Bridging thermal infrared sensing and physically-based evapotranspiration modeling: from theoretical implementation to validation across an aridity gradient in Australian ecosystems

Kaniska Mallick1, Erika Toivonen1,2,10,11, Ivonne Trebs1, Eva Boegh3, James Cleverly4, Derek Eamus3, Harri Koivusalo2, Darren Drewry5,9, Stefan K Arndt6, Anne Griebel6, Jason Beringer7, Monica Garcia8,12

1Department of Environmental Research and Innovation (ERIN), Luxembourg Institute of Science and Technology (LIST), Belvaux, Luxembourg
2Department of Built Environment, Aalto University School of Engineering, Espoo, Finland
3Department of Environmental, Social and Spatial Change, Roskilde University, Roskilde, Denmark
4Terrestrial Ecohydrology Research Group, School of Life Sciences, University of Technology Sydney, Broadway, NSW, Australia
5Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Drive, Pasadena, 91109, USA
6School of Ecosystem and Forest Sciences, The University of Melbourne, Victoria, Australia
7School of Agriculture and Environment (SAE), The University of Western Australia, Crawley, WA, 6009, Australia
8Department of Environmental Engineering, Technical University of Denmark, Bygning, Lyngby, Denmark
9Joint Institute for Regional Earth System Science and Engineering, University of California, Los Angeles, California, USA
10Climate System Research, Finnish Meteorological Institute, Helsinki, Finland
11Department of Physics, University of Helsinki, Helsinki, Finland
12International Research Institute for Climate and Society, The Earth Institute, Columbia University, Palisades NY, USA

Corresponding Authors: Kaniska Mallick (Email: kaniska.mallick@gmail.com; Phone: +352 275888425); Erika Toivonen (Email: erika.a.toivonen@gmail.com)

Key points:

(1) Thermal remote sensing of evapotranspiration is critical due to uncertainties in aerodynamic temperature and conductance estimation.

(2) We integrated radiometric temperature into Penman-Monteith Shuttleworth-Wallace framework to directly estimate conductances and evapotranspiration.

(3) Moderate to low systematic errors across an aridity gradient in Australian ecosystems.
Abstract:

Thermal infrared sensing of evapotranspiration (E) through surface energy balance (SEB) models is challenging due to uncertainties in determining the aerodynamic conductance (g_A) and due to inequalities between radiometric (T_R) and aerodynamic temperatures (T_0). We evaluated a novel analytical model, the Surface Temperature Initiated Closure (STIC1.2), that physically integrates T_R observations into a combined Penman-Monteith Shuttleworth-Wallace (PM-SW) framework for directly estimating E, and overcoming the uncertainties associated with T_0 and g_A determination. An evaluation of STIC1.2 against high temporal frequency SEB flux measurements across an aridity gradient in Australia revealed a systematic error of 10% – 52% in E from mesic to arid ecosystem, and low systematic error in sensible heat fluxes (H) (12% – 25%) in all ecosystems. Uncertainty in T_R versus moisture availability relationship, stationarity assumption in surface emissivity, and SEB closure corrections in E were predominantly responsible for systematic E errors in arid and semi-arid ecosystems. A discrete correlation (r) of the model errors with observed soil moisture variance (r = 0.33 to 0.43), evaporative index (r = 0.77 to 0.90), and climatological dryness (r = 0.60 to 0.77) explained a strong association between ecohydrological extremes and T_R in determining the error structure of STIC1.2 predicted fluxes. Being independent of any leaf-scale biophysical parameterization, the model might be an important value addition in working group (WG2) of the Australian Energy and Water Exchange (OzEWEX) research initiative which focuses on observations to evaluate and compare biophysical models of energy and water cycle components.

Keywords: evapotranspiration, thermal infrared sensing, land surface temperature, surface energy balance, Penman-Monteith, Shuttleworth-Wallace, aridity gradient, Australia
1. Introduction

The determination of the aerodynamic temperature \( T_0 \) and conductance \( g_A \) contributes to the principal uncertainty in regional-scale evapotranspiration \( E \) mapping when using models based on thermal infrared sensing [Kustas et al., 2016; Paul et al., 2014; Paul et al., 2013]. To reduce this uncertainty, there is either a sincere need to accommodate and settle on a unified land surface parameterization for estimating \( T_0 \) and \( g_A \); or use analytical models independent of any empirical parameterization of these variables.

Land surface temperature or radiometric surface temperature \( T_R \) obtained through thermal infrared remote sensing governs the land surface energy budget [Kustas and Anderson, 2009; Anderson et al., 2012], and thermal \( E \) models principally focus on surface energy balance (SEB) approach in which \( T_R \) represents the lower boundary condition to constrain the energy-water fluxes [Norman et al., 1995; Anderson et al., 2008; Mallick et al., 2014a, 2015]. It satisfies the SEB equation (eqn. 1, 2, 3 below) by altering \( T_0 \) as well as by imposing constraints arising due to water stress on the biophysical conductances \( g_A \) and \( g_C \) (a list of variables and symbols along with their units are given in Table A1).

\[
R_N = H + \lambda E + G \tag{1}
\]

\[
(R_{S1} - R_{ST}) + (R_L - q \varepsilon T_R^4) = \rho c_p g_A (T_0 - T_A) + \frac{\rho c_p g_A g_C}{g_A + g_C} (e_0^* - e_A) + G \tag{2}
\]

\[
T_R = \left[ (R_{S1} - R_{ST}) + R_L - \rho c_p g_A (T_0 - T_A) - \frac{\rho c_p g_A g_C}{g_A + g_C} (e_0^* - e_A) - G \right]^{1/4} \frac{q \varepsilon}{g_A} \tag{3}
\]
State-of-the-art SEB models are based on estimating $g_A$ and sensible heat flux ($H$) while solving $E$ (or latent heat flux, $\lambda E$) as a residual SEB component (given $R_N$ and $G$ are known).

However, the most serious assumption in estimating $H$ concerns the use of $T_R$ as a surrogate of $T_0$ [Colaizzi et al., 2004; Chavez et al., 2010]. Major drawbacks in the explicit use of $T_R$ in SEB modeling are (a) the inequality between $T_0$ and $T_R$ ($T_0 \neq T_R$) [Chavez et al., 2010; Boulet et al., 2012], (b) the unavailability of a universally agreed model to estimate $T_0$, which controls the transfer of sensible heat [Colaizzi et al., 2004], (c) non-unique relationship between $T_0$ and $T_R$ due to differences between the effective source-sink height of momentum and heat within vegetation substrate complex [Troufleau et al., 1997; Chavez et al., 2010; Holwerda et al., 2012], (d) the lack of a preeminent physically-based $g_A$ model [Holwerda et al., 2012], and (e) bypassing the role of $T_R$ on $g_C$ in $\lambda E$ modeling.

Despite the aforementioned shortcomings, emphasis on estimating $H$ is motivated by the broad acceptance of the Monin-Obukhov Similarity Theory (MOST) or Richardson Number ($R_i$) criteria for estimating $g_A$, and the requirement of minimum inputs for solving both $g_A$ and $H$. However, estimating $g_A$ using MOST or $R_i$ approaches created further problems, particularly in relation to accommodating the inequalities between $T_0$ and $T_R$, as well as in adapting the differences between $g_A$ and the momentum conductance ($g_M$) arising due to the differences in the roughness length of heat and momentum ($z_{0H}$ and $z_{0M}$) [Paul et al., 2014]. The effects due to inequality between $T_0$ and $T_R$ were partially overcome by the inclusion of an ‘extra conductance’ and the $kB^{-1}$ term as a fitting parameter that adjusts the difference between $z_{0H}$ and $z_{0M}$ [Troufleau et al., 1997; Su, 2002; Boegh et al., 2002], and later through the inception of two-source soil-canopy modeling schemes [Norman et al., 1995; Anderson et al., 2007; Colaizzi et al., 2012; Boulet et al., 2015]. However, SEB-based predictions of $H$ (and $\lambda E$) are conditional to empirical response functions of $g_A$ [Liu et al., 2007; Timmermans et al., 2013; Morillas et al., 2013; Paul et al., 2014; Ershadi et al., 2015; Kustas et al., 2016].
that have an uncertain transferability in space and time [Holwerda et al., 2012; van Dijk et al., 2015]. In contemporary SEB modeling, $g_A$ sub-models are stand-alone, and lack the necessary physical feedback it should provide to $g_C$, $T_0$, and vapor pressure deficit surrounding the evaporating surface ($D_0$) [Cleverly et al., 2013]. The feedback of $g_A$ on $g_C$ is critical in arid and semi-arid ecosystems where reduced soil moisture availability in conjunction with very high evaporative potential causes significant water stress in the soil-vegetation-atmosphere system, thereby resulting discrepancy between $T_R$ and $T_0$. Thermal-based $\lambda E$ modeling needs explicit consideration of such important biophysical feedbacks to reduce the existing uncertainties in arid and semi-arid ecosystems [Kustas et al., 2016].

The Penman-Monteith (PM) and Shuttleworth-Wallace (SW) models are mutually related and two of the most preeminent physical models for quantifying surface-to-air $\lambda E$. They are fundamentally constrained to account for the necessary feedbacks between $\lambda E$, $T_R$, $D_0$, $g_A$, and $g_C$ [Monteith, 1965; Shuttleworth and Wallace, 1985]. The elemental connectivity of PM-SW with $T_R$ originates from the first order dependence of $g_C$ and $g_A$ on $T_R$ (through soil moisture and $T_0$). Despite their theoretical integrity, the integration of $T_R$ into the PM-SW model was not yet well established. Although the perception of combining the PM model with $T_R$ was initiated by Jackson et al. [1981] in the Crop Water Stress Index (CWSI) formulation, it had later been acknowledged that using the PM method could produce large errors in $\lambda E$ due to the underlying uncertainties in conductance estimates, particularly in sparsely vegetated and water-stressed ecosystems [Leuning et al., 2008; Morillas et al., 2013], such as the majority of ecosystems in Australia [Beringer et al., 2016].

Invigorated by the potential of thermal infrared data, Mallick et al. [2014a, 2015] proposed an integration of $T_R$ into the PM model to directly estimate the conductances, $\lambda E$, and $H$, and to simultaneously overcome the empirical uncertainties in estimating $g_A$ and $T_0$. The Surface Temperature Initiated Closure (STIC) [Mallick et al., 2014a; 2015] is a unique framework
based on analytical solutions for \( g_A \), \( g_C \), and \( T_0 \). Initial studies with different versions of STIC primarily focussed on validation of \( H \), \( \lambda E \) and its partitioning, using moderate (coarse) spatial (temporal) resolution remote sensing data (STIC1.0; Mallick et al., 2014a), and understanding the impacts of thermal versus humidity based water stress constraints on \( \lambda E \) (STIC1.1; Mallick et al., 2015). However, the early versions of STIC could only partially bridge \( T_R \) and SEB modeling due to structural inadequacies for establishing surface versus aerodynamic feedbacks [Mallick et al., 2015]. A later version of STIC (STIC1.2) [Mallick et al., 2016] integrates \( T_R \) into the PM-SW system to establish the required feedback between \( T_R \) and \( \lambda E \), along with aerodynamic temperature, humidity, and conductances. In a recent study, STIC1.2 was applied for evaluation of biophysical conductances and assessing their controls on evapotranspiration partitioning in the Amazon basin [Mallick et al., 2016]. However, evaluating the performance of STIC1.2 across an aridity gradient with data of high temporal resolution is on one hand essential to understand the role of \( T_R \) in STIC1.2 in hydrologically extreme natural ecosystems, and on the other to evaluate the limitations of this analytical SEB model before extending its future applicability for regional-scale \( E \) mapping.

The combination of prevailing arid/semi-arid ecosystems, ecohydrological heterogeneity, and the availability of continuous SEB flux observations make Australia an excellent testbed. Present study reports an in-depth evaluation of STIC1.2 by exploring eddy covariance (EC) observations from a range of diverse ecosystems of the OzFlux network [Beringer et al., 2016] across a large aridity gradient in Australia as a way forward to reduce \( T_0 \) and \( g_A \) uncertainties in regional-scale \( E \) mapping as well as to efficiently bridge \( T_R \) and SEB modeling. Our study addressed the following research questions:

(1) What is the performance of STIC1.2 when evaluated with high temporal resolution data across an aridity gradient in Australia?
(2) How do $T_R$ and environmental variables affect the performance of STIC1.2 across ecohydrological extremes from arid to humid ecosystems?

