Spatiotemporal variations of $T/ET$ (the ratio of transpiration to evapotranspiration) in three forests of Eastern China

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1. Introduction

Forest, occupying 31% of the land surface, plays an important role in global mass cycles and energy flows (FAO, 2010). Evapotranspiration (ET) of forest, an important component sustaining the forest water and energy balance (Falge et al., 2005), affects the forest water and energy balance (Falge et al., 2005), affects the global energy partition and then climate, whereas ET is comprised by multiple source water vapor fluxes such as evaporation from soil surface ($E$), transpiration ($T$) and evaporation from the intercepted water by canopy ($E_{i}$), which are controlled by different biotic and physical processes (Scanlon and Kustas, 2012). Therefore, to fully clarify the role of each process in forest ET and then in regulating climate, it is critical to quantify the portion of ET components in ET and reveal factors controlling these portions (Hu et al., 2009; Lawrence et al., 2007).

The ratio of $T$ to ET ($T/ET$), the key parameter for productivity and water use efficiency (Hu et al., 2008; Schlesinger and Jasechko, 2014), reflects the role of vegetation ecophysiological processes in water loss through ET (Hu et al., 2009), which is also a parameter indicating the role of plant ecophysiological processes in regulating climate. The variation of $T/ET$ and its affecting factors have been extensively investigated (Hu et al., 2009; Kato et al., 2004), while most studies about the variation of $T/ET$ are conducted in croplands or grasslands (Hu et al., 2009; Kato et al., 2004; Liu et al., 2002), it is still unclear what dominated the spatiotemporal variations of $T/ET$ in forests.

Meanwhile, quantifying $T/ET$ should base on ET partition, which can be fulfilled through various measurements and models (Blyth...
### 2. Materials and methods

#### 2.1. Site description and measurements

#### 2.1.1. Site descriptions

We collected data from three ChinaFLUX sites: Changbaishan temperate broad-leaved Korean pine mixed forest (CBS), Qianyanzhou subtropical coniferous plantation (QYZ), and Dinghushan subtropical evergreen mixed forest (DHS). Brief descriptions about these three sites were listed in Table 1. Detailed information can be found in our previous works (Wen et al., 2010; Yan et al., 2013; Yu et al., 2008; Zhang et al., 2006).

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Site descriptions.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sites</td>
<td>CBS</td>
</tr>
<tr>
<td>Latitude (°N)</td>
<td>42.4025</td>
</tr>
<tr>
<td>Longitude (°E)</td>
<td>128.0928</td>
</tr>
<tr>
<td>Elevation (m.a.s.l.)</td>
<td>738</td>
</tr>
<tr>
<td>Mean annual temperature (°C)</td>
<td>3.6</td>
</tr>
<tr>
<td>Mean annual precipitation (mm)</td>
<td>696</td>
</tr>
<tr>
<td>Stand age (years)</td>
<td>∼200</td>
</tr>
<tr>
<td>Dominated species</td>
<td>Pinus koraiensis, Tilia amurensis, Acer mono, Fraxinus mandshurica, Quercus mongolica</td>
</tr>
<tr>
<td>Canopy height (m)</td>
<td>26</td>
</tr>
<tr>
<td>Mean diameters at breast height (cm)</td>
<td>∼23</td>
</tr>
<tr>
<td>Maximum leaf area index (m² m⁻²)</td>
<td>6.1</td>
</tr>
<tr>
<td>Sapwood area (m² hm⁻²)</td>
<td>47.88</td>
</tr>
<tr>
<td>Total biomass (tC hm⁻²)</td>
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</tr>
<tr>
<td>Mean annual total gross primary productivity (gC m⁻² yr⁻¹)</td>
<td>1338.84</td>
</tr>
<tr>
<td>Mean annual total ecosystem respiration (gC m⁻² yr⁻¹)</td>
<td>1036.51</td>
</tr>
<tr>
<td>Mean annual total ecosystem productivity (gC m⁻² yr⁻¹)</td>
<td>302.33</td>
</tr>
<tr>
<td>Mean annual total evapotranspiration (kg H₂O m⁻² yr⁻¹)</td>
<td>522.35</td>
</tr>
</tbody>
</table>

