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# Energy partitioning between plant canopy and soil, performance of the two-source energy balance model in a vineyard

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# ABSTRACT

Partitioning of evapotranspiration (ET) into soil water evaporation and transpiration allows separate assessment of soil and plant water, energy, and carbon exchange. Remote sensing-based models are ideally suited to monitor ET over large areas, but ET partitioning estimates vary widely. The objective of this study was to evaluate the two-source energy balance (TSEB) model for seasonal ET partitioning using total, soil, and vine canopy energy balance fluxes measured over a vineyard in the Negev desert in Israel. Energy fluxes were evaluated with the original TSEB and three adapted versions using (1) measured soil heat flux, (2) optimized plant transpiration parameterization, and (3) measured soil and vine temperatures instead of composite surface temperature as model inputs. Optimization of plant transpiration parameters revealed a model tendency to underestimate transpiration due to underestimation of available energy and potential transpiration. Adaptations included, among others, accounting for higher leaf radiation absorption expected in dense clumped canopies, which increases available energy, and increasing the Priestley-Taylor coefficient from 1.26 to 2, which increases potential transpiration. While the original TSEB gave reasonable total energy fluxes, the vine energy fluxes were greatly underestimated. Both soil heat flux and plant transpiration adaptations improved modeled vine energy fluxes throughout the season under both well-watered and water-stressed conditions. However, the performance of the TSEB version using measured soil and vine temperatures was inferior to applying the standard TSEB with composite temperature. While daily energy fluxes could be estimated with reasonable accuracy, sub-daily fluxes proved to be more challenging and merit further research. Finally, changes in ET partitioning with canopy development and in response to water stress could be detected quite well albeit it with an underestimation of the transpiration fraction of ET, which, on average, amounted to 39% using standard TSEB and 6% with optimized plant transpiration parameters.

# 1. Introduction

Evapotranspiration (*ET*) is an important part of the hydrological cycle, equaling two thirds of precipitation globally, and connects the hydrological cycle to energy and carbon cycles (Fisher et al., 2017). The primary components of *ET* are plant transpiration and soil water evaporation (*E*) which are both affected by evaporative demand and available water. However, plant transpiration is different from *E* in that water uptake occurs across the root volume and that water, energy, and carbon exchange into the atmosphere are regulated by plant growth and

stomatal control (Kumar et al., 2018). Partitioning of *ET* into its components is of particular interest to agriculture where it can help estimate yield and inform water management decision making, especially in water-scarce environments (Kool et al., 2014a). Evaporation and transpiration are also important boundary conditions for vadose zone models which are used to assess solute transport, irrigation efficiency and plant growth (Anderson et al., 2017). In climate models, *ET* partitioning is used to forecast drought, among other things. Accounting for vegetation greatly improved simulations of the 2002 drought in Australia (Meng et al., 2014), while failure to forecast the 2012 U.S.

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Fig. 1. Vineyard site, photo taken on 26 July 2012 (fully developed canopy).

Midwest megadrought was attributed to an underestimation of vegetation response in climate models (Fisher et al., 2017). Considering these critical applications, partitioning was recently identified as one of ten major knowledge gaps in *ET* research (Fisher et al., 2017). Effective local, regional, and global monitoring of water resources and climate requires reliable *ET* partitioning data with high spatial and temporal resolution and coverage. Specifically, one of the current goals is to improve the temporal resolution of *ET* from daily to sub-daily and reduce the relative error to less than 10% to allow detection of water use and water stress (Fisher et al., 2017).

Models using remotely sensed measurements are ideally suited to maximize global coverage (Kalma et al., 2008), but may give vastly different *ET* partitioning results even when *ET* is reasonable (Talsma et al., 2018b). For example, the estimated average transpiration relative to *ET* for 2002–2012 over the contiguous U.S. ranged between 30% and 83% using eight different remote sensing models (Kumar et al., 2018). These errors were largely ascribed to uncertainty in transpiration. Efforts to validate *ET* partitioning obtained from remote sensing models have been limited. The most validated model is the two-source energy balance (TSEB), but other examples include a trapezoidal remote sensing model that was evaluated over a shrub system in Arizona (Yang et al., 2015). Two studies used a remote sensing model to determine *ET* and combined this with a dual crop coefficient approach (Paço et al., 2014) or a Shuttleworth–Wallace approach (Fuentes-Peñailillo et al., 2018) to assess partitioning. The two-source energy balance (TSEB) model was initially only used to determine ET, estimated by solving soil and plant energy balances (Kustas and Norman, 1999; Norman et al., 1995), using surface temperature, meteorological data, leaf area index (LAI) and a few site-specific parameters. ET partitioning is inherent to the model, and ET components have been evaluated over cotton (Colaizzi et al., 2014), corn (Song et al., 2015), sugar beet and wheat (Diarra et al., 2017), olives (Häusler et al., 2018; Santos, 2018), and vineyards (Kustas et al., 2018). While TSEB ET estimates tend to be reasonable, ET partitioning accuracy has been less consistent, appearing to be season-dependent and lower under water-stressed conditions (Diarra et al., 2017; Kustas et al., 2018; Santos, 2018). Recent advancements of the TSEB model have centered on three primary themes: (1) soil heat flux parameterization (Colaizzi et al., 2016; Nieto et al., 2019; Song et al., 2015); (2) plant transpiration parameterization such as determining the Priestley-Taylor coefficient ( $\alpha_{PT}$ ) (Colaizzi et al., 2014) and the net radiation captured by the plant canopy (Colaizzi et al., 2012a, 2012c; Parry et al., 2019); and (3) the partitioning of surface temperature into soil and plant canopy temperature components (Song et al., 2015).

The first objective of this study was to evaluate the standard TSEB algorithm, specifically focusing on ET partitioning. Particular consideration was given to the importance of and the potential to improve on (1) soil heat flux parameterizations, (2) plant transpiration parameterizations, and (3) the partitioning of surface temperature into soil and plant canopy components. Ground measurements rather than satellite



Fig. 2. Two-source energy balance model schematic. Blue hexagons denote site-specific input parameters and blue parallelograms denote input data (15 min intervals). Rectangles show pre-optimization calculated variables while the rounded rectangle represents variables that are further optimized in the optimization loop.

data were used to avoid errors in input data connected to remotely sensed measurements. The evaluation was conducted for a vineyard in an arid environment (Fig. 1). Vineyards are high-value crops for which an independent estimate of transpiration is particularly relevant due to the commercial practice of using deficit irrigation to induce stress in the vines (Kustas et al., 2018). Furthermore, vineyard canopies have a unique architecture in which a sparse clumped canopy is raised over an open bare soil surface, adding further complexity to energy balance partitioning. The second objective of this study was to evaluate seasonal changes in daily and sub-daily TSEB soil and canopy energy balances in a vineyard in an arid environment. Specifically, we aimed to assess how effectively the model can monitor changes in *ET* partitioning with canopy development and in response to water stress.

# 2. Methods

# 2.1. TSEB model

A schematic of TSEB (Kustas and Norman, 1999; Norman et al., 1995) using the series approach is shown in Fig. 2. The series approach is more widely used than the parallel approach, since it has long been recognized as providing better model performance over a wider range of environmental conditions (Kustas and Anderson, 2009; Kustas and Norman, 1999). A brief discussion of the parallel approach as it applies to this study is given in Section 3.5. Input 15 min average meteorological and radiative temperature data were used to solve for soil and vine canopy energy balances averaged to hourly flux observations. In the model, the composite surface temperature as viewed from above ( $T_{RAD}$ ) is composed of soil (subscript S) and vine (subscript V) temperatures,  $T_S$  and  $T_V$ , respectively. The contributions of  $T_V$  and  $T_S$  are proportional to the vegetation fraction ( $f_V$ ) and (1- $f_V$ ):

$$T_{\rm RAD} \simeq \left( f_{\rm V} T_{\rm V}^4 + (1 - f_{\rm V}) T_{\rm S}^4 \right)^{1/4} \tag{1}$$

for a zenith view angle of the thermal sensor, where

$$f_{\rm V} = 1 - e^{-0.5LAI\Omega},$$
 (2)

and

$$\Omega = \frac{\ln((1 - f_{\text{row}}) + \exp(-0.5\text{LAI}/f_{\text{row}})f_{\text{row}})}{-0.5\text{LAI}},$$
(3)

where  $\Omega$  is the clumping factor and  $f_{\rm row}$  is calculated as vine width over row width (Anderson et al., 2005). Vine canopy albedo, as well as canopy radiation transmittance, are computed based on solar altitude and LAI (Campbell and Norman, 1998) as outlined in Appendix A. In this study, the default soil albedo value of 0.2 was changed to the measured value of 0.275.

