Upscaling instantaneous to daily evapotranspiration using modelled daily shortwave radiation for remote sensing applications: an Artificial Neural Network approach

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Abstract

Upscaling instantaneous evapotranspiration retrieved at any specific time-of-daytime (ET\textsubscript{i}) to daily evapotranspiration (ET\textsubscript{d}) is a key challenge in regional scale vegetation water use mapping using polar orbiting sensors. Various studies have unanimously cited the short wave incoming radiation (R\textsubscript{S}) to be the most robust reference variable explaining the ratio between ET\textsubscript{d} and ET\textsubscript{i} on the terrestrial surfaces. This study aims to contribute in ET\textsubscript{i} upscaling for global studies using the ratio between daily and instantaneous incoming short wave radiation (R\textsubscript{Sd}/R\textsubscript{Si}) as a factor for converting ET\textsubscript{i} to ET\textsubscript{d}. The approach relies on the availability of R\textsubscript{Sd} measurements that in many cases is hindered if not by cost but due to the environmental conditions such as cloudiness.

This paper proposes an artificial neural network (ANN) machine learning algorithm first to predict R\textsubscript{Sd} from R\textsubscript{Si} followed by using the R\textsubscript{Sd}/R\textsubscript{Si} ratio to convert ET\textsubscript{i} to ET\textsubscript{d} across different terrestrial ecosystem. Using R\textsubscript{Si} and R\textsubscript{Sd} observations from multiple subnetworks of FLUXNET database spread across different climates and biomes (to represent inputs that would typically be obtainable from remote sensors during the overpass time) in conjunction with some astronomical variables (derived from simple mathematical computation), we developed ANN model for reproducing R\textsubscript{Sd} and further used it to upscale ET\textsubscript{i} to ET\textsubscript{d}. The efficiency of the ANN is evaluated for different morning and afternoon time-of-day, under varying sky conditions, and also at different geographic locations. Based on the measurements from 126 sites, we found R\textsubscript{S}-based upscaled ET\textsubscript{d} to produce a significant linear relation (R\textsuperscript{2} = 0.65 to 0.69), low bias (-0.31 to -0.56 MJ m\textsuperscript{-2} d\textsuperscript{-1}) (appx. 4%), and good agreement (RMSE 1.55 to 1.86 MJ m\textsuperscript{-2} d\textsuperscript{-1}) (appx. 10%) with the observed ET\textsubscript{d}, although a systematic overestimation of ET\textsubscript{d} was also noted under persistent cloudy sky conditions. An intercomparison with existing upscaling method at daily, 8-day, monthly, and yearly temporal resolution revealed a robust performance of the ANN driven R\textsubscript{S} method and was found to produce lowest RMSE under cloudy conditions. The overall methodology appears to be promising and has substantial potential for upscaling ET\textsubscript{i} to ET\textsubscript{d} for field and regional scale evapotranspiration mapping studies using polar orbiting satellites.

Key Words: Evapotranspiration, upscaling, short wave radiation, artificial neural networks, FLUXNET
1 Introduction

Satellite-based mapping and monitoring of daily regional evapotranspiration ($E_T$ hereafter) (or latent heat flux, $\lambda E$) is considered as a key scientific concern for multitudes of applications including drought monitoring, water rights management, ecosystem water use efficiency assessment, distributed hydrological modelling, climate change studies, and numerical weather prediction (Anderson et al., 2015; Senay et al., 2015; Sepulcre-Canto et al., 2014). $E_T$ variability during the course of a day is influenced by changes in the radiative energy being received at the surface (Brutsaert & Sugita, 1992; Crago, 1996; Parlange & Katul, 1992) and also due to soil moisture variability particularly in the water deficit landscapes. Therefore, one of the fundamental challenges in regional $E_T$ modelling using polar orbiting sensors involves the upscaling of instantaneous $E_T$ retrieved at any specific time-of-daytime ($E_T_1$ hereafter) to daily $E_T$ ($E_T_d$ hereafter). For example, $E_T_1$ retrieved from LANDSAT, ASTER and MODIS sensors typically represent $E_T_1$ at single time snapshot of 1000, 1030 and 1330 local times, which needs to be upscaled to daily timescales for making this information usable to hydrologists and water managers (Cammalleri et al., 2014; Colaizzi et al., 2006; Ryu et al., 2012; Tang et al., 2013).

In order to accommodate the temporal scaling challenges encountered by remote sensing based $E_T$ models, techniques have been proposed and applied by various researchers to upscale $E_T_1$ to $E_T_d$. These include: (1) the constant evaporative fraction (EF) approach which assumes a constant ratio between $\lambda E$ and net available energy ($\phi = R_n – G$) during daytime $[EF = \lambda E/(R_n − G)]$ (Gentine et al., 2007; Shuttleworth et al., 1989), (2) constant reference evaporative fractions ($EF_r$) where the ratio of $E_T_1$ between a reference crop (typically grass measuring a height of 0.12m in an environment that is not water limited) and an actual surface is assumed to be constant during daytime, allowing $E_T_d$ to be estimated from the daily $EF_r$ (Allen et al., 1998; Tang et al., 2013), (3) constant global shortwave radiation method ($R_s$) where $R_s$ is the reference variable at the land surface and it is assumed that the ratio of daily to instantaneous shortwave radiation ($R_{sd}$ and $R_{si}$) values (i.e., $R_{sd}/R_{si}$) determines $E_T_d$ to $E_T_1$ ratio (Jackson et al., 1983; Cammalleri et al., 2014), and (4) constant extra-terrestrial radiation ($R_{S_TOA}$) where exo-atmospheric shortwave radiation ($R_{S_TOA}$) is the reference variable and the ratio of instantaneous to daily i.e. ($R_{S_TOA}$ and $R_{S_TOA}$) is assumed to determine the ratio of $E_T_d$ to $E_T_1$ (Ryu et al., 2012; Van Niel et al., 2012). These methods have been
reviewed and compared in different studies with the view of identifying the most robust approach based on different data sets, time integrals and varying sky conditions (Cammalleri et al., 2014; Ryu et al., 2012; Tang et al, 2013, 2015; Van Niel et al., 2012; Xu et al., 2015).

