236	1013	8960	1034	8869	1018	8799	69,821

Caddo County, using the equation:

$$AI = \frac{P}{PET} \tag{1}$$

where AI is aridity index, P is annual total precipitation, and PET is mean annual potential evapotranspiration (Middleton and Thomas, 1992). Annual departures from mean annual precipitation and aridity index for 1979–2016 (Fig. 5), as recorded by the Ft. Cobb Mesonet station, illustrate the high variability in climate that is characteristic of our study area.

For our study period 2010–2016, we identified 2011 as the most arid year, 2015 as the most humid year, and 2013 as a relatively normal year. Thus, for our site level analyses, we defined 2011 as the drought year, 2015 as the pluvial year, and 2013 as a normal year. For our county-level analyses, we considered the combination of 2010, 2012, 2013, 2014, and 2016 as a baseline to which the 2011 drought and pluvial 2015 could be compared.

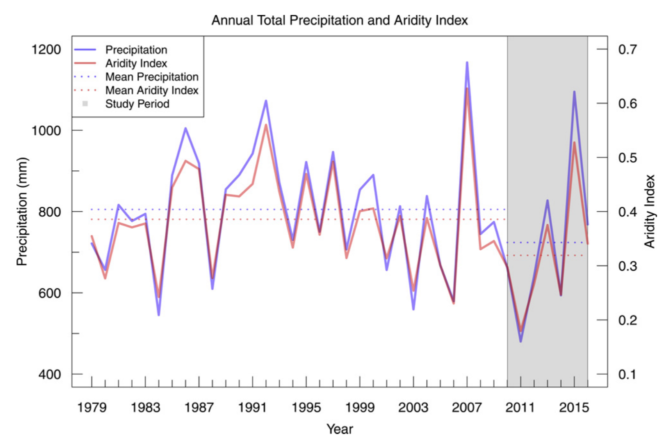

Fig. 5. Annual precipitation and aridity index recorded at the Fort Cobb Mesonet station in Caddo County 1979–2016. The shaded area represents the study period 2010–2016 and the dashed lines are the means for their respective period.

2.2.4. GPP simulations from the vegetation photosynthesis model during 2010–2016

The Vegetation Photosynthesis Model (Xiao et al., 2004) was used to estimate annual total gross primary production (GPP_{VPM}) for 2010–2016 at 500 m spatial resolution. The model partitions the fraction of absorbed photosynthetically active radiation (fPAR) by vegetation into PAR absorbed by chlorophyll ($fPAR_{chl}$) and non-photosynthetic vegetation ($f\mathrm{PAR}_{NPV}$) to estimate GPP of vegetation over the growing season. Thus, GPP_{VPM} is a product of $fPAR_{chl}$, PAR, and light-use efficiency (ε_g):

$$GPP_{VPM} = fPAR_{chl} \times PAR \times \varepsilon_g \tag{2}$$

where $fPAR_{chl}$ value is estimated as a function of the Enhanced Vegetation Index (EVI), calculated from spectral data obtained from the space-borne Moderate Resolution Imaging Spectroradiometer (MODIS) platform (Zhang et al., 2016; Zhang et al., 2017).

The ratio of C3 to C4 plants affects primary production at any given location (Ehleringer et al., 1997; Epstein et al., 1997). Thus, this study calculated average GPP_{VPM} at 8 day intervals for each 500 m MODIS pixel using the ratio of C3/C4 vegetation using the CDL and in-situ derived maximum light-use efficiencies of C3 (0.035 mol CO_2 mol^{-1} PAR) and C4 (0.0525 mol CO_2 mol^{-1} PAR) plants as detailed by Zhang et al. (2017). Thus, GPP_{VPM} for each pixel was calculated as:

$$GPP_{VPM} = \sum_i f_i \times \varepsilon_i \times fPAR_{chl} \times PAR \tag{3}$$

where f_i and εi are the area fraction and light-use efficiency, respectively, for C3 and C4 croplands. Annual GPP_{VPM} was calculated from the 8 day dataset by multiplying each year's multi-day average observation by the number of days observed and summing the totals.

2.2.5. MOD17 GPP dataset during 2010–2016

The 8 day, 500 m GPP_{MOD17} data used in this study was from the MOD17A2H version 6 product (Running et al., 2004). The version 6 product has been improved by using updated Biome Property Look Up Tables (BPLUT) and an updated version of the daily Global Modeling and Assimilation Office (GMAO) meteorological data (Running and Zhao, 2015). The GPP_{MOD17} product also uses a LUE model to estimate GPP. The primary difference between GPP_{MOD17} and GPP_{VPM} is that GPP_{MOD17} uses $FPAR_{canopy}$, which is calculated as the fraction of photosynthetically active radiation absorbed by the canopy (Running et al., 2004), whereas GPP_{VPM} uses $FPAR_{chl}$, which is the fraction of photosynthetically active radiation absorbed by chlorophyll (Xiao et al., 2004). GPP_{MOD17} uses the $FPAR_{canopy}$ data product (MOD15A2H) and GPP_{VPM} uses $FPAR_{chl}$

estimated from the enhanced vegetation index (EVI).

2.2.6. In-situ GPP data from eddy covariance towers

GPP data from two Integrated Grassland Observation Sites (iGOS), iGOS-East (35.54865°N, 98.03759° W) and iGOS-West (35.54679°N, 98.04529° W), and data from the Integrated Cropland Observation System (iCOS) (35.56850° N, 98.05580° W) were used to evaluate GPP_{VPM} and GPP_{MOD17}. These three flux towers are located at the United States Department of Agriculture's Agricultural Research Service (USDA-ARS) Grazinglands Research Laboratory (GRL) in El Reno, Oklahoma. iGOS-East is a native tallgrass prairie, iGOS-West is an old world bluestem (*Bothriochloa caucasica* C. E. Hubb.) pasture that is bailed and grazed by cattle throughout the year (Zhou et al., 2017a), and iCOS is a single-crop winter wheat site.

