

Manuscript Title: Regional evapotranspiration from image-based implementation of the Surface Temperature Initiated Closure (STIC1.2) model and its validation across an aridity gradient in the conterminous United States

Authors: Nishan Bhattarai, Kaniska Mallick, Nathaniel A. Brunsell, Ge Sun, Meha Jain
Correspondence to: Nishan Bhattarai (nbhattar@umich.edu)

Dear Dr. Bob Su,

Thank you for the opportunity to submit a revised manuscript. We would also like to thank all three referees for their comments and suggestions. Please find our responses to referee's comments (both round #1 and 2) and a revised manuscript with track changes attached in this document. In summary, we have made following key changes in the manuscript to address all comments from the referees.

- 1) More discussion on uncertainties associated with the use of a simplified version of surface roughness and kB^{-1} parameter in SEBS (Reviewer # 1)
- 2) More discussion on the performance of the prior version of SEBS on different land cover types (Reviewer # 1)
- 3) Discussion on uncertainties associated with the use of 8-day aggregated data (Reviewer # 2)
- 4) Discussion on uncertainties associated with MOD16 (Reviewer # 2)
- 5) Results from a quick comparison of results with recently developed global SEBS monthly ET product (Reviewer # 3 and Editor)
- 6) Supplementary tables to address Reviewer #2's comments on implementations of ET models at instantaneous scale and 8-day scales.
- 7) Modifications to figure 4 and 5 (Reviewer # 1).

We hope you find the revised version of this manuscript to be greatly improved for publication in HESS.

Sincerely,

Nishan Bhattarai and all the coauthors

Responses¹ to Referee # 1 (Round 2)

The authors should do more analysis on the model evaluation, especially when they are assessing three models. Any conclusion should be careful, which might mis-lead reader who have not deep knowledge of the model physics.

Response: We thank Referee # 1(R#1) for comments and suggestions on explicit evaluation.

We would like to mention that this manuscript does not intend to provide a detailed model inter-comparison of the three models, as there could be up to large uncertainties in the observed fluxes. We intended to demonstrate the regional ET mapping potential of the STIC1.2 model which is independent of any land surface parameterization of aerodynamic conductance. SEBS (thermal) and MOD16 (non-thermal) models were selected because of their widespread use and great potential for regional scale ET mapping. In the revised version, this statement is made explicitly (Page 11, Line 27-30; Page 18 Line 2-4). Further, to avoid potentially misleading information to readers about the tendency of SEBS to overestimate ET, we have stated that a previous version of the SEBS model was used to characterize surface roughness (Page 10, Line 14-16). In addition, a recent version of SEBS (SEBS_{Chen} hereafter) global ET outputs (monthly and annual) is also presented and compared against STIC1.2 and observed annual ET. The relatively better performance of SEBS_{Chen} (Fig. 12) highlights the importance of better aerodynamic resistance characterization in SEBS. In addition, the good correlation between monthly and annual ETs from SEBS_{Chen} and STIC1.2 models provides an interesting insight for designing a multimodal-based thermal ET modeling framework in the future. Please find our responses to the comments below:

Comment # 1. Below table is my result from global daily ET. I did not see overestimation, when I also use satellite data and SEBS model to calculate ET. You need be careful about your input data. I suggest list your canopy height used for SEBS in table 1. When you want to assess a model, all the parameters and input data (LST, air temperature, wind speed) should come from ground truth observation. Unfortunately, most of model users are not responsible for doing this evaluation. Satellite data are easily used to force model and conclude that the model has some problems when they compare remote sensing data based model result with ground flux measurement. To assess a model, we should first to remove bias in the forcing data. Otherwise, the result evaluation is confusing. The readers don't understand where does the errors come from. If you want say the overestimation in SEBS is due to the model problem, It is better to do in-situ simulation with all ground measurement to check whether the conclusion is the same as what from using satellite data.

¹ Page and Line numbers are referred to the clean version of the revised manuscript

Num	Sname	Lat	Lon	IGBP LCT		ET_d vs. EC (mm/d)			Rn_d vs. EC (MJ/m ² d)		
				Site	MO D12	RMSE	MB	r	RMSE	MB	r
112	Tonzi_Ranch	38.4316	-120.966	SAV	SAV	1	0.19	0.61	NaN	NaN	NaN
101	Santa_Rita_Mesquite_Savanna	31.8214	-110.866	SRB	SRB	1.02	-0.24	0.44	4.65	-3.91	0.8

Response: We appreciate R#1 for sharing the results. There could be a number of reasons for the difference in model performances with the most important ones being the use of different versions of SEBS that use z_{OM} parameterizations derived from NDVI and the use of 8-day MODIS LST data and 8-day aggregated gridded data. In addition, we considered one dry, one wet, and one normal precipitation year for each flux site and because cloud free LST pixels are mostly available in dry days than wet days, the results could be positively biased, as the majority of the data points come from dry years (~40%). The use of coarse resolution gridded weather data and model implementation at 8-day temporal scales (please check our response for comment #2 from reviewer #2 and tables S2) are other sources of uncertainties. Prior studies using the same version of SEBS as used in this study have resulted in similar performances (RMSEs of 0.74 mm/day to 1.08 mm/day and PBIASs within 10%), as shown in this table, when implemented at several sites in Florida and Oklahoma (Bhattarai et al., 2016; Wagle et al., 2017). However, in those implementations, z_{OM} was empirically derived from actual canopy height from tower and weather stations using the exponential relationship between remotely sensed NDVI and albedo and z_{OM} (Allen et al., 2007). In this approach, the linear regression model (unique for each day) always forces z_{OM} and canopy height to be close to actual values. In this study, we attempted to reduce such empirically derived parameters and rely on remotely sensed products. In addition, we relied on gridded products (NLDAS) for weather forcing to produce spatially distributed ET maps, as opposed to weather station data used in prior studies (Bhattarai et al., 2016; Wagle et al., 2017). NLDAS wind speed (used in SEBS but not in STIC1.2) was not found to be as reliable as their air temperature and relative humidity, when compared against weather station data in the western US (Lewis et al., 2014). We have explicitly stated these uncertainties in the discussion section (Page 18, Line 28-Page 19, Line 14).

We did not use a static value for canopy height (h_c). We deduced canopy height from z_{OM} ($h_c = z_{OM} / 0.13$) (Brutsaert, 1982). While the point scale implementation using observed data could provide a true evaluation of the model, it cannot be used as a demonstrative tool for estimating ET maps at regional scales, as currently observed data is not possible to obtain for each pixel within an image. In addition, SEBS is one of the most widely used ET models within the thermal ET community. Studies (Vinukollu et al., 2011b; Su et al., 2005) suggest that while SEBS errors range from 1 to 15% when tower data are used, and the error could be significantly increased when remotely sensed and reanalysis data are used (McCabe et al., 2016a). Evaluation of SEBS at the instantaneous scale shows that SEBS ET estimates were within 17% of observed ET and use of 8-day MODIS products and 8-day average gridded products essentially added about 11% additional error (Table S3 and Page 18, Line 28-Page 19, Line 14 in the discussion). We believe

that most model errors associated with remote sensing based implementations of the SEBS model should come from uncertainties associated with input parameters and our study also revealed the same. In the revised version of this manuscript, we have explicitly stated the key uncertainties associated with SEBS implementation and also provided results using recently developed global SEBS ET products (Chen et al. 2013) that potentially overcome the uncertainties associated with surface roughness and kB^{-1} parametrizations (Page 17, Line 30-Page 18 Line 4). Improved results with the latest SEBS global ET products does validate the need for better characterization of aerodynamic resistance through improved kB^{-1} parametrization in the SEBS model.

In the revised version, we have also stated that the paper does not intend to provide a model inter-comparison, as there could be up to 30% uncertainties in the observed fluxes itself and other uncertainties associated with input data (Page 11, Line 27-30; Page 18 Line 1-2). We attempted to demonstrate the regional scale ET mapping potential of the STIC1.2 model using remotely sensed inputs (Page 11, Line 27-30).

Comment # 2. Please give the flux tower names in Figure 4 and 5. GRA, WSA, ENF is kind of misunderstanding information. One GRS site can not represent all ‘GRS’ sites.

Response: Figure 4 and 5 have been modified accordingly. A color code for each site has been used in all figures in the paper when flux sites are separated by colors.

Comment # 3: I don't agree the way you calculate kb_1 . Z0m equation from Van der Kwast is empirical method. You have agreed this by saying that ‘z0M was derived using a simple empirical relationship between the roughness length of momentum transfer, z0M, and NDVI, as suggested by Van der Kwast et al. (2009) [Page 9, Lines 23-24].’. Van der Kwast method cannot be used for forest or all kinds of canopy. Your using of z0h from Yang et al. 2002 also has some problem. Yang's method cannot be used for canopy site, since his method has used a 0.003???? z0m initial value to calculate z0h. This problem is already discussed by Prof. Hotslag and other micrometeorologist. But remote sensing community rarely notice this. I think the code from Abouali, Mohammad also have this problem when he replace SEBS's kb_1 with Yang's heat roughness scheme. The idea in Chen et al. 2013 is to merge Yang's method into SEBS's, due to Yang has a better performance than the Brutsaert method which is the soil part in SEBS kb_1 :

$$kB_s^{-1} = 2.46(\text{Re}_*)^{1/4} - \ln[7.4]$$

from Brusaert.

$$z_{0h} = (70\theta/u_*) \exp(-7.2u_*^{0.5}\theta_*^{0.25}) \quad \text{and} \quad (10a)$$

$$kB_s^{-1} = \log(z_{0m}/z_{0h}), \quad (10b)$$

from Chen et al. 2013

By fusing roughness schemes from both SEBS and Yang, Chen et al. 2013 can not only use the new kb_1 for bare soil but also canopy surface, which idea was already designed by Su 2002. In addition, no publication has tested Yang's scheme seriously over canopy covers. What is your argument for using Yang's method over forest or cropland? If you use yang's

method how did you set the initial z_{0m} value for this land covers? The relationship between these roughness scheme and publications should be clarified in this paper.

Response: We apologize for not better explaining how kB^{-1} , z_{0H} , and z_{0M} were computed. Our rationale for using the van der Kwast et al. (2009) method was to provide a spatial representation of z_{0M} across all study pixels and provide an estimate of canopy height (hc) and displacement height (d_0) for use in the SEBS model. By using van der Kwast et al. (2009) method, we aim to remove the requirement for knowing canopy height for each pixel in the image. We have stated this on Page 10, Line 14-16. The work-flow for kB^{-1} was as follows:

1. kB^{-1} for Full canopy ($kB1_c$) using Choudhury and Monteith (1988)
2. kB^{-1} for mixed canopy ($kB1_m$) using Choudhury and Monteith (1988)
3. kB^{-1} for soil ($kB1_s$) using Brutsaert (1982)
4. $kB^{-1} = fvc^2 * kB1_c + 2 * (fvc * fs) * kB1_m + (fs^2) * kB1_s$; where fvc and fs are fractional vegetation cover and fractional soil coverage, respectively.
5. Use extra parameterization for bare soil and snow, according to Yang et al. (2002)

We used Yang's method of kB^{-1} for pixels whose fractional vegetation cover was less than 1% or LAI was 0. The initial z_{0M} value for bare soil was set as 0.005 and hence essentially this approach was not used for forest and crop covers. This would not affect our results, as our sites are mostly vegetated but could have worked better for potential bare soil pixels across the spatial domain (Fig. 2) used for deriving regional scale ET. Notably, we found SEBS to be working fine under crop and forest conditions.

Comment # 4: About Fig. 13, the only solution is to calculate kb_1 from flux observation. You can use momentum and sensible heat flux to inversely calculate z_{0m} and z_{0h} , Then kb_1 can be calculated from 'observed' z_{0m} and z_{0h} . Otherwise the result in figure 13 is not trustable. In addition, I did not see any 0 values of kb_1 , which is quite popular for forest sites. If the authors cannot derive kb_1 from observation, I suggest to remove this figure and about the analysis of kb_1 . Or land cover could be taken as x-axis.

Response: We do not agree with the reviewer and consider Fig. 13 to be an important part of the manuscript to assess the effects of different components of aerodynamic conductance on model agreements/disagreements. When comparing STIC1.2 with SEBS using remote sensing data it is important to assess the role of kB^{-1} and z_{0M} on STIC1.2 versus SEBS ET difference where kB^{-1} and z_{0M} should be estimated using the same forcing datasets. Besides, for an inverse estimation of kB^{-1} using observed sensible heat flux, we need observations of aerodynamic temperature. The aerodynamic temperature cannot be observed or estimated in the EC tower and using radiometric temperature instead of the aerodynamic temperature will result in the derivation of radiometric kB^{-1} .

To elaborate, through figure 13, we made an attempt to show how the difference between ET estimates from STIC1.2 and SEBS (and observed and SEBS) were associated with kB^{-1} and z_{0M} that are the essential parameters to define the aerodynamic resistance in the SEBS model. Hence, we were more interested in the relationship between the pattern of residual difference between models (STIC1.2 and SEBS) and observed (STIC1.2 and SEBS) than the tower based kB^{-1} values. We have added a sentence in the figure caption to suggest that z_{0M} was derived using NDVI (van

der Kwast et al., 2009) and may not well represent tall canopies. Regarding the use of land cover based analysis, we made an explicit discussion in section 3 and 4 on how STIC1.2 and SEBS performances differ across different land cover types (Page 13, Line 4-25; Page 16, Line 23-Page 17, Line 15; Page 18, Line 2-4).

Comment # 5: Figure 9,10 and 11, I need a plot of land covers, canopy height (its importance has be mentioned in one of your paper) to analyze the possible error source in SEBS, beside your using of Yang`s method.

Response: The objective of the manuscript is to understand ET mapping potential of STIC1.2 across a wide variety of biome and hydrological regimes, and not to present the sources of errors in SEBS.

As stated in the response to comment # 1 (second paragraph), a static value of canopy height (hc) for each flux site (or the map) was not used in this study. Instead, it was deduced from z_{OM} ($hc = z_{OM}/0.13$) (Brutsaert, 1982) that was derived from NDVI (van der Kwast et al., 2009) and hence hc would be different for each image used in the derivation of annual ET. We do believe that this could be one source of uncertainty, as the use of observed canopy height and z_{OM} ($0.13 * hc$) produced much better results both at instantaneous and 8-day scales (Biases within 20% range). We have added this discussion in Page 18, Line 28-Page 19, Line 14 and results in the supplementary (Table S2). The sensitivity of the SEBS model to canopy height parametrization is already reported (Byun et al., 2014). However, such analysis is beyond the objectives and scope of this study.

Regarding the land cover maps in figures 9-11, we believe that it does not add much information to the discussion, as model performances under different land cover types are extensively discussed in sections 3 and 4. Instead, we have added them to the study area figure (Fig. 2), as we think it is more informative this way and could be used as a reference for ET maps in figures 8-11.

Comment # 6. I don't agree that you can use heat roughness to parameterize kB_1 . This is contradict with designing of kB_1 . kB_1 is intermedia variable which connect z_0m and z_0h , due to kB_1 cannot be used in MOST directly. Z_0h should be deduced from kB_1 not the inverse way. Please revise this sentence 'The roughness height for heat transfer proposed by Yang et al. (2002), was used to parametrize $kB-1$ '. And also the following sentences, as I said figure 13 has a problem: z_0M was derived using a simple empirical relationship between the roughness length of momentum transfer, z_0M , and NDVI, as suggested by Van der Kwast et al. (2009). The roughness height for heat transfer proposed by Yang et al. (2002), was used to parametrize $kB-1$. This new parametrization of $kB-1$ was designed to improve the SEBS model performances on bare soil, low canopies, and snow surfaces as was proposed by Chen et al. (2013).'

Response: We apologize for this confusion. Indeed, kB^{-1} was used to derive z_{OH} (Equation 14). We revised this sentence as Yang et al. (2002) was used to parametrize kB^{-1} for bare soil and z_{OH} was estimated using Eq. 14 (Page 10, Line 14-16).

Comment # 7. Please rewrite these sentence:

The source codes for different sub-models within SEBS were either adapted or modified from Abouali et al. (2013). The SEBS codes in this study is adapted from Abouali et al. (2013), which is different from original version in Su 2002 and Chen et al. 2013.

Response: The change has been made (Page 10, Line 14-16).

Comment # 8. Most of SEBS study found ET over ENF and DBF is overestimated, however, this is not reflected in your study. Please give some explanation.

Response: In this study, we did find SEBS to overestimate ET from ENF and DBF by about 8% and 17%, respectively. However, we do not consider this as a poor performance given there are uncertainties associated with flux tower ET and input parameters. The overestimation of ET from ENF and DBF occurred during normal and dry years, as in the wet years ET estimates were within 5% (Supplementary Figs. S3-S5). While several studies (Michel et al., 2016; Ershadi et al., 2014) have reported SEBS to have overestimated ET in ENF and DBF, Ershadi et al. (2014) had also reported that the overestimation tendency of SEBS is not applicable everywhere (e.g. no overestimation of ET from site US-MMS in Ershadi et al., 2014).

Responses to Referee # 3 (Round 2)

The authors have addressed the concerns of the previous reviews adequately.

However, given the fact that the authors have evaluated a previous version of the SEBS with a simple empirical parameterization of z_{0m} with NDVI, it is suggested that a quick comparison is made with a recently completed global application of SEBS.

The data set can be obtained at:

<http://en.tpdatabase.cn/portal/MetaDataInfo.jsp?MetaDataId=249454>

This would be a timely contribution to the advances in remote sensing of land surface energy balance, heat fluxes and evaporation.

Response: We thank Reviewer # 3 for the comments and suggestions. We have compared STIC1.2 results with the recently developed global monthly SEBS ET at monthly and yearly scales (Fig. 14). In addition, we also compared the annual ET from the flux tower with global SEBS ET (Fig. 12). Overall, we find that the global SEBS ET and STIC1.2 ET are well correlated at monthly ($R^2=0.81$) and yearly ($R^2=0.58$) scales. The new SEBS global annual ET (sum of all monthly ET) was within 14% of the observed annual flux ET during years and explained 56% of the variation in the observed flux annual ET. This performance was better than the old version of SEBS we used in this study and the other two models (SEBS and MOD16). We think the better characterization of surface roughness and treatment of canopy height significantly improved the performance of SEBS compared to the version used in our paper. Our main focus of the paper is to demonstrate a remote sensing based application of a new thermal-based ET model, and assessing its performance by comparing with SEBS and MOD16. Intercomparison of the SEBS models with different parametrizations of surface roughness and kB^{-1} or with different forcing data (observed vs gridded data) is beyond objective and the scope of this study (Page 11, Line 27-30; Page 18 Line 2-4). However, this quick comparison does highlight the need for improved characterization of surface z_{0M} and kB^{-1} and careful selection of input forcing data in remote sensing based ET models.

Responses to Referee # 1 (Round 1)

Comment: This paper has enlightened ET remote sensing community about the importance of aerodynamic conductance/resistance. Currently, most of the ET algorithms do not take into account the diurnal variation in this resistance. The authors have implemented STIC model at regional scale. STIC model integrates remote sensed surface temperature into Penman-Monteith equation to derive an analytical solution for the resistance and use the resolved resistance to calculate surface heat fluxes/ET. They also compare its performance with other two ET algorithms, SEBS and MOD16. SEBS model provide direct solution for surface and boundary layer conductance/resistance from momentum/heat roughness and stability. However, MOD16 uses a kind of constant resistance in its ET calculation, which explains its worst performance among the three methods. STIC use an energy balance and meteorological information to inversely retrieve the surface and boundary layer conductance. The results are sufficient to support their conclusions. The paper address very relevant scientific questions within the scope of HESS. Thus I suggest an acceptance for publication.

Response: We thank the reviewer for appreciating our work and considering the manuscript to be interesting and relevant to the HESS community.

Comment: Figure 5 shows that SEBS has a similar performance as STIC, and MOD16 for CRO, DBF, and ENF, but worse result at WSA and GRA. Please check if this is due to inaccuracy of satellite input data.

Response: Fig. 5 suggests significant overestimation of SEBS ET in WSA and GRA sites. Specifically, at one of the WSA sites (e.g., US-Ton), all of the three models performed poorly, where observed ET values were extremely low (0.6 mm per day; Fig. 5). In this specific site, 10% of the observed LST pixels were within 2-3 K LST errors with surface emissivity errors of 0.01 to 0.03, based on the MODIS QA/QC data. Similarly, in another WSA site (i.e. US-SRM), 37% of observed LST pixels were within a similar error range. The literature also suggests high emissivity correction uncertainties and systematic underestimation of MODIS LST in arid and semiarid ecosystems (Wan and Li, 2008; Jin and Liang, 2006; Hulley et al., 2012). The significantly poor performance of SEBS in the US-SRM site could also be attributed to these uncertainties. We have added text in the discussion section about the performance of STIC1.2 at the US-Ton site (Page 16, Lines 7-10). It is also important to note that uncertainties also exist in the Bowen ratio energy balance closure correction of energy balance at the arid and semi-arid sites, which is also discussed on Page 16, Lines 14-19.