Based on the previous studies, we find that the R\textsubscript{S}TOA approach performed consistently good at lower temporal resolution namely eight-day to monthly scales (Ryu et al., 2012; Van Niel et al., 2012) as well as under clear-sky conditions (Cammalleri et al., 2014; Chávez et al., 2008; Colaizzi et al., 2006; Xu et al., 2015). Although the EF\textsubscript{r}-based method produced comparable ET\textsubscript{d} estimates as the R\textsubscript{S}-based method, however the dependence of EF\textsubscript{r} estimates on certain variables (e.g. daily $\phi$ and wind speed, which are difficult to characterise at the daily scale from single acquisition of polar orbiting satellites) (Tang et al., 2015) makes it a relatively less attractive method. Furthermore the EF-based method appeared to consistently underestimate ET\textsubscript{d} in all these studies.

The motivation of the current work is built on the conclusions of Colaizzi et al. (2006), Chavez et al. (2008), Cammalleri et al. (2014), and Xu et al. (2015) that the ratio of the instantaneous to daily R\textsubscript{S} incident on land surface is the most robust reference variable explaining the ratio between ET\textsubscript{d} and ET\textsubscript{i} among all the tested methods. In this work, we aim to contribute in ET\textsubscript{i} upscaling by first developing a method for estimating R\textsubscript{Sd} from any specific time-of-day R\textsubscript{S} information (R\textsubscript{Si}) and further using R\textsubscript{Sd}/R\textsubscript{Si} ratio as a factor for converting ET\textsubscript{i} to ET\textsubscript{d}. We develop an artificial neural network (ANN) machine learning algorithm (McCulloch & Pitts, 1943) in order to estimate R\textsubscript{Sd}. ANN is an approach that has been successfully used in estimating global solar radiation in many sectors and more so in the field of renewable energy (Ahmad et al., 2015; Hasni et al., 2012; Lazzús et al., 2011). ANN is a non-linear model which works by initially understanding the behaviour of a system based on a combination of a given number of inputs and subsequently is able to simulate the system when fed with and independent set of inputs of the same system. Multi-layer perceptron (MLP) is one of the ANN architectures commonly used as opposed to other statistical methods, makes no prior assumptions concerning the data distribution, has ability to reasonably handle non-linear functions and reliably generalise independent data when presented (Gardner & Dorling, 1998; Khatib, Mohamed, & Sopian, 2012; Wang, 2003).
Therefore the objectives of the present study are: (1) using a ANN with MLP architecture to predict $R_{sd}$, (2) applying a method to upscale instantaneous ET$_i$ to ET$_d$ based on $R_{sd}/R_{Si}$ ratio under all sky conditions, and (3) comparing the proposed $R_s$-based method with $R_s$ TOA and EF-based ET upscaling methods.

Even though this study is intended for remote sensing application, we tested the method using meteorological and heat fluxes measurements recorded in-situ by eddy covariance (EC) system at the FLUXNET (Baldocchi et al., 2001) sites mainly for the purpose of temporal consistency. However, we evaluate the performance in consideration with overpass time of polar orbiting satellites commonly used in ET applications namely MODIS and LANDSAT.

By choosing to use data distributed over different ecosystems and climates zones, we are faced with two problems: (1) changing cloud conditions across ecosystems, (2) varying Energy balance closure (EBC) requirements for the fluxes different ecosystems (Foken et al., 2006; Franssen et al., 2010; Mauder & Foken, 2006; Wilson et al., 2002). Cloudiness is a phenomenon that significantly influences the reliability of a model to predict incoming solar radiation as they are directly related to each other. Currently, information on cloudiness is obtainable from geostationary meteorological satellites, at hourly to 3-hourly time steps e.g. from the Clouds and Earth’s Radiant Energy System (CERES), the International Satellite Cloud Climatology Project–Flux Data (ISCCP-FD), and Global Energy and Water cycle Experiment Surface Radiation Budget (GEWEX-SRB). The CERES algorithm uses cloud information from MODIS onboard both Terra and Aqua platforms and combines it with information from geostationary satellites to accurately capture the diurnal cycles of clouds. In this study, cloudiness is not included in the list of variables used to estimate $R_{sd}$ due to inconsistency in spatial resolution of data to match with the other predictive variables used.

Including cloudiness holds a great potential in improving the ANN $R_{sd}$ predications due to their direct relationship. However, we assess the performance of the ANN under cloudy sky conditions based on simple cloudiness index computations as adopted from previous works (Baigorria et al., 2004). The EBC problems have been established to vary over landscapes due to management practices, climate, seasons and plant functional type characteristics (Foken et al., 2006). In this study, in order to test the robustness of the proposed method, we disregard the site specific EBC problems and assume that the systematic bias of fluxes fall within the same range across entire FLUXNET database used.
2 Methodology

2.1 Rationale

The presented method of \( E_T \) upscaling from any specific time-of-daytime to daytime average evaporative fluxes is based on the assumption of self-preservation of incoming solar energy (i.e., shortwave radiation) as proposed by Jackson et al. (1983).

\[ E_{T_d} \approx E_{T_i} \frac{R_{S_d}}{R_{S_i}} \]  

Where, \( E_{T_d} \) is the daytime average evapotranspiration in \( \text{MJ m}^{-2} \text{d}^{-1} \), \( E_{T_i} \) is the instantaneous evapotranspiration at any instance during daytime in \( \text{W m}^{-2} \), \( R_{S_i} \) and \( R_{S_d} \) are the values of shortwave radiation recorded at any instance and the daytime average having units \( \text{W m}^{-2} \) and \( \text{MJ m}^{-2} \text{d}^{-1} \), respectively.

For any remote sensing studies using polar orbiting satellites, although the retrieval of \( E_{T_i} \) and \( R_{S_i} \) is has been carried (Tang et al., 2015; Huang et al., 2012; Laine et al., 1999; Polo et al., 2008), however estimating \( R_{S_d} \) and \( E_{T_d} \) from \( R_{S_i} \) and \( E_{T_i} \) is still challenging. Presently, upscaling \( R_{S_i} \) to \( R_{S_d} \) is primarily based on the clear sky assumption, i.e., for the entire daytime integration period, the sky remains cloud-free (Bisht et al., 2005; Jackson et al., 1983).

