



Environmental controls on seasonal ecosystem evapotranspiration/potential evapotranspiration ratio as determined by the global eddy flux measurements

Chunwei Liu¹, Ge Sun^{2*}, Steve G. McNulty², Asko Noormets³, and Yuan Fang³

- 5
1. Jiangsu Provincial Key Laboratory of Agricultural Meteorology, College of Applied Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China;
 2. Eastern Forest Environmental Threat Assessment Center, Southern Research Station, USDA Forest Service, Raleigh, NC 27606, USA;
 3. Department of Forestry and Environmental Resources, North Carolina State University, Raleigh,
- 10 NC 27695, USA.

**Corresponding author:* Ge Sun, 920 Main Campus Dr., Venture II, Suite 300, Raleigh, NC 27606, USA.
gesun@fs.fed.us; (919)5159498 (Phone); (919)5132978(Fax)

15



Abstract: The evapotranspiration/potential evapotranspiration (AET/PET) ratio is traditionally termed as crop coefficient (K_c) and has been gradually used as ecosystem evaporative stress index. In the current hydrology literature, K_c has been widely used to as a

20 parameter to estimate crop water demand by water managers, but has not been well examined for other type of ecosystems such as forests and other perennial vegetation. Understanding the seasonal dynamics of this variable for all ecosystems is important to project the ecohydrological responses to climate change and accurately quantify water use (AET) at watershed to global scales. This study aimed at deriving K_c for multiple

25 vegetation cover types and understanding its environmental controls by analyzing the accumulated global eddy flux (FLUXNET) data. We examined monthly AET/PET data for 7 vegetation covers including Open shrubland (OS), Cropland (CRO), Grassland (GRA), Deciduous broad leaf forest (DB), Evergreen needle leaf forest (ENF) and Evergreen broad leaf forest (EBF), and Mixed forest (MF) across 81 sites. We found that, except for

30 evergreen forests (EBF and ENF), K_c values had large seasonal variation across all land covers. The spatial variability of K_c was best explained by latitude suggesting site factors has a major control on K_c . Seasonally, K_c increased significantly with precipitation in the summer months. Moreover, Leaf Area Index (LAI) significantly influenced monthly K_c in all land covers except EBF. During the peak growing season, forests had the highest K_c

35 values while Croplands (CRO) had the lowest. We developed a series of multi-variaterlinear monthly regression models for a large spatial scale K_c by land cover type and season using LAI, site latitude and monthly precipitation as independent variables. The K_c models are useful for understanding water stress in different ecosystems under climate change and variability and for estimating seasonal ET for large areas with mixed land covers.



40 **Key words:** crop coefficient, evapotranspiration, eddy covariance, modeling, water stress

1. Introduction

Evapotranspiration (ET) is one of the major hydrological processes that link energy, water, and carbon cycles in terrestrial ecosystems (Fang et al., 2015; Sun et al., 2011a; Sun et al., 2011b; Sun et al., 2010). In contrast to potential ET (PET) that depends only on atmospheric
45 water demand (Lu et al., 2005), actual evapotranspiration (AET) is arguably the most uncertain ecohydrologic variable for quantifying watershed water budgets (Baldocchi and Ryu, 2011; Fang et al., 2015; Hao et al., 2015a) and for understanding the ecological impacts of climate and land use change (Hao et al., 2015b), and climate variability (Hao et al., 2014). In recent years, one of the most important research questions of ecohydrology
50 focused on how ecosystem dynamics, precipitation, AET, and PET interact in different ecosystems at seasonal and long term scales under a changing environment (Vose et al., 2011).

The ratio of AET to PET is traditionally termed as crop coefficient (K_c), and has been widely used to as a parameter to estimate crop water demand by water managers (Allen
55 and Pereira, 2009; Irmak et al., 2013a). However, this parameter has not been well examined for other ecosystems (Zhang et al., 2012; Zhou et al., 2010). The ratio of AET to PET has also been used as an indicator of regional terrestrial water availability, wetness or drought index, and plant water stress (Anderson et al., 2012; Mu et al., 2012). When the AET/PET ratio is close to 1.0, the soil water meets ecosystem water use demand. The ratio of
60 AET/PET or water stress level can be drastically different among different ecosystems in different environmental conditions, because AET is mainly controlled by climate (precipitation and PET) (Zhang et al., 2001) and ecosystem species composition and



structure (i.e., leaf area index, rooting depth, stomata conductance) (Sun et al., 2011a). The seasonal PET values for a particular region are generally stable (Lu et al., 2005; Rao et al., 2011), and deviation of AET/PET from the norm indicates variability in AET, which
65 responds to precipitation and water availability when PET is stable (Rao et al., 2011). However, under a changing climate, the AET/PET patterns can be rather complex since both AET and PET are affected by air temperature and precipitation (Sun et al., 2015a; Sun et al., 2015b) and corresponding changes in ecosystem characteristics (e.g., plant species
70 shift) (Sun et al., 2014; Vose et al., 2011).

In the agricultural water management community, the crop coefficient method remains a popular one for approximating crop water use, despite recent advances in direct ET measurement methods (Allen and Pereira, 2009; Allen et al., 1998; Baldocchi et al., 2001; Fang et al., 2015). The K_c is termed as single crop coefficient (Allen et al., 1998; Allen
75 et al., 2006; Tabari et al., 2013) which is affected by growing periods, crop species, canopy conductance, and soil evaporation in the field scale (Allen et al., 1998; Ding et al., 2015; Shukla et al., 2014b). Moreover, K_c can be influenced by soil characteristics, vegetative soil cover, height, plant species distribution, and leaf area index in a larger spatial scale (Anda et al., 2014; Consoli and Vanella, 2014; Descheemaeker et al., 2011).
80 Although the Food and Agriculture Organization of the United Nations provides various guidelines for several crops (Allen et al., 1998), local measurements are still required to estimate K_c to account for local crop varieties and for year-to-year variation in weather conditions (Pereira et al., 2015).

Although the K_c method has been widely used for estimating AET for crops, it has not
85 been widely used for natural ecosystems for the purpose of estimating AET due to limited



continuous measurements in these systems. However, as discussed earlier, ecologists and hydrologist have started to use K_c to quantify ecosystem stress levels, and consider K_c as a variable rather than a constant. Past studies found that K_c was influenced by the growing stages and leaf area index for maize (Ding et al., 2015;Kang et al., 2003), winter
90 wheat(Allen et al., 1998;Kang et al., 2003), watermelon (Shukla et al., 2014b), and fruit trees (Marsal et al., 2014b;Taylor et al., 2015). Variations of mid-season crop coefficients for a mixed riparian vegetation dominated by common reed (*Phragmites australis*) could be predicted by growing degree days in central Nebraska, USA(Irmak et al., 2013a). K_c ranged from 0.50 to 0.85 for small, open grown shrubs, and from 0.85 to 0.95 for well-
95 developed shrubland. The K_c values had a close logarithmic relationship with the canopy cover fraction in the highlands of northern Ethiopia (Descheemaeker et al., 2011). Overall, the non-agricultural ecosystems such as forests, grasslands and shrublands are heterogeneous in nature and have high soil water availability. Thus, K_c values for natural ecosystems have high variability (Allen and Pereira, 2009;Allen et al., 2011).