Regarding the poor performance of SEBS in the GRA sites, the errors are mostly due to large differences in SEBS ET and observed ET in the two semi-arid desert grasslands sites (US-SRG and US-Wkg) (Supplementary Table S1). In the two other grassland sites (US-Kon and US-KFS), SEBS performed relatively better and was comparable with STIC1.2 (Supplementary Table S1). In those two semi-arid desert grasslands sites (US-SRG and US-Wkg), the MODIS QC/QA bin suggested that 27% (US-Wkg) and 4% (US-SRG) of MODIS LST were within 2-3 K errors with emissivity errors within the 0.01 to 0.02 range, based on the MODIS QA/QC data. These errors are however more predominant in SEBS, and, as in the semi-arid and arid conditions, substantial differences exist between T_R and T_0 due to strong soil water limitations. Such water-limited conditions may not have been properly characterized in the kB^{-1} parameterization, which could lead to large differences between modeled and observed ET. We discussed these potential limitations on Page 16, Line 27-28; Page 16, Line 32 to Page 17, Line 15 and Page 16, Line 24-31. We added additional discussion on the performances of SEBS and other models in GRA and WSA sites and how the model performed differently in two GSA sites in two different climates in the revised paper (Page 16, Line 23-31).

Comment: Fig. 8, 9, 10 shows that SEBS ET maps have higher ET than STIC and MOD16, this is due to sensible heat flux is low-estimated, because of high kB^{-1} . Please check the reference of Chen et al. 2013.

Response: This is a correct statement. The underestimation of sensible heat flux (H) by SEBS (nearly 41% underestimation) was mostly seen in arid and semi-arid sites, which eventually led to an overestimation of ET in these sites. Chen et al. (2013) provided an extensive discussion on how H is underestimated by the original SEBS model and proposed an improved way of estimating roughness Yang et al. (2002) length for heat transfer through a new parametrization of kB^{-1} adopted from Yang et al. (2002) for bare soil and snow surfaces. In this paper, we incorporated the same kB^{-1} formulation from Yang et al. (2002) (source code obtained from Abouali et al., 2013). However, we adapted a simplified version of z_{OM} parametrization (van der Kwast et al., 2009), which could have led to uncertainties in canopy heights. Fig. 13 suggests that ET biases (SEBS ET-Observed ET) were typically random and large when kB^{-1} values were within 5 ($r = -0.03$) and slightly negative when kB^{-1} values were within 5 and 8 ($r = -0.16$). However, for kB^{-1} values > 8 , a linear trend in ET bias was evident (underestimation of H) with an increase in kB^{-1} ($r = 0.24$). We added additional discussions on how uncertainties in kB^{-1} parametrization could lead to biases in estimated fluxes in the revised version (Page 17, Line 29- Page 18, Line 4)

Comment: Which method or model is used to calculate kB^{-1} and z_{0m} in figure 13? Or kB^{-1} and z_{0m} is derived from flux tower measurement?

Response: Please refer to our responses for your comment #3 and 6 on the revised manuscript (Pages 4-7).

Comment: Figure. 12, please have more discussion about the higher SEBS annual ET, is this due to the method in annual accumulation or SEBS model.

Response: We have briefly discussed that this overestimation is mostly due to consistent overestimation of 8-day ET by the SEBS model (Page 15, lines 6-8). In addition, the 8-day average net radiation was also overestimated by 9% (Supplementary: Fig. 1), which could also add some positive biases by SEBS (and also STIC). In the two cropland sites (US-ARM and US-Ne1), SEBS annual ET estimates were within 2% of observed annual ET, which is better than the performance of STIC (22% underestimation) and MOD16 (49% underestimation). SEBS mostly overestimated annual ET from the arid and semi-arid sites (47%). We added these additional discussions in the revised manuscript (Page 15, Line 8- 14).

Comment: Fig. 4 and 5 does not show SEBS ET has different performance over different land covers, at least does not always show high ET estimation.

Response: Here we disagree. According to Fig. 4, RMSE and MAE of SEBS is similar to MOD16 across different precipitation conditions, but STIC1.2 performed better overall. According to Fig. 5, we noticed that SEBS performed best in CRO sites among all the models and its performance was similar to MOD16 in ENF sites compared to its performances in other biomes (GRA and WSA). We agree with the reviewer that SEBS does not overestimate ET all the time; as seen in Fig. 4 and 5, there are several instances when SEBS ET was lower than the observed ET. However, the overestimation tendency of ET by SEBS was predominant during the dry year (Fig. 4). The term “overestimation” refers to the mean ET observed at the flux sites. Notably, SEBS ET estimates were within 3%, 8%, and 17% of observed ET at croplands, ENF, and DBF sites, respectively, which were comparable or sometimes better than the other two models. We have briefly stated these in section 4 (Page 15, Line 8- 14; Page 16, Line 23-28; Page 16-Line 29- Page 17, Line 15; Page 17, Line 24-29).

Response to Referee # 2 (Round #1)

This manuscript provides an evaluation of STIC1.2 in estimating actual evapotranspiration at the spatial scale by combining the model with satellite remote sensing data. In addition, the authors also compare the performance of STIC1.2 with other two existing remote sensing algorithm (i.e., SEBS and MOD16). In general, the topic of this MS is of interest to the HESS' readership and the manuscript is well written. However, there are several major issues in this study, which introduce additional uncertainties and preclude a focused evaluation of the models themselves (as described below). In this light, a MAJOR REVISION is needed.

We thank Referee #2 (R#2 hereafter) for finding our work interesting to the HESS community and providing useful criticism, comments, and suggestions. We also acknowledge R #2 for pointing out potential uncertainties associated with the use of input data. Uncertainties arising from the temporal and spatial mismatches of input datasets from different sources are common in remote sensing based studies. Acknowledging this fact, we made best possible efforts to minimize those. First, it is important to clarify that our study aims to provide a scientific basis for the operational use of STIC1.2 model towards estimating regional ET using remotely sensed data. Since the MODIS daily products suffer greatly due to cloud cover, the 8-day MODIS products are more applicable for regional ET model implementation and hence the validation was done at this temporal scale, which is a common practice (Ichii et al., 2009; Zhang et al., 2010; Yang et al., 2006; Xiong et al., 2015). The MOD11A2 product was considered to provide a better temporal and spatial representation (compared to the daily MODIS products) of regions (i.e. a wide range of biome and aridity conditions in the US). Nevertheless, we have now implemented STIC1.2 and SEBS at instantaneous (at point scale using daily MODIS and instantaneous weather data) and presented main validation results in this response. However, this implementation is not the core part of our paper and hence was only added to the supplementary (2 tables) and with a brief discussion in the main text (highlighted in red font).

In this response, we not only justify our approach (e.g. use of MODIS 8-day LST) with additional analysis and references but also show results from the evaluation of instantaneous ET from SEBS and STIC1.2 models using instantaneous/daily MODIS products (and weather inputs of the same period). Results suggest that the core findings and conclusions of this study will remain the same regardless of whether instantaneous or 8-day products are used. However, additional knowledge on the potential sensitivity of SEBS to input meteorological forcing and the applicability of the STIC1.2 model across different time scales were gained. In the revised version, we have added additional descriptions (Page 18, Line 28-Page 19, Line 14) on potential uncertainties associated with the application of models at 8-day scales, use of 8-day average (daytime) weather inputs, and the MODIS 16 ET products. We believe that the evidence we provided and detailed answers to your concerns with appropriate references will sufficiently address R #2's major concerns that are mostly associated with the use of input data and uncertainties.

Major: 1. My largest criticism lies in the use of MOD11A2, where LST is reported as the average values of clear-sky LSTs during an 8-day period. As there is no information about which day (or days) out of each 8-days contributes to the final 8-day averages, this 8-day

*average LST is highly likely to not correspond to the 8-day averages of meteorological variables (i.e., air temperature, VPD, etc). For example, the 8-day LST might only be a result of day-1 LST, or the average of day-1 and day-7 LSTs. Even they correspond well with each other, using 8-day averages may still lead to additional uncertainties due to differences in the temporal variability between, say, daily LST and air temperature. For example, $H_{day1}+H_{day2} \dots +H_{day8}$ does not equal to $1/8 * (H_{calculated using 8-day average LST and meteorological inputs})$, as all the responses are non-linear. To focus on evaluating the model itself, it is recommended to work on the instantaneous scale rather than 8-day averages.*

Response: The scientific basis for using MOD11A2 comes from an abundance of studies (for e.g. Ichii et al., 2009; Jin et al., 2011; Tian et al., 2013; Garcia et al., 2014; Xiong et al., 2015) that have also used this 8-day product in ET modeling. In our study, SEBS and STIC1.2 models were run at 8-day average scale corresponding to the MODIS daytime overpass time using MOD11A2 (and ancillary MODIS data; Table 2, Page 30) and 8-day average meteorological data corresponding at the MODIS Terra LST overview time (not the entire 8-day average; Page 10, Line 8-12 in the revised manuscript). The 8-day averaged meteorological data (that considers all hours) are only used in extrapolation of daytime ET to 8-day ET using a constant ET approach (Brutsaert and Sugita, 1992; Crago, 1996; Chávez et al., 2008). We evaluated 8-day cumulative ET to compare model performances against those from available MOD16 8-day ET products (Mu et al., 2011). We provide further justifications for using 8-day MODIS products as below:

Comparison of 8-day vs. daily LST (or T_R), air temperature (T_A), and $T_R - T_A$

We find that the 8-day average LST (or T_R), air temperature (T_A), and difference between T_R and T_A ($T_R - T_A$) were good representative of the corresponding instantaneous values during each of the 8-days within the corresponding MODIS 8-day period ($R^2 = 0.80-0.92$, PBIAS within 3%) (Fig. AR1).

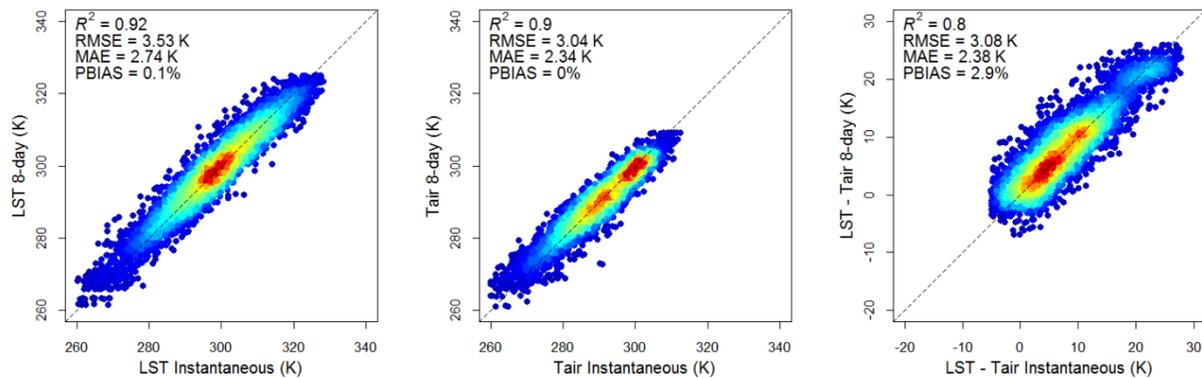


Fig AR1. Scatter plots of 8-day average LST vs. instantaneous LST, 8-day average daytime T_A vs. instantaneous T_A , and 8-day average daytime $T_R - T_A$ vs. instantaneous $T_R - T_A$.

Comparison of 8-day vs. daily ancillary meteorological variables

When 8-day vs. daily ancillary meteorological variables were compared, solar radiation ($R^2 = 0.82$, PBIAS = -5%) and relative humidity ($R^2 = 0.78$, PBIAS = 6%) were also found to be in a

similar range (Table AR1). However, we noted that 8-day average daily wind speed, which is highly variable with time and space, was not well representative of daytime conditions ($R^2 = 0.36$). Note that this uncertainty in wind speed could affect instantaneous ET values from the SEBS model, which uses wind speed to determine sensible heat flux (H) and estimate latent heat flux (λE) as a residual of surface energy balance. In addition, this would also slightly affect 8-day average net radiation that used the FAO-based Penman-Monteith (PM) equation (Allen et al., 1998; ASCE-EWRI, 2005) that is used to upscale instantaneous ET to 8-day cumulative ET. Hence, we think the uncertainties associated with differences in actual meteorological conditions will have more of an effect on SEBS than STIC1.2, which is also supported by results from model evaluation at the instantaneous scale (i.e., MODIS TERRA daytime overpass time).

Table AR1. Comparison of 8-day average daytime meteorological and radiative inputs vs. instantaneous inputs to assess how representative the 8-day average values were of each day within the 8-day period.

Variable	R^2	RMSE	MAE	PBIAS (%)
T_R (K)	0.92	3.53	2.74	0.1
T_A (K)	0.900	3.04	2.34	0
$T_R - T_A$ (K)	0.80	3.16	2.42	3.8
RH (%)	0.78	10	8	6
Wind speed ($m s^{-1}$)	0.36	1.61	1.19	2
Incoming shortwave radiation ($W m^{-2}$)	0.82	69	49	-5%

Model implementation and validation at instantaneous scale showed similar results

STIC1.2 and SEBS were implemented using all the available daily MODIS products (MOD11A1, MOD09GA, etc. and instantaneous weather data from NLDAS-2 forcing data) during the study years (Fig. 3, page 35 in the revised manuscript) and evaluated at the instantaneous scale. We noticed similar overestimation and slight underestimation tendencies of SEBS and STIC1.2, respectively (Table AR2 and Fig. AR2). Overall, model performances at the instantaneous scale during dry, normal, and wet years were also consistent with those observed when validation was done at the 8-day scale (see Fig. 4, Page 36 in the revised manuscript); there was a slight underestimation tendency of STIC1.2 and overestimation of SEBS (better under wetter conditions). The additional 11% overestimation of SEBS (17% vs. 28%) could be attributed to uncertainties associated with widely varied wind speed and other meteorological variables within the 8 days of a given 8-day period as well as the slightly overestimated 8-day average net radiation (Fig. AR3, also in the supplementary, Figure S1). The uncertainty associated with wind speed should not affect STIC1.2, which does not use wind speed; therefore, STIC1.2 performances were more consistent compared to SEBS. These results suggest that regardless of whether 8-day or daily MODIS products are used, the key findings of our research would largely remain the same.

Table AR2. Evaluation of instantaneous ET and 8-day cumulative ET (Table 3, Page 31) from STIC1.2 and SEBS against observed ET from thirteen core AmeriFlux sites in the US combining data from one dry, one wet, and one normal year. Note: the 8-day ET estimates are derived from 8-day MODIS products (MOD11A2, MOD09A2, etc.) and 8-day average weather data (both at the satellite overview time and the 8-day average values).

Scales	Model	R^2	RMSE (mm hr ⁻¹ or mm 8-day ⁻¹)	MAE (mm) (mm hr ⁻¹ or mm 8-day ⁻¹)	PBIAS (%)
Instantaneous	STIC1.2	0.61	0.12	0.09	-5
	SEBS	0.53	0.14	0.10	17
8-day	STIC1.2	0.66	7.5	5.4	-3
	SEBS	0.53	9.8	7.3	28

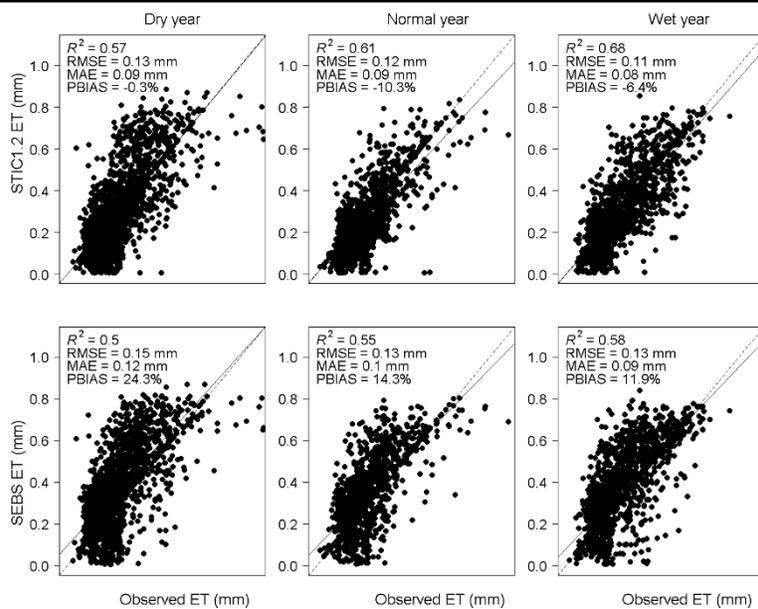


Fig. AR2. Evaluation of ET estimates from the STIC and SEBS models against flux data at the instantaneous scale using daily MODIS products (MOD11A1) during the dry, normal and wet years (see Fig. 4, Page 33).

Good correlation between estimated and observed 8-day average available energy (ϕ)

The 8-day mean (considering all hours) available energy ($\phi = R_n - G$) that was used to upscale 8-day average daytime instantaneous ET to 8-day total ET (Eq. 17, page 10) was found to be strongly correlated with the observed 8-day mean ϕ at the flux towers. While the random noises in instantaneous ϕ (Figure AR3), which was also found to be well correlated with observed values ($R^2 = 0.65$), are removed in the 8-day average ϕ , a small positive bias (i.e. overestimation of 9%) (Fig. AR3, also in the supplementary, Figure S1) was also added. The residual difference in estimated 8-day average ϕ and observed 8-day average ϕ was positively correlated with the residual difference in estimated and observed 8-day cumulative ET ($r = 0.27$ for SEBS and $r = 0.18$ for STIC1.2, p -value < 0.001). This positive bias in estimated 8-day mean ϕ could have reduced biases from STIC1.2 from -5% to -3% (positive shift) and led to further increases in SEBS biases (i.e. 28%, Table AR2).

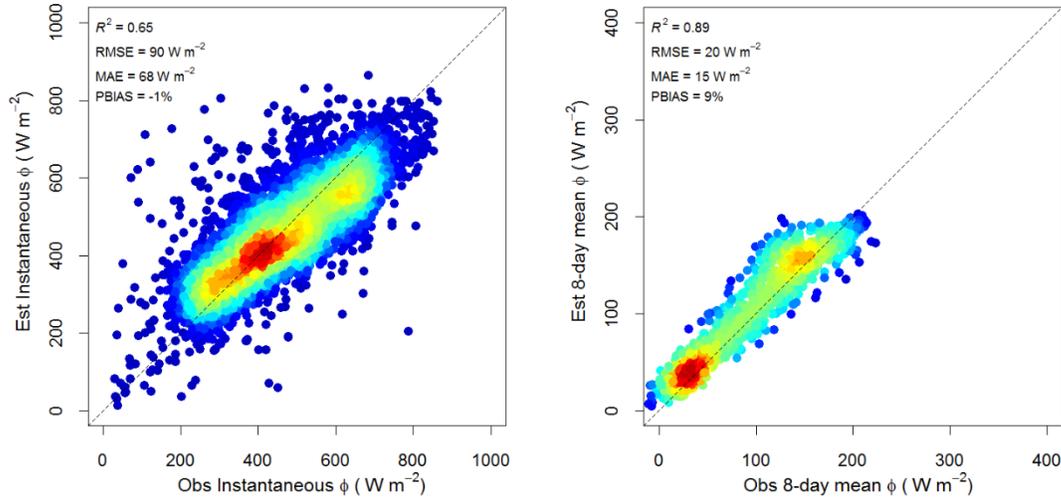


Fig. AR3. Scatter plot of estimated vs. observed available energy (ϕ) at instantaneous (using daily MODIS products) and 8-day averaged conditions (using 8-day products).

Models performed better in areas that are mostly affected by clouds

In the humid regions, all three models performed better than in the arid and semi-arid regions with similar accuracies despite high cloud cover (resulting in a fewer number of cloud-free days in each MODIS 8-day cycle). This is partly because vegetation (forests) is mostly energy-limited in this region and because estimated average 8-day ϕ from the meteorological inputs from the NLDAS-2 forcing (12.5°) were well correlated with observations ($R^2=0.91$) and with 9% error. In the arid sites, the estimated and observed ϕ relationship was also similar ($R^2 = 0.96$ and PBIAS within 6%). In our opinion, the effect of cloud cover is smaller in the arid and semi-arid regions compared to the humid and sub-humid regions and hence most of the differences in model performances could be attributed to the physical differences among the models.

MOD11A2 and aggregated meteorological are commonly used in ET modeling

The model implementation and validation scheme used in this study (i.e. use of MODIS aggregated datasets and n -day averaged meteorological inputs) have been applied in several other studies (Ichii et al., 2009; Senay et al., 2013; Wu et al., 2010; Xiong et al., 2016). In addition, comparison of daily ET, 8-day average ET or the 8-day with respective flux ET has become a common practice in ET model evaluation studies (Yang et al., 2006; Ichii et al., 2009; Senay et al., 2013; Biggs et al., 2016; Xiong et al., 2015; Ryu et al., 2012) and particularly those that use MODIS 8-day datasets.

Changes in the revised manuscript

While we have provided evidence and justifications for using MOD11A2 and aggregated weather information, we do acknowledge that there are uncertainties associated with the use of 8-day average LST and aggregated meteorological variables which should be mentioned in the manuscript. We have now added an extended discussion (Page 18, Line 28-Page 19, Line 14) in the revised manuscript and two tables in the supplementary (Table AR1-AR2).

2. Page11 (Line 8-17) Again, validation should be carried out at an instantaneous scale but not daily (or 8-day averages), as upscaling can introduce additional uncertainties. In my opinion, upscaling from satellite overpass to longer time scales is another scientific question.

Response: For the most part, please refer to our response to the previous comment. We have added few more points below.

Should an ET model always be validated at the instantaneous scale only?

