



# Satellite-based crop coefficient and evapotranspiration using surface soil moisture and vegetation indices in Northeast Asia



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## ABSTRACT

Accurate estimation of the crop coefficient ( $K_c$ ) is crucial for estimating actual crop evapotranspiration ( $ET_a$ ) and planning appropriate irrigation management for efficient crop yield. In this study, satellite-based  $K_c$  values were estimated at cropland and mixed forest sites based on the dual crop coefficient approach using merged soil moisture from the European Space Agency as an indicator of evaporation from soil, as well as the Normalized Vegetation Index (NDVI) and the Leaf Area Index (LAI) to explain the effect of transpiration from plants. Comparison of the seasonal patterns and Pearson's correlation coefficient ( $r$ ) of NDVI, LAI, and surface soil moisture with  $K_c$  indicated that it was reasonable to use the three variables as independent variables to estimate  $K_c$ . Based on these results, the satellite-based  $K_c$  estimated using NDVI, LAI, and soil moisture (Case 1) was compared with the  $K_c$  calculated from NDVI and LAI (Case 2) and the flux towers at the significance level of 0.05. The statistical results confirmed that the  $K_c$  estimated from Case 1 (Bias:  $-0.012$  to  $0.053$ , RMSE:  $0.144$  to  $0.172$ , and  $r$ :  $0.463$  to  $0.800$ ) showed better agreement with the observed  $K_c$  than that estimated from Case 2 (Bias:  $-0.058$  to  $0.088$ , RMSE:  $0.146$  to  $0.221$ , and  $r$ :  $0.434$  to  $0.788$ ). Among the three variables, soil moisture had the greatest impact on the rice paddy, while the NDVI showed the highest influence on the mixed forest. Based on these results,  $K_c$  estimated from Case 1 was multiplied by MODerate resolution Imaging Spectroradiometer (MODIS)-based potential crop evapotranspiration and compared with the latent heat flux from flux towers.  $ET_a$  showed reasonable bias (cropland:  $-0.224$  to  $1.364$ , mixed forest:  $0.711$  to  $1.055$ ), RMSE (cropland:  $1.952$  to  $2.126$ , mixed forest:  $1.085$  to  $1.878$ ) and  $r$  (cropland:  $0.529$  to  $0.832$ , mixed forest:  $0.850$  to  $0.909$ ) at all of the study sites. After validation of the satellite-based  $K_c$  approach under various vegetation types and climate conditions, this approach can be employed not only for developing adequate water and agricultural management plans, but also for analyzing and predicting crop yield productivity and agricultural drought.

## 1. Introduction

The accurate estimation of actual crop evapotranspiration ( $ET_a$ ) is essential for planning efficient irrigation systems and understanding the hydrological cycle, which is directly affected by global climate change (Yang et al., 2008). The most common approach to estimate  $ET_a$  is multiplying the crop coefficient ( $K_c$ ) by the reference evapotranspiration, as suggested by the Food and Agricultural Organization of the United Nations (FAO) Irrigation and Drainage paper No. 56 (Allen et al., 1998).  $K_c$  is defined as the ratio of  $ET_a$  to the potential evapotranspiration (Doorenbos and Kassam, 1979). This value can be affected by evaporation from soil, crop type, weather conditions, and crop growth (Pereira et al., 2015).

Single and dual crop coefficient approaches have been widely used for the calculation of  $K_c$ . The single crop coefficient approach combines the impact of transpiration from the crop with evaporation from the soil in a single coefficient (Odhiambo and Irmak, 2012). The dual crop coefficient represents  $K_c$  as the sum of the basal crop coefficient ( $K_{cb}$ ) related to transpiration and the soil evaporation coefficient ( $K_e$ ), which represents the evaporation from the soil surface (Allen et al., 1998; Jiang et al., 2014). The crop coefficients of various crops were tabulated in Allen et al. (1998) using both the single and dual crop coefficient approaches, assuming that each crop is a standard crop under unlimited irrigation conditions. However, these tabulated coefficients required adjustments before application at local study sites. The local environ-

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mental conditions, such as soil fertility, salinity, climatic conditions (i.e., precipitation, wind speed, and relative humidity), and managerial factors needed to be taken into consideration to develop an adjusted  $K_c$  curve (Hunsaker et al., 2007; Shrestha and Shukla, 2015). In addition, Er-Raki et al. (2010) found that it was difficult to apply both the single and dual crop coefficient approaches under water-stressed conditions or in the presence of high rates of soil evaporation.

