# HOW TO MEASURE EVAPOTRANSPIRATION IN LANDSCAPE-ECOLOGICAL STUDIES? OVERVIEW OF CONCEPTS AND METHODS

TEREZA POHANKOVÁ*, PAVEL VYVLEČKA; VILÉM PECHANEC

*Department of Geoinformatics, Palacký University Olomouc, 17. listopadu 50, Czech Republic*
**Corresponding author email: tereza.pohankova@upol.cz*

**Received:** 26th August 2024, **Accepted:** 8th October 2024

## ABSTRACT

Evapotranspiration (ET) is a key component of the hydrological cycle, encompassing evaporation processes from soil and water surfaces and plant transpiration (Sun *et al*., 2017). Accurate estimation of ET is vital for effective water resource management, agricultural planning, and environmental monitoring (Gowda *et al*., 2008). However, the complex interactions between land surface conditions, vegetation, and atmospheric factors make direct measurement of ET challenging, leading to the development of various estimation methods. Remote sensing has become a widely used approach for estimating ET over large areas because it provides spatially comprehensive data (Xiao *et al*., 2024). Methods like the Surface Energy Balance Algorithm for Land and the Surface Energy Balance System utilise satellite-derived thermal imagery and meteorological inputs to calculate ET by analysing the energy exchanges between the land surface and the atmosphere. These methods are advantageous for their broad spatial coverage, making them particularly useful for regional to global scale studies. However, they require careful calibration and validation, and their accuracy can be affected by the spatial resolution of the satellite data and the quality of meteorological inputs. In addition to remote sensing, several other ET estimation methods are commonly employed.

The Penman-Monteith equation is one of the most widely accepted methods, integrating meteorological data—such as air temperature, humidity, wind speed, and solar radiation— with biophysical properties of vegetation to estimate ET. This method has been validated extensively, making it a standard reference in ET studies. Empirical methods like the Hargreaves-Samani equation provide simpler alternatives that require fewer data inputs, making them suitable for regions with limited meteorological information but with a trade-off in accuracy. Direct measurement techniques offer highly accurate ET data, including lysimeters and eddy covariance systems. Lysimeters measure water loss directly from a soil column, while eddy covariance systems assess the exchange of water vapour and energy between the surface and the atmosphere. Despite their precision, these methods are limited by high costs, maintenance requirements, and their applicability to small-scale, homogeneous areas (Howell, 2005). Choosing the appropriate ET estimation method depends on the scale of the study, data availability, and the specific application. Remote sensing and models like Penman-Monteith offer scalability and broad applicability, while direct measurements provide precise data at localised scales. Integrating these methods can improve the reliability of ET estimates, enhance water resource management, and aid in climate adaptation efforts.

**Keywords**: evapotranspiration, remote sensing, field methods

## INTRODUCTION

One of the most significant ecosystem functions of greenery are its capacity to reduce the surrounding temperature (Zardo *et al*., 2017). The cooling rate is directly proportional to the evapotranspiration occurring at any given time (Allen *et al*., 1998). The rate of ET is contingent upon the current state of the vegetation and the conditions of its surroundings (Aram *et al*., 2019). Consequently, it is a highly variable process, and determining the actual value takes much work (Kirkham, 2014a). Evapotranspiration (ET) is a critical hydrological process encompassing the combined actions of evaporation from the soil surface and transpiration from plants or crops (Fig. 1). As a pivotal component of the surface, water, and atmospheric energy cycles, ET represents the transfer of liquid water to water vapour. Evaporation, the physical component, denotes the phase change of liquid water into vapour. In contrast, transpiration is a biological process wherein water evaporates from plants through stomata, primarily on leaf undersides. This transpired water, replenished by water absorbed from the soil via plant roots, moves through the plant in liquid form before vaporisation at the stomata (Allen *et al*., 1998, 1998; Kozlowski & Pallardy, 1997).

ET is a key factor in several areas, such as water resource management (Volk *et al*., 2024), precision agriculture (Gonzalez *et al*., 2023), drought monitoring (Stoyanova *et al*., 2023), carbon cycling (von Randow *et al*., 2020) or soil moisture measurement (Dong *et al*., 2020). In most instances, these domains overlap, and, in general, ET can indicate the effective or ineffective functioning of ecosystems and is one of the main indicators of climate regulation (Millennium Ecosystem Assessment, 2005). Numerous methods have been developed to measure and estimate ET, encompassing both direct measurement techniques and indirect approaches. Each method has advantages and limitations, and the choice often depends on the spatial and temporal scales of interest, the availability of data, and the specific application. Remote sensing technologies have significantly advanced ET estimation by offering spatially extensive data over large areas.

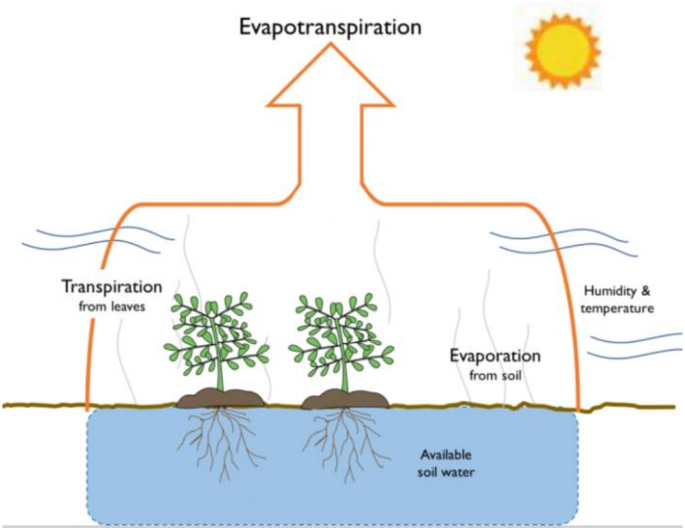
However, accurate estimation of ET can be challenging due to the need to distinguish between different concepts within the term. Potential (PET) and reference ($ET_0$) evapotranspiration have been confused for several decades. Sometimes, they are not described as two separate processes and are referred to as PET altogether (Dinpashoh *et al*., 2011; Mardikis *et al*., 2005).

Reference evapotranspiration ($ET_0$) is usually given in W/m$^2$ or kJ/m$^2$. It refers to ET from a reference area, which is normally described in the literature as a hypothetical grass area with sufficient water supply, a grass height of 0.12 m, a constant surface resistance of 70 s/m, and an albedo of 23 % (Allen *et al*., 1994).

Potential Evapotranspiration (PET) describes the evapotranspiration rate if a sufficient water source is available. Unless the surface is always moist, PET should always reach lower values than Actual Evapotranspiration (AE).

While PET and are similar (both refer to atmospherical and crop demands, additionally referring to abstract/ideal ET), the initial thoughts and concepts differ. As Xiang *et al*. (2020) pointed out, ET applications were originally used in hydrology before extending to various scientific fields. Agricultural applications aimed to calculate water requirements in crops and their irrigation, for which PET could have been a better solution and often caused miscalculations. This was solved by introducing the concept of Actual Evapotranspiration.

**Fig. 1: Schema of evaporation and transpiration resulting in ET (Bates & Jackson, 1980)**




Actual Evapotranspiration (AE; [mm/day]) was scientifically defined by Thornthwaite in 1948 (Stanhill, 2005; Thornthwaite, 1948). AE explains the real water and energy exchange between the oil surface and the atmosphere (Ochoa-Sánchez *et al.*, 2019). Measurement of AE depends on the Crop Coefficient (Kc see Equation 1). allows derivating AE for specific surfaces or crops (Peacock & Hess, 2004). FAO Irrigation and Drainage Paper No. 24 (Doorenbos, 1977) defines several crop growth stages for various climates. However, these values remain unchanged since they were derived and represent an average growth length.

$$AE = K_c \times ET_0 \qquad (1)$$

$K_c$ can further be split into Single Crop Coefficient and Dual Crop Coefficient. Single combines differences in soil evaporation and crop transpiration between the actual and reference surface. Dual separates the soil evaporation and crop transpiration. The Basal Crop Coefficient describes crop transpiration, while the Soil Water Coefficient ($K_e$) describes soil water evaporation (Savva & Frenken, 2002).

Calculation of AE then changes into:

$$AE = (K_{cb} + K_e) \times ET_0 \qquad (2)$$

Understanding the distinctions between $ET_0$, PET, and AE is crucial for accurately estimating ET. Using $ET_0$ and Kc, we can connect the theoretical concepts and actual water-usage.

