On Estimating Wet Canopy Evaporation from Deciduous and Coniferous Forests in the Asian Monsoon Climate

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ABSTRACT

Continuous and direct measurement of evapotranspiration (ET) by the eddy covariance (EC) technique is still a challenge under monsoon climate because of a considerable amount of missing data during the long rainy periods and the consequential gap-filling process. Under such wet canopy conditions, especially in forests, evaporation of the intercepted precipitation ($E_{WC}$) contributes significantly to the total ET. To quantify the role of $E_{WC}$, leaf wetness has been measured at multiple levels in the canopy simultaneously with eddy covariance measurements at the KoFlux Gwangneung deciduous and coniferous forests for the entire year from September 2007 to August 2008. In this study, the measured $E_{WC}$ and the controlling mechanism during the wet canopy conditions have been scrutinized. Based on the evaluation of the four different algorithms of $E_{WC}$ estimation, that of the variable infiltration capacity (VIC) land surface model (LSM) has been adopted. All the missing $E_{WC}$ data are then recalculated by using the algorithm of VIC LSM and compared against the traditionally gap-filled $E_{WC}$ data based on the modified lookup table (MLT) method. The latter consistently underestimated $E_{WC}$ on average by 39% in deciduous forest and by 28% in coniferous forest. Major causes of such differences were due to the failure of considering aerodynamic coupling, advection of sensible heat, and heat storage in the MLT-based gap-filling method. Accordingly, a new gap-filling strategy for $E_{WC}$ is proposed that takes proper controlling mechanisms into account.

1. Introduction

Wet canopy evaporation ($E_{WC}$) is defined as evaporation of the intercepted water by vegetation canopy during and following a rainy period (Stewart 1977). The global average annual precipitation is 840 mm, of which approximately 10% is equivalent to $E_{WC}$ based on the modeling study of the Second Global Soil Wetness Project (Dirmeyer et al. 2006). The quantity $E_{WC}$ has been recognized as a significant proportion of precipitation, especially in forests. Previous studies report that annual $E_{WC}$ ranges from 8% to 29% of total precipitation in broadleaved forests (Rowe 1983; Kim et al. 2005; Deguchi et al. 2006; Šraj et al. 2008), from 17% to 33% in coniferous forests (Johnson 1990; Valente et al. 1997; Link et al. 2004; Kim et al. 2005), and from 10% to 48% in rain forests (Asdak et al. 1998; Schellekens et al. 2000; Vernimmen et al. 2007). In the Asian monsoon climate, annual $E_{WC}$ in forests can also be significant because of an extensive cover of forests and frequent rainfalls.

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AsiaFlux, the Asian network of regional flux tower networks, has been conducting the long-term measurements of evapotranspiration (ET) and CO₂ fluxes using the eddy covariance (EC) system and has provided a series of gap-filled ET datasets. There are 18 forests sites out of 23 sites whose data are available through the AsiaFlux database (https://db.eger.nies.go.jp/asialuxldb/). Considering the important contribution of $E_{WC}$ to ET, it is essential to scrutinize the role of $E_{WC}$ in the Asian forests under monsoon climate. For the estimation of an annual ET, typically 10%–40% of the missing data are gap filled using standardized gap-filling methods such as mean diurnal variation and/or modified lookup table (MLT) (e.g., Falge et al. 2001; Reichstein et al. 2005; Hirano et al. 2003; Li et al. 2006; Kosugi et al. 2007; Kang et al. 2009). Artificial neural networks are another method used to fill gaps in the ET data for forest ecosystems (Papale and Valentini 2003; Leuning et al. 2005). Main causes of these gaps are the malfunctions of open-path EC systems due to precipitation and inadequate environmental conditions such as weak turbulence and storm events. However, the environmental conditions used in the gap-filling statistics are mostly collected during dry or partially wet conditions when the EC systems function properly. Therefore, we question if such gap-filled ET data during the wet canopy conditions are biased toward dry to partially wet canopy because of improper consideration of $E_{WC}$.

The $E_{WC}$ can be either directly observed by the EC method or indirectly estimated as a residual in the energy balance equation (Mizutani et al. 1997; Gash et al. 1999; van der Tol et al. 2003; Czikowsky and Fitzjarrald 2009). During the rainy periods, however, the EC system often fails to operate and results in gaps in flux measurements (Czikowsky and Fitzjarrald 2009; Kang et al. 2009). Hence, the missing observation and the failure of energy balance closure (e.g., Wilson et al. 2002) hinder the use of the residual method from the assessment of annual $E_{WC}$. Alternatively, physically based $E_{WC}$ models have been used and validated with the observed interception rainfall in various climate and vegetation types (Rutter et al. 1975; Gash 1979; Link et al. 2004). The Rutter-type models, in particular, have been widely adopted for $E_{WC}$ algorithms in many hydrological models and land surface models (LSMs) (e.g., Rutter et al. 1971; Valente et al. 1997).

The purpose of this study is to ascertain the role of $E_{WC}$ to ET for establishing an accurate ET database by examining a possible shortcoming of the current gap-filling method. Our specific objectives are 1) to quantify the durations of wet and dry canopy spells and the operation of the open-path EC system under wet canopy conditions; 2) to characterize the magnitudes and patterns of the directly measured $E_{WC}$; 3) to evaluate the various model algorithms for the estimation of $E_{WC}$; 4) to scrutinize the accuracy of the current gap-filling method (i.e., MLT) by comparing with the estimation of $E_{WC}$ based on model algorithms, thereby quantifying the annual difference between the gap-filled and the modeled $E_{WC}$; and 5) to provide a new gap-filling strategy for overcoming the weaknesses of the current gap-filling method.

To accomplish these objectives, we have implemented multi-level leaf wetness sensors into the ongoing ET measurements with typical open-path EC systems at the KoFlux Gwangneung deciduous and coniferous forests for the entire year from September 2007 to August 2008. We employed and tested a wide range of $E_{WC}$ algorithms [i.e., the De Groen method, the Gash sparse model, Variable Infiltration Capacity (VIC) LSM, and Noah LSM] against the measured $E_{WC}$ by the EC method. The algorithm that most accurately measured the magnitude and variability was used to estimate the missing $E_{WC}$ data under wet canopy conditions. These data were used to identify the mechanisms to generate $E_{WC}$ in the current gap-filling process by the MLT method, which should be implemented to minimize the potential biases in ET data from the sites in monsoon climate.

