A modeling approach for reconstruction of annual land surface evapotranspiration using palaeoecological data

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Abstract. A modeling approach to reconstruct the annual land surface evapotranspiration from palaeoecological data was suggested. It is based on assumption that the actual evapotranspiration is proportional to potential surface evapotranspiration and to some decoupling factor characterizing the surface moisture conditions. It was described in our study as a function of the climate moisture index (CMI). The potential evapotranspiration rate was derived using palaeoecological data about past land use and land cover, forest cover age, plant species composition and mean annual air temperature. The value of unknown decoupling factor was approximated using the results of evapotranspiration measurements at selected FLUXNET experimental sites located in the areas with different (ranged from extremely wet to moderately dry) moisture conditions. Comparisons of modeled evapotranspiration rates with results of the field flux measurements showed their good agreement for various forest, shrubland and grassland ecosystems in different geographical regions.

1. Introduction
Adequate information about climate and surface moisture conditions is very important for better understanding of the vegetation changes in past epochs [1-8]. The surface moisture conditions are usually derived using the relationship between precipitation and potential or actual land surface evapotranspiration rates [1, 9-12]. Potential evapotranspiration represents the environmental demand for evaporation, whereas actual evapotranspiration depends both on evaporative demands and surface water supply. The actual evapotranspiration is composed of plant transpiration, soil surface evaporation and evaporation of precipitation intercepted by the plant canopy and it is strongly controlled by both climatic conditions (including incoming solar radiation, air temperature, wind speed and water vapor pressure deficit) and biophysical properties of vegetation influencing the transpiration rate through the physiological (stomatal) regulation. The stomatal regulation is a key mechanism controlling the water vapor and carbon dioxide exchanges between plant leaves and the ambient air and preventing excess water loss by plants. Even in case of unlimited water supply the observed transpiration rate is usually some smaller than potential evaporation rate from e.g. open water area, completely wet plant canopy or oversaturated bare soil [13].

During the last decades numerous modeling approaches to derive the surface potential evaporation or evapotranspiration in past epochs were developed and applied [1, 2, 9, 14-16]. Furthermore, several
models allowing to estimate the actual evapotranspiration from palaeoecological data were also suggested [1, 15, 17, 18].

At present, to derive the actual surface evapotranspiration using known atmospheric and plant canopy parameters a simple "big-leaf" modeling approach initially suggested by Monteith [19, 20] is usually applied. A wide application of this approach for evapotranspiration calculation is mainly limited by uncertainties in estimation of key biophysical parameters describing the stomatal regulation of various plant species under different atmospheric and moisture conditions. More simple approach suggested by Manabe [21] is based on approximation of soil layers as a bucket that receives and retains the incident with precipitation and snow melting water until its storage capacity is filled. The difference between actual and potential evapotranspiration (evaporation) rates depends from the ratio between soil moisture content and field capacity of the soil. The difference between actual and potential evapotranspiration can be also derived using the coupling parameter $\Omega$ that was first proposed by Jarvis and McNaughton [22]. It is ranged between 0 and 1 and quantified the relationship of the atmospheric characteristics at the canopy surface and in the ambient air. Whereas the $\Omega$ values close to 0 correspond to well-coupled conditions indicating the high physiological control of transpiration, the $\Omega$ values close to 1 indicate the opposite, i.e. decoupled conditions and a low stomatal control on transpiration [22]. Peng et al [23] considered the spatial and temporal variability of this coupling parameter and showed its close dependence on surface moisture conditions and on amount of photosynthesizing plant biomass.

The main goal of the study is to develop a simple model algorithm for estimation and reconstruction of temporal variations of annual actual evapotranspiration using available palaeogeographical data about land use/land cover type, forest coverage, plant species compositions, annual temperature and precipitation. For model validation the results of field measurements of evapotranspiration rates in diverse plant communities growing in different geographical regions with various moisture conditions were used.

2. Model description

The modeling algorithm to determine the actual annual evapotranspiration ($ET$) rate is based on well-known "bucket" model and considers the $ET$ as a function of potential annual surface evaporation ($PE$), assumed to be equal to potential evapotranspiration, and the coupling parameter $\Omega$ describing the surface moisture conditions:

$$ET = \Omega \cdot PE$$  \hspace{1cm} (1)

The $PE$ rate is simulated using the well-known Priestley-Taylor equation [24]. The annual $PE$ is calculated by time-integrating the mean daily $PE$ values ($PE_d$):

$$PE = \sum_{i=1}^{N_d} PE_d \cdot dt = \alpha_{PT} \cdot \sum_{i=1}^{N_d} \left( \frac{\Delta}{\Delta + \gamma} \cdot \frac{R_{n_i}}{\lambda} \right) \cdot dt$$  \hspace{1cm} (2)

where $N_d$ is the number of the days per year, $\gamma$ is the psychrometric constant ($\gamma=0.066$ kPa °C$^{-1}$), $\alpha_{PT}$ is the Priestley-Taylor constant ($\alpha_{PT} = 1.26$ mm day$^{-1}$) and $\Delta$ is the slope of the relationship between saturation vapor pressure and the air temperature ($\Delta$, kPa °C$^{-1}$). The annual variability of parameter $\Delta$ is described as a function of the mean annual air temperature, annual temperature range and the sequential day of the year [25, 26].