While we agree that the validation of ET at the instantaneous scale could help reduce uncertainties associated with upscaling and overall meteorological representation, we also disagree that the validation should always be conducted this way. ET is a hydrological process and like precipitation and runoff, these processes (and the errors) are perceived better when reported at daily or seasonal scales (e.g. 0.01 mm hr⁻¹ vs 1 mm/day or 1000 mm year⁻¹). For example, ET at daily or seasonal scales is more meaningful for hydrologists who manage water resources (Tang et al., 2015; Cammalleri et al., 2014; Colaizzi et al., 2006) and for comparing with accumulated precipitation (Baldocchi and Ryu, 2011). There are host of studies (for e.g. Fisher et al., 2008; Senay et al., 2013; Velpuri et al., 2013; Jiang and Ryu, 2016; Bunting et al., 2014) that have conducted ET validation at much larger temporal scales (e.g., 8-day, monthly, seasonal, annual) than the instantaneous scale.

The 8-day cumulative or mean ET corresponds with the cycle of MODIS global coverage (Masuoka et al., 1998) and one of the most widely used forms of ET model implementation and validation (Ryu et al., 2012). The 8-day or other multiday MODIS composites are designed to deal with cloud cover to provide a more routine measurement of Earth's surface than the daily MODIS data. The cloud effect on ET estimation or understanding other physical processes is greatly reduced when a composite 8-day LST product is used (Yang et al., 2013; Hu and Brunsell, 2013).

STIC1.2 has already been validated at an instantaneous scale

STIC1.2 model has been extensively validated at a half-hourly scale using flux tower data (Mallick et al., 2014; Mallick et al., 2015; Mallick et al., 2016), which is a better evaluation than using remotely sensed data, as any bias associated with the spatial and temporal mismatches between input meteorological and land surface variables are distinctly identified. The strength of the present study is to test the ET mapping potential of STIC1.2 at the regional scale using purely remote sensed data and gridded climate data. Therefore, we performed validation of the STIC1.2 model at the 8-day scale and compared our resulting ET estimates with readily available products such as MOD16 or the widely used SEBS model. In addition, our results are consistent with instantaneous scale validation (Table AR2 and Fig. AR2 in this response and Table 3, page 31 and Fig. 4, page 36 in the revised manuscript).

Upscaling errors (instantaneous to 8-day ET) are minimized through reliable estimates of 8-day average ϕ

We agree that the upscaling of ET from satellite overpass time to longer time scales (e.g. 8-day, as done in this study) is a different scientific question, as there are several uncertainties

associated with it. The approach (Page 10, Eq. 17) we used in this paper is a well-established method (Allen et al., 2007;Colaizzi et al., 2006;Ryu et al., 2012;Shuttleworth et al., 1989;Gentine et al., 2007;Chávez et al., 2008). In addition, the estimated 8-day ϕ (the key driving force of ET) was strongly correlated with the 8-day average ϕ at flux towers ($R^2 = 0.89$, RMSE = 20 W m^{-2} , PBIAS = 9%, Fig. AR3, also in the supplementary, Figure S1). Hence, the errors associated with model evaluation at the 8-day scale by upscaling of instantaneous to 8-day cumulative ET should be within 9%. If we had directly used the observed ϕ at the towers, PBIAS from SEBS would have reduced to 18% (from 28%) and STIC biases would have been -10% (from -3%) with increased R^2 (STIC = 0.69 and SEBS = 0.58) and slightly reduced RMSEs (STIC = 6.8 mm and SEBS = 8.6 mm) from both models. However, it should be noted that the evaporative fraction was derived during the image time obtained using the weather information from gridded data, not the flux tower data itself. Hence there are some uncertainties with the use of meteorological data from multiple sources during instantaneous and multiple scales, as data from the same source is typically used to extrapolate instantaneous to daily or other scales (Allen et al., 2007;Chávez et al., 2008;Allen et al., 1998). Overall, we find that the upscaling errors are within 10% for both models.

Major Point 3. Page 11 (L29-30): Any explanation of this model performance: overestimation in dry year and underestimation in wet years? Additionally, according to your Figure 6, it seems that this “overestimation in dry and underestimation in wet” pattern persists across sites (i.e., spatially). This may suggest some systematic uncertainty of the model. Given this, I do not agree with the statement given in Page 15 (Line 4-12). First, does any previous study support this wet/dry patches around the studied sites? If not, this is just your speculation. Second, the footprint issue could lead to random errors rather than a systematic underestimation. Finally, it is the authors’ responsibility to ensure the footprint of a flux site corresponds (or encompasses) the MODIS footprint so that to eliminate data uncertainties and to allow a focused evaluation of the model.

Response: Overestimation of SEBS could be due to uncertainties associated with the kB^{-1} parameter (Chen et al., 2013), as well as the positive biases in 8-day average ϕ (as discussed earlier). Underestimation of ET from STIC1.2 could be due to an excessive moisture constraint applied during initialization of soil moisture availability (M) using T_R and dew point temperature at source/sink and reference heights. In addition, in the dry years, overestimation errors of ϕ ($R^2 = 0.88$, RMSE = 22 W m^{-2} , PBIAS = 12%) was slightly more than in the wet year ($R^2 = 0.91$, RMSE = 18 W m^{-2} , PBIAS = 9%). At the instantaneous scale, we noticed that STIC1.2 did not overestimate ET during the dry year and the SEBS overestimation was within 24% (PBIAS = 24%), which could be due to uncertain conductance parameterization, as in case of 8-day evaluation. We have discussed potential uncertainties in detail in section 4 (Page 18, Line 28-Page 19, Line 14). The manuscript is about first ever regional scale implementation of the STIC1.2 model using remotely sensed data and hence have focused more on the initial validation as well as the comparison with two other commonly used models.

Please check figures AR4-AR7, where annual ET maps from three global ET products: 1) The Global Land Evaporation Amsterdam Model (GLEAM; 0.25° spatial resolution) (Martens et al.,

2017; Miralles et al., 2011); 2) MPI-BGC or Fluxnet: MTE (0.5° spatial resolution) (Jung et al., 2010; Jung et al., 2011) 3) SSEBop (1km spatial resolution; <https://earlywarning.usgs.gov/fews/datadownloads>) (Senay et al., 2013; Velpuri et al., 2013) are added. Here, the annual ET map from one of three study years (the year when datasets from the other three models were also available) is shown. While the first two datasets (GLEAM and MPI) are at relatively coarser spatial resolution, most of these maps clearly show a similar spatial pattern of ET as STIC1.2. Hence, the spatial patterns of ET produced by our model seem to be reasonable and not linked with any systematic uncertainty of the model. In addition, scatter plots of estimated vs. observed ET (both instantaneous and 8-day cumulative; Figure AR2, Figure 3 and 4) show points spread uniformly around the 1:1 line.

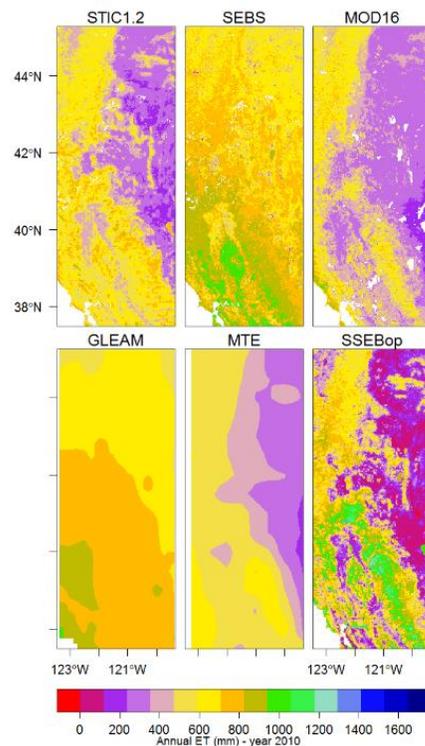


Figure AR4. Annual ET map derived from STIC1.2, SEBS, MOD16, GLEAM, MTE, and SSEBop for the western (W) bounding box covering US-Ton and US-Me2 flux sites (Fig. 2, Page 31).

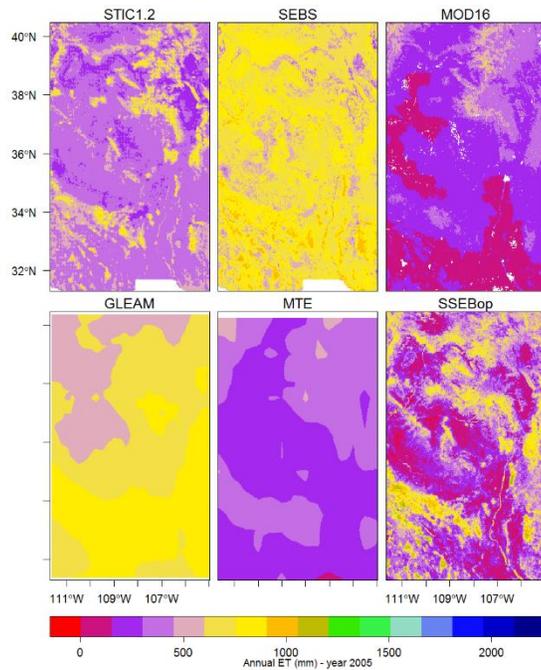


Figure AR5. Annual ET map derived from STIC1.2, SEBS, MOD16, GLEAM, MTE, and SSEBop for the mid-western 2 (MW2) bounding box covering US-ARM, US-SRG, US-Wkg, and US-NR1 flux sites (Fig. 2, Page 31).

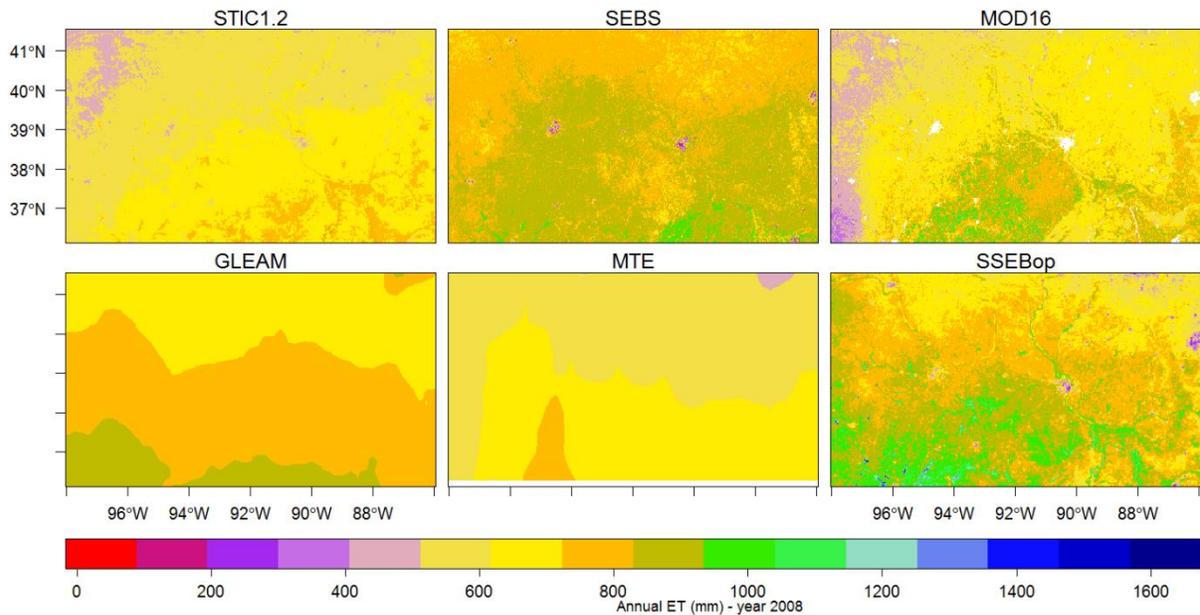


Figure AR6. Annual ET map derived from STIC1.2, SEBS, MOD16, GLEAM, MTE, and SSEBop for mid-western 1 (MW1) bounding box covering US-Kon, US-KFS, US-ARM, US-Ne1, and US-MMS flux sites (Fig. 2, Page 31).

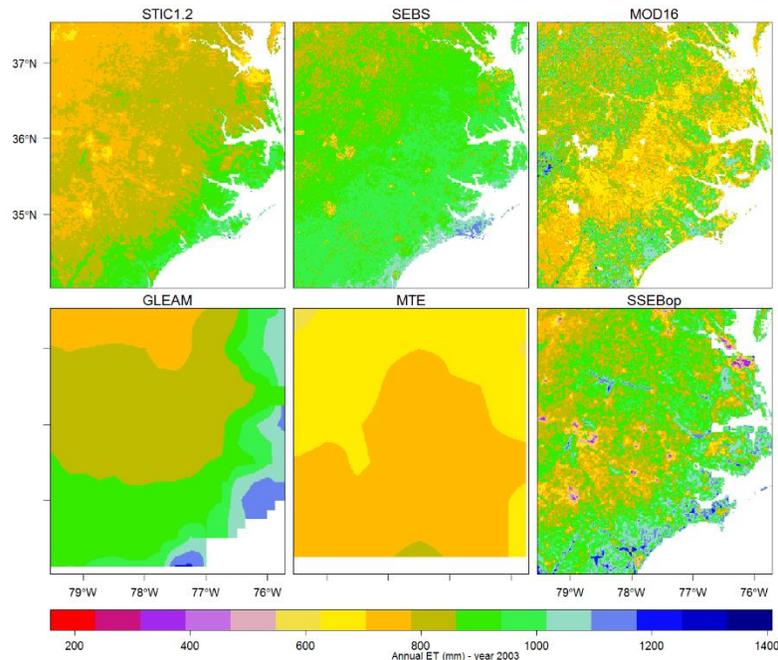


Figure AR7. Annual ET map derived from STIC1.2, SEBS, MOD16, GLEAM, MTE, and SSEBop for the eastern (E) bounding box covering US-NC1 and US-NC2 flux sites (Fig. 2, Page 31).

As demonstrated and discussed in Mallick et al. (2014), although towers are often installed in relatively homogenous terrain, rarely can this be assumed for heterogeneous landscapes in arid and semi-arid environment. The slope of the regression between the observed and estimated λE of individual biome category was significantly related to the average variance of LST surrounding the tower sites (Mallick et al., 2014). The slope of regression varied systematically with the landscape heterogeneity. Similar results are also shown by Stoy et al. (2013), who also found a systematic relationship between the surface energy balance closure, soil moisture variability, and landscape heterogeneity over 173 FLUXNET tower sites.

Currently, there is no consensus on which MODIS footprint size to use to represent fluxes from a flux site and hence any size or method used is subjected to debate. However, most flux sites (other than the arid and some semi-arid sites) used in this study cover vegetated area that is large enough for a $1 \times 1 \text{ km}^2$ MODIS pixel to be represented as a homogenous pixel, which was also verified in Google Earth Engine. Typically, a pixel-to-footprint match is considered adequate if the vegetation and environmental characteristics within the footprint are good representatives of the surrounding area contained by the MODIS pixels (Yuan et al., 2010). The US-Ton site, however, may not be as homogenous as other sites in terms of vegetation type, as the site is dominated by deciduous blue oaks (*Quercus douglasii* sp.) and the understory and open grassland are mainly cool-season C3 annual species (Ma et al., 2007). This could lead to dry and wet patches of LST, as briefly discussed on Page 16, Line 2-5. Blue oaks and grasses have distinct phenology and MODIS is not sensitive to understory canopy (Ma et al., 2007; Xiao et al., 2010). In addition, the US-Wkg site was classified as either open shrublands or grasslands in

different years on MCD12Q1 datasets and was not homogenous beyond a 3×3 neighborhood (i.e. one class was surrounded by pixels of another class).

Nonetheless, the sites considered in our study have been widely used in validation of ET as well as other land surface variables and is currently considered the state of the art observation datasets that can be used as benchmark to assess the performance of the remote sensing based models (Running et al., 2004; Yang et al., 2007; Jung et al., 2010) and several common approaches to extract representative MODIS pixel values include single tower pixel (Yuan et al., 2010; Ryu et al., 2011; Jiang and Ryu, 2016), 3×3 mean value with center pixel as the coordinates of flux towers (Sims et al., 2008; Xiao et al., 2008; Yang et al., 2013), and some foot print analysis (Vinukollu et al., 2011). In this study, we extracted ET values from a single tower pixel located closest to the MODIS pixel, but when a 3×3 mean value of estimated ET with the center pixel as the coordinates of flux towers was considered, only negligible changes in model performances was noticed (Table AR3). In addition, the mean values of 8-day cumulative ET from each model were not significantly different when a single pixel or a 3×3 neighborhood was considered (p -value > 0.75). Hence, we think that in this study, footprint uncertainties are minimized by selecting homogenous core AmeriFlux sites and this method is consistent with what has been done in previous studies.

Table AR3. Evaluation of 8-day cumulative ET (Table 3, Page 31) from STIC1.2 and SEBS against observed ET from thirteen core AmeriFlux sites in the US combining data from one dry, one wet, and one normal year when pixel values of estimated ET were taken as a mean of 3×3 neighborhood with center pixel as the coordinates of flux towers. No significant differences in model performance were noticed when a single tower pixel was considered (Table 3, Page 31).

Model	R^2	RMSE (mm 8-day ⁻¹)	MAE (mm) (mm 8-day ⁻¹)	PBIAS (%)
STIC1.2	0.66	7.3	5.3	-4
SEBS	0.54	9.7	7.2	27
MOD16	0.58	9	6.3	-27

Minor: 4. Page7(L7): Delete “the” between “both” and “variables”

Response: Change has been made (Page 7, Line 14).

Minor: 5. Page9(L20): Please specify the equation for NDVI and/or provide references.

Response: We added the following reference for NDVI in section 2.4.2 (Page 9, Line 24).

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote sensing of Environment*, 8(2), 127-150.

Minor 6. Page 16 (Discussion on MOD16): It is worthwhile reading Yang et al. (2016, WRR; doi: 10.1002/2014WR015619) for a more physical explanation on the MOD16 uncertainty.

Response: Thanks for referring this paper. Based on this literature, we added an extended discussion on MOD16 uncertainties in the revised manuscript (Page 18, Line 10-24).

References

- Allen, R. G., Pereira, L. S., Raes, D., and Smith, M.: Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56, FAO, Rome, 300, D05109, 1998.
- Allen, R. G., Tasumi, M., and Trezza, R.: Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC) - Model, *J Irrig Drain Eng*, 133, 380-394, 10.1061/(Asce)0733-9437(2007)133:4(380), 2007.
- ASCE-EWRI: The ASCE standardized reference evapotranspiration equation: ASCE-EWRI Standardization of Reference Evapotranspiration Task Committee Report, 2005,
- Baldocchi, D. D., and Ryu, Y.: A Synthesis of Forest Evaporation Fluxes – from Days to Years – as Measured with Eddy Covariance, in: *Forest Hydrology and Biogeochemistry: Synthesis of Past Research and Future Directions*, edited by: Levia, D. F., Carlyle-Moses, D., and Tanaka, T., Springer Netherlands, Dordrecht, 101-116, 2011.
- Bhattarai, N., Shaw, S. B., Quackenbush, L. J., Im, J., and Niraula, R.: Evaluating five remote sensing based single-source surface energy balance models for estimating daily evapotranspiration in a humid subtropical climate, *Int J Appl Earth Obs*, 49, 75-86, <https://doi.org/10.1016/j.jag.2016.01.010>, 2016.
- Biggs, T. W., Marshall, M., and Messina, A.: Mapping daily and seasonal evapotranspiration from irrigated crops using global climate grids and satellite imagery: Automation and methods comparison, *Water Resour Res*, 52, 7311-7326, 10.1002/2016WR019107, 2016.
- Brutsaert, W.: *Evaporation in the Atmosphere*, D. Reidel, D. Reidel, 1982.
- Brutsaert, W., and Sugita, M.: Application of self-preservation in the diurnal evolution of the surface energy budget to determine daily evaporation, *Journal of Geophysical Research: Atmospheres*, 97, 18377-18382, 10.1029/92JD00255, 1992.
- Bunting, D. P., Kurc, S. A., Glenn, E. P., Nagler, P. L., and Scott, R. L.: Insights for empirically modeling evapotranspiration influenced by riparian and upland vegetation in semiarid regions, *Journal of Arid Environments*, 111, 42-52, <https://doi.org/10.1016/j.jaridenv.2014.06.007>, 2014.
- Byun, K., Liaqat, U. W., and Choi, M.: Dual-model approaches for evapotranspiration analyses over homo- and heterogeneous land surface conditions, *Agricultural and Forest Meteorology*, 197, 169-187, <https://doi.org/10.1016/j.agrformet.2014.07.001>, 2014.
- Cammalleri, C., Anderson, M., and Kustas, W.: Upscaling of evapotranspiration fluxes from instantaneous to daytime scales for thermal remote sensing applications, *Hydrology and Earth System Sciences*, 18, 1885-1894, 2014.
- Chávez, J. L., Neale, C. M. U., Prueger, J. H., and Kustas, W. P.: Daily evapotranspiration estimates from extrapolating instantaneous airborne remote sensing ET values, *Irrigation Sci*, 27, 67-81, 10.1007/s00271-008-0122-3, 2008.
- Chen, X., Su, Z., Ma, Y., Yang, K., Wen, J., and Zhang, Y.: An Improvement of Roughness Height Parameterization of the Surface Energy Balance System (SEBS) over the Tibetan Plateau, *Journal of Applied Meteorology and Climatology*, 52, 607-622, 10.1175/jamc-d-12-056.1, 2013.

