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Effects of Dynamic Crop Growth on the Simulated Precipitation Response to Irrigation*

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Received 27 May 2015; in final form 14 August 2015

ABSTRACT: The rapid expansion of irrigation since the 1950s has significantly depleted the Ogallala Aquifer. This study examines the warm-season climate impacts of irrigation over the Ogallala using high-resolution (6.33 km) simulations of a version of the Weather Research and Forecasting (WRF) Model that has been coupled to the Community Land Model with dynamic crop growth (WRF-CLM4crop). To examine how dynamic crops influence the simulated impact of irrigation, the authors compare simulations

* Supplemental information related to this paper is available at the Journals Online website: <http://dx.doi.org/10.1175/EI-D-15-0030.s1>.

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DOI: 10.1175/EI-D-15-0030.1

with dynamic crops to simulations with a fixed annual cycle of crop leaf area index (static crops). For each crop scheme, simulations were completed with and without irrigation for 9 years that represent the range of observed precipitation. Reduced temperature and precipitation biases occur with dynamic versus static crops. Fundamental differences in the precipitation response to irrigation occur with dynamic crops, as enhanced surface roughness weakens low-level winds, enabling more water from irrigation to remain over the region. Greater simulated rainfall increases (12.42 mm) occur with dynamic crops compared to static crops (9.08 mm), with the greatest differences during drought years (+20.1 vs +5.9 mm). Water use for irrigation significantly impacts precipitation with dynamic crops ($R^2 = 0.29$), but no relationship exists with static crops. Dynamic crop growth has the largest effect on the simulated impact of irrigation on precipitation during drought years, with little impact during nondrought years, highlighting the need to simulate the dynamic response of crops to environmental variability within Earth system models to improve prediction of the agroecosystem response to variations in climate.

KEYWORDS: Vegetation–atmosphere interactions; Precipitation; Physical meteorology and climatology; Water budget; Models and modeling; Coupled models; Applications; Agriculture; Land use

1. Introduction

Irrigation is responsible for 70% of global freshwater withdrawals and 90% of consumptive water use (Qian et al. 2013; Siebert et al. 2010), which has placed significant stress on numerous groundwater aquifers throughout the globe (Wada et al. 2010). The rapid expansion of irrigation in the semiarid Great Plains since World War II has significantly depleted groundwater (McGuire 2014) as the large volume of pumping is not offset by low aquifer recharge rates (Leng et al. 2014). Reduced groundwater levels are especially apparent in the southern High Plains where saturated thicknesses have declined and the water table has dropped by up to 78 m since 1950 (McGuire 2014). In some areas of the Great Plains, nearly 80% of the land is irrigated, approximately doubling the water available for evapotranspiration (ET) within the confines of the Ogallala Aquifer (Moore and Rojstaczer 2001), driving significant impacts on the regional hydroclimate.

The recent increase in corn acreage for biofuel production (Bagley et al. 2014; USDA-ERS 2014), the potential for expansion of second-generation biofuel crops in the region (Bagley et al. 2014), and warming temperatures with anthropogenic climate change may further increase the demand for irrigation (Döll 2002; Dominguez-Faus et al. 2013; Fischer et al. 2007; Vorosmarty et al. 2000). Because this could accelerate the depletion of the Ogallala Aquifer, it is critically important to more fully understand how irrigation affects the hydroclimate of the Great Plains. In addition, because most of the water applied for irrigation is evapotranspired rather than lost to runoff or drainage (DeAngelis et al. 2010; Moore and Rojstaczer 2001), it is imperative to understand the cumulative atmospheric effect of irrigation on the Ogallala. In this study, we examine how irrigation affects precipitation within the confines of the Ogallala Aquifer using a high-resolution regional climate model with dynamic crop growth that can respond to variations in temperature and moisture stress (Lu et al. 2015).

The Great Plains have been previously identified as one of three global maxima in land–atmosphere coupling (Koster et al. 2004), as variations in soil moisture are positively correlated with precipitation in the region (Koster et al. 2003). The Great Plains low-level jet (GPLLJ), a nocturnal southerly wind maximum, is the primary driver of summertime convective rainfall in the region (Higgins et al. 1997; Means 1954). Abundant low-level convergence, cyclonic shear, and moisture convergence to the north of the GPLLJ maximum dynamically force convective development above the planetary boundary layer at night. For these reasons, the diurnal maximum in warm-season rainfall occurs at night instead of during peak heating when instability is the greatest (Bonner 1968; Helfand and Schubert 1995; Weaver and Nigam 2011). Variations in the GPLLJ are influenced by fluctuations in the gradient between the higher 850-hPa geopotential heights of the North Atlantic subtropical high and lower 850-hPa heights over the Great Plains (Harding and Snyder 2015a; Holton 1967), as well as the decoupling of the surface and boundary layers at night.

Irrigation substantially increases ET (Nazemi and Wheeler 2015; Pokhrel et al. 2012), driving significant evaporative cooling ($\sim 1^{\circ}\text{C}$) within and around irrigated areas (Adegoke et al. 2003; Destouni et al. 2010; Haddeland et al. 2006; Harding and Snyder 2012b; Kueppers et al. 2007; Lobell et al. 2008; Lu et al. 2015; Mahmood et al. 2006; Qian et al. 2013) that can offset increasing temperatures from climate change (Gerten et al. 2011). The additional moisture from irrigation can modify the formation of precipitation by introducing anomalies in temperature, convective available potential energy (CAPE), moist static energy, low-level convergence, and cloud cover (Harding and Snyder 2012b; Qian et al. 2013; Segal et al. 1998). Because CAPE is more sensitive to changes in low-level moisture than temperature (Crook 1996), the additional moisture from irrigation can enhance convection over the Great Plains by increasing CAPE despite reduced surface temperatures (Harding and Snyder 2012b). Irrigation over the Great Plains has been shown to increase precipitation over and downwind of irrigated areas in studies that incorporate regional climate models (Harding and Snyder 2012b; Huber et al. 2014; Qian et al. 2013) and observations (Alter et al. 2015; Barnston and Schickedanz 1984; DeAngelis et al. 2010). Because the strong cooling from irrigation reduces the height of the planetary boundary layer (PBL) and reduces low-level convergence (Harding and Snyder 2012b; Qian et al. 2013), increases in convective rainfall from irrigation typically occur during the evening and overnight hours when convection is elevated above the PBL (Harding and Snyder 2012b; Qian et al. 2013). The precipitation response from irrigation varies depending on antecedent soil moisture (Harding and Snyder 2012b; Qian et al. 2013). Larger rainfall increases from irrigation occurred in pluvial versus drought years over the Great Plains in Harding and Snyder (2012b), but precipitation was enhanced more in a dry year compared with a wet year over the southern High Plains in Qian et al. (2013). However, any simulated increases in rainfall from irrigation in both studies were much lower than the total irrigation water use (Harding and Snyder 2012b; Qian et al. 2013), and most evapotranspired water from irrigated fields ($>80\%$) does not return to the region as precipitation (Harding and Snyder 2012a).

Modeling studies that have examined how irrigation might affect regional rainfall have incorporated vegetation that follows a fixed annual cycle of leaf area index (LAI), a dimensionless measure of the total leaf area per unit ground area.