## FACTORS AFFECTING ET

Several factors play a key role in the presence and effectiveness of ET. Allen et al. divide them into three main groups: atmosphere/weather, crop/soil and environmental conditions (1998).

### Weather conditions

Weather or atmosphere conditions affecting ET are mainly sun radiation, air temperature, air humidity and wind speed. These conditions vary according to several influences, such as daytime, time of year or actual atmospheric conditions (cloud coverage).

As air temperature increases, it can hold smaller amounts of water vapour, promoting evaporation. This warm air also profoundly influences plants. The increase in air temperature leads to more intense metabolic processes in plants, which in turn causes higher rates of transpiration, especially during periods of high air temperature. This is when plants start to show signs of water stress and shut down their transpiration processes (Hatfield & Prueger, 2015).

The movement of air molecules, which translates into wind speed, causes water vapour to be lost around the plant leaf, leading to more transpiration. However, it's important to note that strong winds can also cause significant damage to both plants and soil with their force, a factor that should be carefully considered.

High relative humidity in the air lowers the effects of both evaporation and transpiration. Air particles saturated by humid air are less likely to accept additional humidity caused by evapotranspiration.

Solar radiation is the source of energy for evapotranspiration. A higher rate of solar radiation (having a sunny day) promotes plant physiological processes (Campillo *et al.*, 2012). Solar radiation is also responsible for albedo, the rate of incoming and emitted solar radiation on a surface. Plants and crops with low albedo (vegetation with dark shades) can absorb more solar radiation and, therefore, produce more water vapour.

### Crop and soil conditions

Crop/soil conditions can affect water retention caught in the plant. Specific crop type (ability to retain water during drought, depth of roots, leaf characteristics, etc.) and growth phase should be considered, especially when calculating ET over agricultural plants (Allen *et al.*, 1998).

Over time, vegetation has adapted to regular changes in climate. Physiological aspects of each vegetation type allow plants to survive in places with rough conditions. Specific vegetation can sustain long periods of drought (succulents), and other vegetation types (deciduous) shed their leaves due to seasonal changes, causing significantly lower to minimal ET. The potential green mass available for ET is quantified by the Leaf Area Index (LAI). LAI changes during the growth phase and with the leaf's immediate position (Kirkham, 2014a). The larger the values of LAI, the larger the leaf area and the more potential mass for ET. The very structure of the plant and its adaptive mechanisms for survival influence the presence and efficiency of evapotranspiration.

Soil is a critical factor in quality ET. Its moisture content is the deciding factor in the amount of water available for evaporation. The texture and general physiologic characteristics of the soil influence how much water can be held and the speed of drainage in the ground pores (Kirkham, 2014b). The presence of organic matter in the soil can help retain water during droughts. This highlights the urgency of water conservation, as the soil's moisture content directly impacts water availability for plants.

**External environment**

The last group of factors is connected to environmental conditions and the management of plants and crops and includes a wide variety of characteristics (irrigation, soil fertilization, soil composition, presence of diseases, etc.).

Managing external factors can (especially in agriculture) lead to significant optimization of ET processes (Denager *et al.*, 2020; Abiri *et al.*, 2023; Dimitrijević, 2023). One of the main influences is the irrigation schedule. Using accurate and actual data can influence irrigation schedules and save water. Healthy soil is also important for keeping crops in optimal shape (and therefore to be able to run ET processes). Agricultural practices (such as improving soil retention, mulching, and fertilization) help maintain good conditions.

## ESTIMATING EVAPOTRANSPIRATION

Estimating ET is essential for water resource management in many fields. However, quantifying ET is challenging due to the complex relationships between various environmental and biological factors. Over time, a number of methods for measurement have been developed. Each of these methods has distinct disadvantages, advantages and limitations, and the choice of method often depends on the specific conditions and measurement requirements (Ghiat *et al.*, 2021; Yang *et al.*, 2021). Direct measurement approaches, such as lysimeters or Flux Towers, offer the most accurate data but are limited to small, homogenous areas. This means that for richly diversified landscapes, urban environments or extensively large study areas, these methods are almost inapplicable (Amani & Shafizadeh-Moghadam, 2023).

These measuring types include techniques that directly measure the amount of water lost by evapotranspiration from the soil surface and plants. However, these methods can be expensive to install and maintain and may need to be more easily scalable for large-scale studies.

Therefore, indirect methods of determining evapotranspiration are more efficient for landscape studies (Raza *et al.*, 2023; Rasheed *et al.*, 2022; Raja *et al.*, 2024). These methods are usually less accurate than direct methods, but they can cover large areas and capture/account for spatial variability. They are also inherently cheaper to operate, as there is no need to acquire several identical measuring devices.

Indirect methods of measuring evapotranspiration use various models and calculations based on meteorological data and other factors.

Empirical models utilize meteorological data like temperature, humidity, wind speed, and radiation to estimate ET (Allen *et al.*, 2005; Valipour, 2014). The Penman-Monteith equation is a widely used example, offering a robust theoretical framework. However, empirical models often require calibration for specific locations and vegetation types, and their accuracy can be limited under non- ideal conditions (Ghiat *et al.*, 2021).

More complex approaches involve physical or combined models. These models use detailed information on plant physiology, soil, and atmospheric conditions to simulate the processes leading to ET. These models need extensive data inputs, limiting their widespread application (Subedi & Chávez, 2015; Xiao *et al.*, 2023; Duhan *et al.*, 2023)

**In-Situ Measuring (Direct Methods)**

*Lysimeters*

One of the most commonly used, and remarkably precise, tools for direct ET measurement is the lysimeter. This instrument, with its high level of accuracy, allows the measurement of water movement in the soil and the changes in the weight of the soil column, enabling an estimate of he amount of water that has evaporated and transpired.

Lysimeters, versatile in their applications, fall into several categories. The two most common types are mentioned below.

Weighing lysimeters are containers filled with water placed on a balance. The change in weight allows one to determine the water intake or output. These lysimeters are often used to measure ET or the water balance of plants (Akhavan *et al.*, 2019).

The device needs access to a block of vegetation, and its case, consisting of a culture vessel with plants, determines the weight of the soil block with plant cover over a period of time. If we know the amount of water supplied to the container by rainfall or irrigation, then the weight change is due to ET only.

Drainage lysimeters measure the movement of water at the plant's roots in the soil. They are mainly used in agriculture or air pollution research. Water that flows through the soil remains in separate containers to take samples for chemical analysis. The change in the amount of water in these containers is also used for measurements (Nagler *et al.*, 2005).

- Benefits and advantages:
    - **Accuracy**: Lysimeters provide very accurate measurements because they directly measure the amount of water lost through evapotranspiration
    - **Condition control**: They allow control over soil and plant conditions.
- Limitations and disadvantages:
    - **Cost**: They are expensive to install and maintain.
    - **Site-Specific Results**: Lysimeter results are often specific to the site and may not be easily transferable to other areas, underscoring the need for careful interpretation and application.

*Evaporimeters*

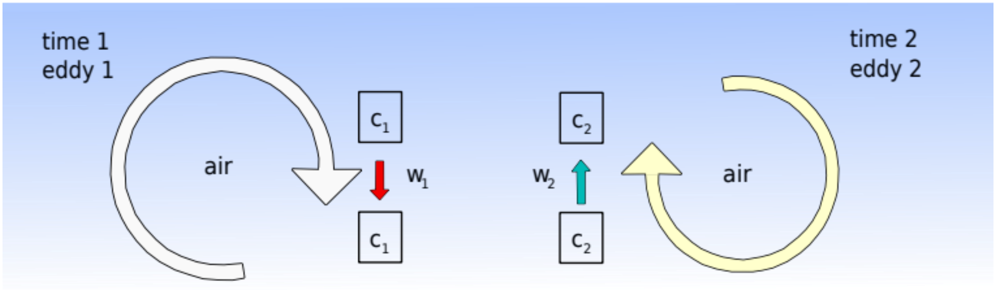
Devices are based on the principle of evaporation, either from the water surface or from a reference evaporating surface of given properties. Evaporation from a water surface is monitored in a container filled with water of a given surface area on the principle of measuring the change in water level (meteorological evaporimeters). The measurement of evaporation from a reference evaporating surface is based on the principle of evaporation from a porous material saturated with water of a given area (Pitche evaporimeter). They are relatively easy to use and provide a direct measurement but may need to be more accurate under different conditions.

