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Discussions

Remote sensing techniques for predicting evapotranspiration from mixed vegetated surfaces

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Abstract

Evapotranspiration (ET) as the key component of hydrological balance is the most difficult factor to quantity. In the last decades, ET estimation has been benefitted from advances in remote sensing particularly in agricultural fields. However, quantifying evapotranspiration from mixed landscape vegetation environs is still complicated and challenging due to the heterogeneity of plant species, canopy covers, microclimate, and because of costly methodological requirements. Extensive numbers of studies have been conducted in agriculture and forestry that alternatively ought to be borrowed for mixed landscape vegetation studies with some modifications. This review describes general remote sensing-based approaches to estimate ET and their pros and cons. Considering the fact that most of them need extensive time investment, medium to high level of skills and are quite expensive, the simplest approach; interface, is recommended to apply for mixed vegetation. Then, VI-based approach was discussed for two categories of agricultural and non-agricultural environs. Some promising studies were mentioned to support the suitability of the method for mixed landscape environs.

1 Introduction

Quantification of evapotranspiration as a fundamental requirement in the local and global assessment and management of climate change, land use, water budget and irrigation is of both interest and concern. Water loss by evaporation can occur from three main sources of soil, vegetation surface or atmosphere (Burt et al., 2005). Soil evaporation is affected by soil moisture status, soil physical and chemical characteristics, tilth conditions, soil cover (e.g. mulch), and ecological parameters. Evaporation of vegetation surface is influenced by vegetation type, species, canopy cover, microclimate, and water availability to the plants by precipitation or irrigation. Atmosphere evaporation may happen from irrigation water (e.g. sprinkler droplets) that varies for different irrigation systems and meteorological conditions. There is a specific form of evaporation from plants tissues that is named transpiration. The sum of evaporation and transpiration is collectively termed evapotranspiration (ET) which is the main consumptive of irrigation and precipitation in vegetation environs (Nouri et al., 2012). ET occurs not only from vegetation leaves but also from stems, flowers and roots. Evapotranspiration, as an important component of the hydrological cycle affects soil water availability, soil water chemistry, and vegetation healthiness and aesthetics (Johnson and Belitz, 2012; Lucke et al., 2011). Considering the fact that more than 90 % of annual rainfall is consumed by ET in arid and semi-arid areas (Glenn et al., 2007), the importance of ET measurement is not deniable.

For decades, weather-based methods (Allen, 2000; Allen et al., 1998), soil moisture measurements (Allen et al., 1998; Nouri et al., 2012), and surface energy balance approaches have been the dominant techniques for predicting vegetation ET (Allen et al., 2011a; Li et al., 2009; Silberstein et al., 2001; Tanaka et al., 2008; Yunusa et al., 2004). Broad numbers of numerical models were introduced for the local and regional ET measurements but they mostly need detailed input data of soil, vegetation and climate. It limits their application to the specific areas with the long-term comprehensive records of required input data (Kustas and Norman, 1996).

Over last decade, ET estimation has been improved through advanced technologies and increasingly well-developed infrastructure and instruments particularly remote sensing. ET estimation using satellites imagery is the most efficient and economic technology that can employ for a broad range of pixel to global scales. It also was coupled to some empirical methods to simplify the ET measurement and shorten the input data requirements. Later on, in order to minimise atmospheric effects on optical data (e.g. clouds in the images), microwave imagery took the place in measuring surface moisture and surface temperature (Kustas and Norman, 1996).

Yet despite a broad range of promising technologies and sophisticated facilities, ET estimation of mixed landscape vegetation remains insufficiency characterized. This complexity of challenge is due to diversity in water needs of the heterogeneous and multi-story mixed vegetation systems (Drexler et al., 2004; Sumantra, 2011).