These three sites use Li-COR 7500 open path gas analyzer and a CSAT3 sonic-anemometer to measure the net ecosystem exchange of CO_2 between land and the atmosphere (NEE). The measured NEE was first gap-filled and then partitioned into GPP and ecosystem respiration (ER) based on the short-term temperature sensitivity of ER (Lloyd and Taylor, 1994; Reichstein et al., 2005). The partitioned half-hourly GPP data was summed to get daily GPP, which was converted into 8 day means to match the temporal resolution of GPP_{VPM} and GPP_{MOD17} data. Our study utilized all years for which GPP data was available from the three towers (GPP_{EC}). The GPP_{EC} data were available for the entire years of 2015 and 2016 for iGOS-East; 05/08/2014–12/31/2014, 01/08/2015–10/25/2015, and the entire year 2016 for iGOS-West; and the entire year 2015 and 01/01/2016–9/30/2016 for iCOS. Simple linear regression analyses were conducted between GPP_{VPM} and GPP_{EC}, and between GPP_{MOD17} and $GPP_{EC,}$ for each tower site in each year to assess the accuracy of GPP_{VPM} and GPP_{MOD17}.

2.3. Statistical data analyses

Eight 500 m pixels from the GPP_{VPM} dataset were chosen from within the study area to illustrate field-scale seasonal dynamics and interannual variation of GPP during the 2011 drought, normal 2013, and pluvial 2015. One pixel was chosen for each of the irrigation-permitted and non-permitted land cover types (grassland, winter wheat, other C3 croplands, and C4 croplands). We made these choices by first filtering potential sites by determining which lands had the same vegetative cover in each of the three years by using the CDL datasets for 2011, 2013, and 2015. Next, we calculated the percentage cover of each land type using a fishnet of 500 m pixels and selected those pixels that had the highest amount of cover. The irrigation-permitted C3 crop pixel was a cotton field, and the non-permitted C3 crop pixel was alfalfa. Both C4 pixels were corn fields.

For each permitted and non-permitted land cover type, we computed the percentage departure of GPP during the 2011 drought and pluvial 2015 from the 5-year reference mean using the following steps. First, we calculated mean GPP for the reference years by averaging annual GPP from 2010, 2012, 2013, 2014, and 2016. Second, annual GPP for the 2011 drought and pluvial 2015 was calculated. Third, the 5-year reference mean was subtracted from mean annual GPP in 2011 and 2015 to calculate the deviation from the mean. Finally, the resultant differences between annual GPP in 2011 and 2015 and the mean annual GPP during the reference years were divided by the 5-year reference mean to compute the percentage departure from the 5-year reference mean.

Permitted and non-permitted sample sizes for each plant type in each year were independent, unequal, and assumed to have unequal variances. Thus, to determine whether the departure from the 5-year reference mean in 2011 or 2015 was statistically significant, a Welch's two-sample *t*-test (Ruxton, 2006; Delacre et al., 2017) was performed for each irrigation-permitted and non-permitted land cover type (Table S2). Welch's two-sample *t*-tests were also conducted to explore whether there was a significant difference between GPP in the 2011 drought or pluvial 2015 for irrigation-permitted and non-permitted lands of each land cover type (Tables S3 and S4).

3. Results

3.1. A comparison of GPP_{VPM}, GPP_{MOD17}, and GPP_{EC} at the three eddy flux tower sites during 2014–2016

GPP_{VPM} more accurately estimated mean daily GPP_{EC} at each of the three GRL sites than GPP_{MOD17}. More specifically, GPP_{VPM} had less underestimation and greater R^2 values than GPP_{MOD17} (Fig. 6). The VPM model performed best at the native prairie site (iGOS-East), where GPP_{VPM} slightly underestimated GPP_{EC} in 2015 and 2016. Performance at the winter wheat site (iCOS) was similar with slight under estimations of GPP_{EC} in both 2015 and 2016. GPP_{VPM} had larger underestimations of GPP_{EC} at the old world bluestem site (iGOS West) relative to the other two sites, but GPP_{VPM} had a greater ability to predict GPP_{EC} than GPP_{MOD17} at each site. The close correlation between GPP_{VPM} to GPP_{EC} at eddy tower sites near our study area indicated that GPP_{VPM} was suitable for use at larger spatial scales.

The seasonal dynamics and interannual variations of GPP_{EC}, GPP_{VPM}, and GPP_{MOD17} were illustrated in Fig. 7. At the old world bluestem site, GPP_{VPM} underestimated GPP_{EC} throughout most of the 2014, 2015, and 2016 growing seasons. GPP_{VPM} underestimated GPP_{EC} during the early growing season in 2015 at the native prairie site, but overestimated GPP_{EC} during the early growing season in 2016. In both years, GPP_{VPM} tended to overestimate GPP_{EC} near the end of the growing season. At the winter wheat site, GPP_{VPM} tracked GPP_{EC} well in both years, but GPP_{VPM} was phase shifted, which indicated that there might be some type of lag effect. This lag effect is evident to a greater degree for GPP_{MOD17}, especially in 2016 when the peaks for both GPP_{MOD17} and GPP_{VPM} occurred well after the peak in GPP_{EC}.

3.2. Seasonal dynamics and interannual variation of GPP at selected irrigation-permitted and non-permitted sites during 2011 drought, normal 2013, and pluvial 2015

The seasonal dynamics and interannual variation of 8 day mean GPP_{VPM} for eight selected pixels in pair-wise comparison (with irrigation permit, without irrigation permit) are illustrated in Fig. 8. For all eight pixels, regardless of water rights, the 2011 drought caused a shortened growing season with lower mean GPP relative to 2013. Conversely, the growing season of all the sites was prolonged in pluvial 2015 and had higher mean GPP than normal.