The remote sensing approach has been employed as an alternative for the calculation of  $K_c$  due to several advantages, including reflection of the actual environmental conditions and ability to obtain the real-time  $K_c$  (Lei and Yang, 2014). Various vegetation indices (VI) derived from satellite data including Leaf Area Index (LAI), Normalized Vegetation Index (NDVI), and Soil Adjusted Vegetation Index (SAVI) have been used on the basis of the findings that various VIs showed high correlations with crop coefficient (Choudhury et al., 1994; Duchemin et al., 2006; Hunsaker et al., 2003; Glenn et al., 2011; Neale et al., 1989). Among various researches, Campos et al. (2010) used the NDVI and SAVI derived from the Landsat-5 TM to develop relationships between  $K_{cb}$  and two VIs for the accurate estimation of grape evapotranspiration in Spain. The relationship between the crop coefficient based on the reference evapotranspiration and the NDVI from four different types of crops (corn, soybean, sorghum, and alfalfa) was identified and validated using the crop coefficient based on the Bowen ratio energy balance system (Singh and Irmak, 2009). Gontia and Tiwari (2010) established relationships between the  $K_c$  and two VIs (NDVI and SAVI) in a wheat field. Lei and Yang (2014) estimated the  $K_c$  based on the dual crop coefficient by elucidating linear relationships between  $K_{cb}$  and  $K_c$  with various VIs (NDVI, modified SAVI, and EVI), and applied them to calculate the  $ET_a$  for wheat and maize fields on the North China Plain. However, soil moisture, which can explain the effects of evaporation from soil, has not yet been considered for the estimation of  $K_c$ . Therefore, the objectives of this study were as follows:

- (1) To compare the seasonal trends of the surface soil moisture, NDVI, and LAI observed through remote sensing with the  $K_c$  from a flux tower in order to evaluate the applicability of these variables in the development of a regression equation for the estimation of  $K_c$ ;
- (2) To estimate satellite-based  $K_c$  with the soil moisture representing the  $K_c$  from the soil surface and two vegetation indices (NDVI and LAI) explaining  $K_{cb}$  based on the dual crop coefficient approach. This satellite-based  $K_c$  was compared with the  $K_c$  observed from the flux tower and LAI-based crop coefficient; and
- (3) To apply satellite-based  $K_c$  for estimation of  $ET_a$  by multiplying satellite-based  $K_c$  by MODIS-based potential crop evapotranspiration ( $ET_p$ ), and to validate the results using the latent heat flux observed from a flux tower.

## 2. Study area, dataset, and methodology

### 2.1. Study area and flux tower

Four flux sites located in East Asia, which contained rice paddies and mixed forest vegetation, were selected as the study area to evaluate the relationships between the crop coefficient and the NDVI, LAI, and soil moisture derived from the satellite data. Fig. 1 depicts the land classification of the study area and indicates that all study sites have relatively homogeneous land cover with complex terrain. The Cheongmi flux tower (CFC) site, located in the Chungmi watershed, Korea, and the Mase Paddy flux site (MSE), located in Tsukuba, Japan (Saito et al., 2005), were selected as the rice paddy sites. The Changbaishan Site (CBS; Yu et al., 2006; Wu et al., 2007) containing *Pinus koraiensis* broad-leaved mixed forest and the Sulma flux tower (SMC) site with mixed forest were chosen as the mixed forest sites. Geographic information and the study period at the four sites are described in Table 1.