2. Materials and methods

a. Study sites

The study was conducted at two KoFlux sites: the Gwangneung deciduous forest (GDK; $37^\circ45'25.37''$N, $127^\circ9'11.62''$E, 291 MSL) and the Gwangneung coniferous forest (GCK; $37^\circ44'54.3''$N, $127^\circ9'45.3''$E, 120 MSL). Both sites are in a complex, hilly catchment ($\sim220$ ha) with a mean slope of $10^\circ$–$20^\circ$ and the two sites are about 1.5 km apart (Fig. 1). The 30-yr climate normal was 11.5°C for temperature and 1332 mm for precipitation (Hong et al. 2008). At the GDK site, the vegetation is dominated by an old natural forest of *Quercus* and *Carpinus* species (80–200 yr old) with a mean canopy height of $\sim18$ m. The GCK site is located in a generally lower and flat area than the GDK site and is a plantation forest with dominant species of *Abies* (90–100 yr old) with a mean canopy height of $\sim23$ m. Soil depth is 0.4–0.8 m and the soil texture is mainly silt loam at the GDK site and sandy loam at the GCK site. Further description of both sites can be found in Kim et al. (2006) and Lee et al. (2007).

b. Eddy covariance and meteorological measurements

Eddy covariance technique was used to measure ET from a 40-m tower at both sites. Vertical and horizontal
wind speeds and temperature were measured with a three-dimensional sonic anemometer (model: CSAT3, Campbell Scientific Inc., Logan, Utah) at 10 Hz for both sites. An open-path infrared gas analyzer (IRGA; model: LI-7500, LI-COR Inc., Lincoln, Nebraska) was used for both sites to measure water vapor concentration. Half-hourly eddy covariances and the associated statistics were calculated online from 10-Hz raw data and stored in the dataloggers (model: CR-5000, Campbell Scientific Inc.). Other measurements such as net radiation, air temperature, soil temperature, ground heat fluxes, and soil water content were sampled every minute, averaged over 30 min, and logged in the dataloggers (models: CR-3000 for the GDK site and CR-1000 for the GCK site, Campbell Scientific Inc.). More information can be found in Lee et al. (2007), Kang et al. (2009), and Kwon et al. (2009).

A multilevel profile system was installed at both sites to measure the vertical profile of concentrations of H₂O and CO₂ and air temperature and to estimate storage effects within the plant canopy using a closed-path IRGA (model: LI-6262, LI-COR Inc.) and a thermocouple (model: Type-E, OMEGA Engineering Inc.) (Hong et al. 2008; Yoo et al. 2009). The profile system, controlled by the dataloggers (models: CR-23X-TD, Campbell Scientific Inc.), was automatically calibrated on a daily basis for H₂O zero and CO₂ zero–span calibrations and was manually calibrated on a weekly to biweekly basis for H₂O and CO₂ zero–span calibrations. We used the data of the H₂O concentration and air temperature at 40 m from the profile system because of their reliability with regular calibrations and robust operation in rainy conditions.

c. Data processing, quality control, and gap filling

The eddy covariance data were processed, quality controlled, and then gap filled using the standardized KoFlux protocol (Hong et al. 2009). The standardized protocol includes planar fit rotation (PFR; Wilczak et al. 2001; Yuan et al. 2010), Webb–Pearman–Leuning (WPL) correction (Webb et al. 1980), spike detection (Papale et al. 2006), and gap filling (Reichstein et al. 2005). The ET data were screened further based on self-diagnostic variables such as warming flag for CSAT3 and auto gain control (AGC) value for LI-7500. When the total counts of CSAT3 warning flag were above 1800 points (10% of 18 000 points) and the AGC value deviated from the default value (i.e., 50 or 56 for the GDK site and 63 or 69 for the GCK site) with large fluctuation over 30 min, we discarded the data, considering them to be contaminated because of water drops or other objects blocking the signals of each instrument. After the quality control, the ET data retrieval rate was 85% at the GDK site and 80% at the GCK site during the study period. Prior to the gap filling of the ET data, the meteorological data were gap filled based on their linear relationship with the auxiliary data such as air temperature observed at the site. The MLT was used for the gap filling of the ET data. Since the ET data were processed following the standardized protocol of data processing proposed by the global flux network (FLUXNET), the MLT was selected as the gap-filling method in this study (Papale et al. 2006), which is known for its easy implementation and good performance (Moffat et al. 2007). ET data were binned by net radiation (\( R_n \)), air temperature (\( T_a \)), and vapor pressure deficit (VPD) over a time window of 28 days. The binning intervals were 50 W m⁻² for \( R_n \), 2.5°C for \( T_a \), and 0.5 kPa for VPD. The missing ET was replaced with the binned ET with similar meteorological conditions. More information can be found in Hong et al. (2009) and Kwon et al. (2010).

d. Plant area index measurements

The measurements of the plant area index (PAI) was conducted every 2 or 3 weeks using plant canopy analyzers (model: LAI-2000, LI-COR Inc.) under diffuse light conditions at 10 sampling points with 50 × 50 m² grid interval at the GDK site and 7 sampling points at the GCK site. Gap fraction was also estimated using LAI-2000 at each sampling point. We applied foliage clumping factor of 1.0 for the GDK site and 1.6 for the GCK site (Gower and Norman 1991), but did not apply shoot clumping factor for both sites. The leaf out occurred in early to mid-April and grew to full size around mid-June with PAI of 5.4 at the GDK site. PAI gradually decreased and reached its minimum of less than 1 in November (data not shown). At the GCK site, the leaf out occurred in early to mid-April and PAI reached its maximum of 7.5 around late May. PAI gradually decreased and reached its minimum of 4.4 in November.
The height to the crown base is about 10 m at the GDK site and about 13 m at the GCK site.

e. Measurement of canopy wetness

Canopy wetness was measured using the leaf wetness sensor (model: 237, Campbell Scientific Inc.), which is a simple resistive grid [a circuit board with interlacing gold-plated copper fingers, 71 mm (width) × 75 mm (length) × 6.4 mm (depth)]. We installed these sensors at four different heights considering the canopy structure (i.e., forest floor, base of the crown, middle of the crown, and the canopy top): 0.1, 10, 15, and 20 m at the GDK site and 0.2, 13, 19, and 24 m at the GCK site, respectively. They were mounted horizontally and the output of the sensor (ranging from 0 kΩ to infinity) was stored every 30 min in the dataloggers (models: CR-23X at the GDK site and CR-1000 at the GCK site, Campbell Scientific Inc.). The threshold of dry–wet conditions was set at 150 kΩ, indicating wet condition with 0–150 kΩ and dry condition with >150 kΩ.

We defined the term “fully wet canopy” as the conditions when precipitation is detected and the four wetness sensors are all wet. Similarly, “dry canopy” is defined as the conditions when all the four wetness sensors are dry. Everything in between fully wet and dry canopy is defined as “partially wet canopy”—that is, when at least one (typically the one at the canopy top) of the four sensors is dry. “Wet canopy” corresponds to “fully and partially wet canopy.”

At the GDK site, the transition time required for the wetness sensors to turn from wet to dry conditions was shortest at 20 m (on average, 0.4 h) because of exposure to higher wind and radiation compared to those below (Fig. 2). As expected, the transition time was longest at the forest floor (~5.1 h at 0.1 m). Similarly, at the GCK site, the transition time was shortest at 24 m (0.5 h on average) and longest at 0.2 m (~5.7 h). Transition times of longer than 10 h are noticed near the forest floor at both sites. Unlike the GDK site, the second-shortest transition time was observed in the middle of the crown (i.e., 19 m) at the GDK site, whereas it was below the crown base (at 13 m) at the GCK site. The unique structure of coniferous trees provided relatively open trunk space between the understory vegetation and the crown base (between 6 to 15 m above the ground), where the second maximum in the within-canopy wind speed profile was observed.

Overall, the partially wet canopy conditions lasted on average 5 h at the GDK site and 6 h at the GCK site.

f. Modeling of wet canopy evaporation

To calculate $E_{WC}$, we examined four algorithms used in various models with a temporal scale ranging from hourly to monthly intervals. First, the De Groen algorithm is an analytical model with a daily time scale based on statistical properties of daily rainfall and interception threshold (De Groen and Savenije 2006). The second is the Gash sparse algorithm—the most widely used analytical interception model that provides a simplified solution to the Rutter model with an output based on individual precipitation events (Gash et al. 1995; Muzylo et al. 2009). The other two algorithms are the VIC and the Noah LSMs (Liang et al. 1994; Chen and Dudhia 2001). Both algorithms are conceptually similar to that of the Rutter sparse model, which provides half-hourly outputs (Valente et al. 1997).

1) A MONTHLY INTERCEPTION ALGORITHM

An analytical model, based on Markov property of daily rainfall, was used to calculate monthly interception following De Groen and Savenije (2006) (hereafter, this
method is called the De Groen method). This method accounts for processes at smaller time scales that govern the monthly interception by considering a daily interception threshold and the statistical distribution of daily rainfall over a month as

\[ I_m = P_m \left[ 1 - \exp \left( - \frac{n_r D_d}{P_m} \right) \right], \quad (1) \]

where \( I_m \) is the monthly interception, \( P_m \) is the monthly rainfall, \( n_r \) is the number of rainy days per month, and \( D_d \) is the daily interception threshold, which is determined by a maximum canopy capacity and evaporation rate. The \( n_r \) is estimated as follows:

\[ n_r = \frac{30 p_{01}}{1 - p_{11} + p_{01}}, \quad (2) \]

where \( p_{01} \) is the probability of a rainy day after a dry day and \( p_{11} \) is the probability of a rainy day after rainy day. Using the power function of monthly rainfall collected from January 2006 to December 2009 at Gwangneung [i.e., \( p_{01} = q (P)^r \) and \( p_{11} = u (P)^s \)], we obtained site-specific coefficients \( q = 0.08, r = 0.14, u = 0.01, \) and \( v = 0.65 \). We used \( D_d \) of 4.2, which was determined by the relationships between precipitation, throughfall, and stemflow observed in mixed forests in Korea (Kim et al. 2005; Lee et al. 2010).

2) GASH SPARSE ALGORITHM

The Gash sparse model is the most widely used analytical interception model that provides a simplified solution to the Rutter model (Gash et al. 1995; Muzyllo et al. 2009). The primary assumption of the model is that it is possible to represent the real rainfall pattern by a series of discrete storms, separated by sufficiently long intervals for the canopy and trunks until they become dry (Gash 1979). The Gash sparse model considers rainfall as a series of discrete events (i.e., wetting up, saturation, and drying out of the canopy). Wetting up is the period when the rainfall, \( P \), is less than the threshold value \( (P_G) \) to saturate the canopy. When \( P > P_G \), it is the period of saturation. After rainfall stops, it is defined as a drying-up period until the canopy becomes fully dry. The \( P_G \) is calculated as

\[ P_G = \frac{\overline{R_S}}{\overline{E_c}} \ln \left[ 1 - \left( \frac{E_c}{\overline{R}} \right) \right], \quad (3) \]

where \( \overline{E_c} (= \overline{E}/\sigma_f) \) is the mean evaporation rate from the canopy per unit area of canopy, \( \overline{E} \) is the mean evaporation rate, \( \sigma_f \) is the vegetation fraction (i.e., one-gap fraction), \( \overline{R} \) is the mean rainfall rate for saturated canopy during rainfall, \( S_c (= S/\sigma_f) \) is the canopy capacity per unit area of canopy, and \( S \) is the canopy capacity. The quantities \( \overline{E} \) and \( \overline{R} \) are the mean values of evaporation rate \( (E_p) \)—which is potential evaporation under wet canopy condition—and precipitation \( (P) \), respectively, for hours with \( P > 0.5 \text{ mm} \) from a saturated canopy over a 4-week period (Gash 1979).

The \( E_p \) is calculated using the Penman–Monteith equation (Monteith 1965):

\[ E_p = \frac{eA + (\rho c_p VPD g_a Y)}{\lambda (\varepsilon + 1)}, \quad (4) \]

where \( \lambda \) is the latent heat of vaporization, \( c_p \) is the specific heat of air, \( Y \) is the psychrometric constant, \( \varepsilon \) is the dimensionless ratio of the slope of the saturation vapor pressure curve to psychrometric constant, \( A \) is the available energy \( (= R_N - G - S_E = \lambda E + SH) \), \( G \) is ground heat flux, \( S_E \) is heat storage, \( AE \) is latent heat flux, and \( SH \) is sensible heat flux), and \( g_a \) is the aerodynamic conductance.

By assuming that \( g_a \) for heat and water vapor is identical, \( g_a \) is estimated as

\[ g_a = \frac{1}{r_a} = \frac{1}{r_{am} + r_b}, \quad (5) \]

\[ r_{am} = \frac{U}{u_b^2}, \quad \text{and} \quad (6) \]

\[ r_b = \left( \frac{2}{0.4 u_b^2} \right)^{k (D_v)^{2/3}}, \quad (7) \]

where \( r_a \) is the aerodynamic resistance of heat and water vapor transfer, and \( r_{am} \) and \( r_b \) are the aerodynamic resistance of momentum transfer and the excess resistance (Thom 1972; Kim and Verma 1990). The \( U \) is the mean horizontal wind speed, \( u_b \) is the friction velocity, \( k \) is the thermal diffusivity, and \( D_v \) is the molecular diffusivity of water vapor.

In the Gash sparse model, the total \( E_{WC} \) is calculated as

\[ \sum_{j=1}^{l+m} E_{WC,m} = \sigma_f \sum_{j=1}^{l} P_j + m \sigma_f P_G' - m \sigma_f S_c \]

\[ = \underbrace{A}_{\sum_{j=1}^{l} P_j} + \underbrace{B}_{m \sigma_f P_G'} + \underbrace{C}_{m \sigma_f S_c} + \underbrace{D}_{q S_t + \sum_{j=1}^{m-q} P_j} + \underbrace{E}_{q S_t + \sum_{j=1}^{m-q} P_j}, \quad (8) \]
where \( p_r \) is the proportion of the rainfall diverted to the trunks as stemflow, and \( S_r \) is the trunks storage capacity. We used \( p_r \) of 0.09 for the GDK site and 0.06 for the GCK site and \( S_r \) of 0.21 and 0.07, respectively. These values were determined by the relationships between precipitation and stemflow observed at the deciduous and coniferous forests in Gwangneung (Kim et al. 2005). The first term \( A \) in Eq. (8) is the total \( E_{WC} \) for \( l \) small storms that are insufficient to saturate the canopy, the term \( B \) is \( E_{WC} \) for wetting up the canopy for \( m \) storms > \( P_i \) that saturated the canopy, the third term \( C \) is \( E_{WC} \) from trunks for \( q \) storms > \( S/p_r \) that saturate the trunks and for the \( m - q \), which do not (for further details, see Gash et al. 1995). In this study, the parameterization of \( S \) is as also used in the algorithm of VIC LSM in the following chapter.

3) ALGORITHMS IN VIC AND NOAH LAND SURFACE MODELS

Most LSMs nowadays include a rainfall interception algorithm (i.e., an estimation of \( E_{WC} \)). We adopted the algorithms of VIC LSM (Liang et al. 1994) and Noah LSM (Chen and Dudhia 2001). Although the algorithm of VIC LSM can consider \( N \) vegetation types, we simplified it to consider only one vegetation type for each site (i.e., deciduous forest at the GDK site and coniferous forest at the GCK site). Then, \( E_{WC} \) is estimated as follows:

\[
E_{WC} = \sigma_f E_p \left( \frac{W_c}{S} \right)^n \left( \frac{r_a}{r_a + r_0} \right),
\]

where \( E_p \) is the potential evaporation, \( r_a \) is the aerodynamic resistance, and \( r_0 \) is the architectural resistance (2 s m\(^{-1}\) in the algorithm of VIC LSM; neglected in the algorithm of Noah LSM). The \( r_a/r_a + r_0 \) term is added to consider the variation of the gradient of specific humidity between the leaves and the overlying air in the canopy layer. The \( W_c \) is the intercepted canopy water, and the exponent \( n \) is an empirical coefficient.

The quantity \( W_c \) is estimated as

\[
\frac{\partial W_c}{\partial t} = \sigma_f P - D - E_{WC},
\]

where \( P \) is the input total precipitation and \( D \) is the excess precipitation or drip. When \( W_c > 0 \), canopies are either fully or partially wet. When \( W_c \) exceeds \( S \), drip starts and \( D > 0 \). In the algorithm of VIC LSM, \( S = 0.2 \times \text{PAI} \) (originally not PAI but leaf area index) and \( n = \frac{1}{5} \), whereas \( S = 0.5 \) and \( n = 0.5 \) in the algorithm of Noah LSM. In both LSMs, the value of \( n \) determines the rate of \( E_{WC} \) by adjusting the magnitude of \( W_c/S \). Unlike the Rutter model, which neglects \( n \) (i.e., \( n = 1 \)), the two LSMs force the canopy to become dry faster by empirically setting the value of \( n \) < 1. The \( E_p \) was calculated using the meteorological data (e.g., \( R_n \), \( T_m \), VPD, and \( U \)). The daily PAI was linearly interpolated between the two neighboring samplings. It should be noted that both algorithms of the LSMs only consider \( E_{WC} \) from the canopy by ignoring \( E_{WC} \) from trunk and stemflow.

g. Evaluation of model wet canopy duration

The wet canopy duration estimated from the LSM algorithms was compared with the observations in order to assess their performance using the fraction of the correct estimates (\( \theta_1 \)):

\[
\theta_1 = \frac{H + N}{H + M + F + N},
\]

where \( H \) is the hits, \( M \) is the misses, \( N \) is the correct negatives, and \( F \) is the false alarm. The \( H \) denotes the number of cases when the canopy was observed and estimated as wet, whereas \( M \) denotes when the canopy was observed as wet but estimated as dry. The quantities of \( N \) and \( F \) express the numbers of cases of dry in the observation that accompanied dry and wet estimates, respectively. Exceedingly long hours of dry canopy duration, compared to those of wet canopy duration, resulted in high values of \( N \) and thereby \( \theta_1 \). To correct for the artifact, a \( k \) statistic was used (Dietterich 2000):

\[
k = \frac{\theta_1 - \theta_2}{1 - \theta_2},
\]

where \( \theta_2 \) is an estimate of the probability that the two classifiers (e.g., modeling and measurement) agree by chance, given the observed counts in the contingency table. The term, \( \theta_2 \), is defined as follows:

\[
\theta_2 = \frac{(H + M)(H + F)}{(H + M + F + N)^2} + \frac{(F + N)(M + N)}{(H + M + F + N)^2}. \tag{13}
\]

We calculated both \( \theta_1 \) and \( k \) for the GDK and GCK sites and evaluated the model performance in estimating wet canopy duration. The \( \theta_1 \) and \( k \) range from 0 to 1, where 0 is complete disagreement and 1 is complete agreement.

h. Error assessment

We compared the modeled \( E_{WC} \) against the observed data using three statistical measures, following Willmott
and Matsuura (2005). Mean absolute error (MAE) is the sum of the absolute values of the residuals. A large deviation from zero implies that the estimation generally overestimates or underestimates compared to the observed values. Root-mean-square error (RMSE) is reported with MAE because RMSE is more sensitive to large errors than MAE:

\[
\text{MAE} = \frac{1}{n} \sum |Y_{\text{est}} - Y_{\text{obs}}|, \quad \text{and} \quad (14)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum (Y_{\text{est}} - Y_{\text{obs}})^2}, \quad (15)
\]

Both MAE and RMSE give estimates of the average error, but neither measure provides information about the relative size of the average difference. Thus, we considered an index of agreements (\(d\)) (Willmott 1982):

\[
d = 1 - \frac{1}{N} \sum_{i=1}^{N} \frac{(Y'_{\text{est}} - Y'_{\text{obs}})^2}{(Y'_{\text{est}} + Y'_{\text{obs}})^2}, \quad (16)
\]

where \(Y'_{\text{est}} = Y_{\text{est}} - Y_{\text{obs}}\) and \(Y'_{\text{obs}} = Y_{\text{obs}} - Y_{\text{obs}}\) (where overbar is an averaging operator). It ranges from 0 to 1, where 0 is for complete disagreement and 1 for complete agreement between the observation and the estimates. It is both a relative and bounded measure that can be widely applied in order to make cross comparison between models.

3. Results and discussion

a. Characteristics of precipitation and wet canopy conditions

In this analysis, we separated the data into the daytime (when incoming solar radiation \(R_s > 0 \text{ W m}^{-2}\)) and nighttime periods \((R_s = 0 \text{ W m}^{-2})\) because the mechanism of energy partitioning is different between day and night. For simplicity, we excluded the snow events from our analysis, which amounted to ~1.5% of the total precipitation.

1) GDK SITE

During the 1-yr study period, the precipitation added up to 1503 mm (i.e., 10% higher than the 30-yr normal). The rainfalls occurred 68 times with the highest frequency (of 14 times) in September (Fig. 3). About 60% of the rainfall events occurred between June and September, which coincided with the period of summer monsoon including typhoons. In terms of the amount, the precipitation during these four months accounted for 77% of the annual total. The duration of precipitation was in a total 642 h (i.e., ~27 days), which spread out evenly to daytime and nighttime. Although the duration of precipitation was similar, the precipitation amount during the nighttime \((824 \text{ mm})\) was 20% greater. The duration was longest in July with 155 h, followed by September and August with ~100 h each. As expected, longer duration accompanied with larger amount of precipitation (e.g., 630 mm in July and 292 mm in August).

In comparison to the duration of precipitation, that of the wet (i.e., fully and partially wet) canopy conditions was 1363 h (~57 days), which was twice as long and also spread out almost evenly to daytime and nighttime. The characteristics and seasonality of frequency and duration of the wet canopy were similar to those of the precipitation duration.

2) GCK SITE

The total precipitation was 1476 mm. The monthly patterns of precipitation amount, duration, and wet canopy conditions at the GCK site were similar to those at the GDK site, except small quantitative differences in the duration of precipitation (~30 h shorter) and wet canopy conditions (~30 h longer).

3) DATA COLLECTION BY EC

After the precipitation stopped during the daytime, the wet canopy conditions persisted on average 11.5 (~7.5) h at the GDK site and 12.5 (~7.0) h at the GCK site with an overall range of 2–28 h. During the nighttime, it lasted about 11.5 (~6.0) h with a range of 3.5–32 h at both sites (data not shown). During those 57 days of wet canopy conditions, the percentage of the missing wet canopy evaporation \((E_{WC})\) data was about 65% at both sites. The major cause of such data loss was the malfunction of the EC system, of which ~90% of the failure was associated with the open-path infrared gas analyzers. On the contrary, the 3D sonic anemometers operated reasonably well under wet conditions, causing only 10%–25% of data loss, as reported by Czikowsky and Fitzjarrald (2009).

We examined the performance of the sonic anemometer during wet conditions following the Monin–Obukhov similarity theory. The relationship between the standard deviation of the vertical wind \((\sigma_u)\) and \(u_w\) should be constant in neutral conditions and the regression between \(\sigma_u\) and \(u_w\) should be linear.

When the stability was neutral \([-0.1 < (z - d_{\text{zero}})/L < 0.1]\); where \(z\) is the measurement height, \(d_{\text{zero}}\) is the zero-plane displacement, and \(L\) is the Obukhov length] following the previous study on turbulent characteristics.
at the Gwangneung site (Hong et al. 2008), the slope of the linear regression was 1.29 with $r^2$ of 0.77 for the GDK site and 1.20 with $r^2$ of 0.84 for the GCK site (data not shown). These are comparable with the typical value of 1.25 reported by Garratt (1992). These results are similar to those under dry conditions: 1.23 with $r^2$ of 0.85 for the GDK site and 1.16 with $r^2$ of 0.86 for the GCK site. These results demonstrate that the sonic anemometer performed well without being affected by rain during the wet canopy conditions.

Overall, the characteristics of the precipitation and wet canopy conditions were very similar between the two sites. The large amount of precipitation centered around the growing season along with considerably long durations of wet canopy conditions suggest that $E_{WC}$ at these two sites would be substantial, which was further examined below.

b. Wet canopy evaporation and energy partitioning

To characterize the measured wet canopy latent heat flux ($\lambda E_{WC}$) and energy partitioning (in terms of the Bowen ratio, $\beta = SH/\lambda E$), we analyzed their mean diurnal variations and then compared against those observed under dry canopy conditions (Fig. 4). The sign convention is such that negative sign indicates the energy loss from the surface. Because the measured $\lambda E$ cannot be separated into wet canopy evaporation and transpiration, we excluded the $\lambda E$ under partially wet canopy conditions from this analysis.

1) GDK SITE

During the daytime, $\lambda E_{WC}$ ranged from $-420$ to $20$ W m$^{-2}$. The magnitude of $\lambda E_{WC}$ was on average $-53$ ($\pm 73$) W m$^{-2}$. The averaged $\beta$ was 0.14, indicating that most of the available energy was partitioned to $\lambda E_{WC}$ under fully wet canopy conditions. The magnitude of $\lambda E_{WC}$ was comparable to $\lambda E$ under dry canopy conditions, ranging from $-580$ to $60$ W m$^{-2}$ with an average of $-55$ ($\pm 80$) W m$^{-2}$. The $\beta$ under dry canopy conditions was $\sim 1$. During the nighttime, $\lambda E_{WC}$ ranged from $-220$ to $30$ W m$^{-2}$ with an average of $-12$ ($\pm 25$) W m$^{-2}$, which was greater than $\lambda E$ under dry canopy conditions. The latter ranged from $-110$ to $60$ W m$^{-2}$ with an average of $-3$ ($\pm 12$) W m$^{-2}$.

2) GCK SITE

During the daytime, the range of $\lambda E_{WC}$ at the GCK site ($-380$ to $20$ W m$^{-2}$) was similar to that of the GDK. The averaged $\lambda E_{WC}$ [$-57$ ($\pm 70$) W m$^{-2}$] was smaller than that under dry canopy conditions [$-85$ ($\pm 99$) W m$^{-2}$].
The $\beta$ under fully wet canopy conditions was virtually zero whereas the $\beta$ was $\sim$1 under dry canopy conditions. During the nighttime, $\lambda E_{\text{WC}}$ was similar to that at the GDK.

Large magnitudes of $\lambda E_{\text{WC}}$ ($<-100 \text{ W m}^{-2}$) were occasionally observed at nighttime during fully wet canopy conditions at both sites. Several studies have reported large $\lambda E_{\text{WC}}$ at nighttime (Pearce et al. 1980; Czikowsky et al. 2006). The large magnitudes of $\lambda E_{\text{WC}}$ are attributed to an increased $g_a$ and/or additional energy sources such as heat storage and sensible heat advection (Stewart 1977; Schellekens et al. 2000; Czikowsky and Fitzjarrald 2009). For instance, the GCK site had $-210$ to $-90 \text{ W m}^{-2}$ of $\lambda E_{\text{WC}}$ from 2130 on 28 October to 0130 on 29 October. During these hours, the canopy was completely wet following 11 mm of the precipitation, and $\bar{U}$ was above 5.0 m s$^{-1}$ with $u_w$ of 1 m s$^{-1}$, resulting in high values of $g_a$ ($\sim 100 \text{ mm s}^{-1}$). The annually averaged $\bar{U}$ and $u_w$ were 1.0 and $u_w$ of 0.3 m s$^{-1}$ at the GCK site, respectively. Furthermore, the advection of sensible heat (indicated as positive SH ranging from 70 to 225 W m$^{-2}$) was a significant source of additional energy for $\lambda E_{\text{WC}}$.

c. Comparison among the wet canopy evaporation algorithms

The seasonal patterns of the monthly $E_{\text{WC}}$ estimated by the four algorithms were similar and the magnitudes of the monthly $E_{\text{WC}}$ were also similar except $E_{\text{WC}}$ estimated by the algorithm of the De Groen at the GDK.
and GCK sites (Fig. 5). As expected, the magnitudes of the monthly $E_{WC}$ were closely related to wet canopy duration at both sites (Fig. 3). The algorithm of the De Groen method overestimated $E_{WC}$ values by more than a factor of 2 compared to the other algorithms. Such an overestimation was due to unrealistically high values of $D_d$ (of 4.2), which should be lower and also seasonally variable. The annual $E_{WC}$ averaged from the other three methods was 83.6 mm at the GDK site and 83.62 mm at the GCK site. The annual $E_{WC}$ was 6% of the annual precipitation at both sites. For further analysis, we selected the algorithms of VIC and Noah LSMs, which provide half-hourly outputs allowing direct comparison with the measured and gap-filled $E_{WC}$.

d. Validation of the estimated wet canopy duration

The duration of wet canopy is an important determinant of $\lambda E_{WC}$ in the algorithms of the LSMs, in which wet canopy is defined as the canopy when $W_c > 0$ mm, thereby including the conditions of partially wet (or partially dry) canopy.

The observed duration of wet canopy consisted of approximately 16% of the total duration of the field observation at both sites. The VIC LSM identified 93% of the observed duration of wet canopy ($H = 0.15$) at the GDK sites and 97% ($H = 0.15$) at the GCK site (Table 1). The Noah LSM, on the other hand, identified 77% ($H = 0.12$) at the GDK site and 76% ($H = 0.12$) at the GCK site. The different results between the two LSMs were mainly due to the different calculations of $S$ and $n$ [in Eq. (9)]. The $S$ in Noah LSM was constant (=0.5) whereas $S$ in VIC LSM was a function of PAL, varying from 0.3 to 1.1. As a result, $S$ in Noah LSM was lower than in VIC LSM from April to October at the GDK site (and throughout the entire year at the GCK site), causing a faster rate of $E_{WC}$ and reduced duration of wet canopy condition. In addition, the smaller $n$ (=0.5) in Noah LSM shortened the wet canopy duration compared to that (=2/3) of VIC LSM. Accordingly, the total duration of wet canopy with Noah LSM was 1091 h at the GDK site and 1062 h at the GCK site, which was 280–440 h less than the respective total duration of 1373 and 1502 h with VIC LSM.

The overall performance of the algorithms in the estimation of wet canopy duration was evaluated using the fraction of the correct estimates ($\theta_1$) and $k$ statistics [see Eqs. (11) and (12)]. The values of $\theta_1$ were high (0.98 with VIC LSM and 0.96 with Noah LSM) because of high values of $N$ from longer hours of dry canopy duration compared to those of wet canopy duration. The values of $k$, which incorporated the correction for the artifact of high $N$ from longer hours of dry canopy duration compared to those of wet canopy duration. The values of $k$ were 0.92 with VIC LSM and 0.84 with Noah LSM. These $k$ values are higher than those reported from the empirical models based on relative humidity threshold, decision tree, or fuzzy logic system (0.65–0.70 of the 90th percentile among the 15 sites) (Kim et al. 2010). We concluded that both VIC and Noah LSM algorithms performed very well. In particular, the former performed better because of its realistic leaf phenology in the parameterization of $S$.

e. Comparison of wet canopy evaporation

In Fig. 6, we evaluated the algorithms of the VIC and Noah LSMs by comparing the modeled $\lambda E_{WC}$ with the observed at the GDK and GCK sites. The number of the data points used in the comparison with Noah LSM was smaller than that with VIC LSM for both test sites. As indicated earlier, this was due to lower values of $S$ and

<table>
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<th>Algorithm</th>
<th>$H$</th>
<th>$M$</th>
<th>$F$</th>
<th>$N$</th>
<th>$\theta_1$</th>
<th>$k$</th>
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<td>GCK VIC</td>
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<td>0.82</td>
<td>0.98</td>
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<td>0.84</td>
<td>0.96</td>
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TABLE 1. Comparison of the wet canopy duration between the algorithms in VIC and Noah LSMs and the observation. Here $H$ denotes the number of cases when the canopy was observed and estimated as wet, whereas $M$ denotes when the canopy was observed as wet but estimated as dry; $N$ and $F$ express the number of cases of dry in the observation that accompanied with dry estimate and wet estimate, respectively; $\theta_1$ and $k$ express the fraction of the correct estimate and $k$ statistic, respectively.
in the algorithm of Noah LSM [see Eq. (9)], resulting in quickened canopy dryness and shortened wet canopy duration. To minimize the confounding effect of the partially dry canopy in this analysis, the partially wet conditions were excluded.

During the daytime, the algorithm of Noah LSM underestimated $\lambda E_{WC}$ with MAE of 28 and 24 W m$^{-2}$ at the GDK and GCK sites, respectively. Although MAE and RMSE were greater because of larger magnitudes of $\lambda E_{WC}$ during the daytime, the agreement with the observed $\lambda E_{WC}$ was better (with higher $r^2$ and $d$ values) than the nighttime at both sites (Table 2 and Fig. 6). Compared to Noah LSM, the algorithm of VIC LSM showed similar results but better agreement with the observed $\lambda E_{WC}$ because of more realistic leaf phenology. Potential causes of such difference may be attributed to inappropriate parameterization of $S$ and/or unaccounted processes of small droplets produced by splashes. Based on the reliable results in estimating $\lambda E_{WC}$ (Fig. 6 and Table 2), we selected the algorithm of VIC LSM for further analysis.

f. Comparison between the MLT method and the algorithm of VIC LSM

To ascertain the accuracy of the current gap-filling method, we filled up the missing $\lambda E_{WC}$ data during the fully wet canopy conditions by using 1) the MLT gap-filling method ($\lambda E_{WC,MLT}$) and 2) the algorithm of VIC LSM ($\lambda E_{WC,VIC}$). As shown in Fig. 7, $\lambda E_{WC,MLT}$ consistently underestimated $\lambda E_{WC,VIC}$. The mean bias error ($\text{MBE} = \sum(Y_{\text{est}} - Y_{\text{obs}})/n$) was 29 W m$^{-2}$ at the GDK site and 21 W m$^{-2}$ at the GCK site at daytime whereas}

![Fig. 6. Comparison of wet canopy evaporation during fully wet canopy conditions: $\lambda E_{WC,Obs}$ indicates observed $\lambda E_{WC}$, while $\lambda E_{WC,VIC}$ and $\lambda E_{WC,Noah}$ indicate estimated $\lambda E_{WC}$ from the algorithms in VIC and Noah LSMs, respectively: (a),(b) $\lambda E_{WC,VIC}$ vs $\lambda E_{WC,Obs}$ and (c),(d) $\lambda E_{WC,Noah}$ vs $\lambda E_{WC,Obs}$ at the (a),(c) GDK and (b),(d) GCK sites.](image)

| TABLE 2. Statistical parameters for error assessment at the GDK and GCK sites. |
|---------------------------------|-----------------|-----------------|-----------------|-----------------|
|                                | **GDK**         | **GCK**         | **GDK**         | **GCK**         |
|                                | **Algorithm**   | **Night**       | **Day**         | **Night**       | **Day**         | **Night**       | **Day**         |
| **Algorithm**                  | **VIC LSM**     | **Noah LSM**    | **VIC LSM**     | **Noah LSM**    | **VIC LSM**     | **Noah LSM**    | **VIC LSM**     | **Noah LSM**    |
| **MAE (W m$^{-2}$)**           | 13              | 24              | 14              | 28              | 13              | 19              | 13              | 24              |
| **RMSE (W m$^{-2}$)**          | 18              | 37              | 20              | 43              | 18              | 27              | 18              | 41              |
| **$d$**                        | 0.87            | 0.91            | 0.83            | 0.85            | 0.81            | 0.95            | 0.84            | 0.86            |
the MBE at nighttime was 26 and 16 W m\(^{-2}\), respectively. Under fully wet canopy conditions, canopy conductance becomes infinity (hence, unimportant) and \(\lambda E_{WC}\) approaches its potential rate [see Eq. (4)], which depends not only on \(R_N\) (and VPD) but also on \(g_a\). The effect of \(g_a\) is not considered in the current MLT-based gap filling. At both sites, the magnitude and variability of \(R_N\) and VPD were small with nighttime average of 220 (±60) W m\(^{-2}\) and 0.1 (±0.1) kPa and daytime average of 70 (±90) W m\(^{-2}\) and 0.2 (±0.2) kPa. However, \(g_a\) was sizable and variable with nighttime average of 30 (±30 mm s\(^{-1}\)) and daytime average of 40 (±30) mm s\(^{-1}\).

In addition to the aerodynamic effect, we identified additional energy sources (i.e., \(S_E\) and advection of sensible heat) that enhanced \(\lambda E_{WC}\) but were not taken into account in the MLT-based gap filling. To illustrate such a mechanism driving the \(\lambda E_{WC}\) at low \(R_N\), we present two cases: 1) the nighttime wet canopy on 9 April 2008 and 2) the daytime wet canopy on 16 July 2008 at GDK and GCK sites. To estimate \(S_E\), we considered the heat storage of canopy air space and biomass (e.g., Oliphant et al. 2004) and assumed under wet canopy conditions that 1) \(G\) was negligible, 2) \(T_a\) and vapor pressure were constant inside the canopy for canopy air space heat storage, and 3) \(T_a\) and bole temperature were the same for biomass heat storage (e.g., Papale et al. 2006). Based on the study of Lim et al. (2003), we estimated the biomass to be 26.1 kg m\(^{-2}\) at the GDK site and 31.4 kg m\(^{-2}\) at the GCK site. We used the specific heat of vegetation of 3340 J kg\(^{-1}\) K\(^{-1}\) (Wilson and Baldocchi 2000). In Fig. 8, the \(\lambda E_{WC, VIC}\) on both days (with a range of -120–0 W m\(^{-2}\) at nighttime and -260–0 W m\(^{-2}\) at daytime) displayed the mirrored patterns of the sum of the other energy budget components. When \(R_N\) and VPD were low, however, \(\lambda E_{WC,MLT}\) was negligible at nighttime and fluctuated between -40 and 0 W m\(^{-2}\) at daytime. The available energy for \(\lambda E_{WC}\) was provided predominantly by the advection of sensible heat (64 ± 43 W m\(^{-2}\) at the GDK and 36 ± 29 W m\(^{-2}\) at the GCK at nighttime and 42 ± 44 and 25 ± 38 W m\(^{-2}\) at daytime, respectively). The contribution of heat storage was relatively small with daytime average of 10 ± 39 W m\(^{-2}\) at the GDK site and 8 ± 36 W m\(^{-2}\) at the GCK site. The contribution at nighttime was even smaller with an average of 2 ± 24 and -3 ± 37 W m\(^{-2}\), respectively.

Table 3 shows the annually integrated \(E_{WC,MLT}\) and \(E_{WC, VIC}\) under fully wet canopy conditions. The annual \(E_{WC,MLT}\) at the GDK and GCK sites were respectively 24.0 and 24.7 mm whereas the annual \(E_{WC, VIC}\) was much greater with 57.8 and 47.8 mm, respectively. The resulting discrepancies would be site specific and vary considerably according to canopy structure, frequency and intensity of precipitation, and other meteorological conditions. Overall, the above results suggest the necessity of a separate gap-filling procedure during wet canopy conditions.

Prior to suggesting new gap-filling strategies below, it should be noted that so far we have examined fully wet canopy conditions only. However, the duration of partially wet canopy conditions consisted of ¼ of total duration of wet canopy conditions. The annually integrated \(E_{WC,MLT}\) (including both \(E_{WC}\) and transpiration) and \(E_{WC, VIC}\) under partially wet canopy conditions were 32.7 and 24.4 mm at the GDK site and 54.0 and 38.5 mm at the GCK site, respectively. The comparisons contrast with those under fully wet canopy conditions because of the contribution of transpiration under partially wet conditions (Table 4). Neglecting such contribution would result in biased \(E_{WC}\) (e.g., Ohta et al. 2008).
Below, we propose two different gap-filling strategies based on the availability of canopy wetness measurements and canopy wetness conditions.

g. New gap-filling strategies for $E_{WC}$

1) WHEN THE MEASUREMENTS OF MULTILEVEL LEAF WETNESS ARE AVAILABLE

As a first step, fill in all the missing gaps using the gap-filling method (e.g., MLT) in which only the data from dry canopy conditions (i.e., when all wetness sensors are dry) are used. Then, for wet canopy conditions (i.e., when at least one of wetness sensors is wet), replace the gap-filled data (from the first step) with the sum of $E_{WC,VIC}$ and the gap-filled data multiplied by $1 - (W_c/S)^n$ (i.e., contribution from transpiration) [see Eqs. (4), (9), and (10)].

2) WHEN THE MEASUREMENTS OF MULTILEVEL LEAF WETNESS ARE ABSENT

First, as a measure of canopy wetness, calculate the intercepted canopy water [$W_c$; see Eq. (10)]. Then, follow the same procedures as described above. Fill in all the missing gaps using the gap-filling method (e.g., MLT) in which only the data from dry canopy conditions (i.e., when $W_c = 0$). Then, for wet canopy conditions (i.e., when $W_c > 0$), replace the gap-filled data with the sum of $E_{WC,VIC}$ and the gap-filled data multiplied by $1 - (W_c/S)^n$. 

Fig. 8. Diurnal variation of $R_N$, $\lambda E$, $SH$, the sum of three energy components ($= R_N + S_E + SH$, where $S_E$ is heat storage), and wet canopy evaporation simulated by the modified lookup table method ($\lambda E_{WC,MLT}$) and the algorithm of VIC LSM ($\lambda E_{WC,VIC}$) at the GDK and the GCK sites for the dates shown. Shaded area represents the period of wet canopy condition.
As the final check, we applied the above two gap-filling strategies for the entire periods of wet canopy duration (~57 days) for which ET\textsubscript{WC,MLT} was 57 mm at the GDK site and 79 mm at the GCK site. The two new gap-filling strategies yielded virtually identical results: 94 mm (~65% increase) at the GDK site and 110 mm (~40% increase) at the GCK site.

4. Summary and conclusions

Based on the direct measurements of wet canopy evaporation by eddy covariance and canopy wetness by multilevel wetness sensors, we have examined the role of $E\textsubscript{WC}$ in ET from temperate deciduous and coniferous forests in monsoon Asia. The major findings in our study are 1) for the entire year of observation, the duration of precipitation was 27 days in a deciduous forest and 26 days in a coniferous forest in Gwangneung, Korea. Wet canopy duration was ~57 days for both sites, of which 35% was successfully measured by the open-path EC system; 2) the magnitudes of the measured $E\textsubscript{WC}$ were comparable at daytime and greater at nighttime in comparison to those of ET under dry canopy conditions. Particularly at nighttime, sizable $\lambda E\textsubscript{WC}$ (~210 to ~90 W m\textsuperscript{-2}) was frequently observed because of enhanced aerodynamic effect (i.e., high $g_a$) and additional energy sources from sensible heat advection and heat storage; 3) among the four algorithms tested for the estimation of $\lambda E\textsubscript{WC}$, VIC LSM showed the best agreement in terms of wet canopy duration ($k \approx 0.92$), magnitudes, and patterns of $\lambda E\textsubscript{WC}$ ($d = 0.81 \sim 0.95$) in comparison against the direct measurements; 4) the half-hourly values of $\lambda E\textsubscript{WC}$ estimated by a traditional MLT-based gap-filling consistently and significantly underestimated those estimated from the algorithm of VIC LSM by 40%–65% because of the failure of considering aerodynamic coupling, advection of sensible heat, and heat storage; and finally 5) we proposed two different gap-filling strategies based on the availability of canopy wetness measurements and canopy wetness conditions.

Despite the potentially significant contribution of $E\textsubscript{WC}$ to ET, little attention has been given in the process of gap filling of $E\textsubscript{WC}$ in the monsoon regions. For example, among the current 23 sites whose data are available in the AsiaFlux database, more than half of the sites employ open-path EC systems and apply the MLT-based gap filling for ET. Those datasets deserve further scrutiny regarding the potential biases in $E\textsubscript{WC}$. The application of the proposed new gap-filling strategies would improve the reliability of the gap-filled ET database. Alternatively, a better way to resolve the shortcomings of the current gap-filling method may be the direct measurement of $E\textsubscript{WC}$ by an application of aerodynamic-variance method combined with the use of closed-path EC system, which is currently in progress (e.g., Dias et al. 2009; Yoo 2010).

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