The irrigation-permitted grassland field had substantially higher mean GPP_{VPM} during the growing season in 2011 and 2013 than the non-permitted grassland field, but the trends in GPP_{VPM} for these two fields are extremely similar in pluvial 2015 (Fig. 8(a)). Irrigation clearly affects the cropping intensity in the winter wheat pixels (Fig. 8(b)). For the pixel without an irrigation permit, only winter wheat crop was cultivated during the year, with a peak in GPP_{VPM} in mid-April and a harvest in June. For the winter wheat pixel with an irrigation permit, a summer crop rotation was implemented. The seasonal dynamics of GPP also suggested that winter wheat was grown for grain production in 2013 and 2015 but might be grazed in 2011. As for other C3 cropland pixels, the irrigation-permitted cotton site had peak GPP_{VPM} in mid-September with a growing season between mid-July and late October (Fig. 8(c)). GPP_{VPM} in the non-permitted alfalfa field peaked in the spring. We expected a greater difference in the magnitude of GPP_{VPM} for the two C4 cropland pixels in 2011 and 2013 (Fig. 8(d)). The similarity in the trend and magnitude of GPP_{VPM} at these two sites during the drought and normal year suggested that the farmer with an irrigation permit might not have irrigated in these years. In 2015, the irrigation-permitted C4 site had peaks in the spring and again in the fall, which suggested that the site was double cropped, whereas GPP for the non-permitted C4 site had a peak in mid-summer signaling a single crop. The interannual variation of GPP_{VPM} over these eight pixels was clearly due to the complexity of decision making and practice for irrigation, cropping intensity, and crop types.

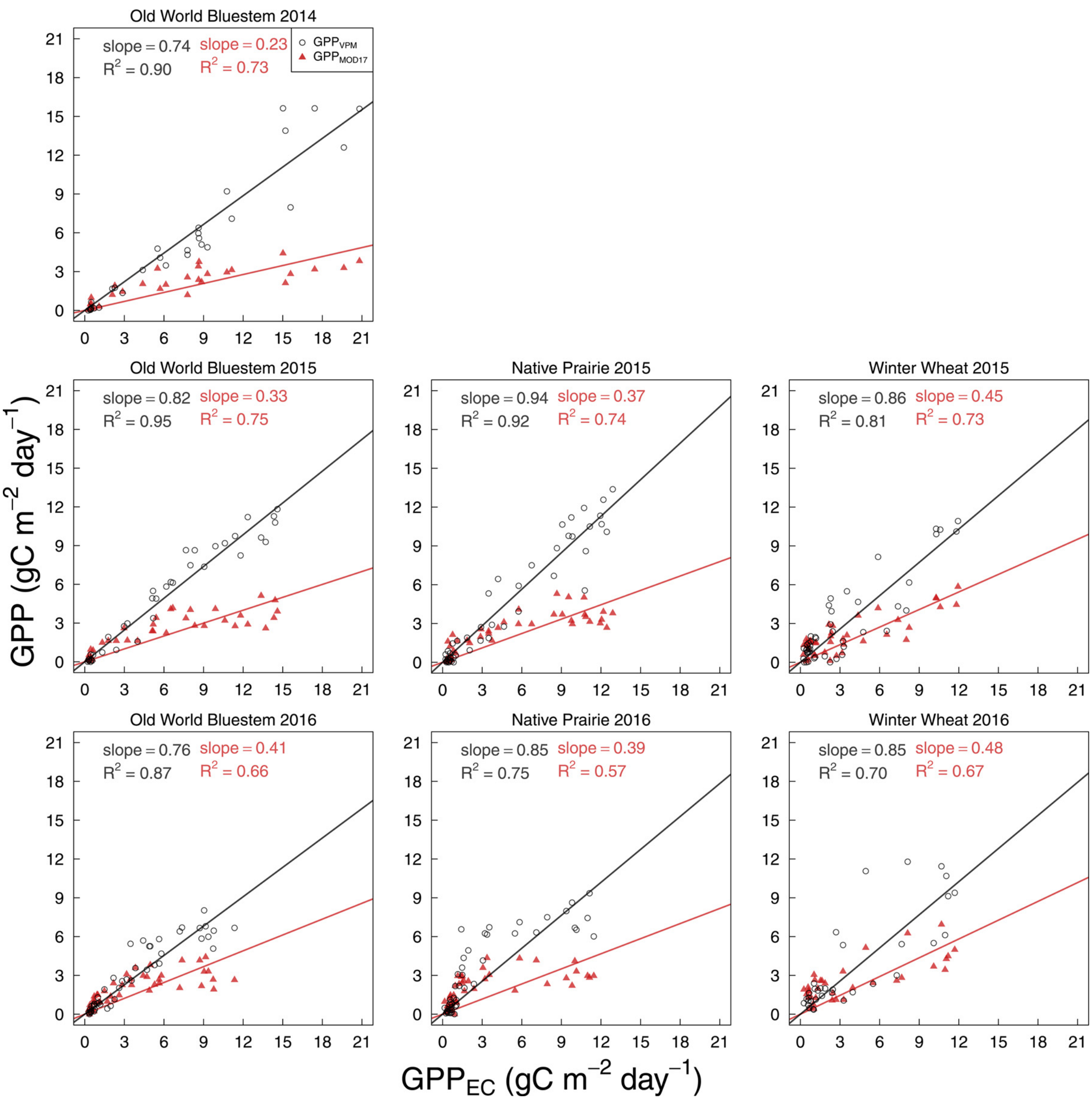

Fig. 6. Simple linear regression of GPP_{EC}/GPP_{VPM} and GPP_{EC}/GPP_{MOD17} at the old world bluestem (iGOS-West), native prairie (iGOS-East), and winter wheat (iCOS) sites in Oklahoma.

