Improving Estimation of Seasonal Evapotranspiration in Australian Tropical Savannas using a Flexible Drought Index

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ABSTRACT

Savannas, occupying a fifth of the global land surface, are characterized by the coexistence of trees and grasses. Accurate estimation of savanna evapotranspiration (ET) is vital for understanding the regional and global water balance and its feedback to climate. However, the overlapping phenology and different water-use patterns of trees and grasses constitute a major challenge for modeling efforts. To estimate savanna ET, we used a three-source ET model, partitioning ET among soil, trees, and grasses. To represent legacy effects of precipitation on ecosystem water use, the Normalized Ecosystem Drought Index (NEDI, i.e. a function of precipitation and potential evapotranspiration) was included to limit canopy conductances in the model and also in two other classic two-layer models (Shuttleworth-Wallace model and Penman-Monteith-Leuning model). The results of our model and the other models were tested and compared using tower-based eddy covariance flux data collected at six sites (including four savanna sites, one pasture site, and one grassland site) along a precipitation gradient in northern Australia, together with satellite-derived leaf area index, which was partitioned to represent the canopy dynamics of trees and grasses. Inclusion of NEDI significantly reduced seasonal biases in ET estimation results for all models compared with observations at savanna sites (fitted slopes were closer to unity by 0.08–0.10, R² increased by 0.03–0.04, and RMSE decreased by 0.07–0.09 mm d⁻¹). The three-source model provides insights into simulation of water fluxes over vegetated areas of complex composition. Our work makes a contribution to savanna research by determining a flexible indicator defining the seasonal water availability limitation on savanna ET. The inclusion of NEDI in ET models could guide future research on modeling ecosystem water and carbon fluxes in response to seasonal droughts.

Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Equation</th>
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<tbody>
<tr>
<td>( \gamma )</td>
<td>psychrometric constant (kPa K⁻¹)</td>
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<tr>
<td>( \lambda )</td>
<td>latent heat of vaporization (J kg⁻¹)</td>
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<tr>
<td>( \lambda_E_C )</td>
<td>latent heat flux from vegetation canopy transpiration (W m⁻²)</td>
</tr>
<tr>
<td>( \lambda_E_S )</td>
<td>latent heat flux from soil evaporation (W m⁻²)</td>
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<tr>
<td>( \lambda_E_T )</td>
<td>latent heat flux from grass transpiration (W m⁻²)</td>
</tr>
<tr>
<td>( \Delta )</td>
<td>slope of the saturation water vapor pressure-temperature curve (kPa K⁻¹)</td>
</tr>
<tr>
<td>( c_p )</td>
<td>specific heat of air at constant pressure (J kg⁻¹ K⁻¹)</td>
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<tr>
<td>( d_0 )</td>
<td>zero-plane displacement (m)</td>
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<tr>
<td>( r_a )</td>
<td>aerodynamic resistance (s m⁻¹)</td>
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<tr>
<td>( r_s )</td>
<td>canopy surface resistance (s m⁻¹)</td>
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<tr>
<td>( r_s^{gr} )</td>
<td>surface resistance of grass layer (s m⁻¹)</td>
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<tr>
<td>( r_s^{tr} )</td>
<td>surface resistance of tree canopy (s m⁻¹)</td>
</tr>
<tr>
<td>( u )</td>
<td>wind speed (m s⁻¹) measured at the reference height</td>
</tr>
<tr>
<td>( z_0 )</td>
<td>aerodynamic roughness (m)</td>
</tr>
<tr>
<td>( z_{ov} )</td>
<td>thermal roughness (m)</td>
</tr>
<tr>
<td>( A_e )</td>
<td>available energy flux for canopy (W m⁻²)</td>
</tr>
<tr>
<td>( A_i )</td>
<td>available energy flux for soil (W m⁻²)</td>
</tr>
<tr>
<td>( D_a )</td>
<td>water vapor pressure deficit measured at the reference height</td>
</tr>
<tr>
<td>( D_m )</td>
<td>water vapor pressure deficit at the canopy source height</td>
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0168-1923/ © 2020 Elsevier B.V. All rights reserved.
Evapotranspiration (ET) is the transfer of water from land to the atmosphere via soil evaporation and plant transpiration (Wang and Dickinson, 2012). As the second largest term (after precipitation) in the terrestrial water balance, ET accounts for two thirds of the global average precipitation of 700 mm per year (Oki and Kanae, 2006). The latent heat consumed in ET amounts to about half of the solar energy absorbed by the land surface (Trenberth et al., 2009; Wild et al., 2013), effectively cooling the biosphere, which is indispensable for maintaining suitable temperatures for terrestrial ecosystems. Linking global water, carbon, and energy cycles, ET is a critical variable in land-atmosphere coupling (Monteith, 1965; Wong et al., 1979; Fisher et al., 2017).

A widely-used mechanistic approach for estimating ET is encompassed in Penman-Monteith (PM) type methods (PM, e.g., Monteith, 1965; Cleugh et al. 2007; Yuan et al. 2010; Mu et al. 2011; Barraza et al. 2017). The basic theories underpinning PM-type methods rely on the principle of resistances to (or conductances of) the transfer of water vapor or heat. The early resistance scheme, namely the one-layer model, treats the land surface as a whole (Fig. 1.a) and does not partition soil evaporation and canopy transpiration (Monteith, 1965).

To overcome such a deficit, two-source resistance models have been developed, either in a two-layer (coupled) way (e.g., Shuttleworth and Wallace, 1985) or in a two-patch (uncoupled) way (e.g., Cleverly et al. 2013). The two-layer model partitions the land surface into the canopy layer and its underlying soil layer, where the upper canopy is treated as semi-transparent for radiation input (Lhomme and Chehbouni, 1999) and the available energy flux is allocated based on Beer’s law. The Shuttleworth and Wallace (1985) model (SW) was first developed to account for the interaction of a homogeneous sparse crop with soil, and now is widely used for crops (Zhang et al., 2009; Wei et al., 2018) and natural vegetation with a distinct understory and overstory, for instance, savannas (Dolman, 1993; Huntingford et al., 1995) and shrubs (Brenner and Incoll, 1997). Leuning et al. (2008) developed a simplified two-layer model (PML) based on PM model (Monteith, 1965). The two-patch method treats soil and canopy as two independently uncoupled patches, where the available energy flux is allocated based on the area-weighted fraction (Blyth and Harding, 1995). To account for more spatial and vertical heterogeneity of ecosystems, multi-layer or hybrid multi-patch, multi-layer resistance models have been developed (Verhoef and Allen, 2000; Lhomme et al., 2012). Montes et al. (2014) proposed a three-source (TS) model (Fig. 1.c) revised from Lhomme et al. (2013) to represent the seasonal dynamics of water fluxes from a grassed yard.

Savannas are a critical and complex biome occupying approximately a fifth of the global land surface (Scholes and Archer, 1997; Sankaran et al., 2005). Savannas cover nearly half of the African continent area (Menaut, 1983; Osborne et al., 2018), 25% of the Australian continent area (Fox et al., 2001), 45% of the South America continent area (Scholes and Archer, 1997; Giambelluta et al., 2009), parts of South and Southeast Asia (Ratnam et al., 2016), California and the Iberian Peninsula (Ryu et al., 2010). As the second-largest tropical ecosystem after rainforests, savannas contribute about 30% of the global terrestrial primary productivity (Grace et al., 2006) and 21% of global land surface evaporation (Miralles, 2011). In the context of climate change and especially changes in rainfall climatology (Zhang et al., 2019), savannas contribute significantly to variations of the global carbon budget and hydrologic cycle. Dominated by savannas, Africa and Australia have made the largest regional contribution to the declining trend in global ET since the onset of the 1998 El Niño event (Jung et al., 2010). Owing to the exceptionally increased precipitation, the carbon uptake increases of Australian ecosystems accounted for 60% of the global land carbon sink increase during the 2011 La Niña Year (Poulter et al., 2014; Meza et al., 2018). The semi-arid savannas and low-latitude shrublands have dominated the trend and variability of the global land carbon sink over recent decades (Ahlström et al., 2015).

To explore Australian savanna functioning in a changing climate, the ‘Australian Savanna Landscapes: Past, Present and Future’ (SPECIAL) campaign (Beringer et al., 2011a), was conducted over the North Australian Tropical Transect (NATT). The project produced continuous eddy covariance (EC) observation data that revealed distinct seasonal and spatial patterns of savanna water and carbon fluxes (Beringer et al., 2011b; Hutyra et al., 2011; Eamus et al., 2013; Shi et al., 2014; Zhuang et al., 2016; Moore et al., 2018). These reliable data have been valuable for land surface modeling and benchmarking over savannas (Whitley et al., 2001, 2016, 2017; Haverd et al., 2013, 2016; Barraza et al., 2017; Gan et al., 2018; Mallick et al., 2018). Whitley et al. (2016) evaluated six ecosystem models over NATT and found that ET was underestimated by most models due to systematic errors. The systematic errors were ascribed to three factors: (1) tree and grass phenology; (2) fire disturbance, and (3) root-water access (Whitley et al. 2017). Typical root-water access models are usually complicated to directly coupled with PM models that they need explicitly represent the water balance and root-water access processes to calculate soil water storage (e.g. Haverd et al., 2016). Therefore, an alternative flexible indicator is necessary to represent large-scale water availability limitations on ET.

