Effects of Irrigation on Water, Carbon, and Nitrogen Budgets in a Semiarid Watershed in the Pacific Northwest: A Modeling Study

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Abstract In this study, we use the Community Land Model Version 5 (CLM5) to investigate how irrigation modulates hydrologic and biogeochemical dynamics in the Upper Columbia-Priest Rapids (UCPR) watershed, a typical semiarid watershed located in the northwestern United States dominated by cropland. To our knowledge, this constitutes the first application of CLM5 with landscape heterogeneity fully resolved over a watershed. The model is calibrated and evaluated against flux measurements from an AmeriFlux site and the Moderate Resolution Imaging Spectroradiometer (MODIS) products. Two numerical experiments (i.e., irrigated and rainfed) are performed at hyperresolution (~1 km) over the period of 2010–2018, accounting for realistic crop types and management practices. Our results show that irrigation fundamentally alters hydrologic and biogeochemical dynamics of the watershed. By adding 79.6 mm year−1 water in addition to the mean annual precipitation of 204.0 mm year−1, irrigation leads to increases in evapotranspiration and runoff, accompanied by shallower groundwater table depths. Increases in crop productivity in response to irrigation result in more carbon storage in the watershed, and drastically large seasonal fluctuations in soil organic carbon in response to changes in soil temperature and moisture. Irrigation also intensifies the rate of denitrification and mineralization during the growing season, enhancing the interactions between soil mineral nitrogen, the atmosphere, and freshwater systems. Our study demonstrates the potential of CLM5 as an effective tool for understanding hydrological and biogeochemical dynamics in highly managed semiarid watersheds.

Plain Language Summary Irrigation plays an important role in the agro-ecosystem, especially over semiarid areas, while its effects on water, carbon, and nitrogen cycle over watershed scale are not well addressed by previous studies. We, therefore, use the Community Land Model Version 5 (CLM5) to simulate the irrigation demands over the Upper Columbia-Priest Rapids (UCPR) watershed, a typical semiarid region located in the northwestern United States. The model is applied at 1 km resolution, considering the landscape heterogeneity and the crop-type rotation. This study shows that the irrigation significantly increases all water budgets, such as evaporation and runoff. The more carbon is stored in the watershed as irrigation intensifies photosynthesis rate of cropland. The nitrogen availability in plant that potentially affects crop yield is slightly increased while soil organic nitrogen is gradually leaching due to irrigation. This modeling study successfully demonstrates the potential of CLM5 to simulate water, carbon, and nitrogen budgets under a changing environment over semiarid areas.

1. Introduction

Irrigation contributes to more than 40% of food production globally (FAO, 2016). Over 88% of the land area in Central Asia and Northern Africa and 65% in Europe have already been equipped for irrigation according to the Food and Agriculture Organization (FAO) report in 2016 (FAO, 2016). In the United States, irrigation is estimated to be about 355 billion gallons per day (Maupin et al., 2014) and plays a significant role economically through improving agricultural productivity (Stubbs, 2015). In semiarid and arid regions of the United States where vegetation growth is limited by water availability, production of crops could become difficult, if not impossible, without irrigation. Previous studies have shown that expected changes in hydroclimatic
conditions in the context of regional climate change and population growth could lead to larger water deficits to satisfy irrigation water demand in these regions (Leng et al., 2016; Zhou et al., 2018). Fischer et al. (2007) suggest that global and regional net irrigation amounts show a general increasing trend in the future that poses huge challenges to water resources and agriculture. Therefore, understanding and developing tools to quantify the role of irrigation in modulating water, carbon, and nitrogen budgets in semiarid watersheds is crucial for better managing water resources and associated goods and services.

Significant progress has been made in quantifying effects of irrigation on the terrestrial water, energy, and biogeochemical cycles in the past decade (Denef et al., 2008; Leng et al., 2013; Leng et al., 2017; Lo & Famiglietti, 2013; Ozdogan et al., 2010; Xiao et al., 2007). As an external water input, irrigation directly influences land surface fluxes (Chen & Xie, 2011) by elevating near-surface soil moisture, leading to increases in evapotranspiration and latent heat fluxes (Lobell et al., 2009) compensated by decreases in sensible heat fluxes. Such perturbations in surface energy and water fluxes not only lead to surface cooling and decreases in Bowen ratios that modulate boundary layer evolution and convective processes in the atmosphere (DeAngelis et al., 2010; Harding & Snyder, 2012; Pei et al., 2016) but also influence the hydrologic budget. For example, previous studies (Leng et al., 2015; Qiu et al., 2019; Xu et al., 2019) have demonstrated that the hydrologic budget terms such as infiltration, percolation to deep soil layers, recharge to aquifers, and in turn baseflow at field, watershed, and large basin scales can be altered by irrigation.

In addition, irrigation increases plant available water to sustain crop productivity through photosynthesis, while accelerating decomposition of litter and soil organic matters (Collins et al., 1992; Mariko et al., 2007). Consequently, the carbon and nitrogen fluxes and stocks in irrigated lands are expected to differ significantly from those in unirrigated lands (Follett, 2001). Irrigation is therefore an indispensable component of the water budget that can strongly modulate agro-ecosystem dynamics and biogeochemical cycling in semiarid watersheds, although its contribution to watershed functioning has not been sufficiently studied (Brown, 2011; Qiu et al., 2019).

Previous investigations on irrigation effects using land surface models are limited in terms of resolving landscape details and representing land management practices and physical processes. For example, focusing on a large region using a relatively coarse resolution, Wu et al. (2018) applied the Weather Research and Forecasting (WRF) model coupled with Noah MultiParameterization (Noah-MP) model at 1° × 1° resolution to study the effect of irrigation on regional climate in north China. Döll and Siebert (2002) applied the Water-GLOBAL Assessment and Prognosis (WaterGAP) model at 0.5° × 0.5° resolution to study irrigation water requirements globally. These studies were designed to understand regional- to global-scale water cycle dynamics with perturbations induced by irrigation, but not to capture watershed-scale processes in sufficient detail. High-resolution modeling is key to supporting analyses of land-atmosphere as well as surface and subsurface interactions (Wood et al., 2011; Xiao et al., 2018). Furthermore, changes in land cover, crop types, and land management practices are typically not realistically accounted for due to limitations in data availability and existing parameterizations in earlier-generation land models (Leng et al., 2015; Ozdogan et al., 2010; Qian et al., 2013).

Recognizing the importance of land use and land cover change in modulating Earth system dynamics (Lawrence et al., 2016; McDermid et al., 2017; Pongratz et al., 2018), progress has been made to crop development into state-of-the-art land models such as the Community Land Model (CLM) Version 5.0 (Lawrence et al., 2019). For example, the key improvements in CLM5 include incorporating physiological and phenological representations of various crop types, land management practices, and improved biogeochemical parameterizations. Such improvements allow us to explore potential effects of irrigation on water and energy budgets, biogeochemical cycling, and their complex interactions in the terrestrial environment.

