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Utility of remote sensing-based surface energy balance models to track water stress in rain-fed switchgrass under dry and wet conditions

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ABSTRACT

The ability of remote sensing-based surface energy balance (SEB) models to track water stress in rain-fed switchgrass (*Panicum virgatum* L.) has not been explored yet. In this paper, the theoretical framework of crop water stress index (CWSI; 0 = extremely wet or no water stress condition and 1 = extremely dry or no transpiration) was utilized to estimate CWSI in rain-fed switchgrass using Landsat-derived evapotranspiration (ET) from five remote sensing based single-source SEB models, namely Surface Energy Balance Algorithm for Land (SEBAL), Mapping ET with Internalized Calibration (METRIC), Surface Energy Balance System (SEBS), Simplified Surface Energy Balance Index (S-SEBI), and Operational Simplified Surface Energy Balance (SSEBop). CWSI estimates from the five SEB models and a simple regression model that used normalized difference vegetation index (NDVI), near-surface temperature difference, and measured soil moisture (SM) as covariates were compared with those derived from eddy covariance measured ET ($CWSI_{EC}$) for the 32 Landsat image acquisition dates during the 2011 (dry) and 2013 (wet) growing seasons. Results indicate that most SEB models can predict CWSI reasonably well. For example, the root mean square error (RMSE) ranged from 0.14 (SEBAL) to 0.29 (SSEBop) and the coefficient of determination (R^2) ranged from 0.25 (SSEBop) to 0.72 (SEBAL), justifying the added complexity in CWSI modeling as compared to results from the simple regression model (R^2 = 0.55, RMSE = 0.16). All SEB models underestimated CWSI in the dry year but the estimates from SEBAL and S-SEBI were within 7% of the mean $CWSI_{EC}$ and explained over 60% of variations in $CWSI_{EC}$. In the wet year, S-SEBI mostly overestimated CWSI (around 28%), while estimates from METRIC, SEBAL, SEBS, and SSEBop were within 8% of the mean $CWSI_{EC}$. Overall, SEBAL was the most robust model under all conditions followed by METRIC, whose performance was slightly worse and better than SEBAL in dry and wet years, respectively. Underestimation of CWSI under extremely dry soil conditions and the substantial role of SM in the regression model suggest that integration of SM in SEB models could improve their performances under dry conditions. These insights will provide useful guidance on the broader applicability of SEB models for mapping water stresses in switchgrass under varying geographical and meteorological conditions.

1. Introduction

The potential use of biofuels as a major renewable energy source for mitigating climate change impacts has been widely discussed (Azadi et al., 2017; Beringer et al., 2011; Neupane and Rubin, 2017; Tilman et al., 2009). Biofuel production over the past decade has increased by nearly six folds that can be attributed to the policies across different countries aiming to increase the share of alternative fuels in country's energy consumption (Fingerman et al., 2010). In the United States (US), the Energy Independence and Security Act of 2007 mandates a goal of attaining energy security by 2022 through increased biofuel production (United States Congress, 2007). Hence, there is an upward trend in the US in cellulosic feedstocks deployment and the necessitated land use and management changes over the last decade (Gelfand et al., 2013; Lark et al., 2015). Switchgrass (*Panicum virgatum L.*)—a C_4 perennial warm-season grass native to North America—is considered a viable alternative biofuel source because of its high productivity, low resource requirement, and large carbon sequestration potential (Wright, 2007). However, the changes in land use and management practices associated with switchgrass cultivation, as with most

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bioenergy crops, can have a huge implication on water availability (Abraha et al., 2016; Dipesh et al., 2015; Schnoor et al., 2008; Wright and Wimberly, 2013; Zhuang et al., 2013). However, the water demand and the process of evapotranspiration (ET) in cultivated bio-energy crops in the US has not been explored much using physical based or ecosystem models (Le et al., 2011; VanLoocke et al., 2012; Zhuang et al., 2013).

The rain-fed biofuel feedstocks such as switchgrass are of particular interest among scientists, water resources managers, and policy makers, as in theory, it would not raise potential concerns over increased irrigation water demand. Although all major crops (rain-fed and irrigated) are likely to experience a significant loss of productivity due to recent climatic trends (Lobell and Field, 2007), the rain-fed agriculture will be more vulnerable to climate variability and extremes. The short-term in-season dry spells that could reduce soil moisture (SM) and plant growth particularly during the key growth periods are often ignored due to the level of complexity associated with characterizing such conditions. The rate at which water is lost to the atmosphere—i.e. ET—provides crucial information on the water demand of crops, but its accurate estimation is a challenging task. Recently, eddy covariance (EC) towers have been widely used to measure ecosystem-level ET. However, the logistical requirements and expensive cost of EC systems make it impossible for extensive installation to measure ET. Further, a few studies (Skinner and Adler, 2010; Wagle and Kakani, 2014; Wagle et al., 2016; Zeri et al., 2013) that have reported EC measured ET in switchgrass, showed that switchgrass ET varied widely across different spatial and temporal scales. Hence, robust ET modeling approaches are needed to monitor both temporal and spatial variations in water status and demand of biofuel crops such as switchgrass to develop sustainable biofuel production systems.