*Eddy Covariance*

This method, known for its accuracy, measures variations in vertical wind speed and specific gravity of water vapor in the atmosphere. It is considered one of the most accurate methods, despite requiring complex and expensive equipment (Shivers *et al.*, 2019). In horizontally homogeneous conditions of the atmosphere, the exchange of mass and heat energy happens only in the vertical direction (Burba & Anderson, 2010). The basics of estimation of Eddy Covariance (EC) is the measurement of changes in the concentration of individual gases and vertical movements of thermal air masses.

Figure 2 shows a schematic of the operation of the individual eddies. Eddy 1, with its movement, propels the air particle at speed, while Eddy 2 propels the air particle at speed in the opposite direction.

**Fig. 2: Schematic principle of turbulent eddies in the atmosphere. Adapted from (Burba & Anderson, 2010).**




- Benefits and advantages:
  - **Direct measurement:** provides a direct measurement of the water exchange between the surface and the atmosphere
  - **High temporal resolution:** Allows for continuous real-time measurements.
- Limitations and disadvantages:
  - **Technical difficulty:** Requires complex and expensive equipment
  - **Sensitivity to conditions:** Results may be affected by local meteorological conditions

A current global trend is a compact sensor solution (*LI-710 from LI-COR*) that allows the actual evapotranspiration from a given cover to be measured directly; the evaporation total is processed by the instrument itself (LI-710 Specifications, n.d.). The values can be read out from the measuring instrument or data logger without any additional calculation, providing data for the user every 30 minutes.

Eddy Covariance applies to any relatively flat and uniform land cover at the scale of a field or an entire ecosystem (Järvi *et al.*, 2018).

*Flux Towers*

Flux Towers (FT) are micrometeorological towers that analyse the interaction between the surface and lower layers of the atmosphere, enabling the long-term collection of field data (e.g., carbon, water or energy fluxes). However, as Ukkola et al. stated in 2021, their data are not always suitable for modelling due to varying data quality or data gaps. FT is also used as a source for reference or dditional data for EC (Gamon, 2015; Wiesner *et al*., 2022).

FLUXNET Network (https://fluxnet.org/) is a global network of flux towers that aggregates smaller networks of EC towers into one dataset. Their products are available for download (https://fluxnet.org/data/fluxnet2015-dataset/); the last version of their data is FLUXNET2015 (Pastorello *et al*., 2020).

*Micrometeorological methods*

Methods based on monitoring physical environmental parameters (such as solar radiation, air and soil temperature and humidity, etc.) and subsequent calculation of meteorological indicators are suitable for the study of ET and other energy flows at the ecosystem level. They can be used to determine potential and actual evapotranspiration.

ET for large masses of land is difficult to determine and requires much testing and calibration of the models. Smaller, more locally-focused models were better for this task; however, because they are locally calibrated, they can give different results depending on the location (Alam *et al*., 2024). According to Hamed *et al*. (2022), the most used two types of classification are based on input data (temperature-based, radiation-based, mass transfer and combination methods) and their physicality (fully physically based combination models, semi-physically based combination models and black box models). To use an empirical model, one usually needs several types of meteorological data, and in the case of Remote Sensing, there are also several satellite images in various parts of the electromagnetic spectrum.

**Empirical and Combined models**

Empirical and combined methods use simple equations based on historical data and the area's specific conditions. The literature includes several groups of overlapping models (empirical, combined, radiation-based, and temperature-based).

- Benefits and advantages:
  - **Simplicity:** Easy to use and does not require complicated equipment
  - **Speed:** They allow quick estimates of evapotranspiration
- Limitations and disadvantages:
  - **Accuracy:** They may be less accurate because they rely on empirical relationships that may not always accurately reflect actual conditions
  - **Limited applicability**: They may need to be more suitable for specific or extreme conditions.

*Thornthwaite Method*

The Thornthwaite method was introduced in 1948 to determine PET (Thornthwaite, 1948). Based on empirical relationships between air temperature. This method is fairly easy to use since it requires only monthly mean air temperature. However, many factors (solar radiation, air humidity) are not considered at all, meaning it is often used in arid and semi-semi-arid areas and for drought indices applications (Aschonitis *et al*., 2021).

*Hargreaves and Samani Method*

Hargreaves and Samani Method (HS) is used to determine and is one of the methods recommended by FAO-56 (Allen *et al*., 1998; Hargreaves & Samani, 1982). HS is easy to use since only temperature and radiation data are needed.

$$ET_0 = K_{ET} \times R_A \times (T + 17.8) \times TD^{0.5} \qquad (3)$$

$K_{ET}$ is the empirical coefficient defined by Hargreaves (Hargreaves & Samani, 1985) with a defined value of 0.0023. sands for extra-terrestrial radiation, and TD is the difference between maximum and minimum air temperature. Similarly to the Thornthwaite method, other climate factors, such as humidity or wind speed, are not considered (Jung *et al*., 2016).

*Priestley-Taylor*

The Priestley-Taylor (PT) model was made in 1972 and used to simplify the Penman-Monteith equation in case information regarding aerodynamic resistance is unavailable (Priestley & Taylor, 1972). This is solved by using the parameter of constant value (α = 1.26), which was later redefined as a function of Vapour Pressure Deficit (VPD) by Steiner *et al.* in 1991. It refers to the Psychrometric Constant, which means latent heat of vaporisation, is the slope of the saturation vapour pressure-temperature curve, and stands for Net Radiation and Ground Heat Flux.

$$PET_{PT} = \frac{1}{\lambda} \times \delta \times \frac{R_n - G}{\delta + \gamma} \times \alpha \quad (4)$$

$$VPD = 1 + (\alpha - 1) \times VPD \quad (5)$$

Due to using constant (not calibrating according to actual atmospheric conditions), PT often underestimates the amount of ET, making it also difficult to use in a spatial context (Tolk & Howell, 2006). It also shows both diurnal and annual fluctuation when applied to larger regions (de Bruin & Keijman, 1979).

*Penman-Monteith*

Penman-Monteith (PM) stands on the borderline, sometimes referred to as an empirical method and other times as a combined method. PM does not need local calibration for usage. However, it counts on several types of meteorological data, which can be hard to come by in certain regions. FAO recommends PM as a standard equation for calculating $ET_0$ (Allen *et al.*, 1998). Since PM sees the landscape as one object, we can also categorise it under one-source models (Zhang *et al.*, 2016; Alam *et al.*, 2024). During the late 1940s, Penman (Penman, 1948) devised an equation to compute evaporation from open water based on the amount of sun radiation, air temperature, air humidity and wind speed. Penman's method was then extended by Monteith in 1965 into what is now known as the Penman-Monteith equation. Since 1990, the Penman-Monteith method has been recommended as a standard definition method (Allen *et al.*, 1998). The basic Penman-Monteith equation was stated as follows; for a detailed explanation of the input variables, see Table 1.

$$ET_0 = \frac{1}{\lambda} \times \frac{\Delta \times (R_n - G) \times \rho_a \times c_p \times \left(\frac{e_s - e_a}{r_a}\right)}{\Delta + \gamma \times \left(1 + \frac{r_s}{r_a}\right)} \quad (6)$$

*Hydrological models*

These models often consist of mathematical relationships that allow for evapotranspiration calculation, often implemented in advanced models (e.g., SWAT -Soil and Water Assessment Tool, MIKE-SHE). Based on hydrological and landscape data, they simulate the entire water cycle in a catchment, including the evapotranspiration process (Zhao *et al.*, 2013).