In this study, we aim to test the hypothesis that irrigation is not only a significant component of the hydrologic budget but also fundamentally changes watershed functioning in cycling carbon and nitrogen in a semiarid watershed. We apply the newly released CLM5 to quantify effects of irrigation in a semiarid agricultural watershed, the Upper Columbia-Priest Rapids (UCPR) watershed, a Level 8 watershed according to the U.S. Geological Survey hydrologic unit code (HUC) system situated in the Pacific Norwest of the United States.
The model simulations are performed during a period with satellite records to provide model inputs and benchmarks for model validation. To fully evaluate the potential of CLM5 in quantifying watershed processes, we (1) apply the model at hyperresolution (~1 km) to explicitly resolve landscape heterogeneity including cropland, natural vegetation, lakes, and urban over the study domain; (2) configure the model to allow explicit land use and land cover transitions including rotation in crop types (e.g., corn, wheat, and soybean) and land management practices (e.g., fertilization) based on best available land cover data sets and agricultural census information; and (3) assemble in situ and remotely sensed data sets as benchmarks to evaluate model performance in capturing land surface fluxes in both natural and agricultural ecosystems. To our knowledge, this constitutes the first attempt to apply CLM5 to a HUC-8 watershed with landscape heterogeneity fully resolved, demonstrating the potential of using CLM5 as the terrestrial water and biogeochemical components of an integrated surface and subsurface model such as those discussed in Maxwell et al. (2014) and Bisht et al. (2017).

The remainder of the paper is organized as follows: In section 2, features of CLM5 that are key to this study are described, followed by model configuration and numerical experiments, as well as strategy of model calibration. In section 3, modeling results are presented, including model performance evaluation and quantitative discussion of irrigation effects over the study domain. We present our conclusions and thoughts on future directions in section 4.

2. Methodology

2.1. Study Domain

The Upper Columbia-Priest Rapids (UCPR) watershed is located in south-central Washington State of the United States (Figure 1) with a drainage area of 4,657 km². The watershed receives an average annual precipitation of less than 180 mm, typical for semiarid regions (Gee et al., 2007). Despite such limited precipitation, availability of water resources and established water management infrastructure including reservoirs and canals, in combination with rich soils, make the region an important productive growing region in the world (https://ipad.fas.usda.gov/rssiws/al/global_cropprod.aspx).

The watershed (Figure 1) is covered by various land types, including natural vegetation, crop, urban, and river. Land surface characteristics from 2010 to 2018 are obtained from the USDA National Agricultural Statistics Service Cropland Data Layer (CDL) (https://nassgeodata.gmu.edu/CropScape). The CDL data set is originally created from satellite imagery and fully trained and assessed based on ground truth data. The categories of CDL are reclassified to the corresponding land types in CLM5 (Table 1). Natural vegetation and crop are two dominant land cover types in the watershed, which account for more than 90% of the drainage area, followed by urban and river (Figure 2a). Natural vegetation covers most areas in the west portion, and crops are mainly located in the east and northwest portions of the watershed.

Our analysis of land use change from 2010 to 2018 shows that there are slight fluctuations in areas covered by natural vegetation and crops from year to year while urban and river stay stable in this period. The dynamic land cover changes are considered in our study; therefore, the simulate irrigation and its effects are changing accordingly with land cover and climate conditions year to year. As shown in Table 1 and Figure 2b, the crop types planted in the watershed are mainly corn, winter wheat, and soybean. Both corn and soybean require irrigation. Winter wheat is rainfed because sufficient winter precipitation repletes rooting-zone soil moisture; thus, it does not rely on irrigation to grow in this region. The C3 unmanaged crop is separated into rainfed and irrigated fractions. The rainfed C3 unmanaged crops include fallow/idle croplands that rely on rainfall, C3 unmanaged irrigated crops are pasture, and a few other irrigated crops not parameterized in CLM5 such as carrots (Figure 2b). The soil hydraulic properties are calculated based on the percentage of soil clay, soil sand, and organic content that are derived from the USDA Digital General Soil Map of United States (USDA-NRCS, 2011), which provides information about soil features on or near the surface of the Earth. Since the soil texture potentially affect water and carbon budgets, therefore, the simulations accounting for soil texture differences are modeled in the study. The soil hydraulic conductivity and porosity over the study domain range from 131 to 2,421 mm day⁻¹ and 0.37 to 0.48 mm³ mm⁻³, respectively.
2.2. Model Description

The CLM is a widely used land surface model (Sheng et al., 2018; Swenson & Lawrence, 2015; Umair et al., 2018). Version 5 of CLM simulates hydrological processes, surface energy fluxes, and biogeochemical processes, including runoff generation, soil moisture hydrology, and carbon and nitrogen allocation. The model is selected in this study because of its following features: (1) capable of representing multiple land use and crop types, which allows the spatial heterogeneity in soil properties, topography, and surface climate to be resolved; (2) fully coupled water, energy, carbon, and nutrient cycle dynamics, which allow for joint investigations of these processes and their interactions in a holistic way; and (3) enhancements in key features needed to represent agricultural landscapes, including land management practices (i.e., irrigation, fertilization, crop planting, and harvest), as well as dynamic land use transitions for capturing crop rotation and potential expansion in agricultural lands.

2.2.1. Biogeophysical and Biogeochemical Processes

The hydrological processes represented in the model include interception, snow hydrology, infiltration, evaporation, surface runoff, groundwater dynamics, and soil water movement (http://www.cesm.ucar.edu/models/cesm2/land/CLM50_Tech_Note.pdf). The liquid precipitation is partitioned into surface runoff, surface water storage, and infiltration. The TOPMODEL-based runoff model is implemented to parameterize surface runoff. Surface water storage and outflow are functions of fine spatial scale elevation variations called microtopography. Soil water is predicted using the one-dimensional (vertical) Richards equation. Soil water is predicted using the one-dimensional (vertical) Richards equation. Lateral subsurface runoff occurs when saturated soil moisture conditions exist within the soil column. CLM5 simulates biogeochemical dynamics in terms of carbon and nitrogen budgets in the plant and soil systems as well as the interactions between these components in a fully coupled fashion.

| CLM5 crop functional types       | CDL crop types                                  |
|----------------------------------|------------------------------------------------|
| C3 unmanaged rainfed crop        | Fallow/idle cropland                           |
| C3 unmanaged irrigated crop      | Pasture, carrots, potatoes, etc.               |
| Corn                             | Corn, sweet corn, double crop corn             |
| Winter wheat                     | Winter wheat, durum wheat, buckwheat          |
| Soybean                          | Alfalfa, peas, dry beans                       |

Figure 1. The UCPR watershed, the spatial distribution of land cover and meteorological stations, and the location of US-Hn1 Ameriflux site.
Plants assimilate and release carbon to the atmosphere through photosynthesis and respiration. The model simulates gross primary production (GPP) to represent the total amount of carbon fixed in the process of photosynthesis by plants and components of total ecosystem respiration (ER) as carbon losses into the ambient atmosphere, and hence the net ecosystem exchange (NEE) calculated as the difference between ER and GPP. Inorganic nitrogen stored in soil mineral is the main source providing nitrogen for plants. Following the growing season, nitrogen in soil organic matters is gradually transferred into soil minerals through mineralization. Denitrification and leaching are two other ways in which nitrogen is lost into the atmosphere and runoff from the soil. All carbon and nitrogen state variables stored in the vegetation, litter, and soil organic matter are fully prognostic (http://www.cesm.ucar.edu/models/clm/biogeochemistry.html).

