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Estimating net irrigation requirement of winter wheat using model- and satellite-based single and basal crop coefficients

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ABSTRACT

Evapotranspiration (ET) is one of the key parameters in water and energy balance equation. According to FAO 56, crop evapotranspiration (ET_c) is calculated from multiplying reference evapotranspiration (ET_0) by crop coefficient (K_c). But, due to excessive simplification of K_c curve in the FAO approach, potential evapotranspiration (ET_p) would be miscalculated. Therefore, accurate estimates of ET_p entail improving K_c estimates. In this study, K_c curves of early- and late-planted winter wheat were obtained based on two main satellite-based methods: (1) ratio approach (2) vegetation indices (VIs) approach. In the ratio approach, basal crop coefficient (K_{cb}) and single crop coefficient (K_c) was directly calculated from the ratio of potential transpiration (T_p) to ET_0 (using SWAP) and ET_p to ET_0 (using SWAP and the Priestly-Taylor equation), respectively. The VI approach makes use of Landsat 7 (ETM +) and 8 (OLI) and also MODIS imagery in order to extract soil adjusted vegetation index (SAVI). The K_{cb} curves were evaluated against field measured leaf area index (LAI) in 2014-15 growing season. After each K_c curve was modeled, net irrigation requirement (NIR) was calculated on daily and season basis. Results showed that the SWAP approach was weak in estimating the K_{cb} and K_c curves especially at the late-season stage. The VI approach could properly detect changes in vegetation cover during an entire growing season. But, when it came to K_c curve modelling, the VI approach was limited to the values given in FAO 56. However, the Priestly-Taylor approach compensated for this limitation therefore yielded more sensible trends in K_c curves. Results indicated that the VI approach reduced estimates of NIR of late-planted winter wheat compared with the FAO-recommended approach by 5.37%. The Priestly-Taylor approach resulted 21.72 and 0.32% lower NIR compared with the FAO-recommended approach respectively for early- and late-planted winter wheat. The decrease in NIR from satellite-based approaches derived from more realistic K_c curves during the entire growing season. Overall, making use of the satellite-based approaches could improve water management on regional scales.

1. Introduction

A very large%age of the water absorbed by crops is spent on evapotranspiration (ET). Therefore, accurate estimates of ET are necessary for regional water consumption management. Allen et al. (1998) simplified crop growth curve and subsequently introduced an approach for estimating crop evapotranspiration under optimum conditions (ET_p) by multiplying reference evapotranspiration (ET_0) by crop coefficient (K_c). K_c is the quantitative form of the growth of a crop in time and it is also called crop growth curve. Two methods of calculating K_c are single crop coefficient and dual crop coefficient (Allen et al., 1998). Single crop coefficient is directly calculated from the ratio of ET_p to ET_0 (Eq. (1)):

$$K_c = \frac{ET_P}{ET_0} \quad (1)$$

ET_p is the upper limit of the crop evapotranspiration (ET_c). The upper limit refers to the condition with no water and fertility stress, pests, salinity, and diseases which have negative effects on crop growth process or on the amount of ET_c (Allen et al., 1998).

In the dual crop coefficient approach, the transpiration (T) and evaporation (E) factors are calculated separately (Eq. (2)). So K_c is divided into basal crop coefficient (K_{cb}) and soil evaporation coefficient (K_e) which are representative of T and E, respectively.

$$(K_{cb} + K_e) = \frac{ET_P}{ET_0} \quad (2)$$

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In the absence of water stress, K_{cb} is the ratio of potential transpiration (T_p) to ET_0:

$$K_{cb} = \frac{T_P}{ET_0} \tag{3}$$

K_c and K_{cb} curves are plotted using the lengths of the four stages of crop growth and the crop coefficients of different stages. But due to the empirical nature of these crop coefficients, they might exert error on final ET_p under different climatic and soil conditions (Neale et al., 1990). Consequently, this error leads to underestimation or overestimation of net irrigation requirement (NIR) of crops during a growing season; therefore, irrigation scheduling would face critical problems and a large amount of water is wasted because of unrealistic K_c estimates. One of the most effective solutions to surface and underground water resources management and optimizing their consumption in agriculture is to determine accurate K_c curves for each crop in different climatic conditions (Kamble et al., 2013).

ET_p can be measured using weighing lysimeters, Eddy correlation and Bowen ratio techniques with high accuracy. But these methods introduce ET for a small area which cannot be generalized to a whole region, and also these methods can be time-consuming and costly. Because of these kinds of limitations, remote sensing became more practical in ET_p estimations (Bastiaanssen et al., 1998). Making use of satellite imagery in K_c calculation is the fastest yet accurate method on a large scale.

Many studies have been done on ET_c calculation using energy balance equation associated with taking advantage of remotely sensed images (Jensen and Haise, 1963; Bastiaanssen et al., 1998; Samani, 2000; Bastiaanssen et al., 2002). These studies only focused on estimating satellite-based ET_c and no K_c curves were represented.

