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Accuracy of the Temperature–Vegetation Dryness Index using MODIS under water-limited vs. energy-limited evapotranspiration conditions

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ABSTRACT

Water deficit indices based on the spatial relationship between surface temperature (*Ts*) and *NDVI*, known as triangle approaches, are widely used for drought monitoring. However, their application has been recently questioned when the main factor limiting evapotranspiration is energy. Even though water is the main control in dryland ecosystems, these can also undergo periods of energy and temperature limitation. In this paper we aimed to: (i) evaluate the *TVDI* (Temperature–Vegetation Dryness Index) to estimate water deficits (e.g. ratio between actual and potential evapotranspiration), and heat surface fluxes using MODIS data; and (ii) provide insights about the factors most affecting the accuracy of results. Factors considered included the type of climatic control on evapotranspiration, λ*E*, (i.e. water-limited vs. energy-limited), the quality of T_{air} estimates, the heterogeneity of land cover types and climatic variables in the region, or the algorithm to extract hydrological boundaries from the images.

The *TVDI* was compared with eddy covariance (EC) data from two shrublands with different climatic controls for λ*E* in South Spain. Evaluations showed that it could be used to estimate the water deficit when water was the main limiting factor (R = 0.81–0.88; Mean Average Error, MAE = 0.16–0.17) but not in energy-limited situations (R < 0.2; MAE = 0.10–0.2). Spatial heterogeneity in climatic variables also had a different impact on accuracy depending on limiting factors. Relative humidity was significant at the water-limited site while solar irradiance and air temperature were more important at the energy-limited site. The skill of the *TVDI* to estimate surface fluxes at the water-limited site was confirmed for the dominant sensible heat flux, *H* ($R^2 = 0.93$; Mean Absolute Percentage Error, MAPE = 12.85%) but not for λ*E* ($R^2 = 0.01$, MAPE = 115.22%) as λ*E* fluxes at this site are just slightly above the error of the eddy covariance system. At the energy-limited site, λ*E* ($R^2 = 0.74$; MAPE = 31.83%) and *H* estimates ($R^2 = 0.80$; MAPE = 26.85%) were better than those from the SEBAL (Surface Energy Balance Algorithm for Land) or the PML (Penman–Monteith–Leuning) models. However, the skill to predict surface fluxes in this case was due to the net radiation inputs and not by the *TVDI* input.

Our analyses also suggest: (1) to apply the *TVDI* excluding energy-limited sites/periods based on climatic knowledge of limiting factors on λ*E*; (2) the best conditions for *TVDI* performance correspond to the situation when the controlling factors are less limiting, e.g. during the growing season (higher *SWC* and lower *VPD*); and (3) to account better for the role of vegetation controls on transpiration.

List of symbols and acronyms used (in alphabetical order)

Latin alphabet

A	CO_2 flux (μmol m^{-2} s^{-1})
BB	Balsa Blanca field site (Spain)
CV	coefficient of variation (standard deviation/mean)

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D > 0.3	dry edge calculated for the *NDVI* range [0.3–0.8]
Dall	dry edge calculated for the *NDVI* range [0.1–0.8]
DT_{obs}	Land surface temperature minus air temperature observed at the pixel (°C)
DT	Land surface temperature minus air temperature (°C)
E	Actual evapotranspiration (mm/day)
$Ep / P = AI$	Aridity index
EBR	Energy Balance Ratio (index of closure error for eddy covariance systems)
EC	eddy covariance system
EF	evaporative fraction, $EF = \lambda E/(Rn - G)$
Ep	Potential evapotranspiration (mm/day)
f_c	Fractional cover
G	Soil heat flux (Wm^{-2})
GS	growing season
H	Sensible heat flux (Wm^{-2})
H_{obs}	Sensible heat flux observed at the pixel (Wm^{-2})
H_w	Sensible heat flux at the wet edge (Wm^{-2})
H_d	Sensible heat flux observed at the dry edge (Wm^{-2})
LJ	Llano de los Juanes field site (Spain)
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error (%)
MODIS	Moderate Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NEF	non-evaporative fraction, $NEF = H/(Rn - G)$
NGS	non-growing season
P	Precipitation (mm)
PT-JPL	Priestley–Taylor Jet Propulsion Laboratory evapotranspiration model
PML	Penman–Monteith–Leuning evapotranspiration model
RH%	relative humidity (%)
Rn	net radiation (Wm^{-2})
$Rn - G$	available energy of the surface (Wm^{-2})
SEVIRI	Spinning Enhanced Visible and Infrared Imager
SEBAL	Surface Energy Balance Algorithm for Land
SVAT	Soil Vegetation Atmosphere Transfer models
SWC	soil water content (m^3/m^3)
T_{air}	air temperature at the time of satellite overpass (°C)
Ts	radiometric surface temperature (°C)
Ts_d	maximum value of surface temperature (dry Ts) (°C)
Ts_{obs}	radiometric surface temperature observed at each pixel (°C)
Ts_w	minimum value of *Ts* (*wet Ts*) (°C)
TVDI	Temperature–Vegetation Dryness Index
$TVDI_{DTest}$	*TVDI* normalized with T_{air} from interpolated maps in all pixels
$TVDI_{DTobs}$	*TVDI* normalized with T_{air} from interpolated maps in all pixels except at the field sites were measured T_{air} is used
$TVDI_t$	*TVDI* without T_{air} corrections
VI	Vegetation Index
VPD	vapor pressure deficit (hPa).
W = 0	wet edge calculated as DT = 0
Wmin	wet edge calculated as the minimum of *DT* or *Ts* for *NDVI* range [0.1–0.8]
Wmean	wet edge calculated as the mean of *DT* or *Ts* for *NDVI* range [0.1–0.8]
Wmean > 05	wet edge calculated as the mean of *DT* or *Ts* for *NDVI* range [0.5–0.8]
WDI	water deficit index; $WDI = 1 - \lambda E / \lambda E_p$
WS	wind speed (ms^{-1})

Greek alphabet

α	evaporative coefficient of Priestley–Taylor in *Ep* formulation
γ	psychrometric constant (Pa °C^{-1})
λ	latent heat of vaporization (kJ kg)
Δ	slope of the saturated vapor pressure (Pa °C^{-1})
λE	latent heat flux (Wm^{-2})
λE_p	potential latent heat flux (Wm^{-2})

1. Introduction

Evapotranspiration (hereafter *E*), defined as the amount of water returned from the land surface to the atmosphere as vapor, is a key variable linking the energy, water and carbon cycles in terrestrial ecosystems (Vinukollu, Wood, Ferguson, & Fisher, 2011). On average, in water-limited regions across the globe, *E* represents around 90% of the precipitation in the annual water budget (Glenn, Huete, Nagler, Hirschboeck, & Brown, 2007) and the annual atmospheric water demand, or potential evapotranspiration, *Ep*, exceeds the precipitation supply by a factor ranging from 1.5 to 20 (D'Odorico & Porporato, 2006). Dryland regions cover around 45% of the earth's land surface and are home of 35% of world's population (Reynolds et al., 2007). Due to their high vulnerability to drought it is critical to provide accurate estimates on surface water deficits and *E* fluxes for numerous ecological, agricultural and hydrological applications (Fisher, Tu, & Baldocchi, 2008). Models using satellite remote sensing inputs in the optical and thermal domains over large areas represent a cost-effective tool to map surface fluxes (reviewed in Glenn et al., 2007; Kalma, McVicar, & McCabe, 2008; Wang & Dickinson, 2012). However, obtaining accurate remote sensing algorithms applicable at global scales without using field calibrations still remains a challenge (Mu, Zhao, & Running, 2011).

Remote sensing spatial variability methods are based on the spatial relationship between the fractional vegetation cover (f_c) and surface radiative temperature minus air temperature ($Ts - T_{air} = DT$) (Kalma et al., 2008). They provide simple estimates of *E* ratios at daily time scales (e.g. *E*/*Ep*). In essence, these methods rely on the definition of hydrological extremes for *E* and soil moisture as calculated from the outer boundaries of a triangle or trapezoid-shaped scatterplot defined by the *DT* and f_c relationship (hereafter referred as "triangle methods") (McVicar & Jupp, 1998; Price, 1990). Daily *E*/*Ep* ratios (Jiang & Islam, 2003; Moran, Clarke, Inoue, & Vidal, 1994; Stisen, Sandholt, Nørgaard, Fensholt, & Jensen, 2008; Venturini, Islam, & Rodriguez, 2008) or the available soil water fraction (Carlson, Gillies, & Schmugge, 1995; Gillies & Carlson, 1995; Goetz, 1997; Sandholt, Rasmussen, & Andersen, 2002) can be retrieved from the relative position of a pixel within the scatterplot. They provide similar error levels of more complex remote sensing approaches, between 15 and 30% (Kalma et al., 2008). A key step in triangle methods is to determine the extreme *DT* values associated to wet and dry boundaries (Long & Singh, 2013), either theoretically or empirically. In the first case, extreme values for dry soil, dry vegetation, wet soil, and wet vegetation are calculated using the Penman–Monteith equation (Moran et al., 1994) or more complex models (Shuttleworth & Wallace, 1985). Theoretical approaches require micrometeorological information such as wind speed, vegetation height or minimum stomatal resistance difficult to obtain regionally. Alternatively, wet and dry boundaries can be estimated empirically by taking advantage of the image information content (Jiang & Islam, 1999).

However, there are some limitations that need to be considered for the application of empirical triangle approaches. First, a critical assumption is that pure pixels representative of the wet and dry hydrological extremes are present in the image, which can be problematic when the conditions are homogeneous like in regions of natural vegetation or rainfed agriculture during the dry season (McVicar & Jupp, 1998) or after rain events (Nishida, Nemani, Glassy, & Running, 2003; Stisen et al., 2008; Tang, Li, & Tang, 2010). Increasing the area or domain of analysis helps to maximize the probability of finding "true" purely wet and purely dry pixels, although at the cost of compromising the assumption of homogeneity regarding atmospheric and surface conditions (Moran et al., 1994; Long & Singh, 2012). Second, the spatial and