

# Mapping Evapotranspiration with High Resolution Aircraft Imagery over Vineyards Using One and Two Source Modeling Schemes

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## Abstract

Thermal and multispectral remote sensing data from low-altitude aircraft can provide high spatial resolution necessary for sub-field ( $\leq 10$  m) and plant canopy ( $\leq 1$  m) scale evapotranspiration (ET) monitoring. In this study, high resolution (sub-meter scale) thermal infrared and multispectral shortwave data from aircraft are used to map ET over vineyards in central California with the Two Source Energy Balance (TSEB) model and with a simple model having operational immediate capabilities called DATTUTDUT (Deriving Atmosphere Turbulent Transport Useful To Dummies Using Temperature). The latter uses contextual information within the image to scale between radiometric land surface temperature ( $T_R$ ) values representing hydrologic limits of potential ET and a non-evaporative surface. Imagery from five days

1 throughout the growing season is used for mapping ET at the sub-field scale. The performance  
2 of the two models is evaluated using tower-based measurements of sensible ( $H$ ) and latent heat  
3 (LE) flux or ET. The comparison indicates that TSEB was able to derive reasonable ET  
4 estimates under varying conditions, likely due to the physically based treatment of the energy  
5 and the surface temperature partitioning between the soil/cover crop inter-row and vine canopy  
6 elements. On the other hand, DATTUTDUT performance was somewhat degraded presumably  
7 because the simple scaling scheme does not consider differences in the two sources (vine and  
8 inter-row) of heat and temperature contributions or the effect of surface roughness on the  
9 efficiency of heat exchange. Maps of the evaporative fraction ( $EF=LE/(H+LE)$ ) from the two  
10 models had similar spatial patterns but different magnitudes in some areas within the fields on  
11 certain days. Large EF discrepancies between the models were found on two of the five days  
12 (DOY 162 and 219) when there were significant differences with the tower-based ET  
13 measurements, particularly using the DATTUTDUT model. These differences in EF between  
14 the models translate to significant variations in daily water use estimates for these two days for  
15 the vineyards. Model sensitivity analysis demonstrated the high degree of sensitivity of the  
16 TSEB model to the accuracy of the  $T_R$  data while the DATTUTDUT model was insensitive to  
17 systematic errors in  $T_R$  as is the case with contextual-based models. However, it is shown that  
18 the study domain and spatial resolution will significantly influence the ET estimation from the  
19 DATTUTDUT model. Future work is planned for developing a hybrid approach that leverages  
20 the strengths of both modeling schemes and is simple enough to be used operationally with high  
21 resolution imagery.

## 22 **1 Introduction**

23 As a key component of the land hydrological, energy and biogeochemical cycles,  
24 evapotranspiration (ET) provides important information about terrestrial water availability and  
25 consumption (Evetts et al., 2012). Detailed knowledge of spatial ET distributions (especially in  
26 near-real time) at field or finer scale is particularly useful in precision agricultural water  
27 management (Anderson et al., 2012a; Sánchez et al., 2014). This is especially relevant as the  
28 need to increase food production for a growing human population is hindered by the reduced  
29 availability of freshwater in many water limited regions, which potentially will be exacerbated  
30 with a changing climate. Remote sensing techniques are considered to be one of the few reliable  
31 methods for mapping and monitoring ET at watershed and regional scales (Su, 2002; Kustas and

1 [Anderson, 2009](#)) since they provide a means for detecting changes in vegetation and soil  
2 moisture conditions at field scale affecting ET over space and time.

3 Over the past several decades, numerous satellite products have been used in ET estimation and  
4 monitoring. Among them, medium to moderate spatial resolution (100-1000 m) satellite data,  
5 e.g., from Landsat and the MODerate resolution Imaging Spectrometer (MODIS), have been  
6 applied with models for mapping ET at field to watershed and regional scales with some success  
7 ([Anderson et al., 2012b](#); [Cammalleri et al., 2013](#)). [In this paper we define satellite imagery with  
8 resolution on order of ~100 m as “medium resolution” and 1000 m as “moderate resolution” to  
9 distinguish from high resolution imagery with meter-scale spatial resolution.] However, as water  
10 resources become more limited, there is a greater need for precision agricultural management at  
11 the field/subfield-scale, particularly for high-valued or specialty crops ([Zipper and Loheide II,](#)  
12 [2014](#)), and moderate resolution data are too coarse to inform variable rate application of water or  
13 nutrients within a field. In addition, obtaining both high spatial and temporal resolution data is  
14 not feasible with the current satellite constellation since medium resolution earth observations  
15 have a long (two or more weeks) revisit cycle, particularly when considering cloud cover  
16 ([Cammalleri et al., 2013](#)).

17 Remote sensing data from low altitude aircraft, especially from unmanned aerial vehicles  
18 (UAVs), can potentially provide the needed spatial and temporal frequency for precision  
19 agriculture applications. Despite the fact that development of airborne scanner-derived thermal  
20 imagery for irrigation applications had begun back in the 1970s ([Jackson et al., 1977](#)), it is not  
21 until the last few years that very high resolution data are being considered for precision  
22 agricultural applications. This is due to the technological advances that have allowed rapid  
23 integration and processing of high-resolution data from cameras mounted on aircraft and more  
24 recently on-board UAVs ([Zarco-Tejada et al., 2013](#)). Current applications of high resolution  
25 thermal remote sensing data are mainly focused on detecting and mapping crop water status  
26 ([Berni et al., 2009a](#); [Gonzalez-Dugo et al., 2012](#); [Zarco-Tejada et al., 2012](#)) since canopy  
27 temperature has historically been used as an indicator of water stress ([Jackson et al., 1981](#);  
28 [Gardner et al., 1981](#); [Fuentes et al., 2012](#)). Sub-meter resolution thermal imagery is able to  
29 retrieve pure canopy temperature, minimizing soil or other background thermal effects ([Leinonen](#)  
30 [and Jones, 2004](#); [Zarco-Tejada et al., 2013](#)).

1 Spatially distributed ET can be obtained using remote sensing-based models with varying  
2 degrees of complexity and utility (Kalma et al., 2008). In terms of treatment of the energy  
3 exchange with the surface, the thermal remote sensing-based ET models can be generally  
4 classified as one source (Bastiaanssen et al., 1998; Su, 2002; Feng and Wang, 2013) and two  
5 source (Norman et al., 1995; Kustas and Norman, 1999; Long and Singh, 2012; Yang and Shang,  
6 2013) parameterizations depending on whether they treat a landscape pixel as a  
7 composite/lumped surface or explicitly partition energy fluxes and temperatures between soil  
8 and vegetation. These models are based on solving the surface energy balance and adopt  
9 radiometric surface temperature ( $T_R$ ) as a key boundary condition (Kustas and Norman, 1996).

10 A commonly used method in one source models is the contextual scaling approach, which uses  
11  $T_R$  and vegetation amount (the normalized difference vegetation index, NDVI, or fractional  
12 vegetation cover,  $f_c$ ) as proxy indicators of ET (Bastiaanssen et al., 1998; Su, 2002; Allen et al.,  
13 2007; Carlson et al., 1994; Jiang and Islam, 1999). Accurate identification of extreme  
14 hydrologic limits, i.e., potential ET (cold/wet limit) and the largest water stress condition  
15 (hot/dry limit), is essential for proper scaling of the surface condition (e.g., the aerodynamic and  
16 air temperature difference,  $dT$ , and evaporative fraction, EF) of the other pixels between these  
17 extremes. Examples include the Surface Energy Balance Algorithm for Land (SEBAL)  
18 (Bastiaanssen et al., 1998), the Mapping Evapotranspiration with Internalized Calibration  
19 (METRIC) model (Allen et al., 2007), the triangle model (Carlson et al., 1994), and the satellite-  
20 based energy balance algorithm with Reference Dry and Wet limits (REDRAW) (Feng and  
21 Wang, 2013).

22 With UAV imagery, the pixel resolution can be very fine (i.e.,  $10^0$  cm –  $10^0$  m) in order to map  
23 the variability in crop condition within a field. This typically restricts the size of the area or field  
24 being monitored and hence reduces the likelihood of sampling the extremes in ET rates (i.e., ET  
25  $\sim 0$  and ET at potential). This issue was raised by Zipper and Loheide II (2014) who indicated  
26 that thermal-based ET models relying on extreme limits are not applicable at field scales since in  
27 agricultural landscapes vegetation cover within a field is fairly homogeneous and ideal extreme  
28 limits may be difficult to identify, especially during mature crop periods when the canopy is  
29 nearly closed. They developed a mixed-input approach combining high resolution airborne and  
30 Landsat imagery with local meteorological forcing in a surface energy balance model they called  
31 High Resolution Mapping of EvapoTranspiration (HRMET). HRMET combines a two-source

1 modeling approach for estimating available energy between the soil and vegetation elements but  
2 uses a single-source scheme for estimating the soil+canopy system  $H$ , with LE solved by residual.  
3 On the other hand, the contextual scaling approach can greatly simplify model computations and  
4 input data requirements (Carlson, 2007), and can reduce ET retrieval errors due to bias errors in  
5  $T_R$  and meteorological inputs such as air temperature and wind speed (Allen et al., 2007). This  
6 facilitates near real-time operational applications for ET monitoring. In the DATTUTDUT  
7 (Deriving Atmosphere Turbulent Transport Useful To Dummies Using Temperature) modeling  
8 scheme introduced by Timmermans et al. (2015), land surface temperature is the only input  
9 needed for ET estimation. DATTUTDUT solves for ET by scaling the evaporative fraction, EF,  
10 between the extreme values associated with potential (cool/wet pixel) and zero (hot/dry pixel)  
11 ET. The main concept of DATTUTDUT is similar to the S-SEBI (the Simplified Surface Energy  
12 Balance Index) proposed by Roerink et al. (2000); however, DATTUTDUT has a more  
13 simplified scheme to obtain radiometric temperature end-members and radiation-related factors.  
14 Although these types of contextual scaling methods have been tested over a variety of landscapes  
15 using mainly moderate resolution remote sensing data, their applicability and performance in  
16 retrieving surface fluxes and ET at the high resolution/sub-field scale, and potential problems or  
17 behavior at the sub-field scale have not been adequately tested.

18 The Two Source Energy Balance (TSEB) scheme originally proposed by Norman et al. (1995)  
19 and modified by Kustas and Norman (1996, 1999, 2000), has proven to be fairly robust for a  
20 wide range of landscape and weather conditions (Li et al., 2005; Kustas and Anderson, 2009;  
21 Colaizzi et al., 2012a). Unlike single-source models based on contextual scaling approaches, the  
22 TSEB model contains a more detailed treatment of the radiative and flux exchange between soil  
23 and vegetation elements without the requirement of extreme hydrological limits existing within  
24 the scene. Consequently, TSEB is still effective when applied over homogeneous landscapes  
25 and environmental conditions.

26 The performance of TSEB and single-source models using  $T_R$ /ET extremes (e.g., SEBAL,  
27 METRIC, Trapezoid Interpolation Model (TIM)) has been compared over a corn and soybean  
28 region in Iowa during SMACEX (French et al., 2005; Choi et al., 2009), sub-humid grassland  
29 and semi-arid rangeland during SGP '97 and Monsoon '90 (Timmermans et al., 2007), as well as  
30 a cotton field in Maricopa, Arizona (French et al., 2015). These studies demonstrated that both

1 TSEB and the single-source models can reproduce fluxes with similar agreement to tower-based  
2 observations, yet they did reveal significant discrepancies in the ET patterns or spatial  
3 distributions especially in areas with bare soil or sparse vegetation. In general, these model  
4 inter-comparisons have mainly used medium resolution satellite imagery such as Landsat and  
5 Advanced Spaceborne Thermal Emission and Reflection radiometer (ASTER). French et al.  
6 (2015) conducted model comparison using both Landsat and aircraft data, and concluded that  
7 daily ET estimations were similar at high and medium spatial resolutions.

8 However, more detailed comparisons between simple one-source contextual-based schemes  
9 versus more complex two-source models using high resolution imagery over different surfaces  
10 are still needed to fully understand the strengths and weaknesses of both modeling schemes.  
11 Such intercomparisons can facilitate development of hybrid schemes that leverage the strengths  
12 of different methodologies (e.g., Cammalleri et al., 2012), while incorporating simplifications for  
13 routine application with airborne imagery. The purpose of this paper is to conduct an inter-  
14 comparison of TSEB with the very simple contextual-based DATTUTDUT model that can be  
15 easily applied operationally using high resolution thermal and multispectral shortwave imagery  
16 for sub-field scale ET estimation. The inter-comparison is conducted over two vineyard fields  
17 having significantly different biomass in central California. ET estimates from the TSEB and  
18 DATTUTDUT models are compared in detail within the contributing source-area of the flux  
19 tower in each field, and the spatial patterns of modeled ET are compared throughout the whole  
20 vineyard field. Additionally, a sensitivity analysis of key inputs to the two models is conducted,  
21 providing insight into the potential for precision agricultural water resource management  
22 applications using such high resolution earth observations.