- Benefits and advantages:
  - **Flexibility:** applicable to various areas and meteorological conditions
  - **Low-cost:** Relatively cheap to use and do not require physical devices.
- Limitations and disadvantages:
  - **Accuracy:** Depends on input data quality and model calibration
  - **Complexity:** Require expert knowledge for optimal setting and result interpretation

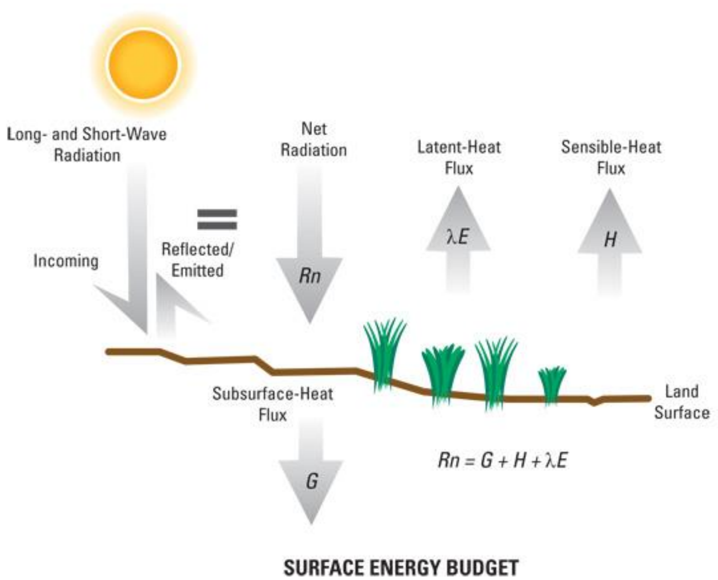
**Table 1: Explanation of PM variables**

| Symbol | Name | Unit |
|---|---|---|
| $R_n$ | Net Radiation | $W/m^2$ |
| $G$ | Soil Heat Flux | $W/m^2$ |
| $e_s$ | Saturated Vapour Air Pressure | kPa |
| $e_a$ | Actual Vapour Air Pressure | kPa |
| $\rho_a$ | Air Density | $kg/m^3$ |
| $c_p$ | Specific Heat of Air | J/kg/˚C |
| $\Delta$ | Slope Saturation Vapour Pres. to Temp. | kPa/˚C |
| $\gamma$ | Psychrometric Constant | kPa/˚C |
| $r_s$ | Surface Resistance | s/m |
| $r_a$ | Aerodynamic Resistance | s/m |

*Surface Energy Balance Methods*

Surface Energy Balance/Budget (SEB) refers to methods focusing on energy and gas exchange between surface and atmosphere (Rahman & Zhang, 2019). The energy is divided into four crucial parts (see Fig. 3)—soil/Ground Heat Flux (G), representing heat absorbed or conducted by soil. Latent Heat Flux (LE) refers to the energy needed to transform liquid water into vapour without a change in temperature. Sensible Heat Flux (H) refers to heat transfer in turbulent convection (without state change of the substance).

**Fig. 3: Schema of surface energy balance using heat fluxes (Survey, n.d.)**



These three fluxes are parts of the basic equation for calculating Net Solar Radiation. Net Solar Radiation (Rn) is a difference between incoming and outgoing solar radiation emitted by the surface. Studies focusing on daily or longer periods sometimes omit G (the soil quickly becomes saturated with heat, and the G value remains constant further on). However, this practice is not recommended (Sauer & Horton, 2005).

Although SEB methods do not calculate ET directly, we can derive ET from the fluxes. ET can be derived from LE using (specific heat of vaporisation), representing the energy needed to vaporise water. Allen (1998) states a constant of 2.45 MJ/kg.

$$R_n = G + H + LE \qquad (7)$$

**Non-direct (Remote Sensing) Methods**

Remote Sensing is based on surface image acquisition, thus obtaining information about objects and phenomena without direct contact. The data obtained is repeatable, non-destructive and covers large areas simultaneously (DeFries, 2013). Due to the spatial nature of remote sensing, it captures the variability of different surfaces within a single image at the same moment.

Using Remote Sensing in ET research has several important advantages. Unlike traditional or in-situ measurements, we can see large-scale areas much more easily since one satellite image of a heterogeneous area can cover hundreds of kilometres of ground. With long-running missions, we can create long-time series. An important aspect is that data recording is realised in a raster representation when one captured image is internally divided into image units - pixels.

Additionally, long-term satellite missions enable the creation of extended time series, offering a broader perspective on landscape changes. Data is typically recorded in raster format, where the image is divided into pixels. Each pixel represents a homogeneous area, and calculations are performed at this per-pixel level (Khatami *et al.*, 2017).

Depending on the ground resolution of the acquired pixel, we can cover a large area and get detailed information about it (unlike ground observations, which usually cover only a specific point). Remote Sensing also helps estimate vegetation characteristics, such as vegetation indices and crop height, which are useful for validation and tracking land cover dynamics. A single image of a heterogeneous landscape can reveal multiple homogeneous areas, enabling precise evapotranspiration calculations and capturing variability within the landscape.

Several satellite missions offer free or commercial data. With several satellite missions being open to the public, we can get satellite data covering the whole world (including the Czech Republic). An example of free-of-charge data can be the American Landsat system (8th and 9th generation satellites currently in operation), which provides data for the territory of the Czech Republic once every eight days using both Landsat 8 and Landsat 9 (*Landsat Science*, 2021) which can be accessed manually or semi-automatically via Earth Explorer (https://earthexplorer.usgs.gov). This data can be processed in open-source GIS tools like QGIS. However, for all the advantages, it is also important to highlight such techniques' limitations. Optical data (necessary for this type of analysis) can be degraded by atmospheric conditions, especially cloud coverage (Baghdady *et al.*, 2022). Sensor limitations and occasional hardware malfunctions are not impossible. Getting actual information from satellite data can be tricky since the data are published at different levels with different corrections (Aber *et al.*, 2010). A certain limit may also pose the spatial resolution of the thermal band necessary for the calculation, which is often much coarser than other bands (for Landsat 8 and Landsat 9 thermal band is 100 m/pixel, while, e.g. Near

InfraRed is 30 m/pixel). However, the suitability largely depends on the study's details. However, there are also commercial alternatives with a more detailed resolution.

*Satellite-Based SEB Models for Evapotranspiration Estimation*

Satellite-based SEB (Surface Energy Balance) models are widely used to estimate evapotranspiration by combining satellite imagery with meteorological data. These models help estimate the energy exchanges between the surface and the atmosphere. Three commonly used models are SEBAL, SEBS, and S-SEBI, each with different approaches and (dis)advantages.

SEBAL (Surface Energy Balance Algorithm for Land) is one of the first evapotranspiration models based on SEB principles. Its main advantages include estimating ET over large areas without requiring extensive ground data. However, it requires site-specific calibration, which can be challenging (Bastiaanssen *et al*., 1998).

SEBS (Surface Energy Balance System), developed by Su (2002), builds on SEBAL's principles but adds complexity by incorporating additional meteorological data, including surface temperature, albedo, and heat fluxes. SEBS provides more detailed calculations of heat fluxes (H, G, and LE) but requires more input data than SEBAL.

S-SEBI (Roerink et al., 2000) are simpler models that result in information about LE. They rely mostly on satellite-measured data but may incorporate additional meteorological data. Compared to SEBAL and SEBS, S-SEBI is easier to apply but generally less accurate (Wagle *et al*., 2017). While SEBAL is useful for large-scale applications, SEBS provides more accurate heat flux measurements, and S-SEBI is a trade-off between ease of use and precision.

In conclusion, SEBAL, SEBS, and S-SEBI offer valuable tools for estimating evapotranspiration (ET) from satellite data. Each model has its own strengths and weaknesses, making them suitable for different applications. SEBAL is well-suited for large-scale ET estimation with minimal ground data, while SEBS provides more accurate heat flux calculations but requires more input data. S-SEBI offers a balance between simplicity and accuracy, making it a good choice for simpler applications or when data limitations exist. By carefully considering the specific research objectives and available resources, researchers can select the most appropriate model for their ET estimation needs.