3.3. County-scale responses of GPP_{VPM} in drought and pluvial years during 2010–2016

GPP_{VPM} for all land cover types were significantly reduced by the 2011 drought, except for irrigation-permitted C4 croplands (Fig. 9). As for pluvial 2015, grasslands, winter wheat, and non-permitted C3 croplands experienced significant gains in GPP_{VPM} relative to the 5-year reference mean, but the response of GPP_{VPM} for permitted C3 croplands and non-permitted C4 croplands was insignificant. Irrigation-permitted C4 crops were the only land cover type to have a significant reduction in GPP during pluvial 2015. Irrigation-permitted croplands (winter wheat, other C3 croplands, and C4 croplands) had significantly higher mean annual GPP than non-permitted croplands in the 2011 drought, pluvial 2015, and across all years in the study period (Fig. 10).

For the 2011 drought, irrigation-permitted and non-permitted grasslands had similar significant negative departures from the 5-year reference mean (Fig. 11(a)). Likewise, irrigation-permitted and non-permitted grasslands had similar gains in mean GPP for pluvial 2015 relative to the 5-year reference mean. These percentage gains in GPP for pluvial 2015 were the highest among all land cover classes. Interestingly, non-permitted grasslands had slightly higher mean GPP in the 2011 drought (22 gC $m^{-2}year^{-1}$), in pluvial 2015 (18 gC $m^{-2}year^{-1}$), and for the entire study period (36 gC $m^{-2}year^{-1}$) than grasslands permitted for irrigation ($p < 0.05$). Fig. 11(a) also illustrates that GPP for non-permitted lands are relatively normally distributed, whereas GPP for irrigation-permitted grasslands tend to be right-skewed during the 2011 drought.

Reductions in mean annual GPP during the 2011 drought for irrigation-permitted winter wheat were significantly less than that of non-permitted winter wheat (Fig. 11(b)). For pluvial 2015, non-permitted winter wheat had larger increases in GPP relative to the 5-year reference mean (8%) than irrigation-permitted winter wheat (6%). Like grasslands, Fig. 11(b) reflects a normal distribution of GPP for winter wheat, except for the 2011 drought when GPP is right-skewed for lands permitted for irrigation.

The 2011 drought had a significant impact on GPP for irrigation-permitted and non-permitted C3 croplands relative to the 5-year reference mean (Fig. 11(c)), but the response of GPP for irrigation-permitted C3 croplands in pluvial 2015 was not significant and for non-permitted the response was a marginal increase (5%). The distribution of GPP for irrigation-permitted and non-permitted C3 croplands are relatively normal, except for non-permitted C3 croplands during the 2011 drought which is right-skewed. This abnormal distribution could

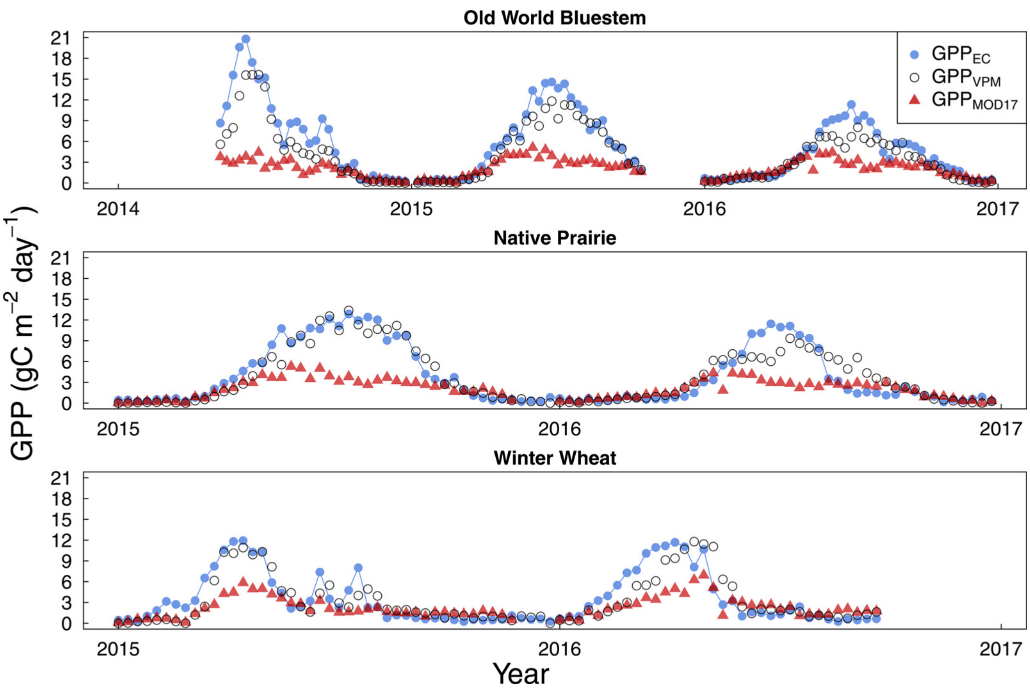

Fig. 7. Eight-day seasonal dynamics and interannual variations of tower-based (GPPEC), VPM-modeled (GPPVPM), and MODIS-modeled (GPPMOD17) gross primary production at the old world bluestem (iGOS-West), native prairie (iGOS-East), and winter wheat (iCOS) sites in Oklahoma.

be caused by differences in how various C3 crop types, such as cotton and alfalfa, respond to drought and/or differences in their growing seasons.