Because interactions between the biosphere and atmosphere can have significant climate impacts at regional and global scales (Bonan 2008; Garraud and Sushama 2015; Lu et al. 2001; Pielke et al. 1998) and the region has been identified as a hotspot for land–atmosphere coupling (Koster et al. 2004), simulating crops that respond to current weather (i.e., dynamic vegetation) instead of a fixed cycle (i.e., static vegetation) can provide a greater representation of the regional atmospheric impacts of irrigation. Vegetation dynamics have been shown to enhance low-frequency precipitation variability over the region (Delire et al. 2004; Delire et al. 2011), and model simulations with dynamic vegetation have found that vegetation growth may play a significant role in amplifying climate sensitivity through albedo changes (O’ishi and Abe-Ouchi 2009). Furthermore, the greening of vegetation from irrigation during droughts may cause larger local to regional meteorological impacts than those that arise just from the additional irrigated water. For these reasons, dynamic vegetation has been recently added to many regional and global climate models after primarily being incorporated only in offline (uncoupled) land surface models. In addition, the large impact that land–atmosphere coupling has on the warm-season climate of the Great Plains (Delire et al. 2004; Koster et al. 2003; Koster et al. 2004) implies that modeling studies that investigate the regional climate impacts of irrigation should incorporate biosphere–atmosphere interactions that may influence the regional climate. The impacts of dynamic crops have been previously investigated using offline models to examine irrigation water demands (aus der Beek et al. 2010) and in a coupled regional climate model to analyze irrigation’s effects on temperature (Lu et al. 2015), but the effect of dynamic crops on irrigation’s influence on precipitation has not been studied.

Previous efforts to estimate the impact of irrigation on the hydroclimate of the central United States have included a wide array of irrigation schemes and datasets. The simulated impact of irrigation on the atmospheric branch of the hydrological cycle is significantly influenced by the choice of irrigation dataset (Ozdogan et al. 2010) and irrigation scheme (Leng et al. 2014). Modeling studies that investigate the atmospheric impacts of irrigation typically apply irrigation either by maintaining soil moisture at saturation (or field capacity) for the duration of the warm season (Adegoke et al. 2003; Harding and Snyder 2012b; Huber et al. 2014; Kueppers et al. 2007; Lobell et al. 2008), applying moisture throughout the growing season based on observed irrigation amounts (Sacks et al. 2009), or using a trigger based on moisture stress and temperature to determine when to irrigate (Leng et al. 2014; Lu et al. 2015; Ozdogan et al. 2010).

Using the same model as this study, Lu et al. (2015) showed that the inclusion of dynamic crop growth enhances simulated ET and soil moisture changes from irrigation over the contiguous United States; however, the impacts on precipitation were not investigated. Here, we expand on the work of Lu et al. (2015) and for the first time examine how dynamic crop growth impacts the simulated effect of irrigation on warm-season precipitation and its drivers. We used high-resolution (6.33-km model grid cell resolution) simulations of a version of the Weather Research and Forecasting (WRF) Model that is coupled to the Community Land Model version 4.0 with dynamic crop growth (WRF-CLM4crop) (Lu et al. 2015). In our model simulations, we applied water to the irrigated portion of grid cells based on the MODIS-derived irrigation dataset from Ozdogan and Gutman (2008)

at a fixed rate whenever water stress limited photosynthesis or the leaf temperature was too high. To examine how dynamic vegetation influences the simulated impact of irrigation, we compared a set of model simulations with dynamic crop growth with another set that used a fixed annual cycle of crop LAI (static crops). For each vegetation scheme (dynamic crops and static crops), model simulations were completed with and without irrigation for 9 years that encompass the full spectrum of hydroclimate regimes in the region, enabling an investigation into the full impact of irrigation on the summer hydroclimate and the atmospheric branch of the hydrologic cycle within the Great Plains.

2. Methods

2.1. WRF-CLM4crop model

We used WRF-CLM4crop, a version of the WRF Model, version 3.3, that has been previously coupled to the Community Land Model, version 4.0 (CLM4) (Lu et al. 2015). WRF is a regional climate model that has been widely used for research and weather forecasting applications (Skamarock et al. 2008). WRF uses a terrain-following vertical coordinate system that extends from the surface to 50 hPa. Because convective processes and shallow clouds cannot be fully resolved within coarsely resolved grid cells (Skamarock et al. 2008), precipitation development is aided by a convective parameterization (CP). CPs are designed to resolve subgrid-scale vertical fluxes of mass, momentum, and latent heating when adequate spatial resolution prevents explicit resolution of these processes. The spatial resolution required to resolve convective precipitation varies by location and season. Over the central United States, convection-permitting simulations can be conducted during the warm season with a 10-km spatial resolution as precipitation is dynamically forced by the GPLLJ (Harding and Snyder 2014, 2015b), but in some cases CPs are needed at spatial resolutions between 5 and 10 km, absent a strong dynamical forcing (Skamarock et al. 2008). In this study, we use a convection-permitting horizontal resolution of 6.33 km within the inner model domain to enable the development of convective precipitation without needing a CP.

2.2. CLM4crop model

The CLM land surface model includes sophisticated representations of surface fluxes, hydrology, biogeophysics, and soil–groundwater interactions. CLM exchanges surface fluxes of energy, momentum, and mass with WRF and includes 10 soil layers and 1 canopy layer. The dynamic crop growth module in WRF-CLM4crop is adapted from the agricultural version of the Integrated Biosphere Simulator (IBIS) model (Agro-IBIS; Kucharik 2003) that simulates the growth and productivity of major annual crops as they respond to environmental conditions. Carbon is allocated to different reservoirs within crops (leaf, stem, and root) based on phenological stages of crop growth (planting, leaf emergence, grain fill, and harvest). The rate of carbon assimilation is affected by water variability, temperature, solar radiation, and atmospheric CO₂ concentration. Extreme temperatures, soil water scarcity, and reduced solar radiation can result in suboptimal assimilation of carbon through photosynthesis on short time scales. LAI is a product of the

specific leaf area (ratio of leaf area to dry mass) and net primary productivity (gross photosynthesis minus autotrophic respiration). Carbon is allocated to the leaf (and stem) and LAI increases after leaf emergence, but it slowly declines during grain fill when the plant allocates carbon from photosynthesis to the reproductive components of the plant and leaf carbon is slowly lost to respiration. CLM4crop simulates C3 (e.g., soybean, wheat, and cotton) and C4 crops (e.g., corn and sorghum). C3 and C4 plants have different photosynthetic pathways that cause C3 plants to be more efficient than C4 plants under cool, moist, and normal light conditions, while C4 plants are more efficient with high temperatures or high solar radiation.

The phenological stages of crop growth are determined through the accumulation of growing degree-days (GDD), which are calculated by subtracting a base temperature from the average daily temperature (negative GDD values set to zero; base 8°C for C3 crops and 10°C for C4 crops). Planting occurs in the model when grid cells reach 50 GDD, and leaf emergence occurs when accumulated GDD for soil temperature (0.05-m depth; base 0°C for C3 crops and 8°C for C4 crops) reaches 3% of the average March–September total from low-resolution WRF simulations over the model domain. Grain fill and a corresponding decline in LAI begins when GDD reaches 85% of $\text{GDD}_{\text{maturity}}$, which is defined as the average March–September total GDD for 2-m temperature. Harvest occurs when grid cells reach 150% of maturity ($\text{GDD}_{\text{maturity}}$). WRF-CLM4crop typically overestimates LAI throughout the growing season, but interannual variability in peak LAI is improved compared to a version of the model with prescribed LAI. The difference in LAI between irrigated and nonirrigated simulations is comparable to observations (Lu et al. 2015). Additional details on WRF-CLM4crop are available in Lu et al. (2015).

