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Technical Note: Smartphone-based evapotranspiration monitoring

Adriaan J. Teuling[1], Jasper F. D. Lammers[1]

[1]Hydrology and Environmental Hydraulics Groups, Wageningen University & Research, Wageningen, 6700AA, Netherlands

Correspondence to: Adriaan J. Teuling (ryan.teuling@wur.nl)

Abstract. Evapotranspiration plays a key role in the terrestrial water cycle, climate extremes and vegetation functioning. However, the understanding of spatio-temporal variability of evapotranspiration is limited by a lack of measurement techniques that are low-cost, and that can be applied anywhere at any time. Here we show that evapotranspiration can be estimated accurately using only observations made by smartphone sensors. Individual variables known to effect evapotranspiration generally showed a high correlation with routine observations during a multi-day field test. In combination with a simple ML-algorithm trained on observed evapotranspiration, the smartphone-observations had a mean RMSE of 0.10 and 0.05 mm/h when compared to lysimeter and eddy covariance observations, respectively. This is comparable to an error of 0.08 mm/h when estimating the eddy covariance ET from the lysimeter or vice versa. The results suggests that smartphone-based ET monitoring could provide a realistic and low-cost alternative for real-time ET estimation in the field.

1 Introduction

In most climates, more rainfall returns to the atmosphere via evapotranspiration than ends up in rivers. Evapotranspiration (commonly referred to as ET) also modulates near-surface climate by limiting the amount of direct warming by sensible heat fluxes. Under conditions of low soil moisture, reduced ET reflects ecosystem water stress, reduced carbon uptake, and a loss of agricultural production, as well as enhanced atmospheric warming through a shift in the land surface energy balance reflected in enhanced land surface temperatures. This makes ET a key indicator of environmental conditions and global change (Seneviratne et al., 2010; Denissen et al., 2022). In spite of its importance, few, if any, government agencies are tasked with the routine monitoring of ET. In addition, important gaps exist in our current ability to monitor ET, in particular limiting our understanding of how ET interacts with droughts and heatwaves (Teuling et al., 2013; Miralles et al., 2019; Lansu et al., 2020). Enhanced ET observation is key to filling those gaps.

Traditionally, ET has been measured through the mass-balance principle applied to catchments or lysimeters. While this approach is accurate, it provides limited spatial and/or temporal detail. Flux towers equipped with eddy covariance sensors also measure ET through turbulent moisture transport, but such sites are expensive to maintain, current tower locations are typically chosen for their relevance to the carbon balance (e.g. bias towards wetter sites with high carbon uptake) rather than to soil moisture-temperature coupling, and the footprint varies with wind conditions. ET can alternatively be estimated from Earth observation, typically using the thermal infrared window. While such approaches give valuable insight into the spatial distribution of ET, they rely on available satellite overpasses and cloud-free conditions. This calls for development of new observation methods to close the observational blind spot – methods that are low-cost, flexible, and operating in real-time at high spatial and temporal resolution.

Over the past decade, application of mobile phone technology to measure the terrestrial part of the hydrological cycle and associated meteorological variables has been gaining traction. It has been shown that precipitation, for instance, can be estimated from microwave links used in commercial cellular communication networks (Messer et al., 2006; Overeem et al., 2013). Several free and commercial apps exist that can be used to monitor river discharge often based on water level and/or surface velocity estimates (Kampf et al., 2018; Fehri et al., 2020, Damtie et al., 2023). Air temperature can be estimated from sensors that monitor phone battery temperatures (Overeem et al., 2013), incoming radiation can be estimated from a calibrated phone's light sensor (Al-Taani and Arabasi, 2018, Hukselfux, 2023), while external sensors have been developed for wind speed, temperature, pressure and humidity normally provided by weather stations. However all these estimates based on mobile phone technology would at best complement routine estimates of temperature, precipitation, or discharge made by dedicated government agencies. Measuring ET directly by smartphone has remained elusive.