2.2.2. Crop Management

Eight actively managed crop types (e.g., temperate corn, spring/winter wheat, and temperate soybean) are represented in CLM5. To capture crop specific characteristics, each crop is separated into rainfed and irrigated fractions coexisting with natural vegetation in the vegetated land unit. All crops must experience four stages during a year from planting to maturity. Each crop type starts growing on its planting day when the local temperature meets the long-term mean growing temperature and ends with leaf emergence. The leaves may emerge when the growing degree days of soil temperature at 0.05 m from the surface meets a crop-specific empirical value. When the leaf area index (LAI) and air temperature reach prescribed thresholds, the grain-fill phase begins. The last stage is harvest when the growing degree days or the number of days past planting reaches physiological maturity or a crop-specific maximum. The model uses an annual time series of percentage area of each crop type and natural vegetation in land unit to represent the transient land use and land cover change. The mass and energy balance associated with expansion and contraction of the land cover is reallocated in the beginning of each year.

Fertilizer application rates and irrigation fraction are set annually to mimic human activities on croplands. Fertilization and irrigation rates are tied to crop types and vary across grid cells. Fertilization is simulated by adding nitrogen directly to the soil nitrogen pool to meet the nitrogen requirement of cropland. The default nitrogen is applied slowly at a rate of 2 gN m$^{-2}$ year$^{-1}$ for each crop type. The application begins during the leaf emergence phase, which lasts for 20 days to limit the denitrification rates. In our simulations, this default fertilization rate is replaced by the rates (Table 2) derived from the USDA fertilizer use and price product (https://www.ers.usda.gov/data-products/fertilizer-use-and-price.aspx) to be more crop-specific.

### Table 2

Areas and Calibrated Parameters of Three Dominant Crop Types

| Crop         | Area percentage | Photosynthesis capacity | Planting date (MM/DD) | Nitrogen fertilizer |
|--------------|-----------------|-------------------------|-----------------------|---------------------|
| Corn         | 7.3%            | 11.5 (9.5–16.5)         | 3/01 (2/01–4/01)      | 16 gN m$^{-2}$ year$^{-1}$ |
| Winter Wheat | 25.5%           | 43.5 (24.5–59.2)        | 10/01 (9/01–12/01)    | 8 gN m$^{-2}$ year$^{-1}$ |
| Soybean      | 20.5%           | 28.5 (23.5–59.2)        | 3/01 (2/01–5/01)      | 2 gN m$^{-2}$ year$^{-1}$ |

Figure 2. The area percentage of (a) land units and (b) crop types in each year.
The irrigation scheme in CLM5 is activated for the prescribed fraction in each grid cell equipped for irrigation. The model checks the LAI and soil water content to determine whether irrigation is needed at 6 a.m. local time every day based on the following criteria: (1) the crop leaf area > 0, and (2) the available soil water is below a specified threshold. The irrigation amount is determined by the soil moisture deficit \( D_{\text{irrig}} \) between available and threshold soil moisture, defined as

\[
D_{\text{irrig}} = w_{\text{thresh}} - w_{\text{avail}},
\]

where \( w_{\text{thresh}} \) is the irrigation moisture threshold (mm) and \( w_{\text{avail}} \) is the available moisture (mm). As for the soil moisture threshold, it is defined as

\[
w_{\text{thresh}} = f_{\text{thresh}} (w_{\text{target}} - w_{\text{wilting}}) + w_{\text{wilting}},
\]

where \( w_{\text{target}} \) is the irrigation target soil moisture (mm), \( w_{\text{wilting}} \) is the wilting point soil moisture (mm), and \( f_{\text{thresh}} \) is a tuning parameter, ranging from 0 to 1. The target soil moisture and wilting point are determined by soil matric potential parameters. Irrigation water is applied directly to the ground surface by evenly distribute the amount of water same, as the soil moisture deficit is calculated over a period of 4 hr each day.

2.3. Calibration and Validation Datasets

In order to improve model performance, some sensitive parameters related to vegetation and crop phenology in CLM5 are calibrated based on in situ observations and remotely sensed variables. For natural vegetation, the phenology of shrubland over UCPR watershed is set as seasonal-deciduous type. The threshold of growing degree day for natural vegetation is also shortened accordingly based on local temperature. The parameters of the crop types including photosynthesis capacity, planting date, and nitrogen fertilizer are summarized in Table 2. As shown in Table 2, the parameters of the three dominant crop types, (e.g., corn, winter wheat, and soybean) are selected for model calibration. The “optimal” parameter values were determined through benchmarking model simulations against observations or remotely sensed products. Recognizing the significant uncertainties of remote sensing data over shrubland (Giri et al., 2005; Tian et al., 2002) and the lack of in situ observations of fluxes over cropland in our study domain, observations from a flux tower located within the watershed and remotely sensed products are used for calibration and validation over regions covered by natural vegetation and crops, respectively.

Observations from the Ameriflux tower site US-Hn1 (Figure 1) located in a semiarid upland sagebrush ecosystem without groundwater access are used to examine model performance over the naturally vegetated fraction (Gao et al., 2017, 2019; Missik et al., 2019). The eddy covariance measurements of water, energy, and carbon fluxes are collected from 2016 to 2018 at a half-hourly time step at the site. The measurement height of the instruments is 5 m while soil water and soil temperature are measured at a depth of 20 cm. Interested readers are referred to Missik et al. (2019) and https://ameriflux.lbl.gov/sites/siteinfo/US-Hn1 for more details about the site.

Three remote sensing products were processed to serve as benchmarks for the simulations: the Moderate Resolution Imaging Spectroradiometer (MODIS) LAI data (8-day, 500 m), the MODIS ET data (8-day, 500 m), and the MODIS GPP data (8-day, 500 m) during 2010 to 2018 obtained from the National Aeronautics and Space Administration (NASA) (https://www.nasa.gov/). The MODIS LAI (MOD15A2) product has been widely evaluated over regions in various climate and land use conditions (Claverie et al., 2013; Fensholt et al., 2004). The MODIS LAI exploits the spectral information content of the MODIS red (648 nm) and near-infrared surface reflectance (858 nm), and the back-up algorithm based on empirical relationships between Normalized Difference Vegetation Index (NDVI) and canopy LAI. The MODIS ET (MOD16A2) product is calculated based on the logic of the Penman-Monteith equation driven by daily meteorological reanalysis data and MODIS products such as vegetation property dynamics, land cover, and albedo information. The MODIS GPP (MOD17A2H) product is derived based on the radiation use efficiency concept, which assumes a linear relationship between the productivity of crops and the amount of absorbed solar energy. The GPP product is generated at 500 m resolution using the MOD15A2 8-day composite and land cover classification data set. To be consistent with the temporal resolution of the MODIS product, we convert CLM5 simulations from daily output to 8 days for comparison purposes.
Three metrics are used to evaluate model performance: (1) the correlation coefficient ($R$), (2) root mean square error (RMSE), and (3) the relative difference (diff; %). The coefficient $R$ is an indication of temporal agreement, RMSE is a measure of the differences between values simulated by the model and the values derived from MODIS, and the diff is used to measure the relative difference between simulations and MODIS (equation 3).