Recent advancements in remote sensing technologies have provided us useful means for monitoring ET over large scales and hence complement the limited land surface coverage of the ground-based ET measurements (Allen et al., 2011; Bhattarai et al., 2012; Glenn et al., 2007; Gowda et al., 2008; Wagle et al., 2017a). As such, several remote-sensing-based ET models, specifically the surface energy balance (SEB) models, have gained an increased popularity over the past two and half decades (Allen et al., 2007; Bastiaanssen et al., 1998; Liou and Kar, 2014; Senay et al., 2013). In this study, we integrated Landsat images, ground-based meteorological data, and SEB algorithms, and tested the feasibility of incorporating ET estimates from five surface energy (SEB) balance models, namely Surface Energy Balance Algorithm for Land (SEBAL) (Bastiaanssen et al., 1998), Mapping ET with Internalized Calibration (METRIC; Allen et al., 2007), Surface Energy Balance System (SEBS; Su, 2002), Simplified Surface Energy Balance Index (S-SEBI; Roerink et al., 2000), and Operational Simplified Surface Energy Balance (SSEBop; Senay et al., 2013), to predict water stress in rain-fed switchgrass during an extreme dry (2011, annual rainfall of 525 mm) and a wet year (2013, annual rainfall of 925 mm) in Oklahoma (OK), US where the long-term (1981–2010) mean annual rainfall was 896 mm. To define the water stress intensity in switchgrass, we used daytime crop water stress index (CWSI; Jackson et al., 1981), which provides an estimate of water status for a crop based on minimum and maximum water stress levels that can occur due to the actual amount of water supplied.

There are a number of ways to assess water status in crops, such as linking commonly used precipitation-based drought indicators (i.e., Palmer Drought Severity Index and Standardized Precipitation Index) with indicators of vegetation activity and growth (Vicente-Serrano et al., 2013); assessing mesophyll conductance (Keenan et al., 2010)stomatal conductance (Medlyn et al., 2011), soil water stress factor and the maximum photosynthetic carboxylation rate (He et al., 2014); linking crop growth with temperature and precipitation extremes (Wang et al., 2016c); analyzing thermal spectra (Buitrago et al., 2016); or using several other drought indicators (Bhuiyan et al., 2017; Ji and Peters, 2003; Rao et al., 2017). In this paper, we considered CWSI for measuring water stress in switchgrass, as the index has been widely used in many studies for measuring water status in a wide range of crops (Berni et al., 2009; Irmak et al., 2000; Sezen et al., 2014). CWSI has been found to be highly sensitive to plant water stress, as reported in several studies (Al-Faraj et al., 2001; Testi et al., 2008). In addition, since the theoretical definition of CWSI (Jackson et al., 1981) suggests it as being the simple measure of actual ET (ET_a) with relative to the potential ET (ET_p; i.e. ET under non-water stressed conditions), ET estimates from the SEB models could be directly used to derive CWSI.

Our study was motivated by the fact that despite several remote sensing based SEB models are proposed for estimating ET (Bhattarai et al., 2016; Chirouze et al., 2014), none have directly compared their ability to characterize crop water stress. With such comparison, we aim to provide useful guidance on which SEB model should be used for monitoring water stress of rain-fed switchgrass under extreme dry and wet conditions. In addition, by evaluating results against a simple empirical model that integrates normalized difference vegetation index (NDVI), near-surface temperature difference, and measured SM as covariates, we evaluate whether added complexity in CWSI estimation through using SEB models is justified or not. Further, we evaluate the performance of SEB models to derive seasonal CWSI estimates for switchgrass under dry and wet conditions.

2. Materials and methods

2.1. Site description

The study site covers an eight-hectare switchgrass (*cv.* Alamo) experimental plot at Oklahoma State University, South Central Research Station, Chickasha, OK (35.04°N, 97.91°W; Fig. 1). Switchgrass seeds were planted with a 0.38 m row spacing under a no-till condition in Spring 2010. An OK Mesonet weather station (Chickasha) is located about 1 km on the southeast.

Carbon dioxide (CO_2), water vapor (H_2O), and energy flux densities were continuously measured during 2011, 2012, and 2013 growing seasons using an EC system, which was set up at the north end of the switchgrass plot facing south (i.e., prevailing wind direction). An infrared gas analyzer (LI-7500, LI-COR Inc., Lincoln, NE, USA) and a three-dimensional sonic anemometer (CSAT3, Campbell Scientific Inc., Logan, UT, USA) were used for the EC system. Above-canopy net radiation (R_n - NR-Lite, Kipp and Zonen, Delft, The Netherlands), air temperature and relative humidity (HMP45C, Vaisala, Helsinki, Finland), near surface (5 cm) soil temperature (TCAV-L, Campbell Scientific Inc., Logan, UT, USA), moisture (CS616, Camp-bell Scientific Inc., Logan, UT, USA), soil heat fluxes (G - HFP01SC, Hukseflux Thermal Sensors B.V., The Netherlands), and photosynthetically active radiation (PAR; LI-190, LI-COR Inc., Lincoln, NE, USA) were collected at 30-min intervals using a data logger (CR3000, Campbell Scientific Inc., Logan, UT, USA). The switchgrass field size was around 8 ha (~275 m × 275 m), which was large enough for a short tower height (2.5 m) since most flux contributing area was generally less than 100 m from the tower. For this field size, a Landsat pixel (30 m multispectral and 60–120 m thermal bands) would represent a homogenous switchgrass field and hence was used as the main satellite input for processing SEB models in this study (discussed later in Section 2.5).

2.2. EC data processing, screening, and gap filling of H_2O flux

The 30-min average fluxes were computed from 10 Hz frequency raw EC data using *EddyPro* software (LI-COR Inc., Lincoln,