The daily net radiation at ground surface is derived as a sum of short-wave ($R_{ns}$) and long-wave ($R_{nl}$) radiation balances:

$$Rn = R_{ns} + R_{nl} = Q \cdot (1 - \alpha) + \left( R_{s} - R_{al} \right)$$  \hspace{1cm} (3)

where $Q$ is the incoming daily solar radiation, $\alpha$ is the surface albedo, and $R_{s}$ and $R_{al}$ are the incoming and outgoing long-wave radiation fluxes, respectively. Surface albedo depends on land cover and
vegetation types (e.g. coniferous forest, deciduous forest, mixed forest, grassland), soil properties and forest cover percentage [27, 28].

The annual variability of \( Q \) is approximated using the model algorithms described by McMahon et al [25] and Novenko et al [26].

To parameterize the coupling parameter \( \Omega \) in equation (1) the annual climate moisture index (CMI) is used. It has been suggested by Willmott and Feddema [10] and in respect of other aridity and moisture indexes it is well adapted to evaluating moisture conditions in both dry and humid regions. The CMI ranges from -1 to +1 and can be computed as:

\[
CMI = \begin{cases} 
(P/PE) - 1 & \text{when } P < PE \\
1 - (PE/P) & \text{when } P \geq PE
\end{cases}
\]  

(4)

Wet climates are characterized by positive CMI, and dry climates - by negative CMI, respectively.

It was assumed that the annual ET rate in the areas with very wet climate (CMI is near to "1") is equal to PE, and it is close to zero in the areas with extremely dry weather conditions (CMI is near to "-1"), respectively.

Taking into account the non-linearity of the response of \( \Omega \) to CMI variation [23], the equation for \( \Omega \) can be written as

\[
\Omega = \left( CMI + 1 \right) / \left( a_1 + a_2 \cdot CMI \right)
\]  

(5)

where \( a_1 \) and \( a_2 \) are empirical constants.

3. Parameterization of the \( \Omega \) response to surface moisture conditions

To derive the response of \( \Omega \) (the ratio of ET to PE) to CMI variation the FLUXNET experimental data (https://fluxnet.fluxdata.org/data/fluxnet2015-dataset/) for diverse forest, shrubland and grassland experimental sites in different geographical regions with various moisture conditions ranged from extremely wet to moderately dry were selected (table 1). For the data analysis the monthly air temperature, precipitation, net radiation and ET rates obtained at the sites in 2012 year were used.

![Figure 1](image-url)  

**Figure 1.** The dependence of the mean annual \( \Omega \) on CMI for selected FLUXNET experimental sites with various moisture conditions. The red dashed line is an approximation of the boundary curve fitting the points with maximum values of \( \Omega \) for different CMI intervals using equation (5).

To approximate the dependence of the mean annual \( \Omega \) on CMI using experimental data the boundary curve method was applied. The method is based on assumption that the boundary line fitting
the maximum values of $\Omega$ obtained for different $CMI$ intervals is well corresponded to maximum $ET$ rates (maximum $\Omega$) under relevant surface moisture conditions (figure 1, table 2).

**Table 1.** FLUXNET experimental sites selected for calibration and validation of the $ET$ model.

| Stations                        | Latitude (°) | Longitude (°) | Elevation (m) | Land-use type | Plant species               |
|---------------------------------|--------------|---------------|---------------|---------------|----------------------------|
| Fontainebleau-Barbeau, France    | 48.48        | 2.78          | 103           | forest        | oak, hornbeam              |
| Puechabon, France               | 43.74        | 3.60          | 270           | forest        | oak                        |
| Lackenberg, Germany             | 49.10        | 13.30         | 1308          | forest        | beeches, oaks              |
| Oberbärenburg, Germany          | 50.79        | 13.72         | 734           | forest        | pine, spruce               |
| Loobos, The Netherlands          | 52.17        | 5.74          | 25            | forest        | pine, larch                |
| Fyodorovskoye, Russia           | 56.46        | 32.92         | 265           | forest        | spruce                     |
| Casteld’Asso, Italy             | 42.38        | 12.02         | 197           | forest        | oak                        |
| Brasschaat, Belgium             | 51.31        | 4.52          | 16            | forest        | pine, oak                  |
| Hyytiala, Finland               | 61.85        | 24.29         | 181           | forest        | spruce, pine               |
| Sodankyla, Finland              | 67.36        | 26.64         | 180           | forest        | spruce, pine               |
| Laguna Seca, Spain              | 37.10        | -2.97         | 2267          | shrubland     | oak                        |
| Vaira Ranch-lone, USA           | 38.41        | -120.95       | 129           | grassland     | purple false brome, smooth cat's ear, rose clover |
| Walnut Gulch, USA               | 31.74        | -109.94       | 1531          | grassland     | black grama                |
| Ti Tree East, Australia         | -22.29       | 133.64        | 754           | shrubland     | acacia                     |