ET estimation using hydrological methods (e.g. water balance), micro-meteorological methods (e.g. energy balance) or direct ET measurement methods can only be considered as point measurements. Extrapolation of ET rates from a point to a large area decreases the accuracy of the estimation. Analysis of satellite or airborne images using remote sensing techniques is a practical method for developing the spatial variation of ET at a regional scale (Vinukollu et al., 2011).

Due to the highly distributed nature of mixed landscape vegetation, remote sensing could be an ideal technique of ET measurement for these types of landscapes. ET measurement by remote sensing provides an area-based estimation that can be updated frequently. Also, because it has the capability of quantifying the vegetation characteristics including species composition, vegetation type and moisture status for a broad area, more accurate results would be obtained.

Variety of complicated RS-based models and algorithms has been introduced and evaluated for different vegetation types in different scales. They are mostly comparable in the pixel-scale spectral homogeneity assumption. In the mixed landscape planting, diversity of vegetation is in contrast with the spectral homogeneity assumption. Additionally, inconsistency in reflectance properties of mixed vegetation may lead in misclassification of land covers. However, image processing advances besides high spatial, spectral and temporal resolution satellite/airborne images diminish the mentioned challenges in classification and permit improved records of land cover changes (Small, 2003; Small and Lu, 2006).

In ET estimation of small urban green spaces, biophysical components of urban ecosystem should be considered. It was comprehensively discussed by Ridd (1995). He introduced a Vegetation-Impervious-Soil surfaces (VIS) model to consider the major urban features affecting evapotranspiration rate in ET measurement. Further studies used the VIS model and match it with the image processing methodology (Phinn et al., 2002) to get a better result. In 2012, Wang and Dickson recommended combination of field and satellites-based measurements to obtain a more precise estimation of daily, monthly and annually ET rates (Wang and Dickinson, 2012). It should be noted that for each particular approach; field-based, RS-based or combined approaches, there are specific assumptions that may impose some limitations or restrictions to the capability and applicability of the method besides some uncertainty or errors to the outcomes. Others have written full reviews of ET and remote sensing (Courault et al., 2005; Glenn et al., 2007; Kalma et al., 2008; Li et al., 2009), thus this paper concentrates on the RS relevant approaches for predicting evapotranspiration from mixed vegetated surfaces. It summarizes the merits and drawbacks of each method.

2 Remote sensing methods for estimating ET

Different categories were introduced for ET estimation using remote sensing (Allen et al., 2011a; Kustas and Norman, 1996; Li et al., 2009). The most comprehensive categorisation was proposed by Courault et al. (2005) and well discussed by Calcagno et al. (2007). They classified remote sensing methods for ET estimation into four groups, namely empirical direct, residual, inference, and deterministic methods.

2.1 Empirical direct methods

Assessing the energy balance using some surface properties like albedo, canopy cover, leaf area index (LAI) and surface temperature is the principle of ET estimation by remote sensing.

$$R_{\mathrm{n}} = \mathrm{LE} + H + G \tag{1}$$

The net radiant energy (R_{n}) is divided to soil heat flux (G) and atmospheric fluxes (sensible heat flux H and latent energy exchanges LE). Observed surface can be considered as a single layer (component) or multiple layers (two components of soil and vegetation). In a single layer approach, net radiation is related to the whole surface and sensible heat flux is related to the aerodynamic resistance between surface and above

surface (2 m height). Dynamic resistance is affected by wind speed, atmospheric stability, roughness lengths for momentum and heat. However, momentum and heat variables (e.g. surface temperature) significantly vary for different vegetation height and density. In multilayer approaches, sensible heat flux considers both soil and vegetation resistance with the equivalent temperature (Courault et al., 2005).

Semi-empirical relationship between net radiation and cumulative surface and air temperature differences characterise the empirical direct method. Air temperature is measured by ground-based weather station while surface temperature is obtained from satellite imageries.