## 23 **2 Model overview**

### 24 **2.1 TSEB model**

25 The TSEB model, developed by Norman et al. (1995), partitions surface temperature and fluxes  
26 into soil and vegetation components. Detailed formulations used in TSEB can be found in  
27 Kustas and Norman (1999) and Li et al. (2005, 2008). In the TSEB model, the surface energy  
28 budgets are balanced for both the soil and canopy components of the scene:

$$R_n = R_{ns} + R_{nc} = H + LE + G \quad (1)$$

$$R_{ns} = H_s + LE_s + G \quad (2)$$

$$R_{nc} = H_c + LE_c \quad (3)$$

1 where  $R_n$  is net radiation ( $\text{W m}^{-2}$ ),  $H$  is sensible heat flux ( $\text{W m}^{-2}$ ),  $LE$  is latent heat flux ( $\text{W m}^{-2}$ ),  
 2 and  $G$  is soil heat flux ( $\text{W m}^{-2}$ ). Subscripts  $s$  and  $c$  represent the soil and canopy flux  
 3 components, respectively. Component  $R_n$  is combined with the component temperature  
 4 ([Colaizzi et al., 2012b](#); [Song et al., 2016](#)):

$$R_{ns} = \tau_l L_d + (1 - \tau_l) \varepsilon_c \sigma T_c^4 - \varepsilon_s \sigma T_s^4 + \tau_s (1 - \alpha_s) S_d \quad (4)$$

$$R_{nc} = (1 - \tau_l) (L_d + \varepsilon_s \sigma T_s^4 - 2\varepsilon_c \sigma T_c^4) + (1 - \tau_s) (1 - \alpha_c) S_d \quad (5)$$

5 where  $L_d$  and  $S_d$  are incoming longwave and shortwave radiation ( $\text{W m}^{-2}$ ),  $\tau_l$  and  $\tau_s$  are the  
 6 longwave and shortwave radiation transmittances through the canopy (-).  $\varepsilon$ ,  $\alpha$  and  $T$  are surface  
 7 emissivity (-), surface albedo (-) and surface temperature (K) with subscripts  $s$  and  $c$  represent  
 8 the soil and canopy.  $\sigma$  is the Stefan-Boltzmann constant ( $\sim 5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$ ).  $S_d$  is either  
 9 computed using sun-earth astronomical relationships under clear-sky conditions as done by  
 10 DATTUTDUT (see below) or measured from a nearby weather station, and  $L_d$  is either measured  
 11 or often computed using formulas based on weather station observations of air temperature and  
 12 vapor pressure (i.e., [Brutsaert, 1975](#)).

13  $T_R$  is partitioned into component soil,  $T_s$ , and canopy,  $T_c$ , temperatures based on the fractional  
 14 vegetation cover ( $f_c$ ):

$$T_R \approx [f_c(\theta) T_c^4 + (1 - f_c(\theta)) T_s^4]^{1/4} \quad (6)$$

15 where  $f_c(\theta)$  is the vegetation cover fraction at the thermal sensor view angle  $\theta$ . A clumping  
 16 factor,  $\Omega$ , is adopted in the  $f_c(\theta)$  calculation to account for the row structure of vineyards (i.e.,  
 17 vine biomass concentrated along trellises) using a formulation from [Campbell and Norman](#)  
 18 ([1998](#)):

$$f_c(\theta) = 1 - \exp\left[\frac{-0.5\Omega(\theta)LAI}{\cos(\theta)}\right] \quad (7)$$

19 where LAI is leaf area index, which is often estimated from NDVI using an empirical  
 20 LAI~NDVI relation ([Anderson et al., 2004](#)). When calculating the flux component  $H$ , “series”

1 and “parallel” schemes are adopted for the resistance network separately for unstable and stable  
 2 conditions. Detailed formulations for the two schemes can be found in [Norman et al. \(1995\)](#) and  
 3 [Kustas and Norman \(1999\)](#).  $LE_c$  is initially estimated using a Priestley-Taylor formulation:

$$LE_c = \alpha_{PT} f_G \frac{\Delta}{\Delta + \gamma} R_{nc} \quad (8)$$

4 where  $\alpha_{PT}$  is Priestley-Taylor parameter, which may vary within different vegetation and climate  
 5 conditions ([Norman et al., 1995](#); [Kustas and Norman, 1999](#); [Kustas and Anderson, 2009](#)). In this  
 6 paper, the initial value of  $\alpha_{PT}$  is 1.26.  $f_G$  is the LAI fraction that is green with active transpiration.  
 7  $\Delta$  is the slope of the saturation vapor pressure-temperature curve ( $\text{Pa K}^{-1}$ ) and  $\gamma$  is the  
 8 psychrometric constant ( $\text{Pa K}^{-1}$ ).  $G$  is parameterized as a fraction of  $R_{ns}$  by:

$$G = cR_{ns} \quad (9)$$

9 where  $c$  is the empirical coefficient which tends to be constant during midmorning to midday  
 10 period.

11 With the above model formulations, energy fluxes for both soil and canopy can be solved.  
 12 Important model inputs for TSEB include  $T_R$ , fractional canopy cover condition (often related to  
 13 NDVI), and a land use map providing canopy characteristics (mainly vegetation height and leaf  
 14 width) obtained using remote sensing imagery. Ancillary meteorological data required in TSEB  
 15 include air temperature, vapor pressure, atmospheric pressure, and wind speed.

## 16 **2.2 DATTUTDUT model**

17 The DATTUTDUT model is an energy balance model that estimates surface energy fluxes solely  
 18 from radiometric surface temperature observations acquired over the area of interest. This model  
 19 assumes that  $T_R$  is an important indicator for the surface status, and scales key parameters for  
 20 flux estimation by  $T_R$  between the extremes of a cool/wet pixel with ET at the potential rate and  
 21 hot/dry pixel where there is essentially no ET. Detailed model formulations are described in  
 22 [Timmermans et al. \(2015\)](#). Similar to other energy balance models,  $R_n$  is estimated by  
 23 computing the net shortwave radiation and the net longwave radiation:

$$R_n = (1 - \alpha) S_d + \varepsilon_a \sigma T_a^4 - \varepsilon \sigma T_R^4 \quad (10)$$



1 where  $\varepsilon_a$  is the atmosphere emissivity (-) and  $\varepsilon$  is the effective (integrated soil + canopy  
 2 emissivity) emissivity. The value of  $S_d$  is obtained from the sun-earth astronomical relationships  
 3 under clear-sky conditions (Allen et al., 2007; Timmermans et al., 2015). In the DATTUTDUT  
 4 model, nominal values are taken for  $\varepsilon$  and  $\varepsilon_a$  for simplicity:  $\varepsilon_a$  is set to be 0.7 and  $\varepsilon$  is taken as  
 5 0.96. Air temperature,  $T_a$  (K), is assumed to be equal to the minimum  $T_R$  identified within the  
 6 scene of interest.  $\alpha$  is scaled with  $T_R$  between extreme values of 0.05 and 0.25 based on the  
 7 assumption that densely vegetated objects are likely to be darker and cooler while bare objects  
 8 tend to appear brighter and hotter:

$$\alpha = 0.05 + \left( \frac{T_R - T_{\min}}{T_{\max} - T_{\min}} \right) 0.2 \quad (11)$$

9 where  $T_{\max}$  is the maximum  $T_R$  within the image, and  $T_{\min}$  is the 0.5% lowest temperature in the  
 10 scene. Soil heat flux is calculated from  $R_n$  with the coefficient  $c_G$  scaled between a minimum  
 11 value of 0.05 for fully covered condition and maximum value of 0.45 for bare soil (Roerink et al.,  
 12 2000; Santanello and Friedl, 2003):

$$c_G = \frac{G}{R_n} = 0.05 + \left( \frac{T_R - T_{\min}}{T_{\max} - T_{\min}} \right) 0.4 \quad (12)$$

13 Similar to  $\alpha$  and  $c_G$ , evaporative fraction, EF, is assumed to be linearly related to  $T_R$ :

$$EF = \frac{LE}{LE + H} = \frac{LE}{R_n - G} = \frac{LE}{A} = \frac{T_{\max} - T_R}{T_{\max} - T_{\min}} \quad (13)$$

14 where  $A$  is available energy ( $W m^{-2}$ ), i.e., the difference between  $R_n$  and  $G$ . With the above  
 15 formulations, LE can be calculated from  $A$  and EF, and  $H$  can be estimated as the residual to the  
 16 energy balance equation.

### 17 **2.3 Daily flux calculation**

18 A common approach used to extrapolate ET from instantaneous (time of satellite overpass) to  
 19 daily time scale is to assume the ratio of instantaneous LE to some reference variable remains  
 20 constant during the day, which is described as “self-preservation” by Brutsaert and Sugita (1992).  
 21 The reference variables typically used include  $A$  (Anderson et al., 2012b), standardized reference  
 22 ET (Allen et al., 2007), solar radiation (Zhang and Lemeur, 1995), top-of-atmosphere irradiance

1 (Ryu et al., 2012). Cammalleri et al. (2014) compared the performances of the scale factors  
2 derived by these four reference variables in ET upscaling at 12 AmeriFlux towers, drawing a  
3 conclusion that solar radiation was the most robust reference variable for operational applications,  
4 particularly in areas where the modeled  $G$  component of  $A$  may have high uncertainties.  
5 However, the applicability of the various reference variables may differ within areas, since the  
6 energy budget is significantly influenced by surface characteristics such as soil moisture,  
7 vegetation condition (Crago, 1996). In this study, EF (defined as the ratio of LE to  $A$  or  $H+LE$ )  
8 is assumed constant during the daytime period when solar radiation is larger than 0. The  
9 extrapolation to daytime ET using a constant EF is reasonable to apply during the main growing  
10 season period (Cammalleri et al., 2014).

11 The ratio of instantaneous to daytime  $A$  at the flux tower site is used to obtain daytime  $A$  for each  
12 pixel within the study area by assuming that the  $A$  ratio between pixel and flux tower is constant  
13 during the daytime. Therefore, daytime  $A$  for the pixel ( $A_{p,d}$ ) can be derived from the pixel-  
14 based instantaneous  $A$  ( $A_{p,i}$ ), and flux tower site values of instantaneous and daytime  $A$  ( $A_{s,i}$  and  
15  $A_{s,d}$ ) using the following expression:

$$A_{p,d} = \frac{A_{p,i}}{A_{s,i}} A_{s,d} \quad (14)$$

16 Then daytime ET for each pixel ( $ET_{p,d}$ ) can be calculated by tower observed daytime  $A$  and the  
17 EF retrieved by either TSEB or DATTUTDUT:

$$ET_{p,d} = A_{p,d} EF \quad (15)$$

18 and daytime  $H$  is computed as the residual in the energy balance equation.

19 In this study, the observed available energy from the two flux towers during the daytime period  
20 for all five days was used to extrapolate instantaneous model estimates to daytime ET totals.  
21 However, in practice tower measurements of  $A$  would not be available, so results using solar  
22 radiation to extrapolate to daytime ET will also be evaluated.

## 1 **3 Data and site description**

### 2 **3.1 Study site**

3 The model comparison was conducted over two vineyard sites located near Lodi in central  
4 California, using data collected as part of the Grape Remote sensing Atmospheric Profiling and  
5 Evapotranspiration eXperiment (GRAPEX) (Kustas et al., 2014). With a Mediterranean climate,  
6 this area has abundant sunshine and large day-and-night temperature differences, making it a  
7 primary wine grape producing area in California. This study focuses on two drip irrigated Pinot  
8 Noir vineyards trained on quadrilateral cordons with a 1.5m space between vines and 3.3m  
9 distance between rows. The north field (Site 1) has an area of about 35 ha with the flux tower  
10 located approximately half-way north-south along the eastern border of the field (38°17.3'N,  
11 121°7.1'W), while the south vineyard (Site 2) is smaller in size, at about 21 ha with the flux  
12 tower also approximately half-way north-south along the eastern border of the field (38°16.8'N,  
13 121°7.1'W) (see Fig. 1). The towers were deployed at these locations to maximize fetch for the  
14 predominant wind direction during the growing season, which is from the west. The vines in  
15 north field (7-8 years old) are more mature than those in south field (4-5 years old), resulting in a  
16 greater biomass/leaf area in the north field (see the LAI map for IOP2 in Fig. 4). Vine height is  
17 similar in both fields and reaches ~2.5 m in height. The vines typically leaf out in late March  
18 and grow through late August before the grapes are harvested in early September. When winter  
19 rains and soil moisture are adequate, a grass cover crop flourishes early in the growing season in  
20 the inter-row until becoming senescent starting in late May, which is typically the beginning of  
21 the dry season. During the growing season in 2013, the average air temperature was nearly  
22 20 °C and the total precipitation was only about 15 mm.

### 23 **3.2 Micrometeorological data**

24 Micrometeorological instruments for measuring the meteorological and flux data were installed  
25 at both the north and south field flux tower sites in late March, 2013. The meteorological data  
26 needed for running the TSEB model include air temperature, vapor pressure, atmospheric  
27 pressure, wind speed, and incoming solar radiation. These were all measured at approximately 5  
28 m above local ground level (AGL) and recorded as 15 minute averages. The eddy covariance

1 (EC) system comprised of a Campbell Scientific, Inc.<sup>1</sup> EC150 water vapor/carbon dioxide sensor  
2 and a CSAT3 three-dimensional sonic anemometer, both collecting data at 20 Hz producing 15-  
3 minute averages. A Kipp and Zonen CNR1 four-component radiometer measured net radiation  
4 at 6 m AGL. Five soil heat flux plates (HFT-3, Radiation Energy Balance Systems, Bellevue,  
5 Washington) buried cross-row at a depth of 8 cm recorded soil heat flux. Each heat flux plate  
6 had two thermocouples buried at 2 and 6 cm depths and a Stevens Water Monitoring Systems  
7 HydraProbe soil moisture sensor buried at a depth of 5 cm used to estimate heat storage above  
8 each plate. Both meteorological and fluxes data were measured through the whole vine growing  
9 season (April to October) in 2013. During this period (including both daytime and nighttime  
10 observations), the slope between  $A$  and  $H+LE$  is 0.83 for both two sites with coefficient of  
11 determination ( $R^2$ ) on order of 0.97. This suggests an average energy balance closure of nearly  
12 85%. In this study, the EC fluxes were closed using both the Residual (RE) and Bowen Ratio  
13 (BR) methods described in [Twine et al. \(2000\)](#) to ensure energy conservation.

### 14 **3.3 Airborne campaigns**

15 Three Intensive Observation Periods (IOPs) were conducted through the 2013 growing season as  
16 part of GRAPEX to capture different vine and inter-row cover crop phenological stages that may  
17 affect ET rates. During IOP1 (April 9-11, 2013; Day of Year (DOY) 99-101) the vines were just  
18 starting to leaf out and the cover crop in the inter-row was green and flourishing. By the time of  
19 IOP2 (June 11-13, DOY 162-164), the vines were fully developed with immature green grapes,  
20 while the cover crop was senescent. Grapes were beginning to ripen and reach maturity while  
21 the vines were still green and growing during IOP3 (August 6-8, DOY 218-220).

