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Comprehensive evaluation of empirical algorithms for estimating land surface evapotranspiration

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ABSTRACT

Many empirical algorithms for obtaining evapotranspiration (ET) from vegetation indices (VIs) have been developed, but there has been little work comparing these algorithms to each other or deriving coefficients for them using large data sets for training and validation. Twelve different vegetation index-based regression algorithms for retrieval of ET on a daily basis are reviewed and evaluated here. New coefficients have been derived for four of these algorithms using data from 181 Ameriflux and Fluxnet2015 sites and 1 km MODIS subsets centered at each site location. Algorithm validation with previously published and new coefficients was performed using one year of data from each Ameriflux and Fluxnet2015 site. There was a wide range of performance of these algorithms, with the median R^2 by site in the 0.6 to 0.7 range, median root mean square error (RMSE) about 25 W/m^2 and median bias within 10 W/m^2. When algorithm coefficients were re-derived, the RMSE and bias of the worst-performing algorithms were largely reduced, but R^2 was little changed. Agricultural and wetland sites had a low bias across most of the algorithms, and wetland sites had a higher RMSE. When several of the algorithms were re-tuned to obtain coefficients specific to each surface type, the biases of the agricultural and wetland sites were reduced to those more typical of other site types, and RMSE for agricultural and wetland sites was also reduced. The effects of linear interpolation of VIs to obtain daily LE and interpolation over periods of rapid VI change at agricultural sites were examined. No significant algorithm performance degradation was found in either case. It is recommended to use more detailed algorithms when possible, with inclusion of net radiation as a parameter along with VI at a minimum.

1. Introduction

1.1. Background and motivation

Increasing demands are being made on water resources globally, and this trend is expected to continue due to anticipated changes in global climate and hydrology (Field et al., 2014). Evapotranspiration (ET) is a major component of the global water cycle and its measurement is also used in water resources, agricultural, and ecosystem health monitoring. Determination of ET on global and regional scales is crucial to understanding trends in the global hydrological cycle (Zeng et al., 2012; Jiménez et al., 2011; Jung et al., 2010; Wang et al., 2010b) and regional impacts of global hydrological change (e.g. Du et al., 2017; Spinoni et al., 2017; Garner et al., 2017; Haileslassie et al., 2009).

A broad review of LE measurement methods has been performed by Wang and Dickinson (2012). Two frequently used methods can provide ET on scales of tens of meters. Weighing lysimeters provide the most direct measurement of ET, and are used to calibrate ET found through other methods (Liu et al., 2017; Hirschi et al., 2017). The frequently-used method for obtaining LE presented in the Food and Agricultural Organization of the United Nations (FAO) Irrigation and Drainage Paper 56 (R. G. Allen, 1998) (FAO56) depends only on meteorological observations and crop coefficients estimated based on surface conditions. The FAO56 method has the advantage of not depending on any instruments besides those used to collect standard weather observations. The lysimeter and FAO56 methods are most useful for estimating ET over scales where meteorological and land cover conditions are relatively uniform, such as that of an individual agricultural field.

ET measurements from eddy correlation flux towers such as the Fluxnet network (Baldocchi et al., 2001) typically have footprints on the order of hundreds of meters. This spatial scale is convenient for many purposes, including validation of ET obtained through remote sensing. There is an issue with energy balance closure (Foken, 2008) for flux tower measurements, which is usually resolved by assuming conservation of energy at the surface and a consistent Bowen ratio between measured and actual sensible and latent heat fluxes. With this

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correction, flux tower measurements are estimated to be accurate within 20% or less (Perez-Priego et al., 2017; Hirschi et al., 2017; Wang and Dickinson, 2012). However, they are limited in their applicability due to their relatively small scale and restricted areal coverage, as well as by the significant overrepresentation of northern hemisphere mid-latitude sites. In addition, there are many sites with temporal records of a few years or less, and where there is no ongoing data collection. As a result, there is a great deal of interest in remote sensing of ET at larger spatial scales and in more remote areas.

There are many remote sensing methods for retrieving ET available (Zhang et al., 2016; Wang and Dickinson, 2012; Kalma et al., 2008) The methods available require various combinations of visible and infrared band data or their derived products such as albedo, land surface temperature, or vegetation index. They also differ in the degree to which the land surface energy and moisture transport processes are modeled explicitly, and with which formulations. Some models, such as SEBAL and its descendants (Bastiaanssen et al., 1998), are based on finding the latent heat transfer rate from the surface (LE = λET, with ET of 1 mm/day = LE of 26.3 W/m^2) residual of the surface energy balance

$$LE = R_n - H - G \tag{1}$$

where R_n is the net radiation at the surface, H is the sensible heat transfer rate, and G the rate of change in ground heat storage. These models consider the entire soil and canopy surface in bulk (one source models) or treat the soil and canopy separately (two source models). Energy balance residual models rely on thermal band observations as indicators of surface temperature. The two source time integrated model TSTIM, later renamed ALEXI (Anderson et al., 2007; Anderson, 1997), relies on multiple daily surface temperature measurements, as a smaller range of surface temperature is indicative of greater moisture availability.