GPP of irrigation-permitted and non-permitted C4 croplands responded very differently to the 2011 drought (Fig. 11(d)). Of all land cover types, non-permitted C4 croplands had the highest percentage drop in GPP from the 5-year reference mean during the 2011 drought, whereas irrigation-permitted C4 croplands had no statistically significant change in mean GPP. There was no significant difference between mean GPP in pluvial 2015 and the 5-year reference mean for non-permitted C4 croplands, but C4 irrigation-permitted croplands experienced a decrease in GPP.

4. Discussion

4.1. Impacts of the 2011 drought on GPP for irrigation-permitted and non-permitted lands

A majority of the irrigation permits in the study area were for groundwater, a water source that is buffered from the effects of drought relative to surface water resources. If our study areas had been in areas irrigated mostly or solely by surface water, then the buffering effect of irrigation during drought may have been muted. For Caddo County, all lands dedicated to irrigation permits tended to have higher productivity than non-irrigated lands during the 2011 drought, except for grasslands.

Responses of GPP for irrigation-permitted and non-permitted grasslands to drought and pluvial conditions were extremely similar at the county scale (Fig. 11(a)). These grasslands could be former croplands on which irrigation occurred in the past, or perhaps some landowners have incorporated pasture and/or grazing into their rotation. The similarity in mean annual GPP for irrigation-permitted and non-permitted grasslands, and the similar response to drought and pluvial conditions, could occur if many of the land owners did not exercise their right to irrigate. This hypothesis appears plausible, given that our site-level analysis demonstrated that GPP_{VPM} captured increased GPP for the irrigation-permitted site during the 2011 drought and normal 2013, and that irrigation was unnecessary in 2015 given the record rainfall totals (Fig. 8(a)).

There are a couple of possible explanations as to why landowners would not exercise their water right on grass or pasture lands. First, market prices could discourage irrigation in that it may not be profitable to irrigate grasslands because the cost of irrigation is not offset by added profits gained from enhanced grass (hay) production. Second, many of the landowners with irrigation permits for grasslands might be raising cattle on that land, which is an agricultural system that may not benefit from irrigation. For instance, studies have shown that grazing cattle on irrigated lands necessitates intensive management (Volesky and Clark, 2003), and that calf gain-weight is higher per acre for dry lot grazing than irrigated pasture grazing (Dunn and Olson, 2009).

As for winter wheat, some studies have shown that irrigation can boost winter wheat harvests, but only when applied in certain amounts shortly before or after planting and/or before harvest if the soil is dry (Peck, 1979; Eck, 1988; Musick and Lamm, 1990). In fact, irrigation can be a risk to winter wheat productivity, especially in the winter months when the crop is dormant (Yonts et al., 2009). Over-irrigation can cause lodging, leaf rust, or mildew (Bennett, 1984; Roelfs, 1992; Al-Kaisi and Shanahan, 1999). Thus, it is possible that winter wheat croplands dedicated to irrigation permits are not necessarily irrigated every year. Rather, access to irrigation for these landowners may afford them an opportunity to double-crop in certain years when weather and commodity prices create favorable conditions (Shapiro et al., 1992; MacKown et al., 2007), or to boost winter wheat yields in years when soil moisture is low.

Expectedly, irrigation-permitted C3 and C4 croplands had smaller reductions in mean annual GPP during the 2011 drought than their non-permitted counterparts. However, our results indicate that the percentage reduction in GPP in 2011 from the 5-year mean was greater for non-permitted C4 croplands than non-permitted grassland, winter wheat, and other C3 croplands. This result was unexpected given, as previously discussed, that C4 plants have a higher light use efficiency, greater water use efficiency, and are more drought-resistant than C3 plants. However, although maize is a C4 plant, it has been shown to be sensitive to high temperature, particularly during tassel, pollination, and grain fill (Muchow, 1990; Muchow et al., 1990; Kim et al., 2007). C4 croplands may have suffered a greater reduction in mean GPP due to stressors in addition to the drought. For example, management practices such as fertilization, planting date, or tilling may have exacerbated