(3) Is there an association between ecohydrological conditions and $T_R$ in determining the errors and variability of water and energy flux components predicted by STIC1.2?

The novelties of the present study are: (a) an extensive evaluation of STIC1.2 from dry to wet ecohydrological extremes at multiple temporal scales (from half-hourly to annual), (b) intercomparison with previous versions of STIC, (c) sensitivity analyses of $\lambda E$ and conductances to $T_R$, as well as application of multivariate statistics (e.g., principal component analysis) to understand the impacts of $T_R$ and environmental variables on the error characteristics of STIC1.2 derived $\lambda E$ from arid to humid climate, and (d) identification of the integrated role of ecohydrological conditions and $T_R$ on errors and variability of SEB flux predictions by STIC1.2.

2. Why Australia?

Australia is a predominantly dry continent with substantial fluctuations in precipitation and primary production [Cleverly et al., 2016]. Limited water resources, drought vulnerability, high evaporative demand, and growing water requirements are continuously increasing pressure on sustainable management of water resources. The Millennium Drought from 2001 until 2009 dramatically ended with a "big wet" in 2010-2012 coinciding with the largest La Niña in over 70 years [van Dijk et al., 2013; Cleverly et al., 2016]. A major part of the Australian continent is arid (38%) or semi-arid (36%) [Beringer et al., 2016] with canopy cover of less than 50% across most of the continent [Glenn et al., 2011]. In contrast, there are locations where annual average precipitation exceeds 4000 mm [Glenn et al., 2011]. In most areas of the continent, potential evaporation ($E_p$) exceeds precipitation ($P$), and approximately 90% of $P$ returns back to the atmosphere as $E$ [Glenn et al., 2011] with the
residue generating surface and groundwater resources [Guerschman et al., 2009]. Strong land-atmosphere coupling in these regions makes the estimation of SEB fluxes very sensitive to the boundary conditions and underlying assumptions of biophysical parameterization, a situation that is often confounded by extreme heterogeneity in evaporation versus transpiration and their contrasting responses to surface soil water content. Hence, observation, monitoring, and prediction of water and energy flux components are imperative in these regions to meet the challenge of developing and implementing sustainable water resource management decisions [Martens et al., 2016]. Therefore, detailed evaluation of a physically-based SEB model like STIC1.2 is the prerequisite before applying it for a reliable prediction and management of water resources in Australia and globally.

3. Methodology

3.1. Theory

STIC (version STIC1.2) is a one-dimensional physically-based SEB modeling system that treats soil-vegetation as a single unit (Fig. 1). The fundamental assumption in STIC is the first order dependence of $g_A$ and $g_C$ on aerodynamic temperature ($T_0$) and soil moisture ($\theta$) through $T_R$, which allows direct integration of $T_R$ into the PM-SW system [Mallick et al., 2016]. The integration of $T_R$ into PM-SW system is done by first estimating aggregated surface moisture availability ($M$) as a function of $T_R$, followed by simultaneously constraining the two biophysical conductances through $M$ in an analytical framework. STIC1.2 exploits radiation (net radiation ($R_N$), ground heat flux ($G$)) and meteorological variables (air temperature ($T_A$), relative humidity ($R_H$) or vapor pressure ($e_A$) at the reference level) in conjunction with $T_R$ observations as external inputs.

The expressions of $\lambda E$ and $H$ according to the PM equation are as follows [Monteith, 1965]:
\[ \lambda E = \frac{s \phi + \rho c_p g_A D_A}{s + \gamma \left(1 + \frac{g_A}{g_C}\right)} \]  

(4a)

\[ H = \frac{\gamma \phi \left(1 + \frac{g_A}{g_C}\right) - \rho c_p g_A D_A}{s + \gamma \left(1 + \frac{g_A}{g_C}\right)} \]  

(4b)

For a full vegetation and (or) bare surface, \( g_C \) represents the canopy conductance and (or) bare surface conductance, respectively. In the case of partial canopy cover, \( g_C \) represents an aggregated surface conductance of both canopy and soil. The effects of this simplified representation of aggregated \( g_C \) on the performance of STIC1.2 represented in Fig. 9 (b, d, f) which shows the residual \( \lambda E \) error (modeled minus observed \( \lambda E \)) versus \( g_C \) for different vegetation types.

The two unknown ‘state variables’ in eqn. (4a and 4b) are \( g_A \) and \( g_C \), and the main goal of STIC1.2 is to find an analytical solution of the two unobserved conductances from measurements of radiative, meteorological, and radiometric conditions [Mallick et al., 2014a, 2015, 2016]. This will simultaneously find a ‘closure’ of the PM model. As neither \( g_A \) nor \( g_C \) can be measured at the canopy-scale or at large spatial scales [van Dijk et al., 2015], a ‘closure’ of the PM equation is only possible through an analytical estimation of the conductances. Consequently, multiple ‘state equations’ were formulated to obtain closed-form expressions of \( g_A \) and \( g_C \). In the state equations, a direct connection of \( T_R \) (through \( M \)) is initiated in the expression of evaporative fraction (\( \Lambda \)), which is simultaneously propagated into equations of \( g_A, g_C \), and \( T_0 \) (eqn. 5–8 below).

\[ \Lambda = \frac{2as}{2s + 2\gamma + \gamma \frac{g_A}{g_C}(1 + M)} \]  

(5)

\[ T_0 = T_A + \left(\frac{e_0 - e_A}{\gamma}\right)\left(1 - \frac{\Lambda}{A}\right) \]  

(6)
\[ g_A = \frac{\phi}{\rho c_p \left[ (T_0 - T_A) + \left( \frac{e_0 - e_A}{\gamma} \right) \right]} \quad (7) \]

\[ g_C = \frac{(e_0 - e_A)}{g_A (e_0^* - e_0)} \quad (8) \]

The functional forms of eqn. 5 – 8 and their detailed derivations are given in the supporting information (SI) and in Mallick et al. [2014a, 2015, and 2016]. Given values of \( M, R_N, G, T_A, \) and \( R_H \) or \( e_A \), the four state equations (eqn. 5 to 8) can be solved simultaneously to derive analytical solutions for the four unobserved state variables. However, the analytical solutions to the four state equations have three accompanying unknowns; \( e_0 \) (vapor pressure at the source/sink height), \( e_0^* \) (saturation vapor pressure at the source/sink height), and Priestley-Taylor coefficient (\( \alpha \)) [Priestley and Taylor, 1972], and as a result there are four equations with seven unknowns. Consequently, an iterative solution must be found to determine the three unknown variables (as described in SI) (also in Mallick et al., 2016). For estimating source/sink height vapor pressures we applied eqn. (8) from Shuttleworth and Wallace [1985], and thus STIC1.2 uniquely combines both the Penman-Monteith and Shuttleworth-Wallace (PM-SW) models (described in SI) [also Mallick et al., 2016]. In eqn. (8), the Priestley-Taylor coefficient (\( \alpha \)) appeared due to using the Advection-Aridity (AA) hypothesis [Brutsaert and Stricker, 1979] for deriving the state equation of \( \Lambda \) [Mallick et al., 2016, 2015] [details in SI]. However, instead of optimising \( \alpha \) as a ‘fixed parameter’, \( \alpha \) is dynamically estimated by constraining it as a function of \( M, \) conductances, aerodynamic vapor pressure, and temperature [Mallick et al., 2016]. The derivation of the equation for \( \alpha \) is described in SI.

STIC1.2 consists of a feedback loop describing the relationship between \( T_R \) and \( \lambda E \), coupled with canopy-atmosphere components relating \( \lambda E \) to \( T_0 \) and \( e_0 \) [Mallick et al., 2016]. For estimating \( M, T_R \) is extensively used in a physical retrieval framework (detailed in SI) [also in
Mallick et al., 2016], which allows an integration of $T_R$ into a physically-based SEB model. Upon finding analytical solution of $g_A$ and $g_C$, both the variables are returned into eqn. 4a and 4b to directly estimate $\lambda E$ and $H$.

### 3.2. Estimation of $T_R$

Estimation of $T_R$ was based on the observed upwelling longwave radiation ($R_L\uparrow$) and the Stefan-Boltzmann equation

$$T_R = \left(\frac{R_L\uparrow}{\delta \varepsilon}\right)^{0.25}$$

[Sun and Pinker, 2003; Park et al., 2008; Formetta et al., 2016] ($\varepsilon$ is the infrared surface emissivity, $\delta$ is the Stefan-Boltzmann constant). Upwelling longwave radiation was directly measured with pyrgeometer in all the study sites. The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Emissivity Dataset (GED) land surface emissivity data product [Hulley et al., 2015; Göttche and Hulley, 2012] (product name: AG100V003; spatial resolution: 100 m, temporal frequency: static) (https://lpdaac.usgs.gov/dataset_discovery/community/community_products_table) was used in the inverted Stefan-Boltzmann equation for estimating $T_R$. This $\varepsilon$ database is developed by the National Aeronautics and Space Administration’s (NASA) Jet Propulsion Laboratory (JPL), California Institute of Technology, and ASTER data from 2000 to 2008 are used to generate this infrared emissivity record. For every site, the corresponding $\varepsilon$ is given in Table 1.

### 3.3. SEB closure

The statistical intercomparisons of STIC1.2 results against SEB flux observations were performed by forcing energy balance closure by adding energy to $\lambda E$ and $H$ in proportion to the measured Bowen ratio ($H/\lambda E$; BREB-closure) [Bowen, 1926] as described by Chavez et al. [2005] and later adopted by Anderson et al. [2008] and Mallick et al. [2014a, 2015, 2016]. However, in order to understand the effects of SEB closure correction methods on the

This article is protected by copyright. All rights reserved.
statistical error metric, residual SEB closure correction (RES-closure) was also tested in which actual $\lambda E$ observations were neglected [Majozi et al., 2017], and $\lambda E$ was estimated as a residual of $R_N$, $G$, and $H$. Caution in using RES-closure method has been previously given by Barr et al. [2012] because it is very unlikely that measurements of $R_N$, $G$ or $H$ are without error.

4. Datasets and statistical analysis

4.1. Eddy covariance and meteorological quantities

In the present analysis, we have used data from the regional Australian and New Zealand EC flux tower network, OzFlux (http://data.ozflux.org.au/portal/pubListPubCollections.jspx). OzFlux EC stations are distributed among ecohydrologically contrasting landscapes in Australia and New Zealand to provide national data of energy, water, and carbon fluxes at a continental scale to improve our understanding of the responses of these surface-atmosphere fluxes of Australian ecosystems to current climate as well as future climate change [Beringer et al., 2016].

We explored the level-3 quality controlled and harmonised surface flux and meteorological data for the years 2013 and 2014 from 15 (out of 26) active Australian OzFlux sites located across nine different ecoregions in Australia (Fig. 2, Table 1): deserts and xeric shrublands (AU-ASM, AU-TTE), pasture (AU-Rig), Mediterranean woodlands (AU-Cpr, AU-Gin, AU-GWW), temperate broadleaf (and mixed) forest (AU-Tum, AU-Wom), temperate grassland (AU-Ync), temperate woodlands (AU-Cum, AU-Whr), tropical and subtropical moist broadleaf forest (AU-Cow), tropical grassland (AU-Stp) and tropical savannas (AU-How, AU-Dry). We divided these sites into three broad aridity classes based on their aridity index (AI) (ratio of annual $P$ and $E_P$; i.e., $P/E_P$): arid (0<AI<0.2, AU-ASM, AU-Cpr, AU-GWW and AU-TTE); semi-arid (0.2<AI<0.5, AU-Gin, AU-Rig, AU-Stp, AU-Whr, AU-Wom and
AU-Ync); and mesic (sub-humid and humid) (0.5<Ai, AU-Cow, AU-Cum, AU-Dry, AU-
How and AU-Tum) ([http://www.bom.gov.au](http://www.bom.gov.au)). In Table 1, annual values of P and TA are the
climatological averages of every site which are reported in
http://www.ozflux.org.au/monitoringsites/. Annual E and RN were computed from the
available EC tower datasets for 2013 and 2014. Annual Ep was computed from FAO (Food
and Agricultural Organisation) Penman-Monteith equation [Allen et al., 1998].

The main reason for selecting 2013 and 2014 was the rainfall deficit which followed the
anomalously wet period of 2010 and 2011 in Australia [Cleverly et al., 2016; Ma et al., 2016]
and continued to worsen to severe drought through 2014 across the continent
availability in these two years coincided for the selected fifteen sites.