$$\text{Diff} = \frac{\text{Simulations} - \text{MODIS}}{\text{MODIS}} \times 100\%$$ (3)

### 2.4. Model Setup and Experiment Design

The forcing data of CLM5 are originally from the North American Land Data Assimilation System Phase 2 (NLDAS2) including precipitation, wind speed, air temperature, radiation, and relative humidity. Observational data from meteorological stations over the domain are used wherever available (Figure 1). We bilinearly interpolate the hourly NLDAS2 land-surface forcing data (1/8th degree grid) onto 1/16th degree grid over the study domain. For grid cells on the 1/16th grid, which are closest to one of the 30 meteorological stations, we use that station’s available observational data (2013–2018) to substitute the values interpolated from NLDAS2. The monthly climatology over 2000–2015 calculated based on NLDAS2 and observations from stations at the overlapping grid cells were then used to derive monthly averaged NLDAS2/observations ratios for solar radiation and wind and the average monthly biases (i.e., NLDAS2 – Observations) for air temperature. Finally, we apply the ratios and difference to the interpolated hourly NLDAS2 data on the other 1/16th grid cells to bias correct the NLDAS2 data against the observational data, using the approach from Wood et al. (2004).

During the spin-up, CLM5 is run for 500 years using the calibrated parameters with irrigation turned on by recycling bias-corrected NLDAS forcing in 2010–2018 until all water, carbon, and nitrogen state variables reach equilibrium. Two numerical experiments are performed using CLM5 in two slightly different configurations using the same initial condition obtained from the spin-up: The first experiment is a rainfed simulation with the irrigation module turned off over all grid cells (denoted as CLMrainfed hereafter), and the second is an irrigated simulation with the irrigation module turned on over irrigated crop areas (denoted as CLM_{irrig} hereafter). The spatial resolution of the modeling grid is 1 km for both cases, initiated at the same spin-up states. The parameters are kept the same for the two cases. Therefore, the only difference between the two numerical experiments is whether the irrigation scheme is turned on or off during the simulation period.

### 2.5. Water, Carbon, and Nitrogen Budgets

Based on the validated simulations, we assess the impacts of irrigation on water, carbon, and nitrogen budgets. Irrigation directly affects hydrological fluxes and states, such as ET, surface runoff ($R_{surr}$), baseflow ($R_b$), and water table dynamics (i.e., terrestrial water storage [TWS] and depth to groundwater table [ZWT]). We apply the water balance equation (equation 4) to analyze irrigation effects on the water budget over the UCPR watershed:

$$\text{TWS} = P + \text{Irrigation} - \text{ET} - R_{surr} - R_b,$$ (4)

where TWS is the average total water storage changes including the changes of soil moisture and groundwater storage.

Irrigation is also known to exert a strong influence on carbon and nitrogen dynamics (Denef et al., 2008; Gheysari et al., 2009). Hence, we select a number of key carbon cycle variables, such as GPP, NEE, ER, autotrophic respiration (AR), heterotopic respiration (HR), and total ecosystem carbon (TOTECOSYSC) and its components (i.e., total litter carbon (TOTLITC), total soil organic matter carbon (TOTSOMC), and total vegetation carbon (TOTVEGC)), to investigate irrigation effects on the carbon budget. Irrigation-induced changes in rates of denitrification and mineralization, and total ecosystem nitrogen (TOTECOSYSN) and its components (i.e., total litter nitrogen (TOTLITN), total soil organic matter nitrogen (TOTSOMN), total vegetation nitrogen (TOTVEGN), and soil mineral nitrogen (SMINN)) are also analyzed. Soil organic matters can act as both a source and a sink of carbon and nitrogen (Bullock, 2005), mainly derived from the
decomposition of plant litter, loss through respiration to CO₂, and mineralization to soil mineral nitrogen. The rates of changes in soil organic matters are strongly modulated by soil water (QSOI) and soil temperature (TSOI) in semiarid regions (Bhattacharyya et al., 2009; Lai et al., 2013; Onwuka & Mang, 2018). Therefore, the interactions between water, carbon, and nitrogen in soil organic matter with and without irrigation are also investigated.

3. Results

3.1. Model Performance

3.1.1. Comparison With Observations From the Flux Tower

To evaluate model performance over natural vegetation in terms of water, energy, and carbon fluxes, simulated latent heat fluxes (LH), sensible heat fluxes (SH), net radiation (NETRAD), QSOI, and NEE are compared to flux tower observations. Figure 3 shows comparisons between observed and simulated fluxes at

Figure 3. Comparisons between simulated fluxes and observations at the US-Hn1 flux tower site.
US-Hn1 during the period from 2016 to 2018. CLM5 captures the observed fluxes well in terms of both magnitude and seasonality. The LH and SH peak in late spring when net radiation and plant available water in the rooting zone are high and decline after the growing season (Figures 3a and 3b). The average $R$ ranges from 0.76 to 0.89, relatively low RMSE values for comparison in the energy budgets. Simulated top soil water in the depth of 5 mm strongly correlate with the observations (Figure 3d).

As for the carbon budget, CLM5 captures the flux tower observations fairly well. The NEE, ER, and GPP reach their minimum or maximum in the spring, consistent with the growing seasons for natural vegetation.

Table 3
Comparisons Between CLM5grown Simulated Variables and MODIS Products

|         | MODIS ET | MODIS GPP | MODIS LAI |
|---------|----------|-----------|-----------|
|         | $R$      | RMSE (mm) | $R$       | RMSE (gC m$^{-2}$ day$^{-1}$) | $R$ | RMSE (m$^2$ m$^{-2}$) |
| Cropland| 0.87     | 0.50      | 0.84      | 1.14                        | 0.63 | 0.85                  |
| Corn    | 0.91     | 0.73      | 0.79      | 1.85                        | 0.85 | 0.64                  |
| Wheat   | 0.56     | 0.63      | 0.70      | 1.16                        | 0.45 | 0.49                  |
| Soybean | 0.80     | 0.93      | 0.79      | 1.69                        | 0.73 | 0.88                  |

Figure 4. Comparisons of (a) ET, (b) GPP, and (c) LAI between CLM5 simulations and MODIS products with 10% and 90% percentiles (shade areas) of all croplands pixels in the UCPR watershed.
and the period with sufficient moisture for decomposition (Figures 3e–3g). Carbon stored in the plants increases to its highest value in the early summer and decreases in the autumn. Our results demonstrate that the model can capture phenology and physiology as well as land surface energy, water, and carbon budgets over undisturbed sagebrush steppe ecosystems in the semiarid region.