After determining initial canopy and meteorological variables, the energy fluxes are obtained by optimization (Fig. 2), including two steps. First, an initial estimate of soil and vine temperatures along with solar radiation, air temperature, and radiation extinction parameters are used to determine net radiation  $(R_n)$  as the sum of the radiation balance at the canopy  $(R_{nV})$  and the radiation balance at the soil surface  $(R_{nS})$  following Campbell and Norman (1998, Chapter 15) as described in Appendix A. Surface soil heat flux (*G*) is calculated as a fraction of  $R_{nS}$  (0.35; Kustas and Norman, 1999) (step 1). In step 2, the available energy  $(R_n - G)$  is partitioned into latent and sensible heat flux (*LE* and *H*). Initial *LE*<sub>V</sub> is calculated using:

$$LE_{\rm V} = \alpha_{\rm PT} f_{\rm g} \frac{s}{s+\gamma} R_{\rm nV}, \tag{4}$$

where  $\alpha_{PT}$  is normally assumed to be 1.26, *s* is the rate of change of saturated vapor pressure with air temperature and  $\gamma$  is the psychrometric constant (Priestley and Taylor, 1972). In this study the fraction of the vegetation that is green ( $f_g$ ) was assumed to be 1 as the model was

evaluated from bud break until harvest and senescence was not expected to occur until after harvest. Initial  $H_V$  is set as  $R_{nV}$ - $LE_V$ . Using these initial values, the model adjusts  $T_V$  by solving:

$$H_{\rm V} = \rho c_{\rm P} \frac{T_{\rm V} - T_{\rm AV}}{r_{\rm V}},\tag{5}$$

where  $\rho$  and  $c_p$  are air density and specific heat, respectively,  $r_V$  is resistance to heat flow in the vine canopy boundary layer, and  $T_{AV}$  is the computed temperature in the vine canopy air space and is an air temperature in the canopy air layer closely related to the aerodynamic temperature (Kustas and Anderson, 2009) defined as:

$$T_{\rm AV} = \frac{\frac{T_{\rm A}}{r_{\rm A}} + \frac{T_{\rm S}}{r_{\rm S}} + \frac{T_{\rm Y}}{r_{\rm Y}}}{\frac{1}{r_{\rm A}} + \frac{1}{r_{\rm S}} + \frac{1}{r_{\rm Y}}},\tag{6}$$

where  $T_A$  is air temperature, and where  $r_A$ , the resistance to heat flow, and  $r_V$  are calculated from meteorological data and vine canopy parameters following Norman et al. (1995), as detailed in Appendix B. The resistance in the boundary layer near the soil surface ( $r_S$ ) is determined using:

$$r_{\rm S} = \frac{1}{c(T_{\rm S} - T_{\rm V})^{1/3} + bU_{\rm S}},\tag{7}$$

where c = 0.0025, b = 0.012, and  $U_S$  is wind speed near the soil surface calculated using equations developed by Goudriaan (Goudriaan, 1977; Kustas and Norman, 1999). Subsequently  $T_S$  is modified using Eq. (1) and  $H_S$  is determined as:

$$H_{\rm S} = \rho c_{\rm P} \frac{T_{\rm S} - T_{\rm AV}}{r_{\rm S}}.$$
(8)

Soil *LE*<sub>S</sub> is then derived from *R*<sub>nS</sub> and *H*<sub>S</sub> (end of step 2). If this results in an *LE*<sub>S</sub> <0, step 2 is repeated after reducing  $\alpha_{PT}$  by 0.01 increments, until *LE*<sub>S</sub> ≥0 or  $\alpha_{PT}$  = 0. If step 2 results in *LE*<sub>S</sub> ≤ 0, *LE*<sub>S</sub> + *H*<sub>S</sub> = *R*<sub>nS</sub> + *G*, where *LE*<sub>S</sub> is assumed to be 10% of *H*<sub>S</sub>. If step 2 results in *LE*<sub>V</sub> < 0, *LE*<sub>V</sub> + *H*<sub>V</sub> = *R*<sub>nV</sub>, where *LE*<sub>V</sub> is assumed to be one sixth of *H*<sub>V</sub>. Finally, *LE* = *LE*<sub>V</sub> + *LE*<sub>S</sub> and *H* = *H*<sub>V</sub> + *H*<sub>S</sub>. Steps 1 and 2 are repeated until the model converges where:

$$H = \rho c_{\rm P} \frac{T_{\rm AV} - T_{\rm A}}{r_{\rm A}} = H_{\rm S} + H_{\rm V}.$$
(9)

The final energy balance components are determined as those for which the model converges with physically acceptable solutions for  $LE_V$ and LES. To summarize, the model initially assumes that the vines are transpiring at potential rate. This results in a modeled derived  $T_{\rm V}$  and a solution for  $T_{\rm S}$  based on  $T_{\rm RAD}$  and  $f_{\rm V}$ . If the vines are stressed, transpiring at less than the potential, T<sub>V</sub> is higher than estimated by the model. Since  $T_{\rm RAD}$  is partitioned into  $T_{\rm V}$  and  $T_{\rm S}$ , underestimation of  $T_{\rm V}$  leads to overestimation of  $T_S$ , which can result in a calculated  $H_S$  that exceeds the available energy at the soil surface. Since  $LE_S$  is solved as a residual, it becomes a negative value, implying conditions of absorption of water into the soil or condensation, which is a non-physical solution under daytime convective conditions. This requires the model to reduce the transpiration rate which is performed by iteratively reducing  $\alpha_{\rm PT}$ , meaning the canopy is transpiring at a rate lower than the potential, which increases the  $T_{\rm V}$  and thereby reduces estimated  $T_{\rm S}$ . This incremental reduction in  $\alpha_{PT}$  continues until a model solution yields a nonnegative soil evaporation. More details on model convergence and justification for the assumptions used can be found in Norman et al. (1995) and Kustas and Norman (1999). Note that heat storage within the canopy is not considered in the TSEB formulation, which is reasonable in sparse canopies like wine-grape vineyards. The model was run for 15-minute time steps and then averaged for hourly and daytime ( $R_n$  >  $100 \text{ W} \text{ m}^{-2}$ ) values.

# 2.2. Model configurations

## 2.2.1. Model versions assessed

The standard TSEB model (TSEB\_0) was evaluated along with three modified configurations of the model aiming to improve ET partitioning. The first modified configuration (TSEB\_G) considered the hypothesis that errors in ET partitioning are due to errors in modeled soil heat flux (Song et al., 2015). In TSEB\_G, instead of calculating the G as a fraction of  $R_{nS}$ , measured G is used as a model input. The second modified configuration (TSEB\_GV) considered the hypothesis that errors in ET partitioning are due to errors in vine transpiration parameterizations such as  $\alpha_{PT}$  (Colaizzi et al., 2014) or plant canopy parameters. Since there is no measured equivalent of the combined effect of these parameters, potential TSEB improvement was determined by parameter optimization, described in more detail below (Section 2.2.2). In TSEB GV, optimized plant transpiration parameters are used in addition to measured G. The third modified configuration (TSEB\_2T), considered the hypothesis that errors in ET partitioning are due to inaccurate partitioning of surface temperature into soil and canopy components. In TSEB\_2T, instead of using a single composite temperature measurement that includes both vine canopy and soil  $(T_{RAD})$ , two independent temperature measurements,  $T_{s}$  and  $T_{v}$ , were used as model inputs, while all other model parameters were the same as for TSEB\_G. Individual energy balance components for each model configuration was evaluated against measurements (see Section 2.3) for the average root mean squared difference (RMSD =  $\sqrt{\text{average}(\text{modeled} - \text{observed})^2)}$ , relative error = 100  $\times \frac{\text{RMSD}}{\text{average(observed)}}$ , and bias = average(modeled - observed).

# 2.2.2. Transpiration parameterization

To obtain the best possible transpiration parameterizations for TSEB\_GV, three parameters were assessed.

*Priestley-Taylor coefficient* ( $\alpha_{PT}$ ): First, initial values of  $\alpha_{PT}$  were evaluated as this parameter limits potential transpiration. The default value for initial  $\alpha_{PT}$  is 1.26, however in advective dry environments a value as high as 2.00 may be more reasonable (Agam et al., 2010; Kustas et al., 2012). Optimization was done for four initial values of  $\alpha_{PT}$ : the default value 1.26, and higher values 1.50, 1.75, and 2.00.

Radiation absorption and retention by the vine canopy: Second, available energy for plant transpiration and sensible heat  $(R_{nV})$  was assessed. The TSEB model modifies the LAI using a clumping factor to account for the fact that the vine canopy is not uniformly distributed across the surface. The clumping factor reduces LAI, which increases the amount of radiation transmitted to the soil surface. This is reasonable considering the large open spaces between vine rows (Fig. 1). However, it does not account for locally higher absorption of radiation in the dense vine canopy. Mabrouk et al. (1997) showed that the local leaf area density within a vine canopy may be so high that LAI has very little effect on photosynthetically active radiation (PAR) interception. Heilman et al., (1996) showed that in a vineyard for which management changed from tight trellising to a more open trellising structure, LAI increased by 55% but  $R_{nV}$  increased by >300% on average, from 11-18% of  $R_n$  to 42-50% of R<sub>n</sub>. These findings indicate that for tightly trellised canopies, the density of the canopy, rather than LAI, strongly limits  $R_{nV}$  and that absorption is likely near 100%. Whether or not considering the high density of the vine canopy affects  $R_{nV}$  computations can be assessed by simply comparing the default leaf radiation absorption values of 85% for visible light and 15% for near infrared light to maximum leaf radiation absorption of 100% (Campbell and Norman, 1998).

In addition,  $R_{nV}$  may be underestimated by overvaluing the longwave radiation at the bottom of the canopy. While the top of the canopy is exposed to sun, the bottom of the canopy is shaded and its temperature is likely closer to air temperature. Thus, modified  $R_{nV}$  parameters included a leaf radiation absorption of 100% and downward canopy longwave radiation as a function of  $T_A$  rather than  $T_V$  for  $T_V > T_A$ .

