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Hyperspectral narrowband and multispectral broadband indices for remote sensing of crop evapotranspiration and its components (transpiration and soil evaporation)

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ABSTRACT

Evapotranspiration (ET) is an important component of micro- and macro-scale climatic processes. In agriculture, estimates of ET are frequently used to monitor droughts, schedule irrigation, and assess crop water productivity over large areas. Currently, in situ measurements of ET are difficult to scale up for regional applications, so remote sensing technology has been increasingly used to estimate crop ET. Ratio-based vegetation indices retrieved from optical remote sensing, like the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index, and Enhanced Vegetation Index are critical components of these models, particularly for the partitioning of ET into transpiration and soil evaporation. These indices have their limitations, however, and can induce large model bias and error. In this study, micrometeorological and spectroradiometric data collected over two growing seasons in cotton, maize, and rice fields in the Central Valley of California were used to identify spectral wavelengths from 428 to 2295 nm that produced the highest correlation to and lowest error with ET, transpiration, and soil evaporation. The analysis was performed with hyperspectral narrowbands (HNBs) at 10 nm intervals and multispectral broadbands (MSBBs) commonly retrieved by Earth observation platforms. The study revealed that (1) HNB indices consistently explained more variability in ET ($\Delta R^2 = 0.12$), transpiration ($\Delta R^2 = 0.17$), and soil evaporation ($\Delta R^2 = 0.14$) than MSBB indices; (2) the relationship between transpiration using the ratio-based index most commonly used for ET modeling, NDVI, was strong ($R^2 = 0.51$), but the hyperspectral equivalent was superior ($R^2 = 0.68$); and (3) soil evaporation was not estimated well using ratio-based indices from the literature (highest $R^2 = 0.37$), but could be after further evaluation, using ratio-based indices centered on 743 and 953 nm ($R^2 = 0.72$) or 428 and 1518 nm ($R^2 = 0.69$).

1. Introduction

Evapotranspiration (ET) is the process by which mass/energy is exchanged between the surface and atmosphere via evaporating moisture from soil, open water, and wet plant canopies or transpiring moisture from photosynthesizing canopies (Chapin et al., 2011). It is therefore a critical component of several physical and biological processes at the cellular, leaf, plant, canopy, and landscape scale (Katul et al., 2012). In most regions of the world, water loss (the ratio of ET to precipitation) is increasing in response to global warming (Huntington, 2006). This has particularly strong implications for irrigated agriculture, which currently accounts for 70% of the world's surface water and groundwater withdrawals and whose demand is expected to increase by 22% in 2050 (Rosegrant et al., 2009). The increase in demand from irrigated agriculture combined with increasing demand from other competing and expanding sectors, means that better agricultural water management is necessary. Effective water management includes improved monitoring, assessment, and forecasting of crop ET, in order to develop and evaluate water-saving strategies (Evans and Sadler, 2008). In situ estimates of crop ET are difficult to extrapolate to scales for regional processes and applications (Jung et al., 2009), so Earth observation remote sensing-based ET models calibrated/validated with in situ data are increasingly used (Dam et al., 2006). These models, however, have bias and error, particularly with regards to the

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partitioning of ET into its components (transpiration and soil evaporation) (Gowda et al., 2008).

Evapotranspiration modeling approaches involving Earth observation remote sensing data are reviewed in Biggs et al. (2015), Courault et al. (2005), Diak et al. (2004), Glenn et al. (2007), Kalma et al. (2008), Kustas and Norman (1996), and Wang and Dickinson (2012). These models can be categorized as vegetation-based, temperature/energy balance, and scatterplot approaches. Vegetation-based methods estimate ET or its energy equivalent (LE: latent heat) as a function of ratio-based vegetation indices derived from optical Earth observation, the atmospheric demand for water vapor (PET: Potential Evapotranspiration) or vegetation specific analog (crop reference ET: Allen et al., 1998), and temperature/moisture constraints. PET is estimated using either the Penman–Monteith (Leuning et al., 2008; Mu et al., 2011, 2007; Nishida et al., 2003) or Priestley–Taylor (Fisher et al., 2008) equations. Temperature/energy balance approaches estimate temperature from thermal infrared remote sensing, which is either used to estimate LE directly (Simplified Surface Energy Balance: Senay et al., 2007) or indirectly as a residual of the energy balance equation. The two-source energy balance approaches (Two Source Energy Balance – Norman et al., 1995 and Atmosphere-Land Exchange Inverse – Anderson et al., 1997) use a ratio-based index to separate land surface temperature into canopy and soil heat components from which transpiration and evaporation are estimated, respectively. Scatterplot methods (Gillies et al., 1997; Moran et al., 1994) are a close relative of temperature/energy balance methods. Latent heat is bounded by vertices of a triangle or trapezoid that represent fully transpiring (high ratio-based index, "cold" temperature) or low-transpiring vegetation (low ratio-based index, "hot" temperature) over an area of interest.

Whether vegetation-based, temperature/energy balance, or scatterplot methods are used, ratio-based indices, derived from the optical range of remote sensing, play a critical role in crop ET models (Glenn et al., 2010), particularly for ET partitioning (Wang et al., 2014). The primary indices used are the Normalized Difference Vegetation Index (NDVI – Rouse, 1974) and Soil Adjusted Vegetation Index (SAVI – Huete, 1988) from which the fraction of photosynthetically active radiation intercepted by the canopy (F_{IPAR}) is computed. These indices are derived from visible red and near infrared (NIR) remote sensing reflectance representing several convolved wavelengths (i.e. MSBBs: multispectral broadbands), because plant material strongly absorbs visible red light and scatters NIR due to the spectral properties of plant chlorophyll, accessory pigments, and the alignment of cell walls (Ollinger, 2011). SAVI is used together with or in place of NDVI, because it is less sensitive to soil background and saturation in dense canopies. The Enhanced Vegetation Index (EVI) (Huete et al., 2002) has become a widely used alternative to SAVI, because it incorporates a blue reflectance broadband, which reduces atmospheric effects that impact NDVI and SAVI. The Normalized Difference Water Index (NDWI) and Global Vegetation Moisture Index exploit leaf water absorption in the Shortwave Infrared (SWIR) and are the most commonly used non-red-NIR indices for ET estimation (Guerschman et al., 2009; Lu and Zhuang, 2010).

Hyperspectral remote sensing, unlike MSBB remote sensing, involves hundreds of spectral narrowbands that are sensitive to distinct biophysical and biochemical characteristics, and facilitate atmospheric correction and the unmixing of heterogeneous surfaces with "idealized" spectra (Goetz, 2009). Although hyperspectral remote sensing has been used for agricultural modeling applications that require direct or relative estimates of light-absorbing plant pigments, plant water content, or dry plant residues (Ustin et al., 2004), its application in ET modeling is relatively unstudied (see Rodriguez et al., 2011 for a review of relevant opportunities).

There is a general lack of studies that utilize MSBB ratio-based vegetation indices (MSVIs) other than NDVI, SAVI, EVI, NDWI, and more importantly, HNB ratio-based vegetation indices (HVIs) in crop ET models. This paper employs empirical methods and in situ spectroradiometric and eddy covariance/surface renewal data to (1) identify potentially useful MSVIs and HVIs over the entire optical range for estimation of crop ET and its components (transpiration and evaporation) and (2) compare these indices with existing MSVIs and HVIs from the literature to inform the ET modeling community, and more importantly, upcoming global mapping imaging spectroradiometric missions, such as the Hyperspectral Infrared Imager (http://hyspiri.jpl.nasa.gov/).

2. Methods

2.1. Study area

In 2011 and 2012, field campaigns were conducted to estimate ET using field and remote sensing methods in the Central Valley of California – an important agro-ecosystem of the United States (CDFA, 2013). Spectroradiometric and ancillary biophysical data, including crop height, leaf area index, and F_{IPAR} were collected in the fetch of seven micrometeorological stations during three visits in the summer growing season coinciding with the sprouting (May–June), flowering/tasseling (June–July), and senescence (July–August) stages of crop growth (Fig. 1 and Table 1). For two of the stations (Davis and on Twitchell Island), spectroradiometric and ancillary biophysical data were collected for both 2011 and 2012, because they were operational for multiple growing seasons. The other stations only operated over one growing season. Spectroradiometric and ancillary biophysical data were collected on the same day of each visit. Micrometeorological stations recorded weather and energy balance data at regular intervals throughout the growing season.

The fetch consisted of soil, water, and vegetation, which conditioned air parcels recorded as the turbulent energy flux by the station (Schuepp et al., 1990). The fetch extent was defined by the dominant daytime summer wind direction and generally spanned the length of the field adjacent to each station (<450 m). Each station was located in large, flat, irrigated, and homogenous fields. The fields under measurement consisted of three widely cultivated and water-intensive field crops in California: cotton, maize, and rice. Each field represented diverse soil types and climatology of the Central Valley.

2.2. Spectroradiometric data and processing

Field spectra were collected using an Analytical Spectral Devices (ASD) portable spectroradiometer (Field Spec Pro 3: www.asdi.com). The Field Spec Pro 3 detects light scattered by a canopy over the optical range (350–2500 nm) at 1–10 nm intervals depending on the spectral position. Light is captured with a fiber optic cable and was constrained in this study by an 18° field of view (FOV) fore-optic. The fore-optic was mounted to a pole pointed at nadir and at a fixed height (1.5 m for cotton and rice and 2.5 m for maize) ±2 h solar noon to minimize inconsistencies due to canopy shadow and sun angle. The FOV corresponded to 1 m^2 quadrats over which ancillary biophysical data was measured on the same day. Spectra were collected for ten evenly spaced quadrats in the footprint of each micrometeorological station. Approximately five replicates were collected at random locations in the quadrat. A replicate spectrum consisted of Field Spec Pro internally averaged spectra (30 for optimal environmental conditions and 40 for sub-optimal environmental conditions).