However, the clear-sky assumption is not always appropriate for upscaling remote sensing based \( R_{S_i} \) and hence \( E_{T_i} \) because the sky conditions during a specific time-of-daytime may be clear whereas the other part of the day might be cloudy. Under such conditions, the clear-sky assumption of \( E_{T_i} \) upscaling will lead to substantial overestimation of \( E_{T_d} \) in cloudy conditions. Hence reliable estimates of all-sky (i.e., both clear and cloudy) \( R_{S_d} \) would greatly improve the \( E_{T_d} \) estimates in the framework of Eq. (1). Given the unavailability of a definite method proposed to directly estimate all-sky \( R_{S_d} \) from \( R_{S_i} \) information, here we have developed a simple method to upscale \( R_{S_i} \) to \( R_{S_d} \) using ANN. This method uses the observations of both \( R_{S_d} \) and \( R_{S_i} \) from all the available FLUXNET sites in conjunction with some ancillary variables to build the ANN as described below. A schematic diagram of the ANN method is given in Fig. 1.
2.2 Development of Artificial Neural Network (ANN)

We used a multi-layer perceptron (MLP). The MLP was chosen as it has been widely used in many similar studies and cited to be a better alternative as compared to the conventional statistical methods (Ahmad et al., 2015; Chen et al., 2013; Dahmani et al., 2016; Mubiru & Banda, 2008). The MLP is composed of 5 neurons in the input layer, 1 output layer and 10 hidden layers (Fig. 2). The input layer neurons are made up of instantaneous incoming short wave radiation (R$_S$), instantaneous exo-atmospheric shortwave radiation (R$_S^{TOA}$), daily exo-atmospheric shortwave radiation (R$_{SD}^{TOA}$), solar zenith angle ($\theta_Z$), and day length ($L_D$) as the predictor variables whose values are initially standardized to range between -1 to 1. The choice of the inputs is intentionally limited to the variables that cannot only be acquired by measurements from meteorological stations but also derived from simple astronomical computations (Ryu et al., 2012) mainly to help minimize on the spatial distribution problem (as described earlier in the introduction) that is often linked to ground weather stations. In the MLP processing, the input layer directs the values of each input neuron $x_i$ ($i = 1, 2, 3, \ldots, n$) unto each neuron (j) of the hidden layers. In the hidden layer $x_i$ is multiplied by a weight ($w_{ij}$) and then a bias ($b_j$) assigned for each hidden layer also is applied. The weighted sum Eq. (2) is fed into a transfer function. In this work a tangent sigmoid (TANSIG) function is used Eq. (3) in the hidden layer while in the output layer a PURELIN function is applied Eq. (4) to give a single output value which is the predicted daily shortwave radiation ($R_{SD\_pred}$). The training of the ANN is completed by a regression analysis being performed internally by the algorithm between the target variable i.e. the observed and predicted daily shortwave radiation ($R_{SD\_obs}$ and $R_{SD\_pred}$).

\[ x_j = \sum_{i=1}^{n} w_{ij} y_i + b_j \]  
(2)

\[ y_j = \frac{2}{1 + \exp(-2x_j)} - 1 \]  
(3)

\[ y_j = X_j (PURELIN) \]  
(4)

Bayesian regularization algorithm was chosen for the optimization process because it is able to handle noisy datasets by continuously applying adaptive weight minimization and can
reduce or eliminate the need for lengthy cross-validation that often leads to overtraining and overfitting of models (Burden & Winkler, 2009).

2.3 Datasets

Daily and half-hourly data on $R_S$ (W m$^{-2}$), $R_{STOA}$, net radiation ($R_n$, W m$^{-2}$), latent heat flux ($\lambda E$, W m$^{-2}$), sensible heat flux (H, W m$^{-2}$) and ground heat flux (G, W m$^{-2}$) measured by the FLUXNET (Baldocchi et al., 2001) eddy covariance network were used. A total of 126 sites from the years 1999 to 2006 distributed between latitude 0-90 degrees north and south of the equator were used for the present analysis. The data sites covered a broad spectrum of vegetation functional types and climatic conditions and a list of the sites are given in Table S1 in the supplementary section.

Among the 126 sites, 85 sites were used for training and remaining 41 sites were used for validation. Partition of the data into training and validation was randomly selected regardless of the year. These translated into 194 and 86 yearly data for the respective sample. A global distribution of the data sites is shown in Fig. 3. From the training dataset, three samples were internally generated by the algorithm i.e., training datasets, validation datasets, and a testing dataset in a percentage ratio of 80:15:15 respectively. Considering the equatorial crossing time of different polar orbiting sensors like LANDSAT, ASTER, and MODIS Terra-Aqua, unique networks were generated for different time of day from morning to afternoon, and thus we had a total of 8 networks to represent potential satellite overpass times between 1030 to 1400 hours using 30 minutes interval as the closest reference time for each hour. The generated networks were then applied to an externally independent validation data set.

2.4 Intercomparison with other $ET$ upscaling methods

The performance of the $R_S$ method is also compared with two other existing $ET$ upscaling methods: (a) the EF method (Cammalleri et al., 2014), where the reference variable is the net available energy ($\phi$) ($R_n - G$).

$$SF_{EE} = \frac{\lambda E}{R_n - G}$$  (5)

$$ET_d = 1.1(R_n - G)SF_{EE}$$

Where SF is the scaling factor, R\textsubscript{n} is net radiation and G is ground heat flux.

(b) The exo-atmospheric irradiance method (Ryu et al., 2012) where the reference variable is \textit{R}\textsubscript{S}\textsubscript{TOA}.

\[ R_{Sd} \text{TOA} = S_{sc} \left[1 + 0.033 \cos \left( \frac{2\pi t_d}{365} \right) \right] \cos \beta \tag{6} \]

\[ SF_{RTOA} = \frac{R_{Sd} \text{TOA}}{R_{S1} \text{TOA}} \]

\[ ET_d = ET_i SF_{RTOA} \]

Where \textit{S}\textsubscript{sc} is the solar constant (1360 W m\textsuperscript{-2}), \textit{t}\textsubscript{d} is the day of year, and \textit{\beta} is computed solar zenith angle. We tested the performance of the three upscaling algorithms for all possible sky conditions assumed to be represented by daily atmospheric transmissivity (\textit{\tau}\textsubscript{d}) (eq. 7) namely:

(i) \( 0.25 \leq \tau \leq 0 \) (\textit{\tau}\textsubscript{1}, hereafter), (ii) \( 0.5 \leq \tau \leq 0.25 \) (\textit{\tau}\textsubscript{2}, hereafter) (iii) \( 0.75 \leq \tau \leq 0.5 \) (\textit{\tau}\textsubscript{3}, hereafter), and (iv) \( 1 \geq \tau \geq 0.75 \) (\textit{\tau}\textsubscript{4}, hereafter), respectively. We use daily \textit{\tau} because it indicates the overall sky condition throughout a day.

\[ \tau_d = \frac{R_{Sd}}{R_{Sd} \text{TOA}} \tag{7} \]

\textit{R}\textsubscript{Sd} and \textit{R}\textsubscript{Sd TOA} are daily shortwave radiation and the exo-atmospheric shortwave radiation in MJ m\textsuperscript{-2} d\textsuperscript{-1}.