3.1.2. Comparison With MODIS Products

Over the croplands, simulated fluxes and land surface properties match the remotely sensed products well. Figure 4 shows comparisons between model simulations and MODIS products in terms of ET, GPP, and LAI at 8-day time step. The variations of ET for different crop types from CLM5 and MODIS show comparatively good agreement in growing seasons. It is obvious that CLM5 simulates lower ET values in winters for all crop types than the MODIS ET, likely due to MODIS retrievals contaminated by clouds in the winter (Fang et al., 2012, 2013; Kim & Hogue, 2008). CLM5 accurately estimates the values of GPP against MODIS GPP, consistently capturing crop growth conditions such as planting and harvest. As shown in Figure 4b, there is a strange spike at the end of the MODIS record; it might be an error of the MODIS GPP data set, since the MODIS ET and MODIS LAI result is normal at the same time window. To keep the MODIS data set consistency and original, we do not delete this error data when compare the model simulations and MODIS GPP product. The estimated LAI is underestimated by CLM5 in springs and early summers when the winter wheat is harvested, while the LAI of corn and soybean match well with the MODIS product (not shown). The LAI is underestimated for wheat because in CLM5; some crop parameters of winter wheat are set to be the same as spring wheat. This may cause errors in simulating winter wheat phenology. The active winter wheat may be introduced in a future version of the model (http://www.cesm.ucar.edu/models/cesm2/land/CLM50_Tech_Note.pdf). In addition, previous studies have shown that the MODIS LAI product tends to overestimate when compared with observations (Fensholt et al., 2004) and lidar-derived LAI (Jensen et al., 2011). Generally, CLM5 performs equally for ET, GPP, and LAI with MODIS.

Table 3 summarizes the R and RMSE of ET, GPP, and LAI for each crop functional type between simulated and MODIS products. The R and RMSE of ET range from 0.56 to 0.91 and 0.50 to 0.93 mm day$^{-1}$, respectively. As for GPP, R is higher than 0.70, indicating a good agreement between model results and MODIS data. The best performance is found in soybean with an R value of 0.79 and RMSE of 1.69 gC m$^{-2}$ day$^{-1}$. The R value for simulated LAI is generally larger than 0.6, while a large discrepancy is found in winter wheat with a low R value of 0.45 and the RMSE of 0.49 m$^2$ m$^{-2}$, which may be induced by larger uncertainties of MODIS data in springs and winters due to cloud effects. Overall, the comparisons of ET, GPP, and LAI show good agreements between simulations and MODIS products over cropland, especially during growing seasons.

To further evaluate CLM5 performance, MODIS products are also used to evaluate the spatial distributions of model simulations in summers (June–August). As shown in Figures 5a–5c, the percentage differences (equation 3) among each grid of ET, GPP, and LAI over cropland ranges from $-20\%$ to $20\%$. There is a tendency in Figure 5b; systematically, lower GPPs were simulated because these areas are mainly covered winter wheat and C3 unmanaged crops without active agricultural management. As we mentioned above, the LAI of winter wheat is underestimated, leading to a lower GPP compared with MODIS data set. All
Figure 6. (a) CLM_{irrig}-simulated annual irrigation amounts from 2010 to 2018 over cropland, (b) annual precipitation and temperature changes from 2010 to 2018, (c) CLM_{irrig}-simulated mean annual irrigation amount for each crop type, and (d) spatial distribution of CLM_{irrig}-simulated mean annual irrigation from 2010–2018.

Figure 7. Irrigation effects on ET, surface runoff, and subsurface runoff (mm month$^{-1}$) and spatial differences (mm month$^{-1}$).
comparisons show an acceptable performance for the model in this study (Claverie et al., 2013; Fensholt et al., 2004; Lu & Zhuang, 2010).

We note that Figures 3, 4, and 5 clearly demonstrated the need of resolving landscape heterogeneity to better capture observed water and carbon fluxes. In typical global or regional simulations, the entire watershed only occupies a half fraction of one grid cell (e.g., in a 1° × 1° box) or covers 32 grid cells (e.g., 0.125° × 0.125° boxes). The spatial heterogeneity in fluxes and land surface state variables introduced by the differences in vegetation specific parameterizations tends to be averaged out. Given the highly nonlinear features of plant physiology and phenology and their impacts on associated water, energy, and biogeochemical processes, the global and regional simulations are therefore typically biased not comparable to observations at the landscape scale as demonstrated in this study.

### 3.2. Simulated Irrigation Water Use

The total irrigation amount of corn and soybean that covers 30% of the irrigated area accounts for nearly 60% of the crop irrigation amount (Figure 6a). Irrigation over the C3 unmanaged crops also contributes to ~40% of irrigation water use during 2010 to 2018. The irrigation amounts over UCPR estimated by the U.S. Geological Survey (USGS) based on agricultural censuses at county scale and simulated CLM5 are 131 and 81.6 mm year$^{-1}$ in 2010 (Maupin et al., 2017) and 79 and 77.3 mm year$^{-1}$ in 2015 (Maupin, 2018), respectively. The amount of irrigation simulated by CLM5_irrig is close to the census-based estimate from USGS, while slightly underestimated since the irrigation application efficiency is not considered for calculation of gross irrigation because the water loss of water in the transmission process or via evaporation from their sources is ignored due to lack of information or understanding on physical factors. Therefore, the irrigation effects from our simulations should be treated as a lower bound of possible impacts. There is a clear interannual variability of simulated irrigation water use over the UCPR watershed in response to climate variability. In 2016, as the result of a high annual precipitation compared to other years, irrigation water use is the smallest in this simulation period. In 2011, there is a significant increase in irrigation water use (~88.1 mm year$^{-1}$) due to the low precipitation (Figure 6b).

The differences in phenology and physiology among the crop types also lead to different irrigation demands. The simulated amounts of irrigation water use for corn and soybean can reach 329 and 394 mm year$^{-1}$ when

### Table 4

| Water budget changes (CLM_{irrig}–CLM_{rainfed}) | Watershed | Corn$^a$ | Soybean$^b$ |
|-----------------------------------------------|-----------|----------|-------------|
| ET (mm year$^{-1}$)                           | 60.8      | 237      | 316         |
| R_{over} (mm year$^{-1}$)                      | 4.44      | 18.8     | 21.1        |
| R_b (mm year$^{-1}$)                           | 9.14      | 46.3     | 34.6        |
| TWS (mm)                                      | 38.2      | 187      | 164         |
| ZWT (m)                                       | 0.03      | 0.15     | 0.11        |

$^a$ Corn field only.  
$^b$ Soybean field only.

Figure 8. Irrigation effects on water budget total water storage (TWS) and groundwater table depth (ZWT) for annual changes and spatial differences.
averaged over the planting area of each crop. When averaged over the entire watershed, the annual irrigation amounts for corn and soybean are 14.5 and 37.9 mm year\(^{-1}\) respectively, as shown in Figures 6c and 6d. Although corn only covers 7.3% of the total watershed area (Table 2), it requires a larger irrigation amount per unit area to grow. Soybean is heavily dependent on irrigation and has the largest water demand in the growing seasons. Besides, C3 unmanaged crop also accounts for a relatively large proportion of the total crop area, while its per unit area irrigation demand is not as significant (Figures 6d). Therefore, we focus our discussions on irrigation effects over croplands covered by corn and soybean in section 3.3.