- Choudhury, B. J., and Monteith, J. L.: A four-layer model for the heat budget of homogeneous land surfaces, *Quarterly Journal of the Royal Meteorological Society*, 114, 373-398, [10.1002/qj.49711448006](https://doi.org/10.1002/qj.49711448006), 1988.
- Colaizzi, P., Evett, S., Howell, T., and Tolk, J.: Comparison of five models to scale daily evapotranspiration from one-time-of-day measurements, *Transactions of the ASABE*, 49, 1409-1417, 2006.
- Crago, R. D.: Conservation and variability of the evaporative fraction during the daytime, *Journal of Hydrology*, 180, 173-194, 1996.
- Ershadi, A., McCabe, M. F., Evans, J. P., Chaney, N. W., and Wood, E. F.: Multi-site evaluation of terrestrial evaporation models using FLUXNET data, *Agricultural and Forest Meteorology*, 187, 46-61, [10.1016/j.agrformet.2013.11.008](https://doi.org/10.1016/j.agrformet.2013.11.008), 2014.
- Fisher, J. B., Tu, K. P., and Baldocchi, D. D.: Global estimates of the land-atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites, *Remote Sensing of Environment*, 112, 901-919, <https://doi.org/10.1016/j.rse.2007.06.025>, 2008.
- García, M., Fernández, N., Villagarcía, L., Domingo, F., Puigdefábregas, J., and Sandholt, I.: Accuracy of the Temperature-Vegetation Dryness Index using MODIS under water-limited vs. energy-limited evapotranspiration conditions, *Remote Sensing of Environment*, 149, 100-117, <https://doi.org/10.1016/j.rse.2014.04.002>, 2014.
- Gentine, P., Entekhabi, D., Chehbouni, A., Boulet, G., and Duchemin, B.: Analysis of evaporative fraction diurnal behaviour, *Agricultural and Forest Meteorology*, 143, 13-29, <https://doi.org/10.1016/j.agrformet.2006.11.002>, 2007.
- Hu, L., and Brunsell, N. A.: The impact of temporal aggregation of land surface temperature data for surface urban heat island (SUHI) monitoring, *Remote Sensing of Environment*, 134, 162-174, <https://doi.org/10.1016/j.rse.2013.02.022>, 2013.
- Hulley, G. C., Hughes, C. G., and Hook, S. J.: Quantifying uncertainties in land surface temperature and emissivity retrievals from ASTER and MODIS thermal infrared data, *Journal of Geophysical Research: Atmospheres*, 117, n/a-n/a, [10.1029/2012JD018506](https://doi.org/10.1029/2012JD018506), 2012.
- Ichii, K., Wang, W., Hashimoto, H., Yang, F., Votava, P., Michaelis, A. R., and Nemani, R. R.: Refinement of rooting depths using satellite-based evapotranspiration seasonality for ecosystem modeling in California, *Agricultural and Forest Meteorology*, 149, 1907-1918, <https://doi.org/10.1016/j.agrformet.2009.06.019>, 2009.
- Jiang, C., and Ryu, Y.: Multi-scale evaluation of global gross primary productivity and evapotranspiration products derived from Breathing Earth System Simulator (BESS), *Remote Sensing of Environment*, 186, 528-547, <https://doi.org/10.1016/j.rse.2016.08.030>, 2016.
- Jin, M., and Liang, S.: An improved land surface emissivity parameter for land surface models using global remote sensing observations, *Journal of Climate*, 19, 2867-2881, 2006.
- Jin, Y., Randerson, J. T., and Goulden, M. L.: Continental-scale net radiation and evapotranspiration estimated using MODIS satellite observations, *Remote Sensing of Environment*, 115, 2302-2319, <https://doi.org/10.1016/j.rse.2011.04.031>, 2011.

Jung, M., Reichstein, M., Ciais, P., Seneviratne, S. I., Sheffield, J., Goulden, M. L., Bonan, G., Cescatti, A., Chen, J., de Jeu, R., Dolman, A. J., Eugster, W., Gerten, D., Gianelle, D., Gobron, N., Heinke, J., Kimball, J., Law, B. E., Montagnani, L., Mu, Q., Mueller, B., Oleson, K., Papale, D., Richardson, A. D., Roupsard, O., Running, S., Tomelleri, E., Viovy, N., Weber, U., Williams, C., Wood, E., Zaehle, S., and Zhang, K.: Recent decline in the global land evapotranspiration trend due to limited moisture supply, *Nature*, 467, 951, 10.1038/nature09396

<https://www.nature.com/articles/nature09396#supplementary-information>, 2010.

Jung, M., Reichstein, M., Margolis, H. A., Cescatti, A., Richardson, A. D., Arain, M. A., Arneth, A., Bernhofer, C., Bonal, D., Chen, J., Gianelle, D., Gobron, N., Kiely, G., Kutsch, W., Lasslop, G., Law, B. E., Lindroth, A., Merbold, L., Montagnani, L., Moors, E. J., Papale, D., Sottocornola, M., Vaccari, F., and Williams, C.: Global patterns of land-atmosphere fluxes of carbon dioxide, latent heat, and sensible heat derived from eddy covariance, satellite, and meteorological observations, *Journal of Geophysical Research: Biogeosciences*, 116, n/a-n/a, 10.1029/2010JG001566, 2011.

Lewis, C. S., Geli, H. M. E., and Neale, C. M. U.: Comparison of the NLDAS Weather Forcing Model to Agrometeorological Measurements in the western United States, *Journal of Hydrology*, 510, 385-392, <https://doi.org/10.1016/j.jhydrol.2013.12.040>, 2014.

Ma, S., Baldocchi, D. D., Xu, L., and Hehn, T.: Inter-annual variability in carbon dioxide exchange of an oak/grass savanna and open grassland in California, *Agricultural and Forest Meteorology*, 147, 157-171, <https://doi.org/10.1016/j.agrformet.2007.07.008>, 2007.

Mallick, K., Jarvis, A. J., Boegh, E., Fisher, J. B., Drewry, D. T., Tu, K. P., Hook, S. J., Hulley, G., Ardö, J., Beringer, J., Arain, A., and Niyogi, D.: A Surface Temperature Initiated Closure (STIC) for surface energy balance fluxes, *Remote Sensing of Environment*, 141, 243-261, <http://dx.doi.org/10.1016/j.rse.2013.10.022>, 2014.

Mallick, K., Boegh, E., Trebs, I., Alfieri, J. G., Kustas, W. P., Prueger, J. H., Niyogi, D., Das, N., Drewry, D. T., Hoffmann, L., and Jarvis, A. J.: Reintroducing radiometric surface temperature into the Penman-Monteith formulation, *Water Resour Res*, 51, 6214-6243, 10.1002/2014wr016106, 2015.

Mallick, K., Trebs, I., Boegh, E., Giustarini, L., Schlerf, M., Drewry, D. T., Hoffmann, L., von Randow, C., Kruijt, B., Araùjo, A., Saleska, S., Ehleringer, J. R., Domingues, T. F., Ometto, J. P. H. B., Nobre, A. D., de Moraes, O. L. L., Hayek, M., Munger, J. W., and Wofsy, S. C.: Canopy-scale biophysical controls of transpiration and evaporation in the Amazon Basin, *Hydrol. Earth Syst. Sci.*, 20, 4237-4264, 10.5194/hess-20-4237-2016, 2016.

Martens, B., Gonzalez Miralles, D., Lievens, H., van der Schalie, R., de Jeu, R. A., Fernández-Prieto, D., Beck, H. E., Dorigo, W., and Verhoest, N.: GLEAM v3: Satellite-based land evaporation and root-zone soil moisture, *Geosci Model Dev*, 10, 1903-1925, 2017.

Masuoka, E., Fleig, A., Wolfe, R. E., and Patt, F.: Key characteristics of MODIS data products, *IEEE Transactions on Geoscience and Remote Sensing*, 36, 1313-1323, 10.1109/36.701081, 1998.

Michel, D., Jiménez, C., Miralles, D., Jung, M., Hirschi, M., Ershadi, A., Martens, B., McCabe, M., Fisher, J., and Mu, Q.: The WACMOS-ET project—Part 1: Tower-scale evaluation of four remote-sensing-based evapotranspiration algorithms, *Hydrology and Earth System Sciences*, 20, 803, 2016.

Miralles, D., Holmes, T., De Jeu, R., Gash, J., Meesters, A., and Dolman, A.: Global land-surface evaporation estimated from satellite-based observations, *Hydrology and Earth System Sciences*, 15, 453, 2011.

Mu, Q., Zhao, M., and Running, S. W.: Improvements to a MODIS global terrestrial evapotranspiration algorithm, *Remote Sensing of Environment*, 115, 1781-1800, <http://dx.doi.org/10.1016/j.rse.2011.02.019>, 2011.

Running, S. W., Nemani, R. R., Heinsch, F. A., Zhao, M., Reeves, M., and Hashimoto, H.: A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production, *BioScience*, 54, 547-560, 10.1641/0006-3568(2004)054[0547:ACSMOG]2.0.CO;2, 2004.

Ryu, Y., Baldocchi, D. D., Kobayashi, H., van Ingen, C., Li, J., Black, T. A., Beringer, J., van Gorsel, E., Knohl, A., Law, B. E., and Rouspard, O.: Integration of MODIS land and atmosphere products with a coupled-process model to estimate gross primary productivity and evapotranspiration from 1 km to global scales, *Global Biogeochemical Cycles*, 25, n/a-n/a, 10.1029/2011GB004053, 2011.

Ryu, Y., Baldocchi, D. D., Black, T. A., Detto, M., Law, B. E., Leuning, R., Miyata, A., Reichstein, M., Vargas, R., Ammann, C., Beringer, J., Flanagan, L. B., Gu, L., Hutley, L. B., Kim, J., McCaughey, H., Moors, E. J., Rambal, S., and Vesala, T.: On the temporal upscaling of evapotranspiration from instantaneous remote sensing measurements to 8-day mean daily-sums, *Agricultural and Forest Meteorology*, 152, 212-222, <https://doi.org/10.1016/j.agrformet.2011.09.010>, 2012.

Senay, G. B., Bohms, S., Singh, R. K., Gowda, P. H., Velpuri, N. M., Alemu, H., and Verdin, J. P.: Operational Evapotranspiration Mapping Using Remote Sensing and Weather Datasets: A New Parameterization for the SSEB Approach, *J Am Water Resour As*, 49, 577-591, 2013.

Shuttleworth, W., Gurney, R., Hsu, A., and Ormsby, J.: FIFE: the variation in energy partition at surface flux sites, *IAHS Publ*, 186, 1989.

Sims, D. A., Rahman, A. F., Cordova, V. D., El-Masri, B. Z., Baldocchi, D. D., Bolstad, P. V., Flanagan, L. B., Goldstein, A. H., Hollinger, D. Y., Misson, L., Monson, R. K., Oechel, W. C., Schmid, H. P., Wofsy, S. C., and Xu, L.: A new model of gross primary productivity for North American ecosystems based solely on the enhanced vegetation index and land surface temperature from MODIS, *Remote Sensing of Environment*, 112, 1633-1646, <https://doi.org/10.1016/j.rse.2007.08.004>, 2008.

Stoy, P. C., Mauder, M., Foken, T., Marcolla, B., Boegh, E., Ibrom, A., Arain, M. A., Arneth, A., Aurela, M., Bernhofer, C., Cescatti, A., Dellwik, E., Duce, P., Gianelle, D., van Gorsel, E., Kiely, G., Knohl, A., Margolis, H., McCaughey, H., Merbold, L., Montagnani, L., Papale, D., Reichstein, M., Saunders, M., Serrano-Ortiz, P., Sottocornola, M., Spano, D., Vaccari, F., and Varlagin, A.: A data-driven analysis of energy balance closure across FLUXNET research sites: The role of landscape scale heterogeneity, *Agricultural and Forest Meteorology*, 171, 137-152, <http://dx.doi.org/10.1016/j.agrformet.2012.11.004>, 2013.

Tang, R., Tang, B., Wu, H., and Li, Z.-L.: On the feasibility of temporally upscaling instantaneous evapotranspiration using weather forecast information, *Int J Remote Sens*, 36, 4918-4935, 10.1080/01431161.2015.1029597, 2015.

Tian, F., Qiu, G., Yang, Y., Lü, Y., and Xiong, Y.: Estimation of evapotranspiration and its partition based on an extended three-temperature model and MODIS products, *Journal of Hydrology*, 498, 210-220, <https://doi.org/10.1016/j.jhydrol.2013.06.038>, 2013.

van der Kwast, J., Timmermans, W., Gieske, A., Su, Z., Olioso, A., Jia, L., Elbers, J., Karssenbergh, D., and de Jong, S.: Evaluation of the Surface Energy Balance System (SEBS) applied to ASTER imagery with flux-measurements at the SPARC 2004 site (Barrax, Spain), *Hydrol. Earth Syst. Sci.*, 13, 1337-1347, 10.5194/hess-13-1337-2009, 2009.

Velpuri, N. M., Senay, G. B., Singh, R. K., Bohms, S., and Verdin, J. P.: A comprehensive evaluation of two MODIS evapotranspiration products over the conterminous United States: Using point and gridded FLUXNET and water balance ET, *Remote Sensing of Environment*, 139, 35-49, 2013.

Vinukollu, R. K., Meynadier, R., Sheffield, J., and Wood, E. F.: Multi-model, multi-sensor estimates of global evapotranspiration: climatology, uncertainties and trends, *Hydrological Processes*, 25, 3993-4010, 2011.

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

Wan, Z., and Li, Z. L.: Radiance-based validation of the V5 MODIS land-surface temperature product, *Int J Remote Sens*, 29, 5373-5395, 10.1080/01431160802036565, 2008.

Wu, C., Munger, J. W., Niu, Z., and Kuang, D.: Comparison of multiple models for estimating gross primary production using MODIS and eddy covariance data in Harvard Forest, *Remote Sensing of Environment*, 114, 2925-2939, <https://doi.org/10.1016/j.rse.2010.07.012>, 2010.

Xiao, J., Zhuang, Q., Baldocchi, D. D., Law, B. E., Richardson, A. D., Chen, J., Oren, R., Starr, G., Noormets, A., Ma, S., Verma, S. B., Wharton, S., Wofsy, S. C., Bolstad, P. V., Burns, S. P., Cook, D. R., Curtis, P. S., Drake, B. G., Falk, M., Fischer, M. L., Foster, D. R., Gu, L., Hadley, J. L., Hollinger, D. Y., Katul, G. G., Litvak, M., Martin, T. A., Matamala, R., McNulty, S., Meyers, T. P., Monson, R. K., Munger, J. W., Oechel, W. C., Paw U, K. T., Schmid, H. P., Scott, R. L., Sun, G., Suyker, A. E., and Torn, M. S.: Estimation of net ecosystem carbon exchange for the conterminous United States by combining MODIS and AmeriFlux data, *Agricultural and Forest Meteorology*, 148, 1827-1847, <https://doi.org/10.1016/j.agrformet.2008.06.015>, 2008.

Xiao, J., Zhuang, Q., Law, B. E., Chen, J., Baldocchi, D. D., Cook, D. R., Oren, R., Richardson, A. D., Wharton, S., Ma, S., Martin, T. A., Verma, S. B., Suyker, A. E., Scott, R. L., Monson, R. K., Litvak, M., Hollinger, D. Y., Sun, G., Davis, K. J., Bolstad, P. V., Burns, S. P., Curtis, P. S., Drake, B. G., Falk, M., Fischer, M. L., Foster, D. R., Gu, L., Hadley, J. L., Katul, G. G., Matamala, R., McNulty, S., Meyers, T. P., Munger, J. W., Noormets, A., Oechel, W. C., Paw U, K. T., Schmid, H. P., Starr, G., Torn, M. S., and Wofsy, S. C.: A continuous measure of gross primary production for the conterminous United States derived from MODIS and AmeriFlux data, *Remote Sensing of Environment*, 114, 576-591, <https://doi.org/10.1016/j.rse.2009.10.013>, 2010.

Xiong, Y., Zhao, S., Yin, J., Li, C., and Qiu, G.: Effects of Evapotranspiration on Regional Land Surface Temperature in an Arid Oasis Based on Thermal Remote Sensing, *IEEE Geoscience and Remote Sensing Letters*, 13, 1885-1889, 10.1109/LGRS.2016.2616409, 2016.

Xiong, Y. J., Zhao, S. H., Tian, F., and Qiu, G. Y.: An evapotranspiration product for arid regions based on the three-temperature model and thermal remote sensing, *Journal of Hydrology*, 530, 392-404, <https://doi.org/10.1016/j.jhydrol.2015.09.050>, 2015.

- Yang, F., White, M. A., Michaelis, A. R., Ichii, K., Hashimoto, H., Votava, P., Zhu, A. X., and Nemani, R. R.: Prediction of Continental-Scale Evapotranspiration by Combining MODIS and AmeriFlux Data Through Support Vector Machine, *IEEE Transactions on Geoscience and Remote Sensing*, 44, 3452-3461, 10.1109/TGRS.2006.876297, 2006.
- Yang, F., Ichii, K., White, M. A., Hashimoto, H., Michaelis, A. R., Votava, P., Zhu, A. X., Huete, A., Running, S. W., and Nemani, R. R.: Developing a continental-scale measure of gross primary production by combining MODIS and AmeriFlux data through Support Vector Machine approach, *Remote Sensing of Environment*, 110, 109-122, <https://doi.org/10.1016/j.rse.2007.02.016>, 2007.
- Yang, K., Koike, T., Fujii, H., Tamagawa, K., and Hirose, N.: Improvement of surface flux parametrizations with a turbulence-related length, *Quarterly Journal of the Royal Meteorological Society*, 128, 2073-2087, 10.1256/003590002320603548, 2002.
- Yang, Y., Shang, S., Guan, H., and Jiang, L.: A novel algorithm to assess gross primary production for terrestrial ecosystems from MODIS imagery, *Journal of Geophysical Research: Biogeosciences*, 118, 590-605, 10.1002/jgrg.20056, 2013.
- Yuan, W., Liu, S., Yu, G., Bonnefond, J.-M., Chen, J., Davis, K., Desai, A. R., Goldstein, A. H., Gianelle, D., Rossi, F., Suyker, A. E., and Verma, S. B.: Global estimates of evapotranspiration and gross primary production based on MODIS and global meteorology data, *Remote Sensing of Environment*, 114, 1416-1431, <https://doi.org/10.1016/j.rse.2010.01.022>, 2010.
- Zhang, Y., Leuning, R., Hutley, L. B., Beringer, J., McHugh, I., and Walker, J. P.: Using long-term water balances to parameterize surface conductances and calculate evaporation at 0.05° spatial resolution, *Water Resour Res*, 46, n/a-n/a, 10.1029/2009WR008716, 2010.

Regional evapotranspiration from image-based implementation of the Surface Temperature Initiated Closure (STIC1.2) model and its validation across an aridity gradient in the conterminous United States

5 Nishan Bhattarai¹, Kaniska Mallick², Nathaniel A. Brunzell³, Ge Sun⁴, Meha Jain¹

¹ School for Environment and Sustainability, University of Michigan, Ann Arbor, MI 48109, USA

²Remote Sensing and Ecohydrological Modeling, [Water Security and Safety Research Unit](#), Dept. ERIN, Luxembourg Institute of Science and Technology (LIST), L4422, Belvaux, Luxembourg

³Geography and Atmospheric Science, University of Kansas, Lawrence, KS 66045, USA

10 ⁴Eastern Forest Environmental Threat Assessment Center, Southern Research Station, U.S. Department of Agriculture Forest Service, Raleigh, 27606, NC, USA

Correspondence to: Nishan Bhattarai (nbhattar@umich.edu)

Abstract. Recent studies have highlighted the need for improved characterizations of aerodynamic conductance and temperature (g_A and T_0) in thermal remote sensing-based surface energy balance (SEB) models to reduce uncertainties in regional-scale evapotranspiration (ET) mapping. By integrating radiometric surface temperature (T_R) into the Penman-Monteith (PM) equation and finding analytical solutions of g_A and T_0 , this need was recently addressed by the Surface Temperature Initiated Closure (STIC) model. However, previous implementations of STIC were confined to the ecosystem-scale using flux tower observations of infrared temperature. This study demonstrates the first regional-scale implementation of the most recent version of the STIC model (STIC1.2) that ~~physically~~ integrates Moderate Resolution Imaging Spectroradiometer (MODIS)-derived T_R and ancillary land surface variables in conjunction with NLDAS (North American Land Data Assimilation System) atmospheric variables into a combined structure of the PM and Shuttleworth-Wallace ([SW](#)) framework for estimating ET at $1 \text{ km} \times 1 \text{ km}$ spatial resolution. Evaluation of STIC1.2 at thirteen core AmeriFlux sites covering a broad spectrum of climates and biomes across an aridity gradient in the conterminous US suggests that STIC1.2 can provide spatially explicit ET maps with reliable accuracies from dry to wet extremes. When observed ET from one wet, one dry, and one normal precipitation year from all sites were combined, STIC1.2 explained 66 % of the variability in observed 8-day cumulative ET with a root mean square error (RMSE) of 7.4 mm/8-day, mean absolute error (MAE) of 5 mm/8-day, and percent bias (PBIAS) of -4 %. These error statistics showed ~~relatively better-higher~~ accuracies than a widely-used ~~but a prior~~

15
20
25

version of SEB-based Surface Energy Balance System (SEBS) model that utilized a simple NDVI-based parameterization of surface roughness (z_{0M}), and PM-based MOD16 ET, which were found to overestimate (PBIAS = 28 %) and underestimate ET (PBIAS = -26 %), respectively. The performance of STIC1.2 was better in forest and grassland ecosystems as compared to cropland (20 % underestimation) and woody savanna (40 % overestimation). Model inter-comparison suggested that ET differences between the models are robustly correlated with g_A and associated roughness length estimation uncertainties which are intrinsically connected to T_R uncertainties, vapour pressure deficit (D_A), and vegetation cover. A consistent performance of STIC1.2 in a broad range of hydrological and biome categories, as well as the capacity to capture spatio-temporal ET signatures across an aridity gradient, points to ~~the its~~ potential for this simplified analytical model for near real time ET mapping from regional to continental scales.