2.5 Statistical error analysis

The relative performance of the ANN and three upscaling methods is evaluated using statistical indices generated namely: mean absolute percentage error (MAPE), root mean square error (RMSE), coefficient of determination (\textit{R}\textsuperscript{2}), index of agreement (IA), and bias.

\[ ET_d \text{ estimates using the respective upscaling coefficients were compared with measured } ET_d. \]

\[ R^2 = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i)^2} \tag{8} \]
\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (o_i - p_i)^2}{n}}
\]  

(9)

\[
MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{o_i - p_i}{o_i} \right| \times 100
\]  

(10)

\[
IA = \frac{\sum_{i=1}^{n} \left( p_i - o_i \right)^2}{\sum_{i=1}^{n} \left( p_i - o_i + o_i - p_i \right)^2}
\]  

(11)

\[
Bias = \frac{\sum_{i=1}^{n} (p_i - o_i)}{n}
\]  

(12)

Where, \( n \) is the number of validation data; \( o_i \) and \( p_i \) are daily observed and estimated \( R_{sd} \) or \( ET_d \), respectively. \( \bar{o} \) was the mean value of observed \( R_{sd} \) or \( ET_d \).

3 Results and discussion

3.1 Testing the performance of predicted \( R_{sd} \)

Given that the performance of \( ET_d \) upscaling depends on the soundness of \( R_{sd} \) estimation, we feel some justification to demonstrate the efficacy of the ANN method for predicting \( R_{sd} \). Figure 4 summarises the statistical results of predicted \( R_{sd} \) (\( R_{sd,\text{pred}} \), hereafter) as obtained following the methodology described in the section 2.1, showing all the site-year average \( R^2 \), RMSE, IA, and MAPE values for eight different time-of-daytime upscaling slots. From the analysis it is apparent that the RMSE of \( R_{sd,\text{pred}} \) from forenoon upscaling varied between 1.81-1.85 MJ m\(^{-2}\) d\(^{-1}\), with MAPE, \( R^2 \), IA varying between 20-21\%, 0.76-0.77, and 0.79 and 0.80, respectively (Fig. 4). For the afternoon, these statistics were almost similar and varied between 1.83-1.96 MJ m\(^{-2}\) d\(^{-1}\), 19-20\%, 0.75-0.77, and 0.80-0.81 (Fig. 4). Given the minimal discrepancy in error statistics from both forenoon and afternoon integration and considering the MODIS Terra-Aqua average overpass time we have considered 1100 and 1330 hours of daytime for the detailed follow up analysis.
Figure 5 (a and b) shows the two dimensional scatters between $R_{SD\_pred}$ versus $R_{SD\_obs}$ for different levels of $\tau$ with an overall RMSE of 1.81 and 1.83 MJ m$^{-2}$ d$^{-1}$ for the forenoon and afternoon upscaling respectively. Table 1 and Fig. 5 clearly shows overestimation tendency of the current method under persistent cloudy sky conditions ($\tau_1$), whereas the predictive capacity of the ANN model is reasonably strong with increasing atmospheric clearness. The RMSE of $R_{SD\_pred}$ for different $\tau$ class from forenoon upscaling varied between 0.62 to 2.45 MJ m$^{-2}$ d$^{-1}$, with MAPE, $R^2$ and IA of 9.2 to 53%, 0.67 to 0.98, and 0.67 to 0.95, respectively (Table 1). For the afternoon upscaling these statistics were 0.89 to 2.4 MJ m$^{-2}$ d$^{-1}$ (RMSE), 2.4 to 52% (MAPE), 0.65 to 0.98 ($R^2$), and 0.67 to 0.95 (IA) (Table 1).

The overestimation of $R_{SD\_pred}$ at low values of $\tau$ is presumably associated with varying levels of cloudiness during the daytime. Since $R_{SD\_pred}$ depends on the magnitude of $R_{Si}$, $L_D$, $\theta_Z$, $R_{SITO\_A}$, and $R_{S\_TO\_A}$, there will be a tendency of overestimating $R_{SD\_pred}$ on partly cloudy days if $R_{Si}$ at a specific time-of-daytime is not affected by the clouds ($L_D$, $\theta_Z$, $R_{SITO\_A}$, and $R_{S\_TO\_A}$ are not influenced by the clouds).

### 3.2 Evaluation of predicted ET$_d$ based on $R_{SD\_pred}$

Figure 6 summarises the statistical results of predicted ET$_d$ (ET$_{d\_pred}$, hereafter) using $R_{SD\_pred}/R_{Si}$ as a scaling factor following eq. 1 for eight different time-of-daytime slots. Upon statistical evaluation, all the cases showed significantly linear relationship between ET$_{d\_pred}$ and observed ET$_d$ (ET$_{d\_obs}$, hereafter). The RMSE of ET$_{d\_pred}$ from forenoon upscaling varied from 1.67–1.84 MJ m$^{-2}$ d$^{-1}$, with MAPE, $R^2$, IA varying between 30%–34%, 0.62–0.68, and 0.77–0.80, respectively (Fig. 6). For the afternoon upscaling, these statistics varied between 1.5–1.6 MJ m$^{-2}$ d$^{-1}$, 29%–30%, 0.67–0.71, and 0.80 (Fig. 6). These results also indicate that the error statistics were nearly uniform and the accuracy of ET$_{d\_pred}$ varies only slightly when integration was done from different time-of-daytime hours between 1030 to 1400 h. These typical error characteristics can greatly benefit the ET$_d$ modelling using polar orbiting data with varying overpass times between 1030 to 1400 hours. This also opens up the possibility to use either forenoon satellite (e.g., MODIS Terra, LANDSAT, ASTER etc.) or afternoon satellite (i.e., MODIS Aqua) to upscale ET$_i$ to ET$_d$. Following $R_{SD}$, here also we restricted our analysis to the two different time-of-daytime (1100h and 1330h) representing Terra and Aqua overpass times.
Figure 7 (a and b) shows the two dimensional scatter plots between ET\textsubscript{d,pred} versus ET\textsubscript{d,obs} for different levels of daily \( \tau \) with an overall RMSE, MAPE, and \( R^2 \) of 1.86 and 1.55 MJ m\(^{-2}\) d\(^{-1}\), 31\% and 36\%, 0.65 and 0.69 for the forenoon and afternoon upscaling, respectively. As seen in Fig. 7, there is a systematic overestimation of ET\textsubscript{d,pred} relative to the tower observed values under the low range of \( \tau \) (i.e., cloudy sky). It is important to realise that, unlike ET\textsubscript{d,obs}, ET\textsubscript{d,pred} might be an outcome of ET\textsubscript{i} instances when the sky was not overcast, i.e., the sky conditions might be clear at specific time-of-daytime but can be substantially overcast for the remainder of the daytime. As a result, any bias in the daily shortwave radiation prediction (\( R_{Sd,pred} \)) will result in biased ET\textsubscript{d,pred} according to eq. 1, and the omission of non-clear sky conditions at any particular time of daytime would tend to lead to ET\textsubscript{d,pred}>ET\textsubscript{d,obs} for generally overcast days. Since ET\textsubscript{d,obs} are the integrations of multiple ET\textsubscript{i} measurements, such conditions could be conveniently captured in the observations which were not possible in the current framework of ET\textsubscript{d,pred}. Therefore, when upscaling was done under clear skies at nominal acquisition time for generally overcast days, higher errors in ET\textsubscript{d,pred} can be expected (Cammalleri et al., 2014). We examined this cloudy sky overestimation pattern in greater detail by evaluating the error statistics in ET\textsubscript{d,pred} for four different levels of daily \( \tau \) categories (Fig. 8).