100 Therefore, the goal of this study was to explore how K_c varies among multiple ecosystems with various vegetation types over multiple seasons. Another goal was to determine the key biophysical and environmental factors such as latitude, precipitation, and leaf area index that could be used to estimate K_c , and if K_c can be modeled with a reasonable accuracy in a larger spatial scale. We examined the K_c variations for seven land
105 cover types by analyzing the FLUXNET eddy flux data (Baldocchi et al., 2001;Fang et al., 2015). Specifically, our objectives were to 1) understand the variation of monthly K_c for seven distinct land covers by analyzing the influences of environmental factors (e.g., precipitation, site latitude) on K_c ; and 2) to develop simple land cover-specific regression



models for estimating K_c with key environmental factors as independent variables.
110 Specifically, we developed quantitative relationships between environmental factors and
 K_c by land cover type using data from FLUXNET sites for 8 croplands(CRO), 13
deciduous broad leaf forests(DB), 5 evergreen broad leaf forests(EBF), 34 evergreen
needle leaf forests (ENF), 9 grasslands (GRA), 10 mixed forests (MF), and 2 open
shrublands (OS). In-depth understanding of the biophysical controls on K_c for different
115 ecosystems is important for accurately estimating AET and anticipating the impacts of
climate change on ecosystem water stress and water balances.

2. Methods

This synthesis study used the LaThuile eddy flux dataset that was developed by FLUXNET
120 (<http://fluxnet.ornl.gov/>; Fig. 1), a global network that measures the exchanges of carbon
dioxide, water vapor, and energy between the biosphere and atmosphere (Baldocchi et al.,
2001). The FLUXNET data (Baldocchi et al., 2001;Baldocchi and Ryu, 2011) have been
widely used to understand the evapotranspiration processes and trend (Fang et al.,
2015;Jung et al., 2010), develop AET and ecosystem models (Sun et al., 2011b;Zhang et
125 al., 2016) and map continental-scale ecosystem productivity (Xiao et al., 2014;Zhang et al.,
2016).

We used an existing database that was developed from the eddy flux measurements
from 81 sites (Fang et al., 2015). According to the International Geosphere-Biosphere
Program (IGBP) land cover classification system, these eddy flux sites represent nine land
130 cover types: open shrubland (OS), cropland (CRO), grassland (GRA), deciduous broad leaf



forest (DB), evergreen needle leaf forest (ENF) and evergreen broad leaf forest (EBF), and mixed forest (MF). For each eddy flux tower site (Figure 1), we acquired AET and associated micro-meteorological data, such as vapor pressure deficit (VPD), precipitation (P), winds speed (WS), net radiation (R_n). Reference evapotranspiration (ET_0) was
 135 calculated by the FAO Penman–Monteith equation as follows (Allen et al., 1998):

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (1)$$

where R_n is net radiation at the cover surface ($\text{MJ m}^{-2} \text{d}^{-1}$), G is soil heat flux ($\text{MJ m}^{-2} \text{d}^{-1}$), T is mean air temperature at 2 m height ($^{\circ}\text{C}$), u_2 is wind speed at 2 m height (m s^{-1}), e_s is saturation vapour pressure (kPa), e_a is actual vapour pressure (kPa), $e_s - e_a$ is the saturation
 140 vapour pressure deficit (kPa), Δ is slope vapour pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$), and γ is the psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$).

The crop coefficient (K_c) is defined as the ratio of the measured AET and the ET_0 calculated by equation (1) varies by month and vegetation types (Equation 2).

$$K_c = \frac{ET}{ET_0} \quad (2)$$

145 The LAI time series for each tower site were downloaded from the Oak Ridge National Laboratory Distributed Active Archive Center (http://daac.ornl.gov/cgi-bin/MODIS/GR_col5_1/mod_viz.html). MODIS LAI was derived from the fraction of absorbed photosynthetically active radiation (FPAR) that a plant canopy absorbs for photosynthesis and growth in the 0.4–0.7 nm spectral range. LAI is the biomass equivalent
 150 of FPAR. The MODIS LAI/FPAR algorithm exploits the spectral information of MODIS surface reflectance at up to seven spectral bands. We extracted monthly LAI data for the time period from 2000 through 2006 across 77 sites using 8-day GeoTIFF data from the



Moderate Resolution Imaging Spectroradiometer (MODIS) land subsets' 1-km LAI global fields. We estimated monthly LAI for each flux tower by computing the mean of the 8-day
155 daily values for each month (Fang et al., 2015).

3. Results

3.1. Seasonal variations and long term means of K_c by land cover

The average monthly K_c based on eddy flux data from 2000 to 2007 increased gradually from January to July and then decreased (Fig. 2). EBF had the highest mean monthly K_c
160 (1.01 ± 0.17) (mean \pm standard error) in August. K_c for both EBF and ENF varied less seasonally than other forest types (Fig. 2). Standard errors for GRA, ENF and OS (0.10-0.17) were larger than other land cover types (0.03-0.10) for April to August. EBF had higher K_c for all seasons than other land covers with a peak value of 0.91 (± 0.13) in the summer season (Fig. 3). In winter seasons, CRO and OS had the lowest K_c , 0.25 (± 0.006)
165 and 0.22 (± 0.004), respectively.

The mean annual K_c was 0.39 (± 0.04), 0.47 (± 0.05), 0.79 (± 0.03), 0.45 (± 0.02), 0.57 (± 0.06), 0.45 (± 0.05), and 0.40 (± 0.04) for CRO, DB, EBF, ENF, GRA, MF, and OS, respectively. Yearly average AET, ET_0 and precipitation were higher in EBF than other land covers (Fig. 4). The precipitation ranking by land cover type was EBF > DB > MF >
170 GRA > ENF > CRO > OS. Consequently, OS, MF, GRA and ENF had relatively low AET (376-425 mm). In contrast, CRO had relatively low precipitation with a high ET_0 .

3.2. Environmental controls on K_c

At the annual temporal scale, annual K_c was negatively ($p < 0.05$) correlated with the latitude of the sites (Fig.5) for CRO, DB, ENF, GRA and MF with a determination



175 coefficient (R^2) of 0.83, 0.59 and 0.21, 0.72 and 0.52, respectively. For other sites, annual mean K_c also decreased with the increase in site latitude. Most of the study site latitudes fell between 30°N to 60°N except some EBF sites.

At the seasonal scale, the linear relationships between monthly K_c and total monthly precipitation differed among different land cover types (Fig. 6). Monthly K_c increased with
180 monthly precipitation in the same ecosystem type with the R^2 ranking from high to low: OS>MF> GRA> ENF>CRO>DB. The monthly K_c for open shrublands (OS) was especially sensitive to precipitation ($R^2= 0.69, p<0.001$). The monthly K_c for EBF was not as sensitive to precipitation because EBF was generally found in a wet environment with a peak monthly precipitation of 468 mm. Moreover, K_c for OS, GRA and MF in relatively
185 drier environments had lower values (Fig. 2). Therefore, K_c was closely related to the monthly precipitation.

Growing season, site latitude and monthly precipitation affected the monthly K_c , in addition to leaf area index (Fig. 7). K_c was obviously influenced by the leaf area index (LAI) for all land covers except EBF. The determination coefficients for different land
190 covers were OS> MF>GRA> ENF>DB>CRO. The LAI could reach $6\text{ m}^2\text{ m}^{-2}$ in most land covers, while in OS and CRO the LAI were only $3\text{-}4\text{ m}^2\text{ m}^{-2}$.