Empirical direct methods are based on the theoretical assumption of a constant value of the ratio H/R_{n} during the day and no soil flux:

$$\mathrm{ET}_{24} = R_{\mathrm{n}24} + A - B(T_{\mathrm{s}} - T_{\mathrm{a}}) \tag{2}$$

where ET_{24} is daily ET, $R_{\mathrm{n}24}$ is net daily radiation, $T_{\mathrm{s}} - T_{\mathrm{a}}$ is the difference between the mid-afternoon surface temperature and the maximum air temperature (this is termed the Stress Degree Day or SDD), and A and B are calibration parameters. This method can be accurate in a local scale study area if calibrations and interpolations are accurate.

Due to the strong relationship between Vegetation Indices (VI) and surface temperature, Carlson et al. (1995) developed a trapezoidal scheme to determine a relationship between SDD and NDVI (Normalized Difference Vegetation Index) that resulted in an appropriate measurement of soil moisture conditions in different depths. They suggested that the strong relationship between surface radiant temperature and NDVI may yield in more accurate estimation of soil moisture status. Gillies et al. (1997) employed multispectral images to estimate surface soil water content, vegetation cover, and surface energy fluxes in the mixed landscape vegetation of trees and grasses and compared the results with ground measurements. In spite of many uncertainties in mixed vegetation, soil types, shading and etc. results showed comparable errors to ground measurement. Yuan and Bauer (2007) determined the amount of urban mixed vegetation and land surface temperature via satellite image analyses and then measured latent heat flux and evapotranspiration. Their analyses indicated that the relationship between NVDI and land surface temperature varies seasonally so they recommended using thermal infrared remote sensing in mixed landscape environs.

2.2 Residual methods

In this method, empirical and physical relationships are combined to estimate the energy balance components (except ET) directly through remote sensing (Kalma et al., 2008; Su, 2002). ET is estimated as the residual of the energy balance equation. Latent energy exchange is estimated using a linear relationship between latent energy exchanges and surface air temperature differences at a specific time (Boegh et al., 1999; Calcagno et al., 2007). Reasonable accurate results can be obtained from this approach in midday. However, ground-based weather data is required to interpolate the results for the longer periods of daily or monthly records.

Several models have been introduced and employed to investigate the spatial variation of radiance and satellite image reflectance. Reliable but complex methods are based on different models: Surface Energy Balance Algorithm for Land or SEBAL (Teixeira et al., 2009; Sun et al., 2011; Timmermans et al., 2007); Surface Energy Balance Index or SEBI (Yang and Wang, 2011; Galleguillos et al., 2011); Simplified Surface Energy Balance Index or S-SEBI (Roerink et al., 2000; Sobrino et al., 2005); Surface Energy Balance System or SEBS (Rwasoka et al., 2011; Jia et al., 2003); and Two-Source Energy Balance or TSEB (Yao et al., 2010; Tang et al., 2011). The SEBAL method predicts the energy fluxes at a regional scale. Remote sensing images are employed to estimate net radiation and soil heat flux (Bastiaanssen et al., 1998; Tasumi et al., 2005). SEBAL considers groups of pixels inside the analysed area as being either dry or wet. In the dry pixels, the latent heat is assumed to be zero, so the available energy is totally transformed into sensible heat flux. For the wet pixels, sensible heat flux is theorized to zero and surface and air temperatures are assumed to be equal to each other (Calcagno et al., 2007). The SEBI model follows the principles

of SEBAL by hypothesizing the reflectance of maximum temperature for dry pixels and the reflectance of minimum temperature for wet pixels (Roerink et al., 2000). The main distinction between SEBI and SEBAL are the differences in definition, calculation, and interpolation of maximum and minimum latent heat fluxes for a given set of layers (Li et al., 2009). The S-SEBI model simplifies the SEBI model by obtaining the extreme temperatures for the dry and wet pixels (Roerink et al., 2000). The SEBS model involves three data sets of information. The first set includes albedo, emissivity, temperature, LAI, and vegetation height. The second is a meteorological data set including temperature, air pressure, humidity, and wind. The third data set includes direct or modelled solar radiation measurements. In contrast to the SEBAL model, the SEBS model does not assume that the sensible heat flux is zero for wet pixels (Su, 2002). Senay et al. (2011) developed an enhanced version of the Simplified Surface Energy Balance (SSEB) model and to evaluate its performance using the established METRIC model. They claimed that SSEB can be used to estimate ET with inputs of surface temperature, NDVI, DEM, and reference ET.