However, many other individual models are widely used around the world. The OpenET project (Melton *et al*., 2021b), with a spatial resolution of 30 meters, was created in the western United States to help agriculture with water management. The project uses six models: ALEXI/DisALEXI, eeMETRIC, geeSEBAL, PT-JPL, SIMS, and SSEBop. The input satellite data for the models are primarily Landsat TM/ETM+/OLI imagery supplemented by Sentinel-2 and MODIS products. The MODIS sensor replaced the newer VIIRS sensor in 2011 but remains fully operational until 2025. The accuracy of OpenET data, evaluated against ground-based measurements, demonstrated a remarkably high degree of accuracy in cropland regions (Volk *et al*., 2024), instilling confidence in the reliability of the data. In a study by Bajgain et al. (2020b), MODIS ET data products at varying spatial resolutions were compared with eddy covariance-measured ET (ETEC). All products demonstrated an underestimation of ET relative to ETEC; however, the most accurate product was MODET30, which has a resolution of 30 metres. Other approaches use a combination of multiple data sources. The study conducted by Guzinski *et al*. (2020) utilises imagery from Sentinel-2 and Sentinel-3 satellites. This combination presented challenges due to the disparate spatial resolutions, as Sentinel-3 provides land surface temperature (LST) imaging at a spatial resolution of 1 km. At the same time, Sentinel-2 offers a spatial resolution of 20 metres, necessitating resampling. The research compared three thermal-based remote sensing ET models: METRIC, ESVEP, and TSEB-PT. Among these, TSEB-PT yielded the most robust results across different land cover types, with the highest accuracy observed in agricultural areas. New approaches are also being developed to detect ET, such as the optical trapezoid model OPTRAM-ET (Mokhtari *et al.*, 2023). Compared to LST-VI, the model does not require thermal data and relies solely on optical bands from Sentinel-2 or Landsat 8. The model has been successful in estimating ET in agricultural and orchard areas. Its performance was similar to LST- VI, but it provides higher spatial and temporal resolution.

## FUTURE OF EVAPOTRANSPIRATION RESEARCH

Over several decades, technology and scientific applications have significantly advanced, not only in the collection but also in evapotranspiration. In 2015, Pereira *et al.* (2015) published an article regarding the past and future of (primarily). His article predicts wider usage of geographical information systems and related fields, such as Remote Sensing, which will turn towards scripting and automatization (mainly in Python or Java-like applications).

In recent years, the popularity of soft computing has drastically increased. The term refers to computers being able to work on cognitive tasks without human assistance. Soft computing is a general term for applying machine learning methods, deep learning, or artificial neural networks. Since the introduction of observing satellites, large quantities of data have been acquired in various formats. These extensive data volumes can be effectively analysed using highly accurate soft computing methods. The literature shows that artificial neural networks are much better and more accurate in deriving information about evapotranspiration, especially about, and often outperforming the traditional methods (Alam *et al.*, 2024; Elbeltagi *et al.*, 2022; Wanniarachchi & Sarukkalige, 2022). New ways of predicting and analyzing ET has been done using genetic algorithms. Kiraga *et al.* in 2023 used four machine learning models with reference lysimeter measurements, in this case the Penman-Monteith model was also outperformed. According to Pagano *et al.* (2023), these results can generally be further improved by information about soil water content and vegetation indices. The importance of water content was also declared by Babaeian *et al.* (2022). Their model was able to predict ET between satellite overpasses, thereby enabled them to improve the temporal resolution of the satellite mission.

Recently, the vertical structure of vegetation has also been reflected in the calculation of ET, or the cooling function of vegetation (Makarieva & Gorshkov, 2007; Sheil, 2018). This is due to the development of non-contact image technologies, especially LIDAR, supplemented by AI tools, which enable the automated determination of individual stand structures and the calculation of individual densitometric (DBH) parameters. This will subsequently make it possible to determine in great detail the shape, spatial configuration and volume of the green part of the trees (crown), which is responsible for transpiration processes (Zhang *et al.*, 2023).

A deeper understanding of interactions between surface and atmosphere is also needed due to he seemingly inevitable change of global climate and consequences of human activities. ET is often used as one of the main links between energy and water balance. Since it is both affected by water availability and air temperature (Kirschbaum, 2004), it can show us future projections for freshwater presence and availability under changing conditions. However, there is no linear dependency between rising air temperature or the amount of available water and ET (Hamouda *et al.*, 2021). According to Hamouda (2020), more complex approaches to assess the relationship between these two variables are known, although more needs to be tested.

## CONCLUSIONS

The article gives an overview of the principles of determining ET. Direct methods using lysimeters and flux towers offer the most precise data but are expensive and limited in covering large areas (especially in spatial analyses). Empirical or combined models, such as the Thornthwaite method, use available weather data but may require calibration and have limitations under specific conditions. Combined models (Penman-Monteith) can incorporate more detailed data on plants, soil, and atmosphere for a more comprehensive picture. However, they require extensive data inputs, which may only sometimes be available. Finally, remote sensing with satellites provides large-scale coverage but can be affected by factors like cloud cover and complex data processing.

In contrast, remote sensing offers a compelling solution. It provides large-scale coverage, overcoming the limitations of traditional field methods. While factors like cloud cover and complex data processing can affect its effectiveness, advancements are being made to address these challenges.

The future of ET research shows advancements in data fusion techniques that integrate information from multiple sources, including remote sensing data. Machine learning and artificial intelligence can also be used for data analysis and ET estimation methods. Moreover, a deeper understanding of complex natural processes and how climate change impacts ET rates will be crucial for future research. This knowledge, particularly when combined with the advantages of remote sensing, is essential for effective water resource management across vast areas.

## ACKNOWLEDGMENT

The paper was created within the project DH23P03OVV002 "Biocultural diversity-linking cultural and natural heritage in an urban historical environment". The project is funded with state support from the Ministry of Culture of the Czech Republic within the NAKI III programme.

## CONFLICT OF INTEREST

The authors declare that they have no competing interests.

## ABBREVIATIONS

| | |
|---|---|
| ALEXI/DisALEXI | Disaggregation of the Atmosphere-Land Exchange Inverse |
| eeMETRIC | Mapping Evapotranspiration at High Resolution with Internalized Calibration |
| geeSEBAL | Surface Energy Balance Algorithm for Land using Google Earth Engine |
| SIMS | A Simple Remote Sensing EvapoTranspiration Model |
| OPTRAM-ET | Optical Trapezoid Model for Evapotranspiration |
| VIIRS | Visible Infrared Imaging Radiometer Suite |
| ETEC | Evapotranspiration by Eddy Covariance |
| LST-VI | Land Surface Temperature by Vegetation Indices |
| PT-JPL | Priestley-Taylor Jet Propulsion Laboratory |
| SWAT | Soil and Water Assessment Tool |
| PT | Pristley-Taylor |
| SIMS | Satellite Irrigation Management Support |
| SSEBop | Operational Simplified Surface Energy Balance |
| ET | Evapotranspiration |
| PET | Potential Evapotranspiration |
| $ET_0$ | Reference Evapotranspiration |
| AE | Actual Evapotranspiration |
| LAI | Leaf Area Index |
| TD | Air Temperature Difference |
| FAO | Food and Agriculture Organization |
| PM | Penman-Monteith |
| HS | Hargreaves and Samani |
| SEB | Surface Energy Balance |
| G | Ground Heat Flux |
| LE | Latent Heat Flux |
| $R_n$ | Net Radiation |
| M | Molecular Heat Flux |
| SEBAL | Surface Energy Balance Algorithm for Land |
| SEBS | Surface Energy Balance System |
| SEBI | Surface Energy Balance Index |
| S-SEBI | Simplified Surface Energy Balance Index |
| MODIS | Moderate Resolution Imaging Spectroradiometer |
| TM | Thematic Mapper |
| ETM+ | Enhances Thematic Mapper |
| OLI | Operational Land Imager |
| METRIC | Mapping EvapoTranspiration at high Resolution with Internalized Calibration |
| LST | Land Surface Temperature |
| ESVEP | Soil and Vegetation Energy Partitioning |
| TSEB | Two-source Surface Energy Balance |
| EC | Eddy Covariance |
| LIDAR | Light Detection and Ranging |
| AI | Artificial Intelligence |
| DBH | individual densitometric parameters |
| FT | Flux Tower |

## REFERENCES

Aber, J. S., Marzolff, I., & Ries, J. B. (2010). Image processing and analysis. In *Small-Format Aerial Photography* (pp. 159–181). Elsevier. http://dx.doi.org/10.1016/b978-0-444-53260-2.10011-0

Abiri, R., Rizan, N., Balasundram, S. K., Shahbazi, A. B., & Abdul-Hamid, H. (2023). Application of digital technologies for ensuring agricultural productivity. *Heliyon*, *9*(12), e22601. https://doi.org/10.1016/j.heliyon.2023.e22601

Akhavan, S., Kanani, E., & Dehghanisanij, H. (2019). Assessment of different reference evapotranspiration models to estimate the actual evapotranspiration of corn (Zea mays L.) in a semiarid region (case study, Karaj, Iran). *Theoretical and Applied Climatology*, *137*. https://doi.org/10.1007/s00704-018-2634-y

Alam, M. M., Akter, M. Y., Islam, A. R. M. T., Mallick, J., Kabir, Z., Chu, R., Arabameri, A., Pal, S. C., Masud, A., Costache, R., & others. (2024). A review of recent advances and future prospects in calculation of reference evapotranspiration in Bangladesh using soft computing models. *Journal of Environmental Management*, *351*, 119714.