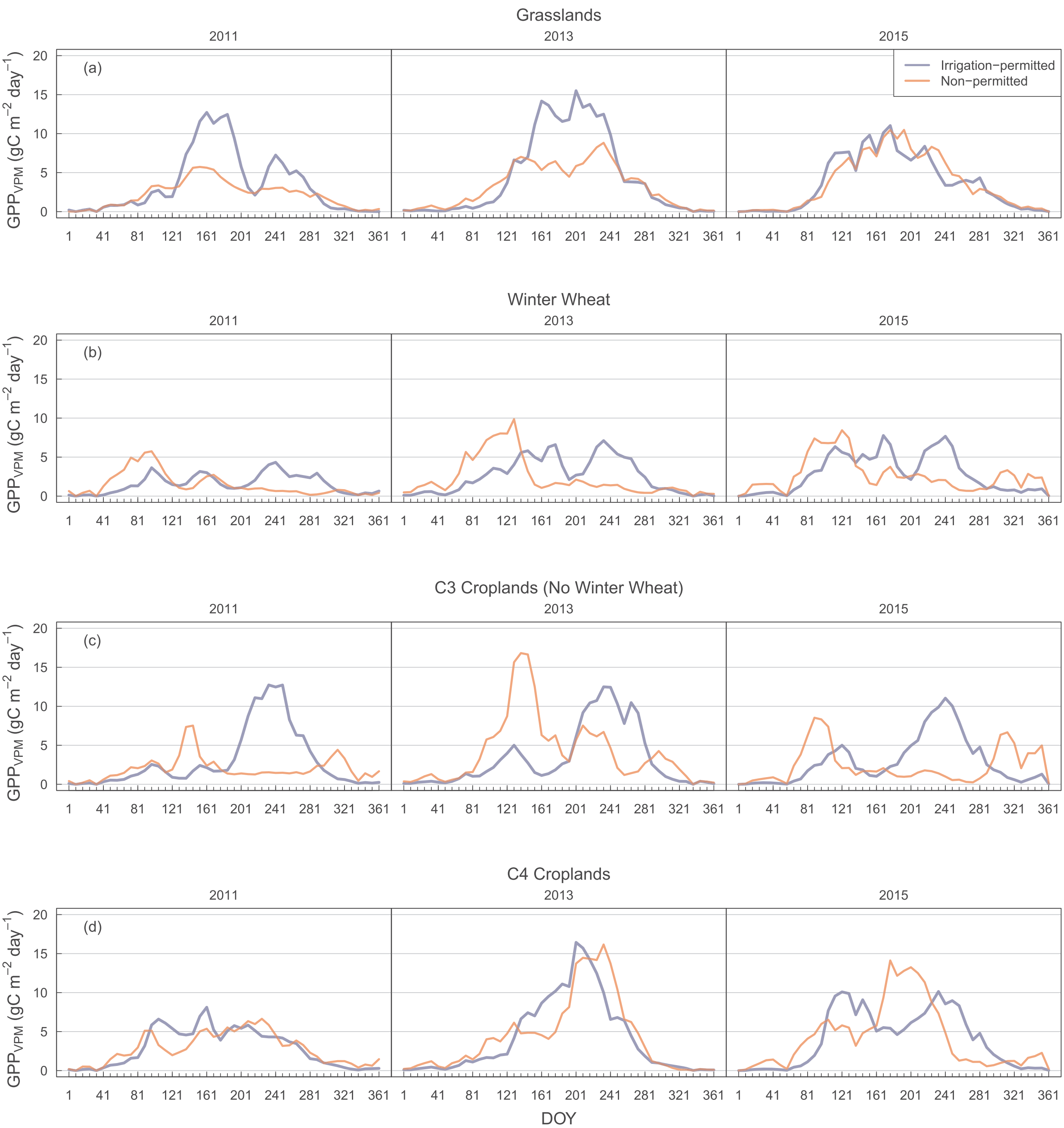

Fig. 8. Pixel-level, 8-day GPP_{VPM} for irrigation-permitted and non-permitted (a) grasslands, (b) winter wheat, (c) other C3 croplands, and (d) C4 croplands in 2011 drought, normal 2013, and pluvial 2015.

the impact of the drought for these non-permitted C4 croplands.

As previously mentioned, the Oklahoma Water Resources Board (OWRB) does not require water meters for groundwater or surface water use. Thus, water managers don't know exactly who has used water or how much water was used. However, future studies may be able to determine which lands were irrigated by monitoring intra-annual and interannual changes in GPP. We demonstrated in our study that the interannual changes in GPP were significantly different for irrigation-permitted and non-permitted croplands, especially during drought (Table S2). Thus, the irrigation-permitted pixels with substantially less annual total GPP than the mean might be considered as non-irrigated lands and those pixels with substantially more GPP than the mean might signal that a landowner was fully utilizing their water permit. Likewise, if the GPP of a pixel during drought is marginally or not significantly different than the GPP of that pixel during non-drought years, then the marginal change in GPP could signal irrigation.

4.2. Impacts of pluvial 2015 on GPP for irrigated and non-irrigated lands

It is not known why mean GPP for non-permitted grassland was slightly higher than irrigation-permitted grassland in 2011, 2015, and the entire study period ($p < 0.05$) (Table S2). Land management practices, such as grazing, bailing, fertilization, and burning can not only influence GPP directly (Fischer et al., 2012; Zhou et al., 2017a), but alter community species composition (Kelting, 1954; Ewing and Engle, 1988; Mitchell et al., 1996; Niu et al., 2013). As previously discussed, it is likely that non-permitted lands are more often grazed by livestock than those lands that are permitted for irrigation. However, it does not seem likely that grazing

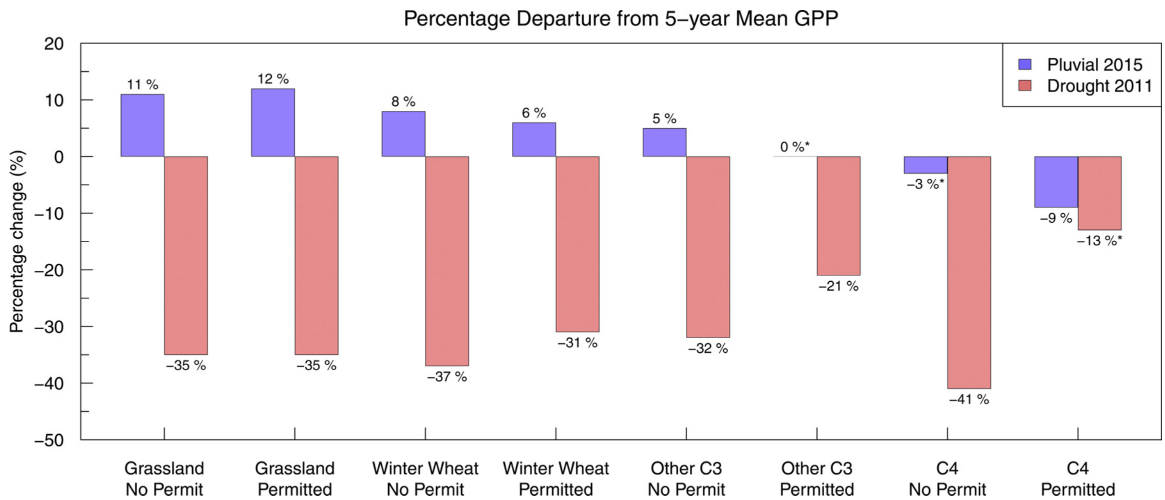

Fig. 9. Percentage departure of GPP_{VPM} from the 5-year reference mean for irrigation-permitted and non-permitted grasslands and croplands during the 2011 drought and pluvial 2015 in Caddo County. The percentage departure calculations and *p*-values for the 2011 drought and pluvial 2015 were reported in Table S3 and Table S4, respectively. *Not significant.