10 1 Introduction

Evapotranspiration (ET) is highly variable in space and time and plays a fundamental role in hydrology and land-atmosphere interactions. Over the past few decades, the use of satellite data to map ~~spatially explicit and~~ regional-scale ET has advanced considerably. This is due to the advancements in ET modeling as well as progress in thermal remote sensing satellite missions, and our ability to retrieve the land surface temperature (LST) or radiometric surface temperature (T_R) that is highly sensitive to evaporative cooling and surface moisture variations. Because LST governs the land surface energy budget (Kustas and Norman, 1996; Kustas and Anderson, 2009), thermal ET models principally focus on the surface energy balance (SEB) approach in which T_R represents the lower boundary condition to constrain energy-water fluxes (Anderson et al., 2012). Contemporary SEB models emphasize on estimating aerodynamic conductance (g_A) and sensible heat flux (H) while solving ET (i.e., latent heat flux, λE) as a residual SEB component. Despite ~~the many~~ advancements in mapping spatially-distributed ET, some fundamental challenges remain in existing SEB algorithms including, (a) the inequality between T_R and the aerodynamic temperature (T_0) which is essentially responsible for the exchanges of H and λE (Chávez et al., 2010; Boulet et al., 2012), (b) a non-unique relationship between T_0 and T_R due to differences between the roughness lengths (i.e., effective source/sink heights) for momentum (z_{0M}) and heat (z_{0H}) within vegetation canopy and substrate complex (Troufleau et al., 1997; Paul et al., 2014; van Dijk et al., 2015b), (c) the unavailability of a universally agreed model to estimate T_0 (Colaizzi et al., 2004), and (d) the lack of a physically-based ~~preeminent or analytical~~ g_A model. To overcome these challenges, we implement the current version of a recently developed analytical ET model, Surface Temperature Initiated Closure (STIC, version 1.2 (Mallick et al., 2014; Mallick et al., 2015; Mallick et al., 2016), using Moderate Resolution Imaging Spectro-Radiometer (MODIS) data to develop spatially-distributed ET maps.

The STIC formulation provides analytical solutions to g_A , T_R , and canopy (or surface) conductance (g_C), and simultaneously captures the critical feedbacks between g_A , g_C , T_R , and vapour pressure deficit surrounding the evaporating surface (D_0) thereby obtaining a 'closure' of the surface energy balance. In state-of-the-art SEB models, an emphasis on estimating g_A and H is motivated due to the perception of the broad applicability of the Monin-Obukhov Similarity Theory (MOST) or Richardson Number (Ri) criteria, and the requirement of minimum inputs for determining these variables. However, these approaches created further problems additional uncertainties, particularly in accommodating T_0 versus T_R inequalities, as well as adapting the differences between z_{0M} and z_{0H} (Paul et al., 2014). Compensating these temperature and roughness length disparities consequently led to the inception of the kB^{-1} term as a fitting parameter (Verhoef et al., 1997a), and later the progress of the two-source ET model (Kustas and Norman, 1997; Norman et al., 1995; Anderson et al., 2011). Although useful, the above approaches still rely on empirical response functions of roughness components to characterize g_A that has an uncertain transferability in space and time (Holwerda et al., 2012b; van Dijk et al., 2015b). In contemporary SEB modeling, g_A sub-models are stand-alone and lack the necessary physical feedbacks between the conductances, T_0 , and vapour pressure deficit surrounding the evaporating surface (D_0) to 'close' the surface energy balance. The feedback of g_A on g_C and D_0 is critical in semiarid and arid ecosystems (Kustas et al., 2016), where soil moisture stress and sparse vegetation can cause substantial disparities between T_R versus T_0 (Kustas et al., 2016; Paul et al., 2014; Timmermans et al., 2013; Gokmen et al., 2012). Therefore, thermal-based ET modeling needs explicit consideration of these important biophysical feedbacks to overcome the existing g_A and T_R related uncertainties in regional-scale ET mapping (Kustas et al., 2016). Hence, a genuine question in regional ET mapping is: *How can state-of-the-art SEB models overcome the existing challenges in regional evapotranspiration mapping that arise due to uncertain conductance parameterizations, and can analytical models help this verification process?*

The STIC formulation provides analytical solutions to g_A , T_0 , and canopy (or surface) conductance (g_C), and simultaneously captures the critical feedbacks between g_A , g_C , T_0 , and vapour pressure deficit surrounding the evaporating surface (D_0) thereby obtaining a 'closure' of the surface energy balance. The prime focus of STIC (Mallick et al., 2014; Mallick et al., 2015; Mallick et al., 2016) is based on physical integration of T_R into the Penman-Monteith (PM) equation, which is fundamentally constrained to account for the necessary feedbacks between ET, T_R , D_A , g_A , and g_C (Monteith, 1965). Monteith (1981) highlighted the fact that the biophysical conductances (i.e., g_A and g_C) regulating ET are heavily temperature dependent, after which a stream of research demonstrated the dominant control of T_R into g_C and associated canopy-scale aerodynamics (Moffett and Gorelick, 2012; Blonquist et al., 2009). Somewhat surprisingly, the idea of integrating T_R into the PM model was never attempted because of complexities associated with g_C parameterization (Bell et al., 2015; Matheny et al., 2014), until the concept of STIC was formulated (Mallick et al., 2014; Mallick et al., 2015). The recent version of STIC, STIC1.2, combines PM with the Shuttleworth-Wallace (SW) model (Shuttleworth and Wallace, 1985) to estimate the source/sink height temperature and vapour pressure (T_0 and e_0) (Mallick et al., 2016). By algebraic reorganization of aerodynamic equations of H and λE , Bowen ratio evaporative fraction hypothesis (Bowen, 1926) and modified advection-aridity hypothesis (Brutsaert and Stricker, 1979), STIC1.2 formulates multiple state equations where the state equations were constrained with an aggregated moisture availability factor (M). Through physically linking M with T_R and the source/sink height dew point temperature (T_{SD}),

STIC1.2 established a direct feedback between T_R and ET, while simultaneously overcoming the empirical uncertainties in conductances and T_0 estimations.

Despite providing analytical solutions for the key conductances in PM-based ET modeling, the STIC 1.2 model has yet to gain a profound interest among the thermal remote sensing community and those interested in regional-scale ET modeling.

5 This could largely be attributed to the fact that the model is only used for understanding ecosystem-scale ET partitioning and their biophysical controls at the eddy covariance (EC) footprints (Mallick et al., 2015; Mallick et al., 2016), where all the necessary forcing variables were measured at the flux tower sites. In this paper, we present the first ever implementation of the STIC1.2 model using MODIS LST and associated land surface products, and its validation in thirteen core AmeriFlux sites across an aridity gradient in the conterminous US in three different precipitation conditions representing dry, normal, and wet
10 years, respectively. ET estimates from STIC1.2 are also compared against two parametric ET models, namely SEBS (Surface Energy Balance System) (Su, 2002) and MOD16 (Mu et al., 2007; Mu et al., 2011). Through the implementation and validation of the STIC1.2 model at a regional-scale, the current study addresses the following research questions:

1. What is the performance of STIC1.2 when applied at the regional-scale across an aridity gradient and during contrasting rainfall years in the conterminous US?
- 15 2. How does STIC1.2-derived ET compare against other global ET models that are driven by T_R and relative humidity (RH)?
3. Under which conditions do the models agree and which factors cause their differences?
4. How well do the models capture spatio-temporal ET variability across an aridity gradient?

A description of methods including models, study sites, dataset, and data processing is given in section 2, followed by the
20 results in section 3. An extended discussion of the results and potential of the method in thermal remote sensing applications is elaborated in sections 4 and 5, respectively. Symbols used for variables in this study are listed in the Appendix in Table A1.

2 Methods

2.1 Model Descriptions

Most surface energy balance models consist of several modules for estimating net radiation (R_N), ground heat flux (G), and
25 partitioning of available energy ($\phi = R_N - G$) into H and λE through the derivation of evaporative fraction (A). A is defined as the ratio of λE to ϕ . In this paper, we used the widely-used net radiation balance equation (Eq. (1)) to compute R_N (Allen et al., 2007; Allen et al., 2011) and the formulation of Bastiaanssen (2000) to compute G (Eq. 4) in SEBS and STIC1.2.

$$R_N = R_S (1 - \alpha_o) + \varepsilon_o R_{ld} - R_{lu} \quad (1)$$

$$G = R_N (T_R - 273.15) / \alpha_o (0.0038 \alpha_o + 0.0074 \alpha_o^2) (1 - 0.98 \text{NDVI}^4) \quad (2)$$

$$H = (1 - A) \times (R_N - G) \quad (3)$$

$$\lambda E = A \times (R_N - G) \quad (4)$$

where R_S is the incoming shortwave radiation, α_o is the surface albedo, ε_o is the surface emissivity, NDVI is the normalized difference vegetation index, λ is the latent heat of vaporization, and R_{ld} and R_{lo} are incoming and outgoing longwave radiation, respectively. Using the formulation of Allen et al. (2007) and Bastiaanssen (2000) for estimating R_N and G , respectively, we found that the estimated eight-day mean R_N and G during the terra overpass time were within 14 % of the observed R_N and G at the flux sites (Fig. S1).

While the derivation of H in SEBS is based on aerodynamic equation (Su, 2002), SEBS estimates λE as the residual of the surface energy balance (i.e., $\lambda E = R_N - G - H$). On the contrary, STIC1.2 directly estimates H and λE through the PM equation (Mallick et al., 2016) by solving state equations for the conductances. MOD16 estimates λE directly using a modified PM framework (Mu et al., 2007; Mu et al., 2011), where the conductances are estimated based on a biome property look up table (BPLUT) and meteorological scaling functions. As discussed in section 1, there exist some fundamental differences among STIC1.2, SEBS, and MOD16. However, since the primary focus of the paper is the regional-scale implementation and evaluation of the STIC1.2 model, we only provide detailed descriptions of STIC1.2 and suggest readers follow associated literature for detailed descriptions of the other two models (see subsections 2.1.2 and 2.1.3). The key model structures of SEBS and MOD16 are briefly explained in subsections 2.1.2 and 2.1.3.

2.1.1 STIC1.2

STIC1.2 is the most recent version of the original STIC formulation (Mallick et al., 2014; Mallick et al., 2015), which is a one-dimensional physically-based SEB model that treats the vegetation-substrate complex as a single unit (Fig. 1). The fundamental assumption in STIC1.2 is the first order dependency of g_A and g_C on T_0 and soil moisture through T_R . Such an assumption allows a direct integration of T_R in the PM equation (Mallick et al., 2016). The common expression for λE in the PM equation is,

$$\lambda E = \frac{s\phi + \rho_A c_p g_A D_A}{s + \gamma \left(1 + \frac{g_A}{g_C}\right)} \quad (5)$$

where ρ_A is the air density (kg m^{-3}), c_p is the specific heat of air ($\text{J kg}^{-1} \text{K}^{-1}$), γ is the psychrometric constant (hPa K^{-1}), s is the slope of the saturation vapour pressure versus T_A (hPa K^{-1}), D_A is the saturation deficit of the air (hPa) at the reference level, and ϕ is the net available energy (i.e., $R_N - G$). The units for all the surface fluxes and conductances are W m^{-2} and m s^{-1} , respectively.

In Eq. (5), the two biophysical conductances (g_A and g_C) are unknown and the STIC1.2 methodology is based on finding analytical solutions for the two unknown conductances to directly estimate ET (Mallick et al., 2014; Mallick et al., 2015). The need for such analytical estimation of these conductances is motivated by the fact that g_A and g_C can neither be measured at the canopy or larger spatial scales, and there is not an appropriate model of g_A and g_C that currently exists (Matheny et al., 2014; van Dijk et al., 2015b). By integrating T_R with standard SEB theory and vegetation biophysical principles, STIC1.2 formulates multiple state equations (Eqs. (7)-(10) below) in order to eliminate the need for empirical parameterization

for g_A , g_C , and T_0 . The state equations for the conductances and T_0 were expressed as a function of those variables that can be estimated by remote sensing observations. In the state equations, a direct connection of T_R is established by estimating an aggregated moisture availability index (M). The information of M is subsequently used in the state equations of g_A , g_C , T_0 , and evaporative fraction (Λ) (Eqs. ~~(7)-(10)~~(4) below), which is eventually propagated into their analytical solutions. M is a unitless quantity, which describes the relative wetness of the surface and also controls the transition from potential to actual evaporation. Therefore, M is critical for providing a constraint against which the conductances can be estimated. Since T_R is extremely sensitive to the surface water content variations, it is extensively used for estimating M in a physical retrieval scheme (detail in Appendix A3) (also in Mallick et al., 2016). We hypothesize that linking M with the biophysical conductances will simultaneously integrate the information of T_R into the PM equation (Eq. ~~(5)~~(5)) in the framework of STIC1.2.

In STIC1.2, the estimation of M is based on Venturini et al. (2008), where M is expressed as the ratio of the vapour pressure difference between the source/sink height and air to the vapour pressure deficit between source/sink height to the atmosphere as follows.

$$M = \frac{(e_0 - e_A)}{(e_0^* - e_A)} = \frac{(e_0 - e_A)}{\kappa(e_s^* - e_A)} = \frac{s_1(T_{SD} - T_D)}{\kappa s_2(T_R - T_D)} \quad (6)$$

Where e_0 and e_0^* are the actual and saturation vapour pressure at the source/sink height; e_A is the atmospheric vapour pressure; e_s^* is the saturation vapour pressure at the surface; T_D is the air dewpoint temperature; s_1 and s_2 are the psychrometric slopes of the saturation vapour pressure and temperature between $(T_{SD} - T_D)$ versus $(e_0 - e_A)$ and $(T_R - T_D)$ versus $(e_s^* - e_A)$ relationship (Venturini et al., 2008); and κ is the ratio between $(e_0^* - e_A)$ and $(e_s^* - e_A)$. Despite T_0 driving the sensible heat flux, the comprehensive dry-wet signature of the underlying surface due to aggregated moisture variability is directly reflected in T_R (Kustas and Anderson, 2009). Therefore, using T_R in the denominator of Eq. ~~(6)~~(6) tends to give a direct signature of the surface moisture availability. In Eq. ~~(6)~~(6), both s_1 and T_{SD} are unknowns, and an initial estimate of T_{SD} is obtained using Eq. ~~(6)~~(6) of Venturini et al. (2008) where s_1 was approximated in T_D . From the initial estimates of T_{SD} , an initial estimate of M is obtained as $M = s_1(T_{SD} - T_D)/s_2(T_R - T_D)$. However, since T_{SD} also depends on λE , an iterative updating of T_{SD} (and M) is carried out by expressing T_{SD} as a function of λE which is described in detail in Appendix A3 (also in Mallick et al., 2016).

The state equations of STIC1.2 are provided below and their detailed descriptions are available in Mallick et al. (2014; 2015; 2016).

$$g_A = \frac{\phi}{\rho_A c_P \left[(T_0 - T_A) + \left(\frac{e_0 - e_A}{\gamma} \right) \right]} \quad (7)$$

$$g_C = g_A \frac{(e_0 - e_A)}{(e_0^* - e_0)} \quad (8)$$

$$T_0 = T_A + \left(\frac{e_0 - e_A}{\gamma} \right) \left(\frac{1 - \Lambda}{\Lambda} \right) \quad (9)$$

$$\Lambda = \frac{2\alpha s}{2s + 2\gamma + \gamma \frac{g_A}{g_C} (1 + M)} \quad (10)$$

Here α is the Priestley-Taylor coefficient (unitless) (Priestley and Taylor, 1972). In Eq. ~~(10)(40)~~, α appeared due to using the Advection-Aridity (AA) hypothesis (Brutsaert and Stricker, 1979) for deriving the state equation of λ (Mallick et al., 2016; Mallick et al., 2015). However, instead of optimising it as a ‘fixed parameter’, α is dynamically estimated by constraining it as a function of M , conductances, source/sink height vapour pressure, and temperature (Mallick et al., 2016). The derivation of the equation for α is described in Appendix A3.

Given values of M , R_N , G , T_A , and RH or e_A , the four state equations (Eqs. ~~(7)(7)-(10)(40)~~) can be solved simultaneously to derive analytical solutions for the four unobserved state variables and to simultaneously produce a ‘closure’ of the PM model that is independent of empirical parameterizations for both g_A and g_C (Appendix A2). However, the analytical solutions to the four state equations contain three accompanying unknowns; e_0 , e_0^* , and α , and as a result there are four equations with seven unknowns. Consequently, an iterative solution must be found to determine the three unknown variables (Appendix A3) (also in Mallick et al., 2016).

In STIC1.2, the key modifications to the original STIC formulation (Mallick et al., 2014) include estimation of the source/sink height vapour pressures by combining PM and Eq. (8) of Shuttleworth-Wallace (Shuttleworth and Wallace, 1985), as detailed in Appendix A3 (also in Mallick et al., 2016). STIC1.2 consists of a feedback loop describing the relationship between T_R and λE , coupled with canopy-atmosphere components relating λE to T_0 and e_0 (Mallick et al., 2016). Upon finding analytical solution of g_A and g_C , both ~~the~~ variables are returned into Eq. ~~(5)(5)~~ to directly estimate λE . For the image-based implementation of STIC1.2, we make a key adjustment to the original ecosystem-scale STIC1.2 version (Mallick et al., 2016) to apply the model at an instantaneous scale (i.e. MODIS image acquisition time) by removing the calculation of hysteresis occurrence using hourly data (Mallick et al., 2015). Such adjustment was necessary to adapt the model to single time-of-day T_R data from MODIS acquisition.

2.1.2 SEBS

SEBS formulation uses an empirical model for estimating z_{0M} , the Bulk Atmospheric Similarity Theory for planetary boundary layer scaling, and the Monin-Obukhov atmospheric surface layer similarity for surface layer scaling for the estimation of surface fluxes from thermal remote sensing data (Su, 2002; Su et al., 2001). To estimate H , SEBS solves the similarity relationships for the profile wind speed (u) and the mean difference between potential temperatures ($\Delta\theta$; K) at the surface and reference height (z):

$$u = \frac{u_*}{k} \left[\ln \left(\frac{z-d_0}{z_{0M}} \right) - \psi_M \left(\frac{z-d_0}{L} \right) + \psi_M \left(\frac{z_{0M}}{L} \right) \right] \quad (11)$$

$$\Delta\theta = \frac{H}{k u_* \rho c_p} \left[\ln \left(\frac{z-d_0}{z_{0H}} \right) - \psi_H \left(\frac{z-d_0}{L} \right) + \psi_H \left(\frac{z_{0H}}{L} \right) \right] \quad (12)$$

$$L = - \frac{\rho_A c_p u_*^3 \theta_v}{kgH} \quad (13)$$

Here L is the Monin-Obukhov length (m), θ_v is virtual potential temperature (K) near the surface (Brutsaert, 2005), k is the Von Karman Constant (0.41), u^* is the friction velocity (m s^{-1}), and g is the acceleration due to gravity (9.8 m s^{-2}). Ψ_M and Ψ_H are the stability corrections for momentum and heat transport, respectively.

One of the key characteristics of the SEBS model is the use of a semi-physical adjustment factor (kB^{-1}) to compensate for the differences between z_{0M} and z_{0H} (Su et al., 2001):

$$z_{0H} = z_{0M} / \exp(kB^{-1}) \quad (14)$$

The pixel-level energy balance at a dry limit ($\lambda E = 0$ or $H = \phi$) and a wet limit (potential ET, E_p , rate based on Penman equation) is used in SEBS to estimate relative evaporation (A_R , the ratio of actual to the maximum evaporation rates) to further compute A (Su, 2002).

$$A_r = 1 - \frac{H - H_{\text{wet}}}{H_{\text{dry}} - H_{\text{wet}}} \quad (15)$$

$$A = \frac{A_R \times \lambda E_{\text{wet}}}{R_N - G} \quad (16)$$

where H_{wet} and H_{dry} are H under the wet and dry limiting conditions, respectively. λE_{wet} is the λE at the wet limit.

10 2.1.3 MOD16 algorithm

The MOD16 algorithm is based on the PM equation (Eq. (5)(5)) and is designed to estimate ET by summing wet soil evaporation, interception evaporation from the wet canopy, and transpiration through canopy over vegetated land surfaces. The original PM equation was modified by Mu et al. (2007, 2011) for estimating global ET components and is primarily driven by MODIS-derived vegetation variables (leaf area index, fractional vegetation cover) and daily meteorological inputs including R_S , T_A , and D_A .