Allen, R. G., Pereira, S. L., Raes, D., & Smith, M. (1998). *Crop evapotranspiration - Guidelines for computing crop water requirements - FAO Irrigation and drainage paper 56*. FAO - Food and Agriculture Organization of the United Nations.

Allen, R. G., Walter, I. A., Elliot, R., & Jensen, M. E. (2005). *The ASCE standardized reference evapotranspiration equation*. American Society of Civil Engineers. http://dx.doi.org/10.1061/9780784408056

Allen, Richard. G., Smith, M., Perrier, A. and P., Luis S., & others. (1994). An update for the definition of reference evapotranspiration. *ICID Bulletin*, *43*(2), 1–34.

Al-Sudani, H. I. Z. (2019). Derivation mathematical equations for future calculation of potential evapotranspiration in Iraq, a review of application of Thornthwaite evapotranspiration. *Iraqi Journal of Science*, *60*(5), 1037–1048.

Amani, S., & Shafizadeh-Moghadam, H. (2023). A review of machine learning models and influential factors for estimating evapotranspiration using remote sensing and ground-based data. *Agricultural Water Management*, *284*, 108324. https://doi.org/10.1016/j.agwat.2023.108324

Anggraini, N., & Slamet, B. (2021). Thornthwaite Models for Estimating Potential evapotranspiration in Medan City. *IOP Conference Series: Earth and Environmental Science*, *912*, 012095.

Aram, F., Higueras García, E., Solgi, E., & Mansournia, S. (2019). Urban green space cooling effect in cities. *Heliyon*, *5*(4), e01339. https://doi.org/10.1016/j.heliyon.2019.e01339

Aschonitis, V., Touloumidis, D., Veldhuis, ten, & Coenders-Gerrits, M. (2021). Correcting Thornthwaite potential evapotranspiration using a global grid of local coefficients to support temperature-based estimations of reference evapotranspiration and aridity indices. *Earth System Science Data Discussions*, *2021*, 1–25.

Babaeian E., Paheding S., Siddique N., Devabhaktuni V. K., Tuller M. (2022), Short- and mid-term forecasts of actual evapotranspiration with deep learning, *Journal of Hydrology*, 612(A), https://doi.org/10.1016/j.jhydrol.2022.128078.

Baghdady, M., Mellon, S., Younts, R., & Aberg Cobo, F. (2022, September 30). Analysis of atmospheric conditions for optimizing optical communications. *Laser Communication and Propagation through the Atmosphere and Oceans XI*. http://dx.doi.org/10.1117/12.2633498

Bajgain, R., Xiao, X., Wagle, P., Kimball, J., Brust, C., Basara, J., Gowda, P., Starks, P., & Neel, J. (2020a). Comparing evapotranspiration products of different temporal and spatial scales in native and managed prairie pastures. *Remote Sensing*, *13*(1), 82. https://doi.org/10.3390/rs13010082

Bajgain, R., Xiao, X., Wagle, P., Kimball, J., Brust, C., Basara, J., Gowda, P., Starks, P., & Neel, J. (2020b). Comparing evapotranspiration products of different temporal and spatial scales in native and managed prairie pastures. *Remote Sensing*, *13*(1), 82. https://doi.org/10.3390/rs13010082

Bastiaanssen, W. G. M., Menenti, M., Feddes, R. A., & Holtslag, A. A. M. (1998). A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation. *Journal of Hydrology*, *212–213*, 198–212. https://doi.org/10.1016/s0022-1694(98)00253-4

Bates, R. L., & Jackson, Julia. A. (1980). *Glossary of Geology*. American Geological Institute, Falls Church, Va.

Burba, G., & Anderson, D. J. (2010). *A Brief Practical Guide to Eddy Covariance Flux Measurements: Principles and Workflow Examples for Scientific and Industrial Applications*. LI-COR Biosciences.

Campillo, C., Fortes, R., & Henar Prieto, M. del. (2012). Solar radiation effect on crop production. In *Solar Radiation*. InTech. http://dx.doi.org/10.5772/34796

de Bruin, H. A. R., & Keijman, J. Q. (1979). The Priestley-Taylor Evaporation Model Applied to a Large, Shallow Lake in the Netherlands. *Journal of Applied Meteorology (1962-1982)*, *18*(7), 898–903.

DeFries, R. (2013). Remote sensing and image processing. In *Encyclopedia of Biodiversity* (pp. 389–399). Elsevier. http://dx.doi.org/10.1016/b978-0-12-384719-5.00383-x

Denager, T., Looms, M. C., Sonnenborg, T. O., & Jensen, K. H. (2020). Comparison of evapotranspiration estimates using the water balance and the eddy covariance methods. *Vadose Zone Journal*, *19*(1). https://doi.org/10.1002/vzj2.20032

Dimitrijević, M. S. (2023). Technological progress in the function of productivity and sustainability of agriculture: The case of innovative countries and the Republic of Serbia. *Journal of Agriculture and Food Research*, *14*, 100856. https://doi.org/10.1016/j.jafr.2023.100856

Dinpashoh, Y., Jhajharia, D., Fakheri-Fard, A., Singh, V. P., & Kahya, E. (2011). Trends in reference crop evapotranspiration over Iran. *Journal of Hydrology*, *399*(3–4), 422–433.

Dong, J., Dirmeyer, P. A., Lei, F., Anderson, M. C., Holmes, T. R. H., Hain, C., & Crow, W. T. (2020). Soil evaporation stress determines soil moisture-evapotranspiration coupling strength in land surface modeling. *Geophysical Research Letters*, *47*(21). https://doi.org/10.1029/2020gl090391

Doorenbos, J. (1977). Crop water requirements. *FAO Irrigation and Drainage Paper*, *24*, 1–144.

Duhan, D., Singh, M. C., Singh, D., Satpute, S., Singh, S., & Prasad, V. (2023). Modeling reference evapotranspiration using machine learning and remote sensing techniques for semi-arid subtropical climate of Indian Punjab. *Journal of Water and Climate Change*, *14*(7), 2227–2243. https://doi.org/10.2166/wcc.2023.003

Elbeltagi, A., Kushwaha, N. L., Rajput, J., Vishwakarma, D. K., Kulimushi, L. C., Kumar, M., Zhang, J., Pande, C. B., Choudhari, P., Meshram, S. G., & others. (2022). Modelling daily reference evapotranspiration based on stacking hybridization of ANN with meta-heuristic algorithms under diverse agro-climatic conditions. *Stochastic Environmental Research and Risk Assessment*, *36*(10), 3311–3334.

Fisher, J. B., Melton, F., Middleton, E., Hain, C., Anderson, M., Allen, R., McCabe, M. F., Hook, S., Baldocchi, D., & Townsend, P. A. and others. (2017). The future of evapotranspiration: Global requirements for ecosystem functioning, carbon and climate feedbacks, agricultural management, and water resources. *Water Resources Research*, *53*(4), 2618–2626.

Gamon, J. A. (2015). Reviews and Syntheses: optical sampling of the flux tower footprint. *Biogeosciences*, *12*(14), 4509–4523.

Ghiat, I., Mackey, H. R., & Al-Ansari, T. (2021). A review of evapotranspiration measurement models, techniques and methods for open and closed agricultural field applications. *Water*, *13*(18), 2523. https://doi.org/10.3390/w13182523

Gonzalez T., F., Pavek, M. J., Holden, Z. J., & Garza, R. (2023). Evaluating potato evapotranspiration and crop coefficients in the Columbia Basin of Washington state. *Agricultural Water Management*, *286*, 108371. https://doi.org/10.1016/j.agwat.2023.108371

Gowda, P. H., Chavez, J. L., Colaizzi, P. D., Evett, S. R., Howell, T. A., & Tolk, J. A. (2007). ET mapping for agricultural water management: Present status and challenges. *Irrigation Science*, *26*(3), 223–237. https://doi.org/10.1007/s00271-007-0088-6

Guzinski, R., Nieto, H., Sandholt, I., & Karamitilios, G. (2020). Modelling high-resolution actual evapotranspiration through sentinel-2 and sentinel-3 data fusion. *Remote Sensing*, *12*(9), 1433. https://doi.org/10.3390/rs12091433

Hamed, M. M., Khan, N., Muhammad, M. K. I., & Shahid, S. (2022). Ranking of empirical evapotranspiration models in different climate zones of Pakistan. *Land*, *11*(12), 2168.