The statistical evaluation of ET\textsubscript{d,pred} for different classes of daily \( \tau \) indicates the tendency of higher RMSE and low \( R^2 \) in ET\textsubscript{d,pred} under the persistent cloudy-sky conditions (\( \tau_1 \)), while the performance of ET\textsubscript{d,pred} is reasonably good with increasing atmospheric clearness (\( \tau_2, \tau_3, \) and \( \tau_4 \)) (Fig. 8). The RMSE of ET\textsubscript{d,pred} for different \( \tau \) class from forenoon upscaling varied between 1.09 to 2.96 MJ m\(^{-2}\) d\(^{-1}\), with MAPE, \( R^2 \) and IA of 25 to 75\%, 0.38 to 0.79, and 0.71 to 0.82, respectively. For the afternoon upscaling, these statistics were 0.98 to 2.02 MJ m\(^{-2}\) d\(^{-1}\) (RMSE), 24 to 87\% (MAPE), 0.40 to 0.68 (\( R^2 \)), and 0.71 to 0.77 (IA). Biome specific evaluation of ET\textsubscript{d,pred} (Fig. 9) revealed lowest RMSE and highest \( R^2 \) both in the grassland (GRA) (0.68 to 1.14 MJ m\(^{-2}\) d\(^{-1}\); 0.53 to 0.79) and shrubland (SH) (0.66 to 1.76 MJ m\(^{-2}\) d\(^{-1}\); 0.60 to 0.82) whereas the RMSE was comparatively high over the tropical evergreen broadleaf forests (EBF) (1.41 to 2.02 MJ m\(^{-2}\) d\(^{-1}\)) and deciduous broadleaf forests (DBF) (1.94 to 2.55 MJ m\(^{-2}\) d\(^{-1}\)).
Figure 10 shows the time series comparisons between observed ET$_d$ and ET$_d$$_{\text{pred}}$ for four different stations representing different latitude bands of both the Northern (Sweden) and Southern (Brazil, Australia, and South Africa) hemispheres. These reveal that the temporal dynamics of ET$_d$ is in general consistently captured by the proposed method throughout year. In Br_SP1, relatively less seasonality was found in both observed and predicted ET$_d$. This is because SP1 is a tropical site having an annual rainfall of 850–1100 mm most of which is evenly distributed between March to end of September. The peaks in ET$_d$ values during the beginning of year and October onwards coincided with the periods of increased $R_S$, and ET$_d$$_{\text{pred}}$ could reasonably capture the observed trends during both rainy and non-rainy periods. Similarly the low ET$_d$ pattern (10 to 50 W m$^{-2}$) (equivalent to 0.1 to 1 mm d$^{-1}$) in the hot arid climate of South Africa (Za-Kru) could also be reasonable captured in ET$_d$$_{\text{pred}}$ (Fig. 10). ET$_d$$_{\text{pred}}$ over two other Southern hemisphere (AU-Tum) and the Northern hemisphere (SE-Fla) sites have shown distinct seasonality (high summer and low winter ET$_d$) coinciding with the observed ET$_d$ patterns.

### 3.3 Comparison with existing ET upscaling methods

ET$_d$$_{\text{pred}}$ from the proposed method was intercompared with two other upscaling schemes ($R_S$TOA and EF) over the 41 FLUXNET validation sites for two different time-of-daytime, 1100h and 1330h, the statistics of which are given in Table 2. This comparison was also carried out according to different $\tau$ classes as defined in section 2.2.3.

From Table 2 it is apparent that the $R_S$-based method has generally produced relatively low RMSE (1.21 to 1.99 MJ m$^{-2}$ d$^{-1}$) and MAPE (23 to 50%) as well as relatively high IA (0.72 to 0.84) as compared to the $R_S$TOA and EF-based upscaling methods. The EF upscaling method appears to systematically underestimate ET$_d$ for both forenoon and afternoon as evident from high negative bias compared to the other two methods (Table 2). On comparing $R_S$ and $R_S$TOA methods, the $R_S$-based method performed relatively better than the $R_S$TOA scheme for the lower magnitude of $\tau$ classes. However, the results suggest comparable performance of $R_S$TOA approach under clear sky conditions which are reflected in lowest RMSE (1.09 and 1.13 MJ m$^{-2}$ d$^{-1}$) in ET$_d$$_{\text{pred}}$ as compared to the other $\tau$ classes. In general, all the schemes performed relatively better from the afternoon upscaling as compared to the morning
upscaling (as evidenced in higher $R^2$ and lower bias) (Table 2 and Fig. 8) which is in agreement with the findings from Ryu et al. (2012).

The tendency of positive bias in ET$_{d_{pred}}$ from both $R_S$ and $R_{S\text{TOA}}$ in clear skies from afternoon upscaling is partly explained by the fact that, during the afternoon the values of both $R_S$ and $R_{S\text{TOA}}$ reached maximum limit and dominates their daily values (Jackson et al., 1983). The post afternoon rate of reduction in ET does not coincide with the shortwave radiation due to stomatal controls on ET, and the total water flux from morning to afternoon (0700h to 1300h) is generally greater than the total water flux from post afternoon (1500h onwards) till sunset. Therefore multiplying 1330h ET$_i$ with high magnitude of $R_{Sd}/R_{Si}$ or $R_{Sd\text{TOA}}/R_{Si\text{TOA}}$ would likely lead to an overestimation of ET$_{d_{pred}}$ in the clear sky days.

