Dear Prof. Yakir,

please find enclosed our revised manuscript *'Predicting evapotranspiration from drone-based thermography – a method comparison in a tropical oil palm plantation'*. We thank you and the reviewers for the provided comments and suggestions, which we all considered in our revised manuscript. They are addressed in detail in the enclosed point-by-point replies. We apologize for the delays in revising the manuscript, which occurred in the wake of the lead author's doctoral thesis submission and defense and subsequent move to a new job and university. We included the suggestions and revised the manuscript accordingly. We hope that the improvements are convincing to you and the reviewers so that the manuscript can move on to publication in Biogeosciences.

Sincerely,

Florian Ellsäßer on behalf of all co-authors

1 Response to reviewer I

Dear Reviewer,

Thank you for taking the time to revise our manuscript. We welcome your comments and think they have helped to improve our manuscript considerably. Please find our point-by point response (in blue color) below.

Sincerely,
Florian Ellsäßer

Peer review for the manuscript: Predicting evapotranspiration from drone-based thermography – a method comparison in a tropical oil palm plantation by Ellsasser et al The manuscript under consideration reports a 9-days study of surface temperature measurements over an oil palm plantation in Indonesia using a thermal camera mounted on a drone. The authors used the temperature data to calculate the latent heat flux using three different models, with/out radiation inputs, and showed good agreement between one of the models and the latent heat estimated from an eddy-covariance (EC) calculation based on an on-site flux tower. The drone-based temperature calculation is more flexible than the EC, also providing spatial information at high resolution. This is a very nice paper reporting an elegant study. The text and figures are carefully prepared and nicely presented.

I have only a few questions and suggestions:

1. Considering the rather narrow variation in air temperature over the tropical plantation, would you think that the fact that the study was performed at this site is a challenge? Or rather an easier case? I think that this point is touched upon, but further discussion would be appreciated.

We agree with the reviewer that there was rather narrow variation during the time of study (canopy air temperature ranged from 22.5 to 32.3 °C), as is typical for the region. Generally, the study site was rather challenging. We added a short section taking up these points to the discussion (L605-L611):

Generally, the equatorial study site was rather challenging due to high temperatures and humidity and frequent occurrence of haze, as well as for logistical reasons. Additionally, many previous drone-based studies were conducted on grasslands (e.g. Brenner et al. (2017, 2018)) or on low-growing crops such as wheat fields (Hoffmann et al., 2016), but not on crops with a rather complex canopy structure such as oil palm. On the other hand, our study site showed large temperature differences between soil and canopy, which simplified the distinguishing of each fraction.

2. Considering the aggravating situation of deforestation in the studied region,

and the implications on surface warming (L110-113), it would be highly interesting to make a comparison study between the palm plantation and the natural rainforest. I assume that the higher spatial heterogeneity in the latter would offer a better test case for the spatial distribution of ET (Fig. 5). Can the authors include such information?

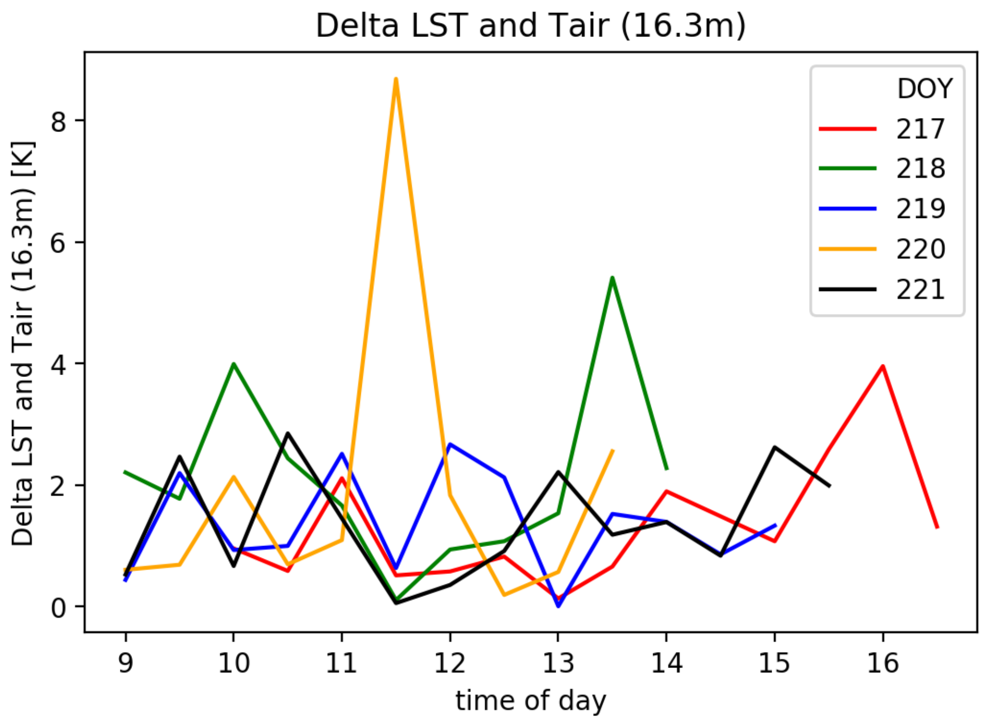
We thank the reviewer for this very interesting point. Indeed the comparison of land surface temperatures and modelled evapotranspiration of natural rainforest and an oil palm plantations would provide valuable spatial insight into the current transformation of transpiration patterns caused by local- and regional-scale land-use changes, as e.g. described in Röll et al., 2019 and Sabajo et al., 2017. However, the present study focuses on the comparison of different drone-based methods as a baseline for future ecological studies, rather than applying the methods to different land-use types. We will however follow up on this in the future, as we also performed flight missions over flooded and non-flooded natural forest sites and a variety of adjacent areas including mixed oil palm stands and small holder rubber and oil palm plantations.

To clarify this point in the manuscript, we updated the introduction section with the following sentence (L124-L125):

The present study focuses on the comparison of different drone-based methods as a baseline for future ecological studies, rather than applying the methods to different land-use types.

3. It would be good to include in the paper some information on the measured air-surface temperature differences as function of time and space.

The differences of mean land surface and air temperatures were rather low during our study period ranging from 0.005K to a single peak of 8.689K and daily means ranged from daily means of 1.32K to 2.13K. The following figure provides an overview of the air-surface temperature differences over the study period in the Fig. 1 below:



The spatial differences of air-surface temperatures (Tmin and Tmax of the surface temperatures) extracted from the thermal maps are provided in the table below, averaged for the days of the year (DOY):

DOY	Dif. LSTmin and AirTemp16.3 [K]	Dif. LSTmax and AirTemp16.3 [K]
217	4.16	10.39
218	3.89	8.02
219	3.95	7.88
220	4.02	6.71
221	4.26	7.34

As suggested by the reviewer, we added a sentence summarizing this information to the Results (L418-L420):

Temperature differences between measured air temperature at 16.3m (top of canopy) and mean land surface temperatures ranged from 0.005K to a single peak of 8.689K for the single flights while the daily averaged differences ranged from 1.32K to 2.13K.

4. With 90% canopy cover, LST is mostly that of the leaf surfaces, i.e. reflecting the process of evaporative cooling of leaves by transpiration. Can the authors report these (evapo)transpiration values? A value is given in L360. Why are the units mm h-1 m-2? I thought that the mm already includes the area consideration (i.e., 1 mm = 1 L m-2).

We thank the reviewer for this insightful comment and agree that (evapo)transpiration should be provided in mm h^{-1}. We added more ET values to the respective section (L425-L427):

At the time of the drone flights, LE from the EC method ranged between 87 and 596 W m^{-2} (mean: 337 W m^{-2}) and eddy covariance-derived evapotranspiration was on average, 0.43 $\pm$0.21 mm h^{-1}, with peak evapotranspiration of up to 0.87 mm h^{-1} during midday.

5. By using the EC data as absolute reference, the text seems to assume that the EC data are independently true. However, the EC is also an estimate based on an indirect measurement. If there are any additional measurements that could further constrain these data, it would be very helpful. Regardless, the text should be adjusted to reflect that two estimates are compared, rather than an estimate to a direct measurement.

We thank the reviewer for this comment and fully agree. Since we used an errors-in-variables model (Deming regression) in our analysis, we did account for these measurement errors in both the x- and the y-axis (eddy covariance and drone-based method, respectively).

To further clarify this in the manuscript, we added the following sentence to the statistics section (L356-L359):

Both methods, the reference EC technique and the drone-based estimates, are associated with a certain degree of uncertainty. To account for the uncertainty in both, a model II Deming regression (Deming, 1964) was applied for the analysis to consider uncertainties in both x and y variables (Cornbleet and Gochman, 1979; Glaister, 2001).

6. In case that one doesn't have radiation measurements, would the DTD model be the best option to make use of the thermal information? In L400 the authors should note that such sensors must be tested independently in a separate study.

In case that no radiation measurements at all are available, the radiation budget can potentially be modelled according to location, date and time and under the assumption of cloud and haze free skies, which we tested in our study for all three models. However, these assumptions were frequently not met during our time of study, resulting in relatively poor net radiation estimates translating to inaccurate results for the DTD, TSEB-PT and DATTUTDUT model.

The reviewer also makes an important point regarding the testing of potential on-board sensor schemes. We adjusted the sentence accordingly (L540-L546):

In our study, these measurements were taken with the EC equipment, but future stand-alone drone approaches are possible by using on-board miniaturized radiation sensors (Castro Aguilar et al., 2015; Suomalainen et al., 2018). However, the accuracy of such on-board radiation sensors should first be tested against reference methods, e.g. visually by scatter or inter-comparison plots (Castro Aguilar et al., 2015; Suomalainen et al., 2018) or with a model II regression procedure evaluating the interchangeability of methods and measurements (Passing and Bablok, 1983).

7. The authors discuss measurements in drier sites. It would be interesting to compare these results with measurements of palm water-use and its effect on temperature. Below are a few studies on date palm, evidencing the high transpiration rates in a plantation, and the effect on temperature in an urban context.

We thank the reviewer for this interesting suggestion. The new drone-based method can likely help to link surface temperatures, e.g. in urban settings, and vegetation water use; however, this falls outside of the scope of the presented study. As mentioned before, we focus mainly on a method comparison rather than on applied ecological questions for now.

To clarify this further, we added a sentence to the discussion (L644-L646):

Drone-based methods have a large untapped potential for ecological applications, e.g. regarding ecohydrological optimization in land use systems and designing the climate-smart urban landscapes of the future.

8. Finally, another potential comparison could be made with a study of transpiration of forest trees estimated by spatial temperature data from a thermal camera (see reference below).

Sperling, O., Shapira, O., Cohen, S., Tripler, E., Schwartz, A., & Lazarovitch, N. (2012). Estimating sap flux densities in date palm trees using the heat dissipation method and weighing lysimeters. Tree Physiology, 32(9), 1171-1178.

Potchter, O., Goldman, D., Kadish, D., & Iluz, D. (2008). The oasis effect in an extremely hot and arid climate: The case of southern Israel. Journal of Arid Environments, 72(9), 1721-1733.

Potchter, O., Goldman, D., Iluz, D., & Kadish, D. (2012). The climatic effect of a manmade oasis during winter season in a hyper arid zone: The case of Southern Israel. Journal of arid environments, 87, 231-242.

Lapidot, O., Ignat, T., Rud, R., Rog, I., Alchanatis, V., & Klein, T. (2019). Use of thermal imaging to detect evaporative cooling in coniferous and broadleaved tree species of the Mediterranean maquis. Agricultural and forest meteorology, 271, 285-294.

We thank the reviewer for this suggestion; as mentioned previously, this manuscript focuses on a method comparison rather than on the ecological application of the method and a comparison to other land-use types; in the (near) future, further work will certainly also include further land-use types including old-growth and secondary tropical forest patches, agroforestry systems and smallholder plantations in lowland Sumatra and beyond.

We took up the reference suggested by the reviewer in the introduction (L59-L61):

Transpiration from leaf surfaces leads to evaporative cooling of the canopy; LSTs, along with air temperature, can thus be used as a reliable indicator of plant water use, both in monocultures and in spatially highly heterogeneous systems such as natural forests (Lapidot et al., 2019).

References:
Brenner, C., Thiem, C.E., Wizemann, H.-D., Bernhardt, M., Schulz, K., 2017. Estimating spatially distributed turbulent heat fluxes from high-resolution thermal imagery acquired with a UAV system. Int. J. Remote Sens. 38, 3003–3026. https://doi.org/10.1080/01431161.2017.1280202

Brenner, C., Zeeman, M., Bernhardt, M., Schulz, K., 2018. Estimation of evapotranspiration of temperate grassland based on high-resolution thermal and visible range imagery from unmanned aerial systems. Int. J. Remote Sens. 39, 5141–5174. https://doi.org/10.1080/01431161.2018.1471550

Castro Aguilar, J.L., Gentle, A.R., Smith, G.B., Chen, D., 2015. A method to measure total atmospheric long-wave down-welling radiation using a low cost infrared thermometer tilted to the vertical. Energy 81, 233–244. https://doi.org/10.1016/j.energy.2014.12.035

Cornbleet, P.J., Gochman, N., 1979. Incorrect Least-Squares Regression Coefficients in Method- Comparison Analysis. Clin. Chem. 432–438.