**Table 2.** Coefficients of the equation (5) for $\Omega$ calculation and standard errors of their estimates $(p<0.005)$.

| Parameters | $a_1$     | $a_2$     |
|------------|-----------|-----------|
| Fitting values | 1.27 ± 0.02 | 0.73 ± 0.02 |

This approach allows us also to avoid the possible underestimations of $\Omega$ values due to non-stationarity in temperature and precipitation distributions throughout the year and to possible flux measurement uncertainties caused by existed limitations of the eddy covariance method used for flux measurements at FLUXNET sites [29-31].

4. **Model validation**

The validation of the developed model for $PE$ and $ET$ was provided using available experimental data from the FLUXNET database (table 1) in two steps. In the first step, the modeled $PE$ rates were compared with $PE$ derived from the measured net radiation and air temperature values using the Priestley-Taylor equation. In the second step we compared the modeled and measured annual $ET$ rates for different experimental sites.
Comparisons of modeled and experimentally determined annual $PE$ rates show their relatively good agreement (figure 2). The determination coefficient ($R^2$) is about 0.89 at $p<0.05$. Slight overestimation of annual $PE$ rate predicted by the model can be explained by several reasons including used model assumptions and limited experimental data set involved in the model calibration and validation procedure. Taking into account that the algorithm for $PE$ estimation from experimental data is based on measured net radiation, the differences between modeled and measured fluxes can be explained also by uncertainties in the measurements of reflected short-wave radiation, as one of the key parameters determining the surface net radiation, using equipment installed at meteorological towers. According to results of Gravenhorst et al [32] the forest canopy albedo is characterized by significant spatial heterogeneity that can result in both over- and underestimations of reflected solar radiation using any measuring equipment installed at a meteorological tower above the canopy at one stationary point. The similar results were obtained by Widlowski et al [33] and Levashova et al [34] for non-uniform forest canopies with different tree density and various soil surface albedo.

**Figure 2.** The scatter plots between modeled and measured annual $PE$ and $ET$ for selected experimental sites. The red dashed lines are linear regressions.

Comparisons of modeled and measured $ET$ showed also some overestimation of $ET$ rate predicted by the model by about 23%. It is clear that such effect can be a result of found slight model overestimation of $PE$ rates. Moreover, it can be also explained by existed uncertainties of $ET$ estimations using the eddy covariance technique. The accuracy of flux estimations by the method is strongly depended on turbulent conditions within the atmospheric surface layer, thermal atmospheric stratification, surface topography and vegetation heterogeneity [35]. Complex topography and vegetation heterogeneity can lead to the air flow disturbances, increase of horizontal flux divergence, and consequently to inaccurate vertical flux estimations [35-38]. Numerous studies on the lack of
energy balance closure (the sum of latent and sensible heat fluxes divided by the available energy or net radiation) for eddy-covariance flux measurements showed that it can significantly vary at different sites from 53 to 99% depending on atmospheric conditions, landscape heterogeneity and averaging time [39, 40]. The worse the energy balance closure, the higher underestimation of the atmospheric fluxes.

It is clear that the developed model is based on a relatively simplified algorithm to approximate the decoupling factor $\Omega$ and to derive the plant water availability in the land surface area. More accurate $\Omega$ estimations require obviously more sophisticated description of the stomatal regulation mechanisms and their variation under changing environmental conditions that is still a very complicated scientific task even in the studies of $ET$ changes under present climate conditions.

5. Conclusion
The modeling algorithm to reconstruct the land surface evapotranspiration from palaeoecological data was suggested and validated using the modern FLUXNET experimental data. Analysis of the ratio between actual and potential evapotranspiration rates, $\Omega$, for different land-use and vegetation types under diverse surface moisture conditions enabled us to find a close relationship between $\Omega$ and the annual climate moisture index, $CMI$. Comparisons of modeled and measured annual evapotranspiration rates for selected FLUXNET experimental sites showed their good agreement. Small differences between modeled and measured fluxes can be explained by both the simplicity of developed model and existed technical limitations of water vapor flux estimations using the eddy covariance measuring technique. Developed algorithm can be used as an effective tool to derive the surface moisture conditions required for better understanding of the vegetation dynamics and land surface processes in past epochs.

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