Plant functional types (PFTs) were assigned to each grid cell based on the global CLM land surface parameters from Lawrence and Chase (2007), which include a generic crop type. To differentiate between C3 and C4 crops in our model domain, C3 crops representing soybean and wheat, and C4 crops representing corn and sorghum, were distributed based on the ratio of corn to soybean from the 5-arc-min resolution areal estimates of percent coverage of corn and soybean from Monfreda et al. (2008). This differs from the Lu et al. (2015) study in which all grid cells were split evenly between C3 and C4 crops.

2.3. Irrigation representation

We used a subgrid-scale precision agriculture-type irrigation scheme from Lu et al. (2015) that simulates realistic changes in latent heat flux, sensible heat flux, soil moisture, and temperature, while approximating USGS water use (Lu et al. 2015). The irrigation scheme mimics sprinkler irrigation by applying water as rain at a rate of 0.0002 mm s^{-1} , within the range of current irrigation systems ($4\text{--}20 \text{ gal min}^{-1} \text{ acre}^{-1}$), after leaf emergence ($\text{LAI} > 0.1 \text{ m}^2 \text{ m}^{-2}$) when photosynthesis is limited by water (model root water stress function is less than 0.99) or leaf temperature is too high ($T_{\text{veg}} > 35^\circ\text{C}$). Irrigated croplands were determined from Ozdogan and Gutman (2008) and interpolated from the 500-m native resolution to the WRF domain (Figure 1) using bilinear interpolation. For grid cells in which the irrigated area exceeded the cropland area, cropland was increased to match the total irrigated area at the expense of the least dominant PFT(s). This irrigation scheme is similar to that of Leng et al. (2014), except that it also includes

Figure 1. Percentage of irrigation from [Ozdogan and Gutman \(2008\)](#) in grid cells within WRF Model domain. The outer and inner grids in the WRF domain as well as the Ogallala Aquifer study region are outlined in black.

a temperature threshold added by [Lu et al. \(2015\)](#) and a rule that irrigation is applied at a continuous rate when needed to eliminate the soil moisture deficit instead of every morning for 4 h.

2.4. Experimental design

Model simulations were conducted using the dynamic crop module with irrigation (DYN-IRR) and without (DYN-NOIRR) for a set of 9 years that represent the full spectrum of precipitation regimes (drought, normal, and pluvial) over the Ogallala Aquifer ([Table 1](#)). A second set of simulations was also conducted using static crops in WRF that follow a fixed annual cycle based on MODIS data with

Table 1. Summary of model simulations and precipitation regimes used in this study.

Vegetation Scheme	Irrigation	Precipitation regimes		
		Drought	Normal	Pluvial
Dynamic crop growth (DYN)	None (NOIRR)	2000, 2002, 2012	1987, 2001, 2005	1993, 1996, 2007
Standard annual cycle of LAI (STAT)	Irrigated (IRR)			
	None (NOIRR)			
	Irrigated (IRR)			

irrigation (STAT-IRR) and without (STAT-NOIRR). A total of 36 simulations were completed from 1 March to 1 October and were initialized using 6-hourly data from the NCEP–DOE reanalysis (Kanamitsu et al. 2002). The start of model simulations on 1 March ensured proper accumulation of GDDs for phenological stages. All analyses were completed for May–September, the period during which irrigation significantly impacts LAI and surface fluxes. A nested grid configuration (Figure 1) was used with a 31.67-km outer domain, a 6.33-km inner domain, and 31 vertical levels. The WRF double-moment six-class microphysics scheme (Hong et al. 2010), Yonsei University (YSU) planetary boundary layer scheme (Hong et al. 2006), CAM longwave radiation scheme (Collins et al. 2004), Mellor–Yamada–Nakanishi–Niino (MYNN) surface layer scheme (Nakanishi and Niino 2006), and Dudhia shortwave radiation scheme (Dudhia 1989) were used. The Kain–Fritsch CP scheme (Kain 2004) was used in the outer domain, with no CP in the inner domain.

Model simulations encompass three precipitation regimes that represent the range of climatic and antecedent soil moisture conditions observed over irrigated areas of the Ogallala Aquifer (outlined in Figure 1). To determine drought, normal, and pluvial years, precipitation from the Climate Prediction Center (CPC)’s precipitation dataset (Higgins et al. 2000) was weighted by the irrigated fraction of grid cells within the model domain, and area-weighted averages were calculated for each April–September for 1979–2013 (period when NCEP-2 is available). Drought years were defined as the three driest years, pluvial years as the three wettest, and normal years as the closest to average (Table 1; Figure S1). While our analysis was conducted for May–September, we included April in the determination of precipitation regimes to consider the lingering impacts of April precipitation on soil moisture. All area-weighted averages were calculated over the Ogallala Aquifer (Figure 1) as defined by Cederstrand and Becker (1999), unless otherwise noted. Because of the high computational cost of the large number of model simulations in this study, we only examine the local effects of irrigation within the Ogallala Aquifer even though irrigation has significant downstream effects on precipitation (Alter et al. 2015; Barnston and Schickedanz 1984; DeAngelis et al. 2010; Harding and Snyder 2012a; Huber et al. 2014).

2.5. Observations

The Mead, Nebraska, Ameriflux maize–soybean rotation rainfed (41.1797°N, 96.4396°W) and irrigated sites (41.1649°N, 96.4701°W) were used to evaluate simulated LAI, latent heat flux, and 2-m temperature for all years in which both WRF and Ameriflux data were available (2001, 2002, 2005, 2007, and 2012) (Verma et al. 2005). Simulated irrigation water use was compared to the reported

water use from the USGS for 2000 (Hutson et al. 2004) (a drought year) and 2005 (Kenny et al. 2009) (a normal year). WRF temperature and precipitation were compared with the PRISM gridded monthly dataset from Oregon State University (Daly et al. 2002), a high-resolution dataset based on station observations and a digital elevation model, for all simulated years. PRISM is desirable because both temperature and precipitation are available and it has a similar spatial resolution (4 km) as our model simulations. The diurnal cycle of precipitation for all simulated years was compared with the first 10 years of the Stage IV dataset (2002–11) (Lin and Mitchell 2005), which is available at a 4-km spatial resolution from 2002 to the present and is commonly used as a benchmark for subdaily observations (AghaKouchak et al. 2011).

3. Results

3.1. Land surface evaluation

Within the inner model domain, reported irrigated water use from the USGS was 30.6 billion gal day⁻¹ in 2000 (Hutson et al. 2004) and 29.3 billion gal day⁻¹ in 2005 (Kenny et al. 2009). On average, WRF uses 27.4 billion gal day⁻¹ in all DYN-IRR simulations (32.6 billion gal day⁻¹ in 2000 and 21.7 billion gal day⁻¹ in 2005) and 23.3 billion gal day⁻¹ in STAT-IRR (27.1 billion gal day⁻¹ in 2000 and 20.0 billion gal day⁻¹ in 2005). The greatest simulated water use for irrigation occurs in 2012 when DYN-IRR simulations use 37.7 billion gal day⁻¹ and STAT-IRR simulations use 32.1 billion gal day⁻¹. In DYN-IRR simulations, substantially more water is used during drought years (35.34 billion gal day⁻¹) than normal (23.41 billion gal day⁻¹) and pluvial years (23.38 billion gal day⁻¹). Similarly, more water is applied for irrigation during drought years in STAT-IRR simulations (29.30 billion gal day⁻¹) than in normal (21.13 billion gal day⁻¹) and pluvial years (19.60 billion gal day⁻¹).