The data are available at half-hourly temporal resolution, with an exception at AU-Tum
where the temporal resolution of the data is one hour. Data used for this analysis included
time series of surface energy balance fluxes (RN, λE, H, G), shortwave and longwave
radiation components (RS↓, RS↑, RL↓, RL↑), and hydrometeorological variables (e.g., TA, RH, u,
υ*, θ, and P). A general description of the site characteristics can be found in Table 1 and also
in Beringer et al. [2016]. Daily SEB fluxes (in W m⁻²) were computed by averaging half-
hourly (hourly for AU-Tum) observed fluxes and those predicted by STIC1.2. Monthly and
annual E (in mm) and H (converted to water equivalent in mm)
([http://www.fao.org/docrep/x0490e/x0490e07.htm](http://www.fao.org/docrep/x0490e/x0490e07.htm)) were computed by summing daily λE and
H values. We did not perform any gap filling, which implies that missing observed or
estimated sub-daily or daily λE and H values (for data availability see Table 1) were not
included in the computation.

Performance of STIC 1.2 was also evaluated for dry and wet seasons (Appendix A2),
whereby the seasons were defined based on monthly P and θ. The timing and duration of the
seasons varied between different sites. A table of dry and wet seasons for individual sites are given in Table A3.

4.2. Statistical analysis

4.2.1. Multi-temporal SEB flux assessment

In order to evaluate the performance of STIC1.2, we used different statistical metrics: root mean square deviation (RMSD), relative root mean square deviation (RRMSD), the coefficient of determination ($R^2$), mean absolute percentage deviation (MAPD), and the ratio of squared systematic RMSD to squared RMSD ($\text{RMSD_s}^2/\text{RMSD}^2$) (eqn. A1 to A4 in Appendix). Predicted $\lambda E$ and $H$ were compared with observed values for each study site at sub-daily, daily, and annual scales. Results and discussions on multi-temporal SEB flux estimation statistics are given in section 5.1 and 6.1, respectively.

4.2.2. Assessing the role of $T_R$ and associated environmental variables on the performance of STIC1.2

A sensitivity analysis and a Principal Component Regression (PCR) analysis [Jolliffe, 2002] were performed to assess the impact of $T_R$ and environmental variables on the relative change in $\lambda E$ error (in percent) and residual error of $\lambda E$ (i.e., $\Delta_{\lambda E} =$ difference between $\lambda E$ predicted by STIC1.2 and observed $\lambda E$). Sensitivity of $\lambda E$ to $T_R$ was tested by introducing random uncertainty in the surface emissivity to generate uncertain $T_R$ scenarios at half-hourly time steps. The relative change in $\lambda E$ error due to the relative change in $T_R$ was estimated for every time step and correlation between them was evaluated for different classes of $\theta$ and $E_p/\phi$ ratios. PCR was performed on a correlation matrix of five variables which are: $T_R$, $D_A$, $\phi$, wind speed ($u$), and $\Delta_{\lambda E}$. The correlation between $\Delta_{\lambda E}$ and principal component (PC) is known as ‘loading’. Loadings close to ±1 indicate that the variable has substantial impact on $\Delta_{\lambda E}$. PCs with high loadings generally explain maximum variances in $\Delta_{\lambda E}$ and are considered
in evaluating the impacts on $\Delta \lambda E$. Results of the sensitivity analysis and PCR are presented in section 5.2 with extended discussions in section 6.2.

4.2.3. Relationship between ecohydrological factors and $T_R$ in determining the errors and variability of SEB fluxes predicted by STIC1.2

To examine the link between ecohydrological conditions and $T_R$ on the SEB flux predictions, we further investigated the patterns of MAPD in daily $\lambda E$ and $H$ in comparison to coefficient of variation of observed soil moisture ($cV_\theta$), annual evaporative index (i.e., annual $E/R_N$), climatic dryness (i.e., annual $E_P/P$) [Donohue et al., 2010], and emissivity ($\varepsilon$), which are considered to represent the ecohydrological characteristics of ecosystems that are intrinsically related to $T_R$. Arid and semi-arid ecosystems generally have large variations in $\varepsilon$ [Masiello et al., 2014; Hulley et al., 2010] which is mostly associated with high $cV_\theta$, low $E/R_N$, and high $E_P/P$ (high evaporative demand and low precipitation). Therefore, assessing the effects of a single value of $\varepsilon$ on the predictive capacity of STIC1.2 is crucial. Results of the correlation analysis between MAPD of daily $\lambda E$ (and $H$) with $\varepsilon$, annual $cV_\theta$, annual $E/R_N$, and annual $E_P/P$ of each site is presented in section 5.3 and discussions are elaborated in section 6.3.

5. Results

5.1. Performance of STIC1.2 across an aridity gradient in Australia

The box-plots of statistical errors of half-hourly $\lambda E$ for three ecohydrologically contrasting ecosystem classes revealed STIC1.2 to explain 60% to 85% of the observed $\lambda E$ variability ($R^2$ 0.60 to 0.85), with mean MAPD of 30% to 50%, and mean RMSD 36 to 55 W m$^{-2}$ in the mesic and semi-arid sites (Fig. 3a, 3c, and 3e, please see Table 2 for site statistics). For the arid sites, STIC1.2 explained 40% of the observed $\lambda E$ variability, with RMSD of 26 to 46 W m$^{-2}$ (average 36 W m$^{-2}$) (78% of the observed mean) and relatively high MAPD (60%) (Fig. 3a, 3c, 3e). The average ratio of $\text{RMSD}^2/\text{RMSD}^2$ [i.e., systematic RMSD (%)] was moderate
to low in semi-arid (35%, range 24% to 48%) and mesic (10%, range 3% to 23%) ecosystems (Fig. 3g), which increased to 45% (range 30% to 60%) in the arid ecosystems, thus revealing high systematic $\lambda E$ error (along with high percent RMSD) in the water-limited ecosystems as compared to the radiation-limited ecosystems (Fig. 3g). The predictive accuracy of $H$ followed the opposite pattern compared to $\lambda E$, featuring maximum $R^2$ (0.85 - 0.95) and minimum errors (10 - 25% MAPD and 35 - 50 W m$^{-2}$ RMSD) in the water-limited ecosystems as compared to the wet ecosystems with $R^2$ of 0.80, MAPD 37%, and RMSD 55 W m$^{-2}$, respectively (Fig. 3b, 3d, 3f). Interestingly, the average ratio of $\text{RMSD}_E^2/\text{RMSD}_H^2$ varied between 10–25% (Fig. 3h), thus revealing low systematic errors in $H$ estimates for a broad spectrum of ecohydrologically contrasting environments.

The statistical metrics of daily $\lambda E$ and $H$ was better than the half-hourly error statistics in the semi-arid and mesic ecosystems, with RMSD 11 - 18 W m$^{-2}$ (12 - 20 W m$^{-2}$ for $H$), MAPD of 20–39% (24–37% for $H$), $R^2$ of 0.65–0.84 (0.73–0.87 for $H$), slope and offsets of regression to the order of 0.70–0.84 (0.67–0.79 for $H$) and 9–10 W m$^{-2}$ (19–20 W m$^{-2}$ for $H$), respectively (Fig. 4c to 4f). As for sub-daily statistics, the predictive errors in daily $H$ were lowest (12 W m$^{-2}$ RMSD and 12% MAPD) in the arid ecosystems, whereas percent $\lambda E$ errors were highest (55% MAPD) (due to low mean $\lambda E$) (Fig. 4a, 4b). An evaluation of the annual SEB fluxes revealed a very good agreement between observed and predicted $E$ and $H$, where STIC1.2 explained 97% of the measured variability, with MAPD and RMSD to the order of 10% and 55 – 84 mm, respectively (Fig. 5a and 5b).

An intercomparison of STIC1.2 half-hourly error statistics with the two previous versions (STIC1.0 and STIC1.1) revealed maximum improvement in the performance of STIC1.2 for arid and semi-arid ecosystems (as compared to mesic ecosystems) (Fig. A1). Among the different model versions, notable differences in MAPD (20 – 60%, 8 – 40%, and 5 – 30%) and RMSD (25 – 50 W m$^{-2}$, 20 – 40 W m$^{-2}$, and 18 – 60 W m$^{-2}$) were found between STIC1.2
and STIC1.0, whereas the differences were relatively lower (5 – 40%, 3 – 22%, and 5 – 18% in MAPD; 3 – 10 W m⁻², 2 – 8 W m⁻², and 4 – 18 W m⁻² in RMSD) between STIC1.2 and STIC1.1 (Fig. A1). Statistical metrics of individual site-year is given in Table A2 with description in Appendix A1.

5.2. Effects of $T_R$ and environmental variables on the performance of STIC1.2 in different ecosystems

Sensitivity analysis revealed that the relative change in $\lambda E$ error is inversely related to the relative change in $T_R$, thus a 10% reduction in $T_R$ can lead up to 50% increase in percent $\lambda E$ error for these ecosystems (Fig 6a, c, e) (Table 3). Maximum sensitivity of $\lambda E$ to $T_R$ was found for arid and semi-arid ecosystems with significant correlations of (-0.35) – (-0.92) and (-0.30) – (-0.35) ($p <0.05$) for soil moitures above 0.05 m³ m⁻³ and 0.10 m³ m⁻³ (Table 3), respectively. In mesic ecosystems, the sensitivity of $\lambda E$ errors to $T_R$ was relatively uniform across all the ranges of soil moisture [$r = (-0.26) – (-0.29), p<0.05$] and $E_p/\phi$ [$r = (-0.27) – (-0.31), p<0.05$] (other than conditions of extremely high evaporative potential) (Table 3). In arid and semi-arid ecosystems the sensitivity of the $\lambda E$ error to $T_R$ was confounded due to $E_p/\phi$ (Fig 6a, c) (also evident from the principal component analysis described below).

Principal component regression (PCR) of $\Delta\lambda E$ versus $T_R$ and environmental variables ($\phi$, $D_A$, and $u$) revealed $T_R$, $D_A$, and $\phi$ to be the first principal component (PC1) affecting $\Delta\lambda E$ variance in all the ecosystems (Fig. 6b, d, f). However, the relative effect of $T_R$ in conjunction with different environmental factors in controlling the variance of $\Delta\lambda E$ varied among ecosystems.

Maximum PC1 loading was found for $T_R$ and $D_A$ followed by $\phi$ in arid and semi-arid ecosystems (Fig. 6b and d) where their correlation with $\Delta\lambda E$ varied between 0.70 – 0.75 ($T_R$), 0.65 – 0.70 ($D_A$) and 0.50 – 0.55 ($\phi$), respectively (Fig. 6b, 6d). Contrarily, in the mesic ecosystem, all the three variables had equal loadings (correlation 0.50) with $\Delta\lambda E$ variance in
PC1 axis (Fig. 6f). The effects of wind speed ($u$) on the $\Delta \lambda E$ variance was reflected in the second principal component (PC2) axis with correlation varying from 0.55 to 0.75. The residual errors in sensible heat flux ($\Delta H$) showed similar behavior of the $\Delta H$ variance as the variance of $\Delta \lambda E$ against $T_R$ and environmental variables (not shown).

### 5.3. Relationship between ecohydrological conditions and $T_R$ in determining errors and variability of SEB flux components predicted by STIC1.2

The scatter between MAPD and ecohydrological indicators in Fig. 7 show opposite relationships for $\lambda E$ and $H$. Annual $E/R_N$ ratio and $\varepsilon$ had the strongest impacts on the MAPD of both fluxes. As evident from the slopes of the regression lines, 1% increase in $\varepsilon$ was found to cause approximately 17% decrease (15% increase) in MAPD$_{\lambda E}$ (MAPD$_H$) (Fig. 7a). An increase of 10% in $E/R_N$ would cause a 76% decrease and 55% increase in MAPD$_{\lambda E}$ and MAPD$_H$, respectively (Fig. 7c). A systematic increase in MAPD$_{\lambda E}$ was found with increasing $cV_\phi$, where a 10% increase in $cV_\phi$ resulted in 34% increase in MAPD$_{\lambda E}$ (Fig. 7b). However, the impact of variation in $\theta$ was approximately 50% less for the accuracy of predicted $H$, as evident from the slope of the regression line (slope = 0.19) (Fig. 7b). Interestingly, a logarithmic increase in MAPD$_{\lambda E}$ was found with increasing climatic dryness (Fig. 7d). MAPD$_{\lambda E}$ varied from 18 – 30% for $E_p/P$ ratio of 0 – 2.5 and it progressively increased from 55 – 100% when $E_p/P$ ratio exceeded 5 (Fig. 7d).