3.3. K_c models

A series empirical K_c model were developed using a multiple linear regression approach with precipitation, leaf area index (LAI), and site latitude as independent variables (Table
195 1). The monthly precipitation, LAI and site latitude influenced K_c ($p<0.1$) for most ecosystems studied in different seasons except at EBF in summer and fall, and for OS in



the spring. As annual precipitation increases, total leaf area increases, therefore K_c increases for ENF in all seasons and most of the time for DB and MF. As site latitude increases, K_c values were found to decrease in some periods at CRO, DB, EBF and MF sites. In addition, K_c was closely correlated to LAI, site latitude, and monthly precipitation at ENF in fall and OS in winter with R^2 0.55 and 0.99. All land covers had a peak values 0.53 (\pm 0.04)-1.01 (\pm 0.17) in the summer months. Except for EBF and GRA, K_c values had a close relationship with the monthly precipitation in the summer with R^2 ranging from 0.21 to 0.90. The linear relationships were significant for most vegetation types, suggesting the regression models (Table 1) can be used to estimate monthly K_c if LAI and precipitation are for a specific ecosystem are available.

4. Discussion

Our study estimated annual and seasonal crop coefficient (K_c) for seven land cover types using measured global eddy flux data. We comprehensively evaluated environmental controls (i.e., precipitation, LAI, and site latitude) on annual and growing seasons K_c and developed a series of multiple linear regression models that can be used for estimating monthly AET over time and space.

4.1. Crop coefficient variation in different seasons

Several recent studies had shown that K_c reached the maximum value in middle of the growing season in many ecosystems, such as a *P. euphratica* forest in the riparian area (Hou et al., 2010) in a desert environment, a watermelon crop covered with plastic mulch in Florida (Shukla et al., 2014a; Shukla et al., 2014b), soybean in Nebraska (Irmak et al., 2013b), a temperate desert steppe in Inner Mongolia (Zhang et al., 2012). As Fig. 2 shows, most of the land covers had peak K_c during June to August, while the seasonal patterns of



220 ENF and EBF varied less than other surfaces. Vegetation growth for both the EBF sites is active throughout the year and some EBF sites distributed in the southern hemisphere lead to the stable K_c that varied little. The crop coefficients for early period mid-density fruit trees is about 0.5 (Allen and Pereira, 2009; Allen et al., 1998) which is similar to those found for DB or MF during April and May. In addition, the middle season K_c values for
225 apple and peach trees with active ground cover were higher than K_c for DB sites during the summer. It is likely that the orchards had higher evapotranspiration rates than natural forests due to irrigation in orchards.

4.2. Environmental control factors for K_c

The ecosystem covers and the distributions of the vegetation classes were determined by
230 the latitude (Potter et al., 1993). Crop coefficient varied predominately by ecosystems, K_c increased as the site latitude decreased for the same land cover (Fig. 5). As the latitude decreased, the temperature and the solar radiation increased and the vegetation characteristics would be different for the same land cover type. Models developed from the FLUXNET data may be best used on flat areas for a given latitude given that eddy
235 covariance towers were generally installed on flat lands (Baldocchi et al., 2001). For areas with complex topography, the relationship between K_c and site latitude may be more complicated.

Spatial variations of K_c are characteristic of ecosystems, but K_c is also affected by climate factors such as rainfall and temperature. For example, K_c was highly correlated
240 with precipitation for most land covers (Fig. 6). The rainfall is the major source of soil water and AET in natural ecosystems (Parent and Anctil, 2012). During dry years or periods, a



lack of precipitation may cause a reduction of the leaf area index and K_c will decrease to
response the ecosystem function. During rainy seasons, as, leaf area index and stomatal
conductance of trees and rain-fed crops increases, so does K_c (Kar et al., 2006;Zeppel et
245 al., 2008). Irrigation of cropland is a primary mechanism for increasing yield (Du et al.,
2015;Fereres and Soriano, 2007), so the CRO may have a high monthly K_c even at sites
with a low precipitation. In contrast, K_c does not have a close relationship with
precipitation under a wet environment. For example, the EBF site had a monthly
precipitation as high as 468 mm/month and generally exceeded monthly AET. In an
250 opposite case for the OS sites, monthly precipitation values were between 0.7 to 69 mm,
and K_c was highly correlated to monthly precipitation.

Besides precipitation, leaf area index (LAI) also impacted K_c in dry and semi-humid
area (Kang et al., 2003;Zhang et al., 2012). Unlike precipitation, LAI directly affects K_c in
AET calculations (Novák, 2012;Tolk and Howell, 2001). Inter-annual K_c values are stable
255 at the GRA and OS sites due to the steady seasonal LAI between years while the plantation
forest sites had a more dynamic LAI pattern(Marsal et al., 2014a). As the growth rate of
the perennial plants could have large effects on relationship between K_c and LAI, long term
data are needed to estimate K_c as a function of all environmental factors.

4.3. Modeling the dynamics of K_c

260 Our study results are consistent with previous studies that show that the growing stage
is a key factor for estimating K_c in agricultural crops (Alberto et al., 2014;Allen et al.,
1998;Wei et al., 2015;Zhang et al., 2013), fruit trees (Abrisqueta et al., 2013;Marsal et al.,
2014b), salt grass (Bawazir et al., 2014) and *Populus euphratica Oliv* forest (Hou et al.,



2010). Additionally, our study showed that K_c fluctuated more dramatically in DB, GRA,
265 and MF than other land covers in different seasons (Table 1). Studies also show that
monthly leaf resistance that varies over time is important in estimating the seasonal crop
coefficient for a citrus orchard (Taylor et al., 2015). The LAI and total monthly precipitation
varied in both time and space while the site latitude only represents spatial influences on
 K_c . Thus, the multiple linear regression equations developed from this study take account
270 of both spatial and temporal changes in land surface characteristics and offer a powerful
tool to estimate of seasonal dynamic K_c for different ecosystems (Table 1).

5. Conclusions

To seek a convenient method to calculate monthly AET in large spatial scale, we
comprehensively examined the relations between K_c and environmental factors using eddy
275 flux data from 81 sites with different land covers. We found that K_c values varied largely
among CRO, DB, EBF, GRA and MF and over seasons. Precipitation determined K_c in the
growing seasons (such as summer), and was chosen as a key variable to calculate K_c . We
established multiple linear equations for different land covers and seasons to model the
dynamics of K_c as function of LAI, site latitude and monthly precipitation. These empirical
280 models could be helpful in calculating monthly AET at the regional scales with readily
available climatic data and vegetation structure information. Our study extended the
applications of the traditional K_c method for estimating crop water use to estimating AET
rates and evaporative stress for natural ecosystems. Future studies should further test the
applicability of the empirical K_c models under extreme climatic conditions.