Alternative calculation of vegetation fraction: Third, the default

calculation of the vegetation fraction was compared to an alternative calculation that accounts for the relatively vertical architecture of vinerows. The alternative calculation considered that, since vine canopies are tall and exposed on all sides due to wide row spacing, the narrow strip of vegetation that is visible from above may not accurately represent the contribution of the vegetated area to total energy fluxes. Since  $T_{\rm RAD}$  is observed from above, the vegetation fraction used to partition  $T_{\rm RAD}$  into  $T_{\rm V}$  and  $T_{\rm S}$  (Eq. (1)) may underestimate the contribution of  $T_{\rm V}$ to total fluxes. The degree to which the contribution of  $T_{\rm V}$  is underestimated may depend on the viewing angle of the infrared thermometer, with the greatest error occurring when the vegetation is observed from nadir as is the case in this study (see experimental setup, Section 2.3). In addition to this, depending on the time of day and the angle of the sun, the section of the vine canopy where most of the transpiration occurs may change both in size and position. Non-uniform canopy temperature is a known phenomenon in row crops (Wanjura and Upchurch, 1991). A recent study in a vineyard showed that differences in crop water stress index values calculated for different sides of the vine canopy can be as large as 0.4 (ranging from 0.8 to 0.4 on a scale of 0-1) (Prueger et al., 2019) indicating a strongly non-uniform canopy temperature.

With a north-south vine-row orientation, the east side of the canopy is sunlit in the mornings while the west side is shaded, and vice versa in the afternoons. With only temperature measurements from above it is hard to determine to what extend this heterogeneity in canopy temperature affects energy balance calculations. However, it is clear that when the surface temperature is viewed from above, the contribution of  $T_{\rm V}$  to total fluxes is likely underestimated and can be expected to be undervalued to a greater extent when the canopy is more developed. Since the canopy mostly develops in a vertical direction, the transpiring area visible from above stays relatively constant, while the canopy area contributing to transpiration increases. Because in this system  $T_{\rm S} >> T_{\rm V}$ and canopy width << canopy height, the "real" composite temperature of the system may be quite different from the composite temperature  $T_{\rm RAD}$  as viewed from above. However, increasing  $f_{\rm V}$  would actually result in higher  $T_V$ , and lower  $LE_V$  as  $T_V$  is calculated from  $T_{RAD}$  as viewed from above. And, counterintuitively, decreasing  $f_V$  would result in lower  $T_V$ , and an increased modeled  $LE_V$  and thus increases the contribution of  $T_{\rm V}$  to total fluxes in an indirect manner.

A very rough estimation of the potential effect this has on transpiration was tested by a simple adaptation, where the initially computed  $f_V$ was multiplied by  $\frac{Canopy width}{Canopy width+Canopy height}$ . When the canopy height is small the adjustment is minimal, but it increases as the vine canopy height increases, considering that, as the vine canopy develops, less of the total canopy is visible from above. However, it does not consider diurnal changes in the size and position of the vine canopy area contributing to transpiration.

Evaluating vine canopy parameter combinations: The best combination of these three parameters was determined by evaluating four values for  $\alpha_{\rm PT}$  for default and modified  $R_{\rm nV}$  parameters, with and without the alternative calculation of the vegetation fraction. This resulted in  $4 \times 2 \times 2 = 16$  vine canopy parameter combinations. TSEB\_G was used as the baseline, where TSEB\_G represented no changes in  $R_{\rm nV}$  or  $f_{\rm V}$  parameters, while TSEB\_GR and TSEB\_GF represented changes in only  $R_{\rm nV}$  or  $f_{\rm V}$  parameters, respectively, and TSEB\_GRF represented changes in both  $R_{\rm nV}$  and  $f_{\rm V}$ . TSEB\_GV was determined by selecting the combination of parameters for which modeled versus measured energy fluxes yielded the lowest RMSD and smallest bias.

#### 2.3. Experimental site and measurements

Field measurements for model assessment were collected in a commercial vineyard in the arid Negev Highlands in Israel over the year 2012 (Kool et al., 2018, 2016, 2014b). The drip-irrigated Cabernet Sauvignon vineyard had an area of about 10 ha and was surrounded by

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# Table 1

Vine transpiration parameterization statistics.

	TSEB_G					TSEB_GR				TSEB_GF				TSEB_GRF			
		αpt	(-)			άρτ	(-)		αρτ (-)					αpt	(-)		
	1.26	1.50	1.75	2.00	1.26	1.50	1.75	2.00	1.26	1.50	1.75	2.00	1.26	1.50	1.75	2.00	
Average d	aytime	RMSD	(W m <sup>-2</sup>	<sup>2</sup> )													
R <sub>n</sub>	29	27	26	25	14	14	15	15	25	22	20	18	14	15	16	16	
$R_{ m nS}$	72	69	66	64	28	28	27	26	75	71	68	64	29	29	27	26	
$R_{ m nV}$	96	91	87	83	28	27	26	25	94	88	81	74	27	25	22	21	
Н	45	40	34	30	79	76	74	72	32	29	33	43	65	57	50	46	
Hs	44	46	48	50	23	23	24	24	35	37	39	41	22	22	23	23	
$H_{\rm V}$	38	39	42	46	68	64	61	60	41	48	60	75	57	49	42	38	
LE	39	33	30	29	51	48	46	45	29	34	46	62	39	35	33	35	
LEs	43	38	33	29	19	18	16	15	53	47	41	34	20	18	15	13	
$LE_{\rm V}$	72	59	48	38	63	58	54	53	58	43	35	44	50	42	36	35	
Average	53	49	46	44	42	40	38	37	49	47	47	51	36	32	29	28	
Hourly RM	ASD (V	V m <sup>-2</sup> )															
R <sub>n</sub>	40	39	38	38	36	37	37	37	35	34	33	33	35	35	36	36	
$R_{\rm nS}$	115	112	110	109	87	87	87	87	117	114	111	108	88	87	87	86	
$R_{ m nV}$	103	100	98	96	76	76	77	77	101	98	94	91	76	77	79	80	
Н	79	79	82	86	103	104	105	105	63	65	72	84	91	92	96	101	
$H_{\rm S}$	52	54	56	58	37	38	39	39	42	44	45	48	35	36	37	38	
$H_{\rm V}$	74	80	89	99	103	106	108	110	71	79	93	111	97	102	109	116	
LE	95	98	104	111	106	109	112	114	80	87	100	117	98	106	116	124	
LEs	56	51	46	42	38	37	36	36	64	59	54	48	39	38	36	35	
$LE_{\rm V}$	101	97	99	106	106	108	112	114	84	78	82	97	94	99	110	120	
Average	79	79	80	83	77	78	79	80	73	73	76	82	73	75	78	82	
Average d	aytime	bias (W	/ m <sup>-2</sup> )														
R <sub>n</sub>	-23	-21	-19	-18	0	1	2	2	-18	-16	-13	-10	4	5	7	8	
$R_{ m nS}$	69	66	64	61	24	24	23	22	72	69	65	61	26	25	23	21	
$R_{ m nV}$	-92	-88	-84	-80	-25	-23	-22	-21	-91	-85	-78	-71	-23	-20	-17	-14	
Н	36	29	22	15	73	70	67	65	15	3	-11	-26	58	49	42	35	
Hs	39	41	44	46	16	17	17	18	29	31	33	35	13	14	15	17	
$H_{\rm V}$	-3	-12	-21	-30	58	53	49	47	-13	-28	-44	-62	45	35	26	19	
LE	-26	-18	-9	-1	-41	-37	-33	-32	-2	13	30	48	-25	-15	-6	2	
LEs	41	36	31	26	17	15	14	12	50	45	38	32	17	15	12	9	
$LE_{\rm V}$	-64	-51	-37	-24	-55	-49	-44	-41	-49	-29	-6	19	-39	-28	-15	-5	

Four TSEB configurations: (1) default parameters 'G', (2) adjusted radiation parameters 'GR', (3-4) 'G' and 'GR' with alternative vegetation fraction calculation 'GF' and 'GRF'. Root mean square deviation (RMSD) and bias of total, vine (subscript V), and soil (subscript S) net radiation ( $R_n$ ), latent heat flux (*LE*) and sensible heat flux (*H*) were evaluated for four initial Priestley-Taylor coefficients ( $\alpha_{PT}$ ). The number of observations *n* pertain to hours where  $R_n > 100 \text{ W m}^{-2}$ , (hourly *n*=1112, average daytime *n*=89). Colors indicate negative (blue) and positive (yellow) values with lighter colors for values closer to 0.

bare desert. Average annual precipitation of <100 mm occurred primarily during winter months (November-March) and annual minimum and maximum temperature averaged 12°C and 25°C, respectively. During the winter of 2011–2012 precipitation totaled 48 mm, ending with a 2.5 mm rain event on 16 March. Vine-rows were 3 m apart with a north-south orientation, and trained on a vertical-shoot-positioned system to 1 and 1.8 m high trellis wires (Fig. 1). Canopy width reached a maximum of 0.6 m. Measurements were conducted from bud-break on April 1 until July 23, which was right before harvest. A measurement station was set up with a fetch of 300 m toward the predominant wind

direction (north-west), and about 150 m in all other directions. Standard meteorological measurements included wind speed and direction (4 m height, Wind Sentry, R.M. Young, Traverse City, MI), air temperature and relative humidity (3.3 m height, HMP45C, Vaisala Inc., Woburn, MA and 10-Plate Gill Radiation Shield, R.M. Young, Traverse City, MI), and solar radiation (LI- 200SA Pyranometer, Li-Cor Biosciences, Lincoln, NE). Surface temperature was measured using five infrared thermometers (IRTS-P, field-of-view 28° half angle, Apogee Instruments Inc., Logan, UT), two at 7 m representing  $T_{RAD}$  (target diameter of 7.44 m), one at 2.15 m directly above the vine representing  $T_{\rm V}$ , and two representing  $T_{\rm S}$  at 2.5 m between vine-rows (target diameter of 2.66 m) and at 0.3 m directly underneath the vine (target diameter of 0.32 m). The two infrared thermometers at 7 m were placed above the vine-row and above the interrow, and the average was used to represent  $T_{RAD}$ . Considering that the area below the vine is not visible from above,  $T_{\rm S}$  representing the interrow was used in TSEB 2T. LAI was determined using a LAI2000 (Li-Cor Bioscience Inc., Lincoln, NE) along with manual measurements of plant height and width. Soil albedo was measured 13-16 February 2012 using four pyranometers (CMP3, Kipp & Zonen, Delft, Netherlands) at 0.3 m height, with one facing upward and one facing downward in the interrow and below the vine, respectively.