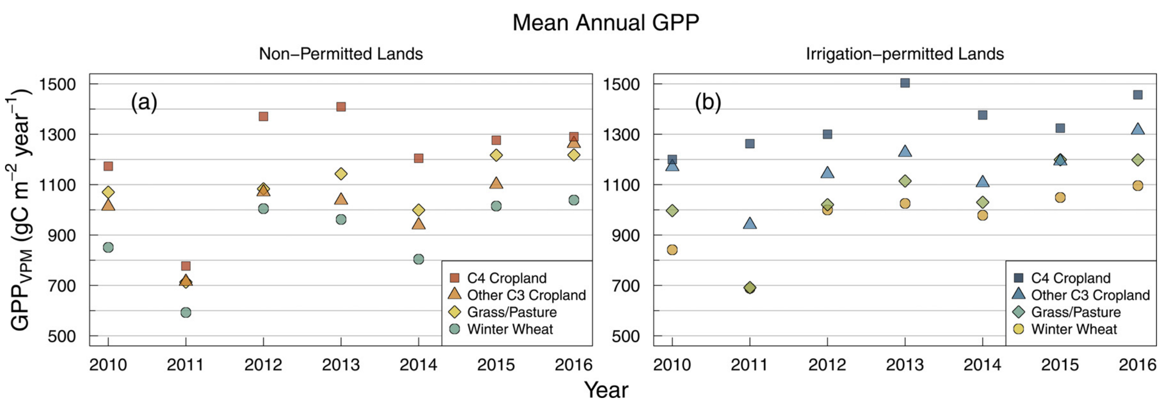

Fig. 10. Mean annual GPP for (a) non-permitted and (b) irrigation-permitted grasslands and croplands in Caddo County 2010–2016.

promoted GPP for these land types as several studies have shown grazing can inhibit overall GPP (Rogiers et al., 2005; Oates and Jackson, 2014), that the effect of grazing on GPP is negligible (Senapati et al., 2014), or that increases in GPP are temporary (Zhang et al., 2015). Nevertheless, grasslands experienced the largest percentage gains in mean annual GPP than the other land cover types, which reflected the year-long growing season of grassland systems.

Irrigation-permitted C4 croplands were the only land cover type to exhibit a significant decrease in GPP during pluvial 2015. The decrease might be attributed to a saturation of soil water content above what is beneficial to the growth of C4 crops due to excessive rainfall, leaching of nitrates beyond the root zone, or the timing of rainfall. For example, a study of drip-irrigated corn (*Zea mays* L.) by Payero et al. (2008) found that over-irrigated treatments could dramatically reduce water use efficiency (WUE), aboveground dry biomass, and grain yield. Irrigation and fertilization techniques can minimize leaching of nitrates out of the root zone (Sexton et al., 1996; Gheysari et al., 2009), but with record-breaking rainfall in 2015 such techniques might not have been possible to implement. Also, persistent cloud cover may have reduced photosynthetically active radiation in the month of May, which would have interfered with the early growth of corn and sorghum.

4.3. Implications of irrigation for carbon budgets and food security

This study indicates that irrigation may buffer reductions in terrestrial carbon uptake due to drought and increased asynchronousity between precipitation and temperature. Results also indicate, at the landscape scale, that C4 croplands can respond differently to drought than grasslands, winter wheat, and other C3 croplands. Such drought responses could provide additional insight into why Wolf et al. (2016) found little annual change in the terrestrial uptake of carbon during the 2012 North American drought. In consideration of overall greenhouse gas (GHG) emissions, however, irrigation also plays a role in soil organic carbon fluxes, and the emission of methane (CH_4) and nitrous oxide (N_2O) (Lal, 2004; Snyder et al., 2009; Trost et al., 2013).

Clearly, plants are more productive in arid conditions when they are irrigated. Although groundwater is often considered a renewable resource, Earth's groundwater resources are being depleted faster than they are being recharged (Wada et al., 2010). For example, between 2001 and 2016 the groundwater levels of the Rush Springs Aquifer and the Ogallala Aquifer (an important groundwater resource for 8 midwestern states) declined by 3 m and 5.8 m, respectively (Khand et al., 2017). Our analysis provides insight into how the productivity of irrigated grasslands and croplands, and how their responses to drought and pluvial events, may change in the future if groundwater resources were to become inaccessible due to depletion, pollution, or technological limitations.

4.4. Socioecological insights

Some farmers in the United States are uncertain about Earth's changing climate. For instance, Arbuckle et al. (2013) reported that out of a survey of almost 5000 corn farmers, 31% of respondents were uncertain if climate change is occurring. Using the same survey data, Mase et al. (2017) noted that only 16% of corn farmers report that changing weather patterns are hurting their farm operation. However, our results indicate that farmers' experiences in a changing climate