Since extraterrestrial shortwave radiation is not affected by the clouds, ET$_{d_{pred}}$ from $R_{S\text{TOA}}$ performed comparably with the $R_S$-based ET$_{d_{pred}}$ with increasing atmospheric clearness (i.e., for the higher levels of daily $\tau$). However, increased differences in the RMSE of ET$_{d_{pred}}$ between $R_S$ and $R_{S\text{TOA}}$ upscaling in the predominantly cloudy days indicates that more deviations can be expected in ET$_{d_{pred}}$ from these two different method of upscaling under principally overcast conditions (Tang et al., 2013). This happens because the ratio of $R_{Sd\text{TOA}}/R_{Si\text{TOA}}$ is not impacted by the clouds and the magnitude of this ratio becomes markedly different from $R_{Sd}/R_{Si}$ ratio in the presence of clouds, which leads to the differences in ET$_{d_{pred}}$ between them. The $R_S$-based method is relatively efficient to discriminate the impacts on ET by $R_{Sd}/R_{Si}$ due to the clouds. The generally good performance of $R_S$-based method and comparable error statistics with $R_{S\text{TOA}}$-based ET$_d$ estimates are consistent with the findings of Cammalleri et al. (2014) and Van Niel et al. (2012).

The systematic ET$_d$ underestimation by EF method and nearly similar pattern of bias from two different time-of-daytime upscaling (Table 2) further points to the fact that the concave-up shape of the EF during daytime (Hoedjes et al., 2008; Tang et al., 2013) will tend to underestimate ET$_d$ if EF is assumed to be conservative during the daytime. EF remains conservative during the daytime under extremely dry conditions when ET$_d$ is solely driven by deep layer soil moisture. The systematic underestimation of ET$_d$ from EF upscaling method corroborates with the results reported by other researchers (Cammalleri et al., 2014; Delogu et al., 2012; Gentine et al., 2007; Hoedjes et al., 2008) which suggests that the self-preservation
of EF is not generally achieved, and this systematic underestimation of ET$_d$ can be partially
compensated if EF based ET upscaling is done from morning 0900h or afternoon 1600h time-
of-daytime.

We further resampled ET$_d$ (both predicted and observed) from daily to 8-day, monthly, and
annual scale, and statistical metrics from the three different upscaling methods at three
different temporal scales are shown in Fig. 11 and Table 3. Averaging ET$_d$ over 8-day,
monthly and annual scale substantially reduced the RMSE to the order of 60 to 70\% for all
the three upscaling methods. The R$_S$-based upscaled ET from morning and afternoon showed
reduction in RMSE from 1.79 MJ to 0.57 MJ and 1.74 MJ to 0.51 MJ from daily to annual
ET, respectively. For the other two upscaling method these statistics varied from 1.85 and
1.89 MJ to 0.62 and 0.53 MJ (R$_S$TOA method), and 2.16 and 1.33 MJ to 2.20 and 1.31 MJ
(EF method) (Fig. 11 and Table 3). The impact of daily cloud variability might have
smoothed out in 8-day, monthly and annual scale which led to reduced RMSE and higher
correlation between observed and predicted ET$_d$. Nearly the same error statistics in ET$_d$$_{\text{pred}}$
from both the morning and afternoon upscaling also substantiates the findings of Ryu et al.
(2012) and greatly stimulate the use of either morning satellite (i.e., Terra) or after satellite
(i.e., Aqua) to upscale ET$_i$ to ET$_d$ or 8-day mean ET$_d$.

4 Summary and Conclusions

Given the significance of ET$_d$ in remote sensing based water resource management from polar
orbiting satellites, this study developed and evaluated a temporal upscaling method for
estimating ET$_d$ from different time-of-daytime instantaneous ET (ET$_i$) measurements with the
assumption that the ratio between daytime to instantaneous R$_S$ (R$_{Sd}$/R$_{Si}$) is the predominant
factor governing ET$_d$/ET$_i$ ratio. However, since R$_{Sd}$ is not measurable from the polar orbiting
satellites, we first developed a robust ANN based method to upscale R$_{Si}$ to R$_{Sd}$ followed by
using the ratio of R$_{Sd}$/R$_{Si}$ to further upscale ET$_i$ to ET$_d$. The overarching goal of this study is
to provide an operational and robust ET$_i$ upscaling protocol for estimating ET$_d$ from any polar
orbiting satellite.

Based on the measurements from 126 flux tower sites, we found R$_S$-based upscaled ET$_d$ to
produce a significant linear relation ($R^2 = 0.65$ to 0.69), little bias (-0.31 to -0.56 MJ m$^{-2}$ d$^{-1}$)
(appx. 4\%), and good agreement (RMSE 1.55 to 1.86 MJ m$^{-2}$ d$^{-1}$) (appx. 10\%) with the
observed ET_d. While the RsTOA-based method appeared to produce slightly lower RMSE (10% lower) under cloud-free conditions (Table 2), Rs method demonstrates more robust performance and was found to be better under cloudy conditions. Despite the Rs method yielded relatively better overall accuracy in ET_d_pred statistics when compared with the RsTOA and EF-based method, statistical analysis of the ET_d_pred accuracy of the different temporal upscaling methods (as discussed in section 3.3) suggests that Rs and RsTOA to produce commensurate results under coarse temporal resolutions (Table 3). Therefore, at the coarse temporal scale (8-day and above), there was no preferred ET_i scaling method between Rs and RsTOA.

Among all the upscaling method tested, Rs–based method carries maximum information on the cloudiness and produced generally lowest RMSE, low bias (Table 3), and, therefore, overall the preferably robust scaling mechanism (at the daily scale) among all the other methods tested. However, upscaling large-area satellite-based ET_i by using retrieved Rs_i would require accurate Rs_i retrieval techniques, which are currently commonplace (Ahmad et al., 2015; Boulifa et al., 2015; Dahmani et al., 2016; Hasni et al., 2012; Li, Tang, Wu, & Liu, 2013) to support regional scale hydrological applications. Of the two other upscaling methods, RsTOA could be easily applied over large areas, had lower errors than EF, had second best RMSD, and overall lowest bias among the two. We conclude that using modelled Rs to upscale ET_i at daily scale appears to be viable for large-area hydrological remote sensing applications from polar orbiting satellites irrespective of any sky conditions.

The principal limitation of the approach is the dependence of ET_d and Rs_d on single snapshot of ET_i and Rs_i. Although hourly Rs data from geostationary satellite are becoming available; but these are available as sectorial products (i.e. for particular continents) instead of full global coverage. Ongoing efforts to develop geostationary based data by merging multiple geostationary satellites tend to overcome this limitation.

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eddy covariance data acquired by the FLUXNET community and in particular by the following networks: AmeriFlux (U.S. Department of Energy, Biological and Environmental Research, Terrestrial Carbon Program (DE-FG02-04ER63917 and DE-FG02-04ER63911)), AfriFlux, AsiaFlux, CarboAfrica, CarboEuropeIP, CarboItaly, CarboMont, ChinaFlux, Fluxnet-Canada (supported by CFCAS, NSERC, BIOCAP, Environment Canada, and NRCan), GreenGrass, KoFlux, LBA, NECC, OzFlux, TCOS-Siberia, USCCC. We acknowledge the financial support to the eddy covariance data harmonization provided by CarboEuropeIP, FAO-GTOS-TCO, iLEAPS, Max Planck Institute for Biogeochemistry, National Science Foundation, University of Tuscia, Université Laval, Environment Canada and US Department of Energy and the database development and technical support from Berkeley Water Center, Lawrence Berkeley National Laboratory, Microsoft Research eScience, Oak Ridge National Laboratory, University of California–Berkeley and the University of Virginia. The authors declare no conflict of interest.
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Table 1: Statistical analysis of the performance of ANN in predicting $R_{Sd}$ under varying sky conditions represented by four different classes of daily atmospheric transmissivity ($\tau$). Here the statistical metrics of $R_{Sd,pred}$ for two different upscaling hours (1100 and 1330 h) are presented.

<table>
<thead>
<tr>
<th>Time-of-daytime (h)</th>
<th>$\tau$</th>
<th>$R^2$</th>
<th>RMSE (MJ m$^{-2}$ d$^{-1}$)</th>
<th>IA</th>
<th>MAPE</th>
<th>Bias (MJ m$^{-2}$ d$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1100</td>
<td>$\tau_1$</td>
<td>0.67</td>
<td>1.84</td>
<td>0.67</td>
<td>53.56</td>
<td>1.12</td>
</tr>
<tr>
<td></td>
<td>$\tau_2$</td>
<td>0.79</td>
<td>2.45</td>
<td>0.80</td>
<td>16.69</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td>$\tau_3$</td>
<td>0.88</td>
<td>2.30</td>
<td>0.82</td>
<td>9.17</td>
<td>-0.74</td>
</tr>
<tr>
<td></td>
<td>$\tau_4$</td>
<td>0.98</td>
<td>0.63</td>
<td>0.95</td>
<td>1.69</td>
<td>0.08</td>
</tr>
<tr>
<td>1330</td>
<td>$\tau_1$</td>
<td>0.65</td>
<td>1.77</td>
<td>0.67</td>
<td>51.50</td>
<td>1.06</td>
</tr>
<tr>
<td></td>
<td>$\tau_2$</td>
<td>0.81</td>
<td>2.44</td>
<td>0.81</td>
<td>16.83</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>$\tau_3$</td>
<td>0.89</td>
<td>2.23</td>
<td>0.83</td>
<td>8.94</td>
<td>-0.85</td>
</tr>
<tr>
<td></td>
<td>$\tau_4$</td>
<td>0.98</td>
<td>0.89</td>
<td>0.95</td>
<td>2.40</td>
<td>-0.46</td>
</tr>
</tbody>
</table>
Table 2: A summary of ETd error statistics by comparing the performance of RS, RS TOA and EF upscaling methods with regard to different sky conditions. Here $\tau_1$ represents low atmospheric transmissivity due to high cloudiness while $\tau_4$ represents high transmissivity under clear sky conditions.

<table>
<thead>
<tr>
<th>Time of daytime (h)</th>
<th>$\tau$</th>
<th>$R^2$</th>
<th>RMSE (MJ m$^{-2}$ d$^{-1}$)</th>
<th>IA</th>
<th>MAPE</th>
<th>Bias (MJ m$^{-2}$ d$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Rs</td>
<td>Rs TOA</td>
<td>Rs</td>
<td>Rs TOA</td>
<td>Rs TOA</td>
</tr>
<tr>
<td>1100</td>
<td>$\tau_1$</td>
<td>0.49</td>
<td>0.32</td>
<td>0.32</td>
<td>1.34</td>
<td>1.65</td>
</tr>
<tr>
<td></td>
<td>$\tau_2$</td>
<td>0.72</td>
<td>0.70</td>
<td>0.69</td>
<td>1.73</td>
<td>1.81</td>
</tr>
<tr>
<td></td>
<td>$\tau_3$</td>
<td>0.72</td>
<td>0.73</td>
<td>0.79</td>
<td>1.99</td>
<td>1.94</td>
</tr>
<tr>
<td></td>
<td>$\tau_4$</td>
<td>0.77</td>
<td>0.81</td>
<td>0.68</td>
<td>1.32</td>
<td>1.13</td>
</tr>
<tr>
<td>1330</td>
<td>$\tau_1$</td>
<td>0.52</td>
<td>0.34</td>
<td>0.29</td>
<td>1.21</td>
<td>1.68</td>
</tr>
<tr>
<td></td>
<td>$\tau_2$</td>
<td>0.73</td>
<td>0.72</td>
<td>0.71</td>
<td>1.71</td>
<td>1.93</td>
</tr>
<tr>
<td></td>
<td>$\tau_3$</td>
<td>0.75</td>
<td>0.75</td>
<td>0.76</td>
<td>1.89</td>
<td>1.96</td>
</tr>
<tr>
<td></td>
<td>$\tau_4$</td>
<td>0.79</td>
<td>0.86</td>
<td>0.80</td>
<td>1.32</td>
<td>1.09</td>
</tr>
</tbody>
</table>
Table 3: Error statistics of ET$_{d\_pred}$ at four different temporal scales from three ET$_i$ upscaling methods.

<table>
<thead>
<tr>
<th>Time-of-day (h)</th>
<th>Temporal scale</th>
<th>$R^2$</th>
<th>RMSE (MJ m$^{-2}$ d$^{-1}$)</th>
<th>IA</th>
<th>MAPE</th>
<th>Bias (MJ m$^{-2}$ d$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$R_S$</td>
<td>$R_i$TOA EF $R_S$</td>
<td>$R_i$TOA EF</td>
<td>$R_S$</td>
<td>$R_i$TOA EF</td>
</tr>
<tr>
<td>1100</td>
<td>Daily</td>
<td>0.71</td>
<td>0.71  1.79  1.85  2.16  0.82  0.88  0.67</td>
<td>28.80</td>
<td>32.98</td>
<td>57.00</td>
</tr>
<tr>
<td></td>
<td>8-days</td>
<td>0.86</td>
<td>0.84  0.83  1.17  1.22  1.65  0.87  0.86  0.67</td>
<td>18.50</td>
<td>20.63</td>
<td>46.96</td>
</tr>
<tr>
<td></td>
<td>Monthly</td>
<td>0.89</td>
<td>0.88  0.88  0.99  1.04  1.61  0.89  0.67  0.67</td>
<td>15.52</td>
<td>17.22</td>
<td>49.72</td>
</tr>
<tr>
<td></td>
<td>Annually</td>
<td>0.92</td>
<td>0.91  0.91  0.57  0.62  1.33  0.87  0.84  0.54</td>
<td>11.12</td>
<td>12.54</td>
<td>45.88</td>
</tr>
<tr>
<td>1330</td>
<td>Daily</td>
<td>0.75</td>
<td>0.74  0.69  1.74  1.89  2.2  0.83  0.82  0.67</td>
<td>26.59</td>
<td>29.89</td>
<td>56.45</td>
</tr>
<tr>
<td></td>
<td>8-days</td>
<td>0.87</td>
<td>0.86  0.84  1.11  1.21  1.7  0.88  0.88  0.68</td>
<td>16.80</td>
<td>17.97</td>
<td>50.36</td>
</tr>
<tr>
<td></td>
<td>Monthly</td>
<td>0.90</td>
<td>0.90  0.87  0.93  1.00  1.59  0.90  0.89  0.68</td>
<td>13.69</td>
<td>14.85</td>
<td>48.08</td>
</tr>
<tr>
<td></td>
<td>Annually</td>
<td>0.93</td>
<td>0.93  0.92  0.51  0.53  1.31  0.88  0.88  0.54</td>
<td>9.00</td>
<td>9.70</td>
<td>44.13</td>
</tr>
</tbody>
</table>
**Figure 1.** A conceptual diagram of the methodology. On the left side is a representation of predicting daily incoming short wave radiation ($R_{sd,\text{pred}}$). The ANN is trained to learn the system response to a combination of explanatory variables i.e. instantaneous incoming short wave radiation ($R_{si}$), instantaneous exo-atmospheric shortwave radiation ($R_{si,\text{TOA}}$), daily exo-atmospheric shortwave radiation ($R_{sd,\text{TOA}}$), solar zenith angle ($\theta_z$), and day length ($L_D$), by being fed with a sample data of observed daily incoming short wave radiation ($R_{sd}$) which is the dependant variable. On the right side are methods of upscaling instantaneous (ET$_i$) to daily ET (ET$_d$) using our $R_{sd}$ method (a) and other two approaches (b, c) are the $R_{STOA}$ and EF methods respectively used which are used for comparison.

**Figure 2.** Schematic representation of a simple artificial network model. The artificial neuron has five input variables, for the intended output. These inputs are then assigned weights (W) and bias (b), and the sum of all these products ($\sum$) is fed to an activation function (f). The activation function alters the signal accordingly and passes the signal to the next neuron(s) until the output of the model is reached (Mathworks, 2015).
**Figure 3.** Distribution of 126 sites of the FLUXNET eddy covariance network used in the present study with 85 and 41 sites for training and validation, respectively between the years 1999 and 2006.
**Figure 4.** Statistical metric of $R_{\text{Sd, pred}}$ by ANN for different time-of-daytime. As the study is intended for remote sensing application, we demonstrate the potential of the method for future research in the case where satellite will be used and as such we pick MODIS overpass time as an example to highlight on the predictive ability of the ANN at the specific overpass times.
Figure 5. Scatter plots between $R_{Sd,\text{pred}}$ versus $R_{Sd,\text{obs}}$ for different levels of daily atmospheric transmissivity classes ($\tau$) from (a) 1100 and (b) 1330 hours upscaling. Here $\tau_1$–$\tau_4$ represent daily atmospheric transmissivity of four different class, $0.25 \geq \tau \geq 0$, $0.5 \geq \tau \geq 0.25$, $0.75 \geq \tau \geq 0.5$, and $1 \geq \tau \geq 0.75$, respectively, with $\tau_1$ signifying high degree of cloudiness (or overcast skies) whereas $\tau_4$ indicates clear skies.
Figure 6. Statistical summary of ET$_{d,\text{pred}}$ for different time-of-daytime using Eq. (1) based on $R_{Si}$ and $R_{Sd,\text{pred}}$. As the study is intended for remote sensing application, we once again demonstrate the potential of the method for future research in the case where satellite will be used and as such we pick MODIS Terra-Aqua overpass time.
Figure 7. $\text{ET}_{\text{d, pred}}$ obtained through eq. (1) versus $\text{ET}_{\text{d, obs}}$ for different levels of $\tau$ from both forenoon and afternoon upscaling (1100 and 1300 daytime hours).
Figure 8. Assessing the statistical metrics of $\text{ET}_{d,\text{pred}}$ (using eq.1) for different levels of daily atmospheric transmissivity classes (representing cloudy to clear skies) for both 1100h and 1330h time-of-daytime ET, scaling.
Figure 9. Biome specific error characteristics of ET_{d,\text{pred}} displaying the box plots of (a) RMSE and (b) coefficient of determination (R^2). The biome classes are evergreen broadleaf forest (EBF), evergreen needleleaf forest (ENF), deciduous broadleaf forest (DBF), shrubland (SH), cropland (CRO), and grassland (GRA), respectively.

(a)  
(b)  

Figure 10. Time series comparison between measured and predicted ET_d for four representative sites located in Australia, Brazil, South Africa and Sweden.
Figure 11. Statistical metrics of ET$_{d,\text{pred}}$ from three different ET$_i$ upscaling approaches [shortwave incoming radiation ($R_S$), exo-atmospheric shortwave radiation ($R_S^{\text{TOA}}$) and evaporative fraction (EF)] at different temporal scales based on ET$_i$ measurements at (a) 1100h and (b) 1330h time-of-daytime.