The dynamic crop module overestimates LAI for rainfed and irrigated crops over the model grid cell closest to Mead, Nebraska, compared to observations from the Mead Ameriflux sites in all years that WRF simulations were conducted and Ameriflux data were available. The peak monthly LAI occurs in July and is overestimated compared to observations by 38.4% and 5.0% for the irrigated and rainfed rotation fields, respectively. WRF overestimates the LAI response to irrigation in DYN simulations (i.e., IRR LAI minus NOIRR LAI), with no LAI response by definition in STAT runs (Figure 2a). July LAI errors of 0.75 m² m⁻² (36.5%) occur, with the greatest errors occurring in August and September (Figure 2a). Despite overestimating the LAI response to irrigation, WRF slightly underestimates the average warm-season (May–September) change in latent heat flux and sensible heat flux with irrigation compared to the Mead site (Figures 2b,c). However, much of the underestimation of July latent heat flux is related to large observed changes during July 2012 at the Mead site compared to other years (not shown). Despite these smaller simulated latent and sensible heat flux differences between irrigated and rainfed fields compared to observations, particularly in July, WRF simulates a larger difference in 2-m temperature for DYN and STAT (Figure 2d). This may be an artifact of the regionwide change in temperature from irrigation in model simulations, whereas Ameriflux observations represent local temperature differences between a single rainfed and irrigated field.

Figure 2. (a) Observed and simulated seasonal cycle of difference in (a) LAI, (b) latent heat flux, (c) sensible heat flux, and (d) 2-m temperature between irrigated and rainfed fields at the Mead, Nebraska, Ameriflux site for all simulated years for which Ameriflux data were available.

Although latent heat flux values in Figure 2 do not differ greatly between DYN and STAT simulations, unrealistic changes in the components of ET are present in simulations with static vegetation. Because LAI in STAT simulations is unable to respond to the addition of water, the change in ET (summed over May–September) over irrigated grid cells is driven almost entirely by soil evaporation, with much smaller increases in transpiration and canopy evaporation (Figure 3). The increase in LAI from irrigation in DYN simulations primarily increases transpiration and canopy evaporation, with much smaller changes in soil evaporation (Figure 3) as found by Lu et al. (2015). The response in DYN simulations is much more realistic than in the STAT simulations because soil evaporation is a much smaller part of ET than transpiration over irrigated croplands (Lascano et al. 1987; Lu et al. 2015).

3.2. Examination of atmospheric variables in DYN-NOIRR and STAT-NOIRR simulations

Underestimated LAI in STAT-NOIRR simulations causes a substantial warm bias (relative to PRISM observations) as compared with DYN-NOIRR runs (Figure 4) because less energy is partitioned into latent heat flux and more into sensible heating (Figure S2). The inclusion of dynamic crop growth reduces the warm bias in WRF-CLM significantly (Figure 4; Table 2), with the greatest improvement during normal and pluvial years (Table 2). More accurate temperatures over much of the Great Plains in DYN simulations are associated with increases in sea level pressure compared to STAT runs (Figure S3d). Because the GPLLJ is driven by pressure

Figure 3. (a) May–September area-weighted average of simulated total ET components (summed over May–September) over all grid cells with at least 10% irrigation within the Ogallala region (outlined in Figure 1) for all simulated years. (b) Irrigated minus nonirrigated ET components from DYN and STAT simulations.

differences between the North Atlantic subtropical high and low pressure over the Great Plains, higher pressure over the Great Plains with dynamic crop growth reduces the pressure gradient and weakens the GPLLJ (Figure S3c). The slight reduction in southerly winds in DYN simulations results in a small improvement in simulated wind speeds within the GPLLJ, as STAT-NOIRR simulations overestimate the strength of the GPLLJ (Figures S3a,b).

The greater ET in DYN-NOIRR compared with STAT-NOIRR results in much more column-integrated precipitable water (Figure 5a), despite slightly weaker southerly flow within the GPLLJ (Figure S3). More abundant low-level moisture with dynamic crop growth also increases CAPE (Figure 5b), while reducing convective inhibition (CIN; Figure 5c) over most of the region where crop LAI is increased (Figure 5d). These changes have substantial effects on precipitation, as variations in CAPE and precipitable water have a significant impact (44% and 52% of precipitation variability explained, respectively) on total May–September rainfall over the region in both sets of NOIRR simulations. Convection is more favorable in WRF simulations with dynamic vegetation because of increased CAPE and precipitable water in the presence of reduced CIN, which drives an additional 5.21 mm of precipitation over the Ogallala in DYN simulations, with a smaller increase of 0.75 mm outside the Ogallala (Figure 5e).

WRF typically underestimates warm-season rainfall over much of the Ogallala region (Figure 6), with an average error of -23.1% over the region for all DYN simulations compared to PRISM (Table 3). Because the environment is less favorable for convective precipitation development with static vegetation, the underestimation of rainfall in STAT simulations is slightly worse for all scenarios (Table 3). WRF-simulated precipitation more closely matches regional averages, and the spatial variability seen in the PRISM dataset is better when dynamic vegetation is included, slightly

May-September Temperature For All Simulated Years

Figure 4. (a) May–September average observed 2-m temperature (°C) from PRISM dataset for all years that model simulations were conducted. (b) As in (a), but for the average from all DYN-NOIRR simulations. (c) Average DYN-NOIRR simulated temperature minus PRISM. (d),(e) As in (b) and (c), but for STAT-NOIRR simulations.

reducing the simulated dry bias (Figure 6). While rainfall is underestimated in WRF, both sets of simulations reasonably capture the west-to-east precipitation gradient that is a prominent feature of warm-season regional rainfall (Figure 6). In addition, WRF captures the nocturnal peak (at 0300 UTC) in precipitation associated with the GPLLJ seen in the Stage IV observations (Figure 7) as well as the observed eastward propagation of convective precipitation over the Great Plains (Figure S4). The fact that WRF can simulate the timing and behavior of convective precipitation in the region suggests that WRF can reasonably simulate warm-season rainfall in this configuration without a convective parameterization, despite the simulated dry bias.

Table 2. May–September WRF-simulated average 2-m temperature compared to PRISM dataset over Ogallala region (outlined in Figure 1) for all, drought, normal, and pluvial years without irrigation in simulations with dynamic crop growth (DYN-NOIRR) and standard fixed crops (STAT-NOIRR). Values in boldface indicate which model had better performance.

	Difference (°C)		RMSE (°C)		Pattern correlation	
	DYN-NOIRR	STAT-NOIRR	DYN-NOIRR	STAT-NOIRR	DYN-NOIRR	STAT-NOIRR
All Years	1.339	1.925	1.356	1.934	0.960	0.933
Drought	1.672	2.113	1.702	2.133	0.931	0.902
Normal	1.029	1.711	1.044	1.716	0.965	0.952
Pluvial	1.315	1.951	1.327	1.958	0.966	0.938

3.3. Simulated response to irrigation for all simulated years

In this section, we analyze May–September averages over the Ogallala Aquifer region (Figure 1). “Irrigated grid cells” have irrigation that covers at least 10% of the grid cell, while “nonirrigated grid cells” contain less than 10% irrigation.