**Fig. 1.** Schematic diagrams of resistance networks in the soil-canopy-atmosphere system, corresponding to the (a) one-layer model, (b) two-layer model, and (c) three-source model. For the resistances, the subscripts $a$, $b$, and $s$ refer to aerodynamic, boundary-layer, and surface, respectively; the superscripts $c$, $tr$, $gr$, and $s$ refer to canopy, tree, grass, and soil, respectively.
Surface energy balance (SEB) models comprise an additional group of models that would benefit from a flexible indicator to represent water availability for water-limited ecosystems. The TSEB (Two-Source Energy-Balance) model is a two-source version of SEB-type models (Norman et al., 1995; Kustas et al., 1999). Updated versions of the TSEB model have recently been developed for savanna and savanna-like ecosystems (Andreou et al., 2018; Burchard-Levine et al., 2020). In the TSEB model, the canopy latent heat flux is calculated by the Priestly-Taylor formula (Priestley and Taylor, 1972). A complex iteration procedure is required to obtain the specific values of the Priestly-Taylor coefficient \( a_p \) under water-stress conditions (Anderson et al., 2005). A flexible indicator that we are seeking could replace \( a_p \) to avoid the complex iteration procedure and represent the water availability limitation on the canopy latent heat flux. Thus, a flexible indicator is needed by both PM-type and SEB-type models to facilitate the estimation of ET over seasonally water-limited ecosystems.

For ET estimation of savanna ecosystems, parameterization of the resistance network in the PM-type approach faces unique challenges because they are composed of two distinctly different plant life forms, trees and grasses, which have different patterns of phenological development and soil water extraction by roots (Bond, 2008). According to the phenology separation conceptual model, trees in savannas tend to regrow canopy earlier than grasses with the onset of the wet season and thereby gain priority use of resources (Scholes and Archer, 1997). Evergreen trees are functional during the entire year, while grasses and deciduous trees are only active during the wet season and almost inactive during the prolonged dry season (Bowman and Prior, 2005).

Therefore, to be accurate, either a patch method or a layer method requires that trees and grasses are distinguished from each other. However, savannas lie along a continuum of tree cover from grassland to closed forest, and capturing the fine scale patterns of trees on the landscape with the above-mentioned models is unrealistic. This is particularly the case when applying methods to quantify the fraction of vegetation patches that would require very fine spatial resolution data (Kobayashi et al., 2016), which is both resource- and time-consuming. An alternative statistical approach is to aggregate fine-scale information for fractions of trees and grasses utilizing the persistence of trees and recurrence of grasses (Roderick et al., 1999; Lu et al., 2003; Gill et al., 2006; Donohue et al., 2009; Havard et al., 2016; Whitley et al., 2016, 2017; Ma et al., 2020). Such approaches are easy to apply, providing a convenient way to realize a resistance network that can account for the separate contributions of trees and grasses to ET. The LAI of trees and grasses separated by such approaches (Section 2.3 and 3.1) could be used as an input for a TS model revised from Lhomme et al. (2012) and Montes et al. (2014).

The Normalized Ecosystem Drought Index (NEDI) proposed by Chang et al. (2018) outperformed other drought indicators in identifying ecosystem drought stress. Thus, NEDI was adopted as the drought indicator defining water availability limitation on transpiration from trees and grasses in our modeling scheme. Deep-rooted trees are influenced by precipitation lag effects on delaying vegetation water supply, while shallow-rooted grasses are more responsive to short-term precipitation events than trees (Räsänen et al., 2020), according to a root-niche separation conceptual model (i.e., Walter’s two-layer hypothesis; Walter, 1971; Scholes and Archer, 1997). Thus, we hypothesized that (1) tree transpiration is more influenced by precipitation accumulated in the previous month; and (2) grass transpiration is mainly influenced by precipitation in the current month. Based on this hypothesis, we aimed to answer the following two questions:

1. whether ET estimation for seasonally water-limited savannas is improved using the flexible drought indicator NEDI in conjunction with a three-source ET estimation scheme;
2. which factors are constraining ET models’ ability in accurately representing seasonal changes of ET components.

To answer the first question, we introduced NEDI with different lag months into the TS model to represent seasonal soil water availability for trees and grasses (Section 2.1). To validate whether adding the NEDI function could improve other PM-type models, NEDI was also introduced into the SW and PML two-source models. The three models (i.e., SW, PML, and TS) integrated with NEDI were denoted as models of SW-DI, PML-DI, and TS-DI, respectively. The two groups of models with/without NEDI were compared against measurements from above-canopy EC systems at six sites in northern Australia (Section 3.3). To answer the second question, the ability of the TS and TS-DI models in partitioning ET was tested with above- and below-canopy EC systems at a mesic savanna site (Section 3.4). The novelty of our study lies in that the soil water limit on canopy transpiration was represented in two-layer/three-source ET models through introducing a flexible drought indicator.

2. Materials and Methods

2.1. Model Description

In the one-layer model (Fig. 1.a), vegetation and underlying soil are viewed as a big leaf. Water vapor emanating from the big leaf must overcome canopy surface resistance \( r_{cs} \). In the two-layer SW model (Fig. 1.b), trees and grasses in savannas are viewed as a whole canopy layer over the bare soil. Water vapor emanating from functional canopies must overcome \( r_{g} \) and the boundary-layer resistance \( r_{b} \) before converging at the canopy source height \( z_{cm} \) with water vapor escaping from the soil surface. The three-source model (Fig. 1.c) separates savanna ecosystems into three sources (i.e., layers): overstory tree canopy, understory grass layer, and bare soil layer. To converge at \( z_{cm} \), water vapor emanating from the tree canopy and grass layer must overcome surface resistances \( r_{g} \) and \( r_{p} \), boundary-layer resistances \( r_{b} \) and \( r_{p} \), and in-canopy aerodynamic resistances \( r_{a} \). Savanna ecosystems are represented with two-layer models when grasses sequester during dry-season drought. The natural grassland and improved pasture are also represented with two-layer models rather than the three-source model.

2.1.1. The two-layer Shuttleworth-Wallace (SW) model

In the two-layer SW model, latent heat fluxes from vegetation transpiration \( \lambda E_c \) and soil evaporation \( \lambda E_s \) converge at \( z_{cm} \). The total latent heat flux \( \lambda E \) is expressed as the sum of the two components (Shuttleworth and Wallace, 1985):

\[
\lambda E = \lambda E_c + \lambda E_s \tag{1}
\]

\[
\lambda E_c = \frac{\Delta A_c + \rho C_p D_m r_{a}^{m}}{\Delta + \gamma (1 + r_{a}^{m}/r_{c}^{m})} \tag{2}
\]

\[
\lambda E_s = \frac{\Delta A_s + \rho C_p D_m r_{b}^{m}}{\Delta + \gamma (1 + r_{b}^{m}/r_{c}^{m})} \tag{3}
\]

where \( \lambda \) is the latent heat of vaporization \((2.45 \times 106 \text{ J kg}^{-1})\), \( \Delta \) is the slope of the saturation water vapor pressure-temperature curve, \( \rho \) is air density, \( C_p \) is the specific heat of air at constant pressure, and \( \gamma \) is the psychrometric coefficient \((\text{kPa K}^{-1})\). The unknown parameter \( D_m \) (i.e., water vapor pressure deficit at \( z_{cm} \)) is calculated as:

\[
D_m = D_0 + [(\Delta A - (\Delta + \gamma)\lambda E) r_{a}^{m}/(\rho C_p)] \tag{4}
\]

Introducing Eq. (4) into Eqs. (1-3), the original form of total latent heat flux is obtained as in Shuttleworth and Wallace (1985), Tech (2006) and Lhomme et al. 2012:

\[
\lambda E = C_E PM_c + C_s PM_s \tag{5}
\]

\[
PM_c = \frac{\Delta A + (\rho C_p D_m - \Delta C_p A_s) (r_{a}^{m} + r_{b}^{m})}{\Delta + \gamma (1 + r_{a}^{m}/r_{c}^{m})} \tag{6}
\]
\[ PM_s = \frac{\Delta A + [\rho C_p D_m - \Delta r_s (A - A_s)](r_{s}^2 + r_s^2)}{\Delta + \gamma[1 + r_{s}^2/(r_{s}^2 + r_s^2)]} \]  

(7)

where the coefficients \( C_z \) and \( C_s \) are expressed as in Supplemental Appendix A. Aerodynamic resistance \( (r_s^2) \) and soil surface resistance \( (r_s^2) \) are calculated as in Supplemental Appendix B and C. For the formulation of \( r_s^2 \), see Section 2.1.4. The available energies for soil \( (A_s) \) and canopy \( (A_c) \) are calculated as:

\[
A_K = R_m - G \\
A_r = A - A_K 
\]

(8)

(9)

where the total available energy flux \( (A) \) is the difference between net radiation \( (R_m) \) and soil heat flux \( (G) \): \( A = R_m - G \). The net radiation at the soil surface is calculated as \( R_m = R_i \exp(-k_n L A I) \) and \( k_n \) is the extinction coefficient for \( R_i \).

### 2.1.2. The Penman-Monteith-Leuning (PML) model

The original PML model is a simplified two-layer model with evapotranspiration separated into vegetation transpiration \( (E_C) \) and soil evaporation \( (E_s) \) (Fig. 1 b; Leuning et al., 2008). It simplified the resistance network and has been tested for Australia ecosystems (Zhang et al., 2010), Mediterranean drylands (Morillas et al., 2013) and South African savannas (Khosha et al., 2019). In PML, \( \lambda E \) is expressed as a simple additive form using Eq. (1). Latent heat flux from the canopy surface \( (\lambda E_C) \) is expressed according to the PM approach:

\[
\lambda E_C = \frac{\Delta A_c + r_s^2 D_m / r_s}{\Delta + \nu(1 + r_{s}^2/r_s^2)} 
\]

(10)

Latent heat flux from the soil surface \( (\lambda E_s) \) is simplified as some fraction, \( f \), of the soil surface equilibrium rate:

\[
\lambda E_s = \frac{f A_s}{\nu(1 + 1/r_s^2)} 
\]

(11)

where \( \nu = \Delta/\gamma \), \( A_s \) and \( A_C \) are calculated using Eqs. (8-9). For the formulation of \( r_s^2 \), see Section 2.1.4. \( f \) is a term limiting soil evaporation. A function of precipitation and equilibrium evaporation was used to represent \( f \) due to the absence of observations of soil water content over large areas (Zhang et al., 2010). Continuous observations of soil moisture were available at the selected sites. Therefore, a function of soil water content \( (\theta) \) was used to represent \( f \) (Morillas et al., 2013):

\[
f(\theta) = \min \left[ 1, \max \left( 0, \frac{\theta - \theta_{\text{min}}}{\theta_{\text{max}} - \theta_{\text{min}}} \right) \right] 
\]

(12)

where \( \theta_{\text{min}} \) and \( \theta_{\text{max}} \) are the minimum and maximum \( \theta \) for soil evaporation. The wilting point is often used as the minimum \( \theta \) threshold for vegetation transpiration. However, the minimum \( \theta \) threshold for soil evaporation is often lower than the vegetation wilting point. Thus, here we selected the minimum \( \theta \) threshold of soil evaporation in the limiting function. \( \theta_{\text{max}} \) is estimated as the value of \( \theta \) in the 24-hour period after a large rainfall event, which can be regarded as an estimate of the field capacity (Garca et al., 2013), according to the observed time series of \( \theta \) at each site. At savanna sites, soil water content often reaches minimum values at the end of an extended dry season. However, observation instrument errors may cause inter-annual variations of annual \( \theta_{\text{min}} \). Overestimation of \( \theta_{\text{min}} \) may cause overestimation of soil evaporation. Thus, \( \theta_{\text{min}} \) in the study represents the inter-annual maximum of annual \( \theta \) minimum values. For the values of \( \theta_{\text{min}} \) and \( \theta_{\text{max}} \) of the six sites, refer to Supplemental Table S1.

The aerodynamic resistance \( (r_a) \) is calculated as (Monteith and Unsworth, 1990):

\[
r_a = \frac{\ln[(z_s - d_0)/z_0] \ln[(z_s - d_0)/z_{so}]}{\kappa u} 
\]

(13)

where \( \kappa \) is von Karman’s constant (0.41, dimensionless), and \( u \) is wind speed (m s\(^{-1}\)) measured at the reference height \( z_s \). The zero-plane displacement \( d_0 = 2h_0/3 \), aerodynamic roughness \( z_{so} = 0.123 \ h_0 \), and thermal roughness \( z_{ro} = 0.1z_0 \) (Allen et al., 1998). The canopy height \( (h_c) \) equals the tree canopy height \( (h_m) \) for savannas.

#### 2.1.3. The three-source (TS) model

The three-source model was revised from Lhomme et al. (2013) and Montes et al. (2014) (Fig. 1 c), where \( \lambda E \) is the sum of contributions from three components: latent heat fluxes from tree transpiration \( (\lambda E_{tr}) \), grass transpiration \( (\lambda E_{gr}) \), and soil evaporation \( (\lambda E_{s}) \).

\[
\lambda E = \lambda E_{tr} + \lambda E_{gr} + \lambda E_{s} 
\]

(14)

The three evaporation components are calculated from \( D_m \) and the corresponding resistance items and available energy flux\( (A_{tr}, A_{gr} \), or \( A_s \)) in PM-type models (Lhomme et al., 2013; Montes et al., 2014):

\[
\lambda E_{tr} = \frac{\Delta A_{tr} + \rho C_p D_m (r_{s}^2 + r_{tr}^2)}{\Delta + \gamma(1 + r_{s}^2/r_{tr}^2)} 
\]

(15)

\[
\lambda E_{gr} = \frac{\Delta A_{gr} + \rho C_p D_m (r_{s}^2 + r_{gr}^2)}{\Delta + \gamma(1 + r_{s}^2/r_{gr}^2)} 
\]

(16)

where \( \lambda E_{gr} \) is calculated as in Eq. (3). The available energy flux for trees is given as: \( A_{tr} = R_i \exp(-k_n L A I) \). Assuming the extinction coefficient is the same for tree and grass canopies, the available energy flux for a grass canopy \( A_{gr} = A_C - A_{tr} \), where \( A_C \) is calculated using Eq. (9).

Substituting Eq. (4) into Eqs. (3) and 14-16 and after rearranging as in Lhomme et al. (2012), the total latent heat flux is expressed as:

\[
\lambda E = \frac{1}{\gamma} \left( P_m + P_{gr} + P_{s} \right) \Delta A + \frac{\rho C_p D_m}{\nu} \left( r_s^2 A_s + r_{s}^2 A_{gr} + r_{s}^2 A_{tr} \right) 
\]

(17)

where the coefficients \( (P_m, P_{gr}, \) and \( P_{s}) \) are combinations of aerodynamic and surface resistances, detailed in Supplemental Appendix D. The formulations of aerodynamic resistances and soil surface resistance are given in Supplemental Appendices B and C. For the formulations of the surface conductances of trees and grasses \( (r_{tr}^2 \) and \( r_{gr}^2)) \), refer to Section 2.1.4.

#### 2.1.4. Developing a flexible water availability function for the canopy conductance submodel

The canopy conductance submodel is the core of PM-type models, including SW, PML, and TS. Canopy conductance (i.e., the reciprocal of \( r_g \) is typically upscaled from Jarvis-type models where stomatal conductance, \( g_s \)) is limited by functions of photosynthetically active radiation, \( (Q) \), \( D_m \) and available soil water \( (\omega) \) (Jarvis, 1976; Damour et al., 2010):

\[
g_s = g_{s0} f(Q)/(D_m f(\omega)) 
\]

(18)

where \( g_{s0} \) is the maximum stomatal conductance (mm s\(^{-1}\)).

In our study, the canopy conductance submodel in SW, PML, and TS was adopted from Kellih et al. (1995) (hereafter referred to as K95) for two reasons. Firstly, K95 has been validated for various ecosystems (including savannas). Secondly, the parameter values related to radiation and water vapor pressure deficit have been previously tested, and using the known parameters will reduce the work of optimization. The leaf-scale Jarvis-type model in K95 describes stomatal response to photosynthetically active radiation absorbed by an individual leaf \( (Q_a) \) as:

\[
g_s = \frac{Q_{a0} Q_s}{Q_s + Q_{a0}} 
\]

(19)

where \( Q_{a0} \) equals the value of \( Q_a \) when \( g_s \) is half of \( g_{s0} \). The leaf-scale stomatal conductance is integrated with LAI over the height range of canopy depth, obtaining the canopy conductance response to \( Q \) as (Kellih et al., 1995):
$G_C = \frac{g_w}{k_o} \ln \left[ \frac{Q + Q_o}{Q \exp(-k_o LAI) + Q_o} \right]^{1} + \frac{1}{D_i/D_o}$

where $Q$ is related to $R_{0d}$ (downwelling solar radiation) through a ratio: $Q = 0.45 R_{0d}$ (Meek et al., 1984; Weiss and Norman, 1985). And $k_o$ is the extinction coefficient of $Q$, $Q_o$ and $D_o$ are the values of $Q$ and $D_o$ respectively, at half the maximum of stomatal conductance. Leuning et al. (2008) added the $D_o$ response function, forming a modified version of K95:

$G_C = \frac{1}{r_i^2} = \frac{g_w}{k_o} \ln \left[ \frac{Q + Q_o}{Q(-k_o LAI) + Q_o} \right]^{1} + \frac{1}{D_i/D_o}$

A proper water availability limiting function $f(\omega)$ was absent in Eq. (21). Pre-simulation tests showed that the $f(\omega)$ function as Eq. (12) could not represent savanna transpiration well. To demonstrate the limitation of water availability on transpiration, NEDI adopted from Chang et al. (2018) was used in this study. To represent the lag effects of precipitation to recharge soil water storage, water availability in the $i$th month ($W_i$) defined in Chang et al. (2018) was calculated as the difference between precipitation in the previous $j$ months ($j = 0, 1, 2 \ldots$ month) ($P_{j}$) and potential evapotranspiration in the current month ($PET$):

$W_i = R_{i-j} - PET_i$

where $W_i$ is negative with water stress and positive with water sufficiency. Groundwater exchange and runoff are neglected here. To obtain higher temporal resolution, water availability was calculated at daily time-steps in our study. Assuming there were about 30 days during one month, water availability for the $i$th day of year ($W_i$) was calculated as:

$W_i = \sum_{N=0}^{30} (P_{i-N} - PET_{i-N})$ when $j = 0$

$W_i = \sum_{N=0}^{30} (P_{i-N,0} - PET_{i-N})$ when $j = 1$

PET was calculated according to the Penman approach as in Shuttleworth (1993) and Donohue et al. (2010):

$PET = \frac{\Delta R_o}{\Delta + \gamma} + \frac{\gamma \times 6430(1 + 0.536\Delta)}{\Delta + \gamma} D_k$

Normalizing $W_i$ by dividing the maximum of the absolute values in the $W_i$ series, NEDI was expressed as in Chang et al. (2018):

$NEDI_i = \frac{W_i}{\max(\text{abs}(W_{i-30,0}))}$

where $B$ and $F$ are the beginning and ending day of year for data observation, respectively. NEDI ranges from -1 to 1. When NEDI < 0, water availability becomes a limiting factor. When NEDI ≥ 0, precipitation could meet PET, and water availability is no longer limiting. To ensure that $f(\omega)$ ranges from 0 to 1, $f(\omega)$ in Eq. (21) was expressed by a piecewise function in our study:

$f(\omega) = \begin{cases} m \times NEDI + 1 & \text{when } -1 \leq NEDI < 0 \\ 1 & \text{when } 0 \leq NEDI \leq 1 \end{cases}$

where $m$ is a multiplier defining the effects of NEDI. Incorporated $f(\omega)$ into Eq. (21), a new equation of $G_C$ was expressed as:

$G_C = \frac{1}{r_i^2} = \frac{g_w}{k_o} \ln \left[ \frac{Q + Q_o}{Q(-k_o LAI) + Q_o} \right]^{1} + \frac{1}{D_i/D_o}$

The revised K95 model as given in Eq. (21) was used to represent canopy conductances for models of SW and PML. Canopy conductances were calculated by Eq. (28) for models of SW-DI and PML-DI; and the number of lag months for NEDI was set as one month and zero months for savannas and pasture/grassland sites, respectively. $W_i$ was calculated from Eqs. (24) and (23) for savannas and pasture/grassland sites, respectively.

For the TS model, surface resistances for the tree canopy ($r^t_i$) and grass layer ($r^g_i$) were calculated by Eq. (21) in which $g_w$ and LAI were replaced with values for trees and grasses. For the TS-DI model, $r^t_i$ and $r^g_i$ were calculated by Eq. (28) in which $g_w$ and LAI were replaced with values for trees and grasses. For the photosynthetically active radiation at the top of the grass layer, $Q$ was replaced with $Q \exp(-k_o LAI)$ due to shading by overstory trees. For the TS-DI model, $W_i$ was calculated from Eqs. (24) and (23) for the tree canopy and grass layer, respectively, according to our hypothesis proposed in the Introduction section.

2.2. Study sites and flux data

To validate the models, we applied them across a continental rainfall gradient known as the North Australian Tropical Transect (NATT) that included four flux tower sites (Fig. S1) over natural vegetation including savanna and woodland. These savanna sites were Howard Springs (AU-How), Daly River Savanna (AU-DaS), Dry River (AU-Dry), and Alice Springs (AU-ASM). The improved pasture site, Daly River Pasture (AU-DaP), and the grassland site, Sturt Plains (AU-StP), were also selected to determine the lag month number in NEDI for the grass layer of savannas. Over the 1100 km from the northern site (AU-How) to the central inland site (AU-ASM), mean annual precipitation (MAP) declines by over 1300 mm (Rogers et al., 2017), dryness index (defined as the ratio of annual $R_{0d}/k$ to precipitation; Budyko, 1974) increases from 0.99 to 5.00, climate regimes transform from mesic (> 1200 mm MAP) to semi-arid and arid climates, and vegetation type transforms from open-forest savanna to Acacia woodland savanna (Beringer et al., 2011a; Eamus et al., 2013, Table 1). These ecosystems are subject to distinct wet and dry seasons and highly seasonal rainfall driven by monsoonal weather systems (Nov–Apr; Bowman et al., 2010). According to the timing and duration of the monsoon (Fig. S2), a full year is divided into the wet season (Dec–Mar), the brown-down period (Apr), the dry season (May–Oct), and the green-up period (Nov). These flux sites are underlain by well-drained red kandosols soils (Hutley et al., 2011; Eamus et al., 2013).

Table 1

<table>
<thead>
<tr>
<th>Site ID/name</th>
<th>Location</th>
<th>MAP (mm)</th>
<th>Climate regimes</th>
<th>Dryness Vegetation type index</th>
<th>Data range</th>
<th>Daytime closure ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>AU-How Howard Springs</td>
<td>12.4943'S 131.1523'E</td>
<td>1714</td>
<td>Mesic</td>
<td>0.99</td>
<td>Open-forest savanna</td>
<td>2002/01-2017/11</td>
</tr>
<tr>
<td>AU-DaP Daly River Pasture</td>
<td>14.0633'S 131.3181'E</td>
<td>1170</td>
<td>Mesic</td>
<td>1.29</td>
<td>Improved tropical pasture</td>
<td>2008/01-2013/09</td>
</tr>
<tr>
<td>AU-DaS Daly River Savanna</td>
<td>14.1592'S 131.3881'E</td>
<td>1170</td>
<td>Mesic</td>
<td>1.26</td>
<td>Woodland savanna</td>
<td>2008/01-2017/10</td>
</tr>
<tr>
<td>AU-Dry Dry River</td>
<td>15.2588'S 132.3706'E</td>
<td>850</td>
<td>Arid subhumid</td>
<td>1.82</td>
<td>Woodland savanna</td>
<td>2008/09-2009/07</td>
</tr>
<tr>
<td>AU-StP Sturt Plains</td>
<td>17.1575'S 133.3003'E</td>
<td>535</td>
<td>Semi-arid</td>
<td>1.90</td>
<td>Mitchell grassland</td>
<td>2008/09-2017/09</td>
</tr>
<tr>
<td>AU-ASM Alice Spring Mulga</td>
<td>22.2830'S 133.2490'E</td>
<td>309</td>
<td>Semi-arid</td>
<td>5.00</td>
<td>Acacia savanna woodland</td>
<td>2010/09-2017/10</td>
</tr>
</tbody>
</table>

* The MAP was taken from Cleversley et al. (2016) and Whitley et al. (2016).

* For AU-StP, time series during the years 2009 and 2015 were removed due to the low quality of the soil water content data.
Surface energy and water exchange data from the EC flux towers were used to calibrate and then validate the models. The EC flux data from the six sites along NATT were obtained from the Australia and New Zealand Flux (OzFlux) Research and Monitoring Network data portal (http://data.ozflux.org.au). The tower-based observation data measured at reference height (zr) included air temperature (Tr), water vapor pressure deficit (Dv), wind speed (u), the downwelling solar radiation (Rsd), net radiation (Rn), latent heat flux (LE), and sensible heat flux (H). Soil water content (θ) of the 10–30 cm soil layer was measured with TDR probes (CS616, Campbell Scientific, Townsville, Australia) buried at 10 cm below the soil surface. The data were processed using PyFluPro to Level 3 that included quality control and corrections but not gap-filling (Isaac et al., 2017). The Level 3 data were then gap-filled using the Dynamic INtegrated Gap filling and partitioning for the Oz-Flux (DINGO) system. The gap-filling of meteorological data were based on multiple data sources. An artificial neural network (ANN) model was used to gap-fill flux data, including λE, soil heat (G), etc (Beringer et al., 2017).

The EC flux measurements generally underestimate nighttime transpiration due to low turbulence (Fisher et al., 2007; Moore et al., 2008). Thus, night-time flux data were discarded when the friction velocity (u*) value was below an annually calculated u* threshold determined using the Barr et al. (2013) approach. These missing data were then gap-filled by the DINGO system using an ANN model that was trained on all available data using Rn, Dv, θ, Tr, u and as predictors (Beringer et al., 2017). To ensure high data quality for model validation, only daily daytime eddy flux data were used for data analysis and model simulation. Days with over 20% gap-filled daytime data were excluded to avoid the potential influence of a functional relationship between environmental variables and ET introduced by gap-filling methods. Daytime was defined as the period when Rsd was greater than 12 W m⁻² in our study.

The daily daytime energy balance closure ratio ranged from 0.80 to 0.92 across the five sites (Table 1) which is within the range of global Fluxnet sites (0.84 ± 0.20, Stoy et al. 2013) indicating acceptable flux density. The closure ratio outside of the range of 0.7-1.3 were not selected for parameter optimization and model evaluation. To mitigate the effects of energy imbalance on ET estimation, the flux data was forced energy balance closure correction as in Twine et al. (2000), Chávez et al. (2005) and Mallick et al. (2018).

To validate and further improve the models, overstory and understory water fluxes were measured by dual-tower measurement systems at AU-How. With a horizontal distance of 10 m, the two sets of EC systems were installed above the understory (at 5 m height) and above the overstory (at 23 m height), respectively (Kool et al., 2014; Moore et al., 2016; Fig. 2). The understory tower measured a representative understory flux footprint within the main tower footprint (Moore et al., 2017). The dual-tower observations have been used to evaluate carbon flux partitioning between trees and grasses (Moore et al., 2016, 2017, 2018). In this study, we used dual-tower observations to validate the predicted tree transpiration and understory ET components (grass transpiration plus soil evaporation). The understory eddy flux tower was used from September 2012 to November 2017 at AU-How (available at http://www.ozflux.org.au/). For detailed descriptions of these sites and flux data, refer to Hutley et al. (2011) and Beringer et al. (2016).

2.3. LAI retrieval and partitioning

MODIS C6 LAI/FPAR product MOD15A2H (8-day, 500 m resolution) was used to retrieve LAI, a key variable for calculating canopy resistance. The product was downloaded from https://modis.ornl.gov/data/modis_webservice.html through MODISTools (Tuck et al., 2014) package in R 3.5.1 (R Core Team, 2018). To match the footprint of the eddy flux tower, a central 3 × 3 km window was extracted at each flux tower site (Rahman et al., 2005). Poor-quality LAI data were removed and replaced with linearly interpolated data. The 8-day LAI data for the two pasture/grassland sites (AU-DaP and AU-StP) were interpolated to create daily values using cubic spline interpolation and then smoothed with a Savitzky-Golay filter in the R package 'phanex' (Lange and Doktor, 2017) to remove noise.

To partition satellite-retrieved LAI into tree and grass components, we adopted an improved decomposition method based on methods described by Roderick et al. (1999) and Lu et al. (2003). Lu et al. (2003) proposed a time series decomposition approach for tree-grass coexisting ecosystems which had contrasting seasonal patterns: low-level seasonal variations of tree vegetation and high-level seasonal variations of grass vegetation. In the Lu et al. (2003) approach, remotely sensed vegetation signal is represented with X(t). The 8-day MODIS-retrieved LAI time-series was used to represent X(t) directly in our study. The X(t) time-series were reconstructed with seasonal-trend decomposition based on the locally weighted regression (LOESS) smoother in Lu et al. (2003). Singular Spectrum Analysis (SSA) was robust to noise caused by cloud or aerosol contaminations (Alexandrov, 2009; Ma et al., 2013b). Thus, SSA was used to retrieve the signal's long-term trend Xλ and annual amplitude Xa as in Ma et al. (2013a) in our study. The X(t) time-series were reconstructed with Xr and Xa as:

\[ X(t) = Xr + Xa[\lambda(t) - s] \] (29)

where \( \lambda(t) \) is the dimensionless shape factor determining the strength of the seasonal phenological wave, \( s \) is the average of \( \lambda(t) \). The baseline of tree signals \( X_{\text{tr}}(t) \) equals:

\[ X_{\text{tr}}(t) = Xr - sXa - d \] (30)

where \( d \) is soil background value.

\( X(t) \) was partitioned into three components (i.e., contributions from trees \( X_{\text{tr}}(t) \), grasses \( X_{\text{gr}}(t) \), and d) as in Lu et al. (2003):

\[ X(t) = X_{\text{tr}}(t) + X_{\text{gr}}(t) + d \] (31)

\( X_{\text{tr}}(t) \) was represented by a weak annual phenological wave layered upon a baseline \( X_{\text{base}}(t) \):

\[ X_{\text{tr}}(t) = \left[ 1 + \lambda_{\text{tr}} S(t) \right] X_{\text{base}}(t) \] (32)

where \( \lambda_{\text{tr}} \) is the multiplier defining the magnitude of the seasonal phenological wave for the tree component, relative to the dry baseline.
Lu et al., 2003) and was set equal to 0.4 as in Ma et al. (2013a). Combining Eqs. (29)-(32), \( X_{gr}(t) \) was expressed as a strong seasonal phenological wave:

\[
X_{gr}(t) = S(t)[X_A - \lambda_p X_{0gr}(t)]
\]

(33)

Dry season LAI at the pasture site (AU-StP) often reached zero as grasses senesced. However, the minimum value of MODIS LAI was 0.2 m² m⁻² at the site, most likely caused by soil background influences. Thus, \( d = 0.2 m^2 m^{-2} \) at three of the savanna sites (AU-How, AU-DaS, and AU-Dry). \( d \) was set as zero at AU-ASM since MODIS-retrieved LAI could reach as low as 0.17 m² m⁻² at this site. The 8-day LAI and \( LAI_p \) timeseries partitioned with Eqs. (32-33) were then interpolated to daily values with cubic spline interpolation and used as vegetation information to drive the three-source models.

2.4. Parameter calibration and model evaluation

Global parameter sensitivity analysis is an effective method to screen key parameters affecting model results. A global parameter sensitivity analysis was conducted for the five parameters (i.e., \( g_{sx}, k_p, q_{50}, D_{50}, \) and \( Q_{50} \)) in the canopy conductance submodel (Eq. (21)) using the Sensitivity package (Iooss et al., 2018) and the Multisensi package (Lamboni et al., 2009; Bidot et al., 2018) in R 3.5.1 at AU-How to screen key parameters.

The unknown key parameters for the SW, PML, TS, SW-DI, PML-DI, and TS-DI models were optimized through Bayesian MCMC (Markov chain Monte Carlo) methodology based on the standard Metropolis-Hastings algorithm (Metropolis et al., 1953; Hastings, 1970) using the BayesianTools (Hartig et al., 2019) package in R 3.5.1. A Bayesian Setup was initially created to provide information on the model to be fit (likelihood), and the priors (i.e., lower/upper boundaries) for the model parameters. Then calibration was run with sampler “Metropolis” to obtain posterior averages for optimized parameters.

The mean \( g_{sx} \) measured in September, late dry season, showed a weak decreasing trend with decreasing MAP along NATT (Cernusak et al., 2011). Thus, the prior upper limits of \( g_{sx} \) and \( g_{sx,tr} (g_{sx} \) of trees) were set in a descending order, decreasing from 20 mm s⁻¹ at AU-How to 12 mm s⁻¹ at AU-ASM. The prior lower limits of \( g_{sx} \) and \( g_{sx,tr} \) were set as 5 mm s⁻¹ for all sites. Since the stomatal conductances of C4 grasses were typically lower than that of C3 trees (Collatz et al., 1992; Whiteley et al., 2011), the prior ranges of \( \beta \) (i.e. the ratio of grass \( g_{sx} \) to tree \( g_{sx} \)) were set as 0.6–0.9 in our study. The range of priors was set as 0.5–2.0 for \( m \) in Eq. (27) for the SW-DI, PML-DI, and TS-DI models (Table 2), according to our parameter optimization experiments.

To evaluate model performance, we used the following statistical metrics: the slope (SLP) and coefficient of determination (R²) calculated from linear regression of observed vs. predicted ET, and the root-mean-squared-error (RMSE). SLP evaluates the closeness to unity in the regression of observations and predictions. RMSE evaluates “the amplitude in the variation from the observations” (Ménard et al., 2015).

<table>
<thead>
<tr>
<th>Site ID</th>
<th>( g_{sx} ) and ( g_{sx,tr} )</th>
<th>( \beta )</th>
<th>( m )</th>
</tr>
</thead>
<tbody>
<tr>
<td>AU-How</td>
<td>5–20</td>
<td>0.6–0.9</td>
<td>0.5–2.0</td>
</tr>
<tr>
<td>AU-DaP</td>
<td>5–18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AU-DaS</td>
<td>5–18</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AU-Dry</td>
<td>5–16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AU-StP</td>
<td>5–14</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AU-ASM</td>
<td>5–12</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3. Results

3.1. LAI partitioning

Time series of total LAI, tree LAI (LAI_A), and grass LAI (LAI_p) retrieved from satellites are illustrated in Fig. 3. The ground-observed LAI_p were from Hutley et al. (2011) and Eamus et al. (2013). Time series of LAI_A obtained using the methods of Lu et al. (2003) exhibited weak seasonal patterns at AU-How, AU-DaS, and AU-Dry. The seasonal characteristics of LAI_p were not obvious due to the influence of large interannual variations at AU-ASM. The LAI_p time series showed distinct seasonal variations with peaks during the wet seasons and near-zero values during the end of the dry seasons.

Scatterplots showed that LAI_p separated using the method of Lu et al. (2003) mostly matched LAI_p from ground observations (Hutley et al., 2011; Eamus et al., 2013; Moore, 2016) across the four selected savanna sites (Fig. 4, \( R^2 = 0.97, \text{RMSE} = 0.10 \text{ m}^2 \text{ m}^{-2}, N = 16 \)). The biases of MODIS-retrieved LAI_p from ground-observed LAI_p ranged from −0.27 to 0.16 m² m⁻² for the four sites.

The LAI partitioning method well repeated the observed seasonal patterns of LAI_A at AU-How (\( R^2 = 0.82, \text{RMSE} = 0.07 \text{ m}^2 \text{ m}^{-2}, y = 0.77 x + 0.30, N = 7 \)), but failed at AU-ASM (\( R^2 = 0.04, \text{RMSE} = 0.13 \text{ m}^2 \text{ m}^{-2}, y = 0.30 x + 0.25, N = 7 \)). It is difficult to determine the ability of the Lu et al. (2003) approach in partitioning LAI with only one observation for either AU-DaS or AU-Dry. Thus, we discussed the results from the four sites together and did not discuss the AU-DaS and AU-Dry results individually. The observed ground LAI at AU-DaP and AU-StP during Sep 2008 were −0.05 m² m⁻² and 0.0 m² m⁻², respectively (Hutley et al. 2011). During the prolonged dry season, grass LAI usually approached zero in pastures/grasslands. The satellite-retrieved LAI overestimated true pasture/grassland LAI (Fig. S3) due to the occurrence of evergreen trees nearby and soil background information. To reduce this bias, true LAI at AU-DaP and AU-StP were represented by the satellite-retrieved LAI minus the minimum values in the LAI time series.

3.2. Parameter estimation

The global sensitivity analysis showed that \( g_{sx} \) ranked as the key parameter with the highest sensitivity index (0.88), followed by \( D_{50} \) (0.34, Fig. 5). Thus, optimization of \( g_{sx} \) can be used to reduce prediction errors. The remaining four parameters had relatively low sensitivity indices and were thus assigned fixed values (\( k_p = 0.6, D_{50} = 0.7 \) kPa, and \( Q_{50} = 30 \text{ W m}^{-2} \)) to simplify the canopy conductance submodel.

The posterior averages of parameters optimized by the Bayesian MCMC algorithm are shown for both forced and unforced closure situations in Table 3. The optimized values of grass \( g_{sx} \) (\( g_{sx,gr} \)) were calculated as the multiplication of the optimized values of \( g_{sx,tr} \) and \( \beta \). The optimized values of \( g_{sx}, g_{sx,gr}, g_{sx,tr} \) in forced closure situation were generally larger than those unforced. The optimized values of \( g_{sx} \) for the SW and PML models ranged from 7.79 to 17.01 mm s⁻¹ across the six sites, with the largest values at AU-How (15.8–17.01 mm s⁻¹) in the forced closure situation. For the four savanna sites, \( g_{sx,tr} \) and \( g_{sx,gr} \) showed a decreasing trend with decreasing MAP along the precipitation gradient for TS model. The optimized values of \( g_{sx} \) or \( g_{sx,gr} \) for the SW-DI, PML-DI, and TS-DI models were higher than those for the SW, PML, and TS models. In the situation of unforced closure, the values of \( m \) optimized for SW-DI, PML-DI, and TS-DI were lowest (0.77–1.30) at AU-How, increased to 1.43–1.72 at AU-DaS, and increased further to 1.59–1.75 at AU-Dry.

3.3. Model performance

To select a reliable observation reference for evaluating model prediction, we evaluated how the energy balance closure correction of...
ET observation affected ET estimation. The regression analysis between ET residues and energy balance ratios was conducted in both forced and unforced energy balance closure situation (Fig. 6). Closure ratios equal to 1.0 after forcing closure. The values of closure ratios prior to forcing closure were used for the regression analysis in forced closure situation. Here we chose models of TS and TS-DI as examples. In the unforced closure situation, there were significant negative linear relationships between closure ratios and ET residues at sites of AU-How, AU-DaS and AU-Dry (fitted slopes ranging from -4.49 to -2.16; $R^2 = 0.16–0.27$; $p < 0.05$). There were systematic biases in ET estimation at AU-How and AU-DaS: ET with closure ratios below 0.8 were more likely to be overestimated, and ET with closure ratios above 1.0 tended to be underestimated in the unforced closure situation. Through forcing closure, the significant negative linear relationship between closure ratios and ET residues were avoided at AU-How ($R^2 \leq 0.01$) and partially reduced at AU-Dry (fitted slopes ranging from -1.92 to -1.46; $R^2 = 0.02–0.04$; $p < 0.05$). These systematic biases of ET estimation caused by energy imbalance could be avoided by forcing closure at mesic sites (AU-How and AU-DaS). Thus, ET observation that was forced closure was determined as the reference of ET prediction in our main manuscript. The simulation of ET in unforced closure situation was illustrated in the Supplements as a comparison.

Fig. 3. Decomposition of satellite-retrieved total LAI (black line) into tree LAI (blue dash line) and grass LAI (red dot-dash line) during 2006-2017 at four selected savanna sites located along the North Australian Tropical Transect, Northern Territory, Australia. The grey vertical bars are daily precipitation.

Fig. 4. Scatterplots of tree LAI (satellite-retrieved vs. ground-observed). The corresponding ground observation dates are in Supplemental Table S2. Sites were located along the North Australian Tropical Transect, Northern Territory, Australia. The satellite-retrieved tree LAI was partitioned from daily LAI obtained from 8-day satellite-retrieved LAI interpolation.

Fig. 5. The first-order sensitivity indices of five canopy conductance parameters ($g_{so}$, $k_n$, $k_Q$, $D_{50}$, and $Q_{50}$) in the Penman-Monteith-Leuning (PML) model.

AU-DaS: ET with closure ratios below 0.8 were more likely to be overestimated, and ET with closure ratios above 1.0 tended to be underestimated in the unforced closure situation. Through forcing closure, the significant negative linear relationship between closure ratios and ET residues were avoided at AU-How ($R^2 \leq 0.01$) and partially reduced at AU-Dry (fitted slopes ranging from -1.92 to -1.46; $R^2 = 0.02–0.04$; $p < 0.05$). These systematic biases of ET estimation caused by energy imbalance could be avoided by forcing closure at mesic sites (AU-How and AU-DaS). Thus, ET observation that was forced closure was determined as the reference of ET prediction in our main manuscript. The simulation of ET in unforced closure situation was illustrated in the Supplements as a comparison.

Performance of the three PM-type models with vs. without NEDI in forced closure situation were illustrated in the figures/tables of
Table 3
Site-specific $g_{sx}$ (i.e., maximum stomatal conductance, mm s$^{-1}$), $g_{sx,tr}$ (tree $g_{sx}$, mm s$^{-1}$), $g_{sx,gr}$ (grass $g_{sx}$, mm s$^{-1}$), and $m$ (i.e., a multiplier defining the effects of drought indicator on canopy conductance) estimated by the Bayesian MCMC algorithm for six sites located along the North Australian Tropical Transect, Northern Territory, Australia. Optimized values in the situation of both forced and unforced energy balance closure correction are shown in the table.

<table>
<thead>
<tr>
<th>Force closure</th>
<th>Site ID</th>
<th>SW</th>
<th>PML</th>
<th>TS</th>
<th>SW-DI</th>
<th>PML-DI</th>
<th>TS-DI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>AU-How</td>
<td>15.80</td>
<td>17.01</td>
<td>16.44</td>
<td>14.80</td>
<td>17.56</td>
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<td></td>
<td>AU-DaS</td>
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<td>12.66</td>
<td>12.25</td>
<td>11.02</td>
<td>14.45</td>
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<td>AU-Dry</td>
<td>13.57</td>
<td>13.74</td>
<td>12.61</td>
<td>12.25</td>
<td>16.00</td>
<td>1.25</td>
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<td>11.98</td>
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<td>10.80</td>
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<td>-</td>
<td>-</td>
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<td>0.92</td>
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<td>AU-DaS</td>
<td>9.90</td>
<td>11.36</td>
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<td>9.25</td>
<td>11.93</td>
<td>1.48</td>
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<td></td>
<td>AU-Dry</td>
<td>9.92</td>
<td>9.92</td>
<td>10.01</td>
<td>9.01</td>
<td>13.96</td>
<td>1.59</td>
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<td></td>
<td>AU-ASM</td>
<td>9.47</td>
<td>9.47</td>
<td>9.93</td>
<td>8.94</td>
<td>12.00</td>
<td>1.03</td>
</tr>
<tr>
<td></td>
<td>AU-DaP</td>
<td>7.74</td>
<td>10.34</td>
<td>-</td>
<td>-</td>
<td>9.73</td>
<td>2.00</td>
</tr>
<tr>
<td></td>
<td>AU-StP</td>
<td>6.65</td>
<td>7.79</td>
<td>-</td>
<td>-</td>
<td>7.60</td>
<td>0.50</td>
</tr>
</tbody>
</table>

The model abbreviations are Shuttleworth-Wallace (SW), Penman-Monteith-Leuning (PML), three-source (TS), and drought indicator (DI).

Fig. 6. The relationships between model residuals of evapotranspiration (ET) (predicted ET minus observed ET, mm d$^{-1}$) and energy balance closure ratios for the TS and TS-DI models in the unforced vs. forced closure situations at four savanna sites. Sites were located along the North Australian Tropical Transect, Northern Territory, Australia. The SLP is the slope the regression between ET residues and energy balance closure ratios.
observed vs. predicted timeseries (Figs. 7), scatterplots (Fig. 8 and Table 4) and Taylor diagram (Fig. S4). The corresponding figures/tables in unforced closure situation were illustrated in Supplemental Figs. S7-S10 and Table S3. Both groups of models can replicate the seasonal patterns of observed ET (Fig. 7). However, there were considerable gaps between observed and predicted ET at periods of brown-down and green-up, which was mostly seen at AU-Dry. Adding NEDI reduced the differences between observed and predicted ET during the green-up period at AU-Dry. However, the differences between observed and predicted ET during the brown-down period were relatively large after adding NEDI at AU-Dry.

For the four savanna sites as a whole, adding NEDI to the ET models improved the three performance metrics: the fitted slopes increased from 0.79–0.83 to 0.89–0.91, $R^2$ increased from 0.85–0.87 to 0.89–0.90, and RMSE decreased from 0.58–0.63 to 0.51–0.54 mm d$^{-1}$ (Table 4). The increase of SLP at the four savanna sites was the most obvious feature in the scatterplots of predicted and observed ET shown in Fig. 8. At AU-Dry, the slopes increased from 0.60–0.67 to 0.76–0.82 after adding NEDI to the ET models. Scatter points of predictions vs. observations during the green-up period were distributed closer to the 1:1 line when NEDI was added to the ET models at AU-How. However, scatter points of predictions vs. observations during the brown-down period were always distributed below the 1:1 line even after NEDI was added to the ET models at AU-Dry (Fig. 8). For the pasture/grassland sites (AU-DaP and AU-StP), adding NEDI to the ET models did not improve model performance as manifest as for savanna sites. The model improvement information in Table 4 is intuitively illustrated in the Taylor Diagram in Supplementary Fig. S4.

The model performance of the two groups of models in forced closure situation was further detailed in figures related with model residuals for ET (Fig. S5). The three savanna sites, AU-How, AU-DaS, and AU-Dry, showed similar seasonal patterns of ET residuals during the transiting periods. During the brown-down period (Apr), ET tended to be underestimated at the three savanna sites; and the largest ET underestimation occurred at AU-Dry, ranging from -1.11 to -0.86 mm d$^{-1}$ for the two groups of models. ET residues transformed from positive to negative during July. During the late dry season (Sep-Oct) and the green-up period (Nov), ET residues reached peak values of 0.43–0.87 mm d$^{-1}$ for SW, PML, and TS, and reached peak values of 0.17–0.36 mm d$^{-1}$ for SW-DI, PML-DI, and TS-DI.

3.4. Partitioning of ET

The ability of the TS model without and with DI to partition ET components was tested with the dual-tower observations at Howard Springs (Fig. 9). Observed understory ET and total ET were obtained from the understory and overstory EC systems, respectively (Fig. 2). The observed tree transpiration was calculated as the difference between the observed total ET and understory ET. The observed total ET was forced energy balance closure. The understory ET was not forced energy balance closure due to the absent of representative $R_n$ values for the understory footprint (Moore, 2016). The predicted understory ET

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Fig. 7. Seasonal patterns of daily ET (mm d$^{-1}$) observed and predicted by the Shuttleworth-Wallace (SW), Penman-Monteith-Leuning (PML), and three-source (TS) models, without and with Normalized Ecosystem Drought Index (NEDI) at six selected sites located along the North Australian Tropical Transect, Northern Territory, Australia. The time series were constructed as 7-day moving averages averaged over multiple observation years illustrated in Table 1. The observed ET was forced energy balance closure.

---
was the sum of the grass transpiration and soil evaporation predicted by either the TS or TS-DI models. The understory ET predictions ($R^2 = 0.71$ for TS, 0.72 for TS-DI) were better than the tree transpiration predictions. The TS model poorly captured the seasonal variation of observed tree transpiration: tree transpiration values greater than 2 mm d$^{-1}$ were overestimated, while tree transpiration values less than 2 mm d$^{-1}$ were underestimated. When adding the drought indicator (i.e., NEDI) for tree transpiration, $R^2$ increased from 0.33 for the TS model to 0.51 for the TS-DI model. The fitted slope for the linear regression of predicted vs. observed tree transpiration was 0.35 for the TS model, and improved to 0.53 for the TS-DI model.

4. Discussion

4.1. Observation representability and energy balance closure

Factors affecting ET estimation improvement mainly include: (1) observation representability of ET, (2) canopy conductance parameterization, and (3) water balance. The energy imbalance is a primary factor affecting ET observation representability in the EC flux measurements (Hirschi et al., 2017; Mauder et al., 2020). The average energy balance closure ratios (0.8–0.92) were below 1.0 across the six selected sites (Table 1). This indicated that a majority of the observed ET might be underestimated at these sites. Thus, when using unforced closure flux data as modeling evaluation references, the predicted ET tended to be larger than observed ET if the closure ratios were much lower than 1.0. Forcing closure could avoid the underestimation of ET at mesic sites (Fig. 6). However, forcing closure did not always improve all model evaluation metrics. At four savanna sites, only $R^2$ was improved through forcing closure while SLP and RMSE witnessed decreases and increases, respectively. For arid subhumid and semiarid sites (AU-Dry and AU-ASM), SLP decreased by 0.04–0.08, and RMSE increased by 0.05–0.11 mm d$^{-1}$ for models of SW, PML and TS after forcing closure (Table S4). The increasing of RMSE after forcing closure indicated that the approach of forcing closure could produce additional model errors and may be problematic in water-limited condition. To obtain more reliable observation references for model evaluation, a robust closure method should be designed for semiarid ecosystems (Mallick et al., 2018).

4.2. Canopy conductance parameterization

In PM-type models, canopy conductance is a critical variable affecting ET estimation. Calibration of key parameters in the canopy conductance submodel with local flux data is typically used to improve ET estimation (Leuning et al., 2008; Montes et al., 2014). The
parameter with highest sensitivity in the canopy conductance sub-model, \( g_{sx} \), was optimized as in Zhang et al. (2010). As pointed by Zhang et al. (2010), optimization of \( g_{sx} \) in canopy conductance sub-model could compensate the errors in the remotely sensed values of LAI.

The setting of values of \( g_{sx,gr} \) lower than \( g_{sx,tr} \) in the study was based on previous research (Collatz et al., 1992) and required further validation by future ground experiments.

The SW, PML, and TS models used in this study systematically underestimated total ET during the brown-down period, and over-estimated total ET during the green-up period at three of the savanna sites (AU-How, AU-DaS, and AU-Dry) (Figs 7 and 8). The seasonal under/over-estimations have previously been reported for both carbon and water fluxes over savannas along NATT. Gross primary productivity tended to be overestimated by an ecosystem light-use-efficiency model at AU-How and AU-Dry (Ma et al., 2014). Among the six selected global sites of different ecosystem, land surface models (e.g., CABLE and JULES) produced the largest model errors at the savanna site AU-How where ET in July was generally underestimated (Ukkola et al., 2016). The systematic biases in seasonal ET prediction were significantly reduced by adding a drought indicator (NEDI) that limited canopy conductance for vegetation transpiration (Table 4; Figs 7 and 8).

The water availability pattern over savannas was different for the seasonal transition periods: (1) during the brown-down period, deep soil water storage that accumulated during the previous wet season could still supply water for vegetation transpiration even though surface soil water content was low; (2) during the green-up period, soil water storage was greatly exploited after a prolonged dry season even though surface water content increased with the start of the rainy season. The drought indicator NEDI based on the water balance was able to

### Table 4
Model performance statistics for evapotranspiration estimation with Shuttleworth-Wallace (SW), Penman-Monteith-Leuning (PML), and three-source (TS) models without and with the Normalized Ecosystem Drought Index (NEDI) at six selected sites located along the North Australian Tropical Transect, Northern Territory, Australia.

<table>
<thead>
<tr>
<th>Site ID</th>
<th>Add NEDI</th>
<th>SW</th>
<th>PML</th>
<th>TS</th>
</tr>
</thead>
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<tr>
<td></td>
<td>N</td>
<td>SLP</td>
<td>( R^2 )</td>
<td>RMSE</td>
</tr>
<tr>
<td>AU-How</td>
<td>No</td>
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<td>0.85</td>
<td>0.54</td>
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<td>Yes</td>
<td>0.91</td>
<td>0.78</td>
<td>0.50</td>
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<tr>
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<td>0.76</td>
<td>0.11</td>
<td>0.52</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.67</td>
<td>0.12</td>
<td>0.55</td>
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<tr>
<td>AU-Dry</td>
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<td>0.82</td>
<td>0.16</td>
<td>0.61</td>
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<tr>
<td></td>
<td>Yes</td>
<td>0.85</td>
<td>0.18</td>
<td>0.62</td>
</tr>
<tr>
<td>AU-ASM</td>
<td>No</td>
<td>0.78</td>
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<td>Yes</td>
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<td>0.19</td>
<td>0.62</td>
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<tr>
<td>AU-DaP</td>
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<td>0.61</td>
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<tr>
<td></td>
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<td>0.85</td>
<td>0.20</td>
<td>0.62</td>
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<tr>
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<td></td>
<td>Yes</td>
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<td>0.23</td>
<td>0.63</td>
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<td></td>
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<td>0.20</td>
<td>0.62</td>
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<td>Savanna</td>
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<td>0.80</td>
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<td>0.61</td>
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<td></td>
<td>Yes</td>
<td>0.85</td>
<td>0.20</td>
<td>0.62</td>
</tr>
<tr>
<td>Pasture and grassland</td>
<td>No</td>
<td>0.80</td>
<td>0.18</td>
<td>0.61</td>
</tr>
<tr>
<td></td>
<td>Yes</td>
<td>0.85</td>
<td>0.20</td>
<td>0.62</td>
</tr>
</tbody>
</table>

- \( N \) is the number of data records.
- The unit of RMSE is mm d\(^{-1}\). \( R^2 \) is the coefficient of determination of the regression between observed and predicted evapotranspiration. SLP is the fitted slope.
- The boldfaced and italic values indicate that the corresponding model performance metrics were improved after adding NEDI.
- Savanna sites include AU-How, AU-DaS, AU-Dry, and AU-ASM.
- Pasture and grasslands include AU-DaP and AU-StP.

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The setting of values of \( g_{sx,gr} \) lower than \( g_{sx,tr} \) in the study was based on previous research (Collatz et al., 1992) and required further validation from ground observation at the areas. The C4 grasses flourish during wet season and lose function during dry season. During wet season, it was difficult to access these sites along NATT to conduct ground physiologic observation due to the high rainfall and tall grasses. Thus, most ground physiologic observation during dry season (Cernusak et al., 2011). The observation conducted during wet season were less frequent than those conducted during dry season. The \( g_{sx} \) of four tree species observed during wet season ranged from 0.4 to 1.0 mmol m\(^{-2}\) s\(^{-1}\) (i.e. 9.8–24.4 mm s\(^{-1}\)) at three sites along NATT (Prior et al. 2005). Our optimized values of \( g_{sx} \) and \( g_{sx,tr} \) were in this range. The optimized values of \( g_{sx,gr} \) require validation by future ground experiments.

The SW, PML, and TS models used in this study systematically underestimated total ET during the brown-down period, and over-estimated total ET during the green-up period at three of the savanna sites (AU-How, AU-DaS, and AU-Dry) (Figs 7 and 8). The seasonal under/over-estimations have previously been reported for both carbon and water fluxes over savannas along NATT. Gross primary productivity tended to be overestimated by an ecosystem light-use-efficiency model at AU-How and AU-Dry (Ma et al., 2014). Among the six selected global sites of different ecosystem, land surface models (e.g., CABLE and JULES) produced the largest model errors at the savanna site AU-How where ET in July was generally underestimated (Ukkola et al., 2016).

The systematic biases in seasonal ET prediction were significantly reduced by adding a drought indicator (NEDI) that limited canopy conductance for vegetation transpiration (Table 4; Figs 7 and 8). The water availability pattern over savannas was different for the seasonal transition periods: (1) during the brown-down period, deep soil water storage that accumulated during the previous wet season could still supply water for vegetation transpiration even though surface soil water content was low; (2) during the green-up period, soil water storage was greatly exploited after a prolonged dry season even though surface water content increased with the start of the rainy season. The drought indicator NEDI based on the water balance was able to

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Fig. 9. Observed vs predicted daily daytime tree transpiration and understory evapotranspiration (ET) using the three-source (TS) model without and with drought indicator (DI) (left and right panels, respectively). The ET observations are from Howard Springs from September 2012 to November 2017. The unit of RMSE is mm d\(^{-1}\). The observed total ET was forced energy balance closure.
represent these unique seasonal patterns of water availability for savannas. The time lag of response to precipitation by savanna ecosystems in our study was 1 month, which is the same as reported by Wu et al. (2015) in arid and semiarid areas at the global scale. The modified NEDI function in Eq. (27) (ranging from 0 to 1) was promising for limiting canopy conductance in ET models applicable to tropical savannas, and may have possible applications at other arid and semiarid areas.

Though the application of the modified NEDI function in ET models could reduce ET residues, it was noticeable that there was considerable ET underestimation at AU-Dry during the brown-down period (April) and early dry season (May) (Fig. 7). The underestimation may be caused by the neglect of groundwater exchange and runoff when calculating NEDI. Groundwater exchange and runoff are vital for groundwater-dependent ecosystems and can show considerable spatial and temporal variability. The NEDI function may underestimate the water supply for transpiration for AU-Dry. The representing of water availability by simplified NEDI function may be less precise than the more explicit root-water access model due to the neglect of groundwater exchange and runoff.

4.3. Factors affecting ET Partitioning

With the ability to classify plant functional type control of ET, the partitioning of transpiration into tree and grass components will permit the prediction of savanna ecosystem responses to future climate change. The ability of a coupled three-source model to accurately partition ET was improved after adding NEDI. However, the estimates of tree transpiration were largely scattered around the fitted line (Fig. 9). The low correlation between the predicted and observed tree transpiration may be caused by three factors: (1) the oversimplifying in the process of water supply for transpiration, (2) phenology of different species, and (3) the overestimation of mid-dry-season LAI. Firstly, the deep-rooted trees and shallow-rooted grasses have different water sources along the vertical soil profile. Thus, it was difficult for the NEDI function to fully represent the distinct water limit patterns for trees and grasses. Secondly, the savanna ecosystem is consisted by various tree and grass species that have different phenology and physiological characteristics. The dry-season deciduous, semi- or brevi-deciduous tree species account for a quarter of overstory in mesic savannas (Williams et al., 1997; Whiteley et al., 2011) and may contribute significantly to seasonal variations of overstory tree transpiration. The species-specific phenology and values of $g_{\text{s0}}$ could enhance the complexity and difficulties of ET modeling.

Thirdly, according to observations from the mesic site (Howard Springs) presented by O’Grady et al. (2000), L$\text{AL}_{\text{D}}$ reached its lowest values (0.6 m$^2$ m$^{-2}$) in the mid-dry season and then gradually increased in the late dry season. Our separated L$\text{AL}_{\text{D}}$ during mid-dry season (0.97 ± 0.09 m$^2$ m$^{-2}$; Fig. S10) was about 0.37 m$^2$ m$^{-2}$ greater than the observations from O’Grady et al. (2000), and yet close to the ground observation value of 1.04 ± 0.07 m$^2$ m$^{-2}$ from Hutley et al. (2011). The observations indicated that dry season L$\text{AL}_{\text{D}}$ had great interannual variations due to rainfall changes and disturbances (e.g., fires). Savannas at Howard Springs are subject to fire management to reduce dry biomass accumulation and to protect instruments from fires during the dry season. The abrupt changes of tree cover with the onset of fire is often difficult to be retrieved from remote-sensing information or may be filtered out as noise during the separation of LAI time series. Additionally, the present version of the LAI separation method has difficulties in reflecting that tree regrowth prior to the onset of the wet season occurs earlier than the regrowth of grasses. To further validate and improve LAI separation for savannas, capturing continuous variations of understory and overstory vegetation via automated time-lapse cameras (i.e. PhenoCams) will be helpful (Brown et al., 2016). The high correlations between observed and predicted understory ET by the three-source models (Fig. 9) does not assure that its components (either grass transpiration or soil evaporation) are correctly estimated. Apart from above and below canopy EC systems, additional understory observations (e.g., from soil chambers) will be helpful to accurately validate the separated ET components predicted by the three-source models.

5. Conclusion

Our study made a contribution to savanna research by determining a flexible indicator defining the seasonal water availability limitation on savanna ET. We showed that the flexible drought indicator NEDI, a function of precipitation and potential ET, was easily applied. As a flexible drought indicator accounting for time-lag effects of ecosystems to precipitation, NEDI proved to be capable of improving seasonal ET prediction for Australian tropical savannas. Using the NEDI function to limit canopy conductances for two-layer and three-source PM-type models successfully reduced systematic biases in predicting seasonal variations of ET over savanna ecosystems: fitted slopes were closer to unity by 0.08–0.10, $R^2$ increased by 0.03–0.04, and RMSE decreased by 0.07–0.09 mm d$^{-1}$. The NEDI function has the possibility to be integrated with both PM-type and SEB-type models where the effects of water availability limitations need to be accounted for. Our results may promote and enlighten future research on simulation of water and carbon fluxes over vegetated areas with complex species composition and distinct seasonal droughts.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials


References

Effects of vegetation clumping on two-source model estimates of surface energy fluxes from an agricultural landscape during SMACEX. J. Hydrometeorol. 6, 892–909.