The Penman-Monteith formulation of turbulent heat transfer (Monteith, 1965) is used as a basis for other methods of retrieving LE from remote sensing, such as that of Mu et al. (2011), now used to generate the global MOD16 product from MODIS data. The earlier Penman (1948) formulation was used as a basis for the model developed by Wang et al. (2010a). Another turbulent flux parameterization, the Priestley-Taylor formula (Priestley and Taylor, 1972) has been used in combination with net radiation and vegetation indices (Yao et al., 2015, 2013; Fisher et al., 2008) to obtain ET. In the case of the Yao et al. (2015, 2013) and Wang et al. (2010a) studies, the turbulent flux transfer parameterizations were used as a basis for formulas to which empirical regression coefficients were fitted.

There are also many simpler regression formulas that have been developed for estimation of ET. It has been found (Jiménez et al., 2011) that empirical regression formulas can produce ET values that are comparable in accuracy to more complex models, without as much computational demand or requirements for specific expertise. Many of these regression formulas are based on vegetation indices (VI), as reviewed by Glenn et al. (2010). The most frequently used vegetation indices in ET algorithms are the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI). These ratios between near infrared, red, and blue band reflectances (ρ_{NIR}, ρ_{red}, and ρ_{blue} respectively) are as follows:

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \tag{2}$$

$$EVI = G_{EVI} \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 \cdot \rho_{red} + C_2 \cdot \rho_{blue} + L} \tag{3}$$

The standard EVI product calculated from MODIS data has the constants G_{EVI}, C_1, C_2, and L set to values of 1.0, 6.0, 7.5, and 2.5 respectively.

Vegetation indices have several advantages for use in evapotranspiration algorithms. They are available from multiple instruments and at resolutions down to tens of meters. They have a high degree of consistency between instruments (Brown et al., 2006; Steven et al., 2003) Vegetation indices typically change on time scales of weeks to months, so interpolation can be used between observations separated by multiple days with some confidence. Algorithms that include a dependence on surface temperature are likely to be more responsive on shorter time scales, but the faster rate of change of surface temperature makes interpolation between observations more problematic. Overall, vegetation index-based methods have the advantages of simplicity, utility under a wide range of conditions, and resilience in the presence of data gaps.

Little work has been done evaluating these vegetation index-based algorithms under different conditions or comparing them to each other or to LE values derived through other methods. The goal of this paper is to provide a comprehensive evaluation of a range of VI- based evapotranspiration algorithms, identifying their strengths and weaknesses relative to each other.

1.2. Description of VI-based algorithms to be evaluated

A number of authors have proposed formulas for LE based on vegetation indices, ranging from highly simplified, depending only on the VI value with no additional data, to more complex formulas requiring ancillary data such as net radiation, surface and atmospheric temperatures, and other meteorological variables. All formulas to be

Table 1
Vegetation index based algorithms reviewed and compared, with full algorithm names and short names used to identify the algorithms in the figures. Key to variables: NDVI- Normalized difference vegetation index, EVI- Enhanced vegetation index, R_n- Net radiation at surface, G- Ground heat storage, T_{a_avg} – Daily average atmospheric temperature, T_{a_max}- Daily maximum atmospheric temperature, T_{a_dTr}- Daily atmospheric temperature range, T_{s_avg}- Daily average surface temperature, T_{s_max}- Daily maximum surface temperature, T_{s_dTr}- Daily surface temperature range, LE_0- Potential evapotranspiration, R_s- Incoming solar radiation at surface, RH- relative humidity, e_s- Saturation water vapor pressure, ws- Wind speed, VPD- vapor pressure deficit.

Algorithm	Short name	Reference	Required input data
Yebra direct (ET)	YET	Yebra et al. (2013)	NDVI or EVI
Yebra evaporative fraction (EF)	YEF	Yebra et al. (2013)	NDVI or EVI, R_n, G
Helman exponential	HEx	Helman et al. (2015)	NDVI or EVI
Helman scaled	HSc	Helman et al. (2015)	EVI, T_{s_avg}
Wang 2007	W07	Wang et al. (2007)	NDVI or EVI, R_n, one of T_{a_avg}, T_{a_max}, T_{s_avg}, or T_{s_max}
Wang/ Liang	WL	Wang and Liang (2008)	NDVI or EVI, R_n, T_{s_dTr}, one of T_{a_avg}, T_{a_max}, T_{s_avg}, or T_{s_max}
Choudhury/ FAO56	Ch	Choudhury et al. (1994), Allen (1998)	EVI, LE_0
Kamble/ FAO56	Kmb	Kamble et al. (2013), Allen (1998)	NDVI, LE_0
Wang 2010	W10	Wang et al. (2010a)	NDVI or EVI, R_s, RH, e_s, ws, T_{a_avg}
Yao 2011	Y11	Yao et al. (2011)	NDVI, R_n, T_{a_avg}, T_{a_dTr}
Yao 2013	Y13	Yao et al. (2013)	NDVI, R_n, G, T_{a_avg}, T_{a_dTr} or T_{s_dTr},
Yao 2015	Y15	Yao et al. (2015)	NDVI, R_n, G, T_{a_avg}, RH, VPD