The scatter plots of monthly variances in predicted versus observed $\lambda E$ and $H$ ($\sigma^2_{\lambda E}$ and $\sigma^2_H$) revealed the capacity of STIC1.2 to explain 88 – 90% of the observed flux variances in a broad range of aridity conditions (Fig. 8a, 8b). The correlation matrix of the residual variance in the fluxes ($\Delta \sigma^2_{\lambda E} = \sigma^2_{\lambda E \text{ STIC1.2}} - \sigma^2_{\lambda E \text{ observed}}$ and $\Delta \sigma^2_H = \sigma^2_H \text{ STIC1.2} - \sigma^2_H \text{ observed}$) against a host of ecohydrological and meteorological variables revealed the absence of any strong
systematic relationship between $\Delta \sigma^2_{\lambda E}$ and $\sigma^2_{T_h}$, $\sigma^2_{\theta}$, $\sigma^2_P$ ($r = \pm 0.2$) (Fig. 8c). For $H$, the similar analysis revealed 20 – 40% correlation between $\Delta \sigma^2_H$ and $\sigma^2_{T_h}$, $\sigma^2_{T_A}$ (Fig. 8d).

6. Discussion

Section 6.1 describes SEB flux prediction errors for STIC1.2 in the context of uncertainty in the relationship between $T_R$ and aggregated moisture availability by evaluating the relationship between $M$, $T_R$, and the conductances, and thereby assessing the role of conductances estimates on residual $\lambda E$ error. This section also highlights the impact of SEB closure correction errors in MAPD and systematic RMSD of the predicted fluxes. Section 6.2 discusses how the collective role of $T_R$ and environmental variables affect the predictive errors in STIC1.2. Lastly, section 6.3 discusses the link between $T_R$ and ecohydrological conditions in determining the error and variability of STIC1.2-based SEB flux predictions.

6.1. What is the performance of STIC1.2 when evaluated with high temporal resolution data across an aridity gradient in Australia?

6.1.1. Role of uncertain relationship between $M$ and $T_R$

Evaluation of STIC1.2-derived SEB fluxes at fifteen Ozflux sites of broad aridity classes revealed relatively large differences between predicted and observed $\lambda E$ in the arid ecosystems as compared to the semi-arid and mesic ecosystems. Uncertainty in the relationship between $T_R$ and aggregated moisture availability ($M$) could be a considerable source of error in the predictive power of STIC1.2 in water-limited ecosystems. In STIC1.2, $M$ is modeled as a fraction of the dewpoint temperature difference between evaporating front and atmosphere ($T_{0D} - T_D$) and of infrared temperature – dewpoint differences between surface to atmosphere ($T_R - T_D$). These two factors were weighted by two different slopes of saturation vapor pressure-temperature relationships ($s_1$ and $s_2$; eqn. S26) [Mallick et al., 2016]. This implies that for constant available moisture, this fraction is constant. However,
even for varying $\phi$, $D_A$, and $T_A$, constant moisture availability does not imply invariant $(T_{0D} - T_D)(T_R - T_D)$ because a wet surface has a different sensitivity to these variables than a dry surface with limited surface conductance. Due to $\phi - D_A - T_R$ feedbacks [Zhang et al., 2014], $T_{0D} - T_D$ can actually decrease with increasing $T_R$, $\phi$, and $D_A$, whereas $T_R - T_D$ would increase. In this context, estimation of $T_{0D}$ plays a critical role in arid and semi-arid environments, which further requires sound estimation of $s_1$. From the definition of $s_1 \left[ \frac{(e_0 - e_A)}{(T_{0D} - T_D)} \right]$, $e_0 \rightarrow e_A$ and $s_1 \rightarrow 0$ for an extremely dry surface with insignificant evaporation.

In the present case, the estimates of $s_1$ as a function of $T_D$ tend to be higher than the possible $s_1$-limits in water-limited environments, which is likely to introduce errors in $T_{0D}$ estimation (through eqn. S27). Overestimation of $s_1$ would also lead to an overestimation of $M$ (through the denominator in eqn. S26), thus leading to overestimation of the conductances and $\lambda E$. As seen in Fig. 9 (a, c, e), the relationship between $M$ and $T_R$ is very strong for low magnitudes of $M$ ($M<0.025$ for arid ecosystem; $M<0.10$ for semi-arid and mesic ecosystems), and a significantly strong relationship is also evident between $g_C/g_A$ versus $M$ ($r = 0.81$ to $0.88$; $p<0.05$) in all the ecosystems when the surface is substantially dry ($M<0.15$). $g_C/g_A$ ratios tend to be invariant with increasing moisture availability in the mesic ecosystem ($M>0.25$; Fig. 9e). Therefore, critical errors could be introduced in $\lambda E$ retrieval under dry surface conditions due to the strong association between $M$ and $T_R$, and dependence of the conductances on $M$. Residual error analysis of $\lambda E$ versus both the conductances revealed $\lambda E$ error to be significantly correlated with $g_A$ and $g_C$ in the sparsely vegetated arid and semi-arid ecosystems (Fig. 9b, d) ($r = 0.30 - 0.40$, $p<0.05$; $r = 0.28 - 0.32$, $p<0.05$). There was a general tendency to overestimate $\lambda E$ when $g_C$ was very low, which was eventually reduced with increasing $g_C$. Residual $\lambda E$ error appears to be heteroscedastic with $g_A$, which signifies unequal variability of $\lambda E$ error across a range of $g_A$. A weak relationship between residual $\lambda E$
error and conductances was found in the mesic ecosystem (Fig. 9f), resulting in small predictive errors in $\lambda E$ for this ecosystem.

Significantly lower errors in predicting $H$ than $\lambda E$ might be the result of partial compensation of $g_A/g_C$ in both numerator and denominator of the PM formulation for $H$ (eqn. 4b) [Winter and Eltahir, 2011]. In our study, $g_C$ showed much more variability as a function of $T_R$ ($r = 0.72 – 0.74$; 1% change in $T_R$ would lead to $5.2 – 7.5\%$ change in $g_C$) than did $g_A$ with $T_R$ ($r = 0.26 – 0.65$; 1% change in $T_R$ would lead to $1.6 – 2\%$ change in $g_A$) (Fig. 10), suggesting that error in $g_C$ was larger than error in $g_A$. Compensation of conductance errors in computing $H$ (eqn. 4b) might have resulted in substantial compensation of $H$ errors in all the ecosystems.

By contrast, combined uncertainty due to $g_A$ in the numerator of eqn. (4a) with uncompensated $g_A/g_C$ in the denominator of eqn. (4a) [Mallick et al., 2015; Winter and Eltahir, 2011] resulted large disagreements in measured and modeled $\lambda E$ for the arid and semi-arid ecosystems where $\lambda E$ was small.

6.1.2. Role of SEB closure on statistical metrics

Differences between STIC1.2 versus observed $\lambda E$ may be partly attributed to the BREB-closure correction of $\lambda E$ observations. Although Bowen ratio correction forces SEB closure, in the arid and semi-arid ecosystems major corrections are generally observed in $H$, whereas $\lambda E$ is negligibly corrected [Chavez et al., 2005]. Significant correlations are found between the $\lambda E$ error statistics and BREB-closure corrections ($r = 0.60$ for MAPD in Fig. 11a, $r = 0.66$ for $\text{RMSD}^2/\text{RMSD}^2$ in Fig. 11b). In majority of the arid and semi-arid sites, high MAPD and $\text{RMSD}^2/\text{RMSD}^2$ in $\lambda E$ (>50%) was associated with low percent of closure correction in $\lambda E$ (12 – 20%) (Fig. 11a, b). Both error metrics were relatively high when modeled $\lambda E$ was compared against RES-closure-based $\lambda E$ observations; however, RES-closure revealed a
substantially weaker relationship between errors and percent closure corrections than in BREB-closure (Fig. 11c, d).

BREB-closure correction was found to fail under hot, dry conditions in some previous studies. This is due to the combination of extremely high evaporative potential and sensible heat entrainment from boundary layer desaturating the surface and causing the surface to air vapour pressure gradient to reverse [Perez et al., 1999; Mallick et al., 2014b; McHugh et al., 2015], a condition that prevails in the arid and semi-arid ecosystems during most part the year. The assumption of scalar similarity for heat and water vapor is violated in these conditions and $g_A$ of heat flux can be two to three times higher than $g_A$ of the water vapor flux [Katul et al., 1995]. For the RES-closure, additional uncertainty in $\lambda E$ might be introduced due to neglecting subsurface heat sink in $G$ measurements [Heitman et al., 2010], which themselves can have errors of 18% to 66% [Ochsner et al., 2006]. Similar analysis of $H$ revealed relatively low overall correlation ($r = 0.41$) between MAPD of predicted $H$ and SEB closure (Fig. 11e, f), with a tendency of high MAPD in mesic sites due to overcorrection of $H$. This is due to the fact that $g_A$ responsible for $H$ might be lower than $g_A$ of $\lambda E$ in mesic ecosystems and the assumption of scalar similarity for heat and water vapor may not be true.

For a similar reason, the use of Bowen ratio approximations in the state equation of $T_0$ in STIC1.2 might also be responsible for additional error propagation in all the three ecosystems.

6.2. How do $T_R$ and associated environmental variables affect the performance of STIC1.2 in different ecosystems?

The relationship between the relative change in $\lambda E$ error with the relative change in $T_R$ above a threshold soil moisture content in arid and semi-arid ecosystem (Fig. 6a, c, e; Table 3) indicates the critical role of uncertainty in $T_R$ - soil moisture relationship in STIC1.2 and the role of $M$ in controlling $g_C/g_A$ and resultant $\lambda E$ errors in the water-limited ecosystems, as
discussed previously. As further evident from Fig. 6 (b, d, f), while the accumulated effects of 
\( T_R \) and \( D_A \) were predominant in explaining \( \Delta_{\lambda E} \) variance in arid and semi-arid ecosystems, the
influence of \( \phi \) was comparable to \( T_R \) and \( D_A \) in explaining \( \Delta_{\lambda E} \) variance in the mesic
ecosystem. Since \( T_R \) controls the atmospheric humidity profile by constraining soil moisture,
\( g_c \) and transpiration; \( T_R \) and \( D_A \) have stronger autocorrelation in arid and semi-arid
ecosystems as compared to the mesic ecosystems [Abdi et al., 2017; Crago and Qualls, 2014]; and \( \lambda E \) is mainly limited by combination of these two surface and atmospheric
moisture variables. This explains the dominant role of \( T_R \) and \( D_A \) in controlling the maximum
\( \Delta_{\lambda E} \) variance as reflected in the high correlation (0.65 to 0.75) in the first principal component
(PC1) axis of arid and semi-arid ecosystems (Fig. 6b and 6d). In contrast, \( E \) in mesic
ecosystem is constrained by \( T_R \), \( \phi \), and \( D_A \); and all the three variables had accumulated impact
in explaining the relative error change in \( \lambda E \) (Table 3, Fig 6e) and \( \Delta_{\lambda E} \) variance as seen in the
PC1 axis in this ecosystem (Fig. 6f). Since PC1 had the highest total variance in all the
ecosystems, its variables are the most important in determining the predictive errors in \( \lambda E \).
The effects of wind speed (\( u \)) in explaining \( \Delta_{\lambda E} \) variance (as seen in PC2) might originate
from some collinearity of \( u \) with net radiative heating, \( T_R \) and \( D_A \) as earlier reported by
Mallick et al. [2016].

6.3. Is there an association between ecohydrological conditions and \( T_R \) in determining
the errors and variability of SEB flux components predicted by STIC1.2?
Given the critical role of \( T_R \) in STIC1.2, the estimate of \( T_R \) is an additional source of error
(through \( \varepsilon \)) in predicted \( \lambda E \) and \( H \) for the individual study sites (Fig. 7a) and the error is
consequently propagated into the MAPD of \( \lambda E \) and \( H \) versus \( cV_h \) annual \( E/R_N \), and \( E_p/P \)
relationships (Fig. 7b, 7c, 7d). Low annual \( E/R_N \) and high annual \( E_p/P \) are indicators of water
limitations, where low \( E \) is the result of low \( P \) and \( \theta \) despite an abundance of available energy
in conjunction with high potential evaporative demand. Such water limitations make \( E \) very sensitive to soil moisture variations [Jarvis and McNaughton, 1986], thereby accelerating biophysical feedbacks on \( E \) [Mallick et al., 2016; Siqueira et al., 2008], and the rate of change of \( E \) becomes directly proportional to the canopy (or surface) conductance \( (g_C) \) [Jarvis and McNaughton, 1986]. Since our \( g_C \) estimates are inevitably constrained by \( T_R \) (through \( M \)), accuracy of \( T_R \) is a key factor for enhancing \( E \) retrievals under these conditions.