Glaister, P., 2001. Least squares revisited. Math. Gaz. 85. https://doi.org/10.2307/3620485

Hoffmann, H., Nieto, H., Jensen, R., Guzinski, R., Zarco-Tejada, P., Friborg, T., 2016. Estimating evaporation with thermal UAV data and two-source energy balance models. Hydrol. Earth Syst. Sci. 20, 697–713. https://doi.org/10.5194/hess-20-697-2016

Lapidot, O., Ignat, T., Rud, R., Rog, I., Alchanatis, V., Klein, T., 2019. Use of thermal imaging to detect evaporative cooling in coniferous and broadleaved tree species of the Mediterranean maquis. Agric. For. Meteorol. 271, 285–294. https://doi.org/10.1016/j.agrformet.2019.02.014

Passing, H., Bablok, W., 1983. A new biometrical procedure for testing the equality of measurements from two different analytical methods. Application of linear regression procedures for method comparison studies in clinical chemistry, Part I. Clin. Chem. Lab. Med. 21. https://doi.org/10.1515/cclm.1983.21.11.709

Röll, A., Niu, F., Meijide, A., Ahongshangbam, J., Ehbrecht, M., Guillaume, T., Gunawan, D., Hardanto, A., Hendrayanto, Hertel, D., Kotowska, M.M., Kreft, H., Kuzyakov, Y., Leuschner, C., Nomura, M., Polle, A., Rembold, K., Sahner, J., Seidel, D., Zemp, D.C., Knohl, A., Hölscher, D., 2019. Transpiration on the rebound in lowland Sumatra. Agric. For. Meteorol. 274, 160–171. https://doi.org/10.1016/j.agrformet.2019.04.017

Sabajo, C.R., le Maire, G., June, T., Meijide, A., Roupsard, O., Knohl, A., 2017. Expansion of oil palm and other cash crops causes an increase of the land surface temperature in the Jambi province in Indonesia. Biogeosciences 14, 4619–4635. https://doi.org/10.5194/bg-14-4619-2017

Suomalainen, J., Hakala, T., Alves de Oliveira, R., Markelin, L., Viljanen, N., Näsi, R., Honkavaara, E., 2018. A Novel Tilt Correction Technique for Irradiance Sensors and Spectrometers On-Board Unmanned Aerial Vehicles. Remote Sens. 10, 2068. https://doi.org/10.3390/rs10122068

2 Response to reviewer II

Dear Reviewer,

Thank you for taking the time to revise our manuscript. We welcome your comments and believe that they helped to improve our manuscript considerably. Please find our point-by point replies below.

Sincerely,
Florian Ellsäßer

General comments The manuscript by Ellsasser et al. makes an interesting and useful contribution to the burgeoning literature on using UAVs to measure ecosystem properties and processes, in this case measurements of surface temperature for use in models of the surface energy balance to predict spatial variations in the latent heat flux and for comparison to eddy covariance-derived estimates of the same.

The appendix describing the various energy balance/ET models should be better integrated with the main body of the manuscript, and as noted below some of the model equations need more clarification. In general, a reader should not have to read other previous papers to understand the approaches tested here (e.g., see my comments below regarding lines 174-175).

As suggested by the reviewer we integrated the key information from the appendix into the main body of the manuscript (L164-L308):

2.3 Energy balance models

LSTs are recorded as 'snapshots' representing an instantaneous state of surface temperatures. Soil-Vegetation-Atmosphere Transfer (SVAT) models use these instantaneous observations of LST to solve the energy balance equation and estimate instantaneous fluxes. In our study the one-source energy balance model DATTUTDUT (Timmermans et al., 2015) and two two-source energy balance models, TSEB-PT (Norman et al., 1995) and DTD (Norman et al., 2000), were applied. For the TSEB-PT and DTD model directional radiometric temperatures are used and no further calculation of aerodynamic temperature by using an excess resistance term is needed (Hoffmann et al., 2016). Using drones, the proximity of the thermal camera to the surface is much closer compared to other typical carriers (such as satellites or planes) and hence atmospheric effects are supposed to have only a very minor effect. To use a uniform input for all the applied models, we used directional radiometric temperature recordings from the drone as input without applying further corrections. All models in this study use instantaneous land surface temperatures (LST) to solve the energy balance equation:

$$Rn = G + H + LE \tag{1}$$

Where Rn is the net radiation, G is the ground heat flux and the turbulent fluxes H and LE represent sensible and latent heat flux, respectively. Rn is estimated by calculating the budget of incoming (↓) and outgoing (↑) long- (l) and short-wave (s) radiation:

$$Rn = R_s^{\downarrow} + R_s^{\uparrow} + R_l^{\uparrow} + R_l^{\downarrow} = (1-\alpha) * R_s^{\downarrow} + \varepsilon_{surf} * \varepsilon_{atm} * \sigma * T_{air}^4 - \varepsilon_{surf} * \sigma * T(\theta)_{surf}^4 \tag{2}$$

*Where the short-wave component is calculated by multiplying incoming short-wave radiation Rs↓ [W m^{-2}] with its absorption ratio deducted from the combined soil and vegetation albedo α. The long-wave radiation budget is calculated from surface (soil and vegetation) emissivity ε_{surf} and atmospheric emissivity ε_{atm}, the Stefan-Boltzmann constant σ (5.6704*10^{-8} W m^{-2}*K^{-4}), air temperature T_{air} and radiometric land surface temperature $T(\theta)_{surf}$ (both in K).*

2.3.3 DATTUTDUT

Key input for the DATTUTDUT model is a LST map from where the hottest and the 0.5% quantile of coldest pixels are extracted, assuming that hot pixels are a result of very little to no evapotranspiration and cold pixels origin in a high evapotranspiration rate (Timmermans et al., 2015). Fully modeled Rn is calculated based on down-welling short-wave radiation estimates calculated using sun-earth geometry to solve eq. 2. Surface albedo P0 is calculated as in Timmermans et al. (2015) based on the assumption that dense vegetation appears colder than rocks or soil in the thermal imagery (Brutsaert, 1982; Garratt, 1992):

$$P_0 = 0.05 + ((T_0 - T_{min})/(T_{max} - T_{min})) * 0.2 \tag{3}$$

Down-welling shortwave radiation $R_s\downarrow$ is calculated from the dimensionless atmospheric transmissivity τ and the exo-atmospheric shortwave radiation SWexo = 1360 W m^{-2} (Timmermans et al., 2015). Transmissivity τ is calculated as described in Burridge and Gadd (1977) using the solar elevation angle α that was determined from the geographic position of our site and the coordinated universal time (UTC) of the measurements:

$$\tau = 0.6 + 0.2 * sin(\alpha) \tag{4}$$

$$R_s \downarrow = \tau * SW_{exo} \tag{5}$$

Timmermans et al. (2015) suggest using a constant value of 0.7 for τ and 0.8 atmospheric emissivity (ε_{atm}), but as our flight times range from 09:00 to 16:30 h local time we decided to include the solar elevation angle as in eq. 4. Further, we used a constant surface emissivity (ε_{surf}) of 0.98 and not 1.0 as in the original formulation of the DATTUTDUT model. Since the DATTUTDUT *model is a one-source energy balance model we used a uniform surface emissivity of 0.98 as recommended for vegetation dominated areas (Jones and Vaughan, 2010). Air temperature T_{air} was calculated as the 0.5% quantile of the coldest pixels in the image.*

As the original DATTUTDUT formulation doesn't account for cloud cover, eq. 5 is replaced by measured short-wave irradiance as in Brenner et al. (2018) for model runs with Rn_sw. For model runs with Rn_mes eq. 2 was replaced by Rn measurements recorded at the EC-tower.

The sum of the turbulent fluxes is calculated by subtracting G from Rn. The result is fractioned into its components H and LE, using the evaporative fraction (EF) (Timmermans et al., 2015):

$$EF = LE/(LE + H) = LE/(Rn - G) = (T_{max} - T(\theta)_{surf})/(T_{max} - T_{min}) \quad (6)$$

For our implementation of the DATTUTDUT model we used the QGIS3 plugin QWaterModel (Ellsäßer et al., 2020) that is provided with an easy-to-use graphical user interface.

TSEB-PT

TSEB-PT calculates surface-energy budgets from the recorded LSTs splitting observations into a canopy and a soil fraction (Norman et al., 1995; Song et al., 2016; Xia et al., 2016). The model consists of two parts: First an initialization part where all parameters that do not depend on soil and canopy temperature partition and knowledge of atmospheric stability are computed. Afterwards an iterative part where the Monin-Obukhov length is stabilized and the fluxes are finally derived. To begin this process vegetation cover $f_c(\theta)$ is computed as in Campbell and Norman, (1998):

$$f_c(\theta) = 1 - exp((-0.5\Omega(\theta) * LAI)/(cos(\theta))) \quad (7)$$

where LAI is leaf area index, θ is the sun zenith angle and Ω is a nadir view clumping factor to represent the cross-row structure in which the oil palm is planted (Kustas and Norman, 1999). Guzinski et al., (2014) suggest a maximum limit of 0.95 for $f_c(\theta)$, so that a small fraction of the soil is still visible and extreme magnitudes for soil temperature are avoided. Roughness parameters are calculated from vegetation height. Tair was measured at the EC-tower, $T(\theta)surf$ was recorded with the drone both similar to descriptions in Hoffmann et al. (2016). Calculation of aerodynamic temperature by using an excess resistance term is not needed, since TSEB-PT uses directional radiometric temperature as input (Hoffmann et al., 2016). For the two-source energy balance models we used a canopy emissivity of 0.98 and soil emissivity of 0.95. The emissivity values are based on averages for the 8-14 μm taken from Jones and Vaughan, *(2010). The TSEB-PT model requires additional in situ meteorological measurements of long- and short-wave radiation, wind speed, barometric pressure and relative humidity, which in our case were recorded at the EC tower. Further, measured data on LAI as well as surface and canopy albedo are required. The three resistances in the soil-canopy-atmosphere heat flux network, the aerodynamic resistance to heat transport (R_A), the resistance to heat transport from the soil surface (R_S) and the total boundary layer resistance of the leaf canopy (R_X) are calculated as in Norman et al. (2000, 1995). Net radiation and the three resistances remain constant during the model runs. After finishing the computation of all constant parameters, the iterative part of the model starts assuming Monin-Obukhov length tends to infinity. In the first iteration Rn is partitioned into a soil and canopy fraction by calculating net radiation divergence ΔRn (Hoffmann et al., 2016; Norman et al., 2000):*

$$\Delta Rn = Rn * (1 - exp((-K * LAI * \Omega_0)/\sqrt{((2cos(\theta_s))))} \tag{8}$$

where K is an extinction coefficient that varies according to LAI (Hoffmann et al., 2016). We are aware of the fact, that the determination of K using LAI is disputed as other studies found no significant correlation of K and LAI (Zhang et al., 2014). With ΔRn known, sensible heat flux is then estimated using the Priestley-Taylor approximation following the approach by Hoffmann et al., (2016):

$$H_c = \Delta Rn * (1 - \alpha_{PT} * f_G * (D/(D + \gamma)) \tag{9}$$

αPT is the Priestley-Taylor coefficient and both γ the psychrometric constant and the slope of the saturation pressure curve D were calculated as in Allen et al. (1998). Canopy temperature T_C was computed by summing up the results of the linear approximation in equation (A7) for $T_{C,lin}$ and ΔT_C from equation (A11) both from Norman et al. (1995). Knowing canopy temperature T_C and fraction of view covered by vegetation fθ as in Hoffmann et al. (2016), soil temperature T_S can be calculated:

$$T_s = (T(\theta)R^4 - f_\theta * T_C^4)/(1 - f_\theta)^{(1/4)} \tag{10}$$

With soil and canopy temperatures and the resistances of the soil-canopy-atmosphere heat flux network known, fluxes can be calculated with equations (9), (10), (11) and (13) from Hoffmann et al. (2016). Total latent and sensible heat fluxes are calculated as the sums of canopy and soil fluxes. In the following iterations, a recalculation of Monin-Obukhov length takes place until a stable value is reached and the resulting fluxes are derived. For the model runs with Rn_mod and Rn_mes the model net radiation is forced accordingly.

DTD

The Dual-Temperature-Difference (DTD) model works very similar to TSEB-PT and differs mainly in the way how sensible heat flux is calculated (Hoffmann *et al., 2016). In the DTD model, the absolute temperatures of land surface and air (as used in the TSEB-PT) are supplemented with a second set of early morning reference measurements of LST and air temperature, thus creating a dual-temperature difference (Norman et al., 2000). The first observation is recorded in the early morning hours and the second observation is recorded later on the same day at any given time. We used two IRTs attached to the EC tower (see EC methodology for details and Sect. 2.7 for the limitations) for the necessary early morning reference readings of absolute temperature and used the averaged LSTs to create a uniform map as input for the DTD model (similar as e.g. in Hoffmann et al., 2016). This relates measurements at any time during the day to measurements recorded in the morning, when fluxes are assumed to be minimal, and thereby accounts for measurement biases of LST (Anderson et al., 1997; Hoffmann et al., 2016). H flux is then calculated using the time-differential temperature and a series resistance network as it is recommended for densely vegetated regions to consider interaction of soil and canopy fluxes (Guzinski et al., 2014; Li et al., 2005). A detailed description of the model can be found in Guzinski et al. (2014) and Norman et al. (2000).*

Calculation of evapotranspirated amount of water:

The actual amount of evapotranspirated water (ET_w) in mm h^{-1} was calculated as in Timmermans et al. (2015):

$$ET_w = ((LE * t)/1000000)/(2.501 - 0.002361 * (T_{air} - 273.15)) \quad (11)$$

Where LE is the latent heat flux in W m^{-2}, t is the respective timespan in seconds and T_{air} is the air temperature in Kelvin.

I agree with the other reviewer that more discussion of the various uncertainties in EC-derived ET need to be discussed. While it is the reference method here it is also subject to many uncertainties.

As addressed in the reply to reviewer one, we added the following information regarding uncertainties of the reference EC method:

Methods section (L347-L352):

EC data processing and quality checks were performed following the methodology described in (Meijide et al., 2017). Following (Mauder and Foken, 2006), flux estimates during low turbulence and thus stable atmospheric conditions were removed from the analysis; however, low turbulence mainly occurred during night hours and was not observed during the daytime drone flights. Generally, the EC method is associated with uncertainties of 5 - 20% (Foken, 2008). Further limitations are the high costs and quite specific requirements regarding size and terrain of the study site.

Statistics section (L356-L359):

Both methods, the reference EC technique and the drone-based estimates, are associated with a certain degree of uncertainty. To account for the uncertainty in both, a model II Deming regression (Deming, 1964) was applied for the analysis to consider uncertainties in both x and y variables (Cornbleet and Gochman, 1979; Glaister, 2001).

The writing is generally fine but there are a few very awkward sentences that I suggest re-writing (see below).

We thank the reviewer for taking the time to point out the need for rewording these sentences. We revised them accordingly.