Ongoing advances in sensor developments now provide new opportunities. In particular, thermal infrared imagers have become more compact and affordable, allowing them to be integrated in a smartphone. In combination with other build-in or external handheld sensors for relevant meteorological variables, this allows for direct inference of evapotranspiration through the land surface energy balance. This procedure is conceptually similar to evapotranspiration estimation from Earth observation, but with the added benefits that it can be done in real-time, based on local meteorological conditions, and independent of cloud cover and satellite overpasses. Figure 1a illustrates how smartphone-based ET monitoring might look in practice.

While smartphones can potentially monitor all variables relevant for ET, the question is how these estimates can work in concert under field conditions to produce accurate ET. Therefore, the primary goal of this feasibility study is to investigate how well smartphone-based estimates of surface fluxes validate against routine measurements made by lysimeters and eddy covariance. To this end, two main research questions are addressed, namely: 1) Do handheld sensors provide robust estimates of standard meteorological variables? and 2) Can a machine-learning model trained with smartphone observations provide accurate ET estimates? These questions are addressed using observations made during field testing at a measurement site equipped with standard meteorological instrumentation, a large weighing lysimeter, and an eddy covariance tower to allow for validation of the individual meteorological variables as well as flux estimates.

2 Methods and Data

A smartphone (model CAT S62 Pro) was used to record surface temperature (Ts) using its build-in FLIR Lepton 3.5 thermal sensor. Global radiation was estimated using the S62's build-in light sensor, where the sensor was covered with 2 layers of standard paper in order to avoid saturation. Because a phone's lens typically does not capture light from all angles equally, measurements were taken with the phone held straight-up perpendicular to the sun, and the readings were later corrected for

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the solar angle using the phone's pitch (ϕ, the angle between a plane parallel to the device's screen and a plane parallel to the ground). Both luminance (I) from the light sensor and pitch were recorded using the Sensors app. A Weatherflow WEATHERmeter, connected to the S62 via Bluetooth, was used to simultaneously record air temperature (Ta), pressure, relative humidity (RH), and wind speed (ws). To prevent bias, the WEATHERmeter was kept in a shaded and ventilated place in between measurements. The measurement principle is illustrated in Figure 1a.