285



References

- Abrisqueta, I., Abrisqueta, J. M., Tapia, L. M., Mungu á, J. P., Conejero, W., Vera, J., and Ruiz-Sánchez, M. C.: Basal crop coefficients for early-season peach trees, *Agricultural Water Management*, 121, 158-163, <http://dx.doi.org/10.1016/j.agwat.2013.02.001>, 2013.
- 290 Alberto, M. C. R., Quilty, J. R., Buresh, R. J., Wassmann, R., Haidar, S., Correa, T. Q., and Sandro, J. M.: Actual evapotranspiration and dual crop coefficients for dry-seeded rice and hybrid maize grown with overhead sprinkler irrigation, *Agricultural Water Management*, 136, 1-12, 10.1016/j.agwat.2014.01.005, 2014.
- Allen, R. G., Pereira, L. S., Raes, D., and Smith, M.: Crop evapotranspiration, FAO irrigation and drainage paper No. 56, 1998.
- 295 Allen, R. G., Pruitt, W. O., Wright, J. L., Howell, T. A., Ventura, F., Snyder, R., Itenfisu, D., Steduto, P., Berengena, J., Yrisarry, J. B., Smith, M., Pereira, L. S., Raes, D., Perrier, A., Alves, I., Walter, I., and Elliott, R.: A recommendation on standardized surface resistance for hourly calculation of reference ET_o by the FAO56 Penman-Monteith method, *Agricultural Water Management*, 81, 1-22, <http://dx.doi.org/10.1016/j.agwat.2005.03.007>, 2006.
- 300 Allen, R. G., and Pereira, L. S.: Estimating crop coefficients from fraction of ground cover and height, *Irrigation Sci*, 28, 17-34, DOI 10.1007/s00271-009-0182-z, 2009.
- Allen, R. G., Pereira, L. S., Howell, T. A., and Jensen, M. E.: Evapotranspiration information reporting: I. Factors governing measurement accuracy, *Agricultural Water Management*, 98, 899-920, <http://dx.doi.org/10.1016/j.agwat.2010.12.015>, 2011.
- 305 Anda, A., Silva, J. A. T. d., and Soos, G.: Evapotranspiration and crop coefficient of common reed at the surroundings of Lake Balaton, Hungary, *Aquatic Botany*, 116, 53-59, 10.1016/j.aquabot.2014.01.008, 2014.
- Anderson, M. C., Allen, R. G., Morse, A., and Kustas, W. P.: Use of Landsat thermal imagery in monitoring evapotranspiration and managing water resources, *Remote Sens Environ*, 122, 50-65, 2012.
- 310 Baldocchi, D., Falge, E., Gu, L., Olson, R., Hollinger, D., Running, S., Anthoni, P., Bernhofer, C., Davis, K., and Evans, R.: FLUXNET: A new tool to study the temporal and spatial variability of ecosystem-scale carbon dioxide, water vapor, and energy flux densities, *B Am Meteorol Soc*, 82, 2415-2434, 2001.
- Baldocchi, D. D., and Ryu, Y.: A synthesis of forest evaporation fluxes—from days to years—as measured with eddy covariance, in: *Forest Hydrology and Biogeochemistry*, Springer, 101-116, 2011.
- 315 Bawazir, A. S., Luthy, R., King, J. P., Tanzy, B. F., and Solis, J.: Assessment of the crop coefficient for saltgrass under native riparian field conditions in the desert southwest, *Hydrological Processes*, 28, 6163-6171, Doi 10.1002/Hyp.10100, 2014.
- Consoli, S., and Vanella, D.: Mapping crop evapotranspiration by integrating vegetation indices into a soil water balance model, *Agricultural Water Management*, 143, 71-81, 10.1016/j.agwat.2014.06.012, 2014.
- 320



- Descheemaeker, K., Raes, D., Allen, R., Nyssen, J., Poesen, J., Muys, B., Haile, M., and Deckers, J.: Two rapid appraisals of FAO-56 crop coefficients for semiarid natural vegetation of the northern Ethiopian highlands, *J Arid Environ*, 75, 353-359, DOI 10.1016/j.jaridenv.2010.12.002, 2011.
- 325 Ding, R. S., Tong, L., Li, F. S., Zhang, Y. Q., Hao, X. M., and Kang, S. Z.: Variations of crop coefficient and its influencing factors in an arid advective cropland of northwest China, *Hydrological Processes*, 29, 239-249, Doi 10.1002/Hyp.10146, 2015.
- Du, T., Kang, S., Zhang, J., and Davies, W. J.: Deficit irrigation and sustainable water-resource strategies in agriculture for China's food security, *J Exp Bot*, 66, 2253-2269, 10.1093/jxb/erv034, 2015.
- Fang, Y., Sun, G., Caldwell, P., McNulty, S. G., Noormets, A., Domec, J. C., King, J., Zhang, Z., Zhang, 330 X., and Lin, G.: Monthly land cover - specific evapotranspiration models derived from global eddy flux measurements and remote sensing data, *Ecohydrology*, 2015.
- Fereres, E., and Soriano, M. A.: Deficit irrigation for reducing agricultural water use, *J Exp Bot*, 58, 147-159, 2007.
- Hao, L., Sun, G., Liu, Y., Gao, Z., He, J., Shi, T., and Wu, B.: Effects of precipitation on grassland 335 ecosystem restoration under grazing exclusion in Inner Mongolia, China, *Landscape Ecol*, 1-17, 10.1007/s10980-014-0092-1, 2014.
- Hao, L., Sun, G., Liu, Y., and Qian, H.: Integrated Modeling of Water Supply and Demand under Management Options and Climate Change Scenarios in Chifeng City, China, *JAWRA Journal of the American Water Resources Association*, 51, 655-671, 2015a.
- 340 Hao, L., Sun, G., Liu, Y., Wan, J., Qin, M., Qian, H., Liu, C., Zheng, J., John, R., and Fan, P.: Urbanization dramatically altered the water balances of a paddy field-dominated basin in southern China, *Hydrol Earth Syst Sc*, 19, 3319-3331, 2015b.
- Hou, L. G., Xiao, H. L., Si, J. H., Xiao, S. C., Zhou, M. X., and Yang, Y. G.: Evapotranspiration and crop coefficient of *Populus euphratica* Oliv forest during the growing season in the extreme arid region 345 northwest China, *Agricultural Water Management*, 97, 351-356, 2010.
- Irmak, S., Kabenge, I., Rudnick, D., Knezevic, S., Woodward, D., and Moravek, M.: Evapotranspiration crop coefficients for mixed riparian plant community and transpiration crop coefficients for Common reed, Cottonwood and Peach-leaf willow in the Platte River Basin, Nebraska-USA, *Journal of Hydrology*, 481, 177-190, 10.1016/j.jhydrol.2012.12.032, 2013a.
- 350 Irmak, S., Odhiambo, L. O., Specht, J. E., and Djaman, K.: Hourly And Daily Single And Basal Evapotranspiration Crop Coefficients as a Function Of Growing Degree Days, Days after Emergence, Leaf Area Index, Fractional Green Canopy Cover, And Plant Phenology for Soybean, *T Asabe*, 56, 1785-1803, 2013b.
- Jung, M., Reichstein, M., Ciais, P., Seneviratne, S. I., Sheffield, J., Goulden, M. L., Bonan, G., Cescatti, A., 355 Chen, J., and De Jeu, R.: Recent decline in the global land evapotranspiration trend due to limited moisture supply, *Nature*, 467, 951-954, 2010.