2.3 Inference methods

This method is termed inference method or vegetation indices. It is based on RS application to measure a plant adjustment factor (such as crop factor or landscape factor) to determine the actual evapotranspiration. Given the formula

$$\mathrm{ET}_{\mathrm{plant}} = K_{\mathrm{plant}} \cdot \mathrm{ET}_0 \tag{3}$$

The actual evapotranspiration rate ($\mathrm{ET}_{\mathrm{plant}}$) is readily calculated from the reference evapotranspiration (ET_0) and plant adjustment factor (K_{plant}). Equation (3) has been broadly described in FAO-56 (Allen et al., 1998). Reference evapotranspiration is achieved by the ground measurement and adjustment factor is applied to reduce evapotranspiration rate based on plant water need (Nouri et al., 2012). In this method, the main factors required for analyses are crop characteristics and meteorological data.

Crop resistance to transpiration is related to differences in plant height, roughness, reflection, density, and rooting system and these all vary in the plant's different growth stages. Consequently these variables all need to be measured periodically within the plant growing season. The main meteorological data include solar radiation, temperature, humidity, and wind. For more precise estimation, a complex alternative approach for crop/plant coefficient (dual crop coefficient) is used by separately considering transpiration from the plant canopy and evaporation from the soil. In this approach measuring solar radiation interception by vegetation cover (for non-stressed plants) yields the basal crop coefficient. Predicting available energy at the soil surface can lead to estimate of soil evaporation (Allen, 2000).

Application of the field-based approach in the mixed landscape vegetation introduces comes along with some limitations. Heterogeneity of plant spices, vegetation density and microclimate yields in a high variation of plant evapotranspiration rates even in small scales. However, some approaches were introduced and applied for the mixed vegetation environs. They comprehensively discussed by Nouri et al. (2013). RS-based method is an alternative trustable approach that facilitates considering diversity of mixed vegetation in ET estimation.

Inference methods use the reflectance value of the red (R) and Near Infrared (NIR) bands to predict VI (particularly NDVI) or LAI (Leaf Area Index). Although it requires ground-based calibration, it is still more affordable than empirical and residual methods those need high cost detailed field measurements (Courault et al., 2005). Many studies have been conducted to find the correlation between crop coefficients and VI and particularly NDVI (Consoli et al., 2006; Neale et al., 2005; O'Connell et al., 2009; Trout et al., 2008). However, Allen et al. (2005) found that the relationship between crop coefficients and VI exists but emphasizes that the specific relationship is not transferable. He stresses that this is true particularly because of irrigation effects on soil moisture and water stress conditions.

2.4 Deterministic methods

This method is established based on the complex soil, vegetation, atmosphere transfer models (SVAT). Remote sensing can be employed to either estimate energy balance components or to integrate (or calibrate) particular input data. In order to interpolate remote sensing data temporally, ground measurements are required. The SVAT models can predict energy exchanges without remote sensing information (Baldocchi et al., 2001), although Olioso et al. (2005), Jupp (1998), and Voogt and Oke (2003) highlighted several benefits of combining remote sensing data and SVAT models for ET estimation.

Unlike the residual approach, deterministic methods can be used on cloudy days when remote sensing images are not available. Owen et al. (1998) assessed vegetation factors and surface moisture availability in urban surfaces using the SVAT model. They claimed that a small change in land cover index (the influence of local land cover surrounding urbanized pixels) through urbanization dramatically changes the evapotranspiration rate. Mauser and Schaldich (1998) modelled the spatial variation of ET at micro and macro scales by introducing PROMET (Process Oriented Model for Evapotranspiration), which is in the family of SVAT models.