* Values are the averages from 1985 to 2005 according to Yu et al. (2008).
* Values are the averages from 2003 to 2008 according to Yu et al. (2013).
* Values are the averages from 2003 to 2008 according to ChinaFLUX dataset.

and Harding, 2011; Kool et al., 2014). Shuttleworth–Wallace model (S–W model) is the first model designed for ET partition, which is a physically-based combination model based on Penman–Monteith equation (Shuttleworth and Wallace, 1985). S–W model has also been regarded as an accurate model and the foundation for other ET partition models, which provides a validation for other models (Kool et al., 2014) and has been widely used (Hu et al., 2009; Iritz et al., 2013; Yu et al., 2008; Zhang et al., 2006). while there have been no attempt in using S–W model to partition ET into its components at forests of China, which occupied an important portion in global forests (FAO, 2010).

China has conducted eddy covariance measurements since 2003 at three forests along the north–south transect of Eastern China (NSTEC), which experiences apparent decreasing temperature and precipitation gradients with the increasing latitude (Yu et al., 2008). The continuous flux measurements at three forests along NSTEC, which helps us understand the effects of environmental factors along climate gradients, provides a valuable platform for analyzing the variations of T/ET among different spatiotemporal scales. Using measurements from three forests along NSTEC, we run the S–W model to partition ET into its components and analyzed the variations of T/ET. The specific objectives were: (1) validate the performances of S–W model at forests, (2) quantify the importance of T in ET at forests, (3) reveal factors affecting the spatiotemporal variations of T/ET, and (4) clarify the difference in the effects of various factors on the spatiotemporal variations of T/ET along climate gradients.

2.2.1. Measurement and instruments

At three forests, ecosystem CO₂ and H₂O flux data were determined from the open-path eddy covariance system (OPEC) above the canopy with a sampling frequency of 10 Hz and block averaging over 30 min. The OPEC was consisted of an open-path infrared gas analyser (Model LI-7500; Licor Inc., Lincoln, NB, USA), a 3-D sonic anemometer (Model CSAT3; Campbell Scientific Inc.), Logan, UT, USA), and a datalogger (Model CR5000; Campbell Scientific Inc.). The measuring height of ecosystem CO₂ and H₂O fluxes for CBS, QYZ, and DHS were 40 m, 39 m, and 27 m, respectively. In addition, another OPEC was installed below the canopy and the measuring height were all around 2.5 m for these three forests.

Routine meteorological variables were measured simultaneously with CO₂ and H₂O fluxes. Global radiation (Rg) and net radiation (Rn) above the canopy were measured with radiometers (Model CM11 and Model CNR-1, Kipp & Zonnen, Delft, Netherlands). Photosynthetic active radiation (PAR) above the canopy was measured with a quantum sensor (Model LI190SB, LICOR Inc.), whereas that below the canopy was measured by another OPEC installed below the canopy and the measuring height were all around 2.5 m for these three forests.

Air temperature (Ta) and relative humidity (RH) at different heights above and within canopy were measured with shielded and aspirated probes (Model HMP45C, Campbell Scientific Inc.). Precipitation was recorded with a rain gauge (Model S2203, Rm Young, Traverse City, MI, USA) above the canopy. Soil temperature (Ts) and soil water content (Sws) were measured using thermocouple probes (Model 105T, Campbell Scientific Inc.) and water content reflectometers (Model CS616, Campbell Scientific Inc.), respectively. Soil heat flux (G) was measured with two flux plates (Model HP01SC, Campbell Scientific Inc.) at the depth of 5 cm. All micrometeorological measurements were recorded at 30-min intervals with dataloggers (Model CR10X & CR23X, Campbell Scientific Inc.). The detailed equipment descriptions were also described by previous works (Wen et al., 2010; Yan et al., 2013; Yu et al., 2008; Zhang et al., 2006).
Leaf area index (LAI) was measured at two-week intervals or a longer period during the growing seasons from 2003 to 2005 using a canopy analyzer (Model LAI-2000, LICOR Inc.).

2.2. Data preparing

Flux data measured by eddy covariance technique in two layers (above and below the canopy) were subjected to traditional data quality control routes including three-dimensional rotation (Aubinet et al., 2000), WPL (Webb, Pearman and Leuning) correction (Webb et al., 1980), storage calculation (Hollinger et al., 1994), and spurious data removal caused by rainfall, water condensation, system failure, low turbulence and so on. The u* threshold for determining the low turbulence fluxes was calculated following Reichstein et al. (2005) for two layer fluxes based on u*, CO2 fluxes, and T
d. Following Menzel et al. (2003), we determined the start and the end of growing-season based on daily T
d. Negative CO2 fluxes at nighttime (when the solar elevation angle was lower than 0°) and at non-growing season were then also removed. After data quality control, the average data coverage during 2003 to 2009 was 54%, 46%, and 43% for CBS, QYZ, and DHS, respectively, while that at nighttime was 73%, 77%, and 64%, respectively.

For CO2 fluxes measured above and below the canopy, if data gaps were less than 2 h, they were linearly interpolated. For other gaps, the missing daytime CO2 fluxes were interpolated using the Michaelis–Menten equation with PAR (Falge et al., 2001b), whereas the missing nighttime CO2 fluxes were filled using the Lloyd–Taylor model with T
d. at 5 cm depth following previous studies (Gao et al., 2014; Reichstein et al., 2005). Daytime ecosystem respiration (Re) was calculated with the trained Lloyd–Taylor model at nighttime having T
d. at 5 cm depth as the input variable (Gao et al., 2014; Reichstein et al., 2005). Half-hourly gross primary productivity (GPP) values were obtained based on the calculated daytime Re and the filled half-hourly daytime CO2 fluxes. For the two layer H2O fluxes, data gaps were filled by the look-up table method (Falge et al., 2001a; Reichstein et al., 2005) based on T
d., vapor pressure deficit (VPD), and R
d.

Data gaps of meteorological variables (including Rn, T
d., Swc, and so on) were filled with the mean diurnal variation (MDV) method for longer periods but using the linear interpolation for gaps of less than 2 h (Falge et al., 2001b). Based on the measured RH and T
d., VPD was then calculated as the difference between the actual and saturation vapor pressures.

Based on PAR measured above and within the canopy, we calculated the absorbed PAR. Daily LAI was estimated from integrating the absorbed PAR with the relationship between the absorbed PAR and LAI, which was established by the absorbed PAR at 12:00 pm and the measured LAI (Beer et al., 2009; Gower et al., 1999; Law et al., 2001).

2.3. Model description and parameterizations

2.3.1. Model descriptions

S–W model was firstly developed based on the Penman–Monteith model and regarded ET as the sum of two water vapor fluxes from separate sources: evaporation from the soil surface (E) and transpiration from the canopy (T) (Shuttleworth and Wallace, 1985). Five resistances were explored in S–W model with units of s m⁻¹ (Fig. 1): the soil surface resistance (r
ds), the aerodynamic resistance from the soil surface to the canopy (r
d.s), the canopy stomatal resistance (r
d.aa), the bulk boundary layer resistance (r
d.ac) and aerodynamic resistance from the canopy to the reference height (r
d.ta).

In S–W model, T and E was calculated as:

\[
ET = C_e \cdot PM_e + C_s \cdot PM_s
\]  

(1a)

\[
P_{Ma} = \frac{\Delta (R_n - G) + \rho C_p VPD - \Delta r_{ac} (R_n - G) / (r_{aa} + r_{ac})}{\Delta + \gamma (1 + r_{st} / (r_{aa} + r_{ac}))}
\]

(1b)

\[
P_{Mb} = \frac{\Delta (R_n - G) + \rho C_p VPD - \Delta r_{as} (R_n - R_m) / (r_{aa} + r_{as})}{\Delta + \gamma (1 + r_{st} / (r_{aa} + r_{as}))}
\]

(1c)

where PM
e and PM
b were terms describing T and E, respectively, whereas C_e and C_s were the resistance coefficient for canopy and soil surface, respectively. \( \Delta \) was the slope of the saturation vapor pressure versus temperature curve (kPa K⁻¹) and \( C_p \) was the specific heat at constant pressure (1012 J kg⁻¹ K⁻¹). VPD was the abbreviation of vapor pressure deficit (kPa) and \( \gamma \) was the psychrometric constant (0.067 kPa K⁻¹). \( r_{as} \) was the bulk boundary layer resistance and \( r_{aa} \) was aerodynamic resistance from the canopy to the reference height. \( r_{ss} \) was the soil surface resistance and \( r_{sa} \) was the aerodynamic resistance from the soil surface to the canopy. \( r_{st} \) was the canopy stomatal resistance.

\( C_e \) and \( C_s \) can be drawn as:

\[
C_e = \left[ 1 + \frac{R_a R_o}{R_a (R_e + R_o)} \right]^{-1}
\]

(2a)

\[
C_s = \left[ 1 + \frac{R_a R_o}{R_s (R_e + R_o)} \right]^{-1}
\]

(2b)

where \( R_e \), \( R_o \) and \( R_a \) were given as:

\[
R_e = (\Delta + \gamma) r_{aa}
\]

(3)

\[
R_o = (\Delta + \gamma) r_{as} + \gamma r_{ss}
\]

(3)

\[
R_e = (\Delta + \gamma) r_{ac} + \gamma r_{st}
\]

(3)

\[
R_m \text{ was estimated through Beer’s law using LAI as:}
\]

\[
R_m = R_o \times \exp (-k \times LAI)
\]

(4)

where \( k \) was extinction coefficient, which was set to 0.5 in this study according to previous study (Beer et al., 2009) as the forests were needle forest or mixed forest.

The calculations of each resistances were described in the previous study (Shuttleworth and Wallace, 1985) in detail. In a recent
study, Hu et al. (2009) revised the expressions of soil surface resistance \( r_{ss} \) and the canopy stomatal resistance \( r_{st} \). \( r_{ss} \) was calculated as the function of soil water content \( (S_{sw}) \):

\[
 r_{ss} = b_1 \left( \frac{S_{sw}}{S_{sw0}} \right)^{b_2} + b_3
\]  

(5)

where \( S_{sw} \) was the saturated water content in the surface soil \( (m^3 m^{-3}) \), which was set to 0.48, 0.42, and 0.54 for CBS, QYZ, and DHS, respectively. \( b_1, b_2, b_3 \) were empirical constants. \( r_{st} \) was calculated using a modified Ball–Berry model (Hu et al., 2009; Wang and Leuning, 1998) as:

\[
r_{st} = \frac{1}{g_0 + a_1 \times f(S_{sw}) \times \text{GPP} \times \text{RH}/C_a}
\]

\[
f(S_{sw}) = \frac{S_{sw0} - S_{sw}}{S_{swm} - S_{sw0}}
\]

(6a)

(6b)

where \( g_0 \) and \( a_1 \) were empirical parameters, and \( g_0 \) was set to 0.00001 following Hu et al. (2009). \( S_{swm} \) and \( S_{sw0} \) were the surface soil water content at field capacity and the wilting point, which was set to the observed maximum and the minimum \( S_{sw} \), respectively. \( C_a \) was leaf surface CO2 content, which was calculated from the LI-7500 measurements.

In this study, we run the S–W model following Hu et al. (2009). Moreover, to make the revised S–W model by Hu et al. (2009) more suitable for forests, we revised the calculation of roughness length \( (z_0) \) and displacement height \( (d) \), which were used for calculating the aerodynamic resistances, following the previous study (Shi et al., 2008b) as:

\[
z_0 = 0.075 \times h
\]

\[
d = 0.75 \times h
\]

(7a)

(7b)

where \( h \) was the canopy height.

2.3.2. Model parameterization

The surface resistances, i.e., \( r_{ss} \) and \( r_{st} \), were calculated with Eqs. (5), (6a) and (6b). The empirical parameters \( (b_1, b_2, b_3, \text{and } a_1) \) in Eqs. (5) and (6a) were estimated using the Monte Carlo method in each year and each site following Hu et al. (2009). In each site and each year, 273 days (about 75% of the whole year data) data were randomly selected to estimate the empirical parameters. In the selected days, only data having high confidence according to Reichstein et al. (2005) were used for training the empirical parameters.

2.4. Data analysis

In this study, we run the S–W model with the trained empirical parameters and validated its performance (including its performances on simulating ET and \( T/ET \)) using the independent datasets. The model outputs were then used to analyze the spatiotemporal variations of \( T/ET \).

2.4.1. Model validation

Excluding the 273 days data used for training the model, we selected the remaining 92 (or 93 in 2004 and 2008) day data as the validation dataset to validate the performances of the model. The validation was conducted at two aspects: the performance of S–W model on simulating ET and that on simulating \( T/ET \).

We validated the performance of S–W model on simulating ET at three scales: half-hour scale, daily scale and annual scale. At half-hour scale, the simulated half-hour ET was validated with the high confidence data (Reichstein et al., 2005) in the validation dataset. At daily scale, the validation was conducted at three scenarios. The simulated daily ET was firstly validated with the daily ET in validation dataset after gap-filling. Days in validation dataset having more than 15 high confidence half-hour data at daytime were then selected to validate the simulated corresponding daily ET, which may prevent the effects of gap-filings. In addition, S–W model was also validated in no rain days to exclude the effects of precipitation on the performance of S–W model. At annual scale, we validated our simulated annual total ET with that measured by eddy covariance after gap-filling.

We validated the performance of S–W model on simulating \( T/ET \) through integrating two layer H2O fluxes measured by eddy covariance: above and below the canopy. H2O fluxes from the eddy covariance system below canopy can be regarded as \( E \) (Wilson et al., 2001). \( T \) can therefore be obtained from the difference between H2O fluxes obtained by two layer eddy covariance measurements. The performance of \( T/ET \) was validated at daily and annual scale. The validation of \( T/ET \) at daily scale was conducted by grouping ET with the bin width of 0.1 kg H2O m\(^{-2} \) d\(^{-1} \) to prevent the effects of random errors in measurements.

2.4.2. Model output analysis

With model outputs of \( T \) and ET at half hour scale, we calculated the daily and annual total values. Then \( T/ET \) values at half-hour scale, daily scale, and annual scale, which were used to analyze the spatiotemporal variations of \( T/ET \), were calculated with \( T \) and ET at the corresponding scales.

With model outputs of the canopy stomatal resistance \( (r_{st}) \) and the soil surface resistance \( (r_{ss}) \), we calculated canopy stomatal conductance \( (G_c) \) and the soil surface conductance \( (G_{ss}) \) as the reciprocal of \( r_{st} \) and \( r_{ss} \), respectively. The annual mean \( G_c \) (\( MG_c \)) was calculated as the mean daytime \( G_c \) during growing season.

To illustrate the way that various factors affecting the variation of \( T/ET \), we also calculated the portion that the energy absorbed by canopy \( (P_{Ec}) \), which was calculated as the ratio of the energy absorbed by canopy \( (R_c) \) to that arrived at the canopy \( (R_n) \) from Eq. (4) and can be regarded as the function of LAI:

\[
P_{Ec} = \frac{R_c}{R_n} = \left( \frac{R_n - R_{ss}}{R_n} \right) = 1 - \exp(-0.5 \times \text{LAI})
\]

(8)

2.5. Statistical analysis

We processed data and run the model with MATLAB software (Math Works Inc., Natick, MA). Under Matlab 7.7, we used the generalized linear model (GLM) of regstats to conduct the regression analysis between simulated and measured values to validate the model performances. With paired-sample \( T \)-test, the significance test on the difference between simulated and measured annual \( T/ET \) was conducted (\( \alpha = 0.05 \)). We employed the path-analysis to evaluate the dependence of the seasonal dynamics of \( T/ET \) on various factors. Then the multivariable regression was conducted to build the equation describing the seasonal dynamics of \( T/ET \). The regressions between \( T/ET \) and various factors were also completed with the generalized linear model (GLM) of regstats or nonlinear regressions.

3. Results

3.1. Performances of S–W model

3.1.1. Performance of S–W model on simulating ET

At half-hour scale, the simulated ET by S–W model were well consistent with the measurements, which were the high confidence data in the validation dataset, in three forests (Fig. 2). The slope of the simulated ET: the measured ET were all around 1. The \( R^2 \) of the regression between measurements and the simulated ET ranged from 0.59 to 0.72, all of which were significant in statistics.
At daily scale, S–W model performed well on simulating ET both in the direction and in the magnitude (Fig. 3). In all three scenarios, the simulated ET were positively correlated with measurements, which were the daily ET at validation dataset, and the $R^2$ of the regression between the simulated ET and the measurements increased from all validation days to no rain days. The simulated ET agreed well with the measured values in days in validation dataset, which were calculated after gap-filling (Fig. 3a–c). However, in days of the regression between the simulated ET and the measurements increased from all validation days to no rain days. The simulated ET agreed well with the measured values in days in validation dataset, which were calculated after gap-filling (Fig. 3a–c). However, in days
having more than 15 half-hour high confidence data at daytime and no rain days, the simulated ET slightly overestimated the measurements (Fig. 3d–i).

The high consistency between the simulated ET and the measured ones was also found at annual scale. The simulated annual total ET positively correlated with the measured ET and the values were also comparable (Fig. 4).

### 3.1.2. Performance of S–W model on simulating T\(\text{/ET}\)

At daily scale, S–W model performed well on simulating T\(\text{/ET}\). The simulated T\(\text{/ET}\) agreed well with the measured ones (Fig. 5a–e), with the \(R^2\) between simulated and measured T\(\text{/ET}\) ranging from 0.36 to 0.76. While the value of our simulated T\(\text{/ET}\) differed from that of measured T\(\text{/ET}\). At CBS, our simulated T\(\text{/ET}\) were larger than the measured ones when T\(\text{/ET}\) were lower than 0.5 but it was in reverse when T\(\text{/ET}\) were larger than 0.5. At subtropical forests (QYZ and DHS), most simulated T\(\text{/ET}\) were both lower than the measured values. After excluding the effects of precipitation, we found an improved relationship between simulated and measured T\(\text{/ET}\) at CBS, which was indicated by an improved \(R^2\) (Fig. 5d).

The relationship between simulated and measured T\(\text{/ET}\) got worse at DHS, whereas most data distributed around the 1:1 line (Fig. 5f).

At annual scale, there were obvious difference between our simulated T\(\text{/ET}\) and the measured values (Table 2). At CBS, our simulated T\(\text{/ET}\) (0.68 ± 0.07) were significantly higher than the measured T\(\text{/ET}\) (0.56 ± 0.03). While at subtropical forests (QYZ and DHS), the simulated T\(\text{/ET}\) were both lower than the measured T\(\text{/ET}\) in values, though the difference between two T\(\text{/ET}\) was not significant in statistics (\(p > 0.05\)). In addition, our simulated T\(\text{/ET}\) were comparable with published results in temperate and subtropical forests (Granier et al., 2000; Schlesinger and Jasechko, 2014; Stoy et al., 2006).

### Table 2

<table>
<thead>
<tr>
<th>Ecosystem</th>
<th>Year</th>
<th>Measured T(\text{/ET})</th>
<th>Simulated T(\text{/ET})</th>
</tr>
</thead>
<tbody>
<tr>
<td>CBS</td>
<td>2003</td>
<td>0.56</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>2004</td>
<td>0.59</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>2005</td>
<td>0.52</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>2006</td>
<td>0.55</td>
<td>0.78</td>
</tr>
<tr>
<td></td>
<td>2007</td>
<td>0.53</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>2008</td>
<td>0.60</td>
<td>0.68</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>0.59</td>
<td>0.73</td>
</tr>
</tbody>
</table>

Note: Measured T\(\text{/ET}\) were calculated from two layer eddy covariance measured water vapor fluxes. Simulated T\(\text{/ET}\) were obtained from the revised Shuttleworth–Wallace model (S–W model) following Hu et al. (2009). Different lowercase letters between the Measured T\(\text{/ET}\) and Simulated T\(\text{/ET}\) indicated a significant difference at \(\alpha = 0.05\) in the same site.
3.2. Spatiotemporal variations of T/ET

3.2.1. Diurnal variation

With data obtained from the S–W model at August, 2003, we investigated the diurnal variation of T/ET in three forests. T/ET all showed a single-peak diurnal pattern, with the nearly constant T/ET in the daytime while nearly zero in nighttime (Fig. 6), which was also found in other months and years (data were not shown).

The diurnal variation of T/ET was primarily affected by that of canopy stomatal conductance (Gc) (Fig. 7). With the increasing Gc, T/ET showed an obvious increasing trend. The power function based on Gc explained over 90% of variation in T/ET.

3.2.2. Seasonal variation

With data obtained from the S–W model, we found that T/ET exhibited obvious seasonal variations, while the seasonal variation of T/ET differed among forests (Fig. 8). At CBS, T/ET exhibited a single-peak variation and reached its peak value around July, with the value ranging from 0 to 0.85. At QYZ, T/ET also showed a single-peak variation but the range of T/ET obviously narrowed, which only ranged from 0.3 to 0.8 in most years. At DHS, T/ET exhibited an obvious single-peak pattern in most years but the range of T/ET further narrowed.

The seasonal variation of T/ET was shaped by multi-factors through their direct or indirect effects. The direct factors affecting the seasonal dynamics of T/ET differed among forests (Fig. 9). At CBS, the seasonal dynamics of T/ET was mainly affected by the direct effects of Ta, VPD, and LAI. The increase in Ta and LAI directly enhanced T/ET while the increasing VPD exerted a reverse role (Fig. 9a). However, at subtropical forests (QYZ and DHS), LAI played no direct effects on the seasonal variation of T/ET, whereas Ta, Swc, Re and VPD directly affected the seasonal dynamics of T/ET. With the increasing Re and Ta, T/ET showed obvious increasing trends, while the increasing Swc and VPD decreased T/ET (Fig. 9b and c).

With the direct factors affecting the seasonal dynamics of T/ET, we drew equations describing the seasonal dynamics of T/ET as follows:

CBS: \[
\frac{T}{ET} = 0.017T_a - 0.17V_P D - 0.01LAI - 0.01, \quad R^2 = 0.87,
\]
\[
RMSE = 0.13, \quad n = 2557 \quad (9a)
\]

QYZ: \[
\frac{T}{ET} = 0.02T_a - 0.20V_P D - 0.85S_{wc} + 0.02R_e + 0.38,
\]
\[
R^2 = 0.52, \quad RMSE = 0.16, \quad n = 2557 \quad (9b)
\]

DHS: \[
\frac{T}{ET} = 0.02T_a - 0.12V_P D - 0.44S_{wc} + 0.01R_e + 0.36,
\]
\[
R^2 = 0.45, \quad RMSE = 0.13, \quad n = 2557 \quad (9c)
\]

3.2.3. Interannual and spatial variations

Data from S–W model suggest that annual total T occupied a large portion of annual water loss as ET at three forests. During the measuring period, the mean annual value of T/ET for CBS, QYZ, and DHS were 0.68 ± 0.07, 0.65 ± 0.13, and 0.68 ± 0.07, respectively. Therefore, vegetation at NSTEC played an important role in
regulating the climate, which should be paid more attention in the future.

$T/ET$ showed obvious interannual variations but was not directly affected by climate and biotic factors such as mean annual air temperature (MAT), mean annual precipitation (MAP), and mean leaf area index (LAI). With the increasing MAT, MAP, and LAI, $T/ET$ showed no obvious trend among years (Fig. 10). However, mean canopy stomatal conductance ($MG_c$) did affect the interannual variation of $T/ET$. With the increasing $MG_c$, $T/ET$ exhibited an obvious increasing trend, which was found at all three forests (Fig. 11).

$T/ET$ also exhibited some differences among forests. $T/ET$ in the temperate forest (CBS) was comparable with that at DHS but was slightly higher than that at QYZ. Though $T/ET$ showed a slight decreasing trend with the increasing MAT, MAP, and LAI, the relationship between $T/ET$ and factors (i.e., MAT, MAP, and LAI) was not significant in statistics (Fig. 10). However, with the increasing $MG_c$, $T/ET$ significantly increased among ecosystems (Fig. 11).

Fig. 8. Seasonal dynamics of the ratio of transpiration to evapotranspiration ($T/ET$) at CBS (a), QYZ (b), and DHS (c). Lines are 10-d running average.

Fig. 9. Path diagram of factors affecting the seasonal dynamics of the ratio of transpiration to evapotranspiration ($T/ET$) at CBS (a), QYZ (b), and DHS (c). The abbreviation of factors were as follows: air temperature ($T_a$), net radiation ($R_n$), soil water content ($S_{wc}$), vapor pressure deficit (VPD), leaf area index (LAI).
4. Discussion

4.1. Model performances and uncertainties

Results from model validations suggest that S–W model performed well on simulating the variation trend of ET and T/ET (Figs. 2–5), while the simulated ET and T/ET differed from the measured ones in values, which can be attributed to the uncertainties in measurements and simulations.

The uncertainties in measurements included the following aspects. First, due to the effects of gap-filling in rainy days (Kang et al., 2012), dews (Maestre-Valero et al., 2012), and fogs (Beiderwieden et al., 2008; Eugster et al., 2006), the measured ET may be underestimated. Second, the underestimated ET caused by gap-filling in rainy days (Kang et al., 2012), dews (Maestre-Valero et al., 2012), and fogs (Beiderwieden et al., 2008; Eugster et al., 2006) may overestimate T/ET. Third, during days with open canopy, the low temperature (Shi et al., 2008a) caused small measured water vapor fluxes below the canopy, which made the measured T (the difference between two layers water vapor fluxes) and T/ET overestimated. Fourth, during days having close canopy, water vapor fluxes measured below the canopy may contribute to T, which made the measured T and T/ET underestimated.

The uncertainties in simulations primarily sourced from the lackage of EI session in S–W model. During the period when the measured ET were directly measured by eddy covariance and had high confidence, EI scarcely occurred. The simulated ET and T/ET therefore fully reflected their real values. However, during rainy days or days having much low confidence data, EI appeared but was not simulated by S–W model. The simulation would underestimate the real ET but may overestimate the real T/ET.

The consistent high confidence in simulations and measurements made the values of simulated ET agree well with the measured ones at half-hour scale (Fig. 2). The consistent underestimation in simulations and measurements also made the simulated ET agree well with the measured ones at daily and annual scale (Figs. 3a–c and 4), while during days having more than 15 half-hour high confidence data at daytime and no rain days, the single underestimation in the measured ET made the simulated ET higher than the simulated values (Fig. 3d–i). At the temperate forest (CBS) which experienced obvious canopy developments, during days with the open canopy, the overestimation in measured T/ET made the simulated T/ET lower than the measured ones, while the underestimation in measured T/ET primarily accounted for the higher simulated T/ET (Fig. 4a and d) during days with the close canopy. The overwhelming portion of growing-season ET in annual total ET (Shi et al., 2008b) also made the simulated annual T/ET higher than the measured ones (Table 2). At subtropical forests, the consistent overestimation in simulations and measurements made the simulated annual T/ET be comparable with the measured values (Table 2).

Though there were some uncertainties in the simulated T/ET due to the lackage of EI session in S–W model, EI occupied no more than 20% of ET in these three forests. For example, the portion of EI in ET in temperate forest in a forest in Finland (Ge et al., 2011) and Sweden (Iritz et al., 2001) was around 10%, which had similar climate and vegetation status as CBS, while EI occupied about 15.79% of ET at a tropical rainforest (Kume et al., 2011), which had more precipitation than the two subtropical forests but similar vegetation status. In addition, the simulated T/ET were comparable with the measured ones (Fig. 5 and Table 2) and those published in literatures. We can therefore conservatively conclude that the overestimation in T/ET was relatively small at these three forests. However, to make S–W model more feasible for its application in forests and accurately quantify the portion of each ET components, intergrating an EI session to the S–W model should be paid much attention in the future.

4.2. Factors affecting the Variations of T/ET

The variations of T/ET, including the diurnal variation, seasonal variation and so on, can be fulfilled through changing the canopy
Acknowledgements

This research was supported by the Natural Science Foundation of China (Grant 31290221, 31420103917, and 41301043), National Key Research and Development Program (Grant 2010CB833504), the CAS Strategic Priority Research Program (Grant XDA05050601), and Funding for talent young scientists of ICNSRR (Grant 2013RC203). We gratefully acknowledge the reviewers for spending their valuable time to provide constructive comments.

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