Hamouda, G. B., Tomozeiu, R., Pavan, V., Antolini, G., Snyder, R. L., & Ventura, F. (2021). Impacts of climate change and rising atmospheric CO2 on future projected reference evapotranspiration in Emilia-Romagna (Italy). *Theoretical and Applied Climatology*, *146*(1), 801–820.

Hamouda, G. B., Ventura, F., & others. (2020). Evaluation of some evapotran-spiration estimation models under CO2 increasing concentrations: A review. *Italian Journal of Agrometeorology*, *3*, 85–98.

Hargreaves, G. H., & Samani, Z. A. (1982). *Estimating potential evapotranspiration. J Irrig Drain Div 108: 225--230*.

Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Applied Engineering in Agriculture*, *1*(2), 96–99.

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and Climate Extremes*, *10*, 4–10. https://doi.org/10.1016/j.wace.2015.08.001

Howell, T. A. (2005). LYSIMETRY. In *Encyclopedia of Soils in the Environment* (pp. 379–386). Elsevier. http://dx.doi.org/10.1016/b0-12-348530-4/00391-x

Järvi, L., Rannik, Ü., Kokkonen, T. V., Kurppa, M., Karppinen, A., Kouznetsov, R. D., Rantala, P., Vesala, T., & Wood, C. R. (2018). Uncertainty of eddy covariance flux measurements over an urban area based on two towers. *Atmospheric Measurement Techniques*, *11*(10), 5421–5438. https://doi.org/10.5194/amt-11-5421-2018

Jensen, M. E., & Haise, H. K. (1965). Estimating Evapotranspiration from Solar Radiation. *Journal of the Irrigation and Drainage*, *89*, 15–41.

Jung, C.-G., Lee, D.-R., & Moon, J.-W. (2016). Comparison of the Penman-Monteith method and regional calibration of the Hargreaves equation for actual evapotranspiration using SWAT-simulated results in the Seolma-cheon basin, South Korea. *Hydrological Sciences Journal*, *61*(4), 793–800.

Khatami, R., Mountrakis, G., & Stehman, S. V. (2017). Mapping per-pixel predicted accuracy of classified remote sensing images. *Remote Sensing of Environment*, *191*, 156–167. https://doi.org/10.1016/j.rse.2017.01.025

Kiraga S., Peters, T. R., Molaei, B., Evett S. R. & Marek G. (2023) Reference Evapotranspiration Estimation Using Genetic Algorithm-Optimized Machine Learning Models and Standardized Penman–Monteith Equation in a Highly Advective Environment. *Water, 16*, https://doi.org/10.3390/w16010012

Kirkham, M. B. (2014a). Potential evapotranspiration. In *Principles of Soil and Plant Water Relations* (pp. 501–514). Elsevier. http://dx.doi.org/10.1016/b978-0-12-420022-7.00028-8

Kirkham, M. B. (2014b). Field Capacity, Wilting Point, Available Water, and the Non-Limiting Water Range. In *Principles of Soil and Plant Water Relations* (pp. 101–115). Academic Press.

Kirschbaum, M. (2004). Direct and indirect climate change effects on photosynthesis and transpiration. *Plant Biology*, *6*(03), 242–253.

Kozlowski, T. T., & Pallardy, S. G. (1997). Transpiration and plant water balance. In *Physiology of Woody Plants* (pp. 269–308). Elsevier. http://dx.doi.org/10.1016 /b978-012424162-6 /50029-6

L., J. (1965). The state and movement of water in living organisms. *19th Symposia of the Society for Experimental Biology. Cambridge University Press, London, 1965*, 205–234.

*Landsat Science*. (2021, November 30). Landsat Science | A Joint NASA/USGS Earth Observation Program. https://landsat.gsfc.nasa.gov/data/

*LI-710 specifications*. (n.d.). LI-COR Environmental. Retrieved August 21, 2024, from https://www.licor.com/env/products/LI-710/specs

Makarieva, A. M., & Gorshkov, V. G. (2007). Biotic pump of atmospheric moisture as driver of the hydrological cycle on land. *Hydrology and Earth System Sciences, 11*(2), 1013–1033. https://doi.org/10.5194/hess-11-1013-2007

Mardikis, M., Kalivas, D., & Kollias, V. (2005). Comparison of interpolation methods for the prediction of reference evapotranspiration—an application in Greece. *Water Resources Management*, *19*, 251–278.

Melton, F. S., Huntington, J., Grimm, R., Herring, J., Hall, M., Rollison, D., Erickson, T., Allen, R., Anderson, M., Fisher, J. B., Kilic, A., Senay, G. B., Volk, J., Hain, C., Johnson, L., Ruhoff, A., Blankenau, P., Bromley, M., Carrara, W., … Anderson, R. G. (2021a). OpenET: Filling a critical data gap in water management for the western United States. *JAWRA Journal of the American Water Resources Association*, *58*(6), 971–994. https://doi.org/10.1111/1752-1688.12956

Melton, F. S., Huntington, J., Grimm, R., Herring, J., Hall, M., Rollison, D., Erickson, T., Allen, R., Anderson, M., Fisher, J. B., Kilic, A., Senay, G. B., Volk, J., Hain, C., Johnson, L., Ruhoff, A., Blankenau, P., Bromley, M., Carrara, W., … Anderson, R. G. (2021b). OpenET: Filling a critical data gap in water management for the western united states. *JAWRA Journal of the American Water Resources Association*, *58*(6), 971–994. https://doi.org/10.1111/ 1752-1688.12956

Millennium Ecosystem Assessment. (2005). *Ecosystems and human well-being: Wetlands and water*.

Mokhtari, A., Sadeghi, M., Afrasiabian, Y., & Yu, K. (2023). OPTRAM-ET: A novel approach to remote sensing of actual evapotranspiration applied to Sentinel-2 and Landsat-8 observations. *Remote Sensing of Environment*, *286*, 113443. https://doi.org/10.1016/j.rse.2022.113443

Monteith, J. L. (1965). Evaporation and environment. *Symposia of the Society for Experimental Biology*, 205–234.

Nagler, P. L., Scott, R. L., Westenburg, C., Cleverly, J. R., Glenn, E. P., & Huete, A. R. (2005). Evapotranspiration on western US rivers estimated using the Enhanced Vegetation Index from MODIS and data from eddy covariance and Bowen ratio flux towers. *Remote Sensing of Environment*, *97*(3), 337–351.

Ochoa-Sánchez, A., Crespo, P., Carrillo-Rojas, G., Sucozhanay, A., & Célleri, R. (2019). Actual evapotranspiration in the high Andean grasslands: A comparison of measurement and estimation methods. *Frontiers in Earth Science*, *7*, 55.

Pagano, A., Amato, F., Ippolito M., De Caro D., Croce D., Motisi A., Provenzano G., Tinnirello, I. (2023), Machine learning models to predict daily actual evapotranspiration of citrus orchards under regulated deficit irrigation, *Ecological Informatics*, *76*, https://doi.org/10.1016/j.ecoinf.2023.102133.

Pastorello, G., Trotta, C., Canfora, E., & al., C. et. (2020). The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data. *Scientific Data*, *7*(1), 225. https://doi.org/10.1038/s41597-020-0534-3

Peacock, C., & Hess, T. (2004). Estimating evapotranspiration from a reed bed using the Bowen ratio energy balance method. *Hydrological Processes*, *18*(2), 247–260.

Penman, H. L. (1948). Natural evaporation from open water, bare soil and grass. *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, *193*(1032), 120–145.

Pereira, L. S., Allen, R. G., Smith, M., & Raes, D. (2015). Crop evapotranspiration estimation with FAO56: Past and future. *Agricultural Water Management*, *147*, 4–20.

Priestley, C. H. B., & Taylor, R. J. (1972). On the assessment of surface heat flux and evaporation. *Mon. Weather Rev.*, *106*, 81–92.

Rahman, M. M., & Zhang, W. (2019). Review on estimation methods of the Earth's surface energy balance components from ground and satellite measurements. *Journal of Earth System Science*, *128*(4). https://doi.org/10.1007/s12040-019-1098-5

Raja, P., Sona, F., Surendran, U., Srinivas, C. V., Kannan, K., Madhu, M., Mahesh, P., Annepu, S. K., Ahmed, M., Chandrasekar, K., Suguna, A. R., Kumar, V., & Jagadesh, M. (2024). Performance evaluation of different empirical models for reference evapotranspiration estimation over Udhagamandalm, The Nilgiris, India. *Scientific Reports*, *14*(1). https://doi.org/10.1038/s41598-024-60952-4

Rasheed, M. W., Tang, J., Sarwar, A., Shah, S., Saddique, N., Khan, M. U., Imran Khan, M., Nawaz, S., Shamshiri, R. R., Aziz, M., & Sultan, M. (2022). Soil moisture measuring techniques and factors affecting the moisture dynamics: A comprehensive review. *Sustainability*, *14*(18), 11538. https://doi.org/10.3390/su141811538

Raza, A., Hu, Y., Acharki, S., Buttar, N. A., Ray, R. L., Khaliq, A., Zubair, N., Zubair, M., Syed, N. R., & Elbeltagi, A. (2023). Evapotranspiration importance in water resources management through cutting-edge approaches of remote sensing and machine learning algorithms. In *Springer Hydrogeology* (pp. 1–20). Springer International Publishing. http://dx.doi.org/10.1007/978-3-031-29394-8_1

Roerink, G. J., Su, Z., & Menenti, M. (2000). S-SEBI: A simple remote sensing algorithm to estimate the surface energy balance. *Physics and Chemistry of the Earth, Part B: Hydrology, Oceans and Atmosphere*, *25*(2), 147–157. https://doi.org/10.1016/s1464-1909(99)00128-8

Sauer, T. J., & Horton, R. (2005). Soil Heat Flux. *Micrometeorology in Agricultural Systems* , *47*, 131–154. USDA-ARS / UNL Faculty.

Savva, A. P., & Frenken, K. (2002). *Crop water requirements and irrigation scheduling*. FAO Sub-Regional Office for East and Southern Africa Harare.

Sheil, D. (2018). Forests, atmospheric water and an uncertain future: The new biology of the global water cycle. *Forest Ecosystems*, *5*(1). https://doi.org/10.1186/s40663-018-0138-y

Shivers, S. W., Roberts, D. A., McFadden, J. P., & Tague, C. (2019). An analysis of atmospheric water vapor variations over a complex agricultural region using airborne imaging spectrometry. *PLOS ONE*, *14*(12), e0226014. https://doi.org/10.1371 /journal.pone.0226014

Stanhill, G. (2005). EVAPOTRANSPIRATION. In D. Hillel (Ed.), *Encyclopedia of Soils in the Environment* (pp. 502–506). Elsevier. https://www.sciencedirect.com/science/ article/pii/B0123485304003593

Steiner, J., Howell, T., & Schneider, A. (1991). Lysimetric evaluation of daily potential evapotranspiration models for grain sorghum. *Agronomy Journal*, *83*(1), 240–247.

Stoyanova, J. S., Georgiev, C. G., & Neytchev, P. N. (2023). Drought monitoring in terms of evapotranspiration based on satellite data from meteosat in areas of strong land–atmosphere coupling. *Land*, *12*(1), 240. https://doi.org/10.3390/land12010240

Su, Z. (2002). The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes. *Hydrology and Earth System Sciences*, *6*(1), 85–100.

Subedi, A., & Chávez, J. L. (2015). Crop evapotranspiration (ET) estimation models: A review and discussion of the applicability and limitations of ET methods. *Journal of Agricultural Science*, *7*(6). https://doi.org/10.5539/jas.v7n6p50

Sun, G., Hallema, D., & Asbjornsen, H. (2017). Ecohydrological processes and ecosystem services in the Anthropocene: A review. *Ecological Processes*, *6*(1). https://doi.org/ 10.1186/s13717-017-0104-6

Survey, U. G. (n.d.). *Evapotranspiration Data - Nevada*. https://nevada.usgs.gov/et/ measured.html

Thornthwaite, C. W. (1948). An approach toward a rational classification of climate. *Geographical Review*, *38*(1), 55–94.

Tolk, J. A. and E., Steven R., & Howell, T. A. (2006). Advection influences on evapotranspiration of alfalfa in a semiarid climate. *Agronomy Journal*, *98*(6), 1646–1654.

Ukkola, A. M., Abramowitz, G., & Kauwe, D. (2021). A flux tower dataset tailored for land model evaluation. *Earth System Science Data Discussions*, *2021*, 1–20.

Valipour, M. (2014). Temperature analysis of reference evapotranspiration models. *Meteorological Applications*, *22*(3), 385–394. https://doi.org/10.1002/met.1465

Volk, J. M., Huntington, J. L., Melton, F. S., Allen, R., Anderson, M., Fisher, J. B., Kilic, A., Ruhoff, A., Senay, G. B., Minor, B., Morton, C., Ott, T., Johnson, L., Comini de Andrade, B., Carrara, W., Doherty, C. T., Dunkerly, C., Friedrichs, M., Guzman, A., … Yang, Y. (2024).

Assessing the accuracy of OpenET satellite-based evapotranspiration data to support water resource and land management applications. *Nature Water*, *2*(2), 193–205. https://doi.org/10.1038/s44221-023-00181-7

Wagle, P., Bhattarai, N., Gowda, P. H., & Kakani, V. G. (2017). Performance of five surface energy balance models for estimating daily evapotranspiration in high biomass sorghum. *ISPRS Journal of Photogrammetry and Remote Sensing*, *128*, 192–203. https://doi.org/10.1016/j.isprsjprs.2017.03.022

Wanniarachchi, S., & Sarukkalige, R. (2022). A review on evapotranspiration estimation in agricultural water management: Past, present, and future. *Hydrology*, *9*(7), 123.

Wiesner, S., Desai, A. R., Duff, A. J., Metzger, S., & Stoy, P. C. (2022). Quantifying the natural climate solution potential of agricultural systems by combining eddy covariance and remote sensing. *Journal of Geophysical Research: Biogeosciences*, *127*(9), e2022JG006895.

Xiang, K., Li, Y., Horton, R., & Feng, H. (2020). Similarity and difference of potential evapotranspiration and reference crop evapotranspiration – a review. *Agricultural Water Management*, *232*, 106043. https://doi.org/https://doi.org/10.1016/j.agwat.2020.106043

Xiao, C., Cai, J., Zhang, B., Chang, H., & Wei, Z. (2023). Evaluation and verification of two evapotranspiration models based on precision screening and partitioning of field temperature data. *Agricultural Water Management*, *278*, 108166. https://doi.org/10.1016/j.agwat.2023.108166

Xiao, J., Sun, F., Wang, T., & Wang, H. (2024). Estimation and validation of high-resolution evapotranspiration products for an arid river basin using multi-source remote sensing data. *Agricultural Water Management*, *298*, 108864. https://doi.org/10.1016/j.agwat.2024.108864

Yang, Y., Chen, R., Han, C., & Liu, Z. (2021). Evaluation of 18 models for calculating potential evapotranspiration in different climatic zones of China. *Agricultural Water Management*, *244*, 106545. https://doi.org/10.1016/j.agwat.2020.106545

Yates, D., & Strzepek, K. (1994). *Potential evapotranspiration methods and their impact on the assessment of river basin runoff under climate change*.

Zardo, L., Geneletti, D., Pérez-Soba, M., & Van Eupen, M. (2017). Estimating the cooling capacity of green infrastructures to support urban planning. *Ecosystem Services*, *26*, 225–235. https://doi.org/10.1016/j.ecoser.2017.06.016

Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *Wiley Interdisciplinary Reviews: Water*, *3*(6), 834–853.

Zhang, Z., Wang, T., Skidmore, A. K., Cao, F., She, G., & Cao, L. (2023). An improved area-based approach for estimating plot-level tree DBH from airborne LiDAR data. *Forest Ecosystems*, *10*, 100089. https://doi.org/10.1016/j.fecs.2023.100089

Zhao, L., Xia, J., Xu, C., Wang, Z., Sobkowiak, L., & Long, C. (2013). Evapotranspiration estimation methods in hydrological models. *Journal of Geographical Sciences*, *23*(2), 359–369. https://doi.org/10.1007/s11442-013-1015-9 (2012). In *Plant Responses and Control of Water Balance*. Elsevier.