Specific comments

Lines 90-91: "the hottest and a group of coldest pixels in the image" – This is not and independent clause as it is missing a verb

We adjusted the sentence accordingly (L91-L93):

In the one-source energy balance model DATTUTDUT (Deriving Atmosphere Turbulent Transport Useful To Dummies Using Temperature) (Timmermans et al., 2015) fluxes are estimated by relating single pixel temperatures to local temperature extremes.

Lines 105-107: This sentence is confusing and needs to be re-written.

We adjusted the sentence accordingly (L109-L112):

Since full method comparisons based on model II regression require a sample size of at least n=60 data pairs (Legendre and Legendre, 2003), many previous studies with smaller sample sizes were constrained to using error terms and correlation coefficients.

Line 110: replace "presented" with "current"

We adjusted the sentence accordingly (L114-L116):

The current study was conducted in the lowlands of Jambi province (Sumatra, Indonesia) where over the last decades, large areas of rainforest have been converted to rubber and oil palm plantations (Clough et al., 2016; Margono et al., 2012).

Line 147: Quote the manufacturer's measurement uncertainty here, as you also discuss it later when mentioning thermal cameras. The true uncertainty is surely closer to 1-2 K for cameras like this.

As suggested by the reviewer, we added more differentiated information on relative and absolute thermal accuracy to this section (L151-L152):

The sensor covers spectral bands ranging from 7.5 to 13.5 μm with a relative thermal accuracy of 0.04 K and an absolute thermal accuracy of $\pm 2K$ (FLIR Systems, USA).

Line 164: Provide the assumed surface emissivities used in each model and component

As suggested, we added a sentence on assumed surface emissivities to the Methods (L216-L218):

Further, we used a constant surface emissivity (ϵ_{surf}) of 0.98 as recommended for vegetation dominated areas (Jones and Vaughan, 2010) and not 1.0 as simplified in the original formulation of the DATTUTDUT model.

and (L249-L250):

For the two-source energy balance models we used a canopy emissivity of 0.98 and soil emissivity of 0.95. The emissivity values are based on averages for the 8-14 μm taken from Jones and Vaughan, (2010).

Lines 174-175: Need to better explain this approach. P-T is usually used to predict LH fluxes not SH fluxes.

For the application of the TSEB-PT model we follow the workflow provided in Hoffmann et al., (2016). There, it is described in detail how the Priestley-Taylor (PT) approximation is used to calculate the canopy sensible heat flux from net radiation divergence estimates. This is now pointed out more clearly in the Methods of our manuscript (L266-L267):

With ΔRn known, sensible heat flux is then estimated using the Priestley-Taylor approximation following the approach by Hoffmann et al., (2016).

Lines 196-207: Do these models assume a closed energy balance? If so how does that affect your estimates?

As mentioned in the Methods section, all models assume energy balance closure; in accordance with the reference EC method, we applied the Bowen Ratio method for energy balance closure (L335-L346):

As the applied drone-based models all assume full energy balance closure, we used the Bowen ratio closure method (Pan et al., 2017; Twine et al., 2000) to compute full closure for the EC measurements. The Bowen ratio method was found to produce the most congruent results in conjunction with drone-based latent heat flux estimates (Brenner et al., 2017) and was therefore applied in this study. The energy balance closure (EBC) of the reference EC measurements was 0.77 (r^2= 0.87), which is in line with EBC reported for other tall vegetation canopies (Stoy et al., 2013). Since the used energy balance models assume full EBC, we applied the so-called Bowen ratio closure method to the EC data (Pan et al., 2017). The method assumes that wind measurements miss some of the total covariance and dispersive fluxes. Therefore, underestimations of LE and H are carried over proportionally because of similarity among fluxes (Twine et al., 2000). The Bowen ratio closure method proportionally assigns the underestimated turbulent energy to LE and H fluxes to reach full EBC.

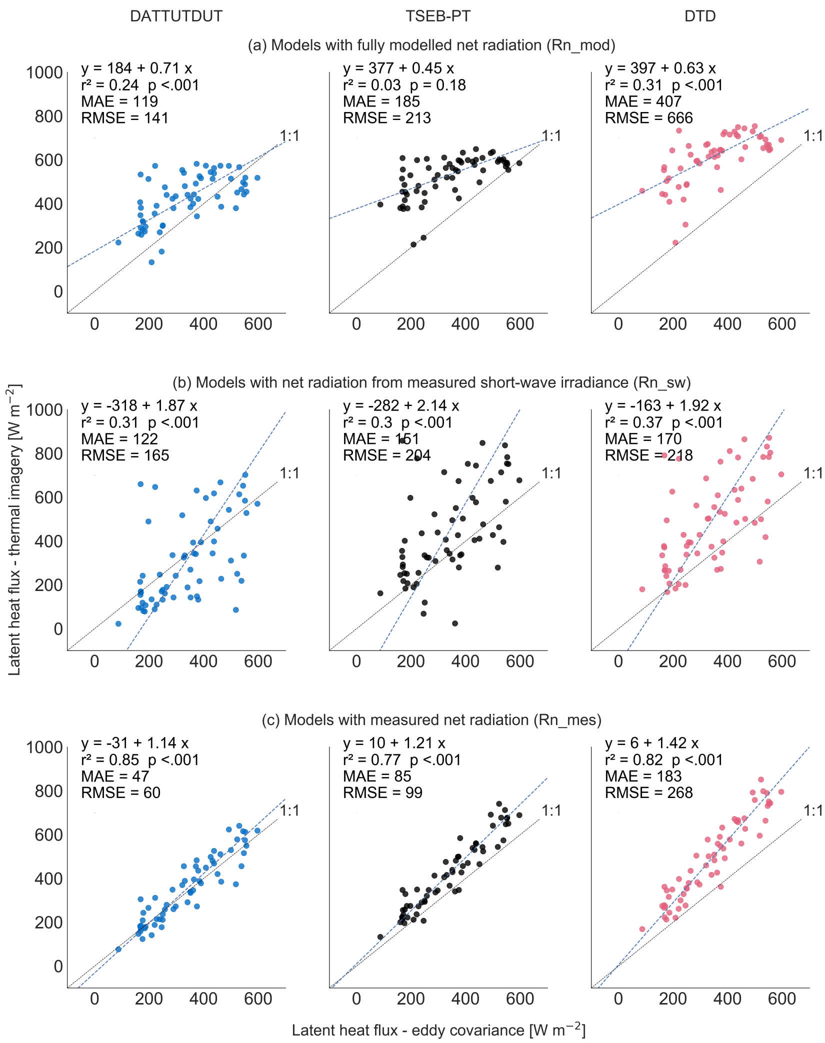
Line 219: Was this an aspirated measurement of Tair?

We appreciate this insightful question by the reviewer. We originally used the Tair measurements at 22m on the EC tower but, inspired by the reviewer's comment, have re-run all models with the temperature measurements at 16.3 m (i.e. ~2m above the canopy). However, the absolute average temperature difference between the two measurement heights is below 0.24 °C.

We have adjusted the following sentence in the methods section (L319-L321):

Air temperature and relative humidity were measured with thermohygrometers (type 1.1025.55.000, Thies Clima, Göttingen, Germany) at 16.3 m height.

We re-ran the models with the temperature measurements at 16.3 m. We further received an email with recommendations on how to improve the model performance (e.g. vegetation parameters) of the two-source energy balance models and implementd these in the models. The revised manuscript includes these fully revised models, as shown in the key figure below:



Line 222: These are IRTs not thermal cameras, so you do not know exactly which canopy elements you are measuring! Were they capturing only leaves all of the time? Also, what surface emissivity was assumed for these measurements of surface temperature? Did you correct for the influences of reflected longwave radiation, relative humidity, distance to object, etc? And what are measurement uncertainties of the IRTs?

We thank the reviewer for this valuable comment. To avoid confusion, we now consistently apply the term IRT throughout the manuscript. We further added more detail on the issues raised by the reviewer to the Methods (L323-L330):

The two IRTs used in our study (IR100 Radiometer, Campbell Scientific Inc., Logan, USA) have a field-of-view (FOV) of 8-10°. Considering the distance from *their fixed location on the tower to the average height of the oil palm canopy, they cover a circular area of 2.2 m^2, over which they average the received thermal signal. The recorded canopy area comprises different functional parts of the canopy (e.g. leaflets, petioles). On average, we assumed a surface emissivity of 0.98 for the canopy area (Jones and Vaughan, 2010). We did not correct the values recorded with the IRTs for any other influences; the distance from the canopy surface to the sensors was only about 10m.*

Line 229: Describe the Bowen ratio closure method in more detail.

As suggested by the reviewer, we added more detail about the Bowen ratio closure method to the Methods (L338-L344):

The energy balance closure (EBC) of the reference EC measurements was 0.77 (r^2 = 0.87), which is in line with EBC reported for other tall vegetation canopies (Stoy et al., 2013). Since the used energy balance models assume full EBC, we applied the so-called Bowen ratio closure method to the EC data (Pan et al., 2017). The method assumes that wind measurements miss some of the total covariance and dispersive fluxes. Therefore, underestimations of LE and H are carried over proportionally because of similarity among fluxes (Twine et al., 2000). The Bowen ratio closure method proportionally assigns the underestimated turbulent energy to LE and H fluxes to reach full EBC.

Line 247: "systematic"

We adjusted the sentence accordingly (L367-L369):

Statistics such as r^2 have their limitations in method comparison since they are designed to indicate how well the resulting model of the regression describes the outcome and are not necessarily a good measure for systematic bias between methods.

Line 273: I think you mean "alive"

We adjusted the sentence accordingly (L391-L392):

The plantation is very well managed, so that all oil palm canopies are alive, no oil palms have died and only dry leaves are removed.

Lines 278-286: As noted above these measurements were not made with thermal camera but with IRTs. Please update.

As mentioned above we now consistently apply the term IRTs throughout the manuscript.

Line 280: Is the 122 number based on 2 maps/flight?

Yes. We re-worded the sentence to point this out more clearly (L398-L402):

To check whether the two IRTs measure similar temperatures compared to drone recorded LSTs, we extracted a total of 122 'IRT-sized' (i.e. ~2.2 m^2) LST footprints from the drone-recorded maps. A correlation of both temperature measurements revealed a small deviation of the measured temperatures resulting in a mean absolute error (MAE) and root mean squared error (RMSE) of 1.59 and 2.15 K respectively.

Line 293-294: Is this peak SW measured during the flight or average SW?

We applied 10 min averages of all SW data that were recorded during a respective flight. We added this information to the discussion section (L550-L552):

The short-wave irradiance measurements used in this study were stored as 10 min averages that probably didn't represent the high level of irradiance variations in the tropical study area adequately.

Line 295: By "canopy air temperature" do you mean the Tair measured at 22m?

We thank the reviewer for this valuable question. As already mentioned in a previous response, we originally used Tair as measured at 22m on the EC tower, but now have re-run all models using Tair measured at 16.3m (i.e. ~ 2m above the canopy).

We have adjusted the following sentence in the methods section (L319-L320):

Air temperature and relative humidity were measured with thermohygrometers (type 1.1025.55.000, Thies Clima, Göttingen, Germany) at 16.3 m height.

Line 302-303: This is an awkward sentence – rewrite.

As suggested, we re-wrote the sentence (L425-LL427):

Congruence of LE estimates with reference EC measurements differed among the three applied models and was further affected by the configuration of the Rn assessment (Fig. 2).

Line 303: The first time you cite Fig. A3 you need to discuss why modeled Rnet is so poor.

As suggested by the reviewer we added a short section discussing the poor performance when applying modelled Rnet (L427-L433):

The assumptions for Rn_mod were not always met as cloud cover was present during several flights; consequently, the corresponding net radiation estimates were too high, leading to a substantial overestimation especially of smaller latent heat fluxes. The short-wave irradiance based Rn_sw configuration resulted in Rn estimates that were by average very comparable with the measured net radiation Rn_mes but also showed a rather high variation (Fig. 2). Generally, error metrics were reduced and agreement was increased the more measurement-controlled the Rn determination process was.

Line 304: Replace “congruence” with “agreement” or “fidelity”

We adjusted the sentence accordingly (L431-L433):

Generally, error metrics were reduced and agreement was increased the more measurement-controlled the Rn determination process was.

Line 307-308: Perhaps this poor agreement in morning and late afternoon is not surprising since the dATTUDUT method is based on modeled Rnet..?

We thank the reviewer for this insightful comment. We added a section to the manuscript that addresses both this comment and the following comment (please refer to the following answer).

Line 308-309: It’s worth breaking out the description of the performance of the TSEBPT estimates into a separate sentence. Are these estimates uniformly higher than the EC estimates or only during part of the day?

We thank the reviewer for this insightful comment. We added a section to the manuscript that addresses both this comment and the previous comment (L437-L442):

DATTUTDUT LE estimates closely agreed with EC measurements around noon, but were higher in the morning and afternoon hours, which is caused by overestimations of Rn from the Rn_mod method (Fig. 3a). LE estimates from TSEB-PT were consistently higher than EC measurements, with particularly large divergences around noon (Fig. 3a). The LE predictions from the DTD model in Rn_mod configuration were rather overestimated, especially around noon when compared with the EC reference measurements (Fig. 3a).

Lines 335-336: Seems like this sentence is missing a word or two.

We adjusted the sentence accordingly (L474-L477):

The TSEB-PT model in Rn_mes configuration also showed no significant continuous errors but was subject to a minor proportional bias (Fig. 5c). The TSEB-PT model overestimated LE particularly around noon, when fluxes are very high (Fig. 3c and 4c).

Line 352: I'm unclear what you mean about the X-level for the bias in EC reference fluxes.

The bias of two applied methods can be expressed in an X- and a Y-level, bias on X-axis (horizontal) and bias on Y-axis (vertical) respectively. We were particularly interested in the bias of the new drone-based methods based on the EC technique (here: X-level).

Lines 405-406: Are you referring to the slope in this sentence?

We agree with the reviewer that the wording was previously unprecise and adjusted the sentence accordingly (L477-L478):

The DTD model also showed no continuous bias but indicated a proportional error in the analytical method and the Jackknife method (Fig. 5c).

Lines 455-457: Well before this discussion of errors you should define what you mean by proportional versus continuous errors.