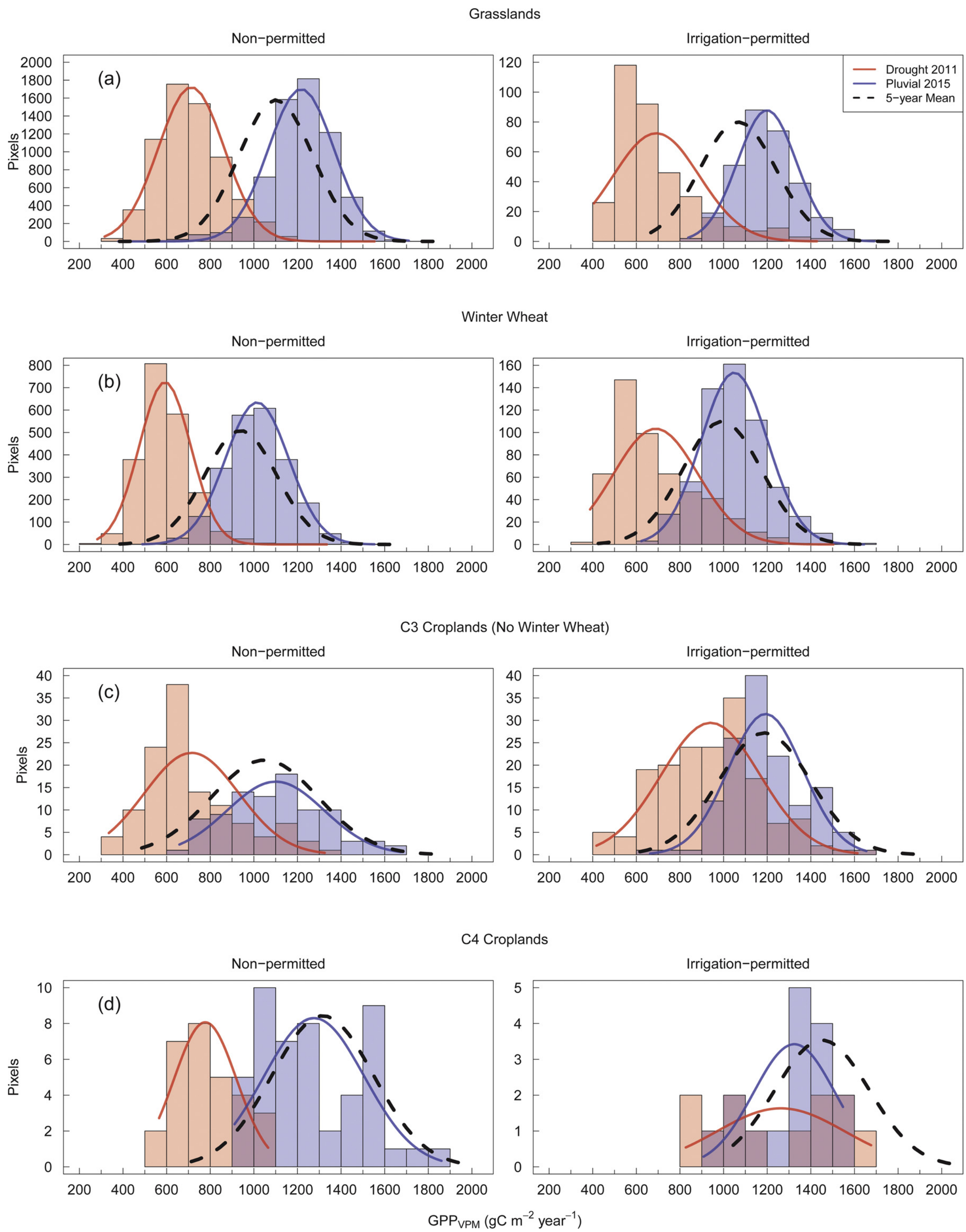

Fig. 11. Responses of GPP to the 2011 drought and pluvial 2015 in Caddo County for irrigation-permitted and non-permitted (a) grasslands, (b) winter wheat, (c) other C3 croplands, and (d) C4 croplands. All responses are significantly different ($p < 0.05$) from the 5-year reference mean, except for C3 irrigation-permitted croplands in 2015, C4 non-permitted croplands in 2015, and C4 irrigation-permitted croplands in 2011 (Tables S3 and S4).

might be influenced by the type of crop they plant and their water rights. Farmers with groundwater irrigation rights may not be experiencing drought, pluvial conditions, increased climate variability, and a changing climate like those with no groundwater access.

For instance, our study indicates that non-permitted C4 croplands experienced the largest percentage decrease in GPP during the 2011 drought compared to grasslands and other cropland types, but irrigation-permitted C4 crops did not experience a significant decline in GPP. Thus, generalizations about farmers that plant the same crop type, such as corn, or pooled responses from a diverse group of crop producers (Rejesus et al., 2013), might be an oversimplification. Ongoing and future surveys of farmers would be more useful if land management practices, such as water use, grazing, fertilization, rotations, harvest, and burning, were paired with geospatial information like precipitation, temperature, and water availability. For example, such information may allow us to further understand why some farmers don’t 'believe' in climate change, although there is little disagreement on what science knows about climate change (Kahan et al., 2012; Kahan, 2015). This additional survey data information can shed new insight into what has shaped farmers' cultural identity in regards to climate change (Kahan, 2016; VanWinkle and Friedman, 2017).

5. Conclusion

Gross primary production of grasslands and croplands respond differently to drought and pluvial conditions. How a certain crop type responds to drought depends on whether the land owner has access to irrigation. This study found that vegetation on irrigation-permitted lands in Caddo County had higher mean GPP during the drought and less variable, more stable GPP during the study period 2010–2016. Responses of GPP for irrigation-permitted and non-permitted grasslands to drought and pluvial conditions were extremely similar, indicating that landowners were likely not exercising their right to irrigate grasslands. Caution should be used when assessing or generalizing how a specific crop species responds to climate variability, drought, and pluvial conditions in the absence of irrigation-related data. Future research into the effect of a changing climate on terrestrial vegetation should not only consider the ratio of C3 and C4 species in grasslands or whether a crop species is C3 or C4, but also consider whether the vegetation is irrigated or not. Thus, it is important to gather geospatial information on irrigation permits, irrigation practices, and the amount of irrigation water used.

Acknowledgements

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.agwat.2018.04.001.

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