Energy balance components used to assess model outputs were measured for soil and vine combined (total), and for the soil independently, while the vine energy balance components were derived as the difference between total and soil measurements (more details can be found in Kool et al., 2016). Soil energy balance components were determined as the weighted average of measurements in the wet drip-irrigated zone directly below the vine-row and in the interrow or dry zone between the vine-rows. The wet drip-irrigated zone was found to represent 14% of the soil surface (Kool et al., 2016), thus soil energy flux  $A_{\rm S}$ , = (0.14 × wet  $A_{\rm S}$  + 0.86 × dry  $A_{\rm S}$ ). Vine energy flux  $A_{\rm V}$  was subsequently calculated as  $A - A_S$ . Net radiation was measured at 0.3 m over the wet and the dry zone, representing  $R_{\rm nS}$ , and at 5 m, representing total R<sub>n</sub>, using three net radiometers (Q\*7, Radiation and Energy Balance Systems, Seattle, WA). In-situ cross calibration was performed using a micro net radiometer (Swissteco Instruments, Hawthorn, VIC, Australia) following Kustas et al. (1998). Surface soil heat flux was computed in the interrow and directly below the vine using the combination method (Fuchs and Tanner, 1968), which sums G measured by a soil heat flux plate (HFT1.1, Radiation and Energy Balance Systems, Seattle, WA) installed at 6 cm depth and the heat storage in the 6-cm layer above the plate. The heat storage was determined using temperature gradients from surface temperature  $T_{s}$  and Type T thermocouples at 2, 4, and 6 cm depth and heat capacity calculated from water content measurements at 6 cm depth adjacent to each plate (SDI-12 Soil Moisture Transducer, Acclima Inc., Meridian, ID). Data were logged at 10 s intervals and stored as 15 min averages (CR23X, CR5000, Campbell Scientific Inc., Logan, UT). An eddy-covariance system (CSAT 3-D sonic anemometer, Campbell Scientific Inc., Logan, UT; with an open path infrared gas analyzer, LI-7500, Li- Cor Biosciences Inc., Lincoln, NE) at 3.3 m provided measurements of total LE and H. Data collected at 10 Hz (CR5000, Campbell Scientific Inc., Logan, UT) were used to calculate half-hourly fluxes. Post-processing and correction details can be found in Kool et al. (2016). Energy balance closure over the measurement period averaged 88%. Closure was not forced, since total seasonal LE matched closely with total seasonal irrigation (Kool et al., 2016). Dry zone  $H_S$  was computed as the residual of dry zone  $R_{nS}$  and G ( $H_S = R_{nS}-G$ ), assuming dry zone  $LE_S$  was zero. For each day, dry zone  $H_S$  was used to determine the  $U_{\rm S}$  multiplication factor b in Eq. (7), which was then used to determine wet zone  $H_S$  using Eq. (8). This is based on the assumption that the wind flow near the surface at both the dry and wet areas is similar, given that the elevated canopy of the vines and short distance between wet and dry areas are unlikely to influence near-surface wind (Fig. 1). Wet zone  $LE_S$  was then calculated as the residual of wet zone  $R_{nS}$ ,  $H_S$ , and G  $(LE_S = R_{nS} - G - H_S)$ . On average, this method underestimated micro-lysimeter measured LEs on 22 May, and 4 and 23 July, by 16%.

Average seasonal  $LE_S$  was 9% of total LE, and a 16% underestimation of  $LE_S$  would increase  $LE_S$  to 11% of total LE (Kool et al., 2016).

## 3. Results and discussion

## 3.1. Vine transpiration parameter optimization

The first objective was to evaluate TSEB 0, TSEB G, TSEB GV, and TSEB 2T. While TSEB G and TSEB T could be assessed by replacing variables computed by TSEB with actual measurements, TSEB\_GV was obtained by optimization. The RMSD and bias for sixteen possible configurations of TSEB\_GV are shown in Table 1. Hourly RMSDs were noticeably larger than average daytime RMSDs, but average daytime and hourly biases were very similar. Only average daytime bias is shown here. The first column represents TSEB G with a default  $\alpha_{PT}$  of 1.26 and without adaptations of  $R_{nV}$  or  $f_V$  parameters and serves as a baseline. It can be observed that  $R_n$  was the energy balance component with the lowest RMSD with an average daytime value of 29 W m<sup>-2</sup>. However,  $R_{nV}$ and  $R_{nS}$  had the highest RMSD, and the bias indicated that  $R_{nV}$  was strongly underestimated while R<sub>nS</sub> was strongly overestimated. This means that there was less available energy for vine turbulent fluxes, which can explain why both  $LE_V$  and  $H_V$  were underestimated while  $LE_S$ and  $H_{\rm S}$  were overestimated. It appears that with an RMSD of 72 W m<sup>-2</sup> LE<sub>V</sub> was the most challenging turbulent flux to compute, with other turbulent flux RMSDs ranging between 28 and 45 W  $m^{-2}$ . Hourly RMSDs likewise show that  $R_n$  estimates were much more accurate than  $R_{nS}$  and  $R_{\rm nV}$ . In addition, it appeared that vine fluxes tended to have higher hourly RMSDs than soil fluxes, even when average daytime RMSDs were similar. Increasing potential  $\alpha_{PT}$  generally lowered average daytime RMSDs and reduced bias for TSEB G, particularly for LE<sub>V</sub>, but did not improve the RMSD of hourly fluxes. Since increasing potential  $\alpha_{PT}$  increases potential  $LE_V$ , it is not surprising that increasing  $\alpha_{PT}$  improves  $LE_V$  that was initially underestimated. While increasing  $\alpha_{PT}$  reduced bias in hourly  $LE_V$  (from -66 to -26 W m<sup>-2</sup>, similar to average daytime bias), it did not improve the estimation of hourly fluxes. Increasing  $\alpha_{\rm PT}$  is appropriate when  $LE_V$  is enhanced because of advection, i.e. when  $LE_V$  is larger than  $R_{\rm nV}$ . In this case, using a high initial  $\alpha_{\rm PT}$ , e.g.  $\alpha_{\rm PT}$ =2.00, enables the model to compensate for the underestimation in  $LE_V$  due to underestimation of R<sub>nV</sub> by assuming higher advection. Measurements indicated that advection significantly contributed to LE<sub>V</sub> but generally not more than 20% on a daily basis (Kool et al., 2018). Thus, while increased  $\alpha_{PT}$  improves estimations of  $LE_V$  (Table 1, TSEB\_G), it would be more physically correct to at least partly increase  $LE_V$  by increasing  $R_{nV}$ .

The configuration TSEB GR, where leaf radiation absorption was set to 100% and downward vine canopy longwave radiation was derived from  $T_A$  for  $T_V > T_A$ , showed reductions of up to 50% in RMSDs of  $R_n$  and up to 70% in  $R_{nV}$  and  $R_{nS}$  relative to TSEB\_G. The bias in  $R_n$  was almost eliminated, while bias in  $R_{nV}$  and  $R_{nS}$  was reduced by two thirds or more. This resulted in lower RMSDs and smaller bias for LE partitioning, but because LEs decreased more than LEv increased, overall LE was underestimated even more than it was originally using TSEB G. While H<sub>S</sub> was better calculated, the overestimation of H and H<sub>V</sub> mirrored the underestimation in LE and LE<sub>V</sub>. On the contrary, configuration TSEB\_GF, where an alternative calculation  $f_V$  enhanced the contribution of  $T_V$  to total canopy fluxes, showed very little improvement in R<sub>n</sub> partitioning, but greatly reduced bias in  $LE_V$ , especially as  $\alpha_{PT}$  increased. This suggests that the underestimation in  $LE_V$  in the original model is not only due to a lack of available energy, and inaccurate parameterization of  $T_{\rm V}$  appears to be a possible explanation. Combining these two adaptations in TSEB\_GRF improves both  $R_n$  and LE, with the smallest bias and lowest RMSDs at  $\alpha_{PT}$ =2.00. Hourly RMSDs showed little improvement indicating that while the adaptations generated much more reasonable magnitudes for the energy fluxes, the diurnal cycles of the energy fluxes remain challenging to approximate. As closure for the measured fluxes was not forced, model  $R_n$  and LE that better approximated measured fluxes did not necessarily result in lower RMSDs for modeled versus



**Fig. 3.** Measured (or residual of measured) and modeled net radiation ( $R_n$ ) as well as sensible and latent heat flux (H and LE) from 1 April to 24 July 2012. Average daytime values for hours where  $R_n$ >100 W m<sup>-2</sup> (n=89). The four two-source energy balance (TSEB) model configurations are (1) default parameters (0), (2) measured instead of modeled soil heat flux (G), (3) TSEB\_G with adjusted vine canopy parameters (GV), and 4) TSEB\_G but using measured vine and soil temperatures instead of a single overall surface temperature (2T).