- Kang, S., Gu, B., Du, T., and Zhang, J.: Crop coefficient and ratio of transpiration to evapotranspiration of winter wheat and maize in a semi-humid region, *Agricultural water management*, 59, 239-254, 2003.
- Kar, G., Verma, H. N., and Singh, R.: Effects of winter crop and supplemental irrigation on crop yield, water use efficiency and profitability in rainfed rice based cropping system of eastern India, *Agricultural Water Management*, 79, 280-292, DOI 10.1016/j.agwat.2005.03.001, 2006.
- Lu, J., Sun, G., McNulty, S. G., and Amatya, D.: A comparison of six potential evapotranspiration methods for regional use in the Southeastern United States, 2005.
- Marsal, J., Casadesus, J., Lopez, G., Girona, J., and Stöckle, C.: Disagreement between tree size and crop coefficient in 'conference' pear: comparing measurements by a weighing Lysimeter and prediction by Cropsyst, *Acta horticulturae*, 2014a.
- Marsal, J., Johnson, S., Casadesus, J., Lopez, G., Girona, J., and Stöckle, C.: Fraction of canopy intercepted radiation relates differently with crop coefficient depending on the season and the fruit tree species, *Agricultural and Forest Meteorology*, 184, 1-11, <http://dx.doi.org/10.1016/j.agrformet.2013.08.008>, 2014b.
- Mu, Q., Zhao, M., Kimball, J., McDowell, N., and Running, S.: A remotely sensed global terrestrial drought severity index, in: *Evapotranspiration in the Soil-plant-atmosphere System, AGU Fall Meeting Abstracts, 2012, L02, 2012.*
- Novák, V.: *Evapotranspiration in the Soil-plant-atmosphere System*, Springer Science & Business Media, 2012.
- Parent, A. C., and Anctil, F.: Quantifying evapotranspiration of a rainfed potato crop in South-eastern Canada using eddy covariance techniques, *Agricultural Water Management*, 113, 45-56, DOI 10.1016/j.agwat.2012.06.014, 2012.
- Pereira, L. S., Allen, R. G., Smith, M., and Raes, D.: Crop evapotranspiration estimation with FAO56: Past and future, *Agricultural Water Management*, 147, 4-20, 2015.
- Potter, C. S., Randerson, J. T., Field, C. B., Matson, P. A., Vitousek, P. M., Mooney, H. A., and Klooster, S. A.: Terrestrial ecosystem production: a process model based on global satellite and surface data, *Global Biogeochem Cy*, 7, 811-841, 1993.
- Rao, L., Sun, G., Ford, C., and Vose, J.: Modeling potential evapotranspiration of two forested watersheds in the southern Appalachians, *T Asabe*, 54, 2067-2078, 2011.
- Shan, N., Shi, Z., Yang, X., Gao, J., and Cai, D.: Spatiotemporal trends of reference evapotranspiration and its driving factors in the Beijing–Tianjin Sand Source Control Project Region, China, *Agricultural and Forest Meteorology*, 200, 322-333, 2015.
- Shukla, S., Shrestha, N. K., and Goswami, D.: Evapotranspiration And Crop Coefficients for Seepage-Irrigated Watermelon with Plastic Mulch In a Sub-Tropical Region, *T Asabe*, 57, 1017-1028, 2014a.
- Shukla, S., Shrestha, N. K., Jaber, F. H., Srivastava, S., Obreza, T. A., and Boman, B. J.: Evapotranspiration and crop coefficient for watermelon grown under plastic mulched conditions in sub-tropical Florida, *Agricultural Water Management*, 132, 1-9, 10.1016/j.agwat.2013.09.019, 2014b.



- Sun, G., Noormets, A., Gavazzi, M. J., McNulty, S. G., Chen, J., Domec, J. C., King, J. S., Amatya, D. M., and Skaggs, R. W.: Energy and water balance of two contrasting loblolly pine plantations on the lower coastal plain of North Carolina, USA, *Forest Ecol Manag*, 259, 1299-1310, DOI 10.1016/j.foreco.2009.09.016, 2010.
- Sun, G., Alstad, K., Chen, J. Q., Chen, S. P., Ford, C. R., Lin, G. H., Liu, C. F., Lu, N., McNulty, S. G., Miao, H. X., Noormets, A., Vose, J. M., Wilske, B., Zeppel, M., Zhang, Y., and Zhang, Z. Q.: A general predictive model for estimating monthly ecosystem evapotranspiration, *Ecohydrology*, 4, 245-255, Doi 10.1002/Eco.194, 2011a.
- Sun, G., Caldwell, P., Noormets, A., McNulty, S. G., Cohen, E., Moore Myers, J., Domec, J. C., Treasure, E., Mu, Q., and Xiao, J.: Upscaling key ecosystem functions across the conterminous United States by a water - centric ecosystem model, *Journal of Geophysical Research: Biogeosciences*, 116, 2011b.
- Sun, S., Chen, H., Ju, W., Yu, M., Hua, W., and Yin, Y.: On the attribution of the changing hydrological cycle in Poyang Lake Basin, China, *Journal of Hydrology*, 514, 214-225, 2014.
- Sun, S., Sun, G., Caldwell, P., McNulty, S., Cohen, E., Xiao, J., and Zhang, Y.: Drought impacts on ecosystem functions of the US National Forests and Grasslands: Part II assessment results and management implications, *Forest Ecol Manag*, 353, 269-279, 2015a.
- Sun, S., Sun, G., Caldwell, P., McNulty, S. G., Cohen, E., Xiao, J., and Zhang, Y.: Drought impacts on ecosystem functions of the US National Forests and Grasslands: Part I evaluation of a water and carbon balance model, *Forest Ecol Manag*, 353, 260-268, 2015b.
- Tabari, H., Grismer, M. E., and Trajkovic, S.: Comparative analysis of 31 reference evapotranspiration methods under humid conditions, *Irrigation Sci*, 31, 107-117, 2013.
- Taylor, N., Mahohoma, W., Vahrmeijer, J., Gush, M., Allen, R. G., and Annandale, J. G.: Crop coefficient approaches based on fixed estimates of leaf resistance are not appropriate for estimating water use of citrus, *Irrigation Sci*, 33, 153-166, 2015.
- Tolk, J. A., and Howell, T. A.: Measured and simulated evapotranspiration of grain sorghum grown with full and limited irrigation in three high plains soils, *Transactions Of the Asae*, 44, 1553-1558, 2001.
- Vose, J. M., Sun, G., Ford, C. R., Bredemeier, M., Otsuki, K., Wei, X., Zhang, Z., and Zhang, L.: Forest ecohydrological research in the 21st century: what are the critical needs?, *Ecohydrology*, 4, 146-158, 2011.
- Wei, Z., Paredes, P., Liu, Y., Chi, W. W., and Pereira, L. S.: Modelling transpiration, soil evaporation and yield prediction of soybean in North China Plain, *Agricultural Water Management*, 147, 43-53, <http://dx.doi.org/10.1016/j.agwat.2014.05.004>, 2015.
- Xiao, J., Ollinger, S. V., Frohling, S., Hurtt, G. C., Hollinger, D. Y., Davis, K. J., Pan, Y., Zhang, X., Deng, F., and Chen, J.: Data-driven diagnostics of terrestrial carbon dynamics over North America, *Agricultural and Forest Meteorology*, 197, 142-157, 2014.
- Zeppel, M. J. B., Macinnis-Ng, C. M. O., Yunusa, I. A. M., Whitley, R. J., and Earnus, D.: Long term trends of stand transpiration in a remnant forest during wet and dry years, *Journal Of Hydrology*, 349, 200-213, DOI 10.1016/j.jhydrol.2007.11.001, 2008.