The observation systems used for the measurement of eddy covariance can be divided into three categories: open-path systems (CFC and

SMC), closed-path systems (MSE), and a combination of both (CBS). The MSE site used a CRN2 net radiometer (Kipp & Zonen, Netherlands) to observe the radiation, while the SMC, CFC, and CBS sites used a CNR1 net radiometer (Kipp & Zonen, Netherlands) at 19.2 m, 10 m, and 32 m, respectively. The soil heat flux, which is defined as the quantity of energy penetrating downward into the soil, was measured at 0.03 m below the soil surface at the CFC and SMC sites with two and three HFT soil heat flux plates (Campbell Sci., Inc., USA), respectively. At the CBS site, two HFP01 heat flux plates (Hukseflux Thermal Sensors, Delft, Netherlands) measured the soil heat flux at 0.05 m below the surface and three Thermopile-type heat flux plates MF-180 M (EKO) were installed at 0.01 m below the surface at the MSE site. To record the data from the flux tower observations, a CR 3000 (Campbell Sci., Inc., USA) data logger and a CR 1000 (Campbell Sci., Inc., USA) data logger were utilized at the SMC and CMC sites, respectively. At the CBS and MSE, CR 5000 (Campbell Sci., Inc., USA) and DRM3 (TEAC, Tokyo, Japan) data loggers were used, respectively.

Before using the flux tower datasets, it is important to conduct quality control because energy balance is frequently disrupted by the systematic error, environmental conditions, and meteorological conditions. Thus, the quality of data obtained from the flux towers was improved using meteorological theory and statistical tests (e.g., spike controlling, coordinate rotation) to ensure the high quality of observations (Park et al., 2015; Choi, 2013; Kwon et al., 2007; Twine et al., 2000). The  $K_c$  values estimated from the flux towers were used as reference data to evaluate the satellite-based  $K_c$ . Climate variables, such as net radiation, wind speed, air temperature, and soil heat fluxes, measured from the flux towers were used as input data to calculate the reference crop evapotranspiration ( $ET_o$ ). In this study, the FAO-56 Penman-Monteith equation was used to calculate  $ET_o$  using meteorological inputs from a flux tower. Then, the instantaneous  $K_c$  values were derived every 30 min based on the ratio of latent heat flux observed from flux tower and  $ET_o$ . Finally, the 8-day  $K_c$  value was calculated by averaging the daily  $K_c$  values, which were estimated by averaging the instantaneous  $K_c$  to produce the same time interval as was used for the satellite-based  $K_c$ . Additionally, the flux footprint of the eddy covariance flux tower was calculated using the Flux Footprint Prediction (FFP) model introduced by Kljun et al. (2015). This model calculates the flux footprint based on the scaling approach using the Lagrangian analytic model and novel parameterization approaches based on Buckingham  $\pi$ -dimensional analysis (Kljun et al., 2015).

### 2.2. MODIS products

The MODERate Resolution Imaging Spectroradiometer (MODIS), launched by the National Aeronautics and Space Administration (NASA) for the Earth Observing System (EOS), was loaded onto the Terra satellite in 1999 and the Aqua satellite in 2002. The MODIS observes the earth every one or two days with 36 different spectral bands, obtaining data at three different spatial resolutions (250 m, 500 m, and 1000 m), which can be provided in the HDF4 format from the MODIS website (<http://modis.gsfc.nasa.gov/data>). The MODIS can observe atmospheric parameters (i.e., aerosols, cloud type, ozone, and air temperature), ocean parameters (i.e., ocean surface temperature and ocean color), and hydrological factors from the land (i.e., land surface temperature, emissivity, albedo, and vegetation). Among these parameters, the 16-day NDVI (MOD13A2) and 8-day LAI (MOD15A2) with 1 km spatial resolution were used in the present study in order to develop a linear equation for the estimation of the satellite-based  $K_c$ .

The daily  $ET_p$  was calculated using the MODIS stand-alone algorithm introduced by Hwang and Choi (2013) utilizing one atmospheric and four land surface products from the MODIS (Table 2). The 8-day averaged  $ET_p$  was multiplied by satellite-based  $K_c$  to determine the  $ET_a$  through the  $K_c$  estimated from the NDVI, LAI, and soil moisture data derived from the satellites. Detailed information regarding the  $ET_p$  calculation procedure can be found in the studies by Baik and Choi (2015), Hwang and Choi (2013) and Kim and Hogue (2008).

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