Table 2	
Statistics for four TSEB model configurations.	
	1

	Aver	age dayti	me RMSD (	W m <sup>-2</sup> )	Averag	ge daytime	e relative e	rror (%)	Average daytime bias (W m <sup>-2</sup> )				
TSEB	_0	_G	_GV	_2T	_0	_G	_GV	_2T	_0	_G	_GV	_2T	
R <sub>n</sub>	30	29	16	37	8%	7%	4%	9%	-23	-23	8	-31	
$R_{\rm nV}$	73	72	26	88	36%	36%	13%	44%	71	69	21	85	
$R_{ m nS}$	98	96	21	122	54%	53%	12%	68%	-95	-92	-14	-117	
Н	49	45	46	80	31%	29%	29%	51%	40	36	35	-67	
Hs	42	44	23	54	32%	34%	18%	42%	36	39	17	-47	
$H_{\rm V}$	40	38	38	48	246%	235%	233%	297%	3	-3	19	-21	
LE	55	39	35	79	39%	28%	25%	56%	-45	-26	2	69	
LEs	39	43	13	139	295%	328%	97%	1051%	37	41	9	133	
$LE_{\rm V}$	86	72	35	72	70%	59%	29%	58%	-80	-64	-5	-62	

Four model configurations: (1) Two-source energy balance (TSEB) with default parameters (0), (2) TSEB with default parameters but measured instead of modeled soil heat flux (G), (3) TSEB\_G and adjusted vine transpiration parameters (GV), (4) TSEB\_G using measured vine and soil temperatures instead of a single overall surface temperature (2T). Energy fluxes evaluated include total, vine (subscript V), and soil (subscript S) net radiation ( $R_n$ ), latent heat flux (LE) and sensible heat flux (H). Total number of average daytime observations (n) were assessed using hours where  $R_n > 100$  W m<sup>-2</sup> (n = 89).

#### Table 3

## Statistics for TSEB performance in the literature.

		RMSD (W $m^{-2}$ )				Bias (W $m^{-2}$ )			
Source	Cover	Time intervals	R <sub>n</sub>	H	LE	R <sub>n</sub>	H	LE	
Cammalleri et al. (2010)	Olive orchard	2 h	28	40	43	+/-	-	+	
Choi et al. (2009)	Maize-Soy (SMACEX)	30 min	30	31-62	53-90	21	6-39	-71-4	
Morillas et al. (2013) and Kustas et al. (2016)	Tussock grassland	15 min	58-62	52-131	72-135	+	-110-18	-114 - 10	
Gan and Gao (2015)	Grass, maize	30 min	23-48	37-85	51-109	9-41	-27-26	-14-75	
Colaizzi et al. (2016)	Cotton (BEAREX)	15 min	27		65	$^{-12}$		-9	
Song et al. (2016a, 2016b)	Maize (HiWATER)	30 min	16-38	33-79	50-87	27-4	-69-13	-41-50	

TSEB evaluations for net radiation ( $R_n$ ), latent heat flux (LE) and sensible heat flux (H). When quantitative data was not available plus (+), minus (-) and neutral (+/-) indicate the direction of the bias.

measured *H* fluxes. Measured energy balance closure ranged from 0.9 to 1.0 between 10:00 and 18:00 and was somewhat lower before 10:00 (Kool et al., 2018). Considering how closely measured eddy-covariance *LE* resembled water balance estimated *LE* (Kool et al., 2016), it may be that either measured *H* or measured *G* was underestimated, or that neglected storage terms played a role. All things considered, TSEB\_GRF with  $\alpha_{\rm PT} = 2.00$  was selected as the configuration that best represented optimal vine transpiration parameterization (TSEB\_GV = TSEB\_GRF with  $\alpha_{\rm PT} = 2.00$ ).

## 3.2. Energy balance evaluation: daytime averages

Daytime averages of measured (or residual of measured) and modeled fluxes for 1 April to 24 July 2012 showed that for all TSEB configurations total energy fluxes were better quantified than their partitioning into soil and vine fluxes (Fig. 3, Table 2). The RMSDs of all fluxes had similar orders of magnitude, resulting in large relative errors for small energy fluxes. Hence the comparatively large relative errors of  $LE_S$  and  $H_V$  which had average daytime values of 13 W m<sup>-2</sup> and 16 W m<sup>-2</sup>, respectively, while all other energy fluxes had average daytime values of 120 to 400 W m<sup>-2</sup>. Using TSEB\_0, average daytime RMSDs for  $R_{\rm n}$ , H, and LE ranged from 30 to 55 W m<sup>-2</sup> with relative errors between 8% and 39% and bias indicating underestimation of  $R_n$  and LE and overestimation of *H*. Average daytime RMSD for *G* was 16 W  $m^{-2}$ , with relative error of 27% and bias of 12 W m<sup>-2</sup>, indicating that modeled *G* was overestimated (data not shown). In TSEB\_0, G is computed as a fraction of  $R_{nS}$ , which is known to be subjected to inaccuracies due to the phase shift of G compared to R<sub>nS</sub> (Gentine et al., 2007; Heusinkveld, 2004). In July 2012, for example, diurnal values for measured G were positive from 06:00 to 16:00 and negative from 16:00 to 06:00, while modeled G was positive from 08:00 to 18:00 and never went below zero (data not shown). While this effect may be small at 24-h time intervals (Leuning et al., 2012), for computations that are restricted to hours when  $R_n > 100$  W m<sup>-2</sup> the phase shift becomes important. Using measured rather than modeled G, TSEB\_G showed similar  $R_n$  and H magnitudes but greatly improved LE values. Lower underestimation of LE can be primarily attributed to decreased underestimation of LE<sub>V</sub>. Using measured instead of modeled G increased available energy, and, as has already been observed in Section 3.1, this results in lower underestimation of  $LE_V$ . Improvements on parameterizations of G, such as proposed by Nieto et al. (2019) can therefore improve LE.

TSEB\_GV reduced absolute bias by two thirds on average: the



**Fig. 4.** Measured (or residual of measured) and modeled net radiation  $(R_n)$  as well as sensible and latent heat flux (*H* and *LE*) between 4:00 and 20:00. Curves are average hourly values for 1, 2, and 6-24 July 2012. The four two-source energy balance (TSEB) model configurations are (1) default parameters (0), (2) measured instead of modeled soil heat flux (G), (3) TSEB\_G with adjusted vine canopy parameters (GV), and (4) TSEB\_G but using measured vine and soil temperatures instead of a single overall surface temperature (2T).



**Fig. 5.** Measured (or residual of measured) and modeled total latent heat flux (*LE*) and vine net radiation ( $R_{nV}$ ) and *LE* (*LE<sub>V</sub>*) from 1 April to 24 July 2012. Average daytime values for hours where  $R_n > 100$ . The four two-source energy balance (TSEB) model configurations are (1) default parameters (0), (2) measured instead of modeled soil heat flux (G), (3) TSEB\_G with adjusted vine canopy parameters (GV), and (4) TSEB\_G but using measured vine and soil temperatures instead of a single overall surface temperature (2T). Red bars indicate days on which water stress occurred.

absolute bias averaged 15 W m<sup>-2</sup> for all energy balance components relative to 48 W m<sup>-2</sup> for TSEB 0. RMSDs and relative errors likewise were on average less than half of those of TSEB 0. In particular, the relative errors of LE and LE<sub>V</sub> reduced from 39% to 28% and from 70% to 19%, respectively. Improved fluxes by better approximating G and  $R_n$ have been observed by others as well. Using a trapezoidal model over a shrub system in Arizona, Yang et al. (2013), found that using measured  $R_{\rm p}$  and G improved RMSD for LE from 48 to 35 W m<sup>-2</sup> and bias from 11 to 9 W m<sup>-2</sup>. For the vineyard system, improved  $R_n$  and G (TSEB\_R, Section 1) improved LE<sub>S</sub> and LE<sub>V</sub>, but overall LE fluxes only improved in combination with increasing potential transpiration parameters. Surprisingly, TSEB\_2T performed very poorly, enhancing the discrepancy in  $R_n$ partitioning and estimating very high LE<sub>S</sub>. This may be attributed to a loss of flexibility in the model when  $T_S$  and  $T_V$  are forced, and indicates that  $T_{\rm S}$  and  $T_{\rm V}$  are not necessarily good indicators of model performance. It also reinforces the suspicion that perhaps  $T_{\rm V}$  as viewed from above is not representative for the whole canopy. To a lesser extent but in the same trajectory, (Colaizzi et al., 2012b) found that TSEB using  $T_{RAD}$ consistently outperformed TSEB using measured  $T_S$  and  $T_V$ . Others found that TSEB using  $T_{RAD}$  only slightly outperformed TSEB using measured T<sub>S</sub> and T<sub>V</sub> (Morillas et al., 2013; Yang et al., 2018). Nieto et al., (2019) did find that TSEB using measured  $T_S$  and  $T_V$  performed as good or better as TSEB using  $T_{RAD}$  over a vineyard in California where the canopy was wider and less densely trained. In those conditions  $T_{RAD}$  may have better represented "real" composite temperature of the system as the more open canopy allowed the sensor from above to observe both sunlit and shaded areas of the canopies.

Few studies have evaluated individual soil and plant energy balances but overall TSEB RMSDs were similar to those found in the literature, where  $R_n$  RMSDs tended to be on the order of 30-50 W m<sup>-2</sup> while *H* and *LE* were on the order of 50-80 W m<sup>-2</sup> (Table 3). The associated bias varied. In comparison to remote sensing models in general, the RMSD for TSEB\_0 *LE* was similar to the average of 55 W m<sup>-2</sup> for *LE* compiled for 29 remote sensing studies (Kalma et al., 2008), while TSEB\_GV fell within the RMSD range of 20-35 W m<sup>-2</sup> found for the top 5 studies.