Given \( \varepsilon \) appears in the denominator of the \( T_R \) retrieval equation, \( T_R \) is extremely sensitive to the uncertainties in \( \varepsilon \) [Hulley et al., 2012]. Underestimation (overestimation) of \( T_R \) would lead to overestimation (underestimation) of \( M \), which further leads to underestimation (overestimation) of \( g_A/g_C \) in the denominator of the PM model, causing the resultant SEB flux estimations to become uncertain. Careful handling of diurnal variations of infrared \( \varepsilon \) is therefore essential for deriving accurate surface skin temperature [Li et al., 2007; Hulley et al., 2012]. Substantial diurnal variations in \( \varepsilon \) are found in arid and semi-arid ecosystems due to the influence of soil moisture (\( \theta \)) [Masiello et al., 2014; Hulley et al., 2010]. For low values of \( \theta \), the rate of change of \( \varepsilon \) per unit change of \( \theta \) (i.e., \( \partial \varepsilon/\partial \theta \)), at wave numbers of reststrahlen absorption is considerably large [Mira et al., 2007; Masiello et al., 2014]; \( \partial \varepsilon \approx 0.05 \) per \( \partial \theta \) of 0.01 kg kg\(^{-1}\). Consequently, exclusion of sub-daily and seasonal variation of \( \varepsilon \) in the \( T_R \) estimation is evident in MAPD of \( \lambda E \) vs. \( \varepsilon \) scatter plots (Fig. 7a).

Despite absolute differences between the predicted and observed SEB fluxes, very good agreement between the flux variances (Fig. 9a, 9b) indicates the ability of STIC1.2 to capture the radiation and water driven variabilities in SEB fluxes from mesic to arid ecosystems. The correlation of \( \pm 12 \sim 15\% \) between \( \Delta \sigma^2_{\lambda E} \) and \( \sigma^2_{\theta}, \sigma^2_{P}, \) and \( \sigma^2_{T_R} \) (Fig 9c) is a result of aforementioned (section 6.1) \( T_R \) uncertainties, in conjunction with SEB closure correction errors of EC \( \lambda E \) observations in arid and semi-arid environments. Besides, the negative
relationship \( r = -0.20 \) between \( \Delta \sigma^2_E \sigma^2_{\text{STIC1.2}} - \sigma^2_{\text{observed}} \) versus \( \sigma^2_{u*} \) is most likely associated with the collinearity between wind shear and \( T_R, D_A, \) and \( \phi \) (also reported in \textit{Mallick et al.,} 2016) as described in section 6.2. Nearly zero correlation between \( \Delta \sigma^2_H \) with ecohydrological variances further indicates that \( H \) was predominant in water-limited regions, and sensible heat flux is the primary pathway by which ecohydrological variances induces variations in atmospheric variables and consequently affects the boundary layer growth [\textit{Koster et al.,} 2015]. This was also supported by 40% correlation between \( \Delta \sigma^2_H \) and \( \sigma^2_{T_A}. \)

Also, the absence of a relationship between \( \Delta \sigma^2_H \) and \( \sigma^2_{u*} \) indicates that the exclusion of wind speed from STIC1.2 (see eqn. 5 to 8) does not significantly affect the SEB flux estimates. This error characterization in a broad range of ecohydrological conditions also indicated that in the ecosystems with low annual evaporative index \( (E/R_N) \) and very high climatic dryness index \( (E_P/P) \), the thermal component of the SEB fluxes (i.e., \( H \)) is dominant and should be given emphasis to assess model performance [\textit{Garcia et al.,} 2008; \textit{Dirmeyer,} 2011].

The overall RMSD of 25 – 61 W m\(^{-2}\) and 11 – 37 W m\(^{-2}\) in half-hourly and daily SEB fluxes and the associated statistical metrics are comparable with the results reported in a host of SEB modeling studies that uses empirical sub-models to parameterize the conductances. Using the two-source energy balance model (TSEB) [\textit{Norman et al.,} 1995], some recent studies have reported RMSD to the order of 72 – 135 W m\(^{-2}\) and 52 – 131 W m\(^{-2}\) in hourly \( \lambda E \) and \( H \) for a semi-arid grassland in Spain [\textit{Kustas et al.,} 2016], 95 – 166 W m\(^{-2}\) in hourly \( \lambda E \) [\textit{Song et al.,} 2016] to 45 – 50 W m\(^{-2}\) in daily \( \lambda E \) for semi-arid irrigated cotton in Texas and Arizona [\textit{Colaizzi et al.,} 2014; \textit{French et al.,} 2015], and 50 – 59 W m\(^{-2}\) in hourly \( \lambda E \) for irrigated maize in China [\textit{Song et al.,} 2016]. A variant of TSEB model (SPARSE model) is found to produce 43 – 47 W m\(^{-2}\) in instantaneous \( \lambda E \) and 50 – 80 W m\(^{-2}\) in hourly \( \lambda E \) in Tunisia and Morocco [\textit{Saadi et al.,} 2017; \textit{Boulet et al.,} 2015]. Considering the error statistics
of state-of-the-art SEB models and their parameterization uncertainties [Timmermans et al., 2013]; the performance of STIC1.2 indicates substantial potential of this model towards bridging thermal infrared sensing and physically-based evapotranspiration modeling. An intercomparison of STIC1.2 with other SEB models is beyond the scope of this manuscript. However, a recent study on regional evapotranspiration mapping study demonstrated a comprehensive intercomparison of STIC1.2 with two other global models across an aridity gradient in the conterminous United States for contrasting rainfall years as well as on a wide variety of biomes [Bhattarai et al., 2017]. This study revealed better performance of STIC1.2 as compared to other models and also demonstrated the critical role of conductances and associated land surface parameterizations on the model errors, inter-model agreements, and disagreements.

A host of literatures reported measurement uncertainties in $H$ and $\lambda E$ to the order of $\pm 15 - 20$ W m$^{-2}$ and $\pm 35 - 50$ W m$^{-2}$ [Wang et al., 2015; Masseroni et al., 2014]. These uncertainties are associated with high magnitude of net radiation [Hollinger and Richardson, 2005], and with stochastic nature of turbulence [Hollinger and Richardson, 2005; Wang et al., 2015]. Landscape heterogeneity may induce large scale turbulence which consequently leads to large $H$ and $\lambda E$ uncertainty in arid and semi-arid ecosystems [Wang et al., 2015]. However, it is unlikely that the entire RMSD in $\lambda E$ and $H$ is attributable solely to the EC measurement uncertainties [Foken, 2008]. As a result, the range of RMSD obtained between STIC1.2 and tower $H$ and $\lambda E$ is likely to be determined by the combination of structural uncertainties in STIC1.2 and SEB flux measurement uncertainties in EC towers.

### 7. Conclusions

By integrating thermal infrared temperature into a combined structure of Penman-Monteith and Shuttleworth-Wallace framework we show the promise of a single-source box modeling
approach towards bridging thermal infrared sensing and physically-based model to retrieve the energy water fluxes. Analysis of STIC1.2 results on fifteen eddy covariance sites across an aridity gradient in Australia led us to the following conclusions.

(1) STIC1.2 overcomes the uncertainties in aerodynamic temperature and biophysical conductances parameterizations, and establishes a direct feedback of $T_R$ on SEB fluxes, source/sink height temperature and vapor pressures, and conductances. The efficiency of STIC1.2 to capture the variances of hourly to annual SEB fluxes across diverse biomes and ecohydrological settings in Australia indicates the skill of the model to capture the water-energy flux variabilities in hydrological extremes.

(2) Uncertainty in the relationship between $T_R$ and moisture availability ($M$) is a considerable source of error in the predictive power of STIC1.2 in the water-limited ecosystems. Use of differential $T_R$ observations (between sunrise and noontime) as a water stress constraint could potentially diminish the uncertainty in $M$ and eventually SEB flux prediction errors in STIC1.2. Besides, the performance of STIC1.2 depends on rigorous surface emissivity ($\varepsilon$) corrections, particularly in arid and semi-arid ecosystems. Since $\varepsilon$ is sensitive to the soil water content variations, assuming a constant surface emissivity for retrieving $T_R$ significantly affects the predictive skills of STIC1.2 in those ecosystems where substantial variations in soil moisture are observed. Spectrometer-based measurements representing appropriate footprint area around EC sites are needed to capture the diurnal variations in $\varepsilon$ for an improved $T_R$ retrieval.

(3) Disparities between predicted and observed $\lambda E$ in arid semi-arid ecosystems also emerge due to the surface energy balance closure (SEB) correction errors of $\lambda E$ observations. A robust SEB closure correction is needed for better interpretation of the predictive capacity of STIC1.2 in water-limited ecosystems.
(4) In the arid ecosystems where evapotranspiration ($E$) signal is small, the thermal component of the energy-water fluxes is predominant and sensible heat flux ($H$) tends to be a better metric to test the skill of any physically-based model, and might be a favoured water stress indicator. Simultaneously, in semi-arid and mesic ecosystems, both $E$ and $H$ appear to be the better metric in detecting the water cycle variability, and STIC1.2 showed substantial promise to capture the magnitude and variabilities of these two most important energy-water cycle variables across these broad aridity classes.

(5) $T_R$ is the most critical variable explaining the error variance of $E$ in arid and semi-arid ecosystems, while both net available energy and $T_R$ explain the error variance of $E$ in mesic ecosystems. Effects of ecohydrological conditions in determining the predictive capacity of STIC1.2 are also associated with $T_R$ and radiation driven SEB flux variability in the two ecohydrological extremes.

STIC1.2 is independent of any biome specific or leaf-scale empirical parameterizations of the conductances, which implies that it does not require any data on plant functional types or vegetation structure. This model is a valuable addition to the recent Australian energy and water exchange research initiative (OzEWEX), in particular to the WG2 (working group 2) that focus on observations to evaluate and compare biophysical models and data products describing energy and water cycle components. Given the significance of aerodynamic and canopy conductances in characterizing the land-atmosphere interactions, STIC1.2 can be used to study the ecohydrological feedbacks on land surface versus boundary layer interactions. With the availability of accurate $T_R$ information from new MOD21 land surface temperature [Hulley et al., 2015], LANDSAT, recently launched Sentinel-3, or future missions with thermal sensors like HyspIRI, a successful application of STIC1.2 is expected for mapping regional-scale vegetation water use with special emphasis in the water limited ecosystems.
Acknowledgements

This study was funded by the Luxembourg Institute of Science and Technology (LIST) under project BIOTRANS (project code 00001145). Partial funding for this research was provided through the FNR-DFG CAOS-2 project grant (INTER/DFG/14/02); and through HiWET (High-resolution modeling and monitoring of Water and Energy Transfers in wetland ecosystems) consortium funded by BELSPO and FNR under the programme STEREOIII (INTER/STEREOIII/13/03/HiWET; CONTRACT NR SR/00/301). We are grateful to all Australian and international collaborators, OzFlux PIs, and all the funding agencies that have contributed to establishing Terrestrial Ecosystem Research Network (TERN) and Ozflux. The authors declare no conflict of interest. This work utilised data collected by grants funded by the Australian Research Council (DP0344744, DP0772981, DP120101735, DP130101566, and LE0882936). Jason Beringer is funded under an ARC Future Fellowship (FT110100602). KM designed the analysis; ET and KM performed the analysis; KM, ET and IT developed the initial version of the manuscript; and all the co-authors make significant contribution in editing the manuscript. The authors declare no conflict of interests.