### 3.3. Irrigation Effects

#### 3.3.1. Water Budget

As an external water input, irrigation changes the water budget directly. As shown in Figure 7, it is evident that irrigation leads to increases in simulated ET and total runoff. From Table 4, ET increases by 60.8 mm year\(^{-1}\) over the watershed on average. Irrigation water use for increased ET for soybean can be as high as 316 mm year\(^{-1}\). Runoff increases dramatically as a result of irrigation throughout the year (Figure 7), especially during growing seasons. Irrigation results in a 13.5 mm year\(^{-1}\) increase in total runoff, and the effect on \(R_b\) is more obvious than that on \(R_{\text{over}}\). Figure 7 also shows the spatial distribution of irrigation effects on ET, \(R_{\text{over}}\), and \(R_b\). The ET increases from 0.0083 to 40.1 mm month\(^{-1}\), while \(R_{\text{over}}\) and \(R_b\) increase from 0.0010 to 3.34 mm month\(^{-1}\) and 0.0013 to 9.35 mm month\(^{-1}\), respectively. Spatially, ET and \(R_{\text{over}}\) show similar spatial patterns. That is, the area with a large increase in ET also shows higher increase in runoff.

Irrigation brings additional water into the watershed, which can increase TWS and raise the groundwater table. Figure 8 shows that TWS is significantly increased with irrigation in each year. The increases in TWS are mainly contributed by those in groundwater storage (Table 4). It can be seen from Figure 8 that TWS overwhelmingly increases over croplands especially over areas covered by soybean and corn, with a maximum increase of more than 395 mm. The changes in ZWT as a result of irrigation share similar temporal and spatial patterns as TWS changes, with the highest decrease in ZWT of ~0.34 m. We note that In the CLM5, irrigation water is assumed as an external water input. In the study domain, irrigation water is generally obtained from a reservoir outside of the watershed. Therefore, treatment of irrigation water withdrawal in the model is consistent with this reality, and do not impact TWS directly.

Driven by interannual variability of climate, simulated TWS/ZWT in CLMrainfed reaches their lowest/deepest levels in 2014 and 2015 as a result of limited precipitation in 2013–2015 and slowly recovers afterward when more precipitation is available. In CLMirrig, however, such interannual variations in groundwater storage/depths are less pronounced because irrigation acts as a buffer to sustain aquifer storage by recharging it through percolation. The water balance of a watershed is an accounting of all water volumes that enter and leave a space over a specified period of time, and changes in internal water storage also must be considered (Burt, 1999). Irrigation changes the water budget significantly as mentioned above making it more complicated to construct water balance. As shown in Figure 9, a major fraction of irrigation water use goes to ET, followed by increased runoff over the UCPR watershed.

#### 3.3.2. Carbon Budget

As shown in Figure 10, the simulated GPP increases from 168 gC m\(^{-2}\) year\(^{-1}\) in CLMrainfed to 324 gC m\(^{-2}\) year\(^{-1}\) in CLMirrig, suggesting that irrigation significantly promotes vegetation growth over this region. Irrigation also leads to a large decrease in NEE during the growing season, with a maximum magnitude of ~19.7 gC m\(^{-2}\) month\(^{-1}\) in June. The change of NEE from positive to negative implies that the crop-land is shifted from a carbon source to a carbon sink by irrigation. Based on Table 5, irrigation clearly leads to increases in both GPP and ER over croplands, with a larger magnitude in the former contributing to a lower NEE. Regionally, the changes caused by irrigation are more evident in the central UCPR watershed covered mainly by corn and soybean that require irrigation to grow.

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**Table 5:** Irrigation water use for corn and soybean in the central UCPR watershed.

| Crop  | Water Use (mm year\(^{-1}\)) |
|-------|----------------------------|
| Corn  | 14.5                        |
| Soybean| 37.9                        |

---

**Table 2:** Crop area and water use for corn and soybean in the central UCPR watershed.

| Crop  | Area (ha) | Water Use (mm year\(^{-1}\)) |
|-------|-----------|----------------------------|
| Corn  | 14,567    | 14.5                        |
| Soybean| 37,989     | 37.9                        |
The changes in GPP and NEE propagate to other carbon budget terms. For example, irrigation is expected to enhance the total root biomass and organo-mineral interactions (Bhattacharyya et al., 2013). Figure 11 shows the irrigation impacts on the carbon pools simulated by CLM\textsubscript{rainfed} and CLM\textsubscript{irrig}. As shown in Table 5, TOTECOSYSC increases by 10.6 gC m\textsuperscript{−2} with irrigation over the watershed. The influences of irrigation on TOTLITC and TOTVEGC are much stronger than TOTSOMC on corn and soybean, while the TOTSOMC decreases obviously over all crop types. Irrigation also modifies the seasonal cycles and magnitudes of the carbon pools (Figure 11). TOTLITC simulated by both CLM\textsubscript{irrig} and CLM\textsubscript{rainfed} starts decreasing in the early spring. It reaches the lowest point in CLM\textsubscript{rainfed} in late springs when the shallow soil layer dries up to limit decomposition, while the declining trend continues during the summer in CLM\textsubscript{irrig} due to available moisture from irrigation. The amount of litter carbon is also generally higher in CLM\textsubscript{irrig} because of higher productivity of crops and hence litterfall. TOTVEGC shows an opposite seasonal variability compared with that of TOTLITC. In CLM\textsubscript{rainfed}, carbon stored in live vegetation peaks in June, consistent with that of natural vegetation (Figure 3). In CLM\textsubscript{irrig}, vegetation carbon continues to increase until late summer, reaching a peak that nearly doubles the value from CLM\textsubscript{rainfed}, and then decreases after harvest. Simulated TOTSOMC in CLM\textsubscript{irrig} is generally lower than that in CLM\textsubscript{rainfed} throughout the year because of the significantly elevated heterotrophic respiration in all croplands (Table 5).