Key inputs in the MOD16 ET product include the global $1 \text{ km} \times 1 \text{ km}$ MODIS collections, including ~~annual~~ land cover (MOD12Q1), 8-day LAI/FPAR (MOD15A2), 8-day albedo (MCD43B2 and MCD43B3 products), and the global GMAO daily meteorological reanalysis data ($1.00^\circ \times 1.25^\circ$ resolution). The MODIS 8-day albedo products and daily surface downwelling shortwave radiation and air temperature from daily meteorological reanalysis data are used to calculate R_N . The vegetation cover fraction from the MODIS 8-day FPAR products is used to allocate the R_N between soil and vegetation. Daily T_A , D_A and RH, and 8-day MODIS LAI information are used to estimate individual resistances from soil and canopy, and soil heat flux, respectively. A Biome-Property-Lookup-Table (BPLUT) is used to assign minimum and maximum resistances for all land cover categories, and the biome-specific resistances are constrained ~~through-by~~ different environmental scalars. Readers are referred to Mu et al. (2011) for a detailed description of the derivation of key ET components and the parameters used in the MOD16 algorithm for estimating ET.

2.2 Study sites

For validating the STIC1.2 model, we selected thirteen core AmeriFlux sites covering a broad spectrum of biomes which also represent a wide range of climatic, elevation (5 to 3050 m), precipitation (P; 380 to 1320 mm year⁻¹), temperature (1.50 to 17.92 °C), and aridity gradients across the conterminous United States (Fig. 2; [Table 1](#)~~Table 1~~). AmeriFlux is a subnetwork of
5 FLUXNET which is a global micrometeorological eddy covariance (EC) network for measuring carbon, water vapour, and energy exchanges between the biosphere and atmosphere (Baldocchi and Wilson, 2001). AmeriFlux core sites are the EC flux tower sites that deliver high-quality continuous data to the AmeriFlux database (<http://ameriflux.lbl.gov>). Currently, there are 44 core sites distributed in 12 clusters. We selected 13 out of 44 sites, which also represent the primary EC sites of the selected clusters. These sites also cover a broad class of aridity index (AI) (Food and Agriculture Organization, FAO, 2015): arid
10 (AI<0.30), semiarid (0.50>AI>0.30), subhumid (0.65>AI>0.50), and humid (AI>0.65). Each of these four AI categories contained at least two validation sites. Four MODIS subsets (Fig. 2) covering at least two validation sites within each region (labeled as East (E), Midwest 1 (MW1), Midwest 2 (MW2), and West (W), from the east to west, respectively) were used for image processing to implement the STIC1.2 model. For the regional-scale intercomparison of ET models, similar MODIS subsets were used.

Formatted: Font: Not Bold

2.3 Datasets

Key remotely sensed data for model implementation were obtained from the MODIS Terra 8-day composites. Meteorological inputs were obtained from hourly NLDAS-2 (North American Land Data Assimilation System - 2) forcing data (Xia et al., 2012). Daily meteorological variables, which were derived from hourly NLDAS and PRISM (Parameter-elevation
20 Relationships on Independent Slopes Model; PRISM Climate Group, Oregon State University, <http://prism.oregonstate.edu>) data, were obtained from the University of Idaho (<http://climate.nkn.uidaho.edu/METDATA/>). A list of datasets used in the present analyses is given in [Table 2](#)~~Table 2~~. The PRISM precipitation dataset was used to select dry, wet, and normal years for each site.

2.4 Data processing

2.4.1 Selection of dry, wet and normal rainfall years

25 Dry, wet, and normal years were selected based on 30-year (1980-2010) precipitation from PRISM data. For each site, we selected the driest (dry), wettest (wet), and closest to the 30-year mean (normal) years based on PRISM precipitation data (Fig. 3).

2.4.2 MODIS-based variables: surface albedo, NDVI, LST, surface emissivity, and LAI

Broadband surface albedo was estimated using all the narrow band surface reflectances from MOD09A1, and NDVI (Tucker, 1979) was computed using near infrared and red band surface reflectance MOD09A1 products. T_R information was obtained from the MOD11A2 LST products for the study years. For estimating surface emissivity, we took mean emissivity from band 31 and 32 (Bisht et al., 2005) from the MOD11A2 products. While the information of LAI from MOD15A2 and MCD15A2 products (mean of the two) were used for computing the extra resistance parameter (kB^{-1}) (Su, 2002; Su et al., 2001), NDVI was used to estimate z_{0M} using a simple empirical relationship between the roughness length of momentum transfer (van der Kwast et al., 2009) in SEBS. Yang et al. (2002) was used to parametrize kB^{-1} for bare soil. This new parametrization of kB^{-1} was designed to improve the SEBS model performances on bare soil, low canopies, and snow surfaces and was proposed by Chen et al. (2013).

2.4.3 Meteorological Variables at the Satellite Overpass: RH, T_A , u , and R_s

Half-hourly gridded meteorological datasets from the North American Land Data Assimilation System (NLDAS-2) at $4\text{ km} \times 4\text{ km}$ spatial resolution were used as inputs in the STIC1.2 (R_s , T_A , and RH) and SEBS (u , R_s , T_A , and RH) models. Because RH was not explicitly available in the NLDAS-2 dataset, we derived RH from surface pressure (Pa) and specific humidity (kg kg^{-1}) information using the method developed by McIntosh and Thom (1978). The half-hourly meteorological variables at the time of MODIS Terra overpass during every 8-day period were averaged to ensure that the weather dataset is well representative of all the corresponding 8 days within each MODIS 8-day period.

Additional inputs of daily meteorology (R_s , T_A , u , and RH) required for computing 8-day ET were obtained from the University of Idaho (<http://climate.nkn.uidaho.edu/METDATA/>), and these data products were derived from hourly NLDAS and PRISM datasets. Daily weather data were also aggregated to the corresponding MODIS 8-day periods. Su (2002) Chen et al. (2013) (Mallick et al., 2016)

2.4.4 Derivation of regional-scale eight-day and annual ET maps (STIC1.2 and SEBS)

The SEBS codes in this study is adapted from Abouali et al. (2013), which is different from original and modified versions of Su (2002) and Chen et al. (2013), respectively. Here we used a simple NDVI-based parametrization of z_{0M} to provide a spatial representation of canopy height ($z_{0M}/0.13$) and zero displacement height ($0.67z_{0M}$) and z_{0H} was estimated using Eq. **Error!** **Reference source not found.** The STIC1.2 source code was modified from the original STIC1.2 code (Mallick et al., 2016) in Matlab (Mathworks Inc, Natick, USA).

Net available energy ($\phi = R_N - G$, W m^{-2}) at MODIS Terra overpass time was partitioned into H and λE by both models as explained in sections 2.1.1 and 2.1.2. Instantaneous λ was then computed as the ratio of λE to ϕ . For the extrapolation of instantaneous λE to daily ET under clear sky conditions, the instantaneous λ is assumed to be constant for the day (Brutsaert and Sugita, 1992; Crago and Brutsaert, 1996) and 8-day cumulative ET (5-day for doy 361) was estimated as follows:

$$ET_8 = \frac{86400 \times 10^3 \times A \times R_{N24-8day} \times n}{\lambda p_w} \quad (17)$$

where $R_{N24-8day}$ is the 8-day net radiation; and n = number of days in the 8-day period (8; $n = 5$ for doy 361) computed using the ASCE standardized PM equation using daily weather inputs (ASCE-EWRI, 2005). Combining all the sites, the estimated $R_{N24-8day}$ from MODIS was within 10 % (i.e., 9 % overestimation) of mean observed 8-day net radiation at the flux sites (coefficient of determination, R^2 , = 0.89, root mean squared error, RMSE, = 20 W m⁻², Fig. S1).

5 Annual ET maps were derived by summing all the corresponding 8-day ET maps within a given year. To fill the missing 8-day ET values, A values from up to the two nearest 8-day periods were used (i.e. mean A values of n prior and after 8-day period, where $n = 1$ or 2). The filled A values were then used in Eq. (17) (~~(17)~~) ($R_{N24-8day}$ from the current 8-day period is used) to fill the missing 8-day ET values. Since there were missing daily flux data in some years, we filled missing values using linear interpolation between available days. For the statistical analysis, we retained those annual ET values when observed λE was available for at least 300 days at each flux tower site. Similarly, annual ET from the models was only compared when at least 38 (out of the 46) 8-day cumulative ET values were available.

2.4.5 Regional-scale eight-day and annual ET maps from MOD16 ET

The MOD16 ET product provides global 8-day (MOD16A2), monthly, and annual (MOD16A3) terrestrial ecosystem evapotranspiration datasets at 1 km × 1 km spatial resolution over 109.03 million km² of global vegetated land areas. The dataset is currently available for the period of 2000-2014 and will be updated for years beyond 2014 in the future. The 8-day and annual MOD16 ET products were acquired from the Numerical Terradynamic Simulation group (ftp://ftp.nts.g.umt.edu/pub/MODIS/NTSG_Products/MOD16/MOD16A2.105_MERRAGMAO/) of the University of Montana. ET values of the corresponding flux sites for every 8-day period within each dry, wet, and normal year were extracted for model intercomparison. The annual ET maps from MOD16 products (MOD16A3) were used for regional-scale model intercomparison of annual ET estimates from STIC1.2 and SEBS.

2.4.6 Preparation of validation datasets

We used half-hourly surface energy balance flux data from the thirteen core EC sites of the AmeriFlux network that covers an aridity gradient (from arid to humid), and a wide range of elevation and biome types in the conterminous US (Table 1). A Bowen ratio (Bowen, 1926) based surface energy balance closure method (Chávez et al., 2005; Twine et al., 2000) was used to force the SEB closure at half-hour time scales. The half-hourly λE (W m⁻²) was converted into ET (mm hr⁻¹) using the proportionality parameter between energy and equivalent water depth unit of ET (Mu et al., 2007; Velpuri et al., 2013).

$$ET = \lambda E / \lambda \quad (18)$$

Here λ is the latent heat of vaporization of water.

Formatted: Font: Not Bold

Half-hourly ET ~~data was were then~~ aggregated to hourly, daily, and eight-day temporal scales corresponding to the MODIS 8-day periods. The 8-day sum of ET was used for validating ET estimates from MOD16, SEBS, and STIC1.2 only when flux data were available for the entire 8-day period. Daytime fluxes (H , λE , R_N , and G) close to MODIS Terra overpass time were also averaged over ~~the~~ 8-day periods corresponding to MODIS 8-day DOYs. We also utilized a recently developed global monthly ET products (5 km × 5 km; <http://en.tpdatabase.cn/portal/MetaDataInfo.jsp?MetaDataId=249454>) that employs the latest version of SEBS (SEBS_{Chen} hereafter) (Chen et al., 2013; Chen et al., 2014) and compared against those from STIC1.2 outputs. SEBS_{Chen} uses an updated parametrization of the kB^{-1} parameter through improved canopy height and surface roughness schemes to better represent surfaces from bare soil to full canopies in SEBS. Since the focus of this study is to test the validity of regional scale implementation and ET mapping potential of STIC1.2 using remotely sensed data, a detailed model intercomparison or assessing the performances of SEBS model with different kB^{-1} parameters or input variables is beyond the scope of this study.

2.4.7 Statistical Analysis

The three ET models were evaluated based on their ability to estimate 8-day cumulative ET at the flux tower sites during dry, normal, and wet years. Widely used statistical metrics, such as RMSE, R^2 , mean absolute error (MAE), and percent bias error (PBIAS) were used for evaluating the model performances. The location information of the AmeriFlux sites (~~Table 1~~~~Table 1~~) was used to extract the pixel values of ET (outputs from STIC1.2, SEBS, and MOD16 products) and other biophysical variables (~~Table 2~~~~Table 2~~) for the statistical analysis.

Comparisons were made for the 8-day periods when flux data were available for all 8 days corresponding to each MODIS 8-day period, and when MODIS inputs for STIC1.2 and SEBS, and MOD16 ET data were available. Overall, the data ~~availability available~~ for statistical analysis ranged from 43 % (59 out of 138 MODIS 8-day periods) at the US-kon site to 93 % (128 out of 138 MODIS 8-day periods) at the US-Wkg site with an average of 65 % (SM, Table S1).

3 Results

3.1 What is the performance of STIC1.2 at the regional-scale across an aridity gradient and during contrasting rainfall years in the conterminous US?

Combining results from thirteen core AmeriFlux sites, it is apparent that STIC1.2 captured 66 % of the observed variability ($R^2 = 0.66$) in 8-day cumulative ET (~~Table 3~~~~Table 3~~) with an overall RMSE, MAE and PBIAS of 7.5 mm, 5.4 mm, and -3 %, respectively. Consistent performance of STIC1.2 was noted throughout dry, wet, and normal rainfall years, explaining about 64–69 % of the variability in 8-day cumulative ET (Fig. 4), with a slight overestimation in dry years (PBIAS 7 %) and an underestimation in wet years (PBIAS -11 %; Fig. 4). Biome-specific analysis revealed relatively better performance of STIC1.2 in forests as compared to non-forest sites (Fig. 5). STIC1.2 explained 73 % - 89 % variability in ET from ENF (evergreen

Formatted: Font: Not Bold

Formatted: Font: Not Bold

needleleaf forests) and DBF (deciduous broadleaf forests) with an RMSE of 5.2 - 6.4 mm. Among the non-forest sites, although STIC1.2 explained 60 % - 70 % of the observed ET variability in CRO (croplands) and GRA (grasslands) (RMSE 7.2 - 9.9 mm/8-day), it explained only 23 % of the observed ET variability in WSA with a PBIAS of 44 % (Figure 5Figure 5).

At the CRO sites, STIC1.2 underestimated ET by about 20 %. At the GRA sites, a better performance of STIC1.2 was noted in the dry year as compared to the wet and normal years (Fig. S2-S4). Regardless of vegetation type, STIC1.2 had a tendency to underestimate ET under high wetness conditions.

Performance evaluation of STIC1.2 across an aridity gradient suggests the better predictive capacity of STIC1.2 in subhumid and humid sites as compared to arid and semiarid sites (Figure 6Figure 6). As seen in Figure 6Figure 6, 41 % - 45 % of the variability in 8-day ET was explained in arid and semiarid ecosystems (RMSE 5 - 7.5 mm/8-day and MAE 4.8 - 5.1 mm/8-day), which increased to 61 % -77 % in the humid and subhumid ecosystems (with RMSE 7 - 10 mm/8-day and MAE 5 - 7.5 mm/8-day). The key reason is that STIC1.2 does not effectively capture very low ET values in the semiarid and arid sites, particularly in woody savannas (Figure 5Figure 5).

3.2 Comparison of STIC1.2 against other global ET models that are constrained by T_R and RH

STIC1.2 showed relatively high accuracy when independently compared against observed ET at thirteen AmeriFlux sites than did SEBS and MOD16. Combining all sites, the predictive capability of STIC1.2 was found to be 7 % - 17 % better than SEBS and MOD16, which explained about 53 % and 59 % of the variability in observed 8-day ET, respectively (Table 3Table 3). As evident from PBIAS, SEBS has a tendency to overestimate and MOD16 has a tendency to underestimate 8-day cumulative ET by over 20% (28% from SEBS and -27 % from MOD16), while STIC1.2 has a small tendency to underestimate (-3 %) (Table 3Table 3). In addition to a high RMSE (9.6 - 10.2 mm for SEBS, 8.5 - 9.4 mm for MOD16), an overestimation tendency of SEBS (PBIAS 13% - 44%) and underestimation tendency of MOD16 (PBIAS -25% to -32%) were consistent throughout dry, wet, and normal years (Figure 4Figure 4).

The biome-specific performance intercomparison revealed that STIC1.2 produced a substantially lower RMSE than SEBS and MOD16 in ENF (12 % - 17 % less RMSE), GRA (18 % - 29 % less RMSE), and DBF (7 % - 37 % less RMSE) in 8-day cumulative ET with better or tantamount skill in capturing the observed ET variability as compared to the two other models (Figure 5Figure 5). While MOD16 was found to produce relatively lower RMSE in WSA (16 % less than STIC1.2 and 49 % less than SEBS), SEBS performed relatively better in CRO (5 % and 33 % less RMSE than STIC1.2 and MOD16, respectively).

Statistical intercomparison of the predictive capacity of STIC1.2 with respect to SEBS and MOD16 across an aridity gradient revealed notable differences in RMSE and MAE between the models (Fig. 6), despite general agreement on the capabilities of individual models to explain the variability in observed ET ($R^2 = 0.34-0.77$). STIC1.2 was found to produce the lowest RMSE in 8-day cumulative ET in arid (31 % and 43 % lower than MOD16 and SEBS, respectively), semiarid (5 % and 32 % lower than MOD16 and SEBS, respectively), and humid (3 % and 19 % lower than MOD16 and SEBS, respectively) ecosystems (Fig. 6). In the subhumid ecosystem, the performance of STIC1.2 was comparable with SEBS (PBIAS from STIC1.2 and SEBS were -20 % and 2 %, other error statistics were comparable) and substantially better than MOD16 (PBIAS=-48 %). A

Formatted: Font: Not Bold

Formatted: Font: Not Bold, Font color: Text 1, Check spelling and grammar

Formatted: Font: Not Bold

Formatted: Font: Not Bold, Font color: Text 1, Check spelling and grammar

Formatted: Font: Not Bold

Formatted: Font: Not Bold

Formatted: Font: Not Bold, Font color: Text 1, Check spelling and grammar

Formatted: Font: Not Bold

Formatted: Font: Not Bold

Formatted: Font: Not Bold

Formatted: Font: Not Bold, Font color: Text 1, Check spelling and grammar

Formatted: Font: Not Bold

Formatted: Font: Not Bold, Font color: Text 1, Check spelling and grammar

consistent overestimation (underestimation) tendency of SEBS (MOD16) in arid and semiarid ecosystems is reflected in positive (negative) PBIAS (58 % to 84 % for SEBS; -67 to -37 % for MOD16) in these two aridity classes.

3.3 Factors affecting agreements/disagreements between ET models

The residual differences in 8-day ET between STIC1.2 versus SEBS ($dET_{STIC1.2-SEBS} = ET_{STIC1.2} - ET_{SEBS}$) as well as SEBS versus observed ET ($dET_{SEBS-obs} = ET_{SEBS} - ET_{obs}$) were found to be significantly associated with T_R ($r = -0.301$ to 0.38 , p -value < 0.005) and D_A ($r = -0.30$ to 0.46 , p -value < 0.005) (Fig. 7a-7b). Negative $dET_{STIC1.2-SEBS}$ (positive $dET_{SEBS-obs}$) was found with increasing T_R and D_A above 290 K and 2 kPa, whereas ET differences were narrowed down below these limits (Fig. 7). A logarithmic pattern was found between $dET_{STIC1.2-SEBS}$ ($dET_{SEBS-obs}$) and NDVI, with a correlation of 0.31 and 0.35, respectively. Major ET differences (both $dET_{STIC1.2-SEBS}$ and $dET_{SEBS-obs}$) (± 20 mm) were found in the NDVI range of 0.15 - 0.35, whereas ET differences were diminished within ± 10 mm above NDVI of 0.5.

A similar analysis of ET differences between STIC1.2 and MOD16 ($dET_{STIC1.2-MOD16} = ET_{STIC1.2} - ET_{MOD16}$) and between MOD16 and the observed ET ($dET_{MOD16-obs} = ET_{MOD16} - ET_{obs}$) also revealed a significant correlation with T_R and D_A (Fig. 7d-7e and inset) ($r = -0.30$ to 0.66 , p -value < 0.005), but the direction of these correlations are opposite to those found with the ET differences between STIC1.2 and SEBS. $dET_{MOD16-obs}$ was found to have no significant relationship (p -value > 0.15) with NDVI, while $dET_{STIC1.2-MOD16}$ appear to have a significant negative relationship with NDVI, which was also opposite of what found with ET differences between STIC1.2 and SEBS.

To examine the relative importance of the meteorological and land surface variables in explaining the variances in $dET_{STIC1.2-SEBS}$ and $dET_{STIC1.2-MOD16}$, a random forest analysis (Liaw and Wiener, 2002) was performed between the residual ET differences and seven climatic/land surface variables (NDVI, D_A , P , u , observed soil moisture [SM], T_A , and T_R) as predictors (Fig. S5). Overall, these variables explained 41 % and 57 % variances in $dET_{STIC1.2-SEBS}$ and $dET_{STIC1.2-MOD16}$, respectively. The most important variables for explaining variance in $dET_{STIC1.2-SEBS}$ were T_A and NDVI. These two variables would lead to about 25-40 % increase in mean residual errors (MSEs) if they are permuted in the random forest model. For $dET_{STIC1.2-MOD16}$, all the variables except u appeared to be important in determining the variance of ET difference, as each variable would lead to about 17 %-22 % increase in MSEs if they are permuted in the random forest model.

3.4 Regional-scale intercomparison of STIC1.2 versus SEBS and MOD16 ET

Annual ETs from STIC1.2 for the driest, wettest, and normal precipitation years for each of four study zones during the period 2001-2014 were compared against those derived from SEBS and the MOD16A3 annual ET products. Because the study years were selected based on the spatial mean of precipitation across 4 km x 4 km PRISM grids, the study years (Table 4) do not necessarily match with those considered for ET analysis over the flux sites as presented in sections 3.1, 3.2, and 3.3.