Crop growth simulation models are based on more complicated models, but more accurate estimates of ET_p are concluded. SWAP is one of the most popular models. It is an agro-hydrological model which calculates ET_p considering water balance and making use of the Penman-Monteith equation (Kroes et al., 2008). Penman-Monteith was introduced as the most accurate equation by FAO (Allen et al., 1998). Jensen et al. (1990) evaluated 20 different evapotranspiration equations using lysimeter data for 11 stations around the world under different climatic conditions. The Penman-Monteith equation was concluded as the most accurate of them all. However, the natural environment is temporally and spatially dynamic and the crop growth simulation models are not based on real-world changes of vegetation cover, but only mathematical equations. Therefore, assimilating satellite observations such as leaf area index (LAI), which is a crop growth curve by itself, into models, would exert real-world growth rate of crops in time and place on crop growth simulation process.

The Penman-Monteith equation as a combination formula requires several crop and meteorological input data. Accordingly, this formula was simplified by Priestly and Taylor (1974) and ET_p was calculated using only the energy flux part of the Penman-Monteith equation. Satellite imagery which contains multispectral and thermal bands such as Landsat made it possible to calculate Priestly-Taylor-based ET_p with proper accuracy. Bastiaanssen et al. (1998), in SEBAL algorithm, introduced an energy-balance-based approach for estimating ET_c using multispectral and thermal bands of Landsat imagery. Afterwards, Parody and Gabriel (2002), in AHAS algorithm which was based on SEBAL, showed that ET_p can be calculated by the means of Landsat imagery using the Priestly-Taylor equation.

Green leaves absorb the red portion of the electromagnetic radiation of sunlight (from 0.4 to 0.7 μm) in order to perform photosynthesis, and due to cellular structure of leaves, a large amount of near-infrared (Near-IR) light (from 0.7 to 1.1 μm) is reflected. So the amount of radiation absorbed or reflected is highly depended on intensity of green crops in a surface area (Weier and Herring, 2015). Therefore, different vegetation indices (VIs) such as normalized difference vegetation index, NDVI (Rouse et al., 1974), soil adjusted vegetation index, SAVI (Houte et al., 1988), weighted difference vegetation index, WDVI (Clevers, 1988), etc. are developed on this concept and are based on red and Near-IR bands of different sensors. VIs are used for monitoring health, size and intensity of crops and VI-time curve indicates alterations in greenness of a crop, so practically it can be identified as crop growth curve. K_{cb} curve modelling is possible using satellite-based VIs with proper accuracy (Jackson et al., 1980). Many studies have been conducted calculating crop coefficients and estimating NIR from satellite imagery with acceptable accuracy using the relationship between VIs and K_{cb} (González-Dugo and Mateos, 2008; Singh and Irmak, 2009; Gontia and Tiwari, 2010; Melton et al., 2012; Mateos et al., 2013; González-Dugo et al., 2013; Kamble et al., 2013).

In this study, we compared different methods of K_{cb} and K_c estimations based on remote sensing. The Priestly-Taylor approach for ET_p estimation was modified and improved using the combination of Landsat and MODIS imagery, and then K_c values were calculated. Four methods of K_{cb} and K_c curves simulation are (1) VI approach, using Landsat and MODIS images, (2) Priestly-Taylor approach, using Landsat and MODIS images, (3) the SWAP model approach, by assimilating LAI into the model and (4) FAO-recommended approach. These approaches were evaluated against field measured LAI time series. In addition, the effect of each approach on NIR estimation was investigated and then compared with FAO-recommended approach.

2. Materials and methods

2.1. Study area

This study was conducted in 2014-15 growing season. Study area was located in the Qazvin irrigation network (Fig.1) with arid climate conditions (Agricultural Planning Economic and Rural Development Research Institute, APERDRI) and average annual rainfall of 100 mm (Long-term meteorological data). Study fields were selected from the farms of the Hezarjolfa agro-industry company. Hezarjolfa situated at 36° 8′ N and 50° 11′ E, eastern side of the Qazvin irrigation network in Abyek country. The Hezarjolfa agro-industry company with 850 ha field area and approximately 1200 m above the sea level is limited to the east by the Hezarjolfa village, to the south by the Abdol Abad village, to the west by the Magsal agro-industry company, and it is 10 km south of the city of Mohammadiye; comprising five center pivots and a few classic and surface irrigation systems. The climate is semi-arid, and predominant soil texture is sandy loam. Wheat, barley, and canola are usually cultivated in the winter and maize and sugar beet are the spring crops. CP.2 (wheat) and the east side of CP.4 (wheat) were chosen for NIR calculation. The meteorological data were obtained from the Magsal station located at 500 m to the west from the Hezarjolfa agro-industry company with latitude of 36° 9′ N and longitude of 50° 10′ 12″ E.

2.2. Field measurements

Crop growth curves of winter wheat were studied in this paper. Winter wheat in CP.4 was planted in 27 September 2014 and the other one was planted in 19 November 2014 and both of them were harvested in 28 June 2015. Field measured data were soil hydraulic parameters, LAI for early- and late-planted winter wheat (Table 1), and also the time and depth of irrigation events (Table 2). LAI measurement plots were based on MODIS pixels, such that the least mixed pixel was chosen for further calculations. Each plot comprised 3 subplots. LAI samples were collected from each subplot destructively, and the average value of every three subplots of each pixel was representative of the LAI of the whole plot. The sampling was done every 7 to 10 days, and samples were transported to laboratory on standard conditions. Then leaf surface area of each subplot was measured using DeltaT Device, Uk (Jonckheere et al., 2004) – which does the measurement by taking digital photos from leaves – and LAI was calculated by dividing the