- 430 Zhang, B., Liu, Y., Xu, D., Zhao, N., Lei, B., Rosa, R. D., Paredes, P., Paço, T. A., and Pereira, L. S.: The
dual crop coefficient approach to estimate and partitioning evapotranspiration of the winter wheat–summer
maize crop sequence in North China Plain, *Irrigation Sci*, 31, 1303-1316, 2013.
- Zhang, F., Zhou, G. S., Wang, Y., Yang, F. L., and Nilsson, C.: Evapotranspiration and crop coefficient for
a temperate desert steppe ecosystem using eddy covariance in Inner Mongolia, China, *Hydrological*
435 *Processes*, 26, 379-386, 2012.
- Zhang, L., Dawes, W. R., and Walker, G. R.: Response of mean annual evapotranspiration to vegetation
changes at catchment scale, *Water Resources Research*, 37, 701-708, 2001.
- Zhang, Y., Song, C., Sun, G., Band, L. E., McNulty, S., Noormets, A., Zhang, Q., and Zhang, Z.:
Development of a coupled carbon and water model for estimating global gross primary productivity and
440 evapotranspiration based on eddy flux and remote sensing data, *Agricultural and Forest Meteorology*, 223,
116-131, 2016.
- Zhou, L., Zhou, G. S., Liu, S. H., and Sui, X. H.: Seasonal contribution and interannual variation of
evapotranspiration over a reed marsh (*Phragmites australis*) in Northeast China from 3-year eddy
covariance data, *Hydrological Processes*, 24, 1039-1047, 2010.

445



Table 1 Multiple linear regression relationships among crop coefficient and LAI, precipitation and site latitude in different seasons.

IGBP	season	<i>N</i>	<i>R</i> ²	<i>K_c</i>	<i>b</i>	<i>a</i> ₁	<i>a</i> ₂	<i>a</i> ₃
CRO	Spring	24	0.16	0.31	0.242***	0.141*		
	Summer	24	0.21	0.57	0.331**			0.0033*
	Fall	23	0.78	0.48	0.036	0.472***		
	Winter	21	0.36	0.26	0.920***		-0.0141**	
DB	Spring	39	0.49	0.30	0.479**		-0.0076*	0.0022***
	Summer	39	0.42	0.65	0.536***			0.0011***
	Fall	39	0.13	0.60	0.462***			0.0014*
	Winter	39	0.15	0.30	0.713***		-0.0094*	
EBF	Spring	15	0.25	0.74	0.875***		-0.0050*	
	Summer	15	-	0.91	0.911***			
	Fall	15	-	0.80	0.798***			
	Winter	15	0.42	0.72	0.676***	0.050*	-0.0050*	
ENF	Spring	96	0.39	0.37	0.225***	0.060***		0.0017***
	Summer	99	0.59	0.49	0.211***	0.053***		0.0020***
	Fall	98	0.55	0.52	-0.040	0.066***	0.0049*	0.0025***
	Winter	92	0.21	0.44	0.293***	0.084*		0.0010*
GRA	Spring	27	0.48	0.45	0.237***			0.0052***
	Summer	27	0.23	0.86	0.572***	0.110*		
	Fall	27	0.30	0.76	0.499***	0.123**		
	Winter	27	0.26	0.41	0.256**			0.0038**
MF	Spring	30	0.67	0.31	0.099**	0.188***		0.0012***
	Summer	30	0.40	0.61	0.372***			0.0029***
	Fall	30	0.54	0.58	0.250***	0.071***		0.0018***
	Winter	30	0.13	0.33	0.961**		-0.0136*	
OS	Spring	6	-	0.23	0.230***			
	Summer	6	0.90	0.35	-5.419*		0.1005*	0.0026*
	Fall	6	0.88	0.42	-9.921*	0.051*	0.1828*	
	Winter	6	0.99	0.14	-4.919*	0.629*	0.0882*	0.0032*

450 Note: *N* is the number of observations used, *R*² the determination coefficient, *K_{cAve}* is the average
K_c for seasons. *b* is the intercept of the multiple linear equation, *a*₁ the coefficient of LAI, *a*₂ the
 coefficient of site latitude (Absolute values), *a*₃ the coefficient of precipitation. IGBP is the
 International Geosphere-Biosphere Program land cover classification system: cropland (CRO),
 deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), evergreen needle leaf forest
 455 (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). ***, **, * stand for *p*<0.001,



$p < 0.01$, $p < 0.1$. Spring is the month of February, March and April; Summer is the month of May, June and July; Fall is August, September and October; Winter is November, December and January.



460 **Figure captions**

Fig. 1 Location of eddy flux sites from which climate and evapotranspiration data are collected.

Fig. 2 The variation of K_c for the different IGBP_code.

Fig.3 Average K_c at spring, summer, fall and winter in different vegetation types.

465 Fig. 4 Annual total precipitation (P), ET and ET_0 in different vegetation types

Fig. 5 The average annual K_c variation at different latitude. (a) stand for cropland (CRO), deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), and (b) evergreen needle leaf forest (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). The absolute values of the latitude were used in EBF in the southern hemisphere sites and all the determination coefficient (R^2) listed in the figure were significant ($p < 0.05$).

470

Fig. 6 Relationships between the average monthly K_c and the total monthly precipitation (P, mm) for different vegetation surfaces. (a)~(g) represent for cropland (CRO), deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), evergreen needle leaf forest (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). All the determination coefficient (R^2) listed in the figure were significant ($p < 0.001$)

475

Fig. 7 Relationships between the average monthly K_c and leaf area index for different vegetation surfaces. (a)~(g) stand for cropland (CRO), deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), evergreen needle leaf forest (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). All the determination coefficient (R^2) listed in the figure were significant ($p < 0.001$)

480

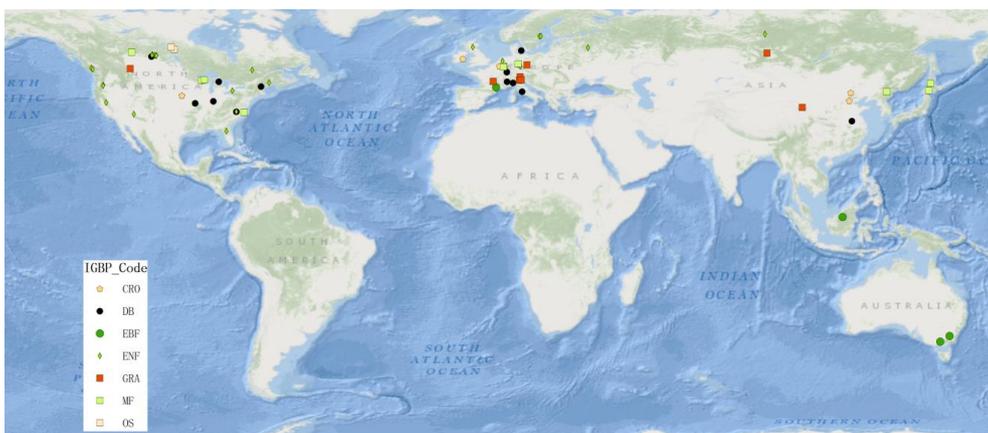


Fig. 1 Location of eddy flux sites from which climate and evapotranspiration data are collected.

485

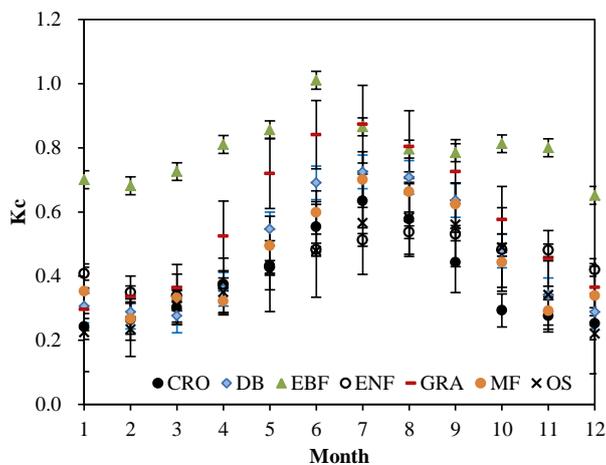


Fig. 2 The variation of K_c for the different IGBP_code.

490

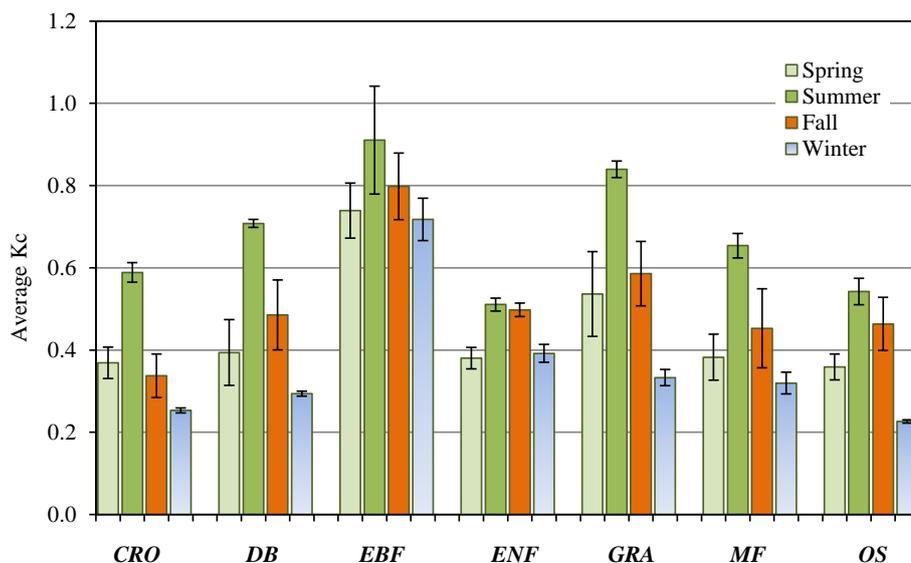


Fig.3 Average K_c at spring, summer, fall and winter in different vegetation types.

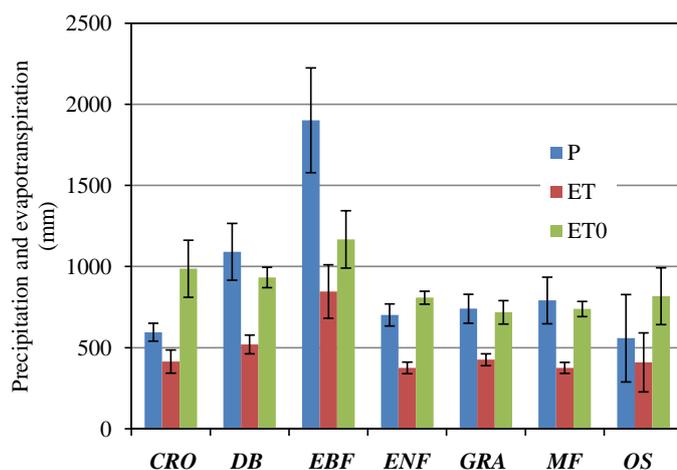


Fig.4 Annual total precipitation (P), ET and ET_0 in different vegetation types

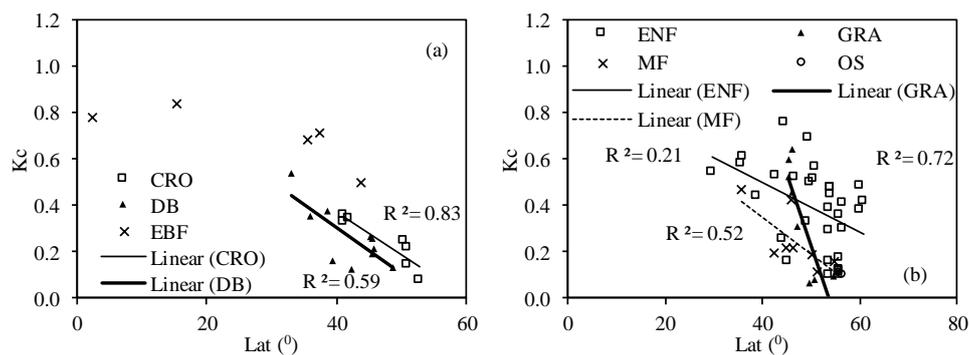
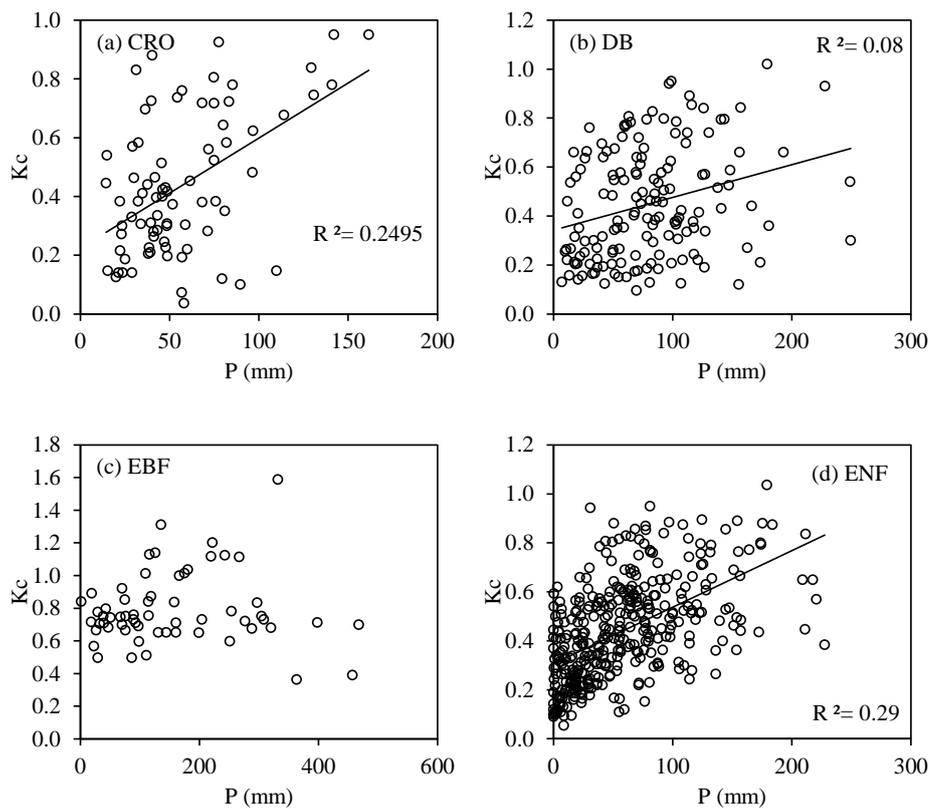


Fig. 5 The average annual K_c variation at different latitude. (a) stand for cropland (CRO), deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), and (b) evergreen needle leaf forest (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). The absolute values of the latitude were used in EBF in the southern hemisphere sites and all the determination coefficient (R^2) listed in the figure were significant ($p < 0.05$).