Figs. 8-11 present annual ET maps for the driest, wettest, and normal years for each of the four study zones covering all thirteen study sites and a distinct positive relationship was found between annual ET computed from the three models. However, the magnitude of annual ET from the three models varied widely, particularly in the relatively dry zones of the

Formatted: Font: Not Bold

Midwestern US (MW1 and MW2). Such differences in annual ET could be attributed to the systematic differences in 8-day cumulative ET among the three models (i.e., overestimation from SEBS and underestimation from MOD16).

The mean percent difference (and standard deviation) in ET between STIC1.2 vs. SEBS and MOD16 (Table 5) from all pixels within the bounding box of four study zones during the contrasting rainfall years (as in Fig. 8 - 11) showed noteworthy disagreements in arid and semiarid (W and MW2) zones, where annual ET from SEBS (MOD16) were 66-85 % more (11-55 % less) than STIC1.2. Conversely, major agreements between the models were found in the humid (E) zone where SEBS and MOD16 annual ET estimates were within 13 % of STIC1.2 ET.

We further compared annual ET estimates from the models against the flux tower estimates for the years listed in Table 5 and annual ET maps corresponding to Figs. 8-11. Comparison of annual ET at the core AmeriFlux sites revealed a consistent overestimation and underestimation from SEBS (PBIAS 23 %) and MOD16 (PBIAS -30 %) (Fig. 12). Despite the uncertainties due to linear interpolation for missing days or the use of neighbouring 8-day A in computing annual ET (as mentioned in section 0), STIC1.2 produced the lowest RMSE (175 mm) and MAE (134 mm) as compared to SEBS (RMSE 239 mm, MAE 188 mm) and MOD16 (RMSE 261 mm, MAE 228 mm) (Fig. 12) and was comparable with annual ET estimates from SEBS_{Chen} (sum of monthly ET maps), with respect to RMSE and MAE (Fig. 12). Biases from STIC1.2 was better (PBIAS=-6%) than SEBS_{Chen} (-14 %) although STIC1.2 only explained 32% variation in observed annual ET, while SEBS_{Chen} explained about 56% variability in observed annual ET.

Figure 12 provides evidence that errors in 8-day cumulative ET from SEBS and MOD16 were largely additive, as indicated by the consistent overestimation or underestimation from the models at different sites. In addition, the 8-day average net radiation was also overestimated by about 9% (Fig. S1). Overestimation of annual ET from SEBS was mostly observed in the arid and semi-arid sites (47%). In the two cropland sites (US-ARM and US-Ne1), SEBS annual ET estimates were within 2% of observed annual ET, where STIC1.2 showed 22% underestimation and MOD16 revealed 49% underestimation. Notably, MOD16 estimates were particularly poor in the MW2 zones, while SEBS was found to be poor both in the MW1 and MW2 zones. Apart from that, differences between STIC1.2 and the other two models were also noticed in other zones.

To further investigate the role of biomes on ET differences between STIC1.2 and other models, we computed the mean percent ET difference (standard deviation) (similar to Table 5) on the five vegetation types, corresponding to those represented by the core AmeriFlux sites. The differences in annual ET between STIC1.2 vs. SEBS and STIC1.2 vs. MOD16 were mostly evident in all five vegetation classes, particularly in the W and MW2 spatial domains, with the maximum ET differences in grasslands (-135 % to 44 %) (Table 6). For almost all of the five vegetation types, ET differences between the models decreased across the aridity gradient from arid to humid ecosystems from western to the eastern US (± 20 %) (Table 6).

In order to quantify the relative contribution of these three categorical variables [e.g., (1) zones (W, MW2, MW2, E), (2) land cover types (five land cover classes), and (3) precipitation extremes (dry, wet, and normal years)] to variations in residual ET differences (annual) between STIC1.2 and the other two models, we performed a random forest analysis (Fig. S6). The three categories together explain 45 % to 60 % of the variances in the residual ET difference between STIC1.2 vs. MOD16

Formatted: Font: Not Bold

Formatted: Font: Not Bold

Formatted: Font: Not Bold

Formatted: Font: Not Bold, Font color: Text 1, Check spelling and grammar

Formatted: Indent: First line: 0.13"

Formatted: Font: Not Bold

and STIC1.2 vs. SEBS. However, study zone increases 51 % - 65 % of mean residual errors (MSEs) in ET if this group is permuted in the random forest model, thus appearing to be the most important factor among the three categorical variables. This finding is also consistent with the results ~~in~~-presented in Tables 5 and 6 that the residual ET differences between the models progressively reduced across an aridity gradient from arid to humid ecosystems. The precipitation extremes appeared to have no effect on the residual ET difference between STIC1.2 and SEBS, similar to the land cover effect on the residual difference between STIC1.2 and MOD16.

4 Discussion

Overall, STIC1.2 performed reasonably well across an aridity gradient and a wide range of biomes in the conterminous US. One noticeable weakness of STIC1.2 appears to be its tendency to underestimate ET in the grassland and cropland ~~biomes~~ (Fig. 4 and 5). These biases could be attributed to the nature of the MODIS LST product that aggregates sub-grid heterogeneity in T_R , vegetation cover, and radiation at $1 \text{ km} \times 1 \text{ km}$ area. Due to the relatively low tower heights in CRO and GRA sites (3 - 10 m), the EC towers aggregate fluxes at scales of approximately $0.009 - 0.10 \text{ km}^2$. Such a critical mismatch of the scales between MODIS pixels and the flux tower footprint could be a potential source of disagreement between STIC1.2 and tower-observed ET (Stoy et al., 2013). Another source of error could be the presence of widely varied dry and wet patches within one MODIS $1 \text{ km} \times 1 \text{ km}$ pixel as well as around the flux towers. For example, if more than 50 % of the area falling within a $1 \text{ km} \times 1 \text{ km}$ MODIS pixel is predominantly dry, the lumped T_R signal in MODIS LST product will be biased due to the dryness of the landscape (Stoy et al., 2013; Mallick et al., 2014; Mallick et al., 2015) and the resultant ET will be underestimated. The overestimation tendency in WSA is mainly due to the poor performance of STIC1.2 in the Tonzi Ranch site, which could be associated with ~~the uncertainties in surface the~~ emissivity correction ~~uncertainties~~ and systematic underestimation of MODIS LST in arid and semiarid ecosystems (Wan and Li, 2008; Jin and Liang, 2006; Hulley et al., 2012). Since T_R plays an important role in constraining the conductances in STIC1.2, an underestimation of T_R would ~~ultimately~~ result in an overestimation of g_C and underestimation of g_A , which would result in overestimation of ET. The differences between STIC1.2 versus observed ET in WSA may also largely be attributed to the Bowen ratio energy balance closure correction of EC λE observations (Chávez et al., 2005; Twine et al., 2000). Although the Bowen ratio correction forces SEB closure, in arid and semiarid ecosystems major corrections are generally observed in sensible heat flux, whereas λE is negligibly corrected (Chávez et al., 2005; Mallick et al., In Review). Besides, direct water vapour adsorption on the land surface occurs in arid and semiarid ecosystems when air close to the surface is drier than the overlying air (McHugh et al., 2015; Agam and Berliner, 2006), and this source of moisture is unaccounted for in the EC measurements. This will automatically result in disagreement between STIC1.2 and observed ET. Nevertheless, the performance of STIC1.2 in forest ecosystems is encouraging, given the uncertainties associated with more complex SEB models that use MOST to parameterize the turbulent mixing in tall canopies (Finnigan et al., 2009; Garratt, 1978; Harman and Finnigan, 2007) that could induce substantial biases in estimated fluxes (Wagle et al., 2017; Numata et al., 2017; Bhattarai et al., 2016).

The overall performance metrics from the three models may be slightly biased due to their strikingly poor performances at some specific sites (Table S1). For example, although SEBS overestimated ET by over 64% in the two semiarid WSA (US-Ton, US-SRM) and GRA (US-SRG and US-Wkg) sites (Table S1); however, its performance in US-Ne1 (CRO), two wet grasslands (US-Kon and US-KFS), and US-NR1 (ENF) were better or comparable than the other two models. This could be

due to the inability of the kB^{-1} parameterization scheme in SEBS to account for the substantial differences between T_R and T_0 due to strong soil water limitations. MOD16 underestimated ET from all but three sites (US-Ton, US-MMS, US-NC1) and underestimated mean ET by over 50% in US-Ne1 (CRO), US-SRM (WSA), US-SRG (GRA), and US-Wkg (GRA) sites. STIC1.2 appears to be relatively consistent among the three models, as the mean bias errors were within 20% for all but three sites (US-Ton, US-Kon, US-Ne1).

Performance intercomparison of STIC1.2 with SEBS and MOD16 indicated overall low statistical errors for STIC1.2, and better agreement than SEBS and MOD16 with observed ET values. The principal differences between STIC1.2 and SEBS (as evident from Fig. 7a and Fig. 8 to 13), in particular, the overestimation of ET through SEBS, is in cases of high T_R and D_A with low vegetation cover (i.e., low NDVI), a characteristic feature of arid and semiarid ecosystems. In these water limited ecosystems, T_R induced water stress and the diminishing ET rate leads to high atmospheric dryness (i.e., high D_A), increased evaporative potential, and very high sensible heat flux. This leads to substantial differences between T_R and T_0 , and the role of radiometric roughness length (z_{0H}) becomes critical, which is estimated empirically through the adjustment factor kB^{-1} (Paul et al., 2014). Although there is a first order dependence of kB^{-1} on T_R , radiation, and meteorological variables (Verhoef et al., 1997b), no physical model of kB^{-1} is available (Paul et al., 2014). Therefore, uncertainties in kB^{-1} estimation are propagated into z_{0H} . Overestimation (or underestimation) of z_{0H} would lead to underestimation (overestimation) of g_A in SEBS, which is mirrored in ET differences between SEBS vs. observations ($dET_{SEBS-obs}$) (Zhou et al., 2012). This is also evident when a logarithmic pattern was found between $dET_{SEBS-obs}$ and kB^{-1} , with a correlation of 0.39 (p -value < 0.005) (Fig. 13a). Major ET differences were found (± 20 mm) within a kB^{-1} range of 2-6 (arid, semiarid, heterogeneous vegetation), whereas ET differences were diminished within ± 10 mm above kB^{-1} of 6 (subhumid, humid, homogeneous vegetation). Apart from z_{0H} , empirical parameterization of z_{0M} and a resultant ± 50 % uncertainties in z_{0M} can also lead to 25 % errors in g_A estimation (Liu et al., 2007; Verhoef et al., 1997a), which will lead to more than 30 % uncertainty in ET estimates. This is also evident from the exponential scatter between z_{0M} and $dET_{SEBS-obs}$ (Fig. 13b) that showed a significant negative correlation between z_{0M} and the residual ET error ($r = -0.40$, p -value < 0.005).

It is important to emphasize that the momentum transfer equation for estimating g_A in SEBS is based on the semi-empirical MOST approach that mainly holds for extended, uniform, and flat surfaces (Foken, 2006; Verhoef et al., 1997c). MOST tends to become uncertain on rough surfaces due to a breakdown of the similarity relationships for heat and water vapour transfer in the roughness sub-layer, which results in an underestimation of the 'true' g_A by a factor 1-3 (Holwerda et al., 2012a; van Dijk et al., 2015a; Simpson et al., 1998). Since g_A is the main anchor in SEBS, an underestimation of g_A would lead to an underestimation of sensible heat flux and an overestimation of ET (Gokmen et al., 2012; Paul et al., 2014). Also, due to the priority of estimating g_A and H , SEBS appears to ignore the important feedbacks between g_C , D_A , ϕ_s and transpiration (which

are included in STIC1.2) which consequently led to differences between STIC1.2 and SEBS. Relatively better performance of SEBS at croplands, as well as in wet years could be attributed to the ability of the model to perform well in predominantly homogeneous vegetation and under wet conditions where the differences between T_R and T_0 are not critical. The overestimation tendency of ET by SEBS was predominant during the dry year (Fig. 4 and Fig. S2). Notably, SEBS ET estimates were within 3%, 8%, and 17% of observed ET in the CRO, ENF, and DBF sites, respectively, which were comparable or sometimes better than the other two models (Fig. 5 and Table S1). In addition, the performance of SEBS was relatively good in cropland (Fig. 5). Overestimation of ET from SEBS is mostly associated with the underestimation of sensible heat flux (H) in the arid and semi-arid sites (nearly 41% underestimation in this study). Such underestimation of H by SEBS is highlighted by Chen et al. (2013), who proposed an improved way of estimating roughness length for heat transfer through a new parametrization of kB^{-1} adopted from Yang et al. (2002) for bare soil and snow surfaces. This could be the main reason for the better performance of SEBS_{Chen} ET product (Fig. 12) than the other models. STIC1.2 ET estimates compared well against those from SEBS_{Chen} ($R^2= 0.81$ and 0.58 , at monthly and annual scales) than the version of SEBS used in this study (Fig. 14). This comparison and better performance of SEBS_{Chen} demonstrated that improved kB^{-1} parametrization and better characterization of surface roughness are key to improve SEBS accuracies, typically in the arid and semi-arid ecosystems. However, it is also important to emphasize that different meteorological forcing was used to generate annual ET in SEBS_{Chen} and an explicit comparison of STIC1.2 with SEBS_{Chen} with same meteorological forcing is beyond the scope of this study.

The wide use of the global MOD16 ET product for calculating regional water and energy balances should be evaluated on a case-by-case basis as one could come to different conclusions using ET outputs from the other two models considered in this study. A significant underestimation of actual ET by the MOD16 ET products, particularly in arid and semiarid conditions has already been reported (Hu et al., 2015; Ramoelo et al., 2014; Feng et al., 2012). Conversely, others have reported better performance of MOD16 ET products in humid climates (Hu et al., 2015) and forest ecosystems (Kim et al., 2012), consistent with the performance of the model in the two flux sites in NC in our study (Table S1). Underestimation of ET by the MOD16 ET products in croplands has also been reported (Velpuri et al., 2013; Kim et al., 2012; Yang et al., 2015; Biggs et al., 2016), though not to the same degree extent as we found in this study. Yang et al. (2015) highlighted four key uncertainties associated with the MOD16 algorithm (Mu et al., 2011), which could explain the relatively poor performance of MOD16 in this study. First, the dependency of the MOD16 algorithm on meteorological forcing (and not the T_R) to account for the soil moisture restriction on evaporation and transpiration results in a slow response of variations in energy and heat fluxes (Long and Singh, 2010). Second, underestimation of transpiration in MOD16 could occur due to overestimation of environmental stresses on canopy conductance that is expressed as the potential canopy conductance multiplied by two empirical scaling factors that represent influences from T_A and VPD (Yang et al., 2013) Third, the empirical nature of the soil moisture constraint function (Fisher et al., 2008) based on the complementary hypothesis (Bouchet, 1963) using VPD and RH leads to large uncertainties in evaporation from the unsaturated soil. Finally, the coarse resolution meteorological data ($1^\circ \times 1.25^\circ$) used in MOD16 may not be well representative of surfaces with high moisture variability. This consistent underestimation of MOD16 ET in croplands and grasslands, and associated statistical errors in other biomes could be associated with both aerodynamic and

canopy conductance parameterizations and use of biome property look-up tables for assigning biome specific minimum and maximum conductances. Additionally, the empirical scaling functions used for constraining the conductances and the spatial scale mismatch between MODIS and flux towers could also introduce additional uncertainties in MOD16 ET. Similarly, our results suggest that caution should be taken when applying SEBS under the extreme dry condition, and also for grasslands, savannas, and deciduous broadleaf forests. The overestimation of grassland ET from SEBS is consistent with a recent study (Bhattarai et al., 2016), which could be attributed to the uncertain characterization of z_{OH} (Gokmen et al., 2012). However, the performance of SEBS was relatively better under wet conditions, and in homogeneous croplands and evergreen needleleaf forests (Fig. 5, Table S1). However, for regional scale ET modelling in heterogeneous landscapes, STIC1.2 appears to be better than the other two models given its consistency across a wide range of biomes and aridity conditions.

Apart from the simple parametrization of z_{OM} and canopy heights using NDVI, another source of uncertainty in the implementation of STIC1.2 and SEBS at the 8-day timescale (using MOD11A2) could be the use of average 8-day daily time meteorological inputs that may not well correspond with LST observation days within each MODIS 8-day cycle. We found all 8-day daytime averaged meteorological variables (those used in STIC1.2 and SEBS models) except wind speed to be well representative of instantaneous measurements within the 8-day period (Supplementary Table S2). This could be a source of additional uncertainty in SEBS since it uses wind speed to parameterize the aerodynamic conductance using MOST theory. Model implementation at instantaneous scale (i.e. MODIS overpass time and using daily MODIS products including MOD11A1 datasets) showed that the performance of STIC1.2 ($R^2=0.61$, PBIAS = -5%) was similar to its performance at the 8-day scale. However, for SEBS ($R^2=0.53$) the performance was marginally better with a PBIAS of 17% (Table S3). In addition to the wind speed, the slight overestimation of 8-day average ϕ (PBIAS=9%), and variations in T_R , T_A , $T_R - T_A$, and other meteorological variables during days within the corresponding 8-day period could have added positive biases to SEBS (increase from 17% to 28%), when evaluated at the 8-day scale. Conversely, the overestimation in ϕ could have slightly reduced STIC1.2 biases (increase from -5% to -3%). SEBS is sensitive to the meteorological input especially the temperature gradient and its performance is expected to degrade with the use of gridded forcing data (Ershadi et al., 2013; McCabe et al., 2016; van der Kwast et al., 2009; Vinukollu et al., 2011). Lewis et al. (2014) suggested that wind speed from NLDAS-2 may not be as reliable as other meteorological variables (T_A and RH) in the western US. (Lewis et al., 2014) Overall, the application of STIC1.2 and SEBS at the instantaneous scale showed similar predictive capacity and potential model strengths and weaknesses. STIC1.2 appears to be consistent through time, which could be due to the analytical nature and STIC1.2 does not rely on wind speed to solve for g_A and g_C . Results also suggest that biases from SEBS could be within 20% if uncertainties associated with meteorological and radiative forcing are reduced.

5 Conclusions

This paper establishes the first ever regional-scale implementation of a simplified thermal remote sensing based model, Surface Temperature Initiated Closure (STIC1.2) for spatially explicit ET mapping, which is independent of any empirical parameterization of aerodynamic/surface conductances and aerodynamic temperature. By combining MODIS land surface temperature, surface reflectances, and gridded weather data, we demonstrate the promise of STIC1.2 to generate regional ET at $1 \text{ km} \times 1 \text{ km}$ spatial resolution in the conterminous US. Independent validation of STIC1.2 using observed flux data from a dry, wet, and normal precipitation years at thirteen core AmeriFlux sites covering a wide range of climatic, biome, and aridity gradients in the US led us to the following conclusions.

(i) Overall, STIC1.2 explained significant variability in the observed 8-day cumulative ET with a root mean square error (RMSE) of less than 1 mm/day and was robust throughout dry, wet, and normal years. Biome-wise evaluation of STIC1.2 suggests the smallest errors in forest ecosystems, followed by grassland, cropland, and woody savannas. Underestimation of ET in croplands is mainly attributed to the spatial scale mismatch between a MODIS pixel and the flux tower footprint in croplands, and an overestimation of ET in woody savannas is mainly attributed to the large uncertainties in the MODIS LST product in savannas, and surface energy balance closure correction of eddy covariance ET observations.

(ii) STIC1.2 performed substantially better or comparable to SEBS and MOD16 in a broad spectrum of aridity, biome, and dry-wet extremes. Model evaluation in different aridity conditions suggests that all three models performed better under sub-humid and humid conditions as compared to arid or semi-arid conditions.

(iii) The principal difference between STIC1.2 and SEBS ET appears to be associated with the differences in aerodynamic conductance estimation between the two models. Empirical characterization of z_{0M} and kB^{-1} in SEBS are found to be the major factors creating uncertainties in aerodynamic conductance and ET estimations in SEBS, which is eventually responsible for large ET differences between the two models. Similarly, the differences in aerodynamic and surface conductance estimation between STIC1.2 and MOD16 could also be responsible for ET differences between the two models.

(iv) STIC1.2 is highly sensitive to uncertainties in T_R and hence accurate T_R maps are needed for reliable ET estimates, which are currently missing in arid and semiarid ecosystems. However with the improved emissivity corrected T_R from new the MODIS LST product (MOD21; Hulley et al., 2014; Hulley et al., 2016), an improved performance of STIC1.2 is expected in woody savannas. Alternatively, the use of time difference T_R from MODIS Terra Aqua can also help diminish STIC1.2 errors in woody savannas. Besides, gridded weather inputs (air temperature, RH, solar radiation), ideally at the resolution of T_R , are required for STIC1.2 implementation and hence any errors associated with the weather inputs will create biased model outputs. These insights should provide guidance for future implementations of STIC1.2 in the US and other regions.

30 Acknowledgements

The study was partly supported by NSF SEES Fellowship (Award # 1415436) and NASA New Investigator Award (NNH15ZDA001N) to Meha Jain. Kaniska Mallick was supported by Luxembourg Institute of Science and Technology (LIST)

through the project BIOTRANS (grant number, 00001145) and CAOS-2 project grant (INTER/DFG/14/02) funded by FNR (Fonds National de la Recherche) - DFG (German Science Foundation). This project also contributes to HiWET consortium funded by Belgian Science Policy (BELSPO) - FNR under the programme STEREOIII (INTER/STEREOIII/13/03/HiWET; CONTRACT NR SR/00/301).