Underestimation of LE<sub>V</sub> is a common problem in remote sensing models. For example, Talsma et al., (2018a) evaluated ET partitioning for three remote sensing models using field data from 35 studies and reported a mean bias error (% MBD, bias as percentage of the average field estimate) of -5% to -66% for LE<sub>V</sub> and -2% to -22% for LE as compared to -65% and -4% for LE<sub>V</sub> and -32% and 1% for LE using TSEB 0 and TSEB GV respectively. The MBDs obtained for LE using TSEB 0 in this study were relatively high which may be attributed to the complexity of estimating energy fluxes in vineyards. Better MBDs have been obtained using TSEB in other systems, e.g. for a sprinkler-irrigated cotton in a semi-arid area of Texas where MBDs for LE<sub>V</sub> and LE amounted to -51% and -7% using TSEB with the Priestley-Taylor equation and 1% and 7% using TSEB with the Penman-Monteith equation (Colaizzi et al., 2014). TSEB with the Penman–Monteith equation however requires information on the bulk canopy resistance. Similarly, using an adapted version of TSEB for a deficit-irrigated olive orchard in Portugal, MBDs were -58% for  $LE_V$  and 5% for LE (Häusler et al., 2018). Thus, while TSEB may generate reasonable LE under some conditions, LE<sub>V</sub> tends to be greatly underestimated. However, TSEB\_GV indicates that there is potential to improve the model and obtain better approximations of *ET* partitioning.

# 3.3. Energy balance evaluation: hourly fluxes

Average hourly energy fluxes are shown for 1, 2 and 6-24 July 2012 when meteorological conditions were uniform and to establish a general pattern rather than looking at one individual day (Fig. 4). Comparison of measured and modeled hourly fluxes indicated that retrieving accurate diurnal patterns, at least for this system, is still very challenging. It should be noted that measured  $R_{nV}$  is the residual of measured  $R_n$  and  $R_{nS}$  and its diurnal curve therefore has higher uncertainty. The greatest discrepancies, however, appear to be in  $H_V$  and  $LE_V$ . Both  $H_V$  and  $LE_V$  are also measured as residuals, but since  $LE_V$  is about 90% of total LE the confidence in the diurnal pattern is fairly high (Kool et al., 2018, 2016). As for H, it appears that the model approximates  $H_{\rm S}$  fairly well and that discrepancies in total H are mostly due to  $H_{\rm V}$ . Residual measurements showed negative  $H_V$  around noon, indicating advective conditions or  $T_V$  $< T_{AV}$ . Around noon the sun is positioned directly above the canopy, and as the row orientation is north-south, at this time only the soil directly underneath the vines is shaded and the soil surface between the vine-rows is completely sunlit, and soil sensible heat is at a maximum. At the same time the vine canopy sides are mostly shaded and only the top of the canopy is sunlit, and sensible heat from the canopy is at a minimum. This results in advection of some of the soil sensible heat to the vine canopy (Kool et al., 2018). The model had difficulty reproducing these patterns showing no advection for TSEB 0, G, and 2T. Colaizzi et al. (2014) also suggested that TSEB underestimates  $LE_V$  because of overestimation of  $T_{\rm V}$  particularly under advective conditions, for a much more uniform (relative to vineyards) cotton field. TSEB\_GV allowed for lower  $T_V$  both by increasing  $\alpha_{PT}$  and by considering the vertical structure of the canopy (by adjusting  $f_V$ ), and showed advection of similar magnitudes as the measured values (measured as residuals). However, TSEB\_GV showed advection earlier in the day, resulting in overestimation of LE<sub>V</sub> in the mornings. Around noon, the models estimated positive  $H_V$ , resulting in underestimation of  $LE_V$  at that time. This indicates that using temperature measurements taken from above the canopy to represent the temperature inside the canopy limits the models' ability to capture diurnal patterns, similar to what Prueger et al. (2019) suggested. Measured versus modeled diurnal fluxes are not often reported but more reasonable diurnal LE fluxes have been observed for full cover soybean and maize (Gan and Gao, 2015). Limited understanding of how to model diurnal canopy fluxes may be part of the reason that underestimation of  $LE_V$  is so ubiquitous in TSEB and other remote sensing models.

# 3.4. ET partitioning: seasonal changes and response to water stress

Average daytime  $R_{nV}$ ,  $LE_V$  and LE for the season are shown (Fig. 5), with specific consideration for days with obvious water stress (indicated by red bars). To assess model ability to detect stress, all days that followed a day of irrigation were considered well-watered days for which  $LE_V/R_n$  was determined. Water stress days were selected as days on which  $LE_V/R_n$  was reduced by at least 35% compared to the weekly average  $LE_V/R_n$  for well-watered days; and for which  $R_n$  was less than 4% different from the weekly average. Using these criteria, 11 wellwatered and 11 water-stressed days were identified, for which average daytime  $R_n$  ranged between 385 and 427 W m<sup>-2</sup>, and 383 and 426 W m<sup>-2</sup> respectively.

The season can be roughly divided in two where the first half of the season (April-May) is characterized by steadily increasing  $R_{\rm NV}$ ,  $LE_{\rm V}$  and LE as the vines develop from bud break to full canopy cover. In the middle of May discrepancies between modeled and measured residual  $LE_{\rm V}$  and measured *LE* temporarily increase which may be due to difficulty in capturing the rapid changes in LAI along with sudden changes in the clumping factor as the vines were being trained. During April and

May, a few days with lower  $R_{nV}$  attributed to clouds can be observed. In June and July  $R_{nV}$  reached a stable maximum of about 230 W m<sup>-2</sup>. As was observed in Section 3.2, TSEB\_0, \_G, and \_2T consistently underestimated  $R_{nV}$  by over 50%, while TSEB\_GV approximated  $R_{nV}$  quite well, and all configurations captured the seasonal changes in  $R_{nV}$ . During the second half of the season (June-July), when the vine canopy was fully developed,  $R_{nV}$  changed very little due to a relatively cloudless summer. However, reductions of over 50% in LE and LE<sub>V</sub> can be observed in response to water stress. Because of the tendency of the model to underestimate LE<sub>V</sub>, TSEB LE<sub>V</sub> tended to be more accurate on water stressed days. Furthermore, statistics differentiating between early and late season (See Appendix C, Table C1), showed that for the first half of the season, when LE was lower, RMSDs for TSEB 0, G, and 2T were lower than for the second half of the season. However, RMSDs of TSEB GV were equally low for both the first and the second half of the season. A possible explanation could be that underestimation of shortwave radiation absorbed by the vine canopy when the canopy is dense affected model performance more strongly when the canopy was fully developed than early in the season. Hourly fluxes (Table C2) also showed generally lower RMSDs for the first half of the season, including for TSEB GV. As noted in the sections above, better performance of TSEB GV for average daytime fluxes did not necessarily correspond to better hourly fluxes.

As for ET partitioning, all model configurations better approximated  $LE_V/LE$  for the latter part of the season. For April-May the bias for the  $LE_V/LE$  fraction was calculated to be -45%, -40%, -9%, and -57% for configurations 0, G, GV, and 2T respectively, while the bias was -32%, -29%, -3%, and -53% for June-July. Overall LE<sub>V</sub>/LE was underestimated by about 39% for the TSEB\_0 and by 6% for TSEB\_GV, while RMSDs were 41% and 10%, indicating that most of the variation was due to bias. This confirms findings by Kustas et al. (2018) that TSEB generally underestimates LE<sub>V</sub>/LE in vineyards, although they show mixed results for variations along the season. Song et al. (2016a) found underestimation of  $LE_V/LE$  for maize, but results clearly improved after the canopy fully developed. Better estimates of LE versus LE<sub>V</sub>/LE for the development stage relative to mid-season was also shown for TSEB evaluated over drip-irrigated sugar beet and flood irrigated wheat (Diarra et al., 2017), and they concluded "that the TSEB model can reasonably be used to map ET on large scale and possibly for the decision-making process of irrigation scheduling."

Average daytime measured residual  $LE_V$  was 177 W m<sup>-2</sup> on wellwatered days and 94 W m<sup>-2</sup> on water-stressed days, an average reduction of 47%. TSEB 2T did not show any reduction while TSEB 0, G, and \_GV, showed a reduction of 18%, 16%, and 33%. TSEB\_GV thus best approximated the difference between stressed and non-stressed days, though still underestimating this difference by 30%, not quite reaching the goal of less than 10% error proposed by Fisher et al. (2017). Since the model accounts for stress by reducing  $\alpha_{\rm PT}$  iteratively until convergence is reached, the percentages of reduction in  $\alpha_{\rm PT}$  were similar to those of LE<sub>V</sub>, with no reduction in TSEB\_2T and 17%, 14%, and 34% in TSEB\_0, \_G, and \_GV, respectively. Even though TSEB\_GV had the highest initial  $\alpha_{\rm PT}$  of 2.00 while the other model configurations had an initial  $\alpha_{\rm PT}$  of 1.26, average daytime  $\alpha_{PT}$  of 0.72 in TSEB\_GV for well-watered days was comparable to 0.64, 0.82, and 1.24, in TSEB\_0, \_G, and \_2T, respectively. This is because available energy for LEV in TSEB\_GV is higher and therefore the model can compute lower  $\alpha_{PT}$  values. What is striking is that TSEB\_GV better estimated the difference between stressed and non-stressed conditions despite a constant initial  $\alpha_{\rm PT}$  of 2.00, confounding the notion that the model's initial assumption of high transpiration results in overestimation of LE under water-stressed conditions (Long and Singh, 2012; Morillas et al., 2013; Song et al., 2016a).

# 3.5. Honorable mentions

The TSEB model was first developed using a parallel rather than a series approach (Norman et al., 1995), which is slightly simpler and

generally works equally well. The parallel approach assumes no interaction between soil and canopy, which is less appropriate in a vineyard system where the canopy energy balance is strongly affected by heat exchange at the soil surface. In this study, initial consideration of the parallel approach was dropped when it became evident that it was greatly outperformed by the series approach. Also, considering the underestimation of  $R_{nV}$  in TSEB\_0, better partitioning of  $R_n$  was attempted using a vineyard radiation model developed by Pieri (2010). However, further assessment indicated that the underestimation of  $R_{nV}$  could not be explained by the amount of shortwave radiation that reached the vine canopy but by how much of it the vine canopy absorbed.

## 4. Conclusion

Average daytime total energy balance components evaluated for TSEB 0 resulted in relative errors of 8-39%, while relative errors of soil and vine energy balance components were 32-70%. Larger relative errors were found for H<sub>V</sub> and LE<sub>S</sub> even though RMSDs were similar due to the small magnitude of these fluxes. Using measured instead of modeled soil heat flux (TSEB G) improved total relative errors to 7-29% and soil and vine relative errors to 34-59%, while additional optimization of plant transpiration parameters (TSEB GV) reduced errors to 4-29% and 18-29% respectively. An adaptation using  $T_{\rm S}$  and  $T_{\rm V}$  rather than allowing the model to partition  $T_{RAD}$  into soil and vine temperatures, TSEB\_2T, resulted in much lower accuracies, likely due to loss of flexibility within the model. Bias in measured temperatures could also be a factor. Thus the best results were obtained with TSEB\_GV, (= TSEB\_GRF with  $\alpha_{PT} = 2.00$ , using (1) measured G, (2) leaf radiation absorption of 100%, and downward longwave radiation derived from  $T_A$  for  $T_V > T_A$ , (3) adjusted  $f_V$ , and (4) initial  $\alpha_{PT} = 2.00$ . This indicates that TSEB could be improved by (1) a better quantification of G; (2) improved radiation partitioning; (3) better accounting for the structure of the canopy and its effect on the vegetation contribution to LE. As for point 4, increasing of  $\alpha$ \_PT corrects artificially to the limitation of TSEB to account for added energy by advection. This is a useful, but a non-physical approach.

Optimization of plant transpiration parameters indicated that model tendency to underestimate  $LE_V$  originated in underestimation of both available energy and potential transpiration. Two possible causes of underestimation of  $R_{nV}$  were identified. First, it appeared that using LAI with a clumping factor allowed the model to correctly estimate the

amount of shortwave radiation reaching the vine canopy, but that the dense clumped canopy also had greater ability to absorb radiation. Therefore, increasing leaf radiation absorption to 100% greatly improved estimations of  $R_{nV}$ . Second, the lower end of the canopy emitting downward longwave radiation is likely to be closer to air temperature than to the temperature at the top of the canopy directly exposed to solar radiation. This adaptation reduced longwave radiation emitted by the vine canopy yielding much more reasonable  $R_{nV}$ . Potential transpiration was increased both by considering that average vine canopy temperature may be lower than the temperature at the top of the canopy and by increasing  $\alpha_{PT}$ . Future research may represent the difference between composite temperature as viewed from above and the "real" composite temperature in a more physically based manner (as opposed to the somewhat crude reduction in  $f_V$  presented here). Despite concerns in the literature that increasing  $\alpha_{\text{PT}}$ , which increases potential transpiration, would adversely affect estimates of LE<sub>V</sub> under stressed conditions, the results in this study clearly show much improved ET partitioning for TSEB\_GV with initial  $\alpha_{PT} = 2.00$  for both stressed and non-stressed conditions. Under stressed conditions, there will be a greater number of incremental reductions of  $\alpha_{PT}$  before the model converges. More detailed measurements of canopy temperature and energy fluxes are needed to confirm the validity of the adaptations evaluated in TSEB GV.

Seasonal changes were correctly detected by all model configurations; where average daytime RMSDs were somewhat lower early in the season, except for TSEB\_GV where average daytime RMSDs were equally low throughout the season. Hourly changes remain rather challenging, which may be partly attributed to the complex architecture of vineyards. Overall, *LE*<sub>V</sub>/*LE* changes over the season were detected quite well but absolute values were underestimated by 39% using TSEB\_0 and 6% using TSEB\_GV. Changes in *LE*<sub>V</sub>/*LE* in response to water stress were detected but underestimated by 62% using TSEB\_0 and 30% using TSEB\_GV.

## **Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

(A.1)

# Appendix A

In the TSEB model, net radiation ( $R_n$ ) is calculated as the sum of the vegetation  $R_n$  ( $R_n$ ) and the soil  $R_n$  ( $R_n$ s):

$$R_{\rm n}=R_{\rm nV}+R_{\rm nS}.$$

In order to obtain the radiation balances for the vegetation (subscript V) and soil (subscript S), first light interception by the vegetation is calculated using the approach described by Campbell and Norman (1998, chapter 15). The leaf area index (LAI) serves as a measure of the pathlength of the radiation through the plant canopy downwards, where the amount of radiation that is transmitted through the canopy decreases exponentially as a function of LAI and an extinction coefficient. For clumped canopies, the LAI is multiplied by a clumping factor ( $\Omega$ ) representing the fact that leaves cover the ground less efficiently when they are not randomly distributed. As the fraction of the vine canopy exposed to sunlight changes throughout the day, LAI is multiplied by a solar-altitude dependent clumping factor  $\Omega(\psi)$  (Kustas and Norman, 1999):

$$\Omega(\psi) = \frac{\Omega}{\Omega + (1 - \Omega)\exp(-2.2\psi^{(3.8 - 0.46D)})},$$
(A.2)

here  $\Omega$ , the clumping factor at zenith angle, is calculated using Eq. (3) described in Section 2.1,  $\psi$  is the angle of the sun relative to true zenith, and *D* is plant canopy height over width. The extinction coefficient for direct radiation (*K*<sub>b</sub>) represents the average direct radiation reaching a leaf inside the canopy divided by the radiation reaching a horizontal plane above the canopy. Since transmittance of direct radiation changes with the angle of the sun, *K*<sub>b</sub> changes with  $\psi$ :

$$K_{\rm b} = \frac{\sqrt{x^2 + \tan^2 \psi}}{x + 1.744(x + 1.182)^{-0.733}},\tag{A.3}$$

where *x* is the leaf angle distribution. The default value x = 1 represents a spherical leaf distribution, which is a good approximation for real plant canopies (Campbell and Norman, 1998). The extinction coefficient for diffuse radiation ( $K_d$ ) is independent of  $\psi$ , and has been approximated to equal 0.9 for LAI < 0.5, 0.8 for 0.5 < LAI < 2, and 0.7 for LAI > 2. For non-black leaves, leaf radiation absorption (*a*) is less than 1, and default values are 0.85 for photosynthetically active radiation (PAR) and 0.15 for near infrared (NIR) radiation. Subsequently plant canopy reflectance ( $\xi$ ) can be calculated as:

$$\xi_{b*} = \frac{2K_b}{1+K_b} \frac{1-\sqrt{a_{b*}}}{1+\sqrt{a_{b*}}},$$
And
(A.4a)

$$\xi_{\rm d*} = \frac{2K_{\rm d}}{1+K_{\rm d}} \frac{1-\sqrt{a_{\rm d*}}}{1+\sqrt{a_{\rm d*}}},\tag{A.4b}$$

where  $\xi$  for direct (beam; subscript b) and diffuse (subscript d) radiation is calculated for both the PAR and NIR wavelengths (subscript \*), giving a total of four  $\xi$  parameters ( $\xi_{bPAR}$ ,  $\xi_{dPAR}$ ,  $\xi_{bNIR}$ , and  $\xi_{dNIR}$ ). Considering the sparse vineyard canopy, radiation that is reflected from the soil is also rereflected from the canopy. The default values for soil albedo are 0.15 for PAR and 0.25 for NIR radiation, with an average albedo ( $A_S$ ) of 0.2. In this study,  $A_S = 0.275$  (measured) was assumed to equal 0.21 for PAR and 0.34 for NIR radiation. Vine canopy albedo ( $A_V$ ) and transmission ( $\tau$ ) for direct (subscript b) and diffuse (subscript d) shortwave radiation is calculated for both the PAR and NIR wavelengths (subscript \*) as:

$$A_{\mathrm{Vb}*} = \frac{\xi_{\mathrm{b}*} + \left(\frac{\xi_{\mathrm{b}*} - A_{\mathrm{S}*}}{\xi_{\mathrm{b}*} A_{\mathrm{S}*} - 1}\right) \exp\left(-2\sqrt{a_{\mathrm{b}*}} K_{\mathrm{b}} \mathrm{LAI}\Omega(\psi)\right)}{1 + \xi_{\mathrm{b}*} \left(\frac{\xi_{\mathrm{b}*} - A_{\mathrm{S}*}}{\xi_{\mathrm{b}*} A_{\mathrm{S}*} - 1}\right) \exp\left(-2\sqrt{a_{\mathrm{b}*}} K_{\mathrm{b}} \mathrm{LAI}\Omega(\psi)\right)},\tag{A.5a}$$

and

$$A_{\mathrm{Vd}*} = \frac{\xi_{\mathrm{d}*} + \left(\frac{\xi_{\mathrm{d}*} - A_{\mathrm{S}*}}{\xi_{\mathrm{d}*} A_{\mathrm{S}*-1}}\right) \exp\left(-2\sqrt{a_{\mathrm{d}*}} K_{\mathrm{d}} \mathrm{LAI}\Omega(\psi)\right)}{1 + \xi_{\mathrm{d}*}\left(\frac{\xi_{\mathrm{d}*} - A_{\mathrm{S}*}}{\xi_{\mathrm{d}*} A_{\mathrm{S}*-1}}\right) \exp\left(-2\sqrt{a_{\mathrm{d}*}} K_{\mathrm{d}} \mathrm{LAI}\Omega(\psi)\right)},\tag{A.5b}$$

and

$$\tau_{b*} = \frac{(\xi_{b*}^{2} - 1) \exp(-\sqrt{a_{b*}} K_{b} \text{LAI}\Omega(\psi))}{(\xi_{b*} A_{S*} - 1) + \xi_{b*} (\xi_{b*} - A_{S*}) \exp(-2\sqrt{a_{b*}} K_{b} \text{LAI}\Omega(\psi))},$$
(A.6a)

and

$$\tau_{d*} = \frac{(\xi_{d*}^{2} - 1) \exp(-\sqrt{a_{d*}} K_{d} \text{LAI}\Omega(\psi))}{(\xi_{d*} A_{S*} - 1) + \xi_{d*}(\xi_{d*} - A_{S*}) \exp(-2\sqrt{a_{d*}} K_{d} \text{LAI}\Omega(\psi))},$$
(A.6b)

giving a total of four parameters for both  $A_V$  and  $\tau$ . Assuming PAR and NIR each account for 50% of total shortwave radiation, and diffuse and direct radiation account for 20% and 80% in the PAR, and 10% and 90% in the NIR radiation,  $A_V$  and shortwave  $\tau$  ( $\tau_{short}$ ) can be calculated as:

$$A_{\rm V} = 0.5(0.2A_{\rm dPAR} + 0.8A_{\rm bPAR}) + 0.5(0.1A_{\rm dNIR} + 0.9A_{\rm bNIR}),\tag{A.7}$$

And

 $\tau_{\text{short}} = 0.5(0.2\tau_{\text{dPAR}} + 0.8\tau_{\text{bPAR}}) + 0.5(0.1\tau_{\text{dNIR}} + 0.9\tau_{\text{bNIR}}).$ (A.8)

Transmission of longwave radiation through the canopy  $(\tau_{long})$  is calculated as:

$$\tau_{\text{long}} = \exp(-0.95\text{LAI}\Omega(\psi)). \tag{A.9}$$
  
Finally,  $R_{\text{nV}}$  and  $R_{\text{nS}}$  are calculated as:

$$R_{\rm nV} = (1 - \tau_{\rm long}) (R_{Lsky} + R_{LS} - 2R_{LV}) + (1 - \tau_{\rm short}) (1 - A_V) S, \tag{A.10}$$

and

$$R_{nS} = (\tau_{long} R_{Lsky} + (1 - \tau_{long}) R_{LV} - R_{LS}) + \tau_{short} (1 - A_V) S,$$
(A.11)

where S is measured incoming solar radiation, and  $R_L$  is longwave radiation calculated with the Stefan-Boltzmann equation for the vine canopy (subscript V), soil surface (subscript S) and the air (subscript sky) using respective temperature and emissivity values.

## Appendix B

The aerodynamic resistance to heat flow ( $r_A$ ), and resistance to heat flow in the vine canopy boundary layer ( $r_V$ ) are calculated from meteorological data and vine canopy parameters following Norman et al. (1995).  $r_A$  is calculated as:

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$$r_A = \frac{\left(\ln\left(\frac{z_u - d}{z_M}\right) - \Psi_M\right) \left(\ln\left(\frac{z_T - d}{z_H}\right) - \Psi_H\right)}{k^2 u},\tag{B.1}$$

where  $z_u$  is the height of the wind speed (*u*) measurement and  $z_T$  the height of the air temperature measurement, *d* is displacement height,  $z_M$  and  $z_H$  are the roughness lengths for momentum and heat transport, respectively, *k* is the von Karman constant, and  $\Psi_H$  and  $\Psi_M$  are stability functions for momentum and heat. Note that is the series version of the TSEB model,  $z_H = z_M$  since  $r_V$  already accounts for the different efficiency between heat and momentum transport (Norman et al. 1995).  $r_V$  is calculated as:

$$r_{V} = \frac{C}{\text{LAI\Omega}} \left( \frac{l}{U_{c} \exp\left( -0.28 \text{LAI}^{2/3} h_{c}^{-1/3} \left( 1 - \frac{d + z_{M}}{h_{c}} \right) \right)} \right)^{1/2},$$
(B.2)

where C = 90 is a weighted coefficient for leaf boundary layer resistance over the height of the canopy, LAI is leaf area index,  $\Omega$  is the clumping factor at zenith angle, l is leaf size, and  $U_{\rm C}$  is wind speed at the top of the canopy at height  $h_{\rm c}$ , which is calculated using equations developed by Goudriaan (1977).

# Appendix C

Tables C1, and C2.

 Table C1

 Average daytime statistics for four TSEB model configurations for early and late season.

		RMSD	(W m <sup>-2</sup> )			relative e	bias (W m <sup>-2</sup> )					
TSEB	_0	_G	_GV	_2T	_0	_G	_GV	_2T	_0	_G	_GV	_2T
April-May												
R <sub>n</sub>	24	24	20	31	7%	7%	5%	8%	-14	-15	11	-22
$R_{\rm nV}$	67	64	25	76	31%	29%	11%	35%	64	61	21	72
R <sub>nS</sub>	84	81	17	101	59%	57%	12%	71%	-81	-78	-12	-96
Н	46	43	38	55	29%	28%	24%	35%	42	39	27	-44
Hs	34	38	22	50	23%	26%	15%	34%	29	33	14	-40
$H_{\rm V}$	32	29	34	32	<-999	<-999	<-999	<-999	13	6	13	-4
LE	48	34	37	61	43%	30%	33%	55%	-41	-25	9	52
LEs	39	42	15	122	314%	345%	120%	990%	36	39	11	114
$LE_{\rm V}$	80	68	35	68	81%	68%	35%	69%	-75	-63	-1	-61
June-July												
R <sub>n</sub>	34	33	12	43	8%	8%	3%	10%	-33	-31	5	-42
$R_{\rm nV}$	80	80	27	100	43%	43%	15%	54%	78	78	22	99
R <sub>nS</sub>	111	109	24	141	48%	47%	10%	60%	-110	-108	-15	-140
Н	51	47	52	101	33%	30%	34%	65%	38	33	44	-93
Hs	49	49	25	59	43%	43%	22%	52%	45	45	19	-55
$H_{\rm V}$	47	46	41	60	121%	118%	105%	156%	-7	-12	25	-38
LE	62	43	32	95	35%	25%	18%	54%	-50	-27	-7	88
LEs	40	44	10	155	289%	324%	75%	1134%	39	44	8	155
$LE_{\rm N}$	92	76	35	75	58%	48%	22%	47%	-84	-66	-10	-63

Four model configurations: (1) Two-source energy balance (TSEB) with default parameters (0), (2) TSEB with default parameters but measured instead of modeled soil heat flux (G), (3) TSEB\_G and adjusted vine transpiration parameters (GV), (4) TSEB\_G using measured vine and soil temperatures instead of a single overall surface temperature (2T). Energy fluxes evaluated include total, vine (subscript V), and soil (subscript S) net radiation ( $R_n$ ), latent heat flux (LE) and sensible heat flux (H). Total number of average daytime observations (n) were assessed using hours where  $R_n > 100$  W m<sup>-2</sup> (April-May: n = 46, June-July: n = 43).

#### Table C2

Hourly	v statistics	for four	TSEB	model	configuration	s for	early	and /	late season	ı.
					()					

5			U									
		RMSD	(W m <sup>-2</sup> )			relative	error (%)			bias (	(W m <sup>-2</sup> )	
TSEB	_0	_G	_GV	_2T	_0	_G	_GV	_2T	_0	_G	_GV	_2T
April-May												
Rn	30	30	31	33	8%	8%	8%	9%	-23	-23	7	-32
$R_{ m nV}$	80	78	55	86	35%	34%	24%	38%	81	80	34	95
$R_{ m nS}$	87	86	48	101	60%	59%	33%	69%	-74	-72	5	-96
Н	72	72	84	70	46%	46%	54%	45%	40	37	35	-63
Hs	39	43	34	55	25%	28%	22%	35%	35	38	15	-46
$H_{ m V}$	63	62	98	61	<-999	<-999	<-999	<-999	5	-1	20	-17
LE	93	75	102	80	80%	65%	89%	70%	-41	-23	4	68
LEs	66	59	44	124	818%	731%	553%	1544%	39	42	12	131
$LE_{\rm V}$	89	80	96	71	87%	77%	94%	69%	-80	-65	-7	-62
June-July												
R <sub>n</sub>	47	47	41	51	11%	11%	10%	12%	-33	-32	6	-42
$R_{\rm nV}$	144	142	108	159	90%	89%	68%	99%	105	104	48	126
$R_{ m nS}$	119	116	102	137	61%	59%	52%	70%	-74	-72	21	-104
Н	90	84	114	112	57%	54%	72%	71%	36	30	39	-94
Hs	58	59	42	64	50%	51%	37%	55%	45	46	21	-54
$H_{ m V}$	86	84	131	80	208%	201%	316%	192%	-9	-16	18	-41
LE	135	111	142	120	78%	64%	82%	69%	-49	-26	-1	88
LEs	61	54	21	167	441%	387%	155%	1208%	40	45	8	157
$LE_{\rm V}$	132	117	139	103	81%	72%	86%	63%	-93	-74	-12	-72

Four model configurations: (1) Two-source energy balance (TSEB) with default parameters (0), (2) TSEB with default parameters but measured instead of modeled soil heat flux (G), (3) TSEB\_G and adjusted vine transpiration parameters (GV), (4) TSEB\_G using measured vine and soil temperatures instead of a single overall surface temperature (2T). Energy fluxes evaluated include total, vine (subscript V), and soil (subscript S) net radiation ( $R_n$ ), latent heat flux (LE) and sensible heat flux (H). Total number of hourly observations (n) were assessed using hours where  $R_n > 100$  W m<sup>-2</sup> (April-May: n = 568, June-July: n = 560).

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