505

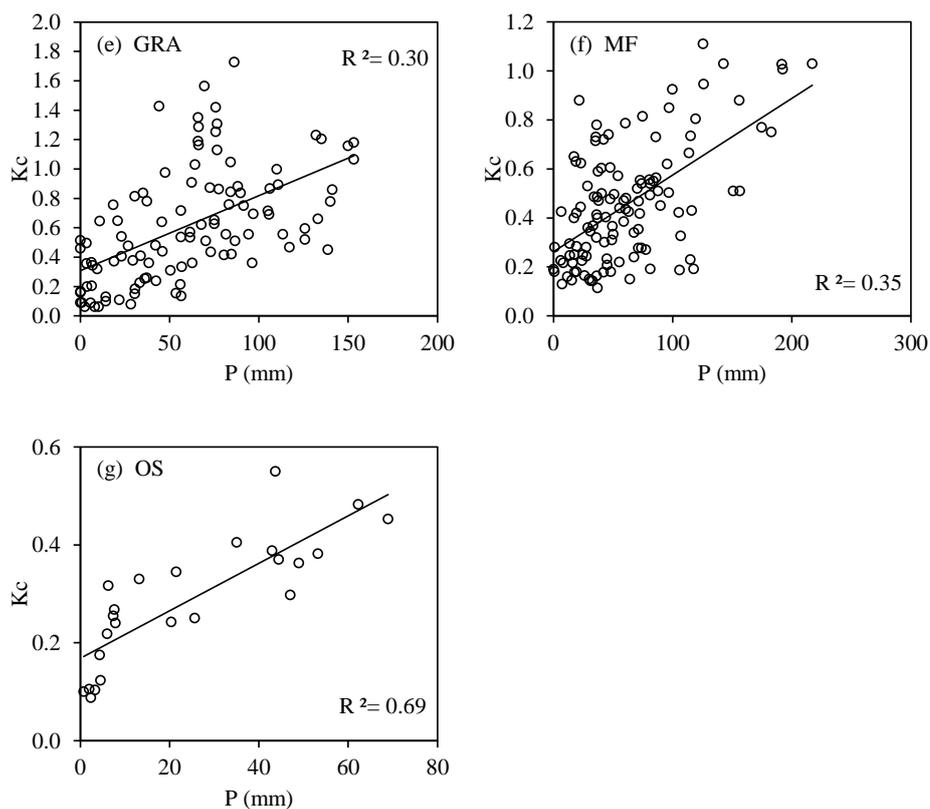
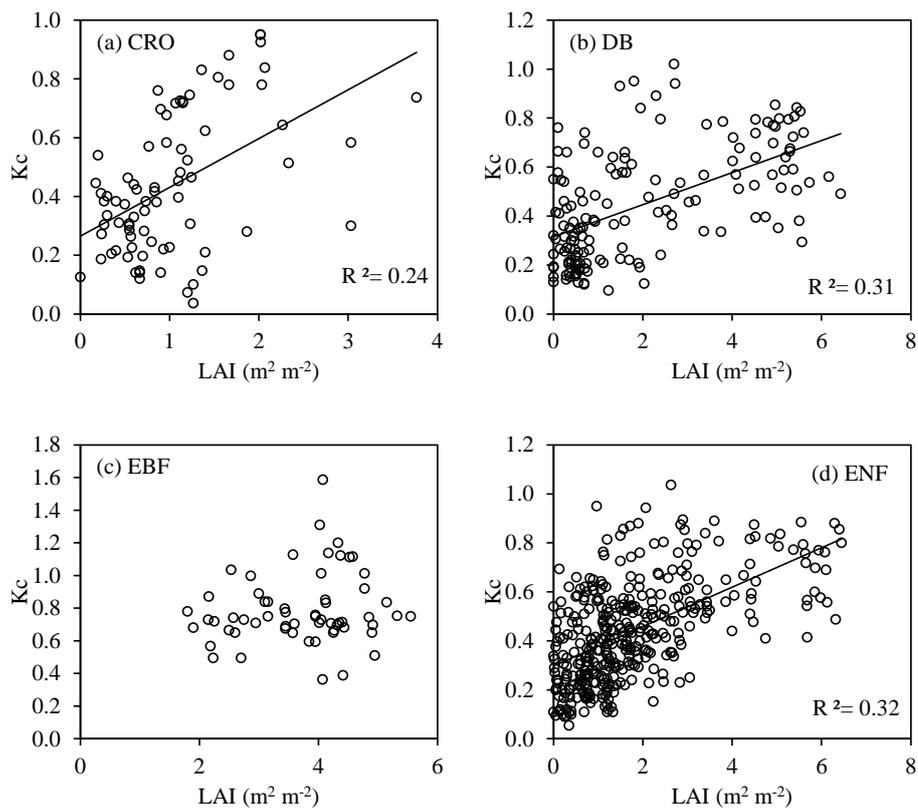
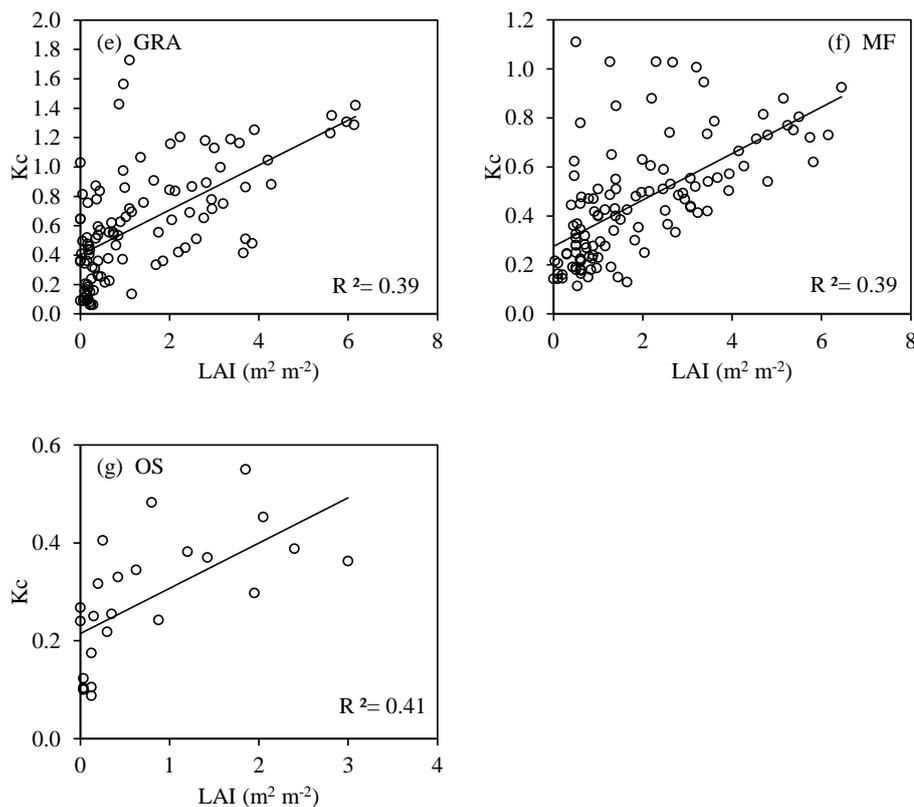


Fig. 6 Relationships between the average monthly K_c and the total monthly precipitation (P , mm) for different vegetation surfaces. (a)~(g) represent for cropland (CRO), deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), evergreen needle leaf forest (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). All the determination coefficient (R^2) listed in the figure were significant ($p < 0.001$)



515





520 Fig. 7 Relationships between the average monthly K_c and leaf area index for different vegetation surfaces. (a)–(g) stand for cropland (CRO), deciduous broad leaf forest (DB), evergreen broad leaf forest (EBF), evergreen needle leaf forest (ENF), grassland (GRA), mixed forest (MF), and open shrubland (OS). All the determination coefficient (R^2) listed in the figure were significant ($p < 0.001$)

525