### 3.3.3. Nitrogen Budget

Nitrogen availability has been long known to influence crop and root growth, and hence influence crop yields directly (Barakat et al., 2016). Therefore, understanding the impact of irrigation practice on the dynamics of the nitrogen budget is imperative for understanding carbon cycling over croplands. From Table 6, the influences of irrigation on the nitrogen budget are complex. Irrigation increases rates of denitrification and mineralization and leads to decreases in soil mineral nitrogen due to its leaching with runoff. The TOTECOSYSN decreases 1.10 gN m\textsuperscript{−2} over the watershed due to irrigation while nitrogen inputs from fertilization stay the same in the simulations. The magnitudes of the nitrogen pools and their seasonal variations are also shown in Figures 11d–11f. The TOTLITN is less in CLM\textsubscript{irrig} than that in CLM\textsubscript{rainfed} over corn fields, while it becomes more abundant over soybean fields, as the latter is able to fix

| Table 5: Effects of Irrigation on Simulated Carbon Budget Terms |
|---------------------------------------------------------------|
| **Carbon budget changes**<br>CLM\textsubscript{irrig}–CLM\textsubscript{rainfed} | Watershed | Corn\textsuperscript{a} | Soybean\textsuperscript{b} |
| GPP (gC m\textsuperscript{−2} year\textsuperscript{−1}) | 100 | 417 | 520 |
| NEE (gC m\textsuperscript{−2} year\textsuperscript{−1}) | −18.9 | −140 | −76.0 |
| AR (gC m\textsuperscript{−2} year\textsuperscript{−1}) | 35.1 | 139 | 187 |
| HR (gC m\textsuperscript{−2} year\textsuperscript{−1}) | 46.5 | 138 | 257 |
| ER (gC m\textsuperscript{−2} year\textsuperscript{−1}) | 81.6 | 277 | 444 |
| TOTECOSYSC (gC m\textsuperscript{−2}) | 10.6 | 39.5 | 96.7 |
| TOTLITC (gC m\textsuperscript{−2}) | 9.49 | 15.5 | 75.9 |
| TOTSOMC (gC m\textsuperscript{−2}) | −8.48 | −7.35 | −33.5 |
| TOTVEGC (gC m\textsuperscript{−2}) | 9.52 | 31.4 | 53.7 |

\textsuperscript{a}Corn field only. \textsuperscript{b}Soybean field only.
nitrogen. Consistent with that of TOTLITC, TOTLITN in CLMinirrig also reaches its lowest value in late summer because of limited litterfall from crops and elevated litter decomposition in the growing season, while litterfall (litter decomposition) starts increasing (decreasing) as early as May in CLMrainfed. Nitrogen stored in TOTSOMN is smaller in CLMinirrig compared to that in CLMrainfed because the loss rates (e.g., mineralization) become larger with irrigation. The TOTVEGN increases with irrigation for all crop types, implying that more nitrogen is assimilated by plants from SMINN. In addition, it starts accumulating in plants from April to August in CLMinirrig but starts declining as early as June in CLMrainfed.

### 3.4. Water, Carbon, and Nitrogen Interactions in Soil Organic Matters

Soil organic matters serve as a reservoir of nutrients and water in the soil. Based on our simulations, the carbon and nitrogen stored as soil organic matters (e.g., TOTSOMC and TOTSOMN) account for around 90% of carbon pools and 50% of nitrogen pools over the UCPR watershed, respectively. As shown in Figure 12, the seasonal change rates of TOTSOMC and TOTSOMN are determined by the combination of QSOI and TSOI. Both TOTSOMC and TOTSOMN illustrate the highest values in the spring when QSOI reaches the maximum. With the decrease of QSOI and the increase of TSOI starting from the late spring, soil organic matter begins declining because of the high decomposition rates in the summer. After harvest, more litter fall becomes available and turns over to soil organic matters, leading to gradual increases in both TOTSOMC and TOTSOMN with declining QSOI and TSOI. As shown in Figures 12a and 12b, TOTSOMC and TOTSOMN in both CLMrainfed and CLMinirrig start accumulating after harvest in September and October, respectively, reach their highest values in January and start declining when both soil moisture and temperature start increasing in the spring. In general, irrigation shifts carbon and nitrogen storages in soil organic matters to lower values but still shares similar seasonal patterns in response to changes in soil moisture and temperature. Due to the

### Table 6

The Effects of Irrigation on the Nitrogen Budget

| Nitrogen Budget Changes | Watershed | Corn<sup>a</sup> | Soybean<sup>b</sup> |
|-------------------------|-----------|-------------------|--------------------|
| Denitrification (gN m<sup>-2</sup> year<sup>-1</sup>) | 0.30 | 2.22 | 0.84 |
| Mineralization (gN m<sup>-2</sup> year<sup>-1</sup>) | 0.96 | 2.29 | 5.10 |
| SMINN (gN m<sup>-2</sup>) | −1.94 | −14.3 | −7.98 |
| TOTECOSYN (gN m<sup>-2</sup>) | −1.10 | −10.7 | −1.03 |
| TOTLITN (gN m<sup>-2</sup>) | −0.002 | −0.18 | 0.53 |
| TOTSOMN (gN m<sup>-2</sup>) | −0.77 | −1.00 | −2.77 |
| TOTVEGN (gN m<sup>-2</sup>) | 1.61 | 4.79 | 9.17 |

<sup>a</sup>Corn field only.  <sup>b</sup>Soybean field only.
higher heat capacity of water, the higher soil moisture in CLM_{irrig} corresponds to a lower soil temperature when the same ambient climate is used to drive the simulations as shown in Figures 12c and 12d. Nevertheless, soil organic matters decompose in higher rates in CLM_{irrig} than in CLM_{rainfed} because the changes in QSOI clearly shift the decomposition rates of soil organic matters to a different regime (Figures 12c and 12d). Therefore, the modulation of environmental factors on soil organic matters is intensified with irrigation.

4. Conclusion and Future Work

Irrigation contributes significantly to the sustainability of agro-ecosystems and food supply. In order to understand the influences of irrigation on watershed scale water, carbon, and nitrogen budgets in the semi-arid UCPR watershed, we apply CLM5 at 1 km resolution during the period from 2010–2018. The simulations are benchmarked using observations from an Ameriflux site within the watershed and remotely sensed products. Our results suggest that the model is capable of capturing the water, energy, and carbon fluxes and their seasonal and spatial variations.

Our simulation suggests that irrigation increases water input to the watershed in addition to precipitation by 40% on average over the 9-year period. The simulated irrigation water use depicts strong interannual variability in response to changes in precipitation and temperature. Corn and soybean contribute to nearly 60% of the total irrigation amount, and the average annual irrigation amounts are 14.5 and 37.9 mm year$^{-1}$ for corn and soybean, respectively. Irrigation therefore significantly increases all water budget components in the watershed. With irrigation, ET and runoff increase by 60.8 and 13.5 mm year$^{-1}$ over watershed, respectively. The changes in soybean are much higher than other crop types as a result of its higher photosynthetic capability when water is not limited. Total TWS is elevated, while depth to groundwater table becomes shallower with irrigation over the watershed.
Irrigation increases GPP and NEE magnitude during growing season, leading to an increase in carbon storage in plants. GPP and NEE changes share similar spatial patterns with the most significant increases occurring over areas covered by soybean.

Irrigation intensifies the rate of denitrification and mineralization of nitrogen during the growing season, thereby enhancing the interactions between soil mineral nitrogen and SOM. As an important component of the agro-ecosystem, the seasonal changes of soil organic matter are strongly modulated by TSOI and QSOI, which affect the processes of decomposition, respiration, and mineralization. Consequently, carbon stored in soil organic matters becomes smaller when irrigated because higher available water results in higher decomposition rates and heterotopic respiration.

Our study also highlighted the need of resolving landscape heterogeneity in land cover and soil properties to better capture observed water and carbon fluxes. Given such heterogeneity and their associated biogeophysical and biogeochemical processes, the magnitudes in simulated fluxes and state variables span wide ranges, which cannot be captured in typical global and regional simulations.

This study presents a quantitative assessment of the effects of irrigation on the interacting water, carbon, and nitrogen dynamics using CLM5. The outcome of this research can serve as a reference for regional water resources and agro-ecosystem management.

A number of challenges and limitations regarding parameter calibration and model mechanisms need to be addressed in the future studies:

1. Limitations in the calibration of parameters of CLM5 should be noted. As shown in section 3.1, the CLM5 simulations are extensively validated with observations and MODIS products in terms of water, energy, and carbon fluxes. Based on calibrated parameter values, the model simulations can match flux tower observations and remotely sensed products well. Nevertheless, the model parameters can be further improved. For example, the fertilizer parameter in the model is calculated based on the average value of the U.S. fertilizer statistics due to lack of local fertilizer information, which may raise errors in estimates the nitrogen budget. We also keep the tuning parameter \( f_{\text{thresh}} \) to be the same as its default value. However, it might be helpful to tune this parameter based on field operations/observations in future studies. Furthermore, the planting date is not directly tied to soil water but potentially affect the timing and amount of irrigation and consequently affect the land surface processes. At the current stage, we are not aware of a good strategy to tie planting dates to soil moisture or water availability. It could be a topic to explore follow-up studies. Therefore, further efforts are needed to reduce uncertainties from model parameter uncertainties and to compare model results with additional observations once they become available.

2. In addition to the parameter uncertainties, we acknowledge that lateral exchange between groundwater and surface water is not well considered in the simulations, which could strongly modulate soil moisture and irrigation. Lateral flow is an important component of water and thermal processes, as well as energy and water exchanges. Leaching carbon and nitrogen can also be transported through lateral flow. Bisht et al. (2017) found that the groundwater-river water interactions strongly modulate land-surface energy partitioning and hydrologic states and fluxes along the river corridor of the UCPR watershed, using an integrated surface and subsurface model that couples an earlier version of CLM and the reactive transport code PFLOTRAN. Such interactions can be enhanced with irrigation as more water infiltrates and percolates into the subsurface. However, migrating the lateral water flow and transport processes documented in Bisht et al. (2017) to the coupling between CLM5 and PFLOTRAN is currently but not a trivial task. Nevertheless, this study extends CLM5 applications to the watershed scale with highly resolved landscape details and serves as a foundation for an ongoing integrated CLM and PFLOTRAN coupling study. We will report progress toward that direction in the near future.

Appendix A.

Summary of water, carbon and nitrogen budget terms and their abbreviations analyzed: Table A1. Water Budget Terms, Table A2. Carbon Budget Terms and Table A3. Nitrogen Budget Terms.
The model parameter variables used as inputs in this study. Sharing the observed meteorological data at the Hanford Meteorological Station for the NorthWest National Laboratory (PNNL). This research was also supported by the National Natural Science Foundation of China (41971030) and the China Scholarship Council. We would like to acknowledge the Hanford Meteorological Station for sharing the observed meteorological variables used as inputs in this study. The model parameter files and driving scripts can be found online (at https://sbrsfa.velo.pnnl.gov/data-sets/?UUID=ef4f2f53-4477-43b3-bd67-e6b55e4543d4).

### Acknowledgments
This study was funded by the by the U. S. Department of Energy (DOE), Office of Biological and Environmental Research (BER), as part of BER’s Subsurface Biogeochemical Research Program (SBR). This contribution originates from the SBR Scientific Focus Area (SFA) at the Pacific Northwest National Laboratory (PNNL). This research was also supported by the National Natural Science Foundation of China (41971030) and the China Scholarship Council. We would like to acknowledge the Hanford Meteorological Station for sharing the observed meteorological variables used as inputs in this study. The model parameter files and driving scripts can be found online (at https://sbrsfa.velo.pnnl.gov/data-sets/?UUID=ef4f2f53-4477-43b3-bd67-e6b55e4543d4).

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### Abbreviation Full Variable Name

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| ET           | Evapotranspiration |
| Rover        | Surface runoff    |
| Rb           | Base flow         |
| TWS          | Terrestrial water storage |
| ZWT          | Depth to groundwater table |
| QSOI         | Soil water        |
| TSOI         | Soil temperature  |

### Water Budget Abbreviations

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| GPP          | Gross primary production |
| NEE          | Net ecosystem exchange |
| ER           | Ecosystem respiration |
| AR           | Autotrophic respiration |
| HR           | Heterotopic respiration |
| TOTECOSYSN   | Total ecosystem nitrogen |
| TOTLITN      | Total litter carbon  |
| TOTSOMC      | Total soil organic matter carbon |
| TOTVEGC      | Total vegetation nitrogen |

### Carbon Budget Terms

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| SMINN        | Soil mineral nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTSOMN      | Total soil organic matter nitrogen |
| TOTVEGN      | Total vegetation nitrogen |

### Nitrogen Budget Terms

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |

### Table A1

| Table A1 Water Budget Abbreviations |
|------------------------------------|
| Abbreviation | Full Variable Name |
|--------------|-------------------|
| ET           | Evapotranspiration |
| Rover        | Surface runoff    |
| Rb           | Base flow         |
| TWS          | Terrestrial water storage |
| ZWT          | Depth to groundwater table |
| QSOI         | Soil water        |
| TSOI         | Soil temperature  |

### Table A2

| Table A2 Carbon Budget Terms |
|-------------------------------|
| Abbreviation | Full Variable Name |
|--------------|-------------------|
| GPP          | Gross primary production |
| NEE          | Net ecosystem exchange |
| ER           | Ecosystem respiration |
| AR           | Autotrophic respiration |
| HR           | Heterotopic respiration |
| TOTECOSYSN   | Total ecosystem nitrogen |
| TOTLITN      | Total litter carbon  |
| TOTSOMC      | Total soil organic matter carbon |
| TOTVEGC      | Total vegetation nitrogen |

### Table A3

| Table A3 Nitrogen Budget Terms |
|-------------------------------|
| Abbreviation | Full Variable Name |
|--------------|-------------------|
| SMINN        | Soil mineral nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTSOMN      | Total soil organic matter nitrogen |
| TOTVEGN      | Total vegetation nitrogen |

### Abbreviation Full Variable Name

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |

### Abbreviation Full Variable Name

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |

### Abbreviation Full Variable Name

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |

### Abbreviation Full Variable Name

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|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |

### Abbreviation Full Variable Name

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|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |

### Abbreviation Full Variable Name

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| TOTVEGC      | Total vegetation nitrogen |
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| TOTECOSYN    | Total ecosystem nitrogen |
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### Abbreviation Full Variable Name

| Abbreviation | Full Variable Name |
|--------------|-------------------|
| TOTVEGC      | Total vegetation nitrogen |
| TOTSOMC      | Total soil organic matter nitrogen |
| TOTLITN      | Total litter nitrogen |
| TOTECOSYN    | Total ecosystem nitrogen |
| SMINN        | Soil mineral nitrogen |
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