Following the suggestion by the reviewer, we added the following information to the Methods section (L465-L470):

If the confidence intervals for the intercept of the Deming regression include zero, there is no constant or continuous error between the two methods. If the confidence intervals for the intercept do not include zero, both methods differ by a constant amount, i.e. the new method has a continuous error compared to the reference method. In contrast, the confidence intervals of the slope of the Deming regression indicate whether there is a proportional error between the methods, which increases proportionally with the magnitude of the predicted value.

Line 500: Replace "results in" with "predict"

We changed the sentence (L507-L509):

Both distributions of the two-source energy balance models show gaps in the histogram, while the histogram of the DATTUTDUT model displays a more con-

tinuous distribution (Fig. 7)

Line 503: eliminate comma after "both"

We adjusted the sentence accordingly (L634-L635):

For the DATTUTDUT model mean and median are very similar indicating close to zero skewness.

Line 520: Which edge? Computer or edge of study area?

We adjusted the sentence for further clarification (L647-L650):

Autonomous acquisition of LSTs over EC stations and the surrounding area scan be supplemented by on-board and ground sensors. Energy-balance models can then potentially be calculated using edge computing schemes on-board the drone to enable a dense temporal resolution of LST, flux and ET maps in almost real-time.

Line 542: Replace "cameras" with "IRTs"

As mentioned above, we will now consistently apply the term IRTs throughout the manuscript.

Line 565: How are the surface epsilon (emissivity) terms estimated? Do they vary spatially across the image?

We thank the reviewer for this insightful comment, and have expanded the according method section to clarify the issues raised by the reviewer. As already mentioned above, we will add this information to the methods part of the manuscript (L216-L218).

Further, we used a constant surface emissivity (ϵ_{surf}) of 0.98 as recommended for vegetation dominated areas (Jones and Vaughan, 2010) and not 1.0 as simplified in the original formulation of the DATTUTDUT model.

Lines 579-580: Show the equations for calculating radiometric LSTs.

Since we used a radiometric thermal camera we did not have to calculate the radiometric LSTs from a greyscale picture (as e.g. in Cohen et al., 2005); there thus is no equation. The energy-balance models in our study use the directional radiometric temperature that was recorded with the thermal camera on the drone. A further substitution of temperatures or correction procedures (e.g. excess resistance) is not necessary (Hoffmann et al., 2016). We will add a sentence to the Methods to point this out more clearly:

For the TSEB-PT and DTD model directional radiometric temperatures are used and no calculation of aerodynamic temperature by using an excess resistance term is needed (Hoffmann et al., 2016). The proximity of the thermal camera to the surface is much closer compared to other typical carriers (such as satellites or planes) and hence atmospheric effects are supposed to be largely reduced. To use a uniform input for all the applied models, we used directional radiometric temperature recordings from the drone as input without applying further corrections.

Line 588: I assume this (Po) is a shortwave albedo?

Correct, Po is the short-wave surface albedo. It was taken from Timmermans et al., (2015). We added a sentence to the Methods to clarify this (L199-L200):

Surface albedo P0 is calculated as in Timmermans et al. (2015) based on the assumption that dense vegetation appears colder than rocks or soil in the thermal imagery (Brutsaert, 1982; Garratt, 1992).

Line 600: This model assumes cloud-free conditions (with a constant transmissivity)?

Yes, in its original formulation the DATTUTDUT model assumes cloud free conditions (Timmermans et al., 2015). For simplicity Timmermans et al. (2015) suggest using a constant value of 0.7 for the transmissivity or to follow a simple parameterization scheme for instantaneous shortwave atmospheric transmissivity following the description in Burridge and Gadd, (1977). We chose the second option and calculated short-wave transmissivity using the solar elevation angle. We added a sentence to the Methods to point this out more clearly (L206-L208):

Transmissivity τ is calculated as described in Burridge and Gadd, (1977) using the solar elevation angle α that was determined from the geographic position of our site and the coordinated universal time (UTC) of the measurements.

Line 605: Is that supposed to be an epsilon symbol as in equation 2?

Yes, this is supposed to be a ϵatm. We have adapted the manuscript accordingly (L214-L216):

Timmermans et al. (2015) suggest using a constant value of 0.7 for τ and 0.8 atmospheric emissivity (ϵatm), but as our flight times range from 09:00 to 16:30 h local time we decided to include the solar elevation angle as in eq. 5.

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3 List of relevant changes

(1) Inclusion of comments and suggestions of both reviewers
(2) Re-evaluation of both two-source energy balance models (using Tair at 16.3m and different vegetation parameters)
(3) Minor adaptions in the results and discussion section due to changes because of (2)

Predicting evapotranspiration from drone-based thermography – a method comparison in a tropical oil palm plantation

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Abstract

For the assessment of evapotranspiration, near-surface airborne thermography offers new opportunities for studies with high numbers of spatial replicates and in a fine spatial resolution. We tested drone-based thermography and the subsequent application of three energy balance models (DATTUTDUT, TSEB-PT, DTD) using the widely accepted eddy covariance technique as a reference method. The study site was a mature oil palm plantation in lowland Sumatra, Indonesia. For the 61 flight missions, latent heat flux estimates of the DATTUTDUT model with measured net radiation agreed well with eddy covariance measurements ($r^2=0.85$; MAE=47; RMSE=60) across variable weather conditions and daytimes. Confidence intervals for slope and intercept of a model II Deming regression suggest no difference between drone-based and eddy covariance method, thus indicating interchangeability. TSEB-PT and DTD yielded agreeable results, but all three models are sensitive to the configuration of the net radiation assessment. Overall, we conclude that drone-based thermography with energy-balance modeling is a reliable method complementing available methods for evapotranspiration studies. It offers promising, additional opportunities for fine grain and spatially explicit studies.

1 Introduction

Evapotranspiration (ET) is a central flux in the hydrological cycle on a regional and on a global scale. Terrestrial ET consumes almost two-thirds of terrestrial precipitation (Oki and Kanae, 2006). There is an interest in better understanding ET and its drivers as climate change is expected to increase atmospheric evaporative demand and droughts are predicted to become more severe and frequent in the future (Prudhomme et al., 2014). ET is also strongly affected by land-cover and land-use changes, which are currently very pronounced in tropical regions (Hansen et al., 2013).

The eddy covariance technique (EC) is a widely accepted and well-established method to quantify ET at the stand scale (Baldocchi et al., 2001; Fisher et al., 2017). It results in a single latent heat flux (LE) value integrated over the footprint of the EC tower at a given time that can be converted to an ET estimate. A spatial fine grain attribution of different surface patches to this overall ET value is generally not possible. The EC method is costly and labor intensive, and therefore, a relatively low number of spatial replicates within a given region and among its different ecosystems are typically available. The EC method also has certain constrains regarding topography, atmospheric turbulence and landscape heterogeneity (Göckede et al., 2008).

A complementary approach for assessing LE at larger spatial scales is the use of remotely sensed land surface temperatures (LST) as boundary conditions for energy balance modeling and subsequent conversion to ET (Brenner et al., 2017; Guzinski et al., 2014; Hoffmann et al., 2016; Ortega-Farías et al., 2016; Xia et al., 2016). Transpiration from leaf surfaces leads to evaporative cooling of the canopy; LSTs, along with air temperature, can thus be used as a reliable indicator of plant water use, both in monocultures and in spatially highly heterogeneous systems such as natural forests (Lapidot et al., 2019). Compared to the EC method, this approach can potentially increase the number of spatial replicates within and among ecosystems and is also applicable in challenging terrain. Remotely sensed LSTs are regarded as good indicators for plant water use, stress and transpiration (Jones and Vaughan, 2010). One approach to obtain LST data is the use of satellite-based observations (Allen et al., 2007; Bastiaanssen et al., 1998; Ershadi et al., 2013). However, the spatial resolution of satellite data such as Landsat TM, ASTER, MODIS or AVHRR ranges from 90 m to 1 km, limiting the distinction of plant canopies and soil (Berni et al., 2009). A higher temporal resolution of satellite-based thermal infrared (TIR) observations is usually associated with a lower spatial resolution, and TIR data from satellites in both high spatial and high temporal resolution are not yet available (Brenner et al., 2017). Additionally, clouds are barriers for thermal radiation and therefore have a strong effect on the quality and availability of satellite-based TIR observations (Guzinski et al., 2013). This is of particular importance in regions with frequent cloud cover such as in tropical environments.

An alternative, recently emerging approach to measure LSTs is the use of drones. Radiometric TIR sensors for LST recording have become light-weight and affordable, and drones are now capable of carrying adequate payloads for reasonable timespans. Near-surface thermography-based studies allow temporal resolutions in flexible, e.g. hourly time steps and a spatial resolution in the decimeter scale or finer. Drone-based TIR recording and subsequent modeling of LE with energy balance models has previously shown promising results for short grass and crop vegetation in Central Europe (Brenner et al., 2018; Hoffmann et al., 2016). However, remote sensing of LST from drones is challenging and involves careful planning. Recording LST close to the surface results in a high resolution but reduces the area covered in a certain time span compared to surveying from a higher altitude. Increasing flight altitude reduces spatial resolution of LST images and thus increases the averaging of surface temperatures from individual canopies, soil patches and branches from neighboring canopies into a single pixel (Still et al., 2019). Further, air humidity can have a major effect on measurement accuracy as water vapor does not only attenuate the signals from the surface of interest to the sensor, but also emits its own thermal radiation (Still et al., 2019).

Different energy balance models are available to compute LE from LST and subsequently calculate ET. In the one-source energy balance model DATTUTDUT (Deriving Atmosphere Turbulent Transport Useful To Dummies Using Temperature) (Timmermans et al., 2015) fluxes are estimated by relating single pixel temperatures to local temperature extremes. Two-source energy balance models such as TSEB (Two-Source Energy Balance) (Norman et al., 1995) and DTD (Dual Temperature Difference) (Norman et al., 2000) divide measured LSTs into a vegetation and a soil fraction. Several adaptions of these models were developed; the TSEB-PT model as described in Hoffmann et al. (2016), uses the Priestley-Taylor coefficient (PT) to determine canopy H flux and subsequently calculate the other fractions from the surface energy balance. TSEB-PT is based on the temperature difference between LST and air temperature (Norman et al., 1995). Expanding this concept, DTD uses a dual-temperature difference from an additional early morning set of measurements to account for biases in remotely sensed LSTs (Hoffmann et al., 2016; Norman et al., 2000). Crucial in applying such energy balance models is how the net radiation (Rn) is implemented. In the original formulation of the DATTUTDUT model Rn is fully modeled, assuming a range of prerequisites and environmental conditions (Timmermans et al., 2015). TSEB-PT and DTD models use measured short and long-wave radiation to estimate Rn as a sum of in- and outgoing long- and short-wave radiation (Norman et al., 1995, 2000). Using airplanes or drones to record LSTs, the three models previously showed promising results for grass and crop surfaces in temperate and subtropical regions (Brenner et al., 2017, 2018; Hoffmann et al., 2016; Xia et al., 2016). However, to our knowledge, a comprehensive method comparison considering potential errors in both a reference method (e.g. the EC technique) and novel drone-based approaches is not yet available. Since full method comparisons based on model II regression require a sample size of at least n=60 data pairs (Legendre and Legendre, 2003), many previous studies with smaller sample sizes were constrained to using error terms and correlation coefficients.

The current study was conducted in the lowlands of Jambi province (Sumatra, Indonesia) where over the last decades, large areas of rainforest have been converted to rubber and oil palm plantations (Clough et al., 2016; Margono et al., 2012). This resulted in regional-scale changes in transpiration (Röll et al., 2019) and land surface warming (Sabajo et al., 2017). We assessed energy fluxes in a mature monoculture oil palm plantation and compared the LE estimates of drone-based methods with the established EC method as measured ground-based reference. Three energy-balance models (DATTUTDUT, TSEB-PT, DTD) were tested, each with three different configurations for the determination of Rn (fully modeling Rn, Rn estimates based on short-wave irradiance and measuring Rn). The objectives of our study were to compare LE estimates from the drone-based methods to the EC technique, with a special focus on the detection of proportional and continuous errors among the methods and an evaluation of the model's prediction performance. The present study focuses on the comparison of different drone-based methods as a baseline for future ecological studies, rather than applying the methods to different land-use types.

2 Methods

2.1 Study site

The study site is located in the lowlands of Jambi province (Sumatra, Indonesia) near the equator (E 103.3914411, N -1.6929879, 76 m a.s.l.). Average annual air temperature in the region is 26.5°C and average annual precipitation is 2235 mm yr^{-1} (Drescher et al., 2016). At the time of our measurement campaign in August 2017, the studied monoculture oil palm (*Elaeis guineensis*) plantation was 15 years old. Palm stem density was 140 palms ha^{-1}, with an average palm height of 14.3 m and an average canopy radius of 4.5 m. Leaf area index (LAI) was estimated at 3.64 m^2 m^{-2} (Fan et al., 2015) and canopy cover was estimated to be 90%. Plantation management included the removal of older and non-vital leaves from the oil palms, herbicide application to remove most understory plants and fertilization (196 kg N ha^{-1} yr^{-1}) (Meijide et al., 2017). The average annual oil palm yield is 27.7 Mg ha^{-1}. An EC tower (22 m height) is situated in the center of the site with a fetch of up to 500 m in each direction (Meijide et al., 2017) (Fig. 1).

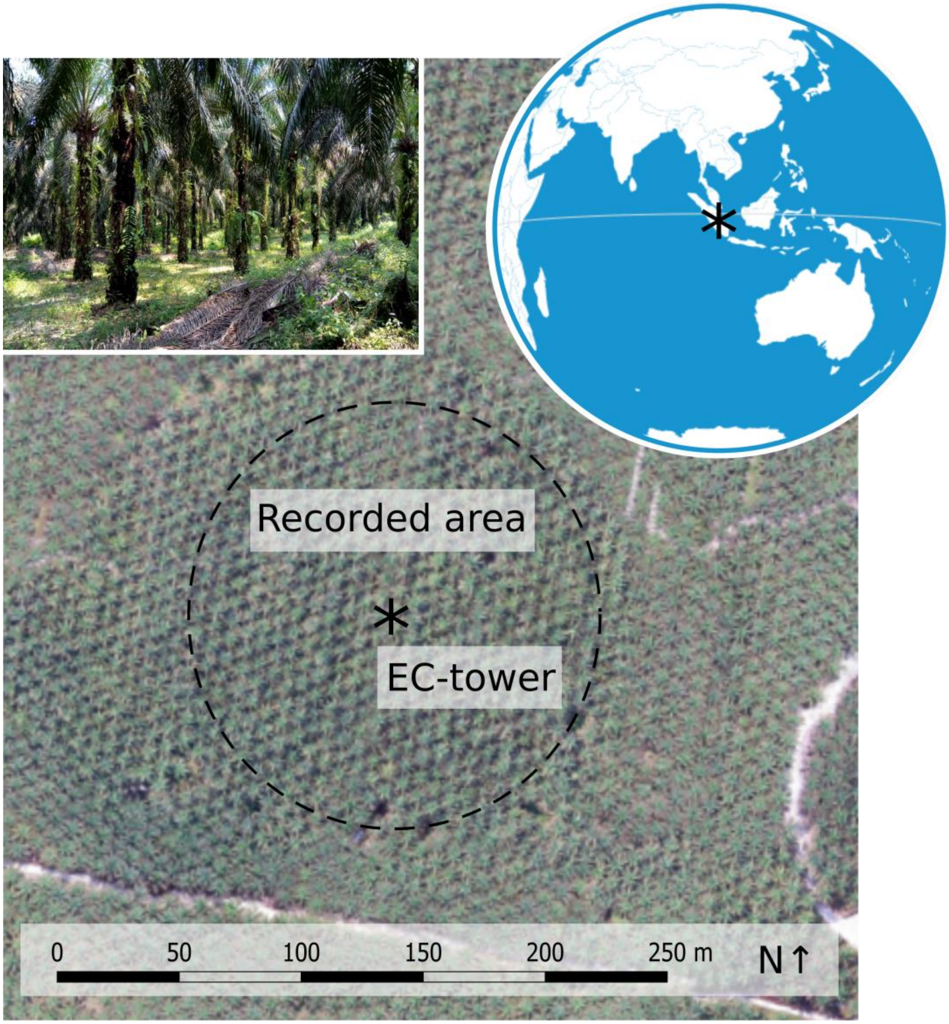

Figure 1: The study site in a mature commercial oil palm plantation in the lowlands of Jambi province, Sumatra, Indonesia.

2.2 Drone-based image acquisition

We used an octocopter drone (MK EASY Okto V3; HiSystems, Germany) equipped with a thermal and an RGB camera mounted in a stereo setup on a gimbal to ensure nadir perspective. The radiometric thermal camera was a FLIR Tau 2 640 (FLIR Systems, USA) attached to a TeAx Thermo-capture module (TeAx Technology, Germany). The sensor covers spectral bands ranging from 7.5 to 13.5 µm with a relative thermal accuracy of 0.04 K and an absolute thermal accuracy of ± 2 K (FLIRSystems, USA). The RGB camera was based on an Omnivision OV12890 CMOS-Sensor (Omnivision, USA) with a 170° FOV fish-eye lens. Instead of the mosaicking approaches applied in most of the mentioned previous studies, we used a single image recording concept as faster image acquisition allows for a denser temporal resolution of LSTs. To capture an area of 100 m radius around the EC tower in a single shot of the thermal camera, images were taken from 260 m altitude. Image corners were removed due to vignetting effects. During a consecutive five-day flight campaign in August 2017, 61 LST data sets and matching EC measurements were recorded. Flights were conducted between 9 am and 4 pm local time, in accordance with the 30 min intervals of the EC averaging cycles, resulting in 10 to 14 flights per day. All LSTs were measured using a fixed emissivity of one as the energy balance models would introduce specific soil and vegetation emissivities in the process.

2.3 Energy balance models

LSTs are recorded as ’snapshots’ representing an instantaneous state of surface temperatures. Soil-Vegetation-Atmosphere Transfer (SVAT) models use these instantaneous observations of LST to solve the energy balance equation and estimate instantaneous fluxes. In our study the one-source energy balance model DATTUTDUT (Timmermans et al., 2015) and two two-source energy balance models, TSEB-PT (Norman et al., 1995) and DTD (Norman et al., 2000), were applied. For the TSEB-PT and DTD model directional radiometric temperatures are used and no further calculation of aerodynamic temperature by using an excess resistance term is needed (Hoffmann et al., 2016). Using drones, the proximity of the thermal camera to the surface is much closer compared to other typical carriers (such as satellites or planes) and hence atmospheric effects are supposed to have only a very minor effect. To use a uniform input for all the applied models, we used directional radiometric temperature recordings from the drone as input without applying further corrections. All models in this study use instantaneous land surface temperatures (LST) to solve the energy balance equation:

$$R_n = G + H + LE \qquad \text{(eq. 1)}$$

Where R_n is the net radiation, G is the ground heat flux and the turbulent fluxes H and LE represent sensible and latent heat flux, respectively. R_n is estimated by calculating the budget of incoming (↓) and outgoing (↑) long- (l) and short-wave (s) radiation:

$$R_n = R_s{\downarrow} + R_s{\uparrow} + R_l{\downarrow} + R_l{\uparrow} = (1 - \alpha) * R_s{\downarrow} + \varepsilon_{surf} * \varepsilon_{atm} * \sigma * T_{air}^4 - \varepsilon_{surf} * \sigma * T(\theta)_{surf}^4 \qquad \text{(eq. 2)}$$

Where the short-wave component is calculated by multiplying incoming short-wave radiation $R_s{\downarrow}$[W m^{-2}] with its absorption ratio deducted from the combined soil and vegetation albedo α. The long-wave radiation budget is calculated from surface (soil and vegetation) emissivity ε_{surf} and atmospheric emissivity ε_{atm}, the Stefan-Boltzmann constant σ ($5.6704*10^{-8}$ W $m^{-2}*K^{-4}$), air temperature T_{air} and radiometric land surface temperature $T(\theta)_{surf}$ (both in K).

2.3.3 DATTUTDUT

Key input for the DATTUTDUT model is a LST map from where the hottest and the 0.5% quantile of coldest pixels are extracted, assuming that hot pixels are a result of very little to no evapotranspiration and cold pixels origin in a high evapotranspiration rate (Timmermans et al., 2015). Fully modeled Rn is calculated based on down-welling short-wave radiation estimates calculated using sun-earth geometry to solve eq. 2. Surface albedo P_0 is calculated as in Timmermans et al. (2015) based on the assumption that dense vegetation appears colder than rocks or soil in the thermal imagery (Brutsaert, 1982; Garratt, 1992):

$$P_0 = 0.05 + ((T_0 - T_{min}) / (T_{max} - T_{min})) * 0.2 \qquad \text{(eq. 3)}$$

Down-welling shortwave radiation $R_s\downarrow$ is calculated from the dimensionless atmospheric transmissivity τ and the exo-atmospheric shortwave radiation SW_{exo}= 1360 W m^{-2} (Timmermans et al., 2015). Transmissivity τ is calculated as described in Burridge and Gadd, A.J. (1977) using the solar elevation angle α that was determined from the geographic position of our site and the coordinated universal time (UTC) of the measurements:

$$\tau = 0.6 + 0.2 * \sin(\alpha) \qquad \text{(eq.4)}$$

$$R_s\downarrow = \tau * SW_{exo} \qquad \text{(eq. 5)}$$

Timmermans et al. (2015) suggest using a constant value of 0.7 for τ and 0.8 atmospheric emissivity (ε_{atm}), but as our flight times range from 09:00 to 16:30h local time we decided to include the solar elevation angle as in eq. 4. Further, we used a constant surface emissivity (ε_{surf}) of 0.98 as recommended for vegetation dominated areas (Jones and Vaughan, 2010) and not 1.0 as simplified in the original formulation of the DATTUTDUT model. Air temperature T_{air} was calculated as the 0.5% quantile of the coldest pixels in the image.

As the original DATTUTDUT formulation doesn't account for cloud cover, eq.5 is replaced by measured short-wave irradiance as in Brenner et al. (2018) for model runs with Rn_sw. For model runs with Rn_mes eq. 2 was replaced by R_n measurements recorded at the EC-tower.

The sum of the turbulent fluxes is calculated by subtracting G from R_n. The result is fractioned into its components H and LE, using the evaporative fraction (EF) (Timmermans et al., 2015):

$$EF = LE / (LE+H) = LE / (Rn - G) = (T_{max} - T(\theta)_{surf}) / (T_{max} - T_{min}) \quad \text{(eq. 6)}$$

For our implementation of the DATTUTDUT model we used the QGIS3 plugin QWaterModel (Ellsäßer et al., 2020) that is provided with an easy-to-use graphical user interface.

TSEB-PT

TSEB-PT calculates surface-energy budgets from the recorded LSTs splitting observations into a canopy and a soil fraction (Norman et al., 1995; Song et al., 2016; Xia et al., 2016). The model consists of two parts: First an initialization part where all parameters that do not depend on soil and canopy temperature partition and knowledge of atmospheric stability are computed. Afterwards an iterative part where the Monin-Obukhov length is stabilized and the fluxes are finally derived. To begin this process vegetation cover $f_c(\theta)$ is computed as in (Campbell and Norman, 1998):

$$f_c(\theta) = 1 - \exp((-0.5\Omega(\theta) * LAI) / (\cos(\theta))) \quad \text{(eq. 7)}$$

where LAI is leaf area index, θ is the sun zenith angle and **Ω** is a nadir view clumping factor to represent the cross-row structure in which the oil palm is planted (Kustas and Norman, 1999). Guzinski et al. (2014) suggest a maximum limit of 0.95 for $f_c(\theta)$, so that a small fraction of the soil is still visible and extreme magnitudes for soil temperature are avoided. Roughness parameters are calculated from vegetation height. T_{air} was measured at the EC-tower, $T(\theta)_{surf}$ was recorded with the drone both similar to descriptions in (Hoffmann et al., 2016). For the two-source energy balance models we used a canopy emissivity of 0.98 and soil emissivity of 0.95. The emissivity values are based on averages for the 8-14 µm spectrum taken from Jones and Vaughan, (2010). The TSEB-PT model requires additional in situ meteorological measurements of long- and short-wave radiation, wind speed, barometric pressure and relative humidity, which in our case were recorded at the EC tower. Further, measured data on LAI as well as surface and canopy albedo are required. The three resistances in the soil-canopy-atmosphere heat flux network, the aerodynamic resistance to heat transport (RA), the resistance to heat transport from the soil surface (RS) and the total boundary layer resistance of the leaf canopy (RX) are calculated as in (Norman et al., 1995, 2000). Net radiation and the three resistances remain constant during the model runs. After finishing the computation of all constant parameters, the iterative part of the model starts assuming Monin-Obukhov length tends to infinity. In the first iteration R_n is partitioned into a soil and canopy fraction by calculating net radiation divergence ΔR_n (Hoffmann et al., 2016; Norman et al., 2000):

$$\Delta R_n = R_n * (1-\exp((-K*LAI*\Omega 0) / \sqrt{(2\cos(\theta_s))})) \quad \text{(eq. 8)}$$

where K is an extinction coefficient that varies according to LAI (Hoffmann et al., 2016). We are aware of the fact, that the determination of K using LAI is disputed as other studies found no significant correlation of K and LAI (Zhang et al., 2014). With ΔR_n known, sensible heat flux is then estimated using the Priestley-Taylor approximation following the approach by Hoffmann et al., (2016):

$$H_c = \Delta R_n * (1-\alpha_{PT} * f_G * (D/(D+\gamma))) \qquad \text{(eq. 9)}$$

α_{PT} is the Priestley-Taylor coefficient and both γ the psychrometric constant and the slope of the saturation pressure curve D were calculated as in (Allen et al., 1998). Canopy temperature T_C was computed by summing up the results of the linear approximation in equation (A7) for $T_{C,lin}$ and ΔT_C from equation (A11) both from (Norman et al., 1995). Knowing canopy temperature T_C and the fraction of view covered by vegetation f_θ as in (Hoffmann et al., 2016), soil temperature T_S can be calculated:

$$T_s = (T(\theta)_R^4 - f_\theta * T_C^4) / (1-f_\theta)^{(1/4)} \qquad \text{(eq. 10)}$$

With soil and canopy temperatures and the resistances of the soil-canopy-atmosphere heat flux network known, fluxes can be calculated with equations (9), (10), (11) and (13) from Hoffmann et al. (2016). Total latent and sensible heat fluxes are calculated as the sums of canopy and soil fluxes. In the following iterations, a recalculation of Monin-Obukhov length takes place until a stable value is reached and the resulting fluxes are derived. For the model runs with Rn_mod and Rn_mes the model net radiation is forced accordingly.

DTD

The Dual-Temperature-Difference (DTD) model works very similar to TSEB-PT and differs mainly in the way how sensible heat flux is calculated (Hoffmann et al., 2016). In the DTD model, the absolute temperatures of land surface and air (as used in the TSEB-PT) are supplemented with a second set of early morning reference measurements of LST and air temperature, thus creating a dual-temperature difference (Norman et al., 2000). The first observation is recorded in the early morning hours and the second observation is recorded later on the same day at any given time. We used two IRTs attached to the EC tower (see EC methodology Sect. 2.4 for details and Sect. 2.7 for the limitations) for the necessary early morning reference readings of absolute temperature and used the averaged LSTs to create a uniform map as input for the DTD model (similar as e.g. in Hoffmann et al. 2016). This relates measurements at any time during the day to measurements recorded in the morning, when fluxes are assumed to be minimal, and thereby accounts for measurement biases of LST (Anderson, 1997; Hoffmann et al., 2016). H flux is then calculated using the time-differential temperature and a series resistance network as it is recommended for densely vegetated regions to consider interaction of soil and canopy fluxes (Guzinski et al., 2014; Li et al., 2005).

The actual amount of evapotranspirated water (ET_w) in mm $h^{-1}$was calculated as in (Timmermans et al., 2015):

$$ET_w = ((LE*t)/1000000)/(2.501-0.002361*(T_{air}-273.15)) \qquad \text{(eq.11)}$$

Where LE is the latent heat flux in W m^{-2}, t is the respective timespan in seconds and T_{air} is the air temperature in Kelvin.

2.4 Eddy covariance measurements

The micrometeorological tower is located in the center of the study site (Fig. 1). The EC technique was used to measure LE and H fluxes from high frequency (10 Hz) measurements of above-canopy water vapor concentration, sonic temperature, and 3-D wind components. The flux system consisted of a sonic anemometer (Metek uSonic-3 Scientific, Elmshorn, Germany) and a fast response open-path CO_2/H_2O infrared gas analyzer (Li-Cor7500A, LI-COR Inc. Lincoln, USA) installed at 22 m height. Meteorological variables were measured every 10 sec, averaged to 10 min means and stored on a DL16 Pro data logger (Thies Clima, Göttingen, Germany). R_n and its components were measured with a net radiometer (CNR4, Kipp & Zonen, Delft, The Netherlands) at 22 m height. Air temperature and relative humidity were measured with thermohygrometers (type 1.1025.55.000, Thies Clima, Göttingen, Germany) at 16.3 m height. Further, a wind direction sensor (Thies Clima, Göttingen, Germany) (22 m height) and 3-cup anemometers (Thies Clima, Göttingen, Germany) (18.5, 15.4, 13, and 2.3 m height) for wind speed measurements were installed on the tower. The two IRTs used in our study (IR100 Radiometer, Campbell Scientific Inc., Logan, USA) have a field-of-view (FOV) of 8-10°. Considering the distance from their fixed location on the tower to the average height of the oil palm canopy, they cover a circular area of 2.2 m^2, over which they average the received thermal signal. The recorded canopy area comprises different functional parts of the canopy (e.g. leaflets, petioles). On average, we assumed a surface emissivity of 0.98 for the canopy area (Jones and Vaughan, 2010). We did not correct the values recorded with the IRTs for any other influences since the distance from the canopy surface to the sensors was only about 10 m. Ground heat flux was measured using heat flux plates (HFP01, Huxeflux, Delft, The Netherlands) at 10 cm depth. Additional soil moisture and temperature measurements (Trime-Pico 32, Imko, Ettlingen, Germany) above the heat flux plate at 5 cm depth were used to calculate heat flux at the soil surface. EC data recording, filtering and processing were carried out identical to the methodology described in Meijide et al. (2017) for the same study site. As the applied drone-based models all assume full energy balance closure, we used the Bowen ratio closure method (Pan et al., 2017; Twine et al., 2000) to compute full closure for the EC measurements. The Bowen ratio method was found to produce the most congruent results in conjunction with drone-based latent heat flux estimates (Brenner et al., 2017) and was therefore applied in this study. The energy balance closure (EBC) of the reference EC measurements was 0.77 (r^2=

0.87), which is in line with EBC reported for other tall vegetation canopies (Stoy et al., 2013). Since the used energy balance models assume full EBC, we applied the so-called Bowen ratio closure method to the EC data (Pan et al., 2017). The method assumes that wind measurements miss some of the total covariance and dispersive fluxes. Therefore, underestimations of LE and H are carried over proportionally because of similarity among fluxes (Twine et al., 2000). The Bowen ratio closure method proportionally assigns the underestimated turbulent energy to LE and H fluxes to reach full EBC.

EC data processing and quality checks were performed following the methodology described in (Meijide et al., 2017). Following (Mauder and Foken, 2006), flux estimates during low turbulence and thus stable atmospheric conditions were removed from the analysis; however, low turbulence mainly occurred during night hours and was not observed during the daytime drone flights. Generally, the EC method is associated with uncertainties of 5 - 20% (Foken, 2008). Further limitations are the high costs and quite specific requirements regarding size and terrain of the study site.

2.6 Statistical analyses

Both methods, the reference EC technique and the drone-based estimates, are associated with a certain degree of uncertainty. To account for the uncertainty in both, a model II Deming regression (Deming, 1964) was applied for the analysis to consider uncertainties in both x and y variables (Cornbleet and Gochman, 1979; Glaister, 2001). We assumed that the error ratio ($\sigma\varepsilon^2/\sigma\delta^2$) of the variances ($\sigma$) of errors on y ($\varepsilon_i$) and on x ($\delta_i$) would not differ from 1 which is the standard procedure if both uncertainties are unknown (Legendre and Legendre, 2003). We used the interquartile range method with a factor k=1.5 to remove outliers from the regression. A Durbin-Watson test was applied to test for correlation in error terms. We checked for heteroscedasticity visually and using a White test. Normal distribution of error terms was tested visually plotting standardized residuals vs. theoretical quantities and performing a Shapiro-Wilk test. Standard errors and confidence intervals for slope and intercept of the Deming regression were calculated using analytical methods (parametric) and the jackknife method (Armitage et al., 2001; Linnet, 1993). As further supporting indicators of model performance, we calculated the coefficients of determination (r^2), the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and slope and intercept from the Deming regression. Statistics such as r^2 have their limitations in method comparison since they are designed to indicate how well the resulting model of the regression describes the outcome and are not necessarily a good measure for systematic bias between methods. However, they are used as a statistic in this study since they represent an additional indicator for interpretation. Linearity was checked visually plotting residuals vs. fitted values.

All modeling procedures and parts of the statistical analyses were computed using Python version 3.7.1 (Python Software Foundation), involving the libraries NumPy 1.14.2, SciPy 1.1.0, pandas 0.23.1, scikit-learn 0.19.1, gdal 2.3.2, Astropy 3.2.2 and tkinter 8.6. The Deming regression was computed using the MethComp and mcr v2.2.1 package (Manuilova et al., 2014) in R version 3.6.1 (R Development Core

Team, 2019). Graphic representation was processed in Python using the Matplotlib 3.0.2 and Seaborn 0.9.0 libraries.

2.7 Dataset characteristics

The dataset offers a comparatively high number of replicates from 61 drone recording flights and the corresponding eddy covariance measurements enabling a method comparison which requires at least n=60 observations (Legendre and Legendre, 2003). The data was recorded in a 30 min frequency, to facilitate the analysis of daily courses of evapotranspiration behavior creating a trade-off situation of more flights per day with shorter flight times per flight. Because flight times were so short, only a smaller footprint with a radius of 100 m around the eddy covariance station was covered, while the footprint recorded with the eddy covariance system ranged up to a 500 m radius around the tower. Therefore, the reduced area of the drone recorded LST maps is often smaller than the extent of the eddy covariance footprint. We have several reasons to assume that this doesn't cause major problems for the comparison though: the study area is very homogenous with an elevation difference of 5 m in the eddy covariance footprint and the biosphere is strongly dominated by only one species (oil palm). The plantation is very well managed, so that all oil palm canopies are alive, no oil palms have died and only dry leaves are removed. A further limitation of the dataset is the lack of morning or night LST measurements that could not be recorded with the drone due to security concerns and limited access to the plantation at night. This doesn't affect the procedure of the DATTUTDUT and TSEB-PT model, but morning measurements are an important factor for the DTD model. We were able to record night and morning measurements with two stationary infrared thermometers (IRTs) that were attached to the tower. As for the DTD model, morning and later recordings should ideally be recorded with the same camera. To check whether the two IRTs measure similar temperatures compared to drone recorded LSTs, we extracted a total of 122 'IRT-sized' (i.e.~2.2 m2) LST footprints from the drone-recorded maps. A correlation of both temperature measurements revealed a small deviation of the measured temperatures resulting in a mean absolute error (MAE) and root mean squared error (RMSE) of 1.59 and 2.15 K respectively. Since LST measurements are subject to a certain degree of uncertainty and thermal cameras usually have a measurement error of up to ±1°C (Aubrecht et al., 2016) we decided to use the morning measurements from the tower IRTs as input for the morning temperature reference. The implementation of the DTD model is therefore strictly experimental and has to be interpreted with the uncertainties of the morning measurements in mind.

3 Results

3.1 Meteorology

During our 61 flight missions, cloudiness was variable from clear sky to full cloud cover; short-wave irradiance ranged from 204 to 1110 W m^{-2}. The prevailing wind direction was from north-east, at an average wind speed of 1.7 m s^{-1}. Canopy air temperature ranged from 22.5 to 32.3°C and relative humidity varied between 62 and 99%. Temperature differences between measured air temperature at 16.3m (top of canopy) and mean land surface temperatures ranged from 0.005K to a single peak of 8.689K for the single flights while the daily averaged differences ranged from 1.32K to 2.13K. The energy balance closure of the reference EC measurements was 0.77 ($r^2 = 0.87$).

3.2 Drone-based modeling methods vs. eddy covariance method

At the time of the drone flights, LE from the EC method ranged between 87 and 596 W m^{-2} (mean: 337 W m^{-2}) and eddy covariance-derived evapotranspiration was on average, 0.43 ± 0.21 mm h^{-1}, with peak evapotranspiration of up to 0.87 mm h^{-1} during midday. Congruence of LE estimates with reference EC measurements differed among the three applied models and was further affected by the configuration of the R_n assessment (Fig. 2). The assumptions for Rn_mod were not always met as cloud cover was present during several flights; consequently, the corresponding net radiation estimates were too high, leading to a substantial overestimation especially of smaller latent heat fluxes. The short-wave irradiance based Rn_sw configuration resulted in R_n estimates that were by average very comparable with the measured net radiation Rn_mes but also showed a rather high variation (Fig. 2). Generally, error metrics were reduced and agreement was increased the more measurement-controlled the R_n determination process was.

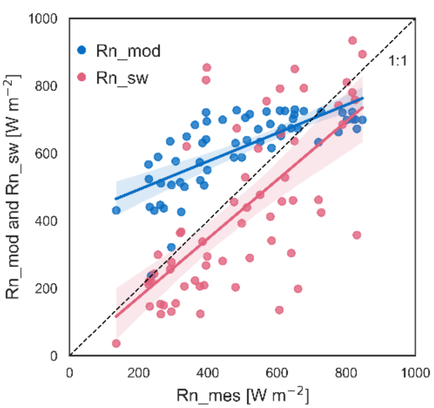

Figure 2: Measured net radiation (Rn_mes) plotted against fully modeled net radiation (Rn_mod) and net radiation estimates based on short-short wave irradiance (Rn_sw).

DATTUTDUT LE estimates closely agreed with EC measurements around noon, but were higher in the morning and afternoon hours, which is caused by overestimations of R_n from the Rn_mod method (Fig. 3a). LE estimates from TSEB-PT were consistently higher than EC measurements, with particularly large divergences around noon (Fig. 3a). The LE predictions from the DTD model in Rn_mod configuration were rather overestimated, especially around noon when compared with the EC reference measurements (Fig. 3a). Models with Rn_sw configuration produced LE estimates that matched LE from EC more closely (Fig. 3b). DATTUTDUT computed similar or higher estimates of LE compared to the EC measurements during noon but mostly underestimated LE fluxes in the morning and afternoon, while TSEB-PT produced more congruent LE estimates for the morning and afternoon hours but also overestimated LE fluxes especially during noon (Fig. 3b). The DTD model showed a very similar pattern with overestimations of LE fluxes around noon and more accurate estimates for morning and afternoon hours (Fig. 3b). Both two-source energy balance models with Rn_sw configuration yielded comparably accurate estimates during the morning and afternoon hours. With Rn_mes configuration, DATTUTDUT computed closely matching LE estimates at all times of day across the five-day measurement period, while TSEB-PT and DTD consistently produced much higher estimates than EC around noon but otherwise calculating mostly accurate results (Fig. 3c).

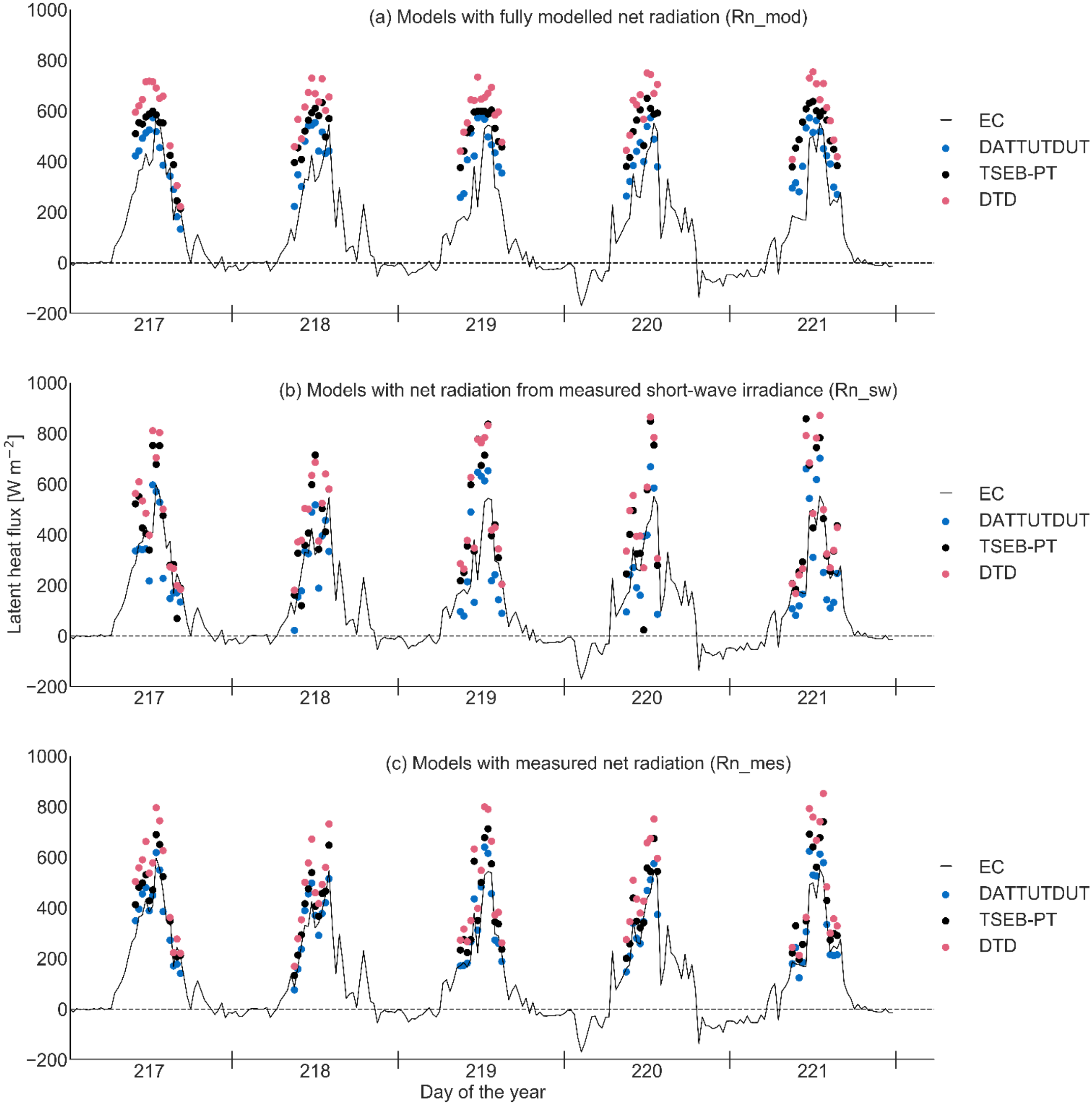

Figure 3: Latent heat flux (LE) from energy balance models (DATTUTDUT, TSEB-PT, DTD) and three different configurations of net radiation (R_n) determination (Rn_mod, Rn_sw, Rn_mod) and eddy covariance measurements (EC) over five consecutive days (n = 61 flight missions).

Across all daytimes and weather conditions (n=61 flight missions), congruence among drone-based LE estimates and reference EC measurements was highest for the DATTUTDUT model with Rn_mes configuration (r^2=0.85); MAE and RMSE were 47 and 60 W m^{-2}, respectively (Fig. 4). To compare the model predictions and the eddy covariance measurements, we computed a Deming regression between both LE predictions from the models and LE estimates by the EC method. The methods are considered to be statistically interchangeable if the confidence intervals of the slope and intercept include one and zero respectively. If the confidence intervals for the intercept of the Deming regression include zero, there is no constant or continuous error between the two methods. If the confidence intervals for the intercept do not include zero, both methods differ by a constant amount, i.e. the new method has a continuous error compared to the reference method. In contrast, the confidence intervals of the slope of the Deming regression indicate whether there is a proportional error between the methods, which increases proportionally with the magnitude of the predicted value. Deming regression of the LE estimates of the DATTUTDUT model with Rn_mes configuration showed no significant proportional or constant error compared to EC measurements as the values one and zero lay within the respective 99% confidence interval ranges of slope and intercept (Fig. 5). It is thus indicated that there is no significant difference between LE estimates from DATTUTDUT with Rn_mes configuration and the EC technique. The TSEB-PT model in Rn_mes configuration also showed no significant continuous errors but was subject to a minor proportional bias (Fig. 5c). The TSEB-PT model overestimated LE particularly around noon, when fluxes are very high (Fig. 3c and 4c). The DTD model also showed no continuous bias but indicated a proportional error in the analytical method and the Jackknife method (Fig. 5c). In the Rn_sw configuration, only the DATTUTDUT model showed no significant proportional and continuous error of LE estimates compared to EC measurements (Fig. 5b). TSEB-PT and DTD model estimates showed no significant constant deviation from the EC measurements but were subject to a proportional error (Fig. 4b and 5b). However, all confidence intervals for models with the Rn_sw configuration were rather wide indicating a large level of uncertainty. All models in the Rn_mod configuration showed significant proportional and constant errors or large biases compared to EC measurements, as well as very large confidence intervals Fig. 4a and 5a).

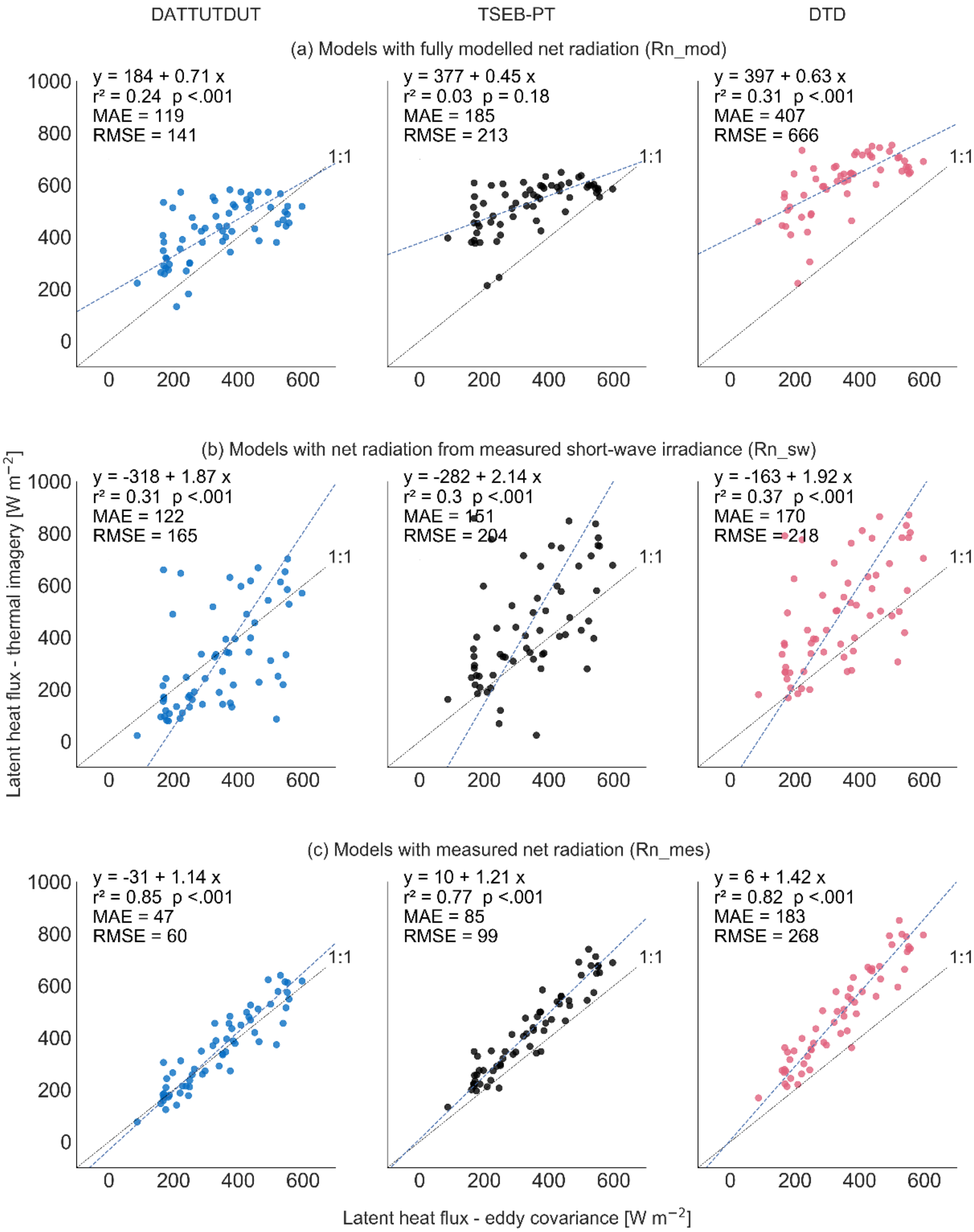

Figure 4: Model II Deming regression of latent heat flux estimates from drone-based energy balance models (DATTUTDUT, TSEB-PT, DTD) and different configurations of net radiation (Rn_mod, Rn_sw, Rn_mes) with the eddy covariance method (n = 61 flight missions).

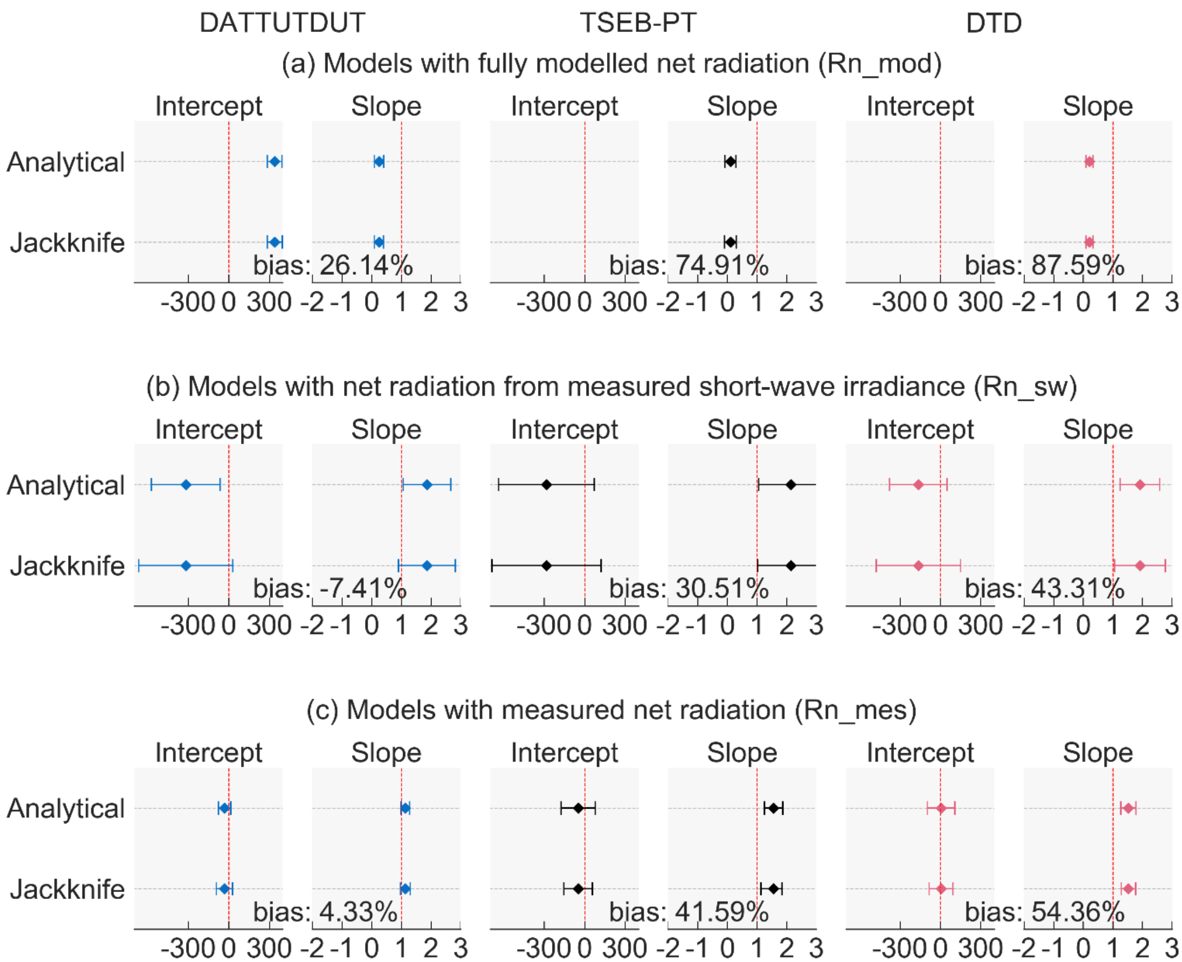

Figure 5: Confidence intervals for intercept and slope of Deming regression for the different LE estimation approaches compared with EC measurements. X-level for the bias is the mean of the established EC reference method. The intercept is displayed in W m^{-2}.

3.3 Spatial distribution of LE

For 9th of August 2017, 12.30 h, the DATTUDUT in Rn_mes configuration suggested a mean of 526 W m $^{-2}$ (minimum of 0 on the corrugated iron roof of the EC tower system, maximum of 637 W m $^{-2}$, coefficient of variation 7.53 %, for the analyzed 18,383 pixels) (Fig. 6), which translates to a mean ET of 0.778 mm m^{-2} h^{-1}. Locally, i.e. in the center of oil palm crowns, high LE of > 400 W m $^{-2}$ was observed, while LE from soil and ground vegetation areas between oil palm canopies was lower. The LE fluxes of all pixels were almost normally distributed for the one-source energy balance model DATTUDUT (Fig. 7), whereas the distribution of the two-source energy balance model TSEB-PT (for the same LST dataset) was more skewed, with more LE observations at the upper end of the range. The spatial LE estimates from the DTD model resulted in a similar distribution than from the TSEB-PT model (Fig. 7). Both distributions of the two-source energy balance models show gaps in the histogram, while the histogram of the DATTUTDUT model displays a more continuous distribution (Fig. 7)

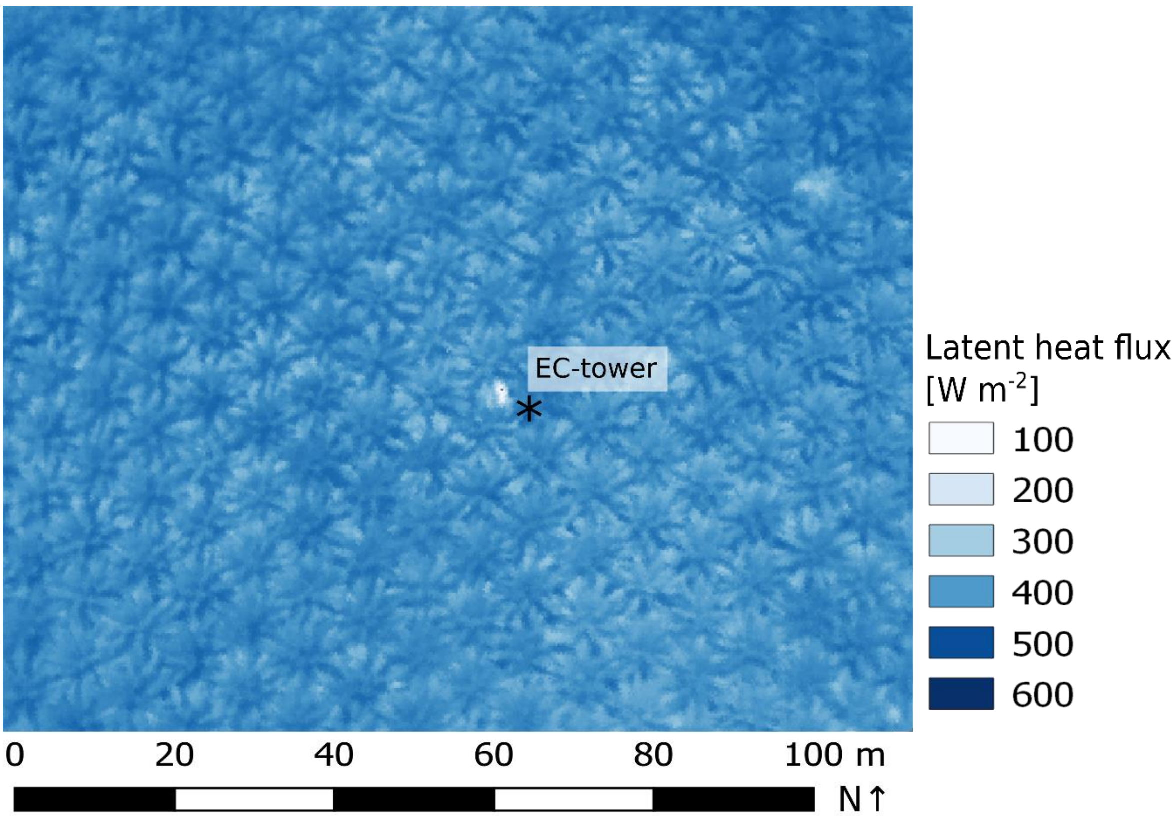

Figure 6: Spatial distribution of latent heat flux from drone-based thermography and subsequent energy balance modeling (DATTUTDUT with Rn_mes configuration, 9 August 2017, 12.30 h).

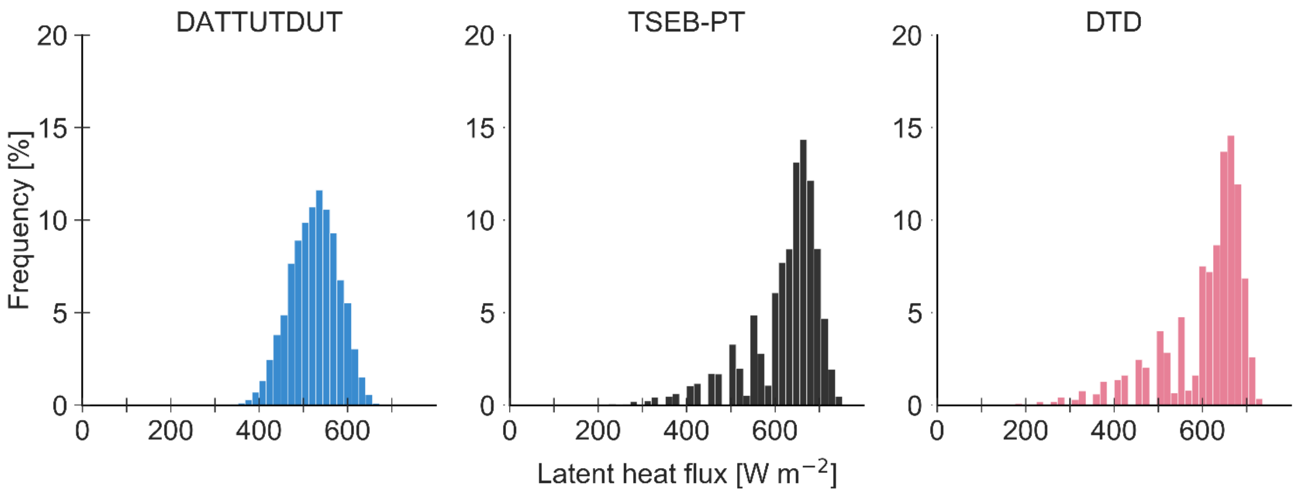

Figure 7: Frequency distribution of latent heat flux for the model output images from the same thermal image as shown in Fig. 5 (9 August 2017, 12.30 h). Absolute histogram bin size was set to 16 W m^{-2}, we used 50 bins from 0 to 800 W m^{-2}.

4 Discussion

Our study indicates a high agreement between latent heat fluxes assessed by drone-based thermography and the eddy covariance technique. However, the performance of the three applied energy balance models differed among each other and among different configurations of net radiation assessments in the models (Fig. 3 and 4). Model II Deming regression analyses and associated quality assessments suggest interchangeability between the DATTUTDUT model in Rn_mes configuration and the EC technique (Fig. 4 and 5). Applying this configuration, a fine grain spatial analysis of latent heat fluxes suggests relatively low heterogeneity of LE in the studied tropical oil palm plantation (Fig. 6).

4.1 Drone-based LE modeling vs. eddy covariance measurements

The confidence intervals of slope and intercept of the Deming regression indicate that the one-source energy balance model DATTUTDUT with Rn_mes configuration is statistically interchangeable with the established EC method for estimating LE fluxes. There are advantages and limitations to both methods. For example, the DATTUTDUT model provides insights on the spatial distribution of LE fluxes within the full extent of the available LST maps, whereas the EC technique averages the LE fluxes within its footprint to a single value. On the other hand, the DATTUTDUT model is temporally limited to the availability of LST maps, whereas the EC method can measure fluxes continuously over several years once the equipment is in place. The DATTUTDUT model with Rn_mes configuration further requires additional measurements of short- and long-wave radiation. In our study, these measurements were taken with the EC equipment, but future stand-alone drone approaches are possible by using on-board miniaturized radiation sensors (Castro Aguilar et al., 2015; Suomalainen et al., 2018). However, the accuracy of such on-board radiation sensors should first be tested against reference methods, e.g. visually by scatter or inter-comparison plots (Castro Aguilar et al., 2015; Suomalainen et al., 2018) or with a model II regression procedure evaluating the interchangeability of methods and measurements (Passing and Bablok, 1983). The two-source energy balance models TSEB-PT and DTD in the Rn_mes configuration showed a very similar behavior. Both were found to have no continuous error when compared to the reference EC method. However, a small bias towards the overestimation of relatively high fluxes around noon was observed, which might be removed by improving the balance of e.g. vegetation parameters for oil palm.

All models with the Rn_sw configuration showed a significant proportional error compared to EC measurements, which was mainly rooted in the high variance of the Rn_sw configuration. The short-wave irradiance measurements used in this study were stored as 10 min averages that probably didn't represent the high level of irradiance variations in the tropical study area adequately. Previous studies have pointed out that Rn derivation based on short-wave irradiance measurements is challenging as long-wave radiation budgets are often completely independent from their short-wave counterparts (Hoffmann et al. 2016). Estimation errors in long-wave radiation budgets have e.g. been reported to be related to high relative air humidity, when some of the original model assumptions are no longer met (Hoffmann et al., 2016). We observed a negative correlation ($r^2 = 0.46$) between incoming long-wave irradiance and relative humidity and assume that the high relative humidity in our tropical study area may have affected the determination of Rn when using the Rn_sw configuration through inaccuracies in estimating long-wave radiation budgets, therefore causing the observed significant continuous errors. Since we recorded the data during very different daytimes and weather situations, the short-wave irradiance based approach might not be the most adequate mean of Rn derivation. However, this approach can be very useful for measurements without the presence of clouds or high levels of relative humidity. We thus also consider the Rn_sw configuration valuable for future research, particularly because measurements of incoming short-wave radiation are much easier to implement than assessing complete short- and long-wave radiation budgets as necessary for the Rn_mes configuration. The application of the Rn_sw configuration for a one-source energy balance model such as DATTUTDUT was also tested in two previous studies, with similar results to our study, i.e. a reduction of errors compared to its original formulation with fully modeled Rn_mod (Brenner et al., 2018; Xia et al., 2016).

Lastly, the model configuration Rn_mod did not produce accurate LE estimates for all three models, as many of the basic assumptions for fully modelled Rn determination are not met in tropical environments such as our equatorial study area. As such, the sky is often cloudy, while haze frequently occurs during periods without rainfall. Even if no clouds are visible, relative humidity is often high, which interferes with the clear-sky assumptions of the Rn_mod configuration (Still et al., 2019). Among the three models applied in our study, the relatively simple DATTUTDUT model produced the most precise LE estimates compared to eddy covariance reference measurements. Similar conclusions were reached by Brenner et al. (2018), where DATTUTDUT marginally outperformed the more complex TSEB-PT model. On the other hand, contrasting observations were made by Xia et al. (2016) in vineyards with more extreme temperature divergences between soil and vegetation, where the TSEB-PT model produced more precise estimates of LE than the DATTUTDUT model. This was explained by the better physical representation of energy and radiative exchange in the TSEB-PT model. The authors further point out that Rn determination is not the only source of error in the DATTUTDUT model (Xia et al., 2016). In our study, the TSEB-PT model slightly outperformed the more complex DTD model in the Rn_mes configuration regarding error terms.

We used the Bowen-ratio method to close the energy balance for the reference EC measurements. As reported by Xia et al. (2016), agreement between measured EC and modeled LE estimates could potentially be increased by using the residual method from Twine et al. (2000) for energy balance closure. Further potential improvements include the aerial sampling alignment with the EC measurement logging cycles. We compared snapshot measurements of LST to 30 min averages of EC measurements for the corresponding times in an environment where key variables such as solar irradiance can change very quickly. Better matching the measurement cycle duration may further improve agreement between the methods and was already suggested in a previous study (Brenner et al., 2018). Further, in our study the aerial-derived LST images represented only the center area of the (at times quite variable and large) EC footprint. Covering the whole potential area of the footprint in all directions could also increase agreement between the measurements, but would require even higher flight altitude or longer flight times to cover the whole area; both options would reduce the number of temporal replicates and increase errors from measurements and processing, but could nonetheless be viable approaches for other research questions.

Only few previous studies have demonstrated applicability and limitations of estimating LE with the three energy balance models from non-satellite data. In these studies, LSTs were e.g. recorded from drones for European grasslands and croplands (Brenner et al., 2018; Hoffmann et al., 2016) and from drones or airplanes for taller vegetation including olive orchards and vineyards (Ortega-Farías et al., 2016; Xia et al., 2016). Our study adds to this an application of these models in a tropical environment, for higher vegetation (i.e. oil palm) and across variable daytimes and weather conditions. Generally, the equatorial study site was rather challenging due to high temperatures and humidity and frequent occurrence of haze, as well as for logistical reasons. Additionally, many previous drone-based studies were conducted on grasslands (e.g. Brenner et al. 2017, 2018) or on low-growing crops such as wheat fields (Hoffmann et al., 2016), but not on crops with a rather complex canopy structure such as oil palm. On the other hand, our study site showed large temperature differences between soil and canopy, which simplified the distinguishing of each fraction. We further analyzed for the first time whether drone-data based models and EC measurements can be used interchangeably, as our large sample size of n=61 flights allowed for a method comparison based on a model II Deming regression (Legendre and Legendre, 2003). We conclude that this is the case for some models and configurations, above all for the DATTUTDUT with Rn_mes configuration.

4.2 Spatial distribution of latent heat fluxes

A particular strength of drone-based thermal imagery is the high spatial resolution which allows for spatially explicit assessments of evapotranspiration, within and potentially also beyond the footprints of EC towers. The outlines of the single oil palm canopies are clearly visible in the LE flux map (Fig. 6), with the highest LE fluxes occurring in the center of the oil palm canopies. We assume that this spatial pattern is caused by an increased local LAI in the centers of the oil palm canopies, while leaf area density decreases towards the outer canopies. Further, the central areas of oil palm canopies are more exposed to sunlight and wind throughout most of the day, increasing their potential for (evapo)transpiration compared to canopy edges. Mixed pixel effects (among soil and canopy) likely also contribute to the observed lower LE fluxes towards the borders of oil palm canopies. Further contributing factors to higher LE fluxes in the centers of oil palm canopies could be leaf age (with younger leaves in the center) and additional ET from pockets in the axils of pruned leaves along the stem, which contain small water reservoirs and epiphytes (Meijide et al., 2017; Tarigan et al., 2018).

While the DATTUTDUT histogram shows only few pixel values of zero and most pixels closely distributed around the mean, the TSEB-PT and DTD histograms are much wider distributed and with a much more pronounced peak. For the DATTUTDUT model mean and median are very similar indicating close to zero skewness. Such a distribution tending towards unimodality is also considered typical for landscapes where ET is highly dominated by one species (Xia et al., 2016). Both, the TSEB-PT and the DTD model show a different, more skewed distribution of LE fluxes (for the same dataset of LST), with the median of the LE estimates located between the mean and the upper end of the LE flux range. We assume that this skewness is caused by the TSEB-PT and DTD models being more sensitive to dry surfaces and hence better represent the lower LE flux from dryer soil areas.

Drone-based methods have a large untapped potential for ecological applications, e.g. regarding ecohydrological optimization in land use systems and designing the climate-smart urban landscapes of the future. We see great potential in the drone-based remote sensing applications presented in this study; especially when recent developments in drone-environment interaction, mobile edge computing (potentially on-board of the drone) and communication technologies such as LoRaWan (Long Range Wide Area Network) or 5G are combined (Becerra, 2019; Marchese et al., 2019). Autonomous acquisition of LSTs over EC stations and the surrounding area scan be supplemented by on-board and ground sensors. Energy-balance models can then potentially be calculated using edge computing schemes on-board the drone to enable a dense temporal resolution of LST, flux and ET maps in almost real-time. This concept can e.g. be used for the attribution of fluxes in mixed species plant communities, the study of edge effects in landscapes, and further be adapted e.g. to detect water stress in agriculture and forests.

5 Conclusions

Drone-based thermography and subsequent energy balance modeling under certain configurations can be considered a highly reliable method for estimating latent heat flux and evapotranspiration; for some configurations statistical interchangeability is suggested with the established eddy covariance technique. They thus complement the asset of available methods for evapotranspiration studies by fine grain and spatially explicit assessments.

Data availability

The final data used for the statistical tests were uploaded in Göttingen Research Online Data with a doi: https://doi.org/10.25625/IOF18T
Raw thermal images, orthomosaics and terrain data, georeferenced rasters and model configurations are available upon request to the corresponding author.

Author Contribution

The study was conceptualized by DH in cooperation with H (drone measurements) and AK in cooperation with TJ (eddy covariance measurements). FE led the writing of the paper with help from AR and DH supervised the work. FE collected and processed the drone data and CS the eddy covariance data. FE conducted data processing, model application, statistical analysis and production of plots in cooperation mainly with DH and AR. FE, DH and AR created a first version of the manuscript, which was further improved in a cooperation of all authors.

Competing interests

The authors declare that they have no conflict of interest.

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