Data availability

Data used in the current analysis is available through the OzFlux data portal (http://data.ozflux.org.au/portal/pub/listPubCollections.jspx), and we have used data level-3 data that was available in csv format in the fluxnet repository (http://data.ozflux.org.au/portal/pub/viewColDetails.jspx?collection.id=1882723&collection.owner.id=450&viewType=anonymous).
Appendix A:

A1. Intercomparison of STIC1.2 with STIC1.0 and STIC1.1

An intercomparison of STIC1.2 error statistics with the previous two versions of STIC (STIC1.0 and STIC1.1) revealed maximum improvement in the performance of STIC1.2 in arid and semiarid ecosystems (as compared to mesic ecosystems) for both the SEB fluxes (Table A2). Statistical metrics of STIC1.0 and STIC1.1 (Table A2) revealed substantially higher RMSD (53 – 90 W m$^{-2}$ and 36 – 49 W m$^{-2}$) and MAPD (91 – 100% and 60 – 100%), and lower $R^2$ (0.23 – 0.64 and 0.28 to 0.67) as compared to STIC1.2 in arid ecosystems. In the semi-arid ecosystems, these statistics were 59 – 91 W m$^{-2}$ and 43 – 73 W m$^{-2}$ (RMSD); 31 – 100% and 28 – 100% (MAPD); and 0.19 – 0.84 and 0.21 – 0.84 ($R^2$), respectively.

A2. Dry season versus wet season statistics in SEB fluxes

The Taylor diagram (Fig. A2) reveals overall lower percentage errors in $H$ as compared to $\lambda E$ in arid and semi-arid ecosystems during both dry and wet seasons (please see Table A3 for dry and wet season), with normalized RMSD (RMSD/standard deviation) and correlation between observed and modeled $H$ of 27 – 60% and 0.78 – 0.95, respectively. Notable differences in $\lambda E$ errors between wet and dry seasons for arid and semi-arid ecosystems (normalized RMSD 90 – 100%) were not found, but the error in $\lambda E$ was lower (52%) during the wet season as compared to the dry seasons (75%) in the mesic ecosystems. This further highlights the fact that the high errors in $\lambda E$ for dry seasons in arid semi-arid ecosystems are associated with uncertainties in $T_R$ and SEB closure corrections, respectively.

A3. Statistical analysis

Total RMSD is the sum of RMSD$_S$ and non-systematic RMSD (RMSD$_U$), and according to Willmott (1982) RMSD$_S$s should be less than RMSD$_U$. The proportion of the total RMSD
arising from systematic biases is reflected in the quantity \( \text{RMSD}^2 / \text{RMSD}^2 \) (Willmott, 1982).

\[
\text{RMSD} = \left[ \frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)^2 \right]^{0.5}
\]  
\[\text{(A1)}\]

\[
\text{RRMSD} = 100 \left[ \frac{\text{RMSD}}{O} \right]
\]  
\[\text{(A2)}\]

\[
\text{MAPD} = 100 \left[ \frac{1}{\bar{O}} \sum_{i=1}^{N} |(P_i - O_i)| \right]
\]  
\[\text{(A3)}\]

\[
\frac{\text{RMSD}_s^2}{\text{RMSD}^2} = 100 \left[ \frac{1}{N} \sum_{i=1}^{N} (P_i - O_i)^2 \right]^{0.5}
\]  
\[\text{(A4)}\]

Where \( O_i \) represents observed value, \( P_i \) is the model-predicted value, \( N \) number of observations, \( \hat{P}_i \) estimated value based on the ordinary least-square regression \((\hat{P}_i = c + mO_i)\); where \( m \) and \( c \) are the slope and intercept of linear regression between \( P \) on \( O \), and \( \bar{O} \) is the mean of observed values.

**References:**


Bhattarai, N., K. Mallick, N.A. Brunsell, G. Sun, and M. Jain (2017), Regional evapotranspiration from image-based implementation of the Surface Temperature Initiated Closure (STIC1.2) model and its validation across an aridity gradient in the


García, M., C., Oyonarte, L. Villagarcía, S. Contreras, F. Domingo, and J. Puigdefábregas (2008), Monitoring land degradation risk using ASTER data: The non-evaporative


Hulley, G.C., S.J. Hook, and A.M. Baldrige (2010), Investigating the effects of soil moisture on thermal infrared land surface temperature and emissivity using satellite retrievals and


Table 1: List of sites, their aridity index (AI) class and characteristics (numbers in the parenthesis represent the coefficient of variation)

<table>
<thead>
<tr>
<th>Aridity index (AI) class</th>
<th>Site name</th>
<th>OzFlux ID</th>
<th>Region</th>
<th>Latitude (S) Longitude (E)</th>
<th>World ecoregion</th>
<th>Land cover</th>
<th>AI</th>
<th>Annual T_A (°C)</th>
<th>Annual P (mm yr⁻¹)</th>
<th>Annual E (mm yr⁻¹)</th>
<th>Annual E/R_N</th>
<th>θ</th>
<th>EBC %</th>
<th>Data availability λE &amp; H (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arid (0.2&gt;AI&gt;0)</td>
<td>Alice Springs</td>
<td>AU-ASM</td>
<td>Northern Territory</td>
<td>-22.28° 133.25°</td>
<td>Deserts and Xeric shrublands</td>
<td>Semi-arid mulga (Acacia aneura) ecosystem</td>
<td>0.04</td>
<td>-0.11</td>
<td>306 (58)</td>
<td>141 (100)</td>
<td>0.10</td>
<td>0.800</td>
<td>60 – 61</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>Calperum</td>
<td>AU-Cpr</td>
<td>South Australia</td>
<td>-34.00° 140.59°</td>
<td>Mediterranean woodlands</td>
<td>Recovering mallee woodland</td>
<td>0.05</td>
<td>0.06</td>
<td>240 (60)</td>
<td>257 (77)</td>
<td>0.13</td>
<td>0.800</td>
<td>72 – 78</td>
<td>79</td>
</tr>
<tr>
<td></td>
<td>Great Western</td>
<td>AU-GWW</td>
<td>Western Australia</td>
<td>-30.19° 120.65°</td>
<td>Mediterranean woodlands</td>
<td>Temperate woodland, shrubland and mallee</td>
<td>0.05</td>
<td>0.14</td>
<td>240 (41)</td>
<td>135 (77)</td>
<td>0.17</td>
<td>0.810</td>
<td>56 – 58</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>Tj Tree East</td>
<td>AU-TTE</td>
<td>Northern Territory</td>
<td>-22.29° 133.64°</td>
<td>Deserts and Xeric shrublands</td>
<td>Grassly mulga woodland and Corymbia/ Triodia savanna</td>
<td>0.05</td>
<td>0.11</td>
<td>305 (80)</td>
<td>144 (100)</td>
<td>0.11</td>
<td>0.835</td>
<td>72 – 75</td>
<td>86</td>
</tr>
<tr>
<td>Semi-arid (0.5&gt;AI&gt;0.2)</td>
<td>Gingin</td>
<td>AU-Gin</td>
<td>Western Australia</td>
<td>-31.38° 115.71°</td>
<td>Mediterranean woodlands</td>
<td>Coastal heath Banksia woodland</td>
<td>0.20</td>
<td>0.26</td>
<td>641 (19)</td>
<td>486 (63)</td>
<td>0.29</td>
<td>0.805</td>
<td>77 – 78</td>
<td>84</td>
</tr>
<tr>
<td></td>
<td>Jaxa (Yanco)</td>
<td>AU-Ync</td>
<td>New South Wales</td>
<td>-34.99° 146.29°</td>
<td>Temperate grassland</td>
<td>Grassland</td>
<td>0.30</td>
<td>0.41</td>
<td>465 (34)</td>
<td>207 (100)</td>
<td>0.10</td>
<td>0.800</td>
<td>57 – 76</td>
<td>86</td>
</tr>
<tr>
<td></td>
<td>Riggs Creek</td>
<td>AU-Rig</td>
<td>Victoria</td>
<td>-36.65° 145.58°</td>
<td>Pasture</td>
<td>Dryland agriculture</td>
<td>0.45</td>
<td>0.46</td>
<td>650 (23)</td>
<td>297 (84)</td>
<td>0.30</td>
<td>0.910</td>
<td>80 – 81</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>Sturt Plains</td>
<td>AU-Stp</td>
<td>Northern Territory</td>
<td>-17.15° 133.35°</td>
<td>Tropical grassland</td>
<td>Low lying plain dominated by Mitchell Grass</td>
<td>0.22</td>
<td>0.33</td>
<td>640 (37)</td>
<td>454 (100)</td>
<td>0.28</td>
<td>0.880</td>
<td>82 – 93</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>Whroo</td>
<td>AU-Whr</td>
<td>Victoria</td>
<td>-36.67° 145.03°</td>
<td>Temperate woodlands</td>
<td>Box woodland</td>
<td>0.20</td>
<td>0.22</td>
<td>558 (52)</td>
<td>443 (62)</td>
<td>0.27</td>
<td>0.810</td>
<td>93 – 95</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>Wombat</td>
<td>AU-Wom</td>
<td>Victoria</td>
<td>-37.42° 144.09°</td>
<td>Temperate broadleaf forest</td>
<td>Dry sclerophyll eucalypt forest</td>
<td>0.23</td>
<td>0.39</td>
<td>650 (10)</td>
<td>653 (62)</td>
<td>0.43</td>
<td>0.925</td>
<td>71 – 73</td>
<td>87</td>
</tr>
<tr>
<td>Mesic (AI&gt;0.5)</td>
<td>CowBay</td>
<td>AU-Cow</td>
<td>Queensland</td>
<td>-16.24° 145.43°</td>
<td>Tropical and sub-tropical moist broadleaf forests</td>
<td>Complex mesophyll vine forest</td>
<td>2.30</td>
<td>2.90</td>
<td>4000 (10)</td>
<td>745 (55)</td>
<td>0.61</td>
<td>0.955</td>
<td>89 – 91</td>
<td>88</td>
</tr>
<tr>
<td></td>
<td>Cumberland Plains</td>
<td>AU-Cum</td>
<td>New South Wales</td>
<td>-33.62° 150.72°</td>
<td>Temperate woodlands</td>
<td>Dry sclerophyll</td>
<td>0.56</td>
<td>0.76</td>
<td>800 (24)</td>
<td>486 (66)</td>
<td>0.43</td>
<td>0.885</td>
<td>81 – 91</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>Dry River</td>
<td>AU-Dry</td>
<td>Northern Territory</td>
<td>-15.26° 132.37°</td>
<td>Tropical savannas</td>
<td>Open forest savanna</td>
<td>0.50</td>
<td>0.73</td>
<td>895 (36)</td>
<td>679 (73)</td>
<td>0.47</td>
<td>0.970</td>
<td>80 – 81</td>
<td>92</td>
</tr>
<tr>
<td></td>
<td>Howard Springs</td>
<td>AU-How</td>
<td>Northern Territory</td>
<td>-12.49° 131.15°</td>
<td>Tropical savannas</td>
<td>Tropical savanna (wet)</td>
<td>0.53</td>
<td>0.64</td>
<td>1700 (25)</td>
<td>1190 (60)</td>
<td>0.56</td>
<td>0.870</td>
<td>85 – 91</td>
<td>96</td>
</tr>
<tr>
<td></td>
<td>Tumbarumba</td>
<td>AU-Tum</td>
<td>New South Wales</td>
<td>-35.66° 148.15°</td>
<td>Temperate broadleaf and mixed forest</td>
<td>Wet temperate sclerophyll eucalypt</td>
<td>0.65</td>
<td>0.77</td>
<td>1000 (15)</td>
<td>955 (90)</td>
<td>0.68</td>
<td>0.970</td>
<td>72 – 75</td>
<td>89</td>
</tr>
</tbody>
</table>
Table 2. Error statistics of sub-daily $\lambda E$ and $H$ derived with STIC1.2 on fifteen EC sites covering three ecohydrologically contrasting OzFlux ecosystems of different aridity classes as defined in Table 1.