The simulation of managed irrigation in WRF stimulates crop growth over much of the Great Plains in DYN-IRR simulations, with the greatest changes in LAI between DYN-IRR and DYN-NOIRR found over the heavily irrigated areas of Nebraska, southwestern Kansas, and the Texas Panhandle (Figure 8a). A larger increase in crop LAI occurs with greater grid cell irrigated fraction (Figure 8c), and the average LAI response to irrigation over the Ogallala region is heavily dependent on the amount of irrigated water applied ($R^2 = 0.869$; Figure 8d). Although irrigation demand and application are lower in STAT-IRR simulations (Table 4), because of the lack of an LAI response (Figure 8b), changes in total ET (summed over May–September) between STAT-IRR and STAT-NOIRR are slightly larger than between DYN-IRR and DYN-NOIRR simulations (Figures 8e,f) for all grid cells (Table 4) and irrigated grid cells (Table 5). These larger increases are a result of the unrealistic enhancement in soil evaporation (Figure 3) and the large warm bias in STAT runs, which increases ET. As with LAI, larger increases in ET occur as the grid cell irrigation fraction rises (Figure 8g), and average changes in ET are closely related to the total amount of irrigated water applied in the region in STAT-IRR ($R^2 = 0.944$) and DYN-IRR ($R^2 = 0.953$) simulations (Figure 8h). Corresponding decreases in sensible heating reduce temperatures over the region, with greater cooling in DYN simulations associated with larger declines in sensible heating (Table 4). While changes in ET are comparable between STAT and DYN simulations, soil moisture increases much more with dynamic crop growth (Figures 8i–k; Table 4) because of more realistic partitioning of water within the soil–plant system in DYN simulations compared to STAT runs (Figure 3). The relationship between soil moisture and water applied for irrigation is weaker in STAT simulations ($R^2 = 0.652$) than in DYN simulations ($R^2 = 0.914$; Figure 8l).

Irrigation increases precipitable water throughout the region (Figures 9a,b) over irrigated and nonirrigated grid cells (Figure 9c; Tables 5 and S1). Despite the similar ET changes between IRR and NOIRR in DYN and STAT simulations, much greater increases in column-integrated precipitable water occur with dynamic crop growth (Figures 9a,b). In addition, the precipitable water response to irrigation is more closely tied to total irrigation water applied when dynamic crop growth is

Figure 5. (a) May–September DYN–NOIRR minus STAT–NOIRR average precipitable water (mm) for all years. (b) As in (a), but for maximum parcel convective available potential energy (CAPE; J kg^{-1}). (c) As in (a), but for CIN (J kg^{-1}). (d) As in (a), but for crop LAI ($\text{m}^2 \text{m}^{-2}$). (e) As in (a), but for precipitation (mm).

enabled (Figure 9d; $R^2 = 0.567$) compared to static vegetation simulations ($R^2 = 0.402$). The larger precipitable water increase from irrigation and the closer relationship with irrigation water applied in DYN simulations is likely related to reduced advection of irrigation water out of the region. Weaker low-level winds with dynamic crop growth enabled (Figure 10) are caused by the increased surface roughness from enhanced LAI (Figure 5d). In addition, a weaker GPLLJ from a smaller warm bias and its effect on sea level pressures (as mentioned in section 3.2. and shown in Figure S3) may also reduce advection of irrigated moisture out of the region in DYN simulations. Overall, weaker low-level winds in DYN simulations enable more of the evapotranspired water from irrigation to remain within the region, causing larger increases in precipitable water as well as CAPE (Figures 9e,f; Table 4). While low-level winds in DYN simulations imply less southerly advection of moisture into the region from the Gulf of Mexico, the fact that

May-September Precipitation For All Simulated Years

Figure 6. (a) May-September average observed precipitation (mm) from PRISM dataset for all years that model simulations were conducted. (b) As in (a), but for the average from all DYN-NOIRR simulations. (c) Average DYN-NOIRR simulated precipitation minus PRISM (%). (d),(e) As in (b) and (c), but for STAT-NOIRR simulations.

precipitable water increases significantly more in DYN-IRR simulations compared with STAT-IRR simulations suggests that the additional moisture that results from weaker advection out of the region overwhelms any reduction in moisture advection from weaker southerly flow into the region. Significant increases in CAPE occur throughout the region in both simulations because of the additional moisture with irrigation, with greater increases in CAPE as the fraction of irrigation increases (Figure 9g). Because more irrigated moisture remains over the region in DYN simulations, CAPE increases are more closely related to irrigated water use in DYN simulations ($R^2 = 0.545$) compared with STAT runs

Table 3. May–September WRF-simulated total precipitation compared to PRISM dataset over Ogallala region (outlined in Figure 1) for all, drought, normal, and pluvial years without irrigation in simulations with dynamic crop growth (DYN-NOIRR) and standard fixed crops (STAT-NOIRR). Values in boldface indicate which model had better performance.

	Difference (mm)		RMSE (mm)		Pattern Correlation	
	DYN-NOIRR	STAT-NOIRR	DYN-NOIRR	STAT-NOIRR	DYN-NOIRR	STAT-NOIRR
All Years	−74.82 (−23.1%)	−80.02 (−24.7%)	78.18 (23.4%)	83.54 (25.0%)	0.699	0.656
Drought	−59.98 (−28.4%)	−64.66 (−29.2%)	63.65 (29.1%)	65.94 (30.1%)	0.464	0.438
Normal	−57.99 (−16.8%)	−61.87 (−18.8%)	73.44 (21.0%)	74.66 (21.5%)	0.515	0.581
Pluvial	−106.49 (−25.7%)	−113.83 (−27.4%)	112.61 (26.4%)	119.80 (28.0%)	0.740	0.683

($R^2 = 0.096$) where no significant relationship exists between CAPE and irrigated water use (Figure 9h).

Enhanced CAPE and precipitable water with irrigation drive statistically significant rainfall increases between IRR and NOIRR in both STAT and DYN simulations (Figures 9i,j, Table 4). This suggests that the enhancement of convection from additional moisture with irrigation overcomes the suppression of convection from latent cooling, as found by Harding and Snyder (2012b). Changes in precipitation are highly variable across the model domain in both model simulations, with simulated increases of over 40% and up to 20% decreases in some locations. On average, precipitation increases over the Ogallala Aquifer with irrigation in all precipitation scenarios (normal, drought, and pluvial years) when considering the average of all grid cells within the region (Table 4), irrigated grid cells alone (Table 5), and nonirrigated grid cells (Table S1). Rainfall increases from irrigation are approximately the same when comparing irrigated and nonirrigated grid cells in DYN simulations, but precipitation increases are greater for nonirrigated grid cells in STAT simulations (Figure 9k; Tables 5 and S1). Because CAPE and precipitable water changes have statistically significant relationships with irrigated water use in DYN simulations, the amount of water applied for irrigation over the Ogallala Aquifer affects the precipitation response to irrigation (Figure 9l; $R^2 = 0.293$; $p = 0.064$).

Figure 7. Diurnal cycle of area-weighted average of May–September precipitation (mm day^{-1}) over the Ogallala region from first 10 years of Stage IV observations (2002–11; black solid), DYN-NOIRR (gray solid), and STAT-NOIRR (gray dashed) simulations.

Figure 8. (a) May–September average crop LAI change ($\text{m}^2 \text{m}^{-2}$) with irrigation in DYN simulations for all simulated years. (b) As in (a), but for STAT simulations. (c) Area-weighted average change in crop LAI ($\text{m}^2 \text{m}^{-2}$) with irrigation vs grid cell irrigation fraction over Ogallala region (outlined in Figure 1). (d) May–September area-weighted average change in crop LAI ($\text{m}^2 \text{m}^{-2}$) with irrigation vs total irrigation water applied over Ogallala region (outlined in Figure 1) for each simulated year. (e)–(h) As in (a)–(d), but for ET (mm). (i)–(l) As in (a)–(d), but for soil moisture ($\text{m}^3 \text{m}^{-3}$).

On the other hand, the connection between irrigated water use and precipitation changes is completely absent in STAT simulations ($R^2 = 0.031$; Figure 9l), as irrigated water use does not exhibit strong relationships with precipitable water or CAPE without dynamic vegetation.

Irrigation also increases rainfall in DYN simulations directly through the enhancement of LAI and its effect on precipitable water. Precipitable water is more closely related to the crop LAI response to irrigation ($R^2 = 0.603$; Figure 11a) than the total water used for irrigation ($R^2 = 0.567$; Figure 9d). Because the LAI response to irrigation has a larger impact on precipitable water, changes in crop LAI explain more of the variance in the precipitation response to irrigation ($R^2 = 0.356$; $p = 0.042$; Figure 11b) than irrigated water use does ($R^2 = 0.293$; $p = 0.064$; Figure 9l). However, because the phenological response to irrigation is highly dependent on the amount of irrigated water applied, the two effects are not mutually

Table 4. May–September area-weighted average of differences between irrigated and nonirrigated simulations for all grid cells in the Ogallala Aquifer region (outlined in Figure 1).

	DYN-IRR minus DYN-NOIRR				STAT-IRR minus STAT-NOIRR			
	All years	Drought	Normal	Pluvial	All years	Drought	Normal	Pluvial
Irrigation water applied (mm)	75.06	96.88	64.18	64.10	63.99	80.33	57.93	53.73
Crop leaf area index ($\text{m}^2 \text{m}^{-2}$)	0.118 (10.3%) ^a	0.157 (15.1%) ^a	0.092 (7.7%) ^a	0.107 (9.0%) ^b	0.000 (0.0%)	0.000 (0.0%)	0.000 (0.0%)	0.000 (0.0%)
Soil moisture ($\text{m}^3 \text{m}^{-3}$)	0.020 (17.5%) ^a	0.027 (30.3%) ^a	0.017 (13.6%) ^a	0.016 (12.5%) ^b	0.017 (15.7%) ^a	0.019 (22.3%) ^a	0.016 (13.8%) ^a	0.016 (13.0%) ^a
Latent heat flux (W m^{-2})	10.175 (21.9%) ^a	14.958 (43.8%) ^a	8.020 (15.3%) ^a	7.547 (14.3%) ^b	10.249 (24.3%) ^a	13.140 (42.6%) ^a	9.085 (19.2%) ^a	8.522 (17.7%) ^a
Total ET (mm)	53.80	79.09	42.41	39.91	54.19	69.48	48.04	45.06
Sensible heat flux (W m^{-2})	−7.772 (−9.2%) ^a	−11.294 (−11.9%) ^a	−6.197 (−7.7%) ^a	−5.826 (−7.3%) ^b	−7.731 (−9.0%) ^a	−9.661 (−10.2%) ^a	−7.285 (−8.9%) ^a	−6.246 (−7.8%) ^a
2-m temperature (°C)	−0.402 (−0.1) ^a	−0.629 (−0.2) ^a	−0.278 (−0.1) ^a	−0.300 (−0.1) ^b	−0.362 (−0.1) ^a	−0.404 (−0.1) ^a	−0.379 (−0.1) ^a	−0.301 (−0.1) ^b
2-m mixing ratio (g kg^{-1})	0.300 (3.2%) ^a	0.465 (5.5%) ^a	0.218 (2.3%) ^a	0.217 (2.2%) ^b	0.305 (3.3%) ^a	0.388 (4.6%) ^a	0.261 (2.8%) ^a	0.266 (2.7%) ^b
Precipitable water (mm)	0.197 (0.9%) ^b	0.358 (1.7%) ^c	0.117 (0.5%) ^b	0.115 (0.5%) ^c	0.149 (0.7%) ^a	0.192 (0.9%) ^b	0.101 (0.4%)	0.153 (0.7%) ^b
CAPE (J kg^{-1})	27.433 (7.8%) ^a	36.320 (12.7%) ^b	21.825 (5.8%) ^b	24.153 (6.1%) ^c	24.414 (7.1%) ^a	26.168 (9.4%) ^a	21.215 (5.9%) ^c	25.859 (6.7%) ^b
CIN (J kg^{-1})	1.691 (3.1%) ^b	2.880 (5.2%) ^c	1.080 (2.0%)	1.114 (2.0%)	2.084 (3.8%) ^a	3.327 (6.0%) ^b	1.559 (2.9%)	1.367 (2.5%)
Precipitation (mm)	12.429 (5.0%) ^b	20.096 (13.3%)	8.383 (2.9%)	8.810 (2.9%)	9.078 (3.7%) ^b	5.942 (4.0%)	8.977 (3.2%)	12.316 (4.1%)
Rainy days	0.540 (2.4%)	0.877 (5.3%)	0.183 (0.8%)	0.560 (2.1%) ^c	0.232 (1.0%)	0.235 (1.4%)	0.186 (0.8%)	0.273 (1.0%)
Precipitation intensity (mm day^{-1})	0.072 (0.6%)	0.145 (1.2%) ^b	0.133 (1.0%)	−0.061 (−0.5%)	0.083 (0.6%)	0.051 (0.4%)	0.093 (0.7%)	0.104 (0.8%)

^a Significance values for paired *t* test: ($p < 0.01$).

^b Significance values for paired *t* test: ($p < 0.05$).

^c Significance values for paired *t* test: ($p < 0.1$).

exclusive. Regardless, the relationship between enhanced crop LAI and increased precipitation with irrigation is an important process that simulations with static vegetation do not capture.

Here, we consider changes in ET and precipitation from irrigation and examine how much water is lost from the region due to irrigation. In this context, irrigated water lost from the region refers to increases in ET that are not offset by additional precipitation from irrigation. Rainfall enhanced by irrigation (12.43 mm over the Ogallala region on average for all years) is significantly lower than total increases in ET over the course of the warm season (53.86 mm) in DYN simulations (Table 4). More water is lost from the Ogallala region in STAT simulations (45.11 mm) compared with DYN simulations (41.37 mm) because irrigation drives greater increases in ET while enhancing precipitation less in STAT simulations compared with DYN runs (Table 4). On average, 23.1% of ET from irrigation is offset by increases in precipitation in DYN simulations, compared to just 16.8% in STAT simulations. Because groundwater depletion is concentrated in heavily irrigated areas, we also consider the water balance for irrigated grid cells in the region. Much larger losses of irrigated water occur over irrigated grid cells as the 105.73-mm ET increase from irrigation in DYN simulations is much larger than the 12.83-mm simulated increase in rainfall (Table 5). Irrigation results in an average 92.90-mm loss of water to the atmosphere that is not returned to irrigated grid cells as precipitation (86.1% of ET) when dynamic crop growth is enabled, with larger losses in STAT simulations (103.06 mm; 92.8% of ET).

Irrigation primarily increases precipitation during the evening and overnight hours when convection is typically elevated above the planetary boundary layer (Figures 12a,b). Rainfall increases occur a few hours after the largest increases in precipitable water (Figure 12d) and CAPE (Figure 12f) but at the same time as the nocturnal maximum in moisture convergence associated with the GPLLJ (Figure 12g). This suggests that increases in rainfall from enhanced precipitable water and CAPE are primarily utilized by moisture convergence from the GPLLJ rather than by thermals or boundary layer mixing associated with peak heating. Warm-season rainfall over the region is both more frequent and more intense with irrigation (Table 4), but the additional rainfall is primarily associated with an increase in the number of rainy days (≥ 1 mm) rather than heavier rainfall rates (Table 4). In addition, much greater increases in the number of rainy days occur in simulations with dynamic crop growth compared to STAT simulations (Table 4).

3.4. Contrast between drought and nondrought years

Because of lower antecedent soil moisture during droughts, much more water is used for irrigation during drought years compared with normal and pluvial years (Table 4). Irrigation in normal and pluvial years has a similar effect on all variables we analyze (Tables 4 and 5); therefore, we focus on the contrast between drought and nondrought (normal and pluvial) years for the remainder of this section.

The LAI response to irrigation is stronger during drought years ($R^2 = 0.852$) compared with nondrought years ($R^2 = 0.68$) (Table 4; Figure 8c). Similarly, the increase in ET from irrigation is much larger during drought years, especially over heavily irrigated grid cells in both sets of simulations (Figure 8g). During

Table 5. As in Table 4, but for grid cells with at least 10% irrigation within the Ogallala Aquifer region (outlined in Figure 1).

	DYN-IRR minus DYN-NOIRR			
	All years	Drought	Normal	Pluvial
Irrigation water applied (mm)	143.87	188.03	121.61	121.99
Crop leaf area index ($\text{m}^2 \text{m}^{-2}$)	0.573 (34.7%) ^a	0.750 (52.8%) ^a	0.452 (25.5%) ^a	0.516 (29.3%) ^a
Soil moisture ($\text{m}^3 \text{m}^{-3}$)	0.040 (31.0%) ^a	0.053 (54.5%) ^a	0.034 (24.4%) ^a	0.032 (21.8%) ^b
Latent heat flux (W m^{-2})	19.996 (39.5%) ^a	29.310 (79.8%) ^a	15.966 (27.9%) ^a	14.712 (25.5%) ^b
Total ET (mm)	105.73	154.98	84.42	77.79
Sensible heat flux (W m^{-2})	−15.833 (−18.6%) ^a	−23.011 (−23.8%) ^a	−12.709 (−16.0%) ^a	−11.780 (−15.0%) ^b
2-m temperature ($^{\circ}\text{C}$)	−0.656 (−0.2) ^c	−1.030 (−0.3) ^a	−0.465 (−0.2) ^a	−0.474 (−0.2) ^b
2-m mixing ratio (g kg^{-1})	0.468 (5.1%) ^c	0.726 (8.7%) ^a	0.351 (3.7%) ^a	0.326 (3.4%) ^b
Precipitable water (mm)	0.218 (0.9%) ^b	0.407 (1.9%) ^c	0.132 (0.6%) ^a	0.115 (0.5%)
CAPE (J kg^{-1})	38.015 (10.6%) ^c	50.433 (17.3%) ^a	31.350 (8.2%) ^b	32.262 (7.9%) ^c
CIN (J kg^{-1})	2.701 (4.8%) ^b	4.601 (7.9%) ^c	1.794 (3.3%) ^c	1.709 (3.0%)
Precipitation (mm)	12.827 (4.9%) ^a	22.168 (14.6%)	8.944 (3.0%)	7.369 (2.2%)
Rainy days	0.823 (3.8%)	1.457 (10.0%)	0.557 (2.3%) ^c	0.454 (1.7%)
Precipitation intensity (mm day^{-1})	0.133 (1.2%)	0.264 (2.6%) ^b	0.043 (0.4%)	0.092 (0.8%)

^a Significance values for paired *t* test: ($p < 0.01$).^b Significance values for paired *t* test: ($p < 0.05$).^c Significance values for paired *t* test: ($p < 0.1$).

drought years, DYN simulations have a much larger increase in soil moisture than STAT simulations (Tables 4–5; Figure 8k) because excessive soil evaporation depletes soil moisture in STAT simulations. Much larger increases in precipitable water occur during drought years compared with nondrought years in both sets of simulations (Tables 4–5; Figure 9c). During drought years, precipitable water increases are much larger in DYN simulations than in STAT simulations (Figure 9c; Table 4) because of the reduced advection of moisture out of the region by weaker low-level winds in DYN simulations (Figure 10).

Greater increases in low-level moisture during drought years cause large increases in CAPE throughout the region, especially over the heaviest irrigated grid cells in DYN simulations (Figure 9g; Tables 4–5). During drought years, the large difference in precipitable water and CAPE responses between DYN and STAT simulations causes much different precipitation responses. This is especially true over irrigated grid cells where rainfall increases by 14.6% on average in DYN simulations but by only 2.8% in STAT simulations (Table 5). In STAT simulations, precipitation decreases with increasing grid cell irrigation fraction during drought years because of large increases in CIN and smaller increases in CAPE,

Table 5. *Extended*

	STAT-IRR minus STAT-NOIRR			
	All years	Drought	Normal	Pluvial
Irrigation water applied (mm)	125.79	160.01	112.80	104.57
Crop leaf area index ($\text{m}^2 \text{m}^{-2}$)	0.000 (0.0%)	0.000 (0.0%)	0.000 (0.0%)	0.000 (0.0%)
Soil moisture ($\text{m}^3 \text{m}^{-3}$)	0.035 (29.2%) ^a	0.040 (43.8%) ^a	0.033 (25.4%) ^a	0.031 (23.0%) ^a
Latent heat flux (W m^{-2})	20.993 (47.1%) ^a	27.729 (86.5%) ^a	18.449 (36.8%) ^a	16.801 (32.6%) ^a
Total ET (mm)	111.00	146.62	97.55	88.84
Sensible heat flux (W m^{-2})	−16.063 (−18.7%) ^a	−21.041 (−21.8%) ^a	−14.421 (−17.8%) ^a	−12.726 (−15.8%) ^a
2-m temperature ($^{\circ}\text{C}$)	−0.579 (−0.2) ^a	−0.697 (−0.2) ^a	−0.572 (−0.2) ^a	−0.469 (−0.2) ^b
2-m mixing ratio (g kg^{-1})	0.502 (5.5%) ^a	0.659 (7.9%) ^a	0.434 (4.6%) ^a	0.412 (4.3%) ^b
Precipitable water (mm)	0.170 (0.7%) ^a	0.234 (1.1%) ^b	0.117 (0.5%)	0.160 (0.7%) ^b
CAPE (J kg^{-1})	33.960 (9.7%) ^a	37.332 (13.2%) ^a	29.616 (8.1%) ^c	34.932 (8.8%) ^a
CIN (J kg^{-1})	3.223 (5.7%) ^a	5.318 (9.2%) ^a	2.634 (4.9%) ^c	1.717 (3.0%)
Precipitation (mm)	7.944 (3.1%) ^b	4.221 (2.8%)	7.834 (2.7%)	11.776 (3.7%) ^a
Rainy days	0.377 (1.8%)	0.344 (2.4%)	0.097 (0.4%)	0.689 (2.7%)
Precipitation intensity (mm day^{-1})	0.097 (0.9%)	−0.047 (−0.5%)	0.292 (2.5%) ^b	0.046 (0.4%)

as strong cooling over heavily irrigated grid cells is accompanied by smaller increases in moisture (Table 5). In nondrought years, DYN and STAT simulations have similar overall precipitation responses to irrigation, with slightly larger rainfall increases in STAT simulations (Table 4). The small difference in rainfall responses to irrigation between STAT and DYN simulations in nondrought years is likely related to minimal differences in precipitable water and CAPE changes with irrigation between the two sets of simulations when drought conditions are not present (Table 4). These results suggest that the inclusion of dynamic vegetation has the greatest impact on precipitation during drought years, with a smaller impact during normal and pluvial years when antecedent soil moisture is higher and the phenological response to irrigation is reduced. During drought years, DYN simulations have a much larger increase in the number of rainy days than STAT simulations (Table 4), and irrigation increases precipitation intensity more in DYN simulations over irrigated grid cells (Table 5).

In DYN simulations of drought years, irrigation increases ET by 79.09 mm, while rainfall is only enhanced by 20.10 mm (Table 4). Conversely, the smaller increase in rainfall from irrigation during drought years in STAT simulations results in a greater loss of water out of the region (evapotranspiration minus precipitation changes from irrigation) in WRF runs with static crops (63.54 mm)

Figure 9. As in Figure 8, but (a)–(d) for precipitable water (mm), (e)–(h) for maximum parcel CAPE (J kg^{-1}), and (i)–(l) for precipitation (mm).

Figure 10. May–September DYN-NOIRR minus STAT-NOIRR simulated 10-m wind speed (m s^{-1}) and vectors (m s^{-1}) for all simulated years. Difference shown only for grid cells found to be significant using a two-tailed, paired t test at the 95% confidence level.

compared to those with dynamic crops (59.00 mm). Losses of water from irrigation over the Ogallala Aquifer are much smaller during nondrought years, with similar losses of irrigated water in DYN (32.56 mm) and STAT simulations (35.90 mm). Considering irrigated grid cells, the largest loss of water occurs during drought years in both sets of model simulations. In DYN simulations, a 132.81-mm loss of water occurs over irrigated grid cells, and rainfall increases (22.17 mm) only offset 14.3% of the flux of irrigated water to the atmosphere. Much smaller increases in precipitation during drought simulations with static vegetation result in a much larger loss of water over irrigated grid cells (142.40 mm), and only 3.0% of ET is offset by increases in precipitation in those grid cells.

4. Discussion and conclusions

In this study, including the dynamic vegetation response to irrigation results in fundamental differences in the simulated impact of irrigation on warm-season rainfall over the Ogallala Aquifer. WRF simulations with dynamic crop growth include more land–atmosphere feedbacks than simulations with a fixed annual cycle of LAI. Including these feedbacks is critical when investigating the impact of irrigation on rainfall, especially in a region that is considered a “hotspot” of land–atmosphere coupling (Koster et al. 2004). In simulations with dynamic crop growth, the response of LAI to irrigation provides a critical link between irrigation

Figure 11. (a) May–September area-weighted average change in precipitable water (mm) with irrigation vs change in crop LAI (m^2m^{-2}) over the Ogallala region (outlined in Figure 1) for each simulated year from DYN simulations. (b) As in (a), but for precipitation (mm).

and enhanced rainfall, an effect that is not realized with a fixed annual cycle of LAI. In static vegetation runs, lower surface roughness from underestimated LAI over crop areas and an overestimated GPLLJ related to a stronger warm bias cause greater advection of irrigated moisture out of the region. This advection of moisture out of the region explains why irrigation has weaker relationships with precipitable water and rainfall in simulations with static crops compared to those with dynamic crop growth. Consequently, changes in surface roughness from the inclusion of dynamic crop growth into WRF and its impact on the advection of evapotranspired moisture from irrigated fields may affect the simulated downwind effects of irrigation on precipitation. Lack of representation of dynamic crop growth in previous studies (i.e., [Harding and Snyder 2012b](#); [Huber et al. 2014](#)) suggests that downwind increases in precipitation with irrigation might have been overestimated.

The inclusion of dynamic crop growth in WRF-CLM4crop improves the simulation of temperature, precipitation, and low-level wind fields over the Ogallala Aquifer compared with model runs using a fixed annual cycle of LAI. Increases in precipitable water, CAPE, and rainfall in nonirrigated simulations associated with the inclusion of dynamic crops (Figure 5) have a similar magnitude as the simulated response to irrigation (Figure 9), demonstrating the importance of dynamic crop growth on the simulation of warm-season convective precipitation in the region. Collectively, irrigation and dynamic crop growth improve simulated precipitation

Figure 12. (a) May–September area-weighted average diurnal cycle of precipitation (mm month^{-1}) from nonirrigated simulations over Ogallala region (outlined in Figure 1). (b) As in (a), but for irrigated minus nonirrigated simulations. (c),(d) As in (a) and (b), but for precipitable water (mm). (e),(f) As in (a) and (b), but for maximum parcel CAPE (J kg^{-1}). (g),(h) As in (a) and (b), but for moisture convergence (mm).

over the Ogallala Aquifer compared to observations (-24.7% in STAT-NOIRR vs -19.3% in DYN-IRR) and diminish the simulated warm bias from 1.93° to 0.94°C . In addition, because the environment is more conducive for the development of convective precipitation when dynamic crop growth is included, the effects of irrigation on warm-season rainfall are much more likely to be realized in simulations with

dynamic vegetation than those with static vegetation. WRF simulations with dynamic crop growth also improve the partitioning of water budget components, which allows more realistic estimations of the ET and soil moisture response to irrigation.

In this study, we show that irrigation has significant impacts on the hydroclimate of the Great Plains, especially during drought years when antecedent soil moisture is low and the largest vegetation response to irrigation occurs. The elevated LAI change from irrigation during drought years is coincident with a large increase in rainfall in simulations with dynamic vegetation, while much smaller increases in rainfall occur in STAT simulations. Likewise, irrigation in DYN simulations induces a large increase in rainy days during drought years, a result that is not captured in simulations with static vegetation. However, small differences between DYN and STAT simulations during nondrought years suggest that the inclusion of dynamic crop growth is less important for simulating the atmospheric response to irrigation in normal and pluvial years.

Overall, irrigation causes large increases in ET and significant reductions in sensible heating, driving widespread cooling that is coincident with enhanced low-level moisture. The additional CAPE and precipitable water from irrigation overwhelm the suppression of convection from evaporative cooling, driving enhanced precipitation with irrigation. Rainfall increases occur primarily in the evening and overnight hours when convection is typically elevated above the boundary layer and is dynamically forced by the GPLLJ, similar to results from [Harding and Snyder \(2012b\)](#) as well as [Qian et al. \(2013\)](#). However, the vegetation response to irrigation in WRF-CLM4crop enhances column-integrated precipitable water more than in [Harding and Snyder \(2012b\)](#), driving larger increases in rainfall. Irrigation increases precipitation the most during drought years in simulations with dynamic vegetation, similar to results from [Qian et al. \(2013\)](#).

Rainfall increases with irrigation in all precipitation regimes in this study; however, increases in precipitation with irrigation are much smaller than increases in ET, suggesting that only a small amount of evapotranspired water from irrigated fields falls back into the region as precipitation. This suggests that while irrigation increases rainfall over the Ogallala Aquifer, more water from irrigation is advected out of the region than is returned as rainfall that could replenish groundwater supplies. Greater demand for biofuel crops in the region as well as higher temperatures and possible increases in drought frequency, intensity, and severity with anthropogenic climate change ([Alexander et al. 2013](#); [Harding and Snyder 2014](#); [Patricola and Cook 2013](#)) will likely continue to increase water losses over the next several decades. These potential future changes might place greater pressure on an aquifer that is already heavily depleted in some locations. Further understanding of how potential increases in demand for irrigated water could impact groundwater supplies for irrigation is critical for such an important agricultural region that is exceedingly reliant on consistent groundwater supplies.

Acknowledgments. Support for this project was provided by the United States Department of Energy under Award DE-EE0004397. This work was carried out in part using computing resources at the University of Minnesota Supercomputing Institute. The WRF Model used herein can be acquired from the WRF home page online (at http://www2.mmm.ucar.edu/wrf/users/download/get_source.html). All other data and programs used to replicate the results in this study are available upon request from the corresponding author at twine@umn.edu. We thank Dr. Mutlu Ozdogan for providing the

fractional irrigation dataset, Dr. Shashi Verma for use of the Ameriflux data at the Mead FLUXNET site, and two anonymous reviewers for their thorough and constructive feedback.

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