a **b**

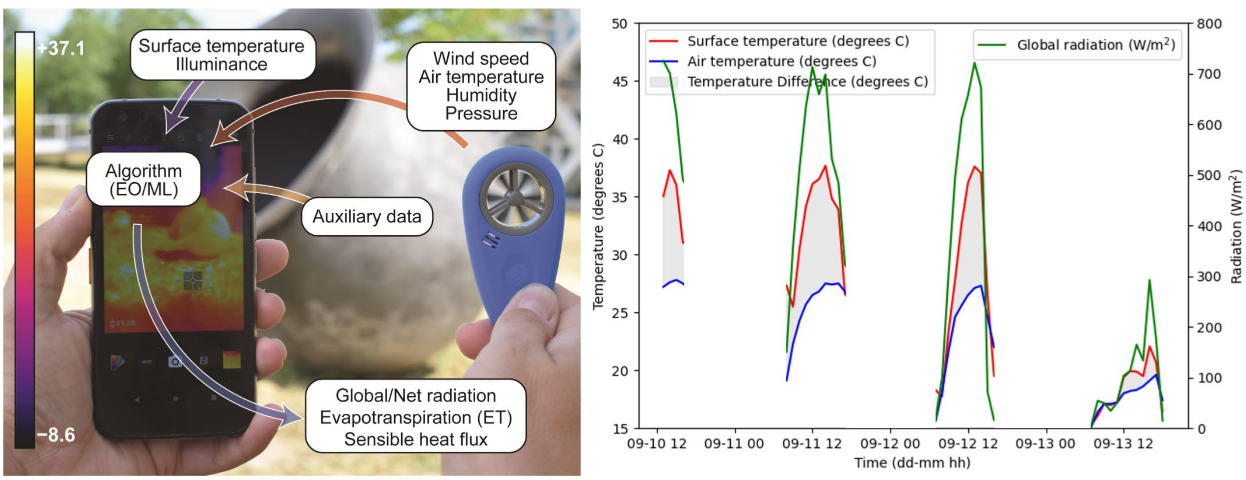

Figure 1: Principle of smartphone-based monitoring and field campaign overview. a) Due to the cooling effect of evapotranspiration, surface temperature ultimately reflects soil moisture through its impact on partitioning of incoming solar radiation into evapotranspiration and sensible heat. Both can be measured by phone's internal sensors, while an external sensor provides routine meteorological variables related to evapotranspiration. Colour bar indicates surface temperature (°C) as seen on screen. Picture taken on 5/8/22 by Janneke Remmers on Wageningen campus amid the 2022 summer drought (ambient air temperature 21°C). b) Smartphone temperature observations and Buël global radiation during the field campaign.

The field data were collected during daytime under rainless conditions from 10–13 September 2023 at the Büel meteorological station (Gähwil, Sankt Gallen, Switzerland), which is located within the pre-alpine Rietholzbach catchment. Data from this site has been used for numerous hydro(meteoro)logical studies (Teuling et al., 2010; Seneviratne et al., 2012; Hirschi et al., 2017; Michel & Seneviratne, 2022). Hourly values for standard meteorological variables, eddy covariance fluxes of sensible and latent heat, and lysimeter evapotranspiration were used. The smartphone and Büel observations are available from Teuling and Lammers (2023).An overview of the conditions during the data collection is given in Figure 1b, revealing a wide range of temperature and radiation conditions. During the field campaign, estimating one direct ET observation (lysimeter or eddy covariance) by the other resulted in an RMSE of 0.084 mm/h, which can be seen as a practical upper limit for errors associated with ET estimation in these conditions since it reflects the inherent uncertainty between two state-of-the-art methods. The sum of latent and sensible heat fluxes over the field campaign explained 98.7% of the net radiation, so a lack energy balance closure likely does not explain this uncertainty. From both theoretical considerations and observational evidence it is known that ET

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depends on a range of environmental variables. For our initial testing, and given the limited amount of data available for this study, we use the following multivariate regression as a simple form of machine learning to estimate the evapotranspiration:

$$\mathrm{ET_{phone}} = \alpha_I \times I \times \cos\phi + \alpha_{\mathrm{RH}} \times \mathrm{RH} + \alpha_{Ta} \times T_a + \alpha_{Ts} \times T_s + \alpha_{ws} \times w_s + c$$

This ML model calculates the individual contribution of each variable to the total reference ET. E.g., when $\alpha_I > 0$, the illuminance will add to the ET budget. If the coefficient is negative, the component (coefficient multiplied with variable) will be subtracted from the ET budget. Ultimately, the coefficients are calibrated such that the calculated ET resembles reference ET best. From the collected data, two thirds were randomly selected to calibrate the regression models for $\mathrm{ET_{phone}}$, while the remainder were used to validate the obtained model. For $\mathrm{ET_{phone}}$, this procedure was repeated 2000 times, and validation error statistics were calculated as the mean over the resulting sample.

3. Results

Instantaneous observations from individual variables by smartphone sensors generally showed a good correlation with hourly values recorded at Buël. Air temperature (R^2 = 0.88), relative humidity (R^2 = 0.80) and air pressure (R^2 =0.98) showed the highest correlations. Wind speed showed a satisfactory correlation (R^2 = 0.57), likely because of its higher temporal variability in combination with a discrepancy between the instantaneous smartphone-based observations and the hourly average values at Buël. Incoming shortwave radiation could not be measured directly, but instead a linear model for its estimation was calibrated on the subset of the pitch-corrected luminance values. Validation on the remaining part of the data revealed a high correlation (validation R^2 = 0.97, see Figure 2a). Besides information on meteorological conditions and energy driving the land-atmosphere exchange, it is clear that the measurements also reflect key land-atmosphere exchange processes. This is illustrated by the high correlation between the smartphone surface-air temperature difference and the observed sensible heat flux (validation R^2 = 0.90, see Figure 2b).

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a **b**

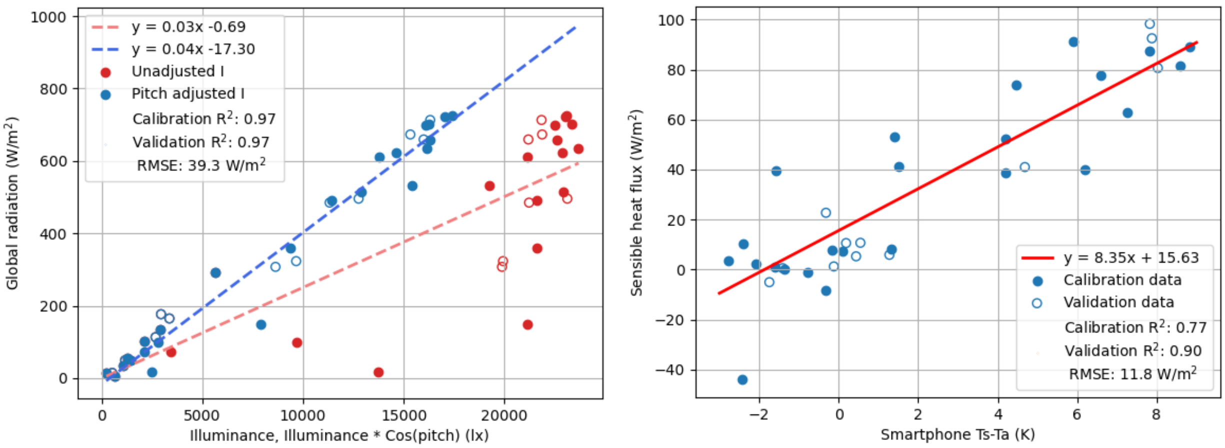

Figure 2: Smartphone monitoring of radiation and heat fluxes. a) Impact of pitch-adjustment on estimation of global radiation from smartphone-measured illuminance. b) Estimation of sensible heat flux from smartphone-measured $T_s - T_a$.

In a next step, we estimate the evapotranspiration as observed by lysimeter and eddy covariance by training Eq. 1 solely with smartphone observations. Validation of this model reveals a good performance, with relatively small mean RMSE values of 0.102 mm/h (lysimeter) and 0.050 mm/h (eddy covariance) across the 2000-member ensembles. Figure 3a illustrates the performance for ensemble members that are representative for the mean performance. These values present the expected error of the proposed smartphone method when trained on a small site-specific dataset. Interestingly, the errors are considerably smaller (eddy covariance) and only slightly larger (lysimeter) in comparison to the uncertainty arising from a direct comparison between the two state-of-the-art methods (Figure 3b). This suggests that even with limited site-specific training, the method might perform as well as other standard methods.

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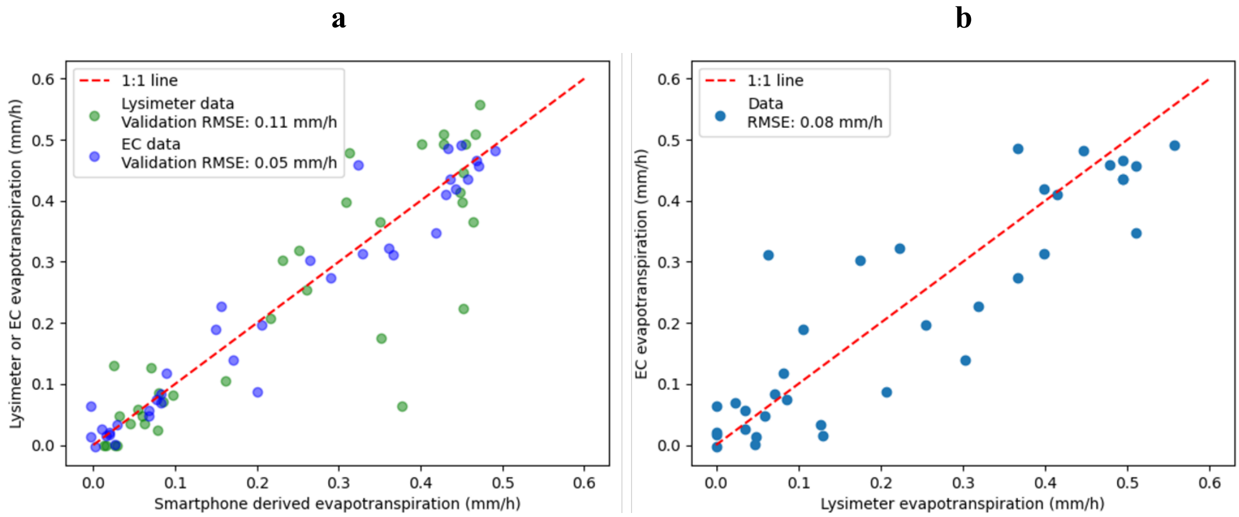

Figure 3: Illustration of ET prediction performance. a) Illustration of ET_{phone} vs ET observed by lysimeter and eddy covariance. The 2 models used for ET_{phone} were each selected out of a 2000-member ensemble because of their RMSE values being close to the mean across all sets. Shown RMSE values are for validation points only, whereas the graph shows all data. b) Relation between ET as observed by lysimeter and eddy covariance as reference.

In the ML model, it was found that most observations contributed information to ET_{phone} (Figure 4). Surface temperature, air temperature, and relative humidity were found to contribute most information, while wind speed was found to play a neglectable role (it should be noted that wind was generally light during the field campaign). In spite of the site being well-known for having an energy-limited evapotranspiration regime (Teuling et al., 2013, Michel & Seneviratne, 2022), and global or net radiation generally being a sufficient sole predictor for daily ET under these condition (Maes et al., 2019), the luminance term (as a proxy for global radiation) on average contributed less to the ET budget than temperature and humidity. This can be explained by the strong cross-correlations between states at or near the land surface and radiation, in particular at hourly timescales, combined with the relatively short length of the training data. It should be noted that the magnitude of the offset term is directly related to the units used for the variables in combination with the linearity of their relation to ET. In addition, the relative contribution of the different terms, in particular the temperature and RH terms, showed considerable spread. Nonetheless, this analysis shows that hourly ET estimation benefits from having observations of all relevant variables.

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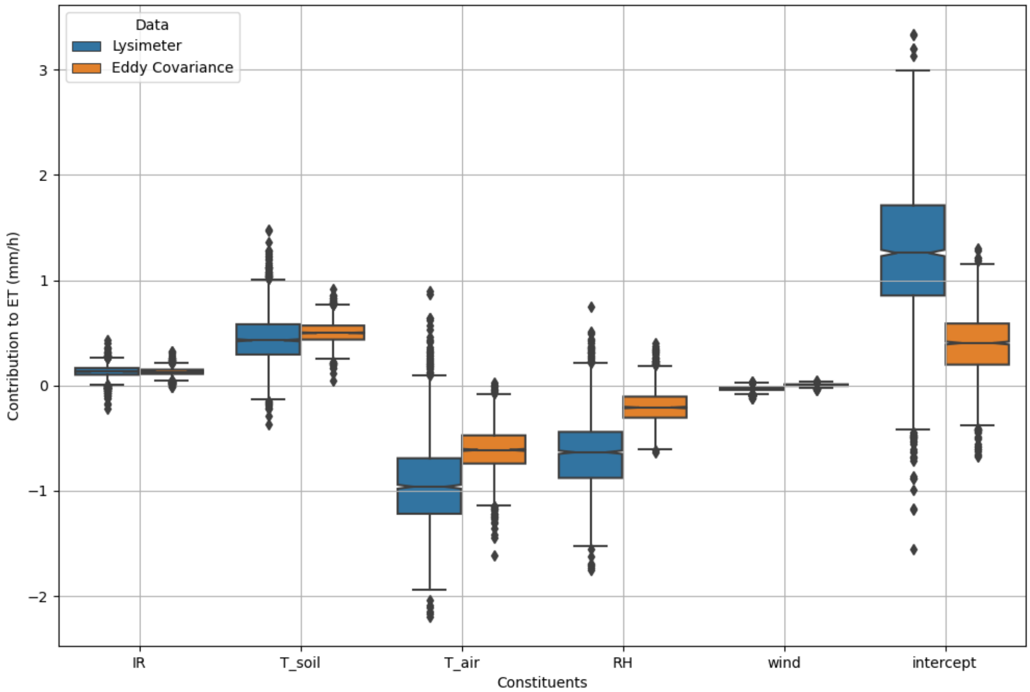

140 **Figure 4: Distribution of the contributions to the ET budget in the ML model. Each distribution contains 2000 values (see Methods).**

4. Discussion and Outlook

In this research, we presented the first results of a feasibility study aimed at monitoring evapotranspiration solely using smartphone-based sensors. Based on observations made during a short field campaign at a well-instrumented site in the Swiss pre-alps, we conclude that most meteorological variables relevant to ET estimation are monitored with good to sufficient accuracy by smartphone sensors. When a simple machine learning algorithm is trained on a subset of the observations, validation on independent lysimeter and eddy covariance observations shows mean RMSE values in the range of 0.05–0.11 mm/h. This is comparable to the difference between these two state-of-the-art techniques during the field campaign (RMSE 0.08 mm/h), and similar to errors found in comparison between large-scale estimates and eddy covariance (RMSE 0.04–0.14 with median 0.07 mm/h, see Bayat et al., 2024). Analysis of the machine learning algorithm outputs showed that for this short feasibility study, observations of radiation, temperature (both surface and air) and humidity all provided information, but wind less so. These results suggest that smartphone-based ET monitoring can be a useful addition to our current methods for ET estimation.

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The technology used in this study can be considered low cost at a price tag of around 750 USD (650 for phone and 90 for WEATHERmeter). Most common smartphones can be equipped with an external thermal camera for around 230 USD. It should be noted that the sensors in these phones, in particular the light sensor and its lens, have not been optimized for the current application. Further future improvements should thus be possible. This is also true for the algorithm. The flux data used here reflects humid conditions over grassland as evidenced by a Bowen ratio of 0.22 based on average fluxes during the field campaign. In the future, the algorithm should be trained with data from a range of climatological, geographical, and land cover conditions. The current study was designed as a feasibility study, where ET was estimated in hindsight. Ideally, in future applications a dedicated app would receive input from the various sensors in real-time, and directly infer ET from those using a further optimized algorithm. Such algorithm could for instance also use additional information on albedo (Leeuw and Boss, 2018), time, location, and land cover that was not used in this study.

The prospect to measure evapotranspiration using an affordable, handheld device marks a watershed moment in hydrology. For the first time, hydrologists might be able to measure evapotranspiration anywhere and anytime. We call upon the community to embrace this opportunity, by developing and calibrating algorithms, possibly aided by the latest generation of precision lysimeters and online data, that will translate the observations into a real-time ET imagery. Such a new data sources would complement current ET monitoring by filling the existing blind-spot, thereby not only helping science but moreover directly supporting operational water management, spatial planning, and irrigation scheduling. With smartphone-based ET monitoring linked to crowdsourcing-based data acquisition, it will be possible to monitor future droughts and their impacts quickly, and in unprecedented detail.

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Code and data availability

Smartphone observations and matching observations at Büel are available at https://www.hydroshare.org/resource/bfdb0c003e2248cc90bc75845d008887/. The Python script used for analysis and creating the figures is available at https://github.com/JasperLammers99/Handheld_Evapotranspiration.

Author contribution

AJT developed the initial idea and designed the experiments. JFDL carried out the experiments. JFDL developed the model code and performed the analysis. AJT prepared the manuscript with contributions from JFDL.

Competing interests

At least one of the (co-)authors is a member of the editorial board of Hydrology and Earth System Sciences.

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