<table>
<thead>
<tr>
<th>Aridity class</th>
<th>Site name</th>
<th>Year</th>
<th>$\lambda E$</th>
<th>$H$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>RMSD (W m$^{-2}$)</td>
<td>R$^2$</td>
</tr>
<tr>
<td>Arid (0&lt;Ai&lt;0.2)</td>
<td>AU-ASM</td>
<td>2013</td>
<td>26</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>39</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td>AU-Cpr</td>
<td>2013</td>
<td>30</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>25</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>AU-GWW</td>
<td>2013</td>
<td>34</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>34</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>AU-TTE</td>
<td>2013</td>
<td>26</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>46</td>
<td>0.68</td>
</tr>
<tr>
<td>Semi-arid (0.2&lt;Ai&lt;0.5)</td>
<td>AU-Gin</td>
<td>2013</td>
<td>53</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>54</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td>AU-Ync</td>
<td>2013</td>
<td>39</td>
<td>0.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>31</td>
<td>0.20</td>
</tr>
<tr>
<td></td>
<td>AU-Rig</td>
<td>2013</td>
<td>60</td>
<td>0.48</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>59</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>AU-Stp</td>
<td>2013</td>
<td>44</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>50</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td>AU-Whr</td>
<td>2013</td>
<td>43</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>46</td>
<td>0.58</td>
</tr>
<tr>
<td></td>
<td>AU-Wom</td>
<td>2013</td>
<td>40</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>54</td>
<td>0.82</td>
</tr>
<tr>
<td>Mesic (0.5&lt;AI)</td>
<td>AU-Cow</td>
<td>2013</td>
<td>38</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>47</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>AU-Cum</td>
<td>2013</td>
<td>51</td>
<td>0.81</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>52</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>AU-Dry</td>
<td>2013</td>
<td>54</td>
<td>0.88</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>64</td>
<td>0.80</td>
</tr>
<tr>
<td></td>
<td>AU-How</td>
<td>2013</td>
<td>55</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>59</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td>AU-Tum</td>
<td>2013</td>
<td>56</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2014</td>
<td>53</td>
<td>0.88</td>
</tr>
</tbody>
</table>
Table 3. Sensitivity of $\lambda E$ error to $T_R$ in three different types of OzFlux ecosystems, as shown by the cross correlation between the change in % $\lambda E$ error and % change in $T_R$ for a range of soil moisture and potential evaporation-net available energy ratio.

<table>
<thead>
<tr>
<th>$\theta$ and $E_p/\phi$ criteria</th>
<th>Class</th>
<th>Correlation between relative change in $\lambda E$ error (%) and relative change in $T_R$ (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$ ($m^3 m^{-3}$)</td>
<td></td>
<td>Arid</td>
</tr>
<tr>
<td>0&lt;0&lt;.05</td>
<td>-0.17</td>
<td>-0.14</td>
</tr>
<tr>
<td>0.05&lt;0&lt;.10</td>
<td>-0.38</td>
<td>-0.18</td>
</tr>
<tr>
<td>0.10&lt;0&lt;.15</td>
<td>-0.35</td>
<td>-0.30</td>
</tr>
<tr>
<td>0.15&lt;0</td>
<td>-0.92</td>
<td>-0.36</td>
</tr>
<tr>
<td>$E_p/\phi$ ratio</td>
<td></td>
<td>Arid</td>
</tr>
<tr>
<td>3&lt; $E_p/\phi$</td>
<td>-0.16</td>
<td>-0.10</td>
</tr>
<tr>
<td>2&lt;$E_p/\phi$&lt;3</td>
<td>-0.18</td>
<td>-0.19</td>
</tr>
<tr>
<td>1&lt;$E_p/\phi$&lt;2</td>
<td>-0.17</td>
<td>-0.17</td>
</tr>
<tr>
<td>0&lt;$E_p/\phi$&lt;1</td>
<td>-0.14</td>
<td>-0.14</td>
</tr>
</tbody>
</table>
### Table A1. Variables and symbols and their description used in the present study.

<table>
<thead>
<tr>
<th>Variables and symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>λE</td>
<td>Evapotranspiration (evaporation + transpiration) as latent heat flux (W m$^{-2}$)</td>
</tr>
<tr>
<td>H</td>
<td>Sensible heat flux (W m$^{-2}$)</td>
</tr>
<tr>
<td>$R_N$</td>
<td>Net radiation (W m$^{-2}$)</td>
</tr>
<tr>
<td>G</td>
<td>Ground heat flux (W m$^{-2}$)</td>
</tr>
<tr>
<td>φ</td>
<td>Net available energy (W m$^{-2}$) (i.e., $R_N - G$)</td>
</tr>
<tr>
<td>$R_{S\downarrow}$</td>
<td>Downwelling shortwave radiation (W m$^{-2}$)</td>
</tr>
<tr>
<td>$R_{S\uparrow}$</td>
<td>Upwelling shortwave radiation (W m$^{-2}$)</td>
</tr>
<tr>
<td>$R_{L\downarrow}$</td>
<td>Downwelling longwave radiation (W m$^{-2}$)</td>
</tr>
<tr>
<td>$R_{L\uparrow}$</td>
<td>Upwelling longwave radiation (W m$^{-2}$)</td>
</tr>
<tr>
<td>ε</td>
<td>Thermal infrared surface emissivity</td>
</tr>
<tr>
<td>$T_A$</td>
<td>Air temperature (°C)</td>
</tr>
<tr>
<td>$T_D$</td>
<td>Dewpoint temperature (°C)</td>
</tr>
<tr>
<td>$T_R$</td>
<td>Radiometric surface temperature (°C)</td>
</tr>
<tr>
<td>$T_0$</td>
<td>Aerodynamic temperature or source/sink height temperature (°C)</td>
</tr>
<tr>
<td>$T_{0D}$</td>
<td>Dew-point temperature at the source/sink height (°C)</td>
</tr>
<tr>
<td>$R_H$</td>
<td>Relative humidity (%)</td>
</tr>
<tr>
<td>$e_A$</td>
<td>Atmospheric vapor pressure at the level of $T_A$ measurement (hPa)</td>
</tr>
<tr>
<td>$D_A$</td>
<td>Atmospheric vapor pressure deficit at the level of $T_A$ measurement (hPa)</td>
</tr>
<tr>
<td>$e_S$</td>
<td>Vapor pressure at surface (hPa)</td>
</tr>
<tr>
<td>$e_S^*$</td>
<td>Saturation vapor pressure at surface (hPa)</td>
</tr>
<tr>
<td>$e_0$</td>
<td>Vapor pressure at the source/sink height (hPa)</td>
</tr>
<tr>
<td>$e_0^*$</td>
<td>Saturation vapor pressure at the source/sink height (hPa)</td>
</tr>
<tr>
<td>$D_0$</td>
<td>Vapor pressure deficit at the source/sink height (hPa)</td>
</tr>
<tr>
<td>u</td>
<td>Wind speed (m s$^{-1}$)</td>
</tr>
<tr>
<td>$u^*$</td>
<td>Friction velocity (m s$^{-1}$)</td>
</tr>
<tr>
<td>s</td>
<td>Slope of saturation vapor pressure versus temperature curve (hPa K$^{-1}$) (estimated at $T_A$)</td>
</tr>
<tr>
<td>$s_1$</td>
<td>Slope of the saturation vapor pressure and temperature between ($T_{SD} - T_D$) versus ($e_0 - e_A$) (approximated at $T_D$) (hPa K$^{-1}$)</td>
</tr>
<tr>
<td>$s_2$</td>
<td>Slope of the saturation vapor pressure and temperature between ($T_R - T_D$) versus ($e_S^* - e_A$) (hPa K$^{-1}$)</td>
</tr>
<tr>
<td>Symbol</td>
<td>Description</td>
</tr>
<tr>
<td>--------</td>
<td>-------------</td>
</tr>
<tr>
<td>$s_3$</td>
<td>Slope of the saturation vapor pressure and temperature between $(T_R - T_{SD})$ versus $(e_S^* - e_S)$ (approximated at $T_R$) (hPa K$^{-1}$)</td>
</tr>
<tr>
<td>$s_0$</td>
<td>Slope of the saturation vapor pressure and temperature between $(T_0 - T_A)$ versus $(e_0^* - e_A^*)$ (approximated as $s$) (hPa K$^{-1}$)</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Ratio between $(e_0^* - e_A)$ and $(e_S^* - e_A)$</td>
</tr>
<tr>
<td>$E$</td>
<td>Evapotranspiration (evaporation + transpiration) as depth of water (mm)</td>
</tr>
<tr>
<td>$\lambda E_P$</td>
<td>Potential evaporation as flux (W m$^{-2}$)</td>
</tr>
<tr>
<td>$\lambda E_T^*$</td>
<td>Potential transpiration as flux (W m$^{-2}$)</td>
</tr>
<tr>
<td>$\lambda E_W$</td>
<td>Wet environment evaporation as flux (W m$^{-2}$)</td>
</tr>
<tr>
<td>$\lambda E_{PM}^*$</td>
<td>Potential evaporation as flux according to Penman-Monteith (W m$^{-2}$)</td>
</tr>
<tr>
<td>$\lambda E_{PT}^*$</td>
<td>Potential evaporation as flux according to Priestley-Taylor (W m$^{-2}$)</td>
</tr>
<tr>
<td>$E_p$</td>
<td>Potential evaporation as depth of water (mm)</td>
</tr>
<tr>
<td>$E_p^*$</td>
<td>Potential evaporation as depth of water according to Penman (mm)</td>
</tr>
<tr>
<td>$E_{PM}^*$</td>
<td>Potential evaporation as depth of water according to Penman-Monteith (mm)</td>
</tr>
<tr>
<td>$E_{PT}^*$</td>
<td>Potential evaporation as depth of water according to Priestley-Taylor (mm)</td>
</tr>
<tr>
<td>$E_W$</td>
<td>Wet environment evaporation as depth of water (mm)</td>
</tr>
<tr>
<td>$g_A$</td>
<td>Aerodynamic conductance (m s$^{-1}$)</td>
</tr>
<tr>
<td>$g_M$</td>
<td>Momentum conductance (m s$^{-1}$)</td>
</tr>
<tr>
<td>$g_C$</td>
<td>Canopy (surface) conductance (m s$^{-1}$)</td>
</tr>
<tr>
<td>$g_{Cmax}$</td>
<td>Maximum canopy (surface) conductance (m s$^{-1}$) (= $g_C/M$)</td>
</tr>
<tr>
<td>$M$</td>
<td>Aggregated surface moisture availability (0 – 1)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Latent heat of vaporization of water (J kg$^{-1}$K$^{-1}$)</td>
</tr>
<tr>
<td>$z_R$</td>
<td>Reference height (m)</td>
</tr>
<tr>
<td>$z_{OM}$</td>
<td>Effective source-sink height (roughness length) of momentum (m)</td>
</tr>
<tr>
<td>$z_{OH}$</td>
<td>Effective source-sink height (roughness length) of heat (m)</td>
</tr>
<tr>
<td>$d_0$</td>
<td>Displacement height (m)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Psychrometric constant (hPa K$^{-1}$)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Density of air (kg m$^{-3}$)</td>
</tr>
<tr>
<td>$c_p$</td>
<td>Specific heat of dry air (MJ kg$^{-1}$ K$^{-1}$)</td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>Evaporative fraction (unitless)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Bowen ratio (unitless)</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Priestley-Taylor parameter (unitless)</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>Stefan-Boltzmann constant (5.670373 x 10$^{-8}$ W m$^{-2}$ K$^{-4}$)</td>
</tr>
</tbody>
</table>
Table A2, Error statistics of sub-daily $\lambda E$ and $H$ derived with STIC1.0 and STIC1.1 in fifteen EC sites covering three ecologically contrasting OzFlux ecosystems of different aridity classes as defined in Table 1.