5 Funding for AmeriFlux core site data was provided by the U.S. Department of Energy's Office of Science. The authors would like to thank all the principal investigators: Dr. Russell Scott, USDA- ARS (US-Wkg, US-SRM, and US-SRG); Asko Noormets, North Carolina State University (US-NC1 and US-NC2); Dr. Sebastien Biraud, Lawrence Berkeley National Lab (US-ARM); Dr. Dennis Baldocchi, University of California, Berkeley (US-Ton); Dr. Nathaniel A. Brunsell (NAB), University of Kansas (US-KFS and US-Kon); Dr. Kim Novick, Indiana University (US-MMS); Dr. Peter Blanken, University of Colorado (US-NR1); Andy Suyker, University of Nebraska, Lincoln (US-Ne1); and Dr. Bev Law, Oregon State University (US-Me2) for maintaining and providing access to the flux data for free. NAB acknowledges fundings for the US-Kon site through the NSF Long Term Ecological Research grant to the Konza Prairie (DEB-0823341), and for the US-Kon and US-KFS sites through AmeriFlux core site funding from the US Department of Energy under a sub contract from DE-AC02-05CH11231 and additional funding support through the USDA-AFRI 2014-67003-22070. The authors would also like to thank
10 Dr. Bob Su and Dr. Xuelong Chen from the University of Twente, Netherlands for answering queries related to the SEBS model. Special thanks to Julia Stuart (undergraduate researcher) for helping out with literature search. The authors would like to acknowledge high-performance computing support from Yellowstone (ark:/85065/d7wd3xhc) provided by NCAR's Computational and Information Systems Laboratory, sponsored by the National Science Foundation. Finally, the authors would also like to thanks all the reviewers for useful comments and suggestions to improve this manuscript. Authors declare
15 no conflict of interest.
20

References

- 25 Abatzoglou, J. T.: Development of gridded surface meteorological data for ecological applications and modelling, *International Journal of Climatology*, 33, 121-131, 10.1002/joc.3413, 2013.
- Agam, N., and Berliner, P. R.: Dew formation and water vapor adsorption in semi-arid environments—A review, *Journal of Arid Environments*, 65, 572-590, <http://dx.doi.org/10.1016/j.jaridenv.2005.09.004>, 2006.
- 30 Allen, R., Irmak, A., Trezza, R., Hendrickx, J. M. H., Bastiaanssen, W., and Kjaersgaard, J.: Satellite-based ET estimation in agriculture using SEBAL and METRIC, *Hydrological Processes*, 25, 4011-4027, 10.1002/hyp.8408, 2011.
- Allen, R. G., Tasumi, M., and Trezza, R.: Satellite-based energy balance for mapping evapotranspiration with internalized calibration (METRIC) - Model, *J Irrig Drain Eng*, 133, 380-394, 10.1061/(Asce)0733-9437(2007)133:4(380), 2007.
- Anderson, M. C., Kustas, W. P., Norman, J. M., Hain, C. R., Mecikalski, J. R., Schultz, L., Gonzalez-Dugo, M. P., Cammalleri, C., d'Urso, G., Pimstein, A., and Gao, F.: Mapping daily evapotranspiration at field to continental scales using geostationary and polar orbiting satellite
35 imagery, *Hydrology and Earth System Sciences*, 15, 223-239, 10.5194/hess-15-223-2011, 2011.

- Anderson, M. C., Allen, R. G., Morse, A., and Kustas, W. P.: Use of Landsat thermal imagery in monitoring evapotranspiration and managing water resources, *Remote Sensing of Environment*, 122, 50-65, 10.1016/j.rse.2011.08.025, 2012.
- ASCE-EWRI: The ASCE standardized reference evapotranspiration equation: ASCE-EWRI Standardization of Reference Evapotranspiration Task Committee Report, 2005,
- 5 Baldocchi, D. D., and Wilson, K. B.: Modeling CO₂ and water vapor exchange of a temperate broadleaved forest across hourly to decadal time scales, *Ecological Modelling*, 142, 155-184, [http://dx.doi.org/10.1016/S0304-3800\(01\)00287-3](http://dx.doi.org/10.1016/S0304-3800(01)00287-3), 2001.
- Baldocchi, D. D., Xu, L., and Kiang, N.: How plant functional-type, weather, seasonal drought, and soil physical properties alter water and energy fluxes of an oak-grass savanna and an annual grassland, *Agricultural and Forest Meteorology*, 123, 13-39, <http://dx.doi.org/10.1016/j.agrformet.2003.11.006>, 2004.
- 10 Bastiaanssen, W. G. M.: SEBAL-based sensible and latent heat fluxes in the irrigated Gediz Basin, Turkey, *Journal of Hydrology*, 229, 87-100, [http://dx.doi.org/10.1016/S0022-1694\(99\)00202-4](http://dx.doi.org/10.1016/S0022-1694(99)00202-4), 2000.
- Bell, D. M., Ward, E. J., Oishi, A. C., Oren, R., Flikkema, P. G., and Clark, J. S.: A state-space modeling approach to estimating canopy conductance and associated uncertainties from sap flux density data, *Tree Physiol*, 35, 792-802, 10.1093/treephys/tpv041, 2015.
- Bhattarai, N., Shaw, S. B., Quackenbush, L. J., Im, J., and Niraula, R.: Evaluating five remote sensing based single-source surface energy balance models for estimating daily evapotranspiration in a humid subtropical climate, *Int J Appl Earth Obs*, 49, 75-86, <https://doi.org/10.1016/j.jag.2016.01.010>, 2016.
- 15 Biggs, T. W., Marshall, M., and Messina, A.: Mapping daily and seasonal evapotranspiration from irrigated crops using global climate grids and satellite imagery: Automation and methods comparison, *Water Resour Res*, 52, 7311-7326, 10.1002/2016WR019107, 2016.
- Biraud, S.: AmeriFlux US-ARM Southern Great Plains site- Lamont, Lawrence Berkeley National Laboratory, 2002.
- 20 Bisht, G., Venturini, V., Islam, S., and Jiang, L.: Estimation of the net radiation using MODIS (Moderate Resolution Imaging Spectroradiometer) data for clear sky days, *Remote Sensing of Environment*, 97, 52-67, <http://dx.doi.org/10.1016/j.rse.2005.03.014>, 2005.
- Blonquist, J. M., Norman, J. M., and Bugbee, B.: Automated measurement of canopy stomatal conductance based on infrared temperature, *Agricultural and Forest Meteorology*, 149, 1931-1945, <http://dx.doi.org/10.1016/j.agrformet.2009.06.021>, 2009.
- Boegh, E., Soegaard, H., and Thomsen, A.: Evaluating evapotranspiration rates and surface conditions using Landsat TM to estimate atmospheric resistance and surface resistance, *Remote Sensing of Environment*, 79, 329-343, Doi 10.1016/S0034-4257(01)00283-8, 2002.
- 25 Boegh, E., and Soegaard, H.: Remote sensing based estimation of evapotranspiration rates, *Int J Remote Sens*, 25, 2535-2551, 10.1080/01431160310001647975, 2004.
- Bouchet, R.: Evapotranspiration réelle, evapotranspiration potentielle, et production agricole, *Annales Agronomiques*, 1963, 743-824,
- Boulet, G., Olioso, A., Ceschia, E., Marloie, O., Coudert, B., Rivalland, V., Chirouze, J., and Chehbouni, G.: An empirical expression to relate aerodynamic and surface temperatures for use within single-source energy balance models, *Agricultural and Forest Meteorology*, 161, 148-155, 10.1016/j.agrformet.2012.03.008, 2012.
- 30 Bowen, I. S.: The ratio of heat losses by conduction and by evaporation from any water surface, *Phys Rev*, 27, 779, 1926.
- Brutsaert, W., and Stricker, H.: An advection-aridity approach to estimate actual regional evapotranspiration, *Water Resour Res*, 15, 443-450, 10.1029/WR015i002p00443, 1979.
- 35 Brutsaert, W., and Sugita, M.: Application of self-preservation in the diurnal evolution of the surface energy budget to determine daily evaporation, *Journal of Geophysical Research: Atmospheres*, 97, 18377-18382, 10.1029/92JD00255, 1992.
- Brutsaert, W.: *Hydrology: an introduction*, Cambridge University Press, 2005.

- Chávez, J., Neale, C. M. U., Hipps, L. E., Prueger, J. H., and Kustas, W. P.: Comparing Aircraft-Based Remotely Sensed Energy Balance Fluxes with Eddy Covariance Tower Data Using Heat Flux Source Area Functions, *J Hydrometeorol*, 6, 923-940, 10.1175/jhm467.1, 2005.
- Chávez, J., Howell, T., Gowda, P., Copeland, K., and Prueger, J.: Surface aerodynamic temperature modeling over rainfed cotton, *Transactions of the ASABE*, 53, 759-767, 2010.
- 5 Chen, X., Su, Z., Ma, Y., Yang, K., Wen, J., and Zhang, Y.: An Improvement of Roughness Height Parameterization of the Surface Energy Balance System (SEBS) over the Tibetan Plateau, *Journal of Applied Meteorology and Climatology*, 52, 607-622, 10.1175/jamc-d-12-056.1, 2013.
- Chen, X., Su, Z., Ma, Y., Liu, S., Yu, Q., and Xu, Z.: Development of a 10-year (2001-2010) 0.1° data set of land-surface energy balance for mainland China, *Atmospheric Chemistry and Physics*, 14, 13097-13117, 2014.
- 10 Colaizzi, P. D., Evett, S. R., Howell, T. A., and Tolk, J. A.: Comparison of aerodynamic and radiometric surface temperature using precision weighing lysimeters, *Optical Science and Technology, the SPIE 49th Annual Meeting*, 2004, 215-229,
- Crago, R., and Brutsaert, W.: Daytime evaporation and the self-preservation of the evaporative fraction and the Bowen ratio, *Journal of Hydrology*, 178, 241-255, Doi 10.1016/0022-1694(95)02803-X, 1996.
- Domec, J.-C., King, J. S., Ward, E., Christopher Oishi, A., Palmroth, S., Radecki, A., Bell, D. M., Miao, G., Gavazzi, M., Johnson, D. M.,
- 15 McNulty, S. G., Sun, G., and Noormets, A.: Conversion of natural forests to managed forest plantations decreases tree resistance to prolonged droughts, *Forest Ecology and Management*, 355, 58-71, <https://doi.org/10.1016/j.foreco.2015.04.012>, 2015.
- Ershadi, A., McCabe, M. F., Evans, J. P., Mariethoz, G., and Kavetski, D.: A Bayesian analysis of sensible heat flux estimation: Quantifying uncertainty in meteorological forcing to improve model prediction, *Water Resour Res*, 49, 2343-2358, 2013.
- Feng, X. M., Sun, G., Fu, B. J., Su, C. H., Liu, Y., and Lamparski, H.: Regional effects of vegetation restoration on water yield across the
- 20 Loess Plateau, China, *Hydrol. Earth Syst. Sci.* 16:2617–2628, 16, 2617-2628, 2012.
- Finnigan, J. J., Shaw, R. H., and Patton, E. G.: Turbulence structure above a vegetation canopy, *Journal of Fluid Mechanics*, 637, 387-424, 10.1017/S0022112009990589, 2009.
- Fisher, J. B., Tu, K. P., and Baldocchi, D. D.: Global estimates of the land-atmosphere water flux based on monthly AVHRR and ISLSCP-II data, validated at 16 FLUXNET sites, *Remote Sensing of Environment*, 112, 901-919, <https://doi.org/10.1016/j.rse.2007.06.025>, 2008.
- 25 Foken, T.: 50 Years of the Monin-Obukhov Similarity Theory, *Bound-Lay Meteorol*, 119, 431-447, 10.1007/s10546-006-9048-6, 2006.
- Friedl, M. A., Sulla-Menashe, D., Tan, B., Schneider, A., Ramankutty, N., Sibley, A., and Huang, X.: MODIS Collection 5 global land cover: Algorithm refinements and characterization of new datasets, *Remote Sensing of Environment*, 114, 168-182, <http://dx.doi.org/10.1016/j.rse.2009.08.016>, 2010.
- Garratt, J. R.: Flux profile relations above tall vegetation, *Quarterly Journal of the Royal Meteorological Society*, 104, 199-211,
- 30 10.1002/qj.49710443915, 1978.
- Gokmen, M., Vekerdy, Z., Verhoef, A., Verhoef, W., Batelaan, O., and van der Tol, C.: Integration of soil moisture in SEBS for improving evapotranspiration estimation under water stress conditions, *Remote Sensing of Environment*, 121, 261-274, <http://dx.doi.org/10.1016/j.rse.2012.02.003>, 2012.
- Harman, I. N., and Finnigan, J. J.: A simple unified theory for flow in the canopy and roughness sublayer, *Bound-Lay Meteorol*, 123, 339-
- 35 363, 10.1007/s10546-006-9145-6, 2007.
- Holwerda, F., Bruijnzeel, L., Scatena, F., Vugts, H., and Meesters, A.: Wet canopy evaporation from a Puerto Rican lower montane rain forest: The importance of realistically estimated aerodynamic conductance, *Journal of Hydrology*, 414, 1-15, 2012a.

- Holwerda, F., Bruijnzeel, L. A., Scatena, F. N., Vugts, H. F., and Meesters, A. G. C. A.: Wet canopy evaporation from a Puerto Rican lower montane rain forest: The importance of realistically estimated aerodynamic conductance, *Journal of Hydrology*, 414, 1-15, <http://dx.doi.org/10.1016/j.jhydrol.2011.07.033>, 2012b.
- Hu, G., Jia, L., and Menenti, M.: Comparison of MOD16 and LSA-SAF MSG evapotranspiration products over Europe for 2011, *Remote Sensing of Environment*, 156, 510-526, <http://dx.doi.org/10.1016/j.rse.2014.10.017>, 2015.
- 5 Hulley, G., Veraverbeke, S., and Hook, S.: Thermal-based techniques for land cover change detection using a new dynamic MODIS multispectral emissivity product (MOD21), *Remote Sensing of Environment*, 140, 755-765, <http://dx.doi.org/10.1016/j.rse.2013.10.014>, 2014.
- Hulley, G., Malakar, N., Hughes, T., Islam, T., and Hook, S.: Moderate resolution imaging spectroradiometer (MODIS) MOD21 land surface temperature and emissivity algorithm theoretical basis document, Pasadena, CA: Jet Propulsion Laboratory, National Aeronautics and Space Administration, 2016, 2016.
- 10 Hulley, G. C., Hughes, C. G., and Hook, S. J.: Quantifying uncertainties in land surface temperature and emissivity retrievals from ASTER and MODIS thermal infrared data, *Journal of Geophysical Research: Atmospheres*, 117, n/a-n/a, 10.1029/2012JD018506, 2012.
- Jin, M., and Liang, S.: An Improved Land Surface Emissivity Parameter for Land Surface Models Using Global Remote Sensing Observations, *Journal of Climate*, 19, 2867-2881, 10.1175/jcli3720.1, 2006.
- 15 Kim, H. W., Hwang, K., Mu, Q., Lee, S. O., and Choi, M.: Validation of MODIS 16 global terrestrial evapotranspiration products in various climates and land cover types in Asia, *KSCE Journal of Civil Engineering*, 16, 229-238, 10.1007/s12205-012-0006-1, 2012.
- Kustas, W., and Norman, J.: Use of remote sensing for evapotranspiration monitoring over land surfaces, *Hydrological Sciences Journal*, 41, 495-516, 1996.
- 20 Kustas, W., and Anderson, M.: Advances in thermal infrared remote sensing for land surface modeling, *Agricultural and Forest Meteorology*, 149, 2071-2081, 10.1016/j.agrformet.2009.05.016, 2009.
- Kustas, W. P., and Norman, J. M.: A two-source approach for estimating turbulent fluxes using multiple angle thermal infrared observations, *Water Resour Res*, 33, 1495-1508, 10.1029/97WR00704, 1997.
- Kustas, W. P., Nieto, H., Morillas, L., Anderson, M. C., Alfieri, J. G., Hipps, L. E., Villagarcía, L., Domingo, F., and Garcia, M.: Revisiting the paper "Using radiometric surface temperature for surface energy flux estimation in Mediterranean drylands from a two-source perspective", *Remote Sensing of Environment*, 184, 645-653, <https://doi.org/10.1016/j.rse.2016.07.024>, 2016.
- 25 Lewis, C. S., Geli, H. M. E., and Neale, C. M. U.: Comparison of the NLDAS Weather Forcing Model to Agrometeorological Measurements in the western United States, *Journal of Hydrology*, 510, 385-392, <https://doi.org/10.1016/j.jhydrol.2013.12.040>, 2014.
- Lhomme, J.-P., and Montes, C.: Generalized combination equations for canopy evaporation under dry and wet conditions, *Hydrology and Earth System Sciences*, 18, 1137-1149, 2014.
- 30 Liaw, A., and Wiener, M.: Classification and regression by randomForest, *R news*, 2, 18-22, 2002.
- Liu, S., Lu, L., Mao, D., and Jia, L.: Evaluating parameterizations of aerodynamic resistance to heat transfer using field measurements, *Hydrol. Earth Syst. Sci.*, 11, 769-783, 10.5194/hess-11-769-2007, 2007.
- Logan, K. E., and Brunsell, N. A.: Influence of drought on growing season carbon and water cycling with changing land cover, *Agricultural and Forest Meteorology*, 213, 217-225, <https://doi.org/10.1016/j.agrformet.2015.07.002>, 2015.
- 35 Long, D., and Singh, V. P.: Integration of the GG model with SEBAL to produce time series of evapotranspiration of high spatial resolution at watershed scales, *Journal of Geophysical Research: Atmospheres*, 115, n/a-n/a, 10.1029/2010JD014092, 2010.

- Mallick, K., Jarvis, A. J., Boegh, E., Fisher, J. B., Drewry, D. T., Tu, K. P., Hook, S. J., Hulley, G., Ardo, J., Beringer, J., Arain, A., and Niyogi, D.: A Surface Temperature Initiated Closure (STIC) for surface energy balance fluxes, *Remote Sensing of Environment*, 141, 243-261, 10.1016/j.rse.2013.10.022, 2014.
- Mallick, K., Boegh, E., Trebs, I., Alfieri, J. G., Kustas, W. P., Prueger, J. H., Niyogi, D., Das, N., Drewry, D. T., Hoffmann, L., and Jarvis, A. J.: Reintroducing radiometric surface temperature into the Penman-Monteith formulation, *Water Resour Res*, 51, 6214-6243, 10.1002/2014wr016106, 2015.
- Mallick, K., Trebs, I., Boegh, E., Giustarini, L., Schlerf, M., Drewry, D. T., Hoffmann, L., von Randow, C., Kruijt, B., Araújo, A., Saleska, S., Ehleringer, J. R., Domingues, T. F., Ometto, J. P. H. B., Nobre, A. D., de Moraes, O. L. L., Hayek, M., Munger, J. W., and Wofsy, S. C.: Canopy-scale biophysical controls of transpiration and evaporation in the Amazon Basin, *Hydrol. Earth Syst. Sci.*, 20, 4237-4264, 10.5194/hess-20-4237-2016, 2016.
- Mallick, K., Toivonen, E., Trebs, I., Boegh, E., Cleverly, J., Eamus, D., Koivusalo, H., Dewry, D., Arndt, S. K., Griebel, A., Beringer, J., and Garcia, M.: Bridging thermal infrared sensing and physically-based evapotranspiration modeling: from theoretical implementation to validation across an aridity gradient in Australian ecosystems, *Water Resour Res*, In Review.
- Matheny, A. M., Bohrer, G., Stoy, P. C., Baker, I. T., Black, A. T., Desai, A. R., Dietze, M. C., Gough, C. M., Ivanov, V. Y., Jassal, R. S., Novick, K. A., Schafer, K. V. R., and Verbeeck, H.: Characterizing the diurnal patterns of errors in the prediction of evapotranspiration by several land-surface models: An NACP analysis, *J Geophys Res-Bioge*, 119, 1458-1473, 10.1002/2014jg002623, 2014.
- McCabe, M. F., Ershadi, A., Jimenez, C., Miralles, D. G., Michel, D., and Wood, E. F.: The GEWEX LandFlux project: evaluation of model evaporation using tower-based and globally gridded forcing data, *Geosci Model Dev*, 9, 283-305, 10.5194/gmd-9-283-2016, 2016.
- McHugh, T. A., Morrissey, E. M., Reed, S. C., Hungate, B. A., and Schwartz, E.: Water from air: an overlooked source of moisture in arid and semiarid regions, 5, 13767, 10.1038/srep13767
<https://www.nature.com/articles/srep13767#supplementary-information>, 2015.
- McNaughton, K. G., and Jarvis, P. G.: Using the Penman-Monteith equation predictively, *Agricultural Water Management*, 8, 263-278, [http://dx.doi.org/10.1016/0378-3774\(84\)90057-X](http://dx.doi.org/10.1016/0378-3774(84)90057-X), 1984.
- Mitchell, K. E., Lohmann, D., Houser, P. R., Wood, E. F., Schaake, J. C., Robock, A., Cosgrove, B. A., Sheffield, J., Duan, Q., Luo, L., Higgins, R. W., Pinker, R. T., Tarpley, J. D., Lettenmaier, D. P., Marshall, C. H., Entin, J. K., Pan, M., Shi, W., Koren, V., Meng, