

Meta-analysis of leaf area index, canopy height and root depth of three bioenergy crops and their effects on land surface modeling

Johana Paola Forero Urrego^{*}, Bo Huang, Jan Sandstad Næss, Xiangping Hu, Francesco Cherubini

Industrial Ecology Programme, Department of Energy and Process Engineering, Norwegian University of Science and Technology (NTNU), Trondheim, Norway

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ABSTRACT

The expected large-scale expansion of biofuel production in climate change mitigation scenarios calls for improvements in the representation of bioenergy crops in land surface models. Leaf area index (LAI), canopy height (CH) and root depth (RD) are key parameters that regulate exchanges of heat and moisture between land and atmosphere. This study performs a meta-analysis combining unique data from 34 observational studies and 14 countries to estimate monthly variability in LAI, CH, and RD of three main bioenergy crops: miscanthus (MSC), switchgrass (SWG), and reed canary grass (RCG). Using the Community Land Model v.5.0 and the results from the meta-analysis, we also tested the effects that variability in parameterization of LAI and CH have on key components of the surface energy budget, relative to prescribed values. Results from the meta-analysis show a strong seasonality of LAI and CH, with mean (\pm one standard error) LAI values at the peak summer month of 6.05 ± 0.84 , 5.56 ± 0.75 , and $5.39 \pm 1.15 \text{ m}^2/\text{m}^2$, and maximum CH of 246 ± 23 , 147 ± 16 , and $156 \pm 10 \text{ cm}$, for MSC, SWG, and RCG, respectively. These values are typically larger than the default parameterizations in CLM. Information on RD was limited and average values are 172 ± 56 , 165 ± 46 , and $193 \pm 11 \text{ cm}$, for MSC, SWG, and RCG, respectively. The seasonal cycles of latent heat, sensible heat and surface albedo are primarily affected by the range of LAI values, and less sensitive to variability in CH. Relative to the default values, higher LAI values increase latent heat and decrease sensible heat, with the highest absolute changes in summer. They also decrease surface albedo in winter months due to a larger snow masking effect. Our results offer a basis to compare experimental work and modelling studies, improve parameterization in land surface models, and identify the importance of vegetation structure parameters to evaluate key climate processes in response to bioenergy crops.

1. Introduction

Bioenergy, when sustainably deployed, is a renewable energy source that can replace fossil fuels, help in the transition to a cleaner society, and contribute to climate change mitigation (Chum et al., 2011; Creutzig et al., 2015; Shukla et al., 2019). Many cost-effective future scenarios aiming at stabilizing temperature rise at relatively low levels rely on a large-scale deployment of bioenergy crops. In the Shared Socioeconomic Pathways (SSPs), areas dedicated to bioenergy crops range from less than 1 to about 7 million km^2 by 2100 (Shukla et al., 2019). Conventional food crops like corn and soybean can be used as biofuel feedstocks, but their environmental benefits are limited, and sometimes questioned, with potential adverse effects on food security and land degradation (Creutzig et al., 2015; Rulli et al., 2016). Perennial grasses like miscanthus, switchgrass and reed canary grass, are attractive

second-generation energy crops because of their relatively high yields, low need for nutrient supply, efficient use of light and water, and adaptability to different terrains and climates (Cheng et al., 2020; Leirpoll et al., 2021; Næss et al., 2021; Robertson et al., 2017). They are also frequently associated with positive climate and environmental co-benefits relative to traditional cropland, such as increases in soil carbon storage thanks to their deep root system and avoidance of tillage, capacity to restore degraded land, improved biodiversity and other ecosystem services (Englund et al., 2020; Robertson et al., 2017; Yang et al., 2018; Zhu et al., 2017). For example, substituting maize used for biofuel production in the US with miscanthus would save half of the land and one third of the water (Zhuang et al., 2013).

The establishment of bioenergy crops on agricultural land also induces biophysical mechanisms that can substantially influence the climate from local to regional scales. Neglecting biophysical effects can

^{*} Corresponding author at: NTNU - Industrial Ecology Programme Høgskoleringen 5 NO-7034 Trondheim
E-mail address: johana.p.f.urrego@ntnu.no (J.P.F. Urrego).

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underestimate the mitigation potential of bioenergy crops (Georgescu et al., 2011; Zhu et al., 2017), and prevent the identification of potential synergies between climate change mitigation and adaptation at local and regional scales. The switch from annual crops to perennial bioenergy plantations like miscanthus is associated with regional cooling due to local increases in evapotranspiration and albedo, two key biophysical climate regulating factors (Cai et al., 2016; Georgescu et al., 2013; Miller et al., 2016). Up to 5°C cooling in summer are estimated in large portions of the central US in response to perennial bioenergy crop expansion over suitable abandoned and degraded farmlands (Wang et al., 2017). Seasonal variations are significant, and, in general, bioenergy crops induce a cooling of ambient air during the growing season, but after harvest the decrease in evapotranspiration can induce warming (Georgescu et al., 2013; Harding et al., 2016; Wang et al., 2017). Bioenergy crops have rather different physiological and phenological properties than annual food crops, and their representation in land surface models is essential to understand the effects on the climate system across spatial (local to global) and temporal (seasonal and inter-annual) scales (Cheng et al., 2020; Lawrence et al., 2019; Liu et al., 2016). Leaf area index (LAI), canopy height (CH) and root depth (RD) are important drivers of energy, water, momentum, carbon and nutrient exchanges, encompassing processes such as photosynthesis, evapotranspiration, competition, and carbon and nutrient cycling and allocation (Bonan, 2016; Lawrence et al., 2019). The correct specification of vegetation parameters in land surface and vegetation models is critical to accurately determine the partitioning of the surface energy and evapotranspiration processes. Land surface and vegetation models often use common values according to default parameterization of plant functional types (crops, C3 grass, C4 grass, etc.), although recent advancements also allow prognostic analysis to represent interannual variability (Cheng et al., 2020; Li et al., 2018). A few studies have an explicit representation of bioenergy crops, with vegetation parameters that are largely prescribed with location-specific data (Cheng et al., 2020; Harding et al., 2016; VanLoocke et al., 2012; Zhu et al., 2017). The increasing volume of scientific literature available on field measurements of key vegetation parameters of bioenergy crops offers an opportunity to improve and inform their parameterization with observational datasets, or to validate model simulations.

In this study, we collect empirical estimates from field observational studies that measured on-site vegetation LAI, CH and RD for three bioenergy crops: miscanthus, switchgrass and reed canary grass. We estimate average values and statistical variabilities of these vegetation parameters for each of the crops. The estimated ranges are used to test the significance of different parameterizations of LAI and CH when modeling the local climate response to bioenergy crops with the land surface model Community Land Model v.5.0 (CLM5.0). Two different locations representative of different climatic conditions are considered, one in France and one in Ukraine, and the effects on three key components of the surface energy budget are explored, namely, sensible heat, latent heat and surface albedo.

2. Methodology

2.1. Bioenergy crops

Three types of bioenergy crops are considered in our meta-analysis as representative of species that can grow in different climatic conditions (e.g., tropical, temperate, or boreal/mountainous areas).

Miscanthus x giganteus (hereafter MSC) is a C4 natural sterile hybrid plant, originally from East Asia (Bassam, 2011). It reaches full establishment within 3 to 5 years and can live up to 25 years. The crop has been grown in diverse locations and climates in Europe and North America showing a great tolerance to high and low temperatures, water availability and terrains (Bassam, 2011; Heaton et al., 2009, 2008; Oliveira et al., 2017). It is harvested once a year, with preferred times between November and April (Lewandowski et al., 2003). However,

harvest in late fall is more typical, especially in colder climates. Despite its capacity to survive winter (Bassam, 2011), crop mortality due to frost can occur at high latitudes with more extreme winter conditions or during the establishment period where the plant foundation is not fully developed (Lewandowski et al., 2003, 2000).

Switchgrass (hereafter SWG) is a native C4 grass that was predominant in the great prairies of North America (Dopazo et al., 2009). It has a wide geographic distribution, naturally occurring from Central America to southern Canada, but it can also grow in tropical and warm temperate climates (Christian et al., 2002; Lewandowski et al., 2003). SWG has a wide diversity within the species, with variations in morphology, phenology and adaptation, which makes this grass advantageous for different locations and conditions (Parrish and Fike, 2005). The crop is typically harvested in late autumn, before low winter temperatures arrive (Lewandowski et al., 2003; McLaughlin and Kszos, 2005).

Reed canary grass (hereafter RCG) is a fast growing, competitive, cool-season grass with a lifetime from 10 to 15 years, that follows the photosynthetic pathway C3 (Lewandowski et al., 2003; Ustak et al., 2019). It is found in temperate climates and wet areas in Europe, Asia and North America, with the biggest cultivation areas located in Finland and Sweden (Lewandowski et al., 2003; Ustak et al., 2019; Wrobel et al., 2009). RCG can grow in diverse conditions, especially on a wide variety of soils. Naturally, it grows in wet places, with a great ability to grow in poorly drained soils and tolerates flood (Lewandowski et al., 2003; Ustak et al., 2019; Wrobel et al., 2009). RCG is also drought resistant and it can thrive in dry areas (Christian et al., 2006; Wrobel et al., 2009). Like the other perennial grasses above, it can grow on land that is not suitable for agriculture and can be used to restore degraded or polluted soils (Ustak et al., 2019). The major threat for this grass is the appearance of weed during its first year (Lewandowski et al., 2003). RCG is harvested in late winter or early spring, when the grass is dry and the ash content is low, which improves the quality of the biomass for energy uses (Landström et al., 1996; Lewandowski et al., 2003).

2.2. Vegetation parameters

The vegetation parameters LAI, CH and RD are key regulating factors of land-climate interactions. They characterize the vegetation that interacts with the atmosphere and govern biophysical processes, relevant for the net surface radiation balance, and biogeochemical processes, relevant, for instance, for net ecosystem productivity and the carbon and nitrogen cycles (Bonan, 2016). An accurate characterization that includes the temporal evolution of LAI and CH, e.g., emergence and senescence of leaves due to seasonal changes or harvesting, or growing cycles of canopy height, is key to capture the seasonality of the climate effects of bioenergy crops.

LAI is defined as the projected, or one sided, area of leaves per unit of ground area (Bonan, 2016; Stuart Chapin et al., 2012). This parameter indicates the area that is available to capture light, and the extent to which light is reduced throughout the canopy (Stuart Chapin et al., 2012). It also indicates the area available to intercept and accumulate water and affects evapotranspiration rates. The light that is intercepted is determinant in the photosynthesis and respiration processes of the plant, while the intercepted and through fall water are accounted in the water cycle as either evapotranspiration or water accumulated on land (Bonan, 2016; Stuart Chapin et al., 2012). This parameter is dynamic and the area available changes as leaves emerge, grow, and die throughout the seasons of a year.

The CH of a vegetation is key in the characterization of energy fluxes at the surface, as well as in scaling vegetation activities at the canopy level. Turbulent fluxes near the surface, generated through drag effects, are created when air fluxes, which transport heat, water and momentum, encounter resistance from vegetation. The proportion of the resistance depends on the roughness of the vegetation, with taller vegetation having greater roughness. These turbulent fluxes increase the transfer of water and heat between surface and atmosphere, vertically

and horizontally. They are characterized according to the aerodynamic conductance of the canopy, which is shaped, among others, by the roughness length of the canopy (Bonan, 2016; Pitman, 2003). CH is also used in the light distribution profile of plants used to scale vegetation processes from the leaf to the canopy level (Bonan, 2016), and it is indicative of plant growth, biomass allocation and water transport between leaves and roots (Chu et al., 2018).

The RD of a plant controls its ability to maintain transpiration processes. Deeper roots grant access to soil water in deeper soil layers and allow the replenishment of water resources in the plant, which change soil moisture levels (Bonan, 2016; Finch et al., 2004). Soil moisture influences the distribution of net radiation into latent and sensible heat, as well as the share of water allocated to evapotranspiration and run-off processes (Bonan, 2016). Changes in water and heat surface fluxes can stimulate conditions for precipitation, and a decrease in soil moisture can result in a decrease in precipitation (Bonan, 2016; Pitman, 2003; Tilman et al., 2009), although this is highly dependent on environmental conditions and responses of mechanisms at the local level (Findell and Eltahir, 2003; Huang et al., 2020). RD can also be indicative of soil carbon storage (Monti and Zatta, 2009).

2.3. Literature search

A literature review is carried out to screen peer-reviewed articles containing primary data on vegetation parameters for the different bioenergy crops. The search engines “Google Scholar”, “Mendeley” and “Scopus” are used with keywords based on the common or scientific names of the crops (e.g., “switchgrass” or “*Panicum virgatum*”) and the

name and acronyms of the parameters (e.g., “Leaf Area Index” or “LAI”), in combination with the words “biofuel crop”, “bioenergy crop”, “perennial grass” or “energy crop”.

Once a potential article is identified, it is inspected to check if the terms leaf area index, canopy height, and root depth, together with associated values, are included in the body of the study. If the article includes relevant information, the values, graphs, location, and characteristics of the study are stored. A total of 61 studies were initially identified as containing potentially relevant information. These studies include field experiments, parameters simulated by land surface and vegetation models, and literature reviews. Correlated studies are identified, and cross-citation and reproduction of the same empirical data are excluded. Vegetation parameters produced by modelling tools are also excluded, and only empirical measurements from field studies are considered, including one study that reports LAI values based on indirect measurements (Finch et al., 2004). This leaves 34 articles containing unique data, each article contributing with at least one vegetation parameter for one bioenergy crop. The values collected correspond to experiments that typically provided field observations from 1 to up to 6 years.

A total of 19 studies reported values for LAI (9 for MSC, 6 for SWG, and 7 for RCG), 18 for CH (9 for MSC, 5 for SWG and 7 for RCG, with 12 studies different from those that also reported LAI), and 6 for RD (4 for MSC and SWG, and 2 for RCG, with 5 studies of these that did not include information for LAI or CH). Table 1 shows a summary of the literature review, and Table S1, S2 and S3 in the supplementary material offer detailed information. The geographical distribution of the studies is spread among 14 countries and mainly covers Europe, North America

Table 1

Summary of articles selected in the literature review organized by vegetation parameter and bioenergy crop.

Parameter	Miscanthus Reference	Location	Switchgrass Reference	Location	Reed canary grass Reference	Location
LAI	Zeri et al.,(2011)	Illinois, USA	Zeri et al., (2011)	Illinois, USA	Sahramaa et al.,(2003)	Jokioinen, Finland
	Heaton et al., (2008)	Illinois, USA	Heaton et al., (2008)	Illinois, USA	Ní Choncubhair et al., (2017)	Cashel, Ireland
	J. W. Finch & Riche, (2010)	Bedfordshire, UK	Wagle et al., (2015)	Oklahoma, USA	Lind et al., (2016)	Maaninka, Finland
	Jon W. Finch et al., (2004)	Heredfordshire, UK	Jon W. Finch et al., (2004)	Heredfordshire, UK	Danais, (1986)	Betagne, France
	Danalatos et al., (2007)	Bedfordshire, UK	Kiniry et al., (1999)	Bedfordshire, UK	Kusutani et al., (1977)	Japan
	Clifton-Brown et al., (2000)	Volos, Greece	Eichelmann et al., (2016)	Texas, USA	Williams et al., (2017)	North Dakota, USA
	Cosentino et al., (2007)	Cashel, Ireland		Ontario, Canada	Shurpali et al., (2013)	Joensuu, Finland
	van der Werf et al., (1992)	Catania, Italy				
	(Acharya et al., 2018)	Ter Apel, The Netherlands				
	Heaton et al., (2008)	Arkansas, USA	Heaton et al., (2008)	Illinois, USA	Sahramaa & Jauhiainen, (2003)	Jokioinen, Finland
CH	Uwatoko et al., (2016)	Illinois, USA	Oliveira et al., (2017)	Candas, Spain	Saijonkari-Pahkala, (2001)	Jokioinen, Finland
	J. W. Finch & Riche, (2010)	Japan	D G Christian et al., (2002)	Heredfordshire, UK	Lind et al., (2016)	Maaninka, Finland
	Jon W. Finch et al., (2004)	Bedfordshire, UK	Jon W. Finch et al., (2004)	Heredfordshire, UK	Kusutani et al., (1977)	Japan
	Danalatos et al., (2007)	Bedfordshire, UK	Lemus et al., (2002)	Bedfordshire, UK	Jasinskas et al., (2008)	Lithuania
	Clifton-brown et al., (2007)	Volos, Greece		Iowa, USA	Dudley G. Christian et al., (2006)	Rothamsted, UK
	Cosentino et al.,(2007)	Cashel, Ireland			Weilhoefer et al., (2017)	Portland, OR, USA
	Acharya et al., (2018)	Catania, Italy				
	Oliveira et al., (2017)	Akansas, USA				
	Jon W. Finch et al., (2004)	Candas, Spain	Jon W. Finch et al., (2004)	Heredfordshire, UK	Kätterer & Andrén, (1999)	Ultuna, Sweden
	Neukirchen et al., (1999)	Heredfordshire, UK	Shield et al., (2012)	Bedfordshire, UK	Shield et al., (2012)	Bedfordshire, UK
RD	Monti & Zatta, (2009)	Bedfordshire, UK	Monti & Zatta, (2009)	Bedfordshire, UK		
	Mann et al., (2013)	Rhine Valley, West Germany	Mann et al., (2013)	Bedfordshire, UK		
		Po Valley, Italy		Po Valley, Italy		
	Davis, California, USA		Davis, California, USA			

and Japan, as shown in Fig. 1. No studies were found in the southern hemisphere.

2.4. Data processing

The monthly mean of LAI or CH of a single study (\bar{x}_{im}) is quantified based on the data collected from that study. Values are either extracted from data points in graphs using a visual approximation tool or taken from tables. A study provides multiple values for a single month when experiments ran over multiple years, or considered different conditions such as planting distances, fertilization, and irrigation. Typically, a study does not report values for all months of the year. When the value is given in terms of the day of the year (DOY), the DOY is converted to the respective month. When measurements are reported without a clear month, the month is indirectly identified from the information in the text.

A monthly mean, \bar{X}_m , and standard error of the mean, SEM, is calculated using the sampling mean of the collected studies, \bar{x}_{im} , the number of studies, N_m , and the standard deviation from the set of means, σ_m (Eq. 1). X represents the parameter, either LAI or CH, m refers to the month and i to the individual study.

$$\bar{X}_m = 1 / N_m \left(\sum_{im} \bar{x}_{im} \right), \quad SEM = \sigma_{\bar{x}_m} = \sigma_m / \sqrt{N_m} \quad (1)$$

A similar approach is followed for the parameter RD. An average maximum RD and SEM are calculated based on the maximum values reported by the selected studies, without monthly differentiation.

2.5. Effects of variability in LAI and CH parameterization in CLM5.0

Simulations of implications of different parameterizations of LAI and CH on key components of the surface energy budget like latent heat, sensible heat, and surface albedo are performed with CLM5.0, the land surface model of the Community Earth System Model (CESM). CLM5.0 includes an extensive representation of processes from ecological climatology that describe how changes in vegetation affect climate and ecosystems. The model accounts for physical, chemical, and biological processes across different spatial and temporal scales (Lawrence et al., 2018, 2019).

CLM5.0 is a land-only model. To drive the atmospheric state, we use the atmospheric dataset Global Soil Wetness Project (Dirmeier et al., 2006) version 3 (GSWP3) (spatial resolution of 0.5°x0.5° and temporal

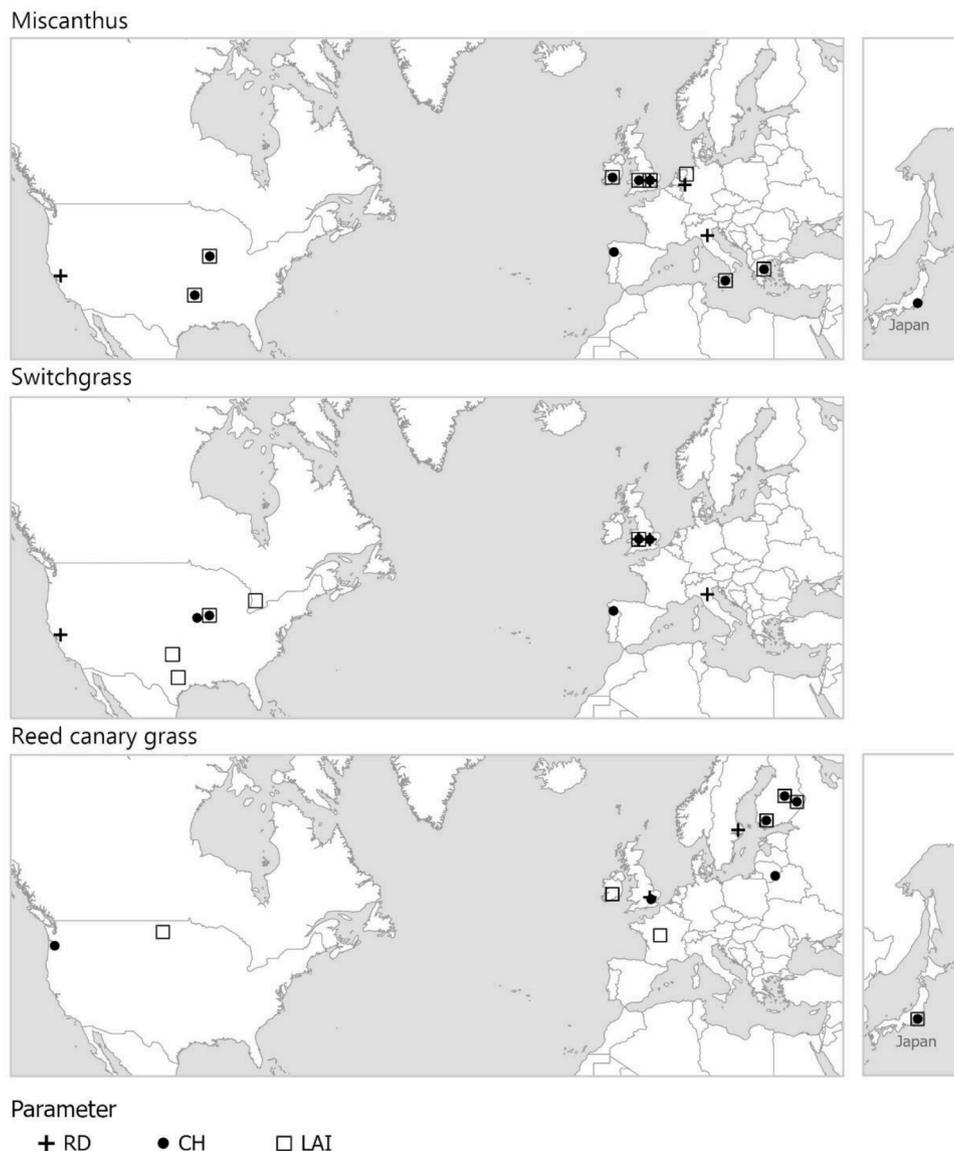


Fig. 1. Location of experimental studies of the articles selected in the literature review.

resolution of three hours). In the default parameterization, LAI is derived from MODIS satellite data and top and bottom CH are acquired from gridded datasets adjusted to specific plant functional types (Lawrence et al., 2018). Our simulations are executed off-line, i.e. the model is not coupled to an atmospheric model, as this is not necessary for the objectives of our study and it allows to maintain our simulations computationally efficient. The use of a stand-alone land surface model is typically sufficient to explore how changes in attributes of vegetation structure influence biophysical factors of the surface energy balance (energy and water fluxes) (Bohn et al., 2018; Chen and Dirmeyer, 2016), because atmospheric feedbacks usually have negligible first order effects on local surface fluxes (Chen and Dirmeyer, 2020; Lagüé et al., 2019).

Given the atmospheric state, CLM5.0 calculates surface energy, momentum and radiative fluxes for any given time step considering snow and soil hydrology conditions from the prior time step. Albedo is calculated from the two-stream approximation radiative transfer model based on the upward and downward diffuse radiative fluxes and the optical properties of the plant, which considers LAI among other factors (Lawrence et al., 2019). These conditions are then updated according to the estimated fluxes. The characteristics of the current time step are passed to the atmosphere in order to proceed with fluxes calculations for the next time step (Lawrence et al., 2018).

CLM5.0 allows models to be run for either a single grid-point or a regional scale. In light of the objectives of our analysis, we run the model for a single grid-point scale in order to better highlight direct effects of variability in parameterization of land cover phenology (LAI and CH) on key elements of the surface energy budget. We select two cropland-dominated grid cells (around 80 km² size each) representative of different background climatic conditions, one in France (48.00°N, 1.60°E) and one in Ukraine (33.63°N, 50.60°E). Climatological conditions (temperature, rainfall, and snow water equivalent) for the two locations are available in supplementary Figure S1. These grid cells originally have about 70% of cropland according to the LUH2 land cover data (Hurt et al., 2020), and they have been entirely converted to either C3 (RCG) or C4 (SWG) grass in our experiments. As both SWG and MSC are C4 grasses, they belong to the same plant functional type (PFT) in CLM5.0 (C4 grass). Only LAI and CH values representative of SWG has been considered in our simulations, because the differences in average values from the two grasses are rather small (thereby leading to similar results). Harvest is modelled in November for the C4 (SWG) grass and March for the C3 (RCG) grass, given that these months fall into the most typical harvest windows of the specific grasses. We performed a total of 16 simulations for each location, 8 for each type of grass (C3/RCG and C4/SWG), using different parameterizations of LAI and CH: a default case based on the prescribed values for LAI and CH as incorporated in CLM5.0, three simulations each where either LAI or (top) CH are changed to the monthly mean, 5th or 95th percentile from the data points collected in the meta-analysis. For the C3 grass in the months where there are no data available (from November to February), the values are linearly extrapolated from the last months with available data. In order to single out the effects of changes in LAI or CH, LAI values are kept equal to the default case when CH parameters are changed, and vice versa. An extra set of simulations incorporates the mean values of both LAI and CH to investigate the combined effects in each location of using observational values for both parameters simultaneously. Table S4 and S5 in the Supplementary Information summarize the values used in the simulations. A time period of ten years (2001–2010) with a time step of 1800 seconds is considered for each simulation, assuming one year of model spin up time. Results for sensible heat, latent heat, and surface albedo are finally averaged per months across the simulation period.

RD is not included in the simulations because it is not a parameter that can be directly manipulated in CLM5.0, as the model characterizes each PFT by its root fraction in each of the soil layers. Other land surface models (such as Noah-MP (Liu et al., 2016)) give the possibility for a more explicit parameterization of RD. Nevertheless, our meta-analysis includes estimates for RD to map the availability of observational data

from the existing literature and offer opportunities for model validation or calibration.

3. Results and discussion

3.1. Analysis of the collected data

There is large variability in the number of studies offering data for the different parameters, months of the year, and bioenergy crop. A detailed distribution of the number of studies and individual data points for LAI and CH by month and crop is available in the supplementary Figure S2. In general, there are more studies providing measurements for LAI than for CH and for the crop MSC than for SWG or RCG. There are more empirical measurements available between May and October, which largely corresponds to the beginning and end of the growing season in the northern hemisphere (for SWG and MSC). LAI is often reported for multiple months, while values for CH are concentrated at the end of the growing season, and reduced to a few months for SWG and RCG (for example: Clifton-brown et al., 2007; Cosentino et al., 2007; Jasinskas et al., 2008; Lind et al., 2016; Oliveira et al., 2017).

The number of studies and data per month is indicative of the robustness of the statistical estimates. Monthly LAI calculations for MSC are based on 8 to 9 studies from May to October, while 5 to 6 studies provide data from May to September for SWG and from May to August for RCG. Monthly CH average estimates for MSC are based on 5 studies from May to November and 8 studies for October. Averages for SWG build on 3 to 5 studies from August to November, and for RCG on 4 studies for June and July. The estimates for maximum RD are based on fewer studies than the ones for LAI and CH (4 studies for MSC and SWG, and 2 studies for RCG). A reason for this limited availability can be that experiments to measure RD (directly or indirectly) are rather complex and time-consuming (Monti and Zatta, 2009). The values collected for RD are based on different experimental methods. For instance, Jon W. Finch et al., (2004) measured the changes in soil water content in the rooting zone of the crop as indicative of plant water use, and the depth where changes in soil water cease to exist were interpreted as the maximum root depth. Other studies reported the spatial distribution of the roots (Neukirchen et al., 1999), the root length density (Kätterer and André, 1999; Monti and Zatta, 2009; Shield et al., 2012), or the root depth explicitly (Mann et al., 2013). Some of the studies often have a restricted depth due to the methodology of the experiment (Clifton-brown et al., 2007; Collins et al., 2010; Lind et al., 2016). Only experiments with a restricted depth of 120 cm or deeper are considered (Monti and Zatta, 2009; Neukirchen et al., 1999; Shield et al., 2012).

Some studies also explicitly report the months when harvest takes place (Supplementary Table S1–S3). In the case of MSC, most empirical studies carried out harvest between January and March. This is consistent with other literature sources (Dopazo et al., 2010; Heaton et al., 2009; Lewandowski et al., 2003, 2000; Lewandowski and Heinz, 2003), which shows that delaying harvest improves the quality of the biomass by decreasing moisture, mineral and ash content, although local conditions like winter severity may require to anticipate harvest to the autumn. For SWG, most studies performed harvest by late autumn, between September and December, which is the optimal harvest time for using this grass as a biofuel feedstock (Lindsey et al., 2013). In the case of RCG, the preferred harvest timing is spring (late April or May), and the grass is left standing during winter (Burvall, 1997; Dopazo et al., 2010; Landström et al., 1996; Xiong et al., 2008).

3.2. Leaf area index (LAI)

All crops follow a similar pattern in the seasonal evolution of LAI, but average values and spread of the measurements from the studies vary (Fig. 2). LAI for MSC increases steadily after May and reaches a peak value in July–August, with a slight decrease afterwards. Average estimates (\pm SEM) give a maximum LAI of 6.05 ± 0.84 m²/m² by August,

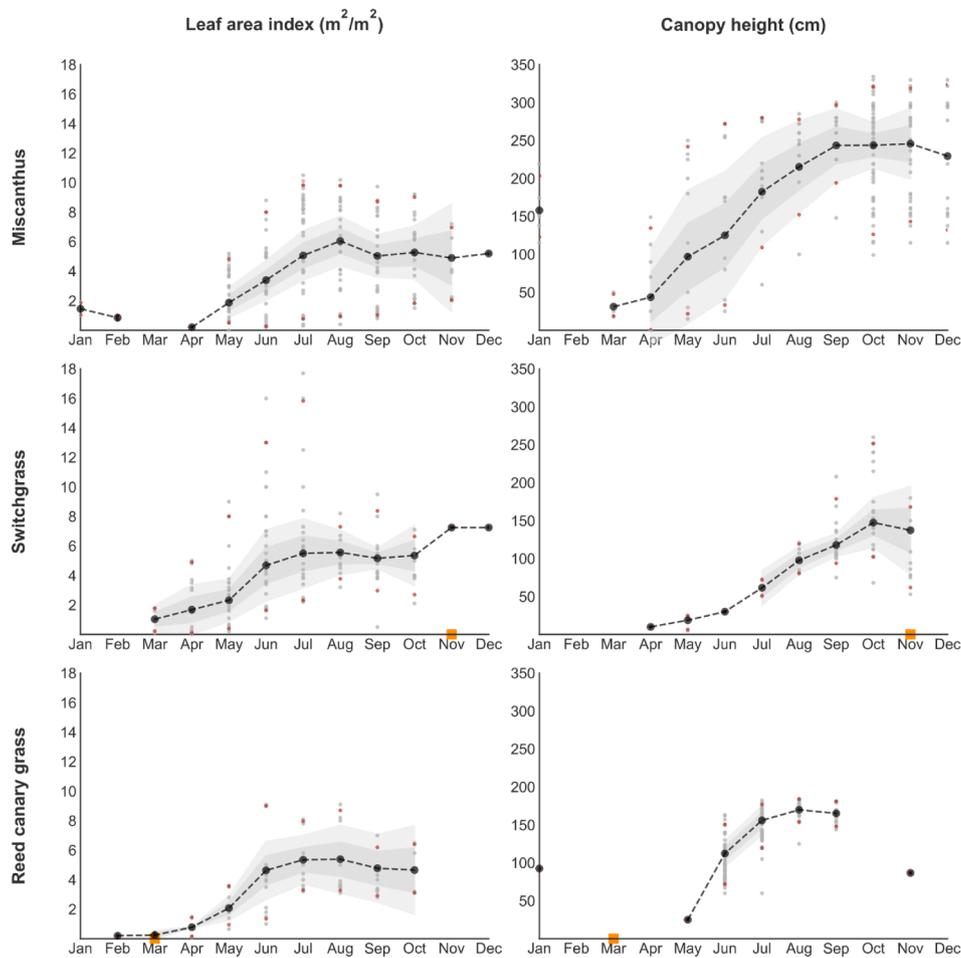


Fig. 2. Leaf area index (left) and canopy height (right) for the 3 bioenergy crops. Black dots show mean estimates from the individual data points, red dots indicate the 5th and 95th percentiles, and the grey dots show individual data points from the different studies. Dark and light grey shaded area indicate one and two standard errors around the mean. The dashed black line is a linear interpolation between two monthly means. The harvest month used in the simulations is indicated by the orange square on the horizontal axis. Values used for the simulations are shown in Table S4 and S5.

and a fairly constant value of about 5 m²/m² is maintained until the end of the year. Individual values in summer months can be as high as 10.5 m²/m² (Heaton et al., 2008) and as low as 1.24 m²/m² (Zeri et al., 2011). The range of values that this parameter can take is wide, as shown by the large distribution of the raw data (grey dots in Fig. 2). There are usually fewer samples in winter months, which usually correspond to the post-harvest period.

The seasonal LAI cycle for SWG shows a sharp increase from March to June, followed by a relatively stable phase until harvest in autumn. The highest average value, 5.56 ± 0.75 m²/m², is reached in August. During the peak months individual data points can be as high as 17.7 m²/m² (Kiniry et al., 1999) and as low as 1.1 m²/m² (Finch et al., 2004). Data points are scattered, particularly for the months of June and July, suggesting that LAI could potentially reach higher values for SWG than for MSC. Again, limited data are available for winter months, thereby hindering a robust interpretation of the dynamics. The higher values in November and December in comparison to the average estimates come from an individual study (Finch et al., 2004) and should be interpreted with care. Expected harvest in late autumn brings LAI close to 0, which likely remains at such low levels until vegetation growth in the spring.

LAI for RCG follows a similar pattern to that of MSC but reaching smaller values. LAI starts to increase in March and peaks between June and August (maximum average of 5.39 ± 1.15 m²/m² in August), followed by a constant (or slight decreasing trend) in the following 2 months. In summer, the highest individual LAI values can be up to 9 m²/m² (Danais, 1986; Kusutani et al., 1977; Ní Choncubhair et al., 2017) and the lowest around 3 m²/m² (Shurpali et al., 2013). Single measurements are less abundant for RCG than for MSC and SWG, and the range of values that the parameter can take is more constrained. No

studies report values for the winter months for RCG. However, since it is preferably harvested in spring, we can expect that LAI remains relatively stable or gradually declines from October until March, largely dependent on the local climatic conditions.

3.3. Canopy height (CH)

CH for MSC (Fig. 2) increases from the lowest post-harvest levels in March until the maximum height of 246 ± 23 cm, achieved between September and November. The data points have large variability, especially after August, and show the varying heights that have been measured by the different studies. The tallest individual height registered is 330 cm (Cosentino et al., 2007; Uwatoko et al., 2016), while the lowest is 99 cm (Clifton-Brown et al., 2001).

There are fewer studies and measurements available for the height of SWG, and the information available is mostly concentrated at the end of the growing season, from September to November. Data points from different studies show considerable variability for those months. The trend indicates that the maximum CH is reached by October with an average value of 147 ± 16 cm. Extreme values range from 240-260 cm (Oliveira et al., 2017) to 68-113 cm (Christian et al., 2002; Heaton et al., 2008).

Information regarding the evolution of RCG's CH throughout a year was overall scarce and limited, and 4 studies provided values for the months of June and July. Values found for the CH in July ranged from 60 to 183 cm with an average value of 156 ± 10 cm. The maximum CH, 170 cm, is reached by August, although the estimation is based on an individual study (Sahramaa and Jauhiainen, 2003).

3.4. Root depth

The average maximum RD for MSC is estimated to be 172 ± 56 cm, with extreme values between 70 cm and 250 cm (Fig. 3). The lowest value of maximum RD, 70 cm, is obtained under rainfed or low water input conditions in a not fully established crop (Mann et al., 2013), while the deepest, 250 cm (limited by the maximum depth of the experiment), is from a well-established plantation in West Germany (Neukirchen et al., 1999).

The average maximum RD for SWG is 165 ± 46 cm, based on 4 field experiments and 6 data points with values ranging between 120 and 250 cm. The maximum values are from a study in California for both high and low water input conditions (Mann et al., 2013). The lowest value serves as an initial low boundary value given that the measurement was limited by the soil profile of the experiment (Monti and Zatta, 2009). Some studies argue that maximum RD for SWG can go as deep as 300 or 350 cm (Elbersen et al., 2004; Lewandowski et al., 2003).

Only two studies with one value each provided information on the maximum RD of RCG, giving an average of 193 ± 15 cm. One value is from an experiment in Sweden (Kätterer and Andrén, 1999) and the other is limited by the depth of the experiment (Shield et al., 2012). A maximum RD of 300 cm for RCG has been previously suggested (Lewandowski et al., 2003).

Due to the lack of data, our estimates of average maximum RD for bioenergy crops are not robust. Additional empirical studies are necessary to refine the estimates, and they should ideally provide information on root depth distribution on different soil layers (as it is typically a key parameter in land surface models).

3.5. Variability and uncertainties

There is a general large variability in the field measurements of vegetation parameters for the bioenergy crops. Variability tends to be larger for the cases in which the number of studies and data points are greater, such as LAI and CH in MSC. The SEM is indicative of how good the average estimation approaches the real average of the parameter, and it is influenced by the number of studies. SEM has lower values when the number of studies is high or when the standard deviation of the sampled studies is low. In the last case, the low SEM does not necessarily indicate a closer approximation to the *real* average if the number of studies is not high enough. SEM of LAI ranges between $1.54 \text{ m}^2/\text{m}^2$ (May) and $2.55 \text{ m}^2/\text{m}^2$ (October) for MSC, $0.34 \text{ m}^2/\text{m}^2$ (September) and $1.20 \text{ m}^2/\text{m}^2$ (June) for SWG, and 0.82 (July) m^2/m^2 and $1.15 \text{ m}^2/\text{m}^2$ (August) for RCG. CH average and SEM estimations are more reliable for specific months: from May through November, especially October (14.9 cm), for MSC, October for SWG (16.3 cm), and June and July for RCG (8.4 cm, and 9.7 cm, respectively). The SEM does not reflect the intrinsic

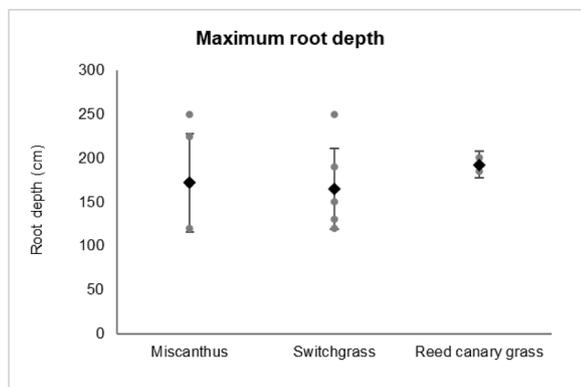


Fig. 3. Average maximum root depth (black diamond) estimated from the field experiment studies (filled grey circles) for MSC, SWG, and RCG. The error bars show 2 standard errors.

variation of the parameters.

Several approaches were used to identify and single out the main drivers behind the difference in values, but a robust relationship did not emerge. For example, despite the evident influence of climatic conditions on crop phenology, it was not possible to identify specific spatial patterns or latitudinal gradients for value distributions of LAI and CH. For instance, MSC's LAI values in Greece and South Italy did not show significant similarities to other random combinations, neither those from England and Ireland. Other factors can drive data variability. The latter can depend on a combination of factors that include irrigation, fertilization, years since plantation establishment, maintenance, water capacity and quality of the soil, precipitation, temperature, and light intensity conditions (Sajjonkari-Pahkala, 2001). This provides potential for future observational studies to investigate the specific significance of these factors on the seasonality of structural attributes of perennial grasses. The conditions that explain variability may also be different among crops. For instance, MSC is more responsive to light and temperature conditions (Lewandowski et al., 2003, 2000), SWG to the cultivated variety and location (Dopazo et al., 2010; Parrish and Fike, 2005) and RCG to the local soil conditions (Christian et al., 2006; Ustak et al., 2019).

3.6. Effects of variability of LAI and CH parameterization in CLM5.0

The effects of phenology parameterization with values representative of mean, 5th and 95th percentiles for LAI and CH are explored for three key components of the surface energy budget that regulate the local climate: sensible heat, latent heat and surface albedo. These components are descriptive of heat, moisture and momentum exchanges between land and atmosphere, and, at the local level, surface albedo is indicative of absorbed solar radiation.

Latent heat is highly sensitive to the LAI parameterization throughout its seasonal cycle for both C3 (RCG) and C4 grasses (SWG), and all the cases based on the values from our meta-analysis give typically larger values than the default parameterization in CLM5.0 (Fig. 4). The largest differences mainly occur from spring to autumn, and latent heat fluxes increase when larger values of LAI are used. However, the marginal increase in fluxes is larger between the 5th percentile and mean values, than between the mean values and the 95th percentile (whose results tend to overlap). Differences in latent heat are larger for the case study in France than Ukraine, and for the C3 grass than the C4 grass (especially in Ukraine). Relative to the results obtained from the default LAI values, the average increment largely takes place from March to October in France (Fig. 4a, c), and from May to September in Ukraine (Fig. 4e, g). This difference can be associated to the different climatic conditions (Figure S1), with a longer growing season in France. On average, latent heat increases of about 1.6 times in these months but can be as high as 2.5 times. In absolute terms, increments during the summer months are in the order of 20 to 50 W/m^2 . For instance, for the C3 grass in France (Fig. 4a), latent heat doubles from $53 \text{ W}/\text{m}^2$ (default case) to $106 \text{ W}/\text{m}^2$ (mean and 95th percentile cases) in July. Particular to this location and grass is a high relative increase in latent heat fluxes in December and January, when values are much larger than the default case. For example, in December latent heat is 22.5 times higher, from $0.22 \text{ W}/\text{m}^2$ (default case) to $5.00 \text{ W}/\text{m}^2$ (95th percentile case). This is not observed in Ukraine, and it is largely due to the colder climate (temperatures in Ukraine during those months are close to -5°C in comparison to about 5°C in France) and seasonal snow cover (the snow water equivalent in Ukraine is between 0.5 and 1 m while France is essentially snow-free), which inhibit latent heat fluxes, independently of the LAI values. Since the C4 grass is harvested in November, there is no difference in the latent heat fluxes from November to March (when growth starts again). In the event that harvest would be delayed to the following year, as it can be the case for Miscanthus, it is expected that the trend would be comparable to that of the C3 grass where latent heat is higher in winter months.

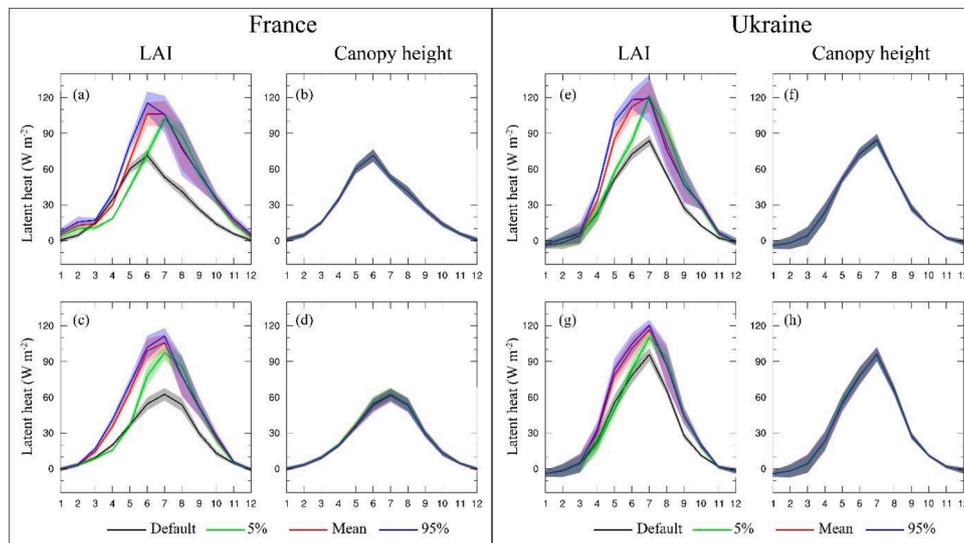


Fig. 4. Seasonal cycle of latent heat for two grasses (C3 and C4) and two locations (a grid cell in France or Ukraine) under 4 different parameterizations of LAI and CH. Shaded areas refer to one standard deviation around the mean (solid lines) and represent inter-annual variability of the 10-year simulation period. Default prescribed values are in black, 5th percentile in green, mean in red and 95th percentile in blue. Panels a, b, e, and f refer to C3 grasses (RCG), c, d, g, and h to C4 grasses (SWG).

The seasonal cycle of sensible heat is generally lower when LAI values from our review are used instead of the default CLM5.0 data (Fig. 5). In general, the higher the LAI the lower the values of sensible heat, although variability is large and uncertainty ranges frequently overlap. This makes sense from a surface energy budget perspective, given that if latent heat increases sensible heat decreases to maintain the balance. Sensible heat based on the 5th percentile LAI values is similar to sensible heat from default LAI values at the beginning of the growing season, but afterwards it resembles the mean and 95th percentile cases pattern. Higher differences occur in the central months of the year, from April to September. The highest reductions are of about 32 W/m² (C3 and C4 grass in France, and C3 grass in Ukraine) in July or August. Differences among simulations also show variations in the peak month of sensible heat fluxes, and interannual variability is typically larger than that of latent heat, especially for the case study located in Ukraine (as measured by a larger shaded area in Fig. 5e, g than Fig. 4e, g). While latent heat typically showed a bell-like shape for the seasonality trend, sensible heat profiles frequently show two peaks, one at the beginning and one at the end of the growing season, which are more pronounced

when higher LAI values are used for the simulations (the second peak in autumn is less pronounced with the default or 5th percentile parameters). These peaks are connected to the precipitation patterns of the locations, as more precipitation and greater LAI usually enhance evapotranspiration. Sensible heat for the C4 grass in Ukraine shows the least robust differences in patterns (Fig. 5g). On average, sensible heat is reduced 9 W/m² when simulations with LAI values corresponding to 5th, mean and 95th percentile are compared to the default values. In the winter months, sensible heat is lower than default values for the C3 grass (harvested in March) in France, while in Ukraine sensible heat is lower than default values at the end of the year but higher in the first trimester of the year. There are no differences in sensible heat values in those months for the C4 grass since it is harvested in November.

The seasonal cycle of land surface albedo is generally lower for simulations with modified LAI values relative to the default case (Fig. 6). In France, differences are distributed throughout the year, except for the winter months for the C4 grass (as it is harvested in autumn and LAI is at minimum). Both C3 and C4 grasses show that the cases based on the 5th percentile have higher values than the default case for a few months in

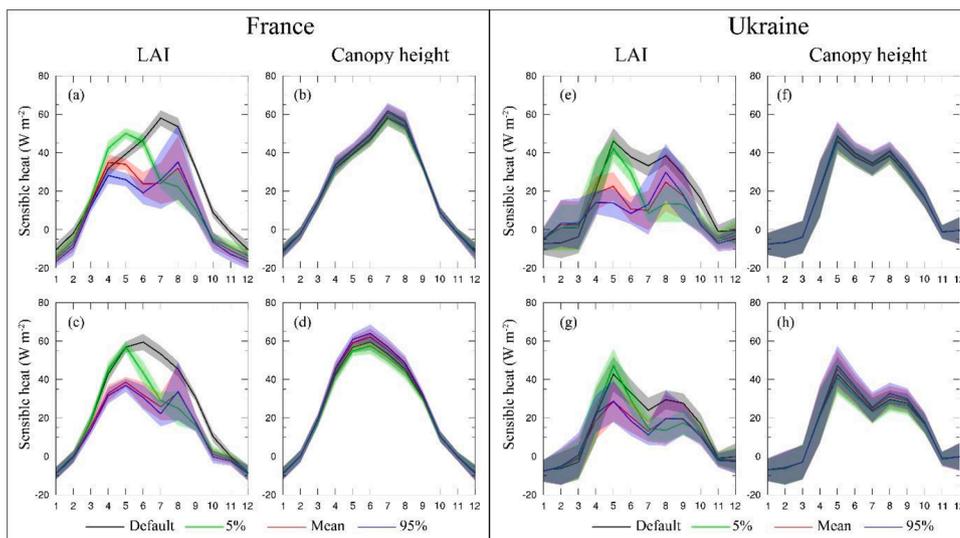


Fig. 5. Seasonal cycle of sensible heat for two grasses (C3 and C4) and two locations (a grid cell in France or Ukraine) under 4 different parameterizations of LAI and CH. Shaded areas refer to one standard deviation around the mean (solid lines) and represent inter-annual variability of the 10-year simulation period. Default prescribed values are in black, 5th percentile in green, mean in red and 95th percentile in blue. Panels a, b, e, and f refer to C3 grasses (RCG), c, d, g, and h to C4 grasses (SWG).

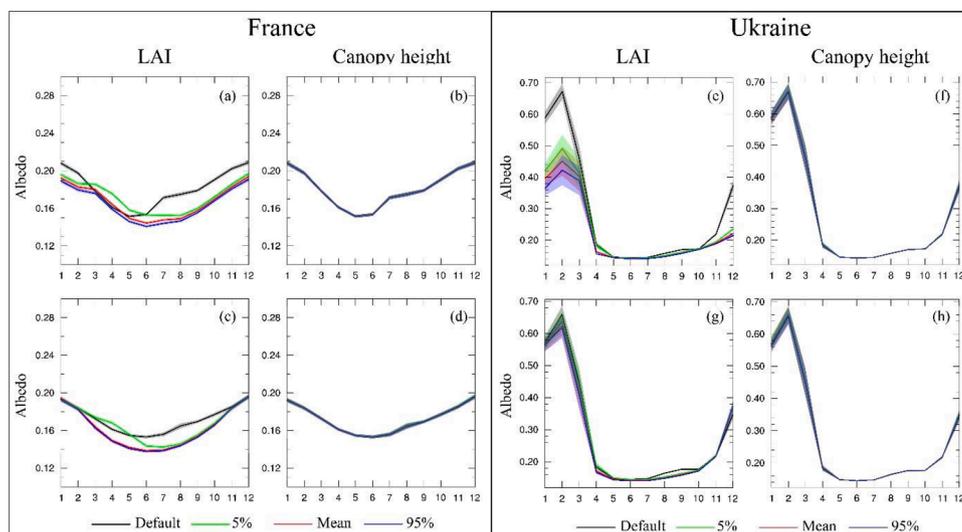


Fig. 6. Seasonal cycle of surface albedo for two grasses (C3 and C4) and two locations (a grid cell in France or Ukraine) under 4 different parameterizations of LAI and CH. Shaded areas refer to one standard deviation around the mean (solid lines) and represent inter-annual variability of the 10-year simulation period. Default prescribed values are in black, 5th percentile in green, mean in red and 95th percentile in blue. Panels a, b, e, and f refer to C3 grasses (RCG), c, d, g, and h to C4 grasses (SWG).

spring (Fig. 6a, c). In Ukraine, albedo values are much higher in winter owing to the seasonal snow cover. Only the simulations for the C3 grass show different values than the default case from November to March, as RCG is set to be harvested in spring. In this period, higher LAI values result in lower albedo than the default case due to the snow masking effect of vegetation (Fig. 6e). For instance, in December, albedo is reduced from 0.37 to 0.22 (mean and 95th percentile cases) and in February from 0.67 to 0.42. The extra absorption of solar radiation at the surface largely lead to higher sensible heat fluxes (Fig. 5e) given that low temperatures prevents significant latent heat fluxes (Fig. 4e). Given that the C4 grass is harvested in November albedo values largely overlap for this grass and are independent of LAI parameterization in winter (Fig. 6g), where LAI and canopy height approach zero and reduce differences in parameterizations with the default case. For the other grasses and location, the highest reductions are on average of 11% and occurring in the late summer or autumn months. The C3 grass in France reduces the land albedo from 0.18 to 0.15 in August (mean, 5th and 95th percentile cases).

The effects of changes in CH parameterization are less significant than changes in LAI for all the variables and locations selected. In general, all simulations have ranges that overlap across the months. The seasonal cycle of latent heat is overall unaffected except for some very limited variations in winter monthly means, especially for the grasses in France. The C3 grass in France increases latent heat from 0.22 W/m² to 0.68 W/m² in December (95th percentile case) (Fig. 5b), and the C4 grass at the same location increases from -0.12 W/m² to 0 W/m² in January (95th percentile case) (Fig. 4d). The seasonal cycle of sensible heat changes on average 5% relative to the default values for both grasses and locations (slightly higher/lower changes for the case with bigger/smaller LAI, respectively). One exception are relatively higher changes occurring in November or December: sensible heat decreases up to 31% in November for the C3 grasses, changing from -1.6 W/m² to -2.1 W/m² in France and from -0.95 to -1.25 W/m² in Ukraine (95th percentile case); for the C4 grass in France, sensible heat in November changes from 0.11 W/m² to 0.18 W/m² or -0.15 W/m² (5th and 95th percentile cases), and for the same grass in Ukraine it decreases from -0.10 W/m² to -0.31 W/m² or -0.18 W/m² in December (5th and 95th percentile cases). Land surface albedo throughout the year does not show significant changes due to changes in CH parameterization.

When both observational mean values of LAI and CH are tested in a single simulation for both grasses and locations (Supplementary Figures S3-S5), the results for the three surface energy components follow the same trend of the results obtained for the LAI mean cases presented above. Sensible heat for both grasses and locations show light

increase for some months of the year because of incorporating a higher CH. The same is observed in the results of latent heat from the C3 grass. These results suggest that the seasonal cycle of latent heat, sensible heat and surface albedo are primarily influenced by the parameterization of LAI, while CH values play a secondary role. This is at least valid for the CH values tested in our simulations which covered values between 50 cm and 181 cm for the C3 grass, and between 25 cm and 240 cm for the C4 grass.

Comparing the outcomes of our simulations with other existing studies is challenging owing to the different conditions in terms of background climate, simulation design, type of perennial grass, land surface model or, when the same model is used, they can differ by model version or configuration. For example, a recent study parameterized perennial bioenergy crops in CLM5.0 using site-level observations in the Central Midwestern United States, and produced trends of latent heat fluxes for switchgrass that range between 100 and 150 W/m² in summer (reaching a peak in July) (Cheng et al., 2020), which is largely consistent with our findings. However, these results were produced with a different model configuration, different time period, and for different climatic conditions than those used in our work. An analysis of the effects of second-generation biofuel feedstock production in the central U.S. found larger values of latent heat fluxes for miscanthus (average peak in mid-summer around 200 W/m²), but they used a coupled model (WRF-CLM4.0) and parameterized version of biofuels crops in CLM4 (with a prescribed maximum LAI of 6.5) (Harding et al., 2016). A study based on an ecosystem model for the cultivation of perennial grasses in the Midwest US achieved maximum summer values between 100 and 150 W/m² (VanLoocke et al., 2012). Higher values of latent heat fluxes are simulated in a study that applied CLM4.5 to assess the changes in the surface energy balance from switchgrass and miscanthus in the conterminous US, which found peaks around 350 W/m² (Zhu et al., 2017). However, this analysis reported results for one year only (2011), rather than multi-year averages, and data have an hourly temporal resolution (monthly mean values are expected to be smaller and more consistent with the findings of the other studies).

4. Conclusions

This study collected field observational values of key vegetation structure parameters like LAI, CH and RD for 3 perennial grasses (MSC, SWG and RCG) that are attractive as feedstocks for bioenergy. We successfully gathered data from 34 empirical studies and compiled a meta-analysis by showing monthly statistics of mean values, SEM, and 5 and 95thile values for LAI and CH, and maximum values for RD. These data

offer an overview of the seasonal trends, plausible range of values, variability, and current gaps in observational records of fundamental parameters that are key drivers of the surface energy budget.

We found that average LAI values for the three grasses follow a similar trend, reaching peak values between June and August with maximum mean LAI values between 5.4 m²/m² and 6.1 m²/m². The trend for CH is less evident and varies for all grasses, with maximum mean values ranging between 147 cm and 246 cm. Available data on maximum RD were overall scarce, but current estimates suggest that average maximum RD for the three grasses is beyond 167 cm.

The identified gaps of observational data mainly concern CH for RCG, RD for all the three crops, values in winter months (when relevant, owing to local climatic conditions) and field studies from the southern hemisphere. Future studies can also explore the effects of different site-specific soil conditions, management intensity or background climate of the various experiments so to favor integrated analysis that explain variability in vegetation structure as a function of the local context. Different factors like fertilization, irrigation, agricultural management, water capacity and quality of the soil, plantation age, precipitation, and temperature conditions are expected to influence seasonal trends of LAI, CH and RD.

The data summarized in our meta-analysis can be used to improve parameterization of LAI and CH of bioenergy crops in land surface models, or for model validation and calibration. Our results show that the seasonal evolutions of latent heat, sensible heat and surface albedo are significantly affected by the parameterization of LAI. Higher LAI values generally tend to increase latent heat, and decrease sensible heat and surface albedo, regardless of grass and location. Default LAI values for C3 and C4 grasses in CLM5.0 underestimate latent heat fluxes of biofuel crops, especially during the growing season, relative to the observational-based values. On the other hand, sensible heat fluxes are overestimated, especially in France in summer months. Albedo values are higher with the default values, especially for the C3 grass in winter in presence of snow. Comparing the results for the C4 grass between the two locations, we can also argue that the parameterization of LAI have different relative effects on the surface energy budget depending on the background climatic conditions. Our simulations also show that different parameterizations of CH are less critical in the seasonal evolution of latent heat, sensible heat, and surface albedo. Some variations were identified for sensible and latent heat in winter months, but they fall within the respective uncertainty ranges.

Accurate parameterization of vegetation structure is important to get a closer approximation of the effects of bioenergy crops in the earth system. The results of our meta-analysis offer a wide empirical basis to compare measurements of key phenological properties of bioenergy crops and can be used for model calibration, validation, and development. Their use in a land surface model has shown the implications that their parameterization can have on the surface energy budget, and hence the local climate. Given the expected key role played by bioenergy crops in future scenarios consistent with climate change stabilization at low level, gradually improving our understanding of the key characteristics of bioenergy crops and their implications for the local climate and hydrological systems can increase the accuracy of modelling tools and ultimately favor their sustainable implementation.

Declaration of Competing Interest

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.agrformet.2021.108444](https://doi.org/10.1016/j.agrformet.2021.108444).

References

- Acharya, M., Burner, D.M., Ashworth, A.J., Fritschi, F.B., Adams, T.C., 2018. Growth rates of giant miscanthus (*Miscanthus × giganteus*) and giant reed (*Arundo donax*) in a low-input system in Arkansas, USA. *Am. J. Plant Sci.* <https://doi.org/10.4236/ajps.2018.912172>.
- Bassam, N.E.I., 2011. *Handbook of Bioenergy Crops: A Complete Reference to Species, Development and Applications*, Experimental Agriculture. Routledge, 2010.
- Bohn, F.J., May, F., Huth, A., 2018. Species composition and forest structure explain the temperature sensitivity patterns of productivity in temperate forests. *Biogeosciences*. <https://doi.org/10.5194/bg-15-1795-2018>.
- Bonan, G.B., 2016. *Ecological Climatology, Concepts and Applications*, Third Edit. ed. Cambridge University Press. <https://doi.org/10.21425/58433332>.
- Burvall, J., 1997. Influence of harvest time and soil type on fuel quality in reed canary grass (*Phalaris Arundinacea* L.). *Biomass Bioenergy*. [https://doi.org/10.1016/S0961-9534\(96\)00064-5](https://doi.org/10.1016/S0961-9534(96)00064-5).
- Cai, H., Wang, J., Feng, Y., Wang, M., Qin, Z., Dunn, J.B., 2016. Consideration of land use change-induced surface albedo effects in life-cycle analysis of biofuels. *Energy Environ. Sci.* 9, 2855–2867. <https://doi.org/10.1039/c6ee01728b>.
- Chen, L., Dirmeyer, P.A., 2020. Reconciling the disagreement between observed and simulated temperature responses to deforestation. *Nat. Commun.* 11, 202. <https://doi.org/10.1038/s41467-019-14017-0>.
- Chen, L., Dirmeyer, P.A., 2016. Adapting observationally based metrics of biogeophysical feedbacks from land cover/land use change to climate modeling. *Environ. Res. Lett.* 11, 34002. <https://doi.org/10.1088/1748-9326/11/3/034002>.
- Cheng, Y., Huang, M., Chen, M., Guan, K., Bernacchi, C., Peng, B., Tan, Z., 2020. Parameterizing perennial bioenergy crops in version 5 of the community land model based on site-level observations in the Central Midwestern United States. *J. Adv. Model. Earth Syst.* 12, 1–25. <https://doi.org/10.1029/2019MS001719>.
- Christian, D.G., Riche, A.B., Yates, N.E., 2002. The yield and composition of switchgrass and coastal panic grass grown as a biofuel in Southern England. *Bioresour. Technol.* 83, 115–124. [https://doi.org/10.1016/S0960-8524\(01\)00201-2](https://doi.org/10.1016/S0960-8524(01)00201-2).
- Christian, D.G., Yates, N.E., Riche, A.B., 2006. The effect of harvest date on the yield and mineral content of *Phalaris arundinacea* L. (reed canary grass) genotypes screened for their potential as energy crops in southern England. *J. Sci. Food Agric.* 86, 1181–1188. <https://doi.org/10.1002/jsfa.2437>.
- Chu, H., Baldocchi, D.D., Poindexter, C., Abraha, M., Desai, A.R., Bohrer, G., Arain, M.A., Griffis, T., Blanken, P.D., O'Halloran, T.L., Thomas, R.Q., Zhang, Q., Burns, S.P., Frank, J.M., Christian, D., Brown, S., Black, T.A., Gough, C.M., Law, B.E., Lee, X., Chen, J., Reed, D.E., Massman, W.J., Clark, K., Hatfield, J., Prueger, J., Bracho, R., Baker, J.M., Martin, T.A., 2018. Temporal dynamics of aerodynamic canopy height derived from eddy covariance momentum flux data across North American Flux Networks. *Geophys. Res. Lett.* 45, 9275–9287. <https://doi.org/10.1029/2018GL079306>.
- Chum, H., Faaij, A., Moreira, J., Berndes, G., Dhaniya, P., Dong, H., Gabrielle, B., Goss, Eng, A., Lucht, W., Mapako, M., Maserera Cerutti, O., McIntyre, T., Minowa, T., Pingoud, K., 2011. *Bioenergy*. In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Seyboth, K., Matschoss, P., Kadner, S., Zwickel, T., Eickemeier, P., Hansen, G., Schlömer, S., von Stechow, C. (Eds.), *IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Clifton-brown, J.C., Breuer, J., Jones, M.B., 2007. Carbon mitigation by the energy crop, *Miscanthus*. *Glob. Chang. Biol.* 13, 2296–2307. <https://doi.org/10.1111/j.1365-2486.2007.01438.x>.
- Clifton-Brown, J.C., Lewandowski, I., Andersson, B., Basch, G., Christian, D.G., Kjeldsen, J.B., Jørgensen, U., Mortensen, J.V., Riche, A.B., Schwarz, K.U., Tayebi, K., Teixeira, F., 2001. Performance of 15 *Miscanthus* genotypes at five sites in Europe. *Agron. J.* <https://doi.org/10.2134/agronj2001.93511013x>.
- Clifton-Brown, J.C., Neilson, B., Lewandowski, I., Jones, M.B., 2000. The modelled productivity of *Miscanthus x giganteus* (GREEF et DEU) in Ireland. *Ind. Crops Prod.* [https://doi.org/10.1016/S0926-6690\(00\)00042-X](https://doi.org/10.1016/S0926-6690(00)00042-X).
- Collins, H.P., Smith, J.L., Fransen, S., Alva, A.K., Kruger, C.E., Granatstein, D.M., 2010. Carbon Sequestration under Irrigated Switchgrass (*Panicum virgatum* L.) Production. *Soil Sci. Soc. Am. J.* 74, 2049–2058. <https://doi.org/10.2136/sssaj2010.0020>.
- Cosentino, S.L., Patané, C., Sanzone, E., Copani, V., Foti, S., 2007. Effects of soil water content and nitrogen supply on the productivity of *Miscanthus × giganteus* Greef et Deu. in a Mediterranean environment. *Ind. Crops Prod.* <https://doi.org/10.1016/j.indcrop.2006.07.006>.
- Creutzig, F., Ravindranath, N.H., Berndes, G., Bolwig, S., Bright, R., Cherubini, F., Chum, H., Corbera, E., Delucchi, M., Faaij, A., Fargione, J., Haberl, H., Heath, G., Lucon, O., Plevin, R., Popp, A., Robledo-Abad, C., Rose, S., Smith, P., Stromman, A., Suh, S., Maserera, O., 2015. Bioenergy and climate change mitigation—an assessment. *GCB Bioenergy* 7, 916–944. <https://doi.org/10.1111/gcbb.12205>.

- Danais, M., 1986. The influence of some environmental factors on the production of *Carex vesicaria* and *Phalaris arundinacea*. *Vegetatio*. <https://doi.org/10.1007/BF00040317>.
- Danalatos, N.G., Archontoulis, S.V., Mitsios, I., 2007. Potential growth and biomass productivity of *Miscanthus × giganteus* as affected by plant density and N-fertilization in central Greece. *Biomass Bioenergy* 31, 145–152. <https://doi.org/10.1016/j.biombioe.2006.07.004>.
- Dirmeyer, P.A., Gao, X., Zhao, M., Guo, Z., Oki, T., Hanasaki, N., 2006. GSWP-2: Multimodel analysis and implications for our perception of the land surface. *Bull. Am. Meteorol. Soc.* <https://doi.org/10.1175/BAMS-87-10-1381>.
- Dopazo, R., Vega-Nieva, D., Ortiz, L., 2009. A review of Herbaceous energy crops for bioenergy production in Europe. 17th European Biomass Conference & Exhibition, pp. 603–613.
- Dopazo, R., Vega-Nieva, D., Ortiz, L., 2010. Herbaceous energy crops: reviewing their productivity for bioenergy production. *Publ. Internet* 1–3.
- Eichelmann, E., Wagner-Riddle, C., Warland, J., Deen, B., Voroney, P., 2016. Comparison of carbon budget, evapotranspiration, and albedo effect between the biofuel crops switchgrass and corn. *Agric. Ecosyst. Environ.* <https://doi.org/10.1016/j.agee.2016.07.007>.
- Elbersen, H.W., Christian, D.G., Bassam, N.E., Sauerbeck, G., Alexopoulou, E., Piscioneri, I., 2004. A management guide for planting and production of switchgrass as a biomass crop in Europe.
- Englund, O., Börjesson, P., Berndes, G., Scarlat, N., Dallemand, J.F., Grizzetti, B., Dimitriou, I., Mola-Yudego, B., Fahl, F., 2020. Beneficial land use change: Strategic expansion of new biomass plantations can reduce environmental impacts from EU agriculture. *Glob. Environ. Chang.* <https://doi.org/10.1016/j.gloenvcha.2019.101990>.
- Finch, J.W., Hall, R.L., Rosier, P.T.W., Clark, D.B., Stratford, C., Davies, H.N., Marsh, T. J., Roberts, J.M., Riche, A., Christian, D., 2004. The hydrological impacts of energy crop production in the UK 151.
- Finch, J.W., Riche, A.B., 2010. Interception losses from *Miscanthus* at a site in south-east England—an application of the Gash model. *Hydrol. Process.* 24, 2594–2600. <https://doi.org/10.1002/hyp.7673>.
- Findell, K.L., Eltahir, E.A.B., 2003. Atmospheric controls on soil moisture-boundary layer interactions. Part II: Feedbacks within the continental United States. *J. Hydrometeorol.* [https://doi.org/10.1175/1525-7541\(2003\)004<0570:ACOSML>2.0.CO;2](https://doi.org/10.1175/1525-7541(2003)004<0570:ACOSML>2.0.CO;2).
- Georgescu, M., Lobell, D.B., Field, C.B., 2011. Direct climate effects of perennial bioenergy crops in the United States. *Proc. Natl. Acad. Sci. U. S. A.* 108, 4307–4312. <https://doi.org/10.1073/pnas.1008779108>.
- Georgescu, M., Lobell, D.B., Field, C.B., Mahalov, A., 2013. Simulated hydroclimatic impacts of projected Brazilian sugarcane expansion. *Geophys. Res. Lett.* <https://doi.org/10.1002/grl.50206>.
- Harding, K.J., Twine, T.E., VanLoocke, A., Bagley, J.E., Hill, J., 2016. Impacts of second-generation biofuel feedstock production in the central U.S. on the hydrologic cycle and global warming mitigation potential. *Geophys. Res. Lett.* <https://doi.org/10.1002/2016GL069981>.
- Heaton, E.A., Dohleman, F.G., Long, S.P., 2009. Seasonal nitrogen dynamics of *Miscanthus × giganteus* and *Panicum virgatum*. *GCB Bioenergy* 1, 297–307. <https://doi.org/10.1111/j.1757-1707.2009.01022.x>.
- Heaton, E.A., Dohleman, F.G., Long, S.P., 2008. Meeting US biofuel goals with less land: The potential of *Miscanthus*. *Glob. Chang. Biol.* 14, 2000–2014. <https://doi.org/10.1111/j.1365-2486.2008.01662.x>.
- Huang, B., Hu, X., Fuglstad, G.-A., Zhou, X., Zhao, W., Cherubini, F., 2020. Predominant regional biophysical cooling from recent land cover changes in Europe. *Nat. Commun.* 11, 1066. <https://doi.org/10.1038/s41467-020-14890-0>.
- Hurttt, G.C., Chini, L., Sahajpal, R., Frolking, S., Bodirsky, B.L., Calvin, K., Doelman, J.C., Fisk, J., Fujimori, S., Golewewijk, K.K., Hasegawa, T., Havlik, P., Heinemann, A., Humpenöder, F., Jungclaus, J., Kaplan, J., Kennedy, J., Kristzin, T., Lawrence, D., Lawrence, P., Ma, L., Mertz, O., Pongratz, J., Popp, A., Poulter, B., Riahi, K., Shevliakova, E., Stehfest, E., Thornton, P., Tubiello, F.N., van Vuuren, D.P., Zhang, X., 2020. Harmonization of Global Land-Use Change and Management for the Period 850–2100 (LUH2) for CMIP6. *Geosci. Model Dev. Discuss.* 2020, 1–65. <https://doi.org/10.5194/gmd-2019-360>.
- Jasinskas, A., Zaltauskas, A., Kryzeviciene, A., 2008. The investigation of growing and using of tall perennial grasses as energy crops. *Biomass Bioenergy.* <https://doi.org/10.1016/j.biombioe.2008.01.025>.
- Kätterer, T., Andrén, O., 1999. Growth dynamics of reed canarygrass (*Phalaris arundinacea* L.) and its allocation of biomass and nitrogen below ground in a field receiving daily irrigation and fertilisation. *Nutr. Cycl. Agroecosyst.* 54, 21–29. <https://doi.org/10.1023/A:1009701422394>.
- Kiniry, J.R., Tischler, C.R., Van Esbroeck, G.A., 1999. Radiation use efficiency and leaf CO₂ exchange for diverse C4 grasses. *Biomass Bioenergy* 17, 95–112. [https://doi.org/10.1016/S0961-9534\(99\)00036-7](https://doi.org/10.1016/S0961-9534(99)00036-7).
- Kusutani, A., Nakaseko, K., Gotoh, K., 1977. Canopy structure and dry matter production in grasses. *Japanese J. Crop Sci.* <https://doi.org/10.1626/jcs.46.205>.
- Lagué, M.M., Bonan, G.B., Swann, A.L.S., 2019. Separating the impact of individual land surface properties on the terrestrial surface energy budget in both the coupled and uncoupled land–atmosphere system. *J. Clim.* 32, 5725–5744. <https://doi.org/10.1175/JCLI-D-18-0812.1>.
- Landström, S., Lomakka, L., Andersson, S., 1996. Harvest in spring improves yield and quality of reed canary grass as a bioenergy crop. *Biomass Bioenergy.* [https://doi.org/10.1016/0961-9534\(96\)00041-4](https://doi.org/10.1016/0961-9534(96)00041-4).
- Lawrence, D., Fisher, R., Koven, C., Oleson, K., Swenson, S., Vertenstein, M., 2018. Technical Description of Version 5.0 of the Community Land Model (CLM). NCAR/TN-478+STR NCAR Tech. Note.
- Lawrence, D.M., Fisher, R.A., Koven, C.D., Oleson, K.W., Swenson, S.C., Bonan, G., Collier, N., Ghimire, B., van Kampenhou, L., Kennedy, D., Kluzek, E., Lawrence, P.J., Li, F., Li, H., Lombardozzi, D., Riley, W.J., Sacks, W.J., Shi, M., Vertenstein, M., Wiedner, W.R., Xu, C., Ali, A.A., Badger, A.M., Bisht, G., van den Broeke, M., Brunke, M.A., Burns, S.P., Buzan, J., Clark, M., Craig, A., Dahlin, K., Drewniak, B., Fisher, J.B., Flanner, M., Fox, A.M., Gentine, P., Hoffman, F., Keppel-Aleks, G., Knox, R., Kumar, S., Lenaerts, J., Leung, L.R., Lipscomb, W.H., Lu, Y., Pandey, A., Pelletier, J.D., Perket, J., Randerson, J.T., Ricciuto, D.M., Sanderson, B.M., Slater, A., Subin, Z.M., Tang, J., Thomas, R.Q., Val Martin, M., Zeng, X., 2019. The community land model version 5: description of new features, benchmarking, and impact of forcing uncertainty. *J. Adv. Model. Earth Syst.* <https://doi.org/10.1029/2018MS001583>.
- Leirpoll, M.E., Næss, J.S., Cavalett, O., Dorber, M., Hu, X., Cherubini, F., 2021. Optimal combination of bioenergy and solar photovoltaic for renewable energy production on abandoned cropland. *Renew. Energy* 168, 45–56. <https://doi.org/10.1016/j.renene.2020.11.159>.
- Lemus, R., Brummer, E.C., Moore, K.J., Molstad, N.E., Burras, C.L., Barker, M.F., 2002. Biomass yield and quality of 20 switchgrass populations in southern Iowa, USA. *Biomass Bioenergy* 23, 433–442. [https://doi.org/10.1016/S0961-9534\(02\)00073-9](https://doi.org/10.1016/S0961-9534(02)00073-9).
- Lewandowski, I., Clifton-Brown, J.C., Scurlock, J.M.O., Huisman, W., 2000. *Miscanthus*: European experience with a novel energy crop. *Biomass Bioenergy.*
- Lewandowski, I., Heinz, A., 2003. Delayed harvest of *Miscanthus* - Influences on biomass quantity and quality and environmental impacts of energy production. *Eur. J. Agron.* [https://doi.org/10.1016/S1161-0301\(02\)00018-7](https://doi.org/10.1016/S1161-0301(02)00018-7).
- Lewandowski, I., Scurlock, J.M.O., Lindvall, E., Christou, M., 2003. The development and current status of perennial rhizomatous grasses as energy crops in the US and Europe. *Biomass Bioenergy.* [https://doi.org/10.1016/S0961-9534\(03\)00030-8](https://doi.org/10.1016/S0961-9534(03)00030-8).
- Li, W., Yue, C., Ciais, P., Chang, J., Goll, D., Zhu, D., Peng, S., Jorner-Puig, A., 2018. ORCHIDEE-MICT-BIOENERGY: An attempt to represent the production of lignocellulosic crops for bioenergy in a global vegetation model. *Geosci. Model Dev.* <https://doi.org/10.5194/gmd-11-2249-2018>.
- Lind, S.E., Shurpali, N.J., Peltola, O., Mammarella, I., Hyvönen, N., Maljanen, M., Rätty, M., Virkajärvi, P., Martikainen, P.J., 2016. Carbon dioxide exchange of a perennial bioenergy crop cultivation on a mineral soil. *Biogeosciences* 13, 1255–1268. <https://doi.org/10.5194/bg-13-1255-2016>.
- Lindsey, K., Johnson, A., Kim, P., Jackson, S., Labbé, N., 2013. Monitoring switchgrass composition to optimize harvesting periods for bioenergy and value-added products. *Biomass Bioenergy.* <https://doi.org/10.1016/j.biombioe.2013.04.023>.
- Liu, X., Chen, F., Barlage, M., Zhou, G., Niyogi, D., 2016. Noah-MP-Crop: introducing dynamic crop growth in the Noah-MP land surface model. *J. Geophys. Res.* <https://doi.org/10.1002/2016JD025597>.
- Mann, J.J., Barney, J.N., Kyser, G.B., DiTomaso, J.M., 2013. Root system dynamics of *Miscanthus × giganteus* and *Panicum virgatum* in response to rainfed and irrigated conditions in California. *Bioenergy Res* 6, 678–687. <https://doi.org/10.1007/s12155-012-9287-y>.
- McLaughlin, S.B., Kszos, L.A., 2005. Development of switchgrass (*Panicum virgatum*) as a bioenergy feedstock in the United States. *Biomass Bioenergy.* <https://doi.org/10.1016/j.biombioe.2004.05.006>.
- Miller, J.N., VanLoocke, A., Gomez-Casanovas, N., Bernacchi, C.J., 2016. Candidate perennial bioenergy grasses have a higher albedo than annual row crops. *GCB Bioenergy.* <https://doi.org/10.1111/gcbb.12291>.
- Monti, A., Zatta, A., 2009. Root distribution and soil moisture retrieval in perennial and annual energy crops in Northern Italy. *Agric. Ecosyst. Environ.* 132, 252–259. <https://doi.org/10.1016/j.agee.2009.04.007>.
- Næss, J.S., Cavalett, O., Cherubini, F., 2021. The land–energy–water nexus of global bioenergy potentials from abandoned cropland. *Nat. Sustain.* <https://doi.org/10.1038/s41893-020-00680-5>.
- Neukirchen, D., Himken, M., Lammel, J., Czipionka-Krause, U., Olf, H.-W., 1999. Spatial and temporal distribution of the root system and root nutrient content of an established *Miscanthus* crop. *Eur. J. Agron.*
- Ní Chonubhair, Ó., Osborne, B., Finnan, J., Lanigan, G., 2017. Comparative assessment of ecosystem C exchange in *Miscanthus* and reed canary grass during early establishment. *GCB Bioenergy* 9, 280–298. <https://doi.org/10.1111/gcbb.12343>.
- Oliveira, J.A., West, C.P., Afif, E., Palencia, P., 2017. Comparison of *Miscanthus* and switchgrass cultivars for biomass yield, soil nutrients, and nutrient removal in northwest Spain. *Agron. J.* <https://doi.org/10.2134/agronj2016.07.0440>.
- Parrish, D.J., Fike, J.H., 2005. The biology and agronomy of switchgrass for biofuels. *CRC. Crit. Rev. Plant Sci.* <https://doi.org/10.1080/07352680500316433>.
- Pitman, A.J., 2003. The evolution of, and revolution in, land surface schemes designed for climate models. *Int. J. Climatol.* 23, 479–510. <https://doi.org/10.1002/joc.893>.
- Robertson, G.P., Hamilton, S.K., Barham, B.L., Dale, B.E., Izaurralde, R.C., Jackson, R.D., Landis, D.A., Swinton, S.M., Thelen, K.D., Tiedje, J.M., 2017. Cellulosic biofuel contributions to a sustainable energy future: Choices and outcomes. *Science* (80). <https://doi.org/10.1126/science.aal2324>.
- Rulli, M.C., Bellomi, D., Cazzoli, A., De Carolis, G., D'Odorico, P., 2016. The water-land-food nexus of first-generation biofuels. *Sci. Rep.* <https://doi.org/10.1038/srep22521>.
- Sahramaa, M., Ihäkä, H., Jauhiainen, L., 2003. Variation in biomass related variables of reed canary grass. *Agric. Food Sci. Finl.* 12, 213–225. <https://doi.org/10.23986/afsci.5749>.
- Sahramaa, M., Jauhiainen, L., 2003. Characterization of development and stem elongation of reed canary grass under northern conditions. *Ind. Crops Prod.* 18, 155–169. [https://doi.org/10.1016/S0926-6690\(03\)00044-X](https://doi.org/10.1016/S0926-6690(03)00044-X).
- Saijonkari-Pahkala, K., 2001. Non-wood plants as raw material for pulp and paper. *Agric. Food Sci. Finl.* 10, 10–95. <https://doi.org/10.23986/afsci.5707>.

- Shield, I.F., Barraclough, T.J.P., Riche, A.B., Yates, N.E., 2012. The yield response of the energy crops switchgrass and reed canary grass to fertiliser applications when grown on a low productivity sandy soil. *Biomass Bioenergy*. <https://doi.org/10.1016/j.biombioe.2012.03.017>.
- IPCC, 2019: summary for policymakers. In: Shukla, P.R., Skea, J., Buendia, E.C., Masson-Delmotte, V., Pörtner, H.-O., Roberts, D.C., Zhai, P., Slade, R., Connors, S., Diemen, R.van, Ferrat, M., Haughey, E., Luz, S., Neogi, S., Pathak, M., Petzold, J., Pereira, J.P., Vyas, P., Huntley, E., Kissick, K., Belkacemi, M., Malley, J. (Eds.), IPCC, 2019: Summary for Policymakers. In: *Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems*. In press.
- Shurpali, N.J., Biasi, C., Jokinen, S., Hyvönen, N., Martikainen, P.J., 2013. Linking water vapor and CO₂ exchange from a perennial bioenergy crop on a drained organic soil in eastern Finland. *Agric. For. Meteorol.* 168, 47–58. <https://doi.org/10.1016/j.agrformet.2012.08.006>.
- Stuart Chapin, F., Matson, P.A., Vitousek, P.M., 2012. Principles of terrestrial ecosystem ecology. *Principles of Terrestrial Ecosystem Ecology*. <https://doi.org/10.1007/978-1-4419-9504-9>.
- Tilman, D., Socolow, R., Foley, J.A., Hill, J., Larson, E., Lynd, L., Pacala, S., Reilly, J., Searchinger, T., Somerville, C., Williams, R., 2009. Beneficial biofuels - the food, energy, and environment trilemma. *Science* 325 (80), 270–271. <https://doi.org/10.1126/science.1177970>.
- Ušák, S., Šinko, J., Muñoz, J., 2019. Reed canary grass (*Phalaris arundinacea* L.) as a promising energy crop. *J. Cent. Eur. Agric.* <https://doi.org/10.5513/JCEA01/20.4.2267>.
- Uwatoko, N., Tamura, K.ichi, Yamashita, H., Gau, M., 2016. Naturally occurring triploid hybrids between *Miscanthus sacchariflorus* and *M. sinensis* in Southern Japan, show phenotypic variation in agronomic and morphological traits. *Euphytica* 212, 355–370. <https://doi.org/10.1007/s10681-016-1760-9>.
- van der Werf, H.M.G., Meijer, W.J.M., Mathijssen, E.W.J.M., Darwinkel, A., 1992. Potential dry matter production of *Miscanthus sinensis* in The Netherlands. *Ind. Crops Prod.* [https://doi.org/10.1016/0926-6690\(92\)90020-V](https://doi.org/10.1016/0926-6690(92)90020-V).
- VanLoocke, A., Twine, T.E., Zeri, M., Bernacchi, C.J., 2012. A regional comparison of water use efficiency for miscanthus, switchgrass and maize. *Agric. For. Meteorol.* <https://doi.org/10.1016/j.agrformet.2012.05.016>.
- Wagle, P., Kakani, V.G., Huhnke, R.L., 2015. Net ecosystem carbon dioxide exchange of dedicated bioenergy feedstocks: Switchgrass and high biomass sorghum. *Agric. For. Meteorol.* 207, 107–116. <https://doi.org/10.1016/j.agrformet.2015.03.015>.
- Wang, M., Wagner, M., Miguez-Macho, G., Kamarianakis, Y., Mahalov, A., Moustauoi, M., Miller, J., VanLoocke, A., Bagley, J.E., Bernacchi, C.J., Georgescu, M., 2017. On the long-term hydroclimatic sustainability of perennial bioenergy crop expansion over the United States. *J. Clim.* <https://doi.org/10.1175/JCLI-D-16-0610.1>.
- Weilhoefer, C.L., Williams, D., Nguyen, I., Jakstis, K., Fischer, C., 2017. The effects of reed canary grass (*Phalaris arundinacea* L.) on wetland habitat and arthropod community composition in an urban freshwater wetland. *Wetl. Ecol. Manag.* <https://doi.org/10.1007/s11273-016-9507-x>.
- Williams, A.S., Kiniry, J.R., Mushet, D., Smith, L.M., McMurry, S., Attebury, K., Lang, M., McCarty, G.W., Shaffer, J.A., Effland, W.R., Johnson, M.V.V., 2017. Model parameters for representative wetland plant functional groups. *Ecosphere* 8. <https://doi.org/10.1002/ecs2.1958>.
- Wrobel, C., Coulman, B.E., Smith, D.L., 2009. The potential use of reed canarygrass (*Phalaris arundinacea* L.) as a biofuel crop. *Acta Agric. Scand. Sect. B Soil Plant Sci.* 59, 1–18. <https://doi.org/10.1080/09064710801920230>.
- Xiong, S., Zhang, Q.G., Zhang, D.Y., Olsson, R., 2008. Influence of harvest time on fuel characteristics of five potential energy crops in northern China. *Bioresour. Technol.* <https://doi.org/10.1016/j.biortech.2007.01.034>.
- Yang, Y., Tilman, D., Lehman, C., Trost, J.J., 2018. Sustainable intensification of high-diversity biomass production for optimal biofuel benefits. *Nat. Sustain.* 1, 686–692. <https://doi.org/10.1038/s41893-018-0166-1>.
- Zeri, M., Anderson-Teixeira, K., Hickman, G., Masters, M., DeLucia, E., Bernacchi, C.J., 2011. Carbon exchange by establishing biofuel crops in Central Illinois. *Agric. Ecosyst. Environ.* 144, 319–329. <https://doi.org/10.1016/j.agee.2011.09.006>.
- Zhu, P., Zhuang, Q., Eva, J., Bernacchi, C., 2017. Importance of biophysical effects on climate warming mitigation potential of biofuel crops over the conterminous United States. *GCB Bioenergy*. <https://doi.org/10.1111/gcbb.12370>.
- Zhuang, Q., Qin, Z., Chen, M., 2013. Biofuel, land and water: Maize, switchgrass or *Miscanthus*? *Environ. Res. Lett.* 8 <https://doi.org/10.1088/1748-9326/8/1/015020>.