<table>
<thead>
<tr>
<th>Aridity class</th>
<th>Site name</th>
<th>STIC versions</th>
<th>$\lambda E$</th>
<th>$H$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>RMSD (W m$^{-2}$)</td>
<td>$R^2$</td>
<td>MAPD (%)</td>
</tr>
<tr>
<td>Arid (0&lt;Ai&lt;0.2)</td>
<td>AU-ASM</td>
<td>STIC1.0</td>
<td>76 – 90</td>
<td>.23 - .54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>36</td>
<td>.28 - .62</td>
</tr>
<tr>
<td></td>
<td>AU-Cpr</td>
<td>STIC1.0</td>
<td>58 – 76</td>
<td>.29 - .30</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>26 – 32</td>
<td>.36 - .38</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>33 – 35</td>
<td>.53 - .60</td>
</tr>
<tr>
<td></td>
<td>AU-TTE</td>
<td>STIC1.0</td>
<td>57 – 71</td>
<td>.26 - .64</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>31 – 49</td>
<td>.35 - .67</td>
</tr>
<tr>
<td>Semi-arid (0.2&lt;Ai&lt;0.5)</td>
<td>AU-Gin</td>
<td>STIC1.0</td>
<td>77 – 83</td>
<td>.50 - .51</td>
</tr>
<tr>
<td></td>
<td>AU-Ync</td>
<td>STIC1.0</td>
<td>73 – 76</td>
<td>.19 - .26</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>35 – 41</td>
<td>.21 - .25</td>
</tr>
<tr>
<td></td>
<td>AU-Rig</td>
<td>STIC1.0</td>
<td>89 – 91</td>
<td>.30 - .33</td>
</tr>
<tr>
<td></td>
<td>AU-Stp</td>
<td>STIC1.0</td>
<td>70 – 85</td>
<td>.65 - .69</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>46 – 53</td>
<td>.75 - .78</td>
</tr>
<tr>
<td></td>
<td>AU-Whr</td>
<td>STIC1.0</td>
<td>66 – 84</td>
<td>.49 - .54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>43 – 44</td>
<td>.56 - .58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>43 – 73</td>
<td>.78 - .84</td>
</tr>
<tr>
<td>Mesic (0.5&lt;Ai)</td>
<td>AU-Cow</td>
<td>STIC1.0</td>
<td>44 – 59</td>
<td>.84 - .90</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>43 – 47</td>
<td>.86 - .92</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>49 – 71</td>
<td>.76 - .84</td>
</tr>
<tr>
<td></td>
<td>AU-Dry</td>
<td>STIC1.0</td>
<td>93 – 101</td>
<td>.70 - .73</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>65 – 69</td>
<td>.77 - .81</td>
</tr>
<tr>
<td></td>
<td></td>
<td>STIC1.1</td>
<td>60 – 72</td>
<td>.86 - .88</td>
</tr>
<tr>
<td></td>
<td>AU-Tum</td>
<td>STIC1.0</td>
<td>63 – 64</td>
<td>.86 - .87</td>
</tr>
</tbody>
</table>
Table A3. Dry and wet seasons of the fifteen OzFlux EC sites used in the present study

<table>
<thead>
<tr>
<th>Aridity class</th>
<th>Site name</th>
<th>Season (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Arid (0&lt;AI&lt;0.2)</strong></td>
<td>AU-ASM</td>
<td>Wet: Jan-Apr, Dry: May-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-GWW</td>
<td>Wet: Jan-May, Dry: Jun-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-TTE</td>
<td>Wet: Jan-Feb, Dry: Mar-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Cpr</td>
<td>Wet: Jan-Mar, Dry: Apr-Sep, Wet: Oct-Dec</td>
</tr>
<tr>
<td><strong>Semi-arid (0.2&lt;AI&lt;0.5)</strong></td>
<td>AU-Stp</td>
<td>Wet: Jan-Mar, Dry: Apr-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Gin</td>
<td>Wet: Jan-Apr, Dry: May-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Ync</td>
<td>Wet: Jan-Mar, Dry: Apr-Sept, Wet: Oct-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Rig</td>
<td>Wet: Jan-Mar, Dry: Apr-Sept, Wet: Oct-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Whr</td>
<td>Wet: Jan-May, Dry: Jun-Sept, Wet: Oct-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Wom</td>
<td>Wet: Jan-Apr, Dry: May-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td><strong>Mesic (0.5&lt;AI)</strong></td>
<td>AU-Cow</td>
<td>Wet: Jan-May, Dry: Jun-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Cum</td>
<td>Wet: Jan-Apr, Dry: May-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Dry</td>
<td>Wet: Jan-Mar, Dry: Apr-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-How</td>
<td>Wet: Jan-Mar, Dry: Apr-Oct, Wet: Nov-Dec</td>
</tr>
<tr>
<td></td>
<td>AU-Tum</td>
<td>Wet: Jan-Mar, Dry: Apr-Oct, Wet: Nov-Dec</td>
</tr>
</tbody>
</table>
Figure captions:

Figure 1. Schematic representation of one-dimensional description of STIC1.2. In STIC1.2, a feedback is established between the surface layer evaporative fluxes and source/sink height mixing and coupling, and the connection is shown in dotted arrows between $e_0$, $e_0^*$, $g_A$, $g_C$, and $\lambda E$. Here, $r_A$ and $r_C$ are the aerodynamic and canopy (or canopy-substrate complex in case of partial vegetation cover) resistances, $g_A$ and $g_C$ are the aerodynamic and canopy conductances (reciprocal of resistances), $e_*^S$ is the saturation vapor pressure at the surface, $e_0^*$ is the saturation vapor pressure at the source/sink height, $T_0$ is the source/sink height temperature (i.e., aerodynamic temperature) that is responsible for transferring the sensible heat ($H$), $e_0$ is the source/sink height vapor pressure, $e_s$ is the vapor pressure at the surface, $z_{0H}$ is the roughness length for heat transfer, $d_0$ is the displacement height, $T_R$ is the radiometric surface temperature, $T_{0D}$ is the source/sink height dewpoint temperature, $M$ is the surface moisture availability or evaporation coefficient, $R_N$ and $G$ are net radiation and ground heat flux, $T_A$, $e_A$, and $D_A$ are temperature, vapor pressure, and vapor pressure deficit at the reference height ($z_R$), $\lambda E$ is the latent heat flux, respectively.

Figure 2. Climatic map of Australia with the distribution of fifteen eddy covariance sites (source of the base map: http://people.eng.unimelb.edu.au/mpeel/Koppen/Australia.jpg).

Figure 3. (a) Boxplots and whiskers of R2, (b) MAPD, (c) RMSD, and (d) RMSD$_S^2$/RMSD$_2$ between $\lambda E$ and $H$ predicted by STIC1.2 versus observations in OzFlux ecosystems of contrasting aridity. The lower and upper bound of the box and the red line inside represents the first and third quartiles, and median values. The lower and upper whiskers represent the minimum and maximum values of the statistics and the red line in the boxplot represent the mean values of the statistical metrics.

Figure 4. Comparison of daily $\lambda E$ (a, c, e) and $H$ (b, d, f) predicted by STIC1.2 with measured SEB flux components in ecohydrologically contrasting OzFlux ecosystems of three aridity classes (as defined in Table 1). Data from the sites falling under same aridity class are combined together.

Figure 5. (a) and (b) Validation of STIC1.2 estimates of annual $E$ and $H$ against EC tower measurements. These are the annual sum of $E$ and $H$ for years 2013 and 2014 at each of the flux tower sites categorized according to their aridity class as defined in Table 1.

Figure 6. (a, c, and e) Scatter plots showing relative change in $\lambda E$ errors due to relative change in $T_R$ in three ecosystems of contrasting aridity. (b, d, and f) Loadings of Principal Component Regression (PCR) between residual error in STIC1.2 $\lambda E$ ($\Delta \lambda E$) with $T_R$ and environmental variables showing the contribution of each principal component in explaining the variance of the residual $\lambda E$ error. Half-hourly data are used for this analysis.

Figure 7. (a-d) Scatters between MAPD in daily $\lambda E$ and $H$ versus ecohydrological and land surface variables combining data from fifteen OzFlux ecosystems representing three broad aridity classes as described in Table 1.

Figure 8. (a and b) Scatters of monthly variance of STIC1.2 versus observed $\lambda E$ ($\sigma^2_{\lambda E}$) and $H$ ($\sigma^2_H$) in contrasting OzFlux ecosystems representing three broad aridity classes as defined in Table 1. (c and d) Correlation matrix showing the relationship between the residual variances.
in $\lambda E$ ($\hat{\sigma}_{\lambda E}^{2} = \sigma_{\lambda E \text{ STIC1.2}}^{2} - \sigma_{\lambda E \text{ observed}}^{2}$) and $H$ ($\hat{\sigma}_{H}^{2} = \sigma_{H \text{ STIC1.2}}^{2} - \sigma_{H \text{ observed}}^{2}$) versus ecohydrological and meteorological variables.

**Figure 9.** (a, c, e) Scatter plots showing the relationship between $g_{C}/g_{A}$ versus $M$ and $M$ versus $T_{R}$ as modeled in STIC1.2 for different ecosystem types. (b, d, f) Scatter plots showing how the residual $\lambda E$ error in STIC1.2 is affected by $g_{C}$ and $g_{A}$ for different types of aridity classes.

**Figure 10.** Scatter plots showing the sensitivity of $g_{C}$ and $g_{A}$ to $T_{R}$ as modeled in STIC1.2 in three different classes of ecosystems. This shows the relative change in the individual conductances due to the relative change in $T_{R}$.

**Figure 11.** (a, b, c, d) Scatters of MAPD and RMSDs^2/RMSD^2 in half-hourly $\lambda E$ predicted by STIC1.2 versus average percent of BREB-closure corrected $\lambda E$ and RES-closure corrected $\lambda E$ measured with the EC method. (e, f) Scatters of MAPD and RMSDs^2/RMSD^2 in half-hourly $H$ predicted by STIC1.2 versus average percent of BREB-closure corrected $H$ measured with the EC method. Data from fifteen OzFlux sites falling under three classes of contrasting aridity (as in Table 1) are grouped. Relative $\lambda E$ and $H$ correction (in percent) is computed as, $\% \lambda E$ correction = $100 \times (\lambda E_{\text{corrected}} - \lambda E_{\text{uncorrected}}) / \lambda E_{\text{uncorrected}}$ and $\% H$ correction = $100 \times (H_{\text{corrected}} - H_{\text{uncorrected}}) / H_{\text{uncorrected}}$. Here $\lambda E_{\text{corrected}}$ and $H_{\text{corrected}}$ are the Bowen ratio corrected $\lambda E$ ($\lambda E_{\text{uncorrected}}$) and $H$ ($H_{\text{uncorrected}}$) observations.

**Figure A1.** (a) Difference in MAPD (%) in $\lambda E$ between STIC1.2 versus STIC1.1 and STIC1.0 for the fifteen OzFlux sites, (b) Difference in RMSD (W m$^{-2}$) in $\lambda E$ between STIC1.2 versus STIC1.1 and STIC1.0 for the fifteen OzFlux sites.

**Figure A2.** Taylor diagram of daily error statistics showing the normalized RMSD and correlation coefficient between observed and predicted $\lambda E$ and $H$ during (a) dry and (b) wet seasons of 2013–2014 in ecohydrologically contrasting OzFlux ecosystems of three aridity classes as defined in Table 1. Data from the sites falling under same aridity class are combined.
(a) Arid
RMSD = 11 W m⁻²
MAPD = 55
R² = 0.55
slope = 0.55
offset = 8

(b) Arid
RMSD = 12 W m⁻²
MAPD = 12
R² = 0.93
slope = 0.92
offset = 6

(c) Semi-arid
RMSD = 17 W m⁻²
MAPD = 39
R² = 0.65
slope = 0.70
offset = 10

(d) Semi-arid
RMSD = 20 W m⁻²
MAPD = 24
R² = 0.87
slope = 0.79
offset = 19

(e) Mesic
RMSD = 18 W m⁻²
MAPD = 20
R² = 0.81
slope = 0.84
offset = 9

(f) Mesic
RMSD = 19 W m⁻²
MAPD = 37
R² = 0.73
slope = 0.67
offset = 20
(a) Annual E tower (mm)
- RMSD = 60 mm
- MAPD = 10
- $R^2 = 0.97$
- slope = 0.94
- offset = 28

(b) Annual H tower (mm)
- RMSD = 92 mm
- MAPD = 10
- $R^2 = 0.93$
- slope = 0.91
- offset = 117

Legend:
- Arid
- Semi-arid
- Mesic
(a) $R^2 = 0.90$
slope = 0.79
offset = 2

(b) $R^2 = 0.88$
slope = 0.81
offset = 6

(c) 

(d)
MAPD (%) in $\lambda E$

$\rho = 0.60$

RMSD$^2$/RMSD$^2$ (%) ($\lambda E$)

$\rho = 0.66$

MAPD (%) in $\lambda E$

$\rho = 0.24$

RMSD$^2$/RMSD$^2$ (%) (RES-closure)

$\rho = 0.17$

RMSD$^2$/RMSD$^2$ (%) ($H$)

$\rho = 0.22$

MAPD (%) in $H$

$\rho = 0.41$
Absolute difference in MAPD (%) in $\lambda_E$

- STIC1.2 - STIC1.1
- STIC1.2 - STIC1.0

Arid
Semi-arid
Mesic

Absolute difference in RMSD (W m$^{-2}$) in $\lambda_E$

- STIC1.2 - STIC1.1
- STIC1.2 - STIC1.0

Arid
Semi-arid
Mesic
(a) Correlation Coefficient
Normalized RMSD (%)

(b) Correlation Coefficient
Normalized RMSD (%)

E Mesic
E Semi-arid
E Arid
H Mesic
H Semi-arid
H Arid