2.5 Other categorisations

Other researchers have proposed their own categories, the most common of which are now discussed. Contreras et al. (2011) suggested two main groups of RS application in ET prediction, namely physically-based algorithms and indirect residual techniques. A physically-based algorithm usually relies on the Penman–Monteith equation (a principle method to estimate reference evapotranspiration). Indirect residual techniques quantify surface energy balance parameters together with surface temperature/vegetation indices and the numerical process of SVAT. Recently, Allen et al. (2011a) proposed two main categories, namely remote sensing energy balance techniques and satellite-based ET using vegetation indices. The former evaluates an energy balance through sensible heat flux using different models (e.g. SEBAL, METRIC – Mapping Evapotranspiration at High Resolution and with Internalized Calibration), mostly coupled with field measurements. Allen et al.'s second category simply employs a vegetation index to estimate crop coefficients based on the close relationship between vegetation (NDVI, VI or LAI) and transpiration. They claimed that the basal coefficient has the most consistent relationship with NDVI.

3 Advantages and disadvantages of remote sensing approaches

Combining satellite image and ground-based techniques has enhanced the accuracy of climatology data and particularly ET measurements (Wilson et al., 2003). Despite the advantages of using remote sensing techniques to measure ET, several disadvantages have also been reported. These include the time period between satellite captures, the high costs associated with obtaining high resolution images particularly airborne images, the uncertainty in estimating aerodynamic components and some errors in measuring narrow vegetation areas such as riparian zones (Allen et al., 2011b; Boegh et al., 2009; Chen et al., 2005; Courault et al., 2005; Jiang et al., 2009; McCabe and Wood, 2006; Min and Lin, 2006; Mutiga et al., 2010; Rana and Katerji, 2000; Stisen et al., 2008; Wu et al., 2010). It should also be noted that temporal differences between satellite/airborne images can result not only from spectral changes but also from daily, monthly, and yearly changes in sun position which directly affect vegetation density (Weng et al., 2004). Bastiaanssen et al. (1998) suggested that SEBAL does not work on cloudy days. Also, SEBAL has a specific regression model that may not be suitable for all locations. Courault et al. (2005) stated that climate data has an important role in the SEBAL method and the accuracy of results is related to the density of meteorological stations in the study area. Moreover, they provided the following table of advantages and disadvantages of remote sensing approaches for ET estimation (Table 2).

Allen et al. (2011a) asserted that in-situ measurements using the energy balance technique is time consuming and needs extensive skills, while remote sensing-based

ET prediction using vegetation indices involves rapid analyses for a large area and that can be performed by a mid-level skilled technician. The authors are thoroughly agreed with Allen's viewpoint in uncomplicatedness and quickness of RS-based ET estimation using vegetation indices. Here the ET-VI relationships for agricultural vegetation and mixed landscape vegetation are reviewed.

4 Relationship between vegetation indices and ET

Remote sensing applications have been expressively involved in estimation of canopy cover, vegetation index, or leaf area index both in agricultural and non-agricultural (urban, forest ...) environments. Canopy cover as a direct driver of plant water demand and its relationship with plant adjustment factor is a suitable indicator of plants evapotranspiration rate.

4.1 Relationship between agricultural vegetation indices and ET

Vegetation indices have been developed and successfully assessed evapotranspiration in the last four decades particularly in the agricultural studies (Glenn et al., 2008). A new generation of vegetation indices data particularly NDVI from Worldview 2, GeoEye, or IKONOS provide high resolution coverage of the earth at less than a meter pixel resolution.