22 Airborne campaigns were conducted on five days (DOY 100, 162, 163, 218 and 219) over the  
23 three IOPs. Multispectral and thermal imagery were acquired over the two vineyards with the  
24 Utah State University airborne digital system installed in a single engine Cessna TU206 aircraft  
25 dedicated for research. The system consists of four ImperX Bobcat B8430 digital cameras with  
26 interference filters forming spectral bands in the Blue (0.465-0.475  $\mu\text{m}$ ), Green (0.545-0.555  $\mu\text{m}$ ),  
27 Red (0.645-0.655  $\mu\text{m}$ ) and Near Infrared (NIR) (0.780-0.820  $\mu\text{m}$ ) wavelengths. The thermal

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<sup>1</sup> The use of trade, firm, or corporation names in this article is for the information and convenience of the reader. Such use does not constitute an official endorsement or approval by the United States Department of Agriculture or the Agricultural Research Service of any product or service to the exclusion of others that may be suitable.

1 infrared (TIR) images were acquired with a ThermaCAM SC640 by FLIR Systems Inc. in the  
2 7.5-13  $\mu\text{m}$  range. The aircraft-based TIR images were provided in degrees Celsius and used in  
3 this analysis without performing atmospheric correction. Details of image acquisition and  
4 processing can be found in Neale et al. (2012). In Table 1, overpass time (UTC), multispectral  
5 and thermal pixel resolution, information and aircraft altitude are listed for the overpass dates.  
6 The high spatial resolution of the visible bands (0.05 or 0.1 m, see Table 1) made it possible to  
7 distinguish vegetation pixels from non-vegetated pixels to some extent. However, with the  
8 coarser thermal pixel resolutions it was difficult to reliably distinguish pure vine canopy  
9 temperatures from background soil and/or inter-row cover crop temperatures (Fig. 1). Since the  
10 imagery for the different overpass dates have different spatial resolutions and the TSEB model  
11 resistance and radiation formulations for the turbulent and radiative exchange for the soil/cover-  
12 crop-vine system are appropriate at the plot/micrometeorological scale, both multispectral and  
13 thermal bands were aggregated to 5 m resolution for creating TSEB input fields to compute ET.  
14 This spatial resolution ensured both an inter-row and vine row would be sampled within the pixel.  
15 The original or native pixel resolution of the thermal imagery was also used as input to  
16 DATTUTDUT.

### 17 **3.4 Model input from aircraft data**

18 The key TSEB model input data from the aircraft observations include maps of NDVI, LAI,  $f_c$ ,  
19 and  $T_R$ . Auxiliary remote sensing data were required to produce multispectral reflectance and  
20 LAI maps. The original multispectral imagery from aircraft was in digital numbers (DN) and  
21 needed to be converted into reflectance. Smith and Milton (1999) introduced an empirical line  
22 method to calibrate remote sensing-derived DN to reflectance with errors of only a few percent  
23 in their case study. Berni et al. (2009b) applied the empirical line method on high resolution data  
24 obtained by UAV yielding calculated reflectances that agreed well with measurements (RMSD =  
25 1.17 %). Since ground-based reflectance measurements were not collected for some of the  
26 airborne acquisition dates, Landsat multispectral band reflectance in the corresponding spectral  
27 bands were used to derive the empirical DN-reflectance relationships for this analysis.

28 Three Landsat images were used to match the three IOP dates: Landsat 7 on DOY 98 from  
29 path44-row33, Landsat 8 on DOY 163 from path43-row33, and Landsat 8 on DOY 218 from

1 path44-row33. Reflectances for Band 5, Band 4, Band 3 from the Landsat 8 images, and Band 4,  
2 Band 3, Band 2 from the Landsat 7 image were used to derive the DN-reflectance relationship  
3 for NIR, red, and green bands, separately. All shortwave bands were calibrated and  
4 atmospherically corrected by the Landsat ecosystem disturbance adaptive processing system  
5 (LEDAPS) proposed by [Masek et al. \(2006\)](#).

6 The DN values with the original aircraft pixel resolution ([Table 1](#)) were aggregated up to 30 m  
7 resolution to match the Landsat multispectral bands resolution and the DN~reflectance  
8 relationship was derived. Visible band reflectance measurements were taken during the IOPs on  
9 DOY 162, 218 and 219 both above the vine row and over cover crop inter-row for both north and  
10 south fields. Estimated NIR, red and green band reflectance at aircraft pixel resolution are  
11 compared with reflectance measurements in [Fig. 2](#). Using 54 data points, including the three  
12 bands for three days at both sites, estimated reflectance from aircraft data agreed well with  
13 observations having a bias (observed-model) of -1.1 % and root mean square difference (RMSD)  
14 of 4.5 %. This accuracy is comparable with that (a few percent) found by [Smith and Milton](#)  
15 [\(1999\)](#) and [Berni et al. \(2009b\)](#).

16 NDVI was assumed to be correlated with fractional vegetation cover and related to LAI ([Carlson](#)  
17 [and Ripley, 1997](#)). The MODIS Terra four-day composite LAI product (MCD15A3) was used to  
18 derive LAI maps at 30 m resolution using the regression tree approach introduced by [Gao et al.](#)  
19 [\(2012\)](#). NDVI maps were generated from NIR (Band 5) and red (Band 4) band of Landsat 8 data.  
20 This permitted the derivation of a LAI~NDVI relation at 30 m resolution which was used to  
21 create a LAI map at aircraft pixel resolution. An exponential equation was used to fit the  
22 LAI~NDVI relationship, which was able to accommodate the effect of NDVI saturation at high  
23 LAI values ([Carlson and Ripley, 1997](#); [Anderson et al., 2004](#)). In [Fig. 3](#), the LAI~NDVI  
24 equation is compared with ground-based LAI measurements using LiCor LAI-2000 on DOY 163  
25 and DOY 218. The ground-based LAI measurements were derived from 5 transects running due  
26 west of the tower at 10-15 m intervals and across 4 rows from south to north. The average LAI  
27 from 5 transects represented a sampling area that was within 75 m due west of the flux tower  
28 sites. Four below vine canopy measurements were made and consisted of a LAI observation  
29 directly underneath vine plants along a row, and  $\frac{1}{4}$ ,  $\frac{1}{2}$  and  $\frac{3}{4}$  distance from the vine row. A LAI  
30 image from IOP2 is displayed in [Fig. 4](#) illustrating the significant spatial variation in LAI  
31 particularly for the north field.

1 Values of  $f_c$  were derived by the aircraft-based visible bands taking advantage of the high spatial  
2 resolution (0.05 to 0.1 m, see [Table 1](#) and [Fig. 1](#)) which allowed separation of the vine canopy  
3 from the inter-row area. Pixels were classified into vegetation and non-vegetation categories by  
4 ENVI image processing software (Exelis, Boulder, CO), and then the percentage of vegetation  
5 pixels was quantified within each 5 m resolution pixel.

## 6 **4 Results and discussion**

### 7 **4.1 Comparison of model estimates and tower data**

8 Fluxes were modeled by both TSEB and DATTUTDUT at 5-m resolution using the spatially  
9 aggregated aircraft-based remotely-sensed observations. In addition, DATTUTDUT used the  
10 native pixel resolution of the thermal imagery since there is no specific spatial scale required by  
11 the model parameterizations. TSEB additionally estimates soil and canopy temperatures. A  
12 two-dimensional flux footprint model described by [Li et al. \(2008\)](#) based on [Hsieh et al. \(2000\)](#)  
13 was used to compute footprint-weighted aggregated model outputs for comparison with the  
14 tower-based measurements. This footprint model contains a lateral dispersion formulation to  
15 obtain a two-dimensional weighted source-area of flux from the upwind direction.

16 Average soil and canopy component temperatures from TSEB were compared to the aircraft-  
17 based observations for the pixels within the flux contributing source area of the towers ([Fig. 5](#)).  
18 The aircraft-based temperature observations were extracted using a classification of vegetation  
19 and non-vegetated areas generated with the high resolution visible bands to identify appropriate  
20 pixels in the thermal imagery. The aircraft thermal band had a pixel resolution on the order of  
21 0.5 m (see [Table 1](#)), which was often slightly coarser scale than the width of the vine canopy and  
22 hence frequently resulted in a mixed pixel, combining both soil and canopy temperatures. Since  
23 obtaining purely vegetated surface temperature observations uncontaminated by background soil  
24 or cover crop temperature was difficult given the resolution of the thermal imagery, the  
25 minimum of the vegetated temperatures detected within the 5 m pixel was assumed to be a pure  
26 vegetated pixel temperature. Then within the footprint source area, the average of the non-  
27 vegetated temperatures (assumed to primarily consist of shaded and sunlit areas in the inter-row)  
28 was taken as the observed  $T_s$  and average of the minimum vegetated temperatures from all 5 m  
29 pixels within the source area was estimated to represent the observed  $T_c$ . TSEB estimates of  $T_s$

1 and  $T_c$  agreed well with the aircraft thermal observations yielding a bias of 0.5 °C and RMSD on  
2 the order of 2.5 °C. This accuracy was comparable with similar types of comparisons reported  
3 by Li et al. (2005), Kustas and Norman (1999, 2000), and Colaizzi et al. (2012a) which had  
4 RMSD values ranging from 2.4-5.0 °C for  $T_s$  and 0.83-6.4 °C for  $T_c$  when comparing observed to  
5 TSEB-derived component temperatures.

6 To assess the utility of the TSEB and DATTUTDUT models in reproducing the observed fluxes  
7 from the tower observations in the north (site 1) and south (site 2) vineyards, instantaneous  
8 modeled fluxes are compared with measurements (adjusted for closure using the RE method) in  
9 Fig. 6. Table 2 lists the statistics of model performance compared with both original and  
10 closure-adjusted measurements. Since the vines were at the very early growth stage during IOP1,  
11 and the inter-row cover crop was the main source of vegetation cover, the observed  $G$  on DOY  
12 100 was significantly larger than other IOPs (Fig. 6).

13 Table 2 clearly shows that the RE closure adjustment method yields better overall agreement  
14 between measured and modeled fluxes with the average error computed as the ratio of RMSD  
15 and average observed flux value of ~27% for  $H$  and LE for the two sites, while the BR method  
16 has an error of ~37%; Instantaneous fluxes from TSEB ( $H$  and LE adjusted by RE method)  
17 agreed well with observations with RMSD ranging between 20-60 W m<sup>-2</sup>, which is considered  
18 acceptable and similar to prior studies (e.g., Neale et al., 2012). DATTUTDUT gave estimated  
19 fluxes with relatively large errors particularly for  $R_n$  (RMSD = ~65 W m<sup>-2</sup>) and LE (RMSD =  
20 ~105 W m<sup>-2</sup>) for Site 1. The larger discrepancies in  $R_n$  from DATTUTDUT might be attributed  
21 to the simplifications in the net radiation computation (see Section 2.2). For DATTUTDUT, the  
22 results using 5 m pixel data indicate the significant error in LE predominantly result from poor  
23 performance on DOY 162 and 219 (Fig. 6b and 6e), likely because the extreme pixels  
24 automatically selected on these two days failed to represent the driest/wettest conditions within  
25 the image (see discussion below).

26 Daytime integrated fluxes are compared with the tower measurements in Fig. 7 and Table 3.  
27 Available energy was slightly overestimated by the models for all the cases, with biases between  
28 -0.5 and -1.7 MJ m<sup>-2</sup> d<sup>-1</sup>. Again, the RE method yielded better agreement with the model  
29 estimates of  $H$  and LE on a daytime scale. The LE values from TSEB at Site 1 agreed well with  
30 the observations with a bias of 0.5 MJ m<sup>-2</sup> d<sup>-1</sup> and RMSD of 1.1 MJ m<sup>-2</sup> d<sup>-1</sup> (Fig. 7a and Table 3).



1 However LE from DATTUTDUT had larger differences with the measurements at Site 1 (bias =  
2  $-1.1$ -- $-1.0$  MJ m<sup>-2</sup> d<sup>-1</sup> and RMSD =  $1.9$ - $2.0$  MJ m<sup>-2</sup> d<sup>-1</sup>) mainly due to the poor agreement in the  
3 instantaneous LE. For 5 m resolution results, the two models were comparable in their  
4 agreement with LE measurements at Site 2, yielding a small bias of  $-0.5$  to  $\sim 0$  MJ m<sup>-2</sup> d<sup>-1</sup> and for  
5 both a RMSD on order of  $1.7$  MJ m<sup>-2</sup> d<sup>-1</sup>.

6 At both instantaneous and daytime time scales, application of DATTUTDUT with the native  
7 (finer) pixel resolution thermal imagery yielded comparable (at Site 1) or significantly greater (at  
8 Site 2) discrepancies with the tower measurements than using the 5 m pixel resolution data (see  
9 [Tables 2 and 3](#)). Changes in the agreement with the tower measurements are mainly attributable  
10 to the new hot and cold temperature pixels selected by the DATTUTDUT procedure with the  
11 finer resolution  $T_R$  data.

12 In practice, we will not have observations of available energy,  $A$ , from a flux tower for  
13 extrapolating the instantaneous ET from a single airborne observation to daytime ET, but instead  
14 are more likely to have weather station observations of incoming solar radiation,  $S_d$ . Results  
15 using  $S_d$  for extrapolating model estimates instead of flux tower measurements of  $A$  are listed in  
16 [Table 4](#). In general, the differences between modeled and measured daytime ET (using RE  
17 method) increase, although not significantly for TSEB. On the other hand, discrepancies with the  
18 ET measurements for DATTUTDUT at the north vineyard (site 1) increase dramatically due to  
19 the large overestimation of instantaneous LE on DOY 162 and 219 (see [Fig. 6b](#)).

20 In general, the TSEB reproduced the measured fluxes with higher accuracy than did  
21 DATTUTDUT, both at the instantaneous and daytime temporal scales. It is hypothesized that  
22 this likely results from a better physical representation of the energy and radiative exchange  
23 within TSEB, since it explicitly considers differences in soil and vegetation radiation and  
24 turbulent energy exchange and affects on the radiative temperature source ([French et al., 2005](#);  
25 [Timmermans et al., 2007](#)). Flux estimation from single-source models based on the use of ET  
26 extremes will be sensitive to the selection of extreme end-member  $T_R$  pixels ([Feng and Wang,](#)  
27 [2013](#); [Long and Singh, 2013](#)), and actual extremes might not exist when applying such models to  
28 to small vineyards that are uniformly irrigated and managed as in this study. This may be a key  
29 factor that caused the fluxes from DATTUTDUT using 5 m resolution data to agree well with

1 measurements on DOY 100, 163 and 218, but not on DOY 162 and DOY 219 when the ET  
2 extremes may not have been readily present or captured in the imagery (see discussion below).

3 **Fig. 8** shows the locations of the extreme  $T_R$  pixels selected according to the DATTUTDUT  
4 modeling approach using 5 m resolution input for the five days. The dark green band in the  
5 lower half of the south field (especially obvious in **Fig. 8b** and **8c**) is an old stream bed which is  
6 likely to have different soil properties than the surrounding field. For DOY 162 and 219, cold  
7 pixels were located at the north vineyard (**Fig. 8b** and **8e**); while for DOY 163 and 218 just one  
8 day later or earlier than DOY 162 and 219, cold pixels were located within this former stream  
9 bed or at the tree pixel near the parking lot to the north (**Fig. 8c** and **8d**). Hot pixels were all  
10 located in bare soil pixels near the parking lot or in the north field without vines.

11 In addition to the issues related to the selection of the  $T_R$  end-members, DATTUTDUT does not  
12 consider effects of aerodynamic resistance (surface roughness) on the heat exchange for a given  
13 surface-air temperature difference. A similar finding was reported by [French et al. \(2005\)](#), where  
14 they found bias for  $H$  from TSEB was typically within  $35 \text{ W m}^{-2}$ , while bias for  $H$  from SEBAL  
15 could reach up to  $150 \text{ W m}^{-2}$ . Nevertheless, the simpler DATTUTDUT modeling scheme is  
16 much easier to apply to an image without *a priori* knowledge or skill required. This is a  
17 significant benefit in operational, realtime applications. Moreover as shown by [Timmermans et](#)  
18 [al. \(2015\)](#), output of fluxes from DATTUTDUT often were in good agreement with flux tower  
19 measurements and resulting flux fields had patterns consistent with more physically-based  
20 models including TSEB and SEBAL.

21 Using measured  $S_d$  from the towers instead of computing from the sun-earth astronomical  
22 relationships routinely applied by DATTUTDUT, there is only a minor reduction in the  
23 differences with the tower fluxes. An overall improvement in DATTUTDUT estimation of LE is  
24 achieved by adopting TSEB estimates of  $R_n$  and  $G$  (see **Table 5**). This is particularly true for the  
25 north vineyard (site 1). However, even with this better agreement in estimated LE, the  
26 discrepancies with observed LE from DATTUTDUT is still larger than with the output of TSEB.  
27 This indicates that the errors in available energy using the DATTUTDUT formulations are not  
28 the only significant source of error in estimating the LE flux.

## 4.2 Comparison of spatial patterns in modeled fluxes

Maps of instantaneous EF (assumed to be constant during the day) over the two vineyards are displayed in Fig. 9, along with frequency histograms of daytime ET from the TSEB and DATTUTDUT models expressed in mass units of  $\text{mm d}^{-1}$ . During IOP1 (DOY 100), the vines were leafing out in early growth stage and the cover crop in the inter-row was the main source of ET. However, the cover crop in the interrow for the north field was mowed shortly before this aircraft overpass, while the cover crop in the south field was unmowed, and was taller and more lush. As a result, EF and daytime ET distribution histograms showed bimodal shape on DOY 100. The histograms become more unimodal in later IOPs as the vine water use begins to dominate total ET.

While spatial patterns of EF from TSEB and DATTUTDUT were quite similar for all the five overpass dates, driven largely by patterns in  $T_R$  (see Fig. 8), the magnitudes in EF differ between the models, some days more significantly than others (Fig. 9a-9e). Use of the finer resolution data had generally a minor to moderate effect on the EF and ET distributions except for DOY 163 where the high resolution output indicates a bimodal distribution in EF and ET compared to the unimodal distributions using the 5 m resolution output from DATTUTDAT and TSEB. Since the DATTUTDUT model always scales EF between 0 and 1, results from the DATTUTDUT model generally had a wider distribution in EF compared to TSEB. An example of a clear difference in the width of the EF distribution can be seen for DOY 162 in IOP 2 (Fig. 9g), while for daytime ET, differences in the distributions were quite evident in IOP 2 and IOP 3 (Fig. 9l, 9n and 9o). A similar result was obtained by Choi et al. (2009), who compared turbulent fluxes estimated by METRIC, TIM and TSEB using Landsat imagery over a corn and soybean production region in central Iowa.

Despite similar model agreement in instantaneous ET with the tower measurements using the 5 m resolution data on DOY 100, 163 and 218 for the three IOPs (Fig. 6), there are in some cases where there are significant differences in maps of EF generated by the two models on these days (Fig. 9). EF discrepancies were particularly large on DOY 162 during IOP2 (Fig. 9b), and on DOY 219 during IOP3 (Fig. 9e). These discrepancies are due primarily to model differences in partitioning  $A$  between  $H$  and  $LE$  within these areas, rather than differences in  $A$  itself. In particular, DATTUTDUT has less sensitivity to dry aerodynamically rough surfaces, which the

1 model does not account for; therefore, DATTUTDUT scheme tends to estimate higher EF  
2 (Timmermans et al., 2015). Similar spatial discrepancies in model output were reported by  
3 Timmermans et al. (2007) and Choi et al. (2009), even though there was good agreement when  
4 the models were compared to flux tower measurements. The selection of improper extreme  
5 pixels is another crucial factor causing the large discrepancies for the DOY 162 and 219, as  
6 analyzed and discussed in Section 4.1.

### 7 **4.3 Sensitivity of TSEB and DATTUTDUT to the key input, $T_R$**

8 The sensitivity of the TSEB and DATTUTDUT models to the key input,  $T_R$ , was analyzed in  
9 order to further investigate the strengths and weaknesses of the two modeling approaches. The  
10 aircraft imagery from DOY 163 was selected as a case study since input data were collected in  
11 the afternoon (see Table 1) with near maximum radiation and air temperature conditions. Since  
12  $T_R$  is the most important input to both TSEB and DATTUTDUT, EF and ET values were  
13 calculated with a bias in  $T_R$  ( $\pm 3$  °C) to evaluate the sensitivity of these two models to absolute  
14 accuracy of this key input. The  $\pm 3$  degree bias in  $T_R$  was selected based on a comparison  
15 between ground-based and the airborne  $T_R$  measurements for IOP 3. For DATTUTDUT, the  
16 influence of extreme pixel selection on the computed EF and ET was also investigated. Values  
17 of EF and ET were also calculated with a 1 degree deviation in the assigned  $T_{max}/T_{min}$  ( $\pm 1$  °C).  
18 In addition, the values of  $T_{max}/T_{min}$  were selected using the native pixel resolution  $T_R$  imagery.  
19 Finally, values of  $T_{max}/T_{min}$  were derived from imagery encompassing a larger study  
20 area/modeling domain both at the aggregated 5 m pixel resolution and the  $T_R$  native ( $\sim 0.6$  m)  
21 resolution. Note that for TSEB, using finer resolution  $T_R$  would not be consistent with the model  
22 formulations for partitioning between soil and canopy convective energy and radiation fluxes and  
23 kinetic temperatures. A list of sensitivity tests conducted, along with the resulting EF and  
24 daytime ET statistics describing model output over the north and south vineyards, is provided in  
25 Table 6.

26 Results for the various tests of sensitivity of output from TSEB and DATTUTDUT to biases in  $T_R$   
27 inputs indicate that the error/uncertainty in EF and ET estimation can be fairly significant for  
28 TSEB (Fig. 10a-10c and Fig. 10l) with an uncertainty in field average ET of  $\sim 1$  mm day<sup>-1</sup>, while  
29 there is no real impact on the output from DATTUTDUT (Fig. 10d-10f and Fig. 10m). For  
30 TSEB, the shape of the ET distribution remains essentially unchanged, just the mean/centroid of

1 the distribution and max/min ET are shifted. This result is not unexpected based on prior  
2 sensitivity studies of both modeling approaches (e.g., [Timmermans et al., 2007](#)). The  $\pm 1$  degree  
3 change in the max/min  $T_R$  also does not impact the output of ET with DATTUTDUT ([Fig. 10g-](#)  
4 [10h](#) and [Fig. 10n](#)). However, changing the size of the modeling domain for defining max/min  $T_R$   
5 and/or the pixel resolution has a measurable impact on the spatially-distributed output from  
6 DATTUTDUT in these tests ([Fig. 10i-10k](#) and [Fig. 10o](#)). Similar to TSEB, the uncertainty in  
7 field average ET is  $\sim 1 \text{ mm day}^{-1}$ . With a larger study domain, the selected hot pixel is likely to  
8 have higher  $T_R$  while the cold pixel will tend to have lower  $T_R$  (see [Table 6](#)) since the number of  
9 pixels available for selection of the extremes are increased. This causes the ET estimation from  
10 larger domain (Case D5 and D7) to have a narrower distribution compared to ET from smaller  
11 domain (Case D0 and D6) (see [Fig. 10o](#)). The finer (native)  $T_R$  resolution also results in greater  
12 temperature extremes in the hot and cold pixels. ([Table 6](#)) since the pixels available for selection  
13 of the end-members were less contaminated containing a mixture of canopy and soil/substrate  
14 surfaces. Owing to the likely difference LE rates for the bare soil/senscent cover crop versus the  
15 irrigated vine vegetation the ET estimation from finer resolution  $T_R$  data (Case D6 and D7)  
16 tended to be more bimodal than that from courser resolution  $T_R$  (Case D0 and D5) (see [Fig. 10o](#)).

17 These tests confirm that simple scaling schemes like DATTUTDUT benefit from insensitivity to  
18 biases in  $T_R$ , but are sensitive to pixel size and range of conditions present within the modeling  
19 domain. This is in contrast to results reported by [French et al. \(2015\)](#), where they concluded that  
20 no significant difference in daily ET estimation accuracy was observed running the METRIC  
21 model at high (aircraft-based) and medium (Landsat) pixel resolutions. Their study fixed  
22 extreme pixels using an objective criteria based on clustered means rather than single pixels,  
23 which may reduce the likelihood of an error in selecting an outlier as an extreme hot or cold  
24 pixel. Moreover they conducted the inter-comparison of model output at the two resolutions  
25 focused on field-averaged ET in comparison to water balance estimates; therefore, the effects on  
26 ET distributions or variability were not evaluated in detail. Lastly, the sources of the input data  
27 at the two spatial resolutions were provided by the different platforms - aircraft and Landsat;  
28 however, the effects of changing the pixel resolution of either the aircraft or satellite data were  
29 not evaluated. While more automated approaches are being developed for determining extreme  
30  $T_R$ -values in applying contextual-based methods such as METRIC ([Morton et al., 2013](#)), the  
31 current study demonstrates that pixel resolution of  $T_R$  and sampling area will influence the

1 selection of extreme limits in the approach used by DATTUTDUT, resulting in differences in  
2 spatial distribution/patterns in ET from DATTUTDUT within a given study area.

#### 3 **4.4 Water consumption analysis**

4 Water consumption estimates at the field scale provide important information for water  
5 management decision making. In this section, estimates of field-scale daytime water  
6 consumption for the north and south fields were calculated by aggregating daytime ET totals for  
7 all pixels encompassed within each field and then converting to a volume (in liters) by the area  
8 of the corresponding field. When using the observed ET (from the flux towers), the field scale  
9 water consumption was computed by simply multiplying the tower measured daytime ET  
10 (forcing closure by residual) by the area (size) of the vineyard. The volume of water use for each  
11 field for the five overpass dates is illustrated in [Fig. 11](#).

12 The discrepancies between field water consumption from TSEB and DATTUTDUT were  
13 relatively small (3% - 6%) on DOY 100, 163 and 218, since the instantaneous and daytime ET  
14 estimates from the two models were similar. However, the water use estimated from TSEB was  
15 25% and 33% less than that computed by DATTUTDUT on DOY 162 and 219, respectively.  
16 Water consumption calculated by TSEB tended to agree with observed daytime ET estimated  
17 from the tower observations, but often had slightly lower ET estimates. This is consistent with  
18 the fact that, particularly for the north (site 1) vineyard, the flux tower footprint generally came  
19 from the center area of the field with highest EF and ET (cf. [Fig. 1](#) and [Fig. 9](#)). On the other hand,  
20 DATTUTDUT tended to estimate higher field scale ET than TSEB and tower measurements,  
21 particularly on DOY 162 and 219. The overall higher estimated water use for IOP2 and IOP3 by  
22 DATTUTDUT is likely due to the simplified parameterization of heat exchange based solely on  
23  $T_R$  and the pixel selection criteria for the hydrologic extremes as analyzed in [Section 4.1](#) and  
24 [Section 4.2](#).

25 Water use from TSEB was separated into soil/inter-row evaporation (E) and vine/vegetation  
26 transpiration (T) for each day by assuming the E/T ratio estimated at the aircraft overpass time  
27 was constant during the daytime period (see the red lines in [Fig. 11](#)). The variation of E between  
28 days was smaller than the variability in T, with standard deviations in E of 95 and 55 kiloliters  
29 for the north and south fields, respectively, as compared 197 and 173 kiloliters for T. On

1 average over the 5 days, the E/ET ratios for site 1 and 2 were estimated by TSEB to be ~0.33 and  
2 0.35, respectively. Although observations of E/ET are not available to validate the TSEB  
3 estimates of partitioning, other studies in drip-irrigated vineyards report E/ET ratios of ~0.3  
4  $\pm$ 0.12 (Yunusa et al., 2004; Ferreira et al., 2012; Poblete-Echeverr á et al., 2012; Kerridge et al.,  
5 2013), indicating TSEB estimates of E/ET partitioning are not unreasonable.

6 While some level of discrepancy is expected between modeled and measured vineyard water use  
7 due to model errors and measurement uncertainties, there are additional factors which may play a  
8 role when there appears to be a fairly large difference in water consumption estimated from the  
9 tower measurements *versus* the models, particularly with the TSEB model which tends to have  
10 better agreement with the tower measurements. The climate in this region is quite arid during  
11 the growing season with the drip irrigation being the only water source for the vines. As a result,  
12 the water availability (or soil water content) condition in the vine root zone plays a crucial role in  
13 the vegetation biomass. Therefore it is reasonable to assume there would be a strong correlation  
14 between ET and vine LAI as representative of the water availability in the root zone. The spatial  
15 variation in vine LAI is likely due to variation in the amount of irrigated water and/or variability  
16 in soil water holding capacity. Specifically, on days like DOY 162 and 163 for the north field  
17 and DOY 100 for the south field where there are significant differences between tower  
18 observations and TSEB estimates, there are also large differences observed between the LAI  
19 within the tower source area and the field average. The lower (higher) LAI of the flux tower  
20 source area is associated with the lower (higher) daytime ET estimated from the flux tower  
21 observations *versus* the spatially-distributed ET output from the TSEB model. The differences in  
22 LAI from the source area and field average are not large (see Table 7), but they do support the  
23 idea that a single measurement of water use within a vineyard is not always representative of the  
24 total vineyard water consumption.

25 In a comparison of ET measurements acquired over irrigated cotton eddy covariance, water  
26 balance and lysimeters, Kustas et al. (2015) show how variability in LAI within the different  
27 source areas associated with each measurement device was correlated to discrepancies between  
28 the measured values ET. In the current study, if the ratio of the field *versus* flux tower source  
29 area average LAI is used to adjust the water consumption estimates from the ET tower  
30 measurements for the two fields, in all cases except one (DOY 100 at site 2) there is closer  
31 agreement with TSEB estimates (see Fig. 11). The continued discrepancy for DOY 100 site 2

1 has more to do with the fact that the  $G$  values from the tower site were significantly higher than  
2 modeled (see Fig. 6) and are suspect since the ratio of  $G/R_n$  for much of the daytime period  
3 ranged from 0.3 to 0.45 which are values expected for bare soil (Santanello and Friedl, 2003).  
4 This resulted in the daytime available energy  $R_n-G$  for the tower site to be ~0.7 of the value  
5 estimated by TSEB. Therefore, closure of the tower-based ET flux did not significantly boost the  
6 observed value for DOY 100.

7 With the ET distributions from the models illustrated in Fig. 12, one sees that often the tower  
8 measurements fall significantly away from the center/mean of the modeled ET distributions. This  
9 is a major advantage with remote sensing-based ET approaches using high pixel resolution data  
10 which can capture the actual variation in key surface conditions (vegetation cover, soil moisture)  
11 affecting ET. While in most cases the LAI adjustment to the ET tower measurements improved  
12 the agreement with model estimated field scale water consumption, the capability of the remote  
13 sensing-based surface energy balance models in mapping ET provides a unique tool for  
14 identifying areas in the field potentially under water stress conditions. This isn't practical using  
15 micrometeorological methods.

16 Current operational techniques for estimating water use of crops primarily rely on the crop  
17 coefficient technique based on the FAO 56 publication (Allen et al., 1998). The actual ET of the  
18 crop is estimated by first computing a reference ET ( $ET_0$ ) which is then multiplied by the crop  
19 coefficient ( $K_c$ ). This single crop coefficient is often divided (called the dual crop coefficient)  
20 into a basal crop coefficient ( $K_{cb}$ ), which is associated with the crop transpiration and has been  
21 related to remotely sensed vegetation indices (Neale et al., 1989) and a soil surface evaporation  
22 coefficient ( $K_e$ ). There is also included a  $K_s$  coefficient to reduce crop transpiration for a deficit  
23 in water availability in the root zone so the expression has the form  $ET=(K_{cb}K_s + K_e)ET_0$ .  
24 Determining  $K_e$  and  $K_s$  requires running a soil water balance model for the surface and root zone.  
25 A recent application of this methodology over corn and soybean croplands is given by Gonzalez-  
26 Dugo and Mateos (2008) where they find this reflectance-based crop coefficient technique can  
27 significantly overestimate ET during a prolonged dry down period. There also appears to be no  
28 consistent or universal relationship between crop coefficients and vegetation indices and so this  
29 approach is not readily transferable to different crops and climatic conditions (Gonzalez-Dugo et  
30 al., 2009).



1 As an example, the spatial distribution of  $K_C$  was computed using FAO 56 estimated  $ET_0$  and the  
2 ET map from TSEB from DOY 163 (Fig. 13). There is a significant spatial variation in  $K_C$  due  
3 in part to the known effect of leaf area/fractional cover (Choudhury et al., 1994), which is seen in  
4 the correlation between the  $K_C$  map and LAI map of Fig. 4, but there are other factors including  
5 the vine variety and the possibility of some level of stress in areas of the vineyard that cannot be  
6 reliably detected by this approach. Using the ET measurements from the flux towers and FAO  
7 56 estimated  $ET_0$ , for the north vineyard site 1, the value of  $K_C$  ranged from 0.55 for DOY 100 to  
8 0.76-0.82 for the other days. For the south vineyard (site 2),  $K_C$  values ranged from 0.59 for  
9 DOY 100 to 0.62-0.65 for the other days, indicating little variation in  $K_C$  with vine phenology.  
10 In contrast, the FAO 56 manual recommends  $K_C$  values for vineyards at early, peak and end of  
11 the growing season of 0.3, 0.7 and 0.45. Clearly, a calibration with this approach is required,  
12 which is not only dependent on vine variety but also on vine management (i.e., row orientation  
13 and spacing, pruning, irrigation scheduling, etc.)

## 14 **5 Conclusions**

15 High resolution multispectral and thermal imagery obtained by aircraft mounted sensors were  
16 used to map evapotranspiration (ET) over two vineyards in central California using both the Two  
17 Source Energy Balance (TSEB) and single-source contextual-based DATTUTDUT (Deriving  
18 Atmosphere Turbulent Transport Useful To Dummies Using Temperature) model which scales  
19 evaporative fraction (EF) between 0 and 1 using only the radiometric surface temperature ( $T_R$ )  
20 extremes of cold/wet and hot/dry pixels in the remotely sensed scene. This study focused on five  
21 aircraft overpass dates (DOY 100, 162, 163, 218 and 219) over the vine growing season in 2013.

22 Component soil and canopy temperatures from TSEB agreed well with the airborne-based  
23 observations derived within the flux-tower source-area yielding a bias on the order of 0.5 °C and  
24 a RMSD-value ~2.5 °C for both soil/cover crop and vine canopy temperatures. Instantaneous  
25 and daytime integrated fluxes from the TSEB and DATTUTDUT models were validated with  
26 flux tower measurements. The TSEB model was able to derive satisfactory estimates of both  
27 instantaneous and daytime sensible heat flux ( $H$ ) and latent heat flux (LE) for all the five  
28 overpass dates, while overall the DATTUTDUT model output of  $H$  and LE were in less  
29 agreement with the tower measurements, particularly for DOY 162 and 219 overpass dates.

1 Spatial distributions of evaporative fraction, EF, and daytime ET from the two models were  
2 compared for all the five overpass dates. While the spatial patterns of relatively high and low  
3 values of EF mapped by TSEB and DATTUTDUT for the two vineyard fields were similar, the  
4 magnitude and range in the EF values were quite different on certain days. Specifically, the  
5 distributions of EF values from DATTUTDUT often yielded a wider range due to the  
6 requirement that each image contains ET at the extremes of potential and  $ET=0$ . This resulted in  
7 EF and daytime ET magnitudes and spatial patterns generated by the two models being fairly  
8 similar on DOY 100, 163 and 218, while having larger discrepancies on DOY 162 and 219. In  
9 general, inter-comparisons between the performance of TSEB and DATTUTDUT using high  
10 resolution (meter-scale) data tended to yield conclusions consistent with results from prior  
11 studies comparing TSEB with single-source models based on contextual scaling of maximum  
12 and minimum ET using moderate resolution data (see e.g., [French et al., 2005, 2015](#);  
13 [Timmermans et al., 2007](#); [Choi et al., 2009](#)). With a more physically-based two-source  
14 formulations explicitly treating soil and vegetation energy and radiation exchanges and reliable  
15  $T_R$  data, the TSEB model is fairly robust and able to derive reliable ET patterns at sub-field scale  
16 under a wide range of environmental conditions. The performance of DATTUTDUT model in  
17 computing reliable ET and generating distributions and patterns over the vineyards was similar  
18 to TSEB on some of the overpass dates, but for other times the DATTUTDUT model  
19 performance was less than satisfactory largely depending on whether there actually existed pixels  
20 in the scene that were representative of the extreme ET conditions, namely “maximum” ET  
21 ( $LE=R_n-G$ ) and no ET ( $LE=0$ ).

22 Differences in daytime ET estimated from the two models directly contributes to the  
23 discrepancies in field-scale water use estimates, which on certain days was quite significant. The  
24 discrepancies in field scale water consumption calculations from the two models ranged from 3%  
25 to 33%, which translated to differences in field scale water use between the two models ranging  
26 from approximately 68 to 899 kiloliters. Field-scale water consumption estimated from TSEB  
27 agreed more closely with estimates based on tower ET observations, while DATTUTDUT  
28 tended to estimate higher water use. Disagreement between modeled and measurements is partly  
29 due to the difference with LAI of the tower source area and the whole field average. Larger  
30 differences in water use occurred when source area LAI failed to represent the field average. A  
31 simple adjustment using the ratio of average LAI from the field and the tower source-area greatly

1 reduced the discrepancy with the TSEB model output. Comparison between tower measured ET  
2 and ET distributions from the models shows that tower measurements generally do not have a  
3 value that is representative of the center/mean of the modeled ET distributions.

4 Compared with water consumption information provided by flux tower observations, the type of  
5 spatially-distributed ET information provided by thermal-based energy balance models has clear  
6 advantages, particularly when imagery is at fine pixel resolution. ET observed by flux tower is  
7 sampling a relatively small area of the field, while the ET models with the  $T_R$  imagery can  
8 provide spatially-distributed water use information over the entire vineyard and consequently  
9 identify the spatial distribution of plant water status, a required input for precision irrigation  
10 systems. Two-source schemes like TSEB are able to provide reliable ET estimation as well as the  
11 partitioning between E and T since the model explicitly parameterizes the radiative and  
12 convective exchanges between the soil and canopy systems.

13 However, the sensitivity analysis indicates that high-quality  $T_R$  input data are needed for TSEB.  
14 The DATATTUDUT contextual scaling approach, with automatic pixel selection, is not sensitive  
15 to errors in  $T_R$  and requires only very basic information as model input, making it relatively easy  
16 to apply operationally. Nevertheless, such one-source approaches fail to provide estimates of the  
17 E and T partitioning, and the ET estimation at least for DATTUTDUT can be sensitive to  
18 domain size and spatial resolution due to the simple model parameterizations.

19 With UAV technology rapidly developing to provide remote sensing products in near real time  
20 ([Berni et al., 2009b](#)), the DATTUTDUT scheme can provide real time ET maps at sub-field  
21 scale that will in many cases yield reliable patterns, but not in all cases appropriate magnitudes in  
22 ET. In cases where the landscape is aerodynamically rough and dry, an adjustment to the end-  
23 member selection for the DATTUTDUT scheme appears to be necessary ([Timmermans et al.,  
24 2015](#)). If routine high-resolution imagery from UAVs become operational, a hybrid  
25 methodology integrating a very simple ET model (DATTUTDUT) with a more robust modeling  
26 scheme (TSEB) should be developed. Moreover, to ensure continuous and reliable daily water  
27 use and vegetation stress monitoring incorporating the crop coefficient based technique linked to  
28 a water balance model with the thermal-based ET approach using data assimilation has shown  
29 utility and addresses to a large extent the shortcomings in estimating/updating the crop  
30 coefficient and the impact of plant stress ([Neale et al., 2012](#)).

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1 **Tables:**

2 **Table 1.** Flight and pixel resolution information concerning the images obtained from the  
3 airborne campaigns.

IOP	Date (DOY)	Flight time (UTC)	Original spatial resolution (m)		Flight height (m)
			Multispectral	Thermal	
1	April 10 (100)	18:29-18:43	0.09	0.7	430
2	June 11 (162)	18:20-18:26	0.05	0.42	240
2	June 12 (163)	21:11-21-16	0.05	0.38	240
3	August 6 (218)	18:34-18:37	0.1	0.66	480
3	August 7 (219)	18:46-18:49	0.1	0.65	480

4

1 **Table 2.** Difference statistics describing comparisons between modeled fluxes from TSEB and  
2 DATTUTDUT at the overpass time and observations (original and with adjustments using the  
3 RE and BR methods for energy balance closure) ( $\text{W m}^{-2}$ ).

Site	Flux	DOY No.	Mean Obs.	TSEB (5 m pixel res.)			DATTUTDUT (5 m pixel res.)			DATTUTDUT (native pixel res.)		
				Bias	MAE	RMSD	Bias	MAE	RMSD	Bias	MAE	RMSD
Site 1	$R_n$	5	593	0	26	33	-43	64	66	-61	61	65
	$G$	5	85	5	28	33	-18	35	40	-24	35	38
	$H$	5	195	13	37	42	48	53	68	41	57	68
	LE	5	268	-63	70	87	-117	117	150	-123	139	157
	LE <sub>RE</sub>	5	313	-18	32	37	-73	76	105	-78	100	106
	$H_{BR}$	5	215	33	55	62	68	71	89	61	76	91
	LE <sub>BR</sub>	5	293	-38	50	58	-92	94	125	-98	119	129
Site 2	$R_n$	5	590	6	15	23	-19	26	27	-40	40	42
	$G$	5	132	41	43	59	6	47	61	12	42	55
	$H$	4	195	-23	43	45	8	31	39	21	53	59
	LE	4	186	-90	90	102	-106	106	119	-149	149	163
	LE <sub>RE</sub>	4	253	-23	43	51	-38	55	63	-81	90	101
	$H_{BR}$	4	231	13	33	48	44	59	68	57	81	90
	LE <sub>BR</sub>	4	217	-59	61	77	-74	77	93	-117	117	136

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1 **Table 3.** Difference statistics describing comparisons between modeled daytime fluxes from  
2 TSEB and DATTUTDUT model and observations (original and with adjustments using the RE  
3 and BR methods) ( $\text{MJ m}^{-2} \text{d}^{-1}$ ).

Site	Flux	DOY No.	Mean Obs.	TSEB (5 m pixel res.)			DATTUTDUT (5 m pixel res.)			DATTUTDUT (native pixel res.)		
				Bias	MAE	RMSD	Bias	MAE	RMSD	Bias	MAE	RMSD
Site 1	$R_n-G$	5	15.0	-0.5	0.7	0.9	-1.2	1.2	1.5	-1.2	1.4	1.6
	$H$	5	4.4	-1.0	1.2	1.4	-0.1	1.0	1.2	-0.1	1.2	1.3
	LE	5	8.5	-1.6	1.6	1.8	-3.2	3.2	3.6	-3.1	3.2	3.6
	LE <sub>RE</sub>	5	10.6	0.5	1.0	1.1	-1.1	1.4	1.9	-1.0	1.9	2.0
	$H_{BR}$	5	9.9	4.4	4.4	5.1	5.4	5.4	6.1	5.4	5.4	6.0
	LE <sub>BR</sub>	5	5.1	-4.9	4.9	5.4	-6.6	6.6	7.1	-6.5	6.5	6.9
Site 2	$R_n-G$	5	13.9	-1.4	1.5	1.9	-1.1	1.5	2.3	-1.7	2.0	2.5
	$H$	4	5.2	-1.8	1.8	2.2	-0.8	1.1	1.3	-0.3	1.1	1.3
	LE	4	6.2	-2.6	2.6	2.9	-3.1	3.1	3.5	-4.3	4.3	4.6
	LE <sub>RE</sub>	4	8.8	0.0	1.7	1.7	-0.5	1.7	1.8	-1.6	2.2	2.3
	$H_{BR}$	4	7.6	0.6	1.9	1.9	1.6	1.6	1.8	2.1	2.1	2.3
	LE <sub>BR</sub>	4	6.4	-2.4	3.0	3.4	-2.9	2.9	3.4	-4.0	4.0	4.2

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1 **Table 4.** Difference statistics for daytime ET ( $\text{MJ m}^{-2} \text{d}^{-1}$ ) extrapolated from instantaneous  
 2 estimates using observed available energy  $A$  (Obs.  $A$ ) from flux towers versus using incoming  
 3 solar radiation measurements ( $S_d$ ).

Site	Stat	TSEB		DATTUTDUT	
		Obs. $A$	$S_d$	Obs. $A$	$S_d$
Site 1	Bias	0.5	-1.4	-1.1	-3.4
	MAE	1.0	1.4	1.4	3.4
	RMSD	1.1	1.6	1.9	4.1
Site 2	Bias	0.0	-0.8	-0.5	-1.3
	MAE	1.7	1.5	1.7	1.3
	RMSD	1.7	1.8	1.8	1.8

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1 **Table 5.** Difference statistics comparing instantaneous output of LE from TSEB and  
 2 DATTUTDUT with current DATTUTDUT algorithms for estimating the available energy versus  
 3 using the estimates from TSEB.

Site	Flux	DOY No.	Mean Obs.	TSEB			DATTUTDUT (5m)			DATTUTDUT using $R_n$ and $G$ from TSEB		
				Bias	MAE	RMSD	Bias	MAE	RMSD	Bias	MAE	RMSD
Site 1	H	5	195	13	37	42	48	53	68	52	59	75
	LE	5	268	-63	70	87	-117	117	150	-101	101	123
	LE <sub>RE</sub>	5	313	-18	32	37	-73	76	105	-56	56	77
	H <sub>BR</sub>	5	215	33	55	62	68	71	89	72	77	96
	LE <sub>BR</sub>	5	293	-38	50	58	-92	94	125	-76	76	97
Site 2	H	4	195	-23	43	45	8	31	39	1	30	37
	LE	4	186	-90	90	102	-106	106	119	-114	114	123
	LE <sub>RE</sub>	4	253	-23	43	51	-38	55	63	-47	47	59
	H <sub>BR</sub>	4	231	13	33	48	44	59	68	37	46	62
	LE <sub>BR</sub>	4	217	-59	61	77	-74	77	93	-83	83	95

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1 **Table 6.** Statistics describing EF and daytime ET produced by TSEB and DATTUTDUT over the north and south vineyards for each  
2 sensitivity test described in the text.

Model	Cases	Input setting	$T_R$ of extreme limits (°C)		EF					Daytime ET (mm)					
			$T_{max}$	$T_{min}$	Mean <sup>1</sup>	Med. <sup>2</sup>	Std. <sup>3</sup>	Max. <sup>4</sup>	Min. <sup>5</sup>	Mean	Med.	Std.	Max.	Min.	RMSD <sup>6</sup>
TSEB	T0	Original Input	-	-	0.61	0.62	0.12	0.91	0.01	4.3	4.4	1.0	6.8	0.1	0.6
	T1	$T_{R+3}$	-	-	0.46	0.48	0.14	0.80	0.02	3.2	3.3	1.1	5.9	0.1	2.0
	T2	$T_{R-3}$	-	-	0.73	0.74	0.11	0.99	0.02	5.3	5.3	1.0	7.6	0.1	0.3
DATTUTDUT	D0	Original Input	54.7	31.4	0.67	0.67	0.11	1	0	4.5	4.5	1.3	8.9	0	0.5
	D1	$T_{R+3}$	57.7	34.4	0.67	0.67	0.11	1	0	4.4	4.3	1.2	8.7	0	0.6
	D2	$T_{R-3}$	51.7	28.4	0.67	0.67	0.11	1	0	4.7	4.6	1.3	9.1	0	0.4
	D3	$T_{max+1}$	55.7	31.4	0.68	0.68	0.11	1	0.04	4.7	4.6	1.2	8.9	0.1	0.4
	D4	$T_{min-1}$	54.7	30.4	0.64	0.64	0.11	0.96	0	4.3	4.2	1.2	8.3	0	0.8
	D5	Whole Area	58.4	23.4	0.55	0.55	0.08	0.77	0.11	3.4	3.3	0.8	5.9	0.3	1.6
	D6	Native Resolution	58.5	25.7	0.62	0.64	0.17	1	0	4.2	4.2	1.8	9.3	0	0.7
D7	Whole Area and Native Resolution	61.4	20.3	0.57	0.58	0.13	0.87	0.07	3.6	3.6	1.4	7.4	0.2	1.3	

3 <sup>1</sup>Mean: mean of the EF or ET distribution

4 <sup>2</sup>Med.: median of the EF or ET distribution

5 <sup>3</sup>Std.: Standard deviation of the EF or ET distribution

6 <sup>4</sup>Max.: Maximum value of the EF or ET distribution

7 <sup>5</sup>Min.: Minimum value of the EF or ET distribution

8 <sup>6</sup>RMSD: the RMSD of the modeled daytime ET at Site 1 and Site 2,  $RMSD = \{[(O_1-M_1)^2 + (O_2-M_2)^2]/2\}^{1/2}$ .

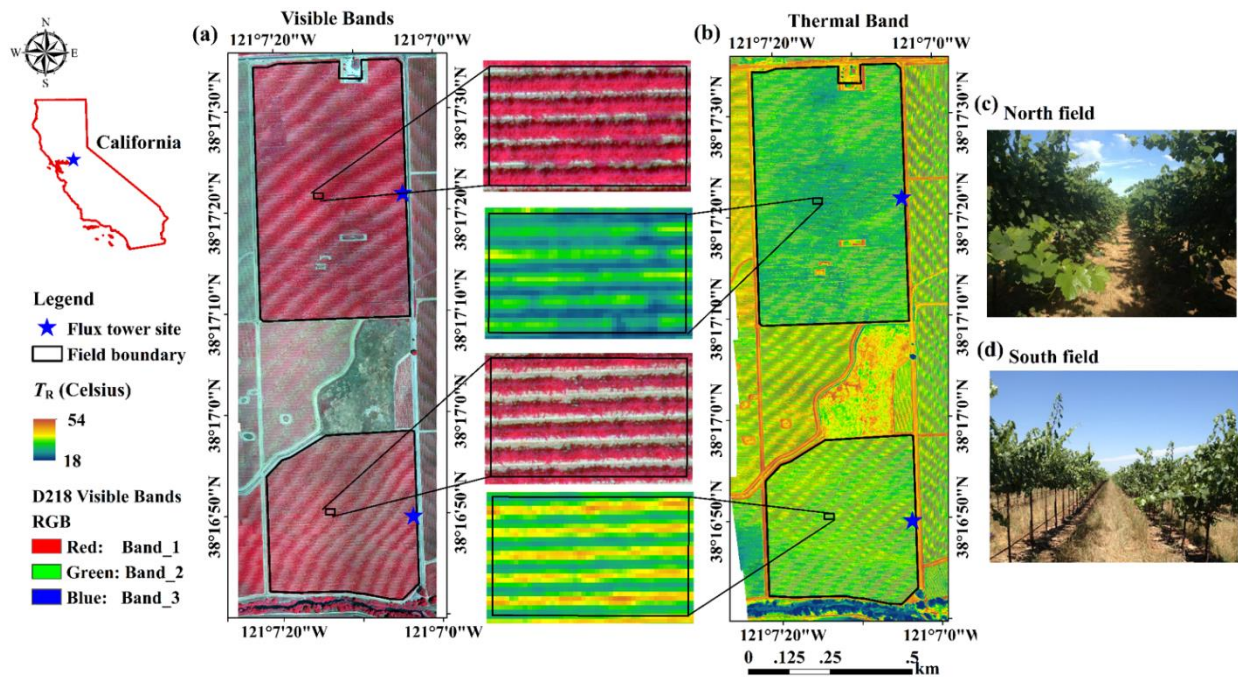
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1 **Table 7.** Average leaf area index (LAI) estimated for the flux tower source area/flux footprint  
 2 versus the whole field derived from the aircraft imagery (NDVI relationship with LAI). The LAI  
 3 values in bold are associated with the days where differences in water consumption estimated by  
 4 TSEB versus using the tower measured ET are significant for site 1 (North vineyard) and site 2  
 5 (South vineyard).

Site	DOY	LAI	
		Source Area	Whole Field
1	100	1.3	1.3
	162	<b>2.0</b>	<b>1.5</b>
	163	<b>1.8</b>	<b>1.5</b>
	218	1.6	1.5
	219	1.7	1.5
2	100	<b>1.7</b>	<b>1.9</b>
	162	1.5	1.5
	163	1.5	1.5
	218	1.2	1.2
	219	1.3	1.2

6

1 **Figures:**

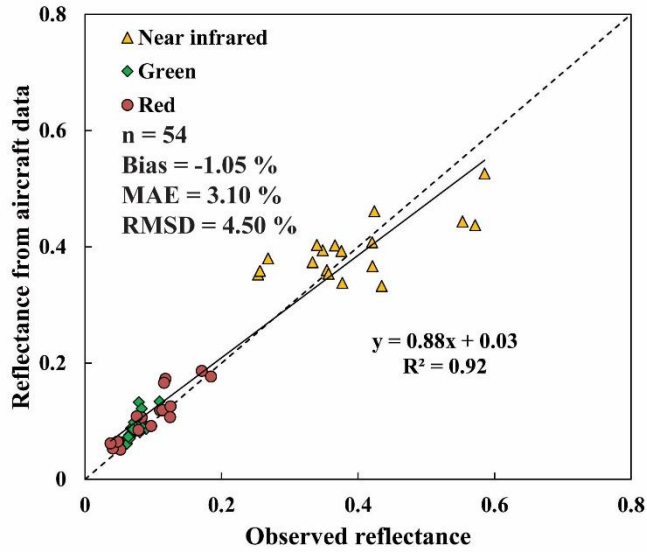


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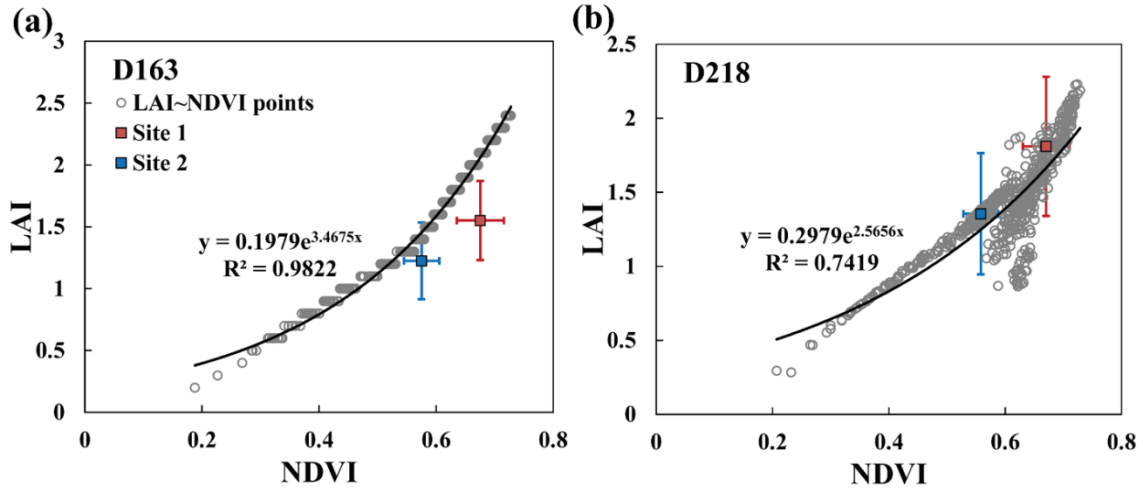
4 **Figure 1.** Location of study area overlaid on a false color composite of near-infrared (NIR), red,  
 5 and green bands with 0.1 m spatial resolution (a) and thermal band with 0.66 m spatial resolution  
 6 (b) obtained by aircraft on August 6, DOY 218, 2013. In the visible band image (a), red and  
 7 gray colors denote the vine and bare soil/senescent cover crop in the inter-row, respectively,  
 8 while in the thermal band image (b), blue/green and yellow/red colors represent vine and bare  
 9 soil/senescent cover crop in the inter-row, respectively. The black line denotes the boundary of  
 10 north and south fields, and the blue stars are the locations of the flux tower sites. The two photos  
 11 of the north and south fields (c and d) were taken on June 11 in 2014 after vines had fully leafed  
 12 out.

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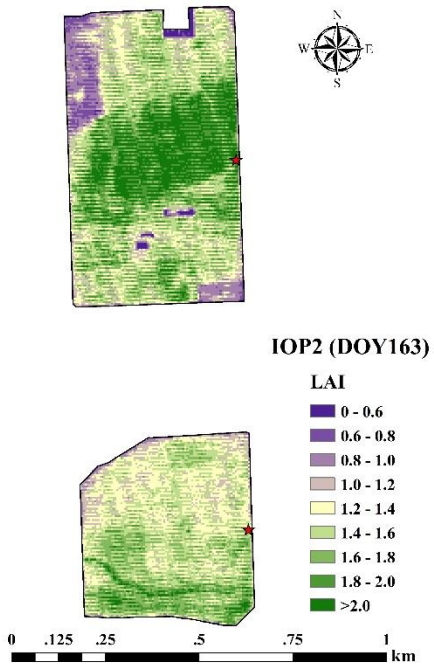
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**Figure 2.** Comparison between observed ( $O$ ) and modeled ( $M$ ) visible band reflectance. The statistics (for the sample size  $n=54$ ) listed in the figure are the Bias ( $\Sigma (O-M)/n$ ), mean absolute error ( $MAE=\Sigma|O-M|/n$ ) and root mean square difference ( $RMSD=[\Sigma(O-M)^2/n]^{1/2}$ ) where the symbol  $\Sigma$  represents a summation over the sample size  $n$ .



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**Figure 3.** Validation of the LAI~NDVI relation using the ground-based LAI measurements on DOY 163 and 218.



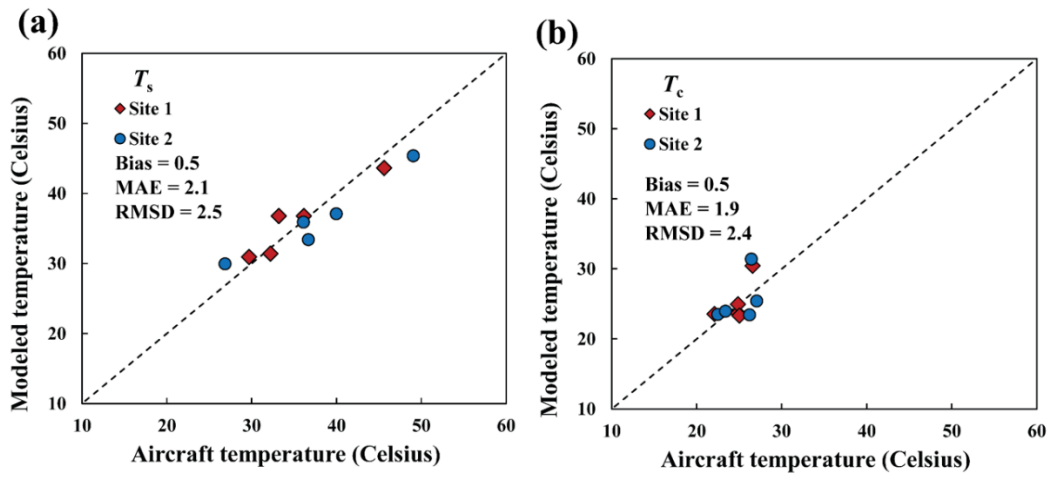
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2 **Figure 4.** The LAI map generated from the NDVI image for IOP 2 DOY 163.

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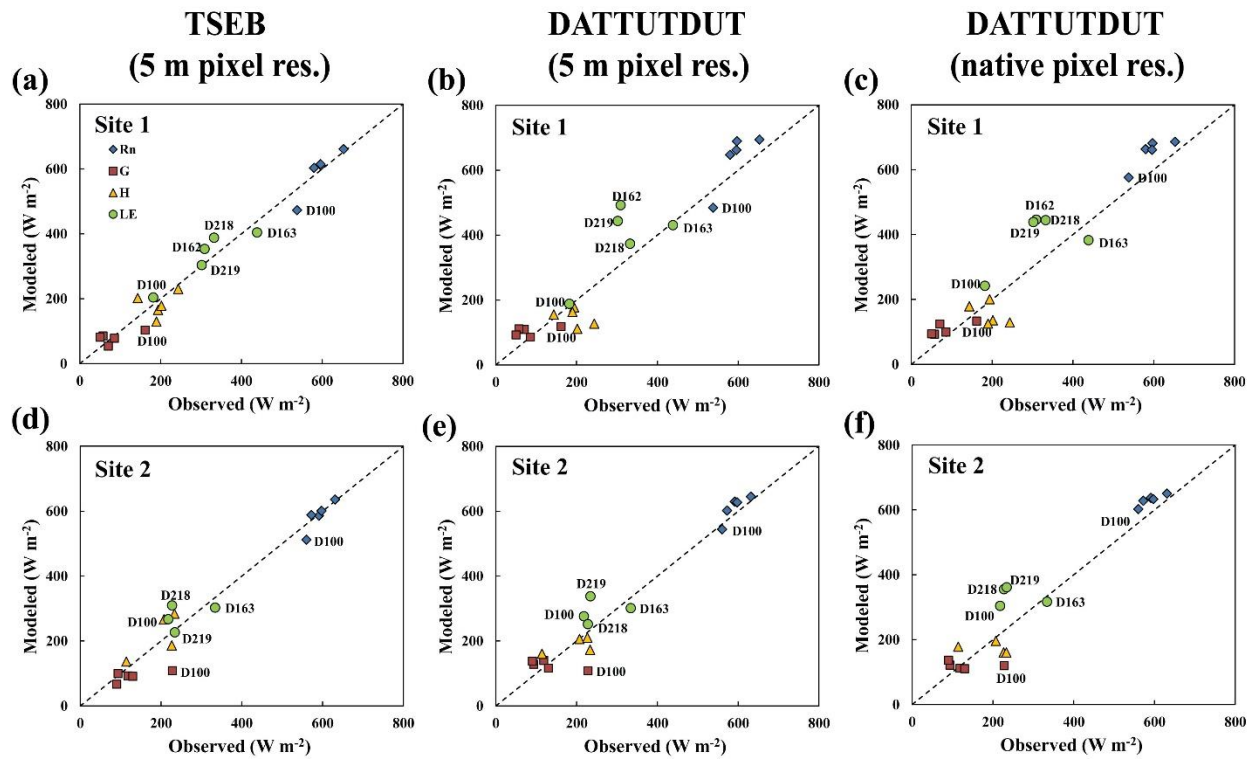


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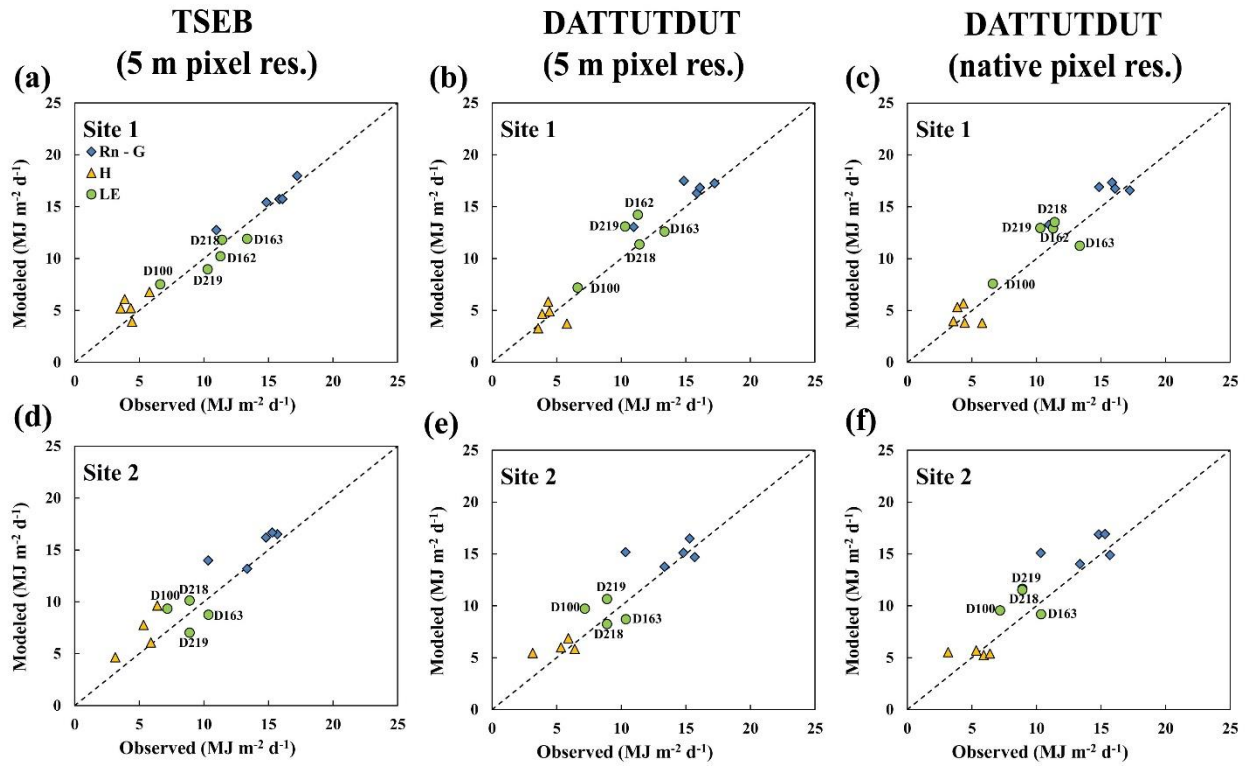
4 **Figure 5.** Comparison between modeled  $T_s$  and  $T_c$  from TSEB and values extracted from the  
5 aircraft imagery on the five acquisition days. All the statistics (Bias, MAE and RMSD) have  
6 units of °C.

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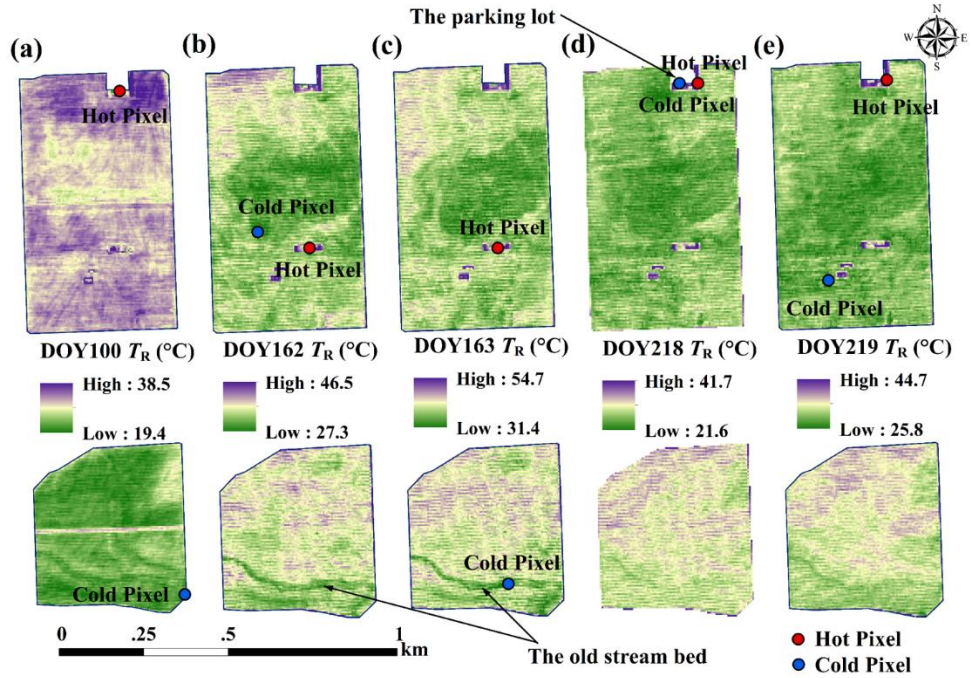
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**Figure 6.** Scatter plot of observed and modeled fluxes from (a) TSEB (5 m pixel resolution), (b) DATTUTDUT (5 m pixel resolution) and (c) DATTUTDUT (native pixel resolution) at the aircraft overpass time for the five days in 2013. The observed  $H$  and  $LE$  use the RE method for energy balance closure. Note for DOY 162, there were no flux data from site 2 due to an EC sensor malfunction.



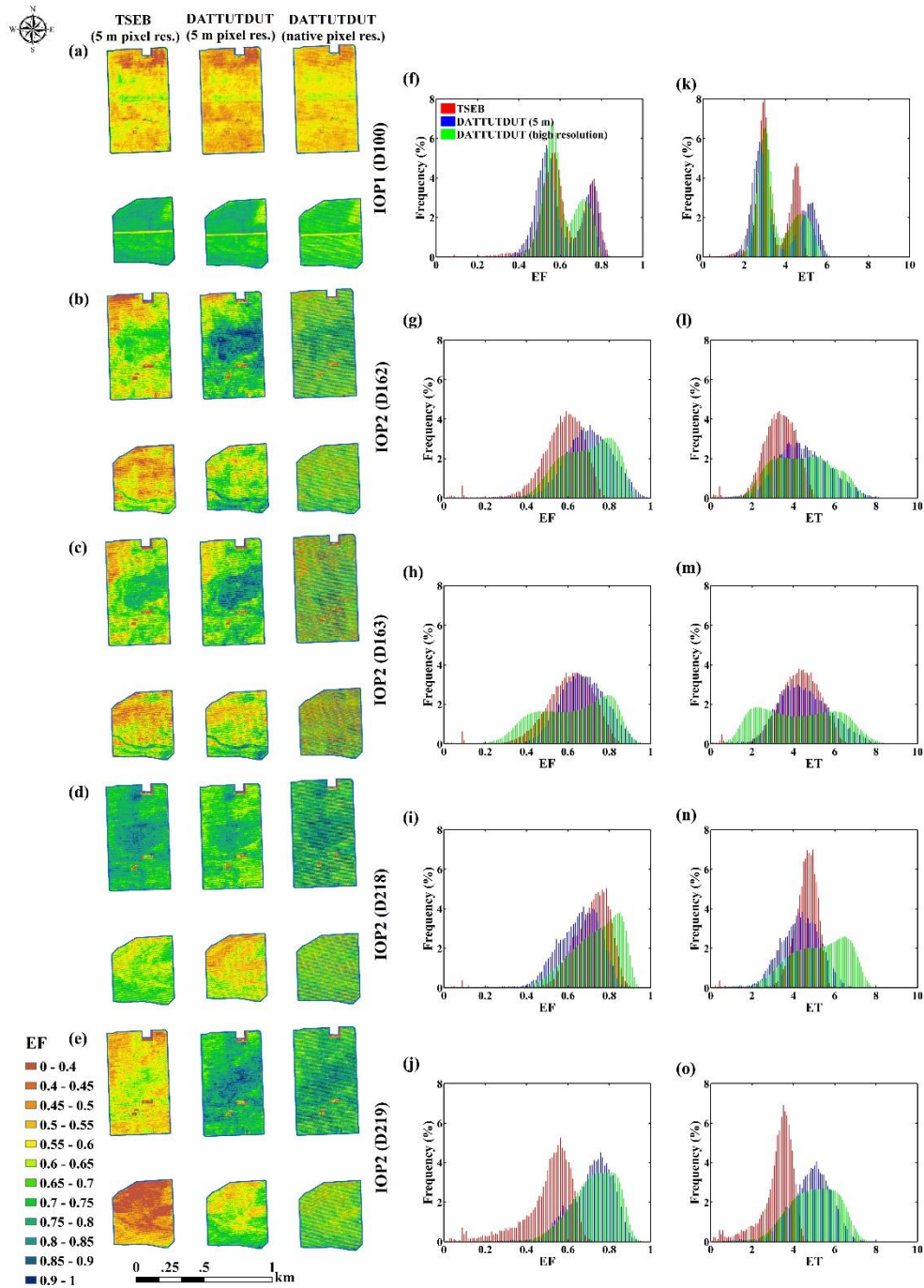
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**Figure 7.** Scatter plot of observed and modeled daytime fluxes from (a) TSEB (5 m pixel resolution), (b) DATTUTDUT (5 m pixel resolution) and (c) DATTUTDUT (native pixel resolution) for the five days in 2013. The observed energy components are adjusted for energy balance using the RE method.



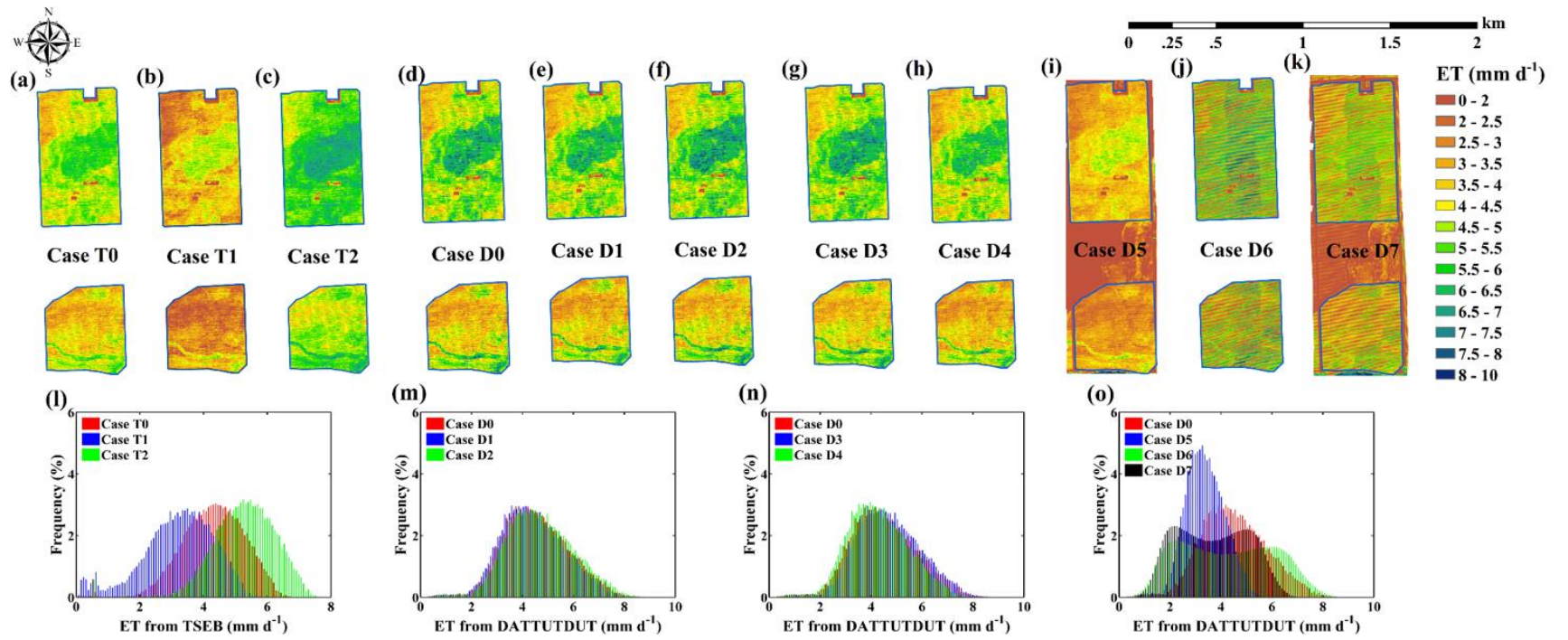
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**Figure 8.** Locations of hot (red points) and cold (blue points) pixels selected from the  $T_R$  maps for DATTUTDUT model on the five days.

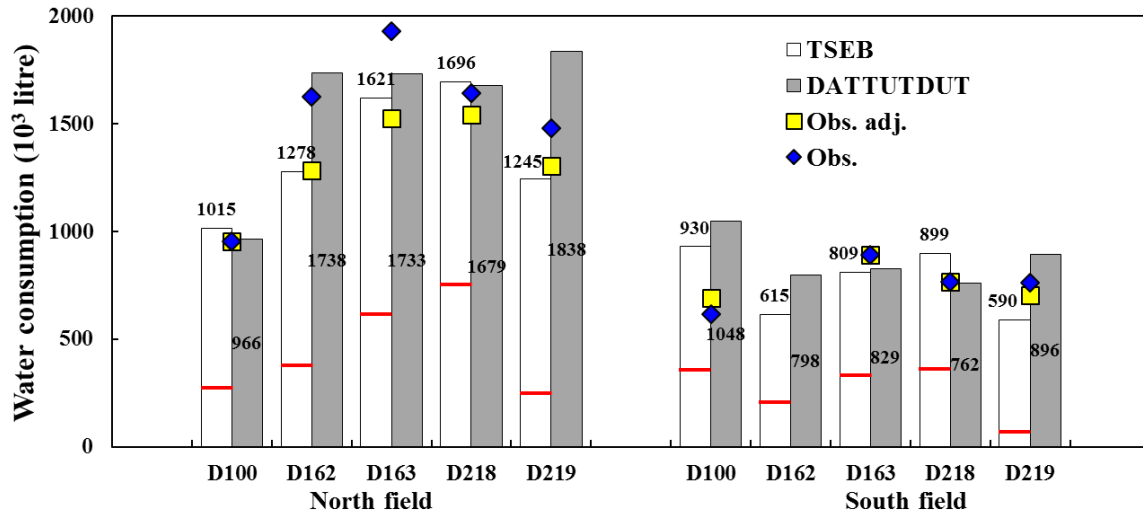


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**Figure 9.** Comparison of TSEB ( 5 m resolution) and DATTUTDUT model output at 5 m and native pixel resolution: spatial distribution of instantaneous EF (a to e), frequency histogram of instantaneous EF (f to j) and daytime ET (k to o).

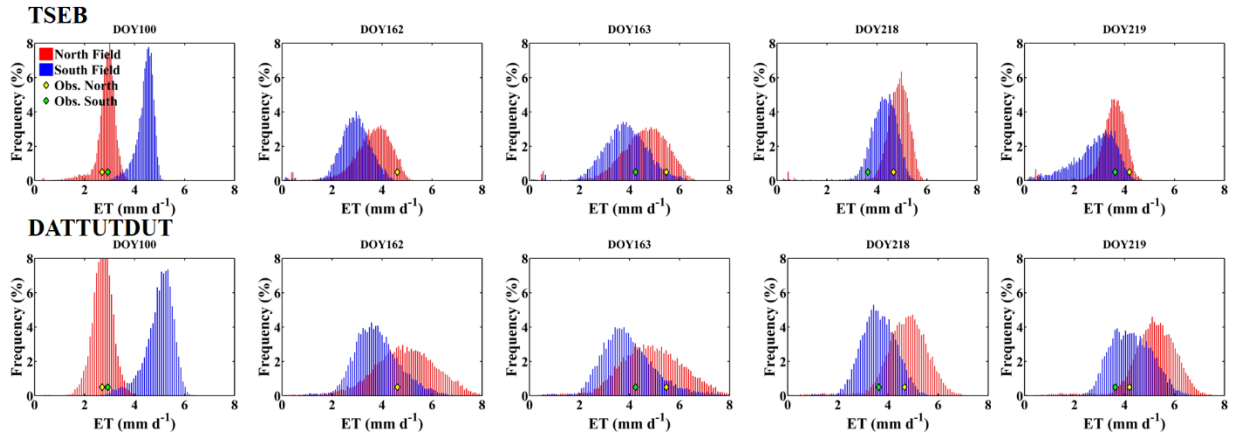


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 2 **Figure 10.** Comparison of the ET patterns and frequency distributions generated by TSEB and DATTUTDUT under the sensitivity  
 3 tests described in Table 6.  
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**Figure 11.** Water consumption calculated from estimates of ET computed by TSEB and DATTUTDUT models for the five aircraft overpass days ( $10^3$  liter). The numerical values above or in the columns denote the total water consumption from each field as estimated by the two models. For results from TSEB, the red lines separate the total water consumption into soil evaporation below the lines and vegetation transpiration above the lines. The blue diamonds denote the water consumption calculated using the EC tower-based daytime ET observed (Obs.) multiplied by the area of the north and south vineyards. The yellow squares are the water consumption values from ET Obs. adjusted (adj.) by multiplying ET Obs. by the ratio of the tower source area LAI and the whole field average LAI.



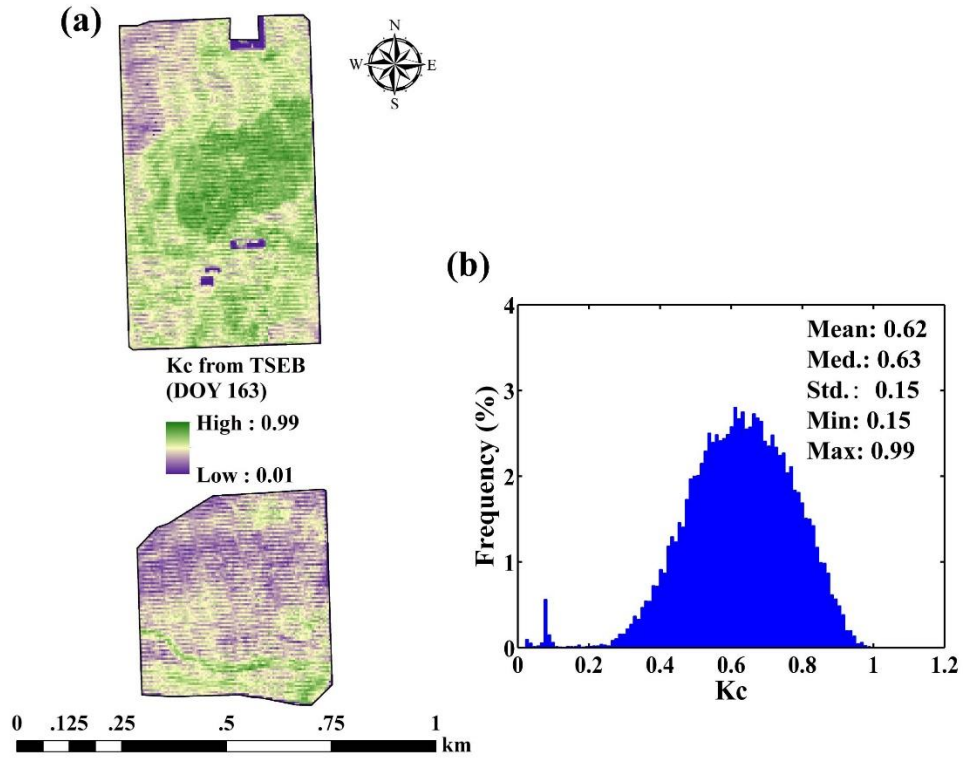
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3 **Figure 12.** Histograms of output of spatially distributed daytime ET estimated from the TSEB  
 4 and DATTUTDUT with the daytime ET values from the flux towers identified in the  
 5 distributions by a yellow and green diamond for the north and south vineyards, respectively.

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**Figure 13.** Spatial variation in the crop coefficient  $K_c$  computed using TSEB output of ET and  $ET_0$  computed from FAO56 for DOY 163 imagery (a). Also the frequency distribution in  $K_c$  for the image is illustrated (b).