Duchemin et al. (2006) investigated the practicality of using remotely sensed NDVI as an indirect method of estimating LAI and reference evapotranspiration, ET_0. They proposed a linear relationship between NDVI and basal crop coefficient for irrigated agricultural fields. Tasumi and Allen (2007) studied the relationship between ET, crop behaviour, vegetation indices (NDVI) and crop coefficients (derived from satellite images) for several crops during their growing stages. They found NDVI as a helpful indicator to understand irrigation consumption and assess irrigation management.

Trout and Johnson (2007) estimated the water demand of agricultural crops by calculating crop coefficients and ET_0 from a weather station. Due to the high variability of crop coefficients, an alternative method of measuring the crop coefficient based on light interception by the canopy cover was introduced. This uncomplicated approach was able to estimate the crop coefficient from its relationship with the basal crop coefficient. The crop coefficients were estimated by remotely sensed NDVI. A multi-spectral camera was employed to measure canopy cover while the basal crop coefficient was derived from lysimeter measurements and meteorological parameters. In another study, Trout et al. (2008) used a multi-spectral camera to measure canopy cover directly from horticultural crops. They then compared the canopy cover derived from this method with that measured using remotely sensed NDVI. They asserted that there was a high correlation and a linear relationship between crop canopy and NDVI and recommended the application of remotely sensed NDVI to predict vegetation water demand.

Later, O'Connell et al. (2009) determined the irrigation demand of citrus, grape, and almond irrigation sites in Australia by ET measurement using the SEBAL model. The relationship between ET and NDVI was also investigated. The results showed a strong relationship between ET and NDVI for three crop species. Trout et al. (2010) compared the two remote sensing techniques of energy balance (SEBAL) and an indirect method using vegetation index in order to predict ET. They confirmed that vegetation cover can be estimated from satellite-based NDVI for a wide variety of crops (Trout, 2011; Trout et al., 2010). Contreras et al. (2011) estimated ET from irrigated and natural oases in central Argentina using a linear relationship between ET and vegetation index at seasonal and annual temporal scales. Season 1 was the growing season from October to April and Season 2 was the dormant season from May to September. They compared remotely sensed ET estimations with ground-based ET measurements at the plot and basin spatial scales (Fig. 1). They concluded that a satellite image approach is an uncomplicated and robust method with two to eighteen percent uncertainty.

4.2 Relationship between non-agricultural mixed vegetation indices and ET

Remotely-sensed spatial, spectral, and temporal data can prominently enhance the ecological knowledge of mixed landscape vegetation environment. Integration of ground-based field measurement and RS-based data to calculate spectral vegetation indices (e.g. NDVI) simplify and enhance the accuracy of ET estimation of mixed planting (Buyantuyev et al., 2007).

Keith et al. (2002) determined the spatial and temporal variability of vegetation greenness through NDVI in Galveston Bay (Texas) for the six continues years. The NDVI time series were compared with ground measurement climate data particularly evapotranspiration. They asserted that remotely-sensed NDVI coupled with weather data is a useful tool to monitor water usage in sub-watershed scales. Nagler et al. (2004) compared LAI measured using a plant canopy analyzer, NDVI measured by a hand-held radiometer and the NDVI calculated using low-level aerial photographs of natural riparian species along the Colorado River. They compared the results from LAI and NDVI and reported 10 % coefficients of variation (CV) for NDVI in contrast to 40 % CVs for LAI measurement. They asserted that for mixed vegetation with different plant cover, NDVI provides more reliable information of physiological processes with lower CVs. Rossato et al. (2005) analysed long-term satellite data to study the spatial and temporal variability of ET in Brazil. They reported a near linear relationship between ET and NDVI and recommended NDVI measurement as an indirect method of ET monitoring for different types of tress and ground covers.

Three independent in-situ methods of evaluating soil moisture conditions; sap flow, open top chamber, and eddy covariance were applied in a varied and multistorey vegetation areas in Australia to measure evapotranspiration (Cook et al., 1998; Hutley et al., 2000). Later on, Palmer et al. (2010) developed the MODIS LAI-ET model to estimate ET over the same place. Results were validated and compared with previous ground-based research. They found results driven from MODIS LAI-ET model closely approximate to ground measurements. This model can be scaled-up to the catchment.

Boegh et al. (2009) used the water balance equation and investigated its relationship to ET for natural vegetation through the vegetation parameters of LAI and crop coefficient. They found a close agreement between canopy growth and evapotranspiration rate predominantly in forests. Devitt et al. (2010) estimated the ET of mixed shrubs and grasslands in three valleys in Nevada (USA) over a three year period. ET prediction was based on an energy balance using the eddy covariance method and this was scaled up for entire catchments using remote sensing data. They also investigated the correlation between ET and NDVI. The vegetation density was categorized into 0 to 0.1 for low density, 0.1 to 0.25 for moderate density, and more than 0.25 for high density. Their results confirmed the strong relationship ($r^2 = 97\%$, $P < 0.001$) between ET and NDVI (Fig. 2).

Recently, Johnson and Belitz (2012) introduced a new approach of using NDVI to quantify urban irrigation. Landsat Thematic Mapper satellite imagery, air photos, land-use maps, and climatic data were employed to predict the location and monthly irrigation rate in urban environments. They found the computed irrigation rate well correlated to actual evapotranspiration data.

5 Conclusions

An accurate estimation of ET is highly important to have sustainable irrigation management and healthy vegetation both in agricultural and non-agricultural environs. Remote sensing had a great contribution in obtaining a more accurate ET estimation in both pixel-scales to global-scale studies. Increasing the accessibility and resolution of remote sensing data enables broad spatial coverage, routine updating, and the ability to provide self-consistent measurements of critical physical properties that would be difficult or expensive to obtain in situ (Miller and Small, 2003). It also provides the opportunity of automated data collection covering spatially extensive and geographically discrete information in mixed vegetation conditions.

This review has compared various remote sensing methods for estimating ET. Based on the most comprehensive categorization of RS application in ET estimation, four main categories of empirical direct, residual, inference, and deterministic were described. Semi-empirical relationship between net radiation and cumulative surface and air temperature differences characterise is the basis of the empirical direct approach. In the residual method, the empirical and physical relationships are combined to estimate the energy balance components directly through remote sensing and ET is estimated as the residual of the energy balance equation. Inference approach is based on RS application to measure a reduction adjustment factor to modify the reference evapotranspiration and achieve the actual ET of the specific plants. Deterministic method investigates the complex relationship of soil, vegetation, atmosphere transfer through complex models.

The spatial and temporal variation of heterogeneous mixed landscape vegetation areas persuades finding a suitable approach with a higher capability of frequent update and spatial resolution. Between all described methods, supporting Allen's view, the authors recommend inference methods for the mixed landscape vegetation environs. Since, this approach is not only simple and rapid compared to others, but also has the capability of observing the heterogeneity of vegetation through Hyperspectral imageries. Some examples ET-VI relationships in agricultural field and mixed landscape vegetation areas were described to support the suitability and practibility of this approach. However, still several challenges are presented in ET estimation using RS images such as long turn-around time of image acquisition and the cost for the high resolution satellites.

The selection of the most appropriate approach is varied be based on the accuracy, budget, time limitations, desired spatial and temporal resolutions, availability of ground data, and particularly meteorological data.

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Table 1. Table of abbreviations.

Remote Sensing	RS
Evapotranspiration	ET
Vegetation Index	VI
Stress Degree Day	SDD
Normalized Difference Vegetation Index	NDVI
Near Infrared	NIR
Surface Energy Balance Algorithm for Land	SEBAL
Surface Energy Balance Index	SEBI
Simplified Surface Energy Balance Index	S-SEBI
Surface Energy Balance System	SEBS
Two-Source Energy Balance	TSEB
Soil-Vegetation-Atmosphere Transfer	SVAT
Leaf Area Index	LAI
Process Oriented Model for Evapotranspiration	PROMET
Mapping Evapotranspiration at High Resolution and with Internalized Calibration	METRIC
Moderate-resolution Imaging Spectroradiometer	MODIS
Urban Heat Island	UHI
Digital Elevation Model	DEM
Food and Agriculture Organization	FAO
Coefficients of Variation	CV

Table 2. Advantages and disadvantages of various remote sensing approaches for estimating ET (after Courault et al., 2005).

Method/model	Advantages	Disadvantages
Empirical direct	Operational from local to regional scales	Spatial variation of coefficients
Interference model	Operational if combined with ground measurement methods or models	Requires calibration for each crop type K_c varies according to water stress
Residual (SEBAL, S-SEBI)	Low cost Needs no additional climatic data	Requires detection of wet and dry pixels
Deterministic (SVAT)	Permits estimation of intermediate variables such as LAI Possible links with climate and/or hydrological models	Requires more parameters Requires accurate remote sensing data

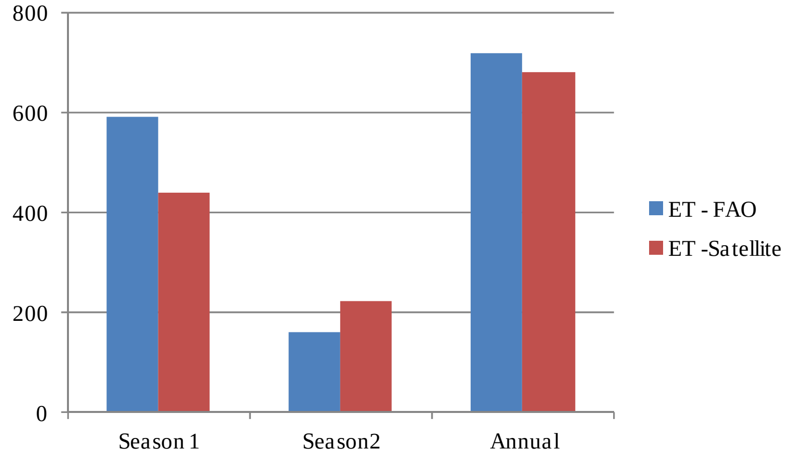

Fig. 1. Comparison of ET rates of ground-based (FAO-crop coefficient) and satellite-based methods (after Contreras et al. 2011).

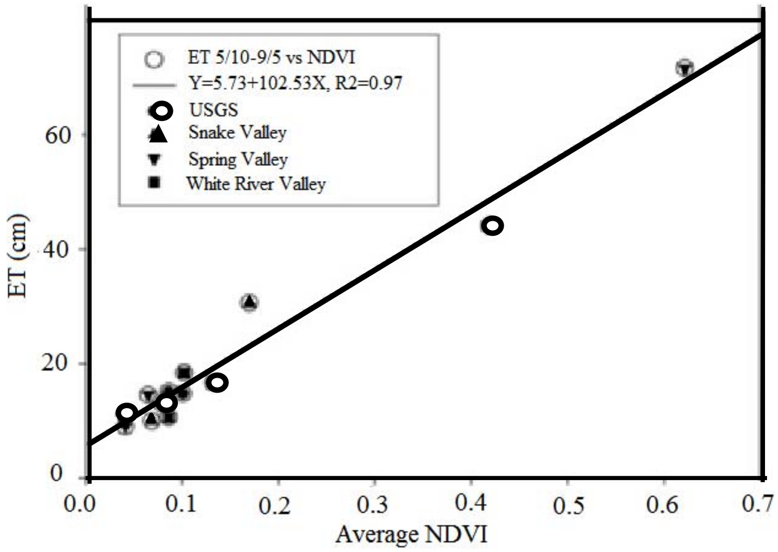

Fig. 2. Relationship between ET and NDVI in three catchments in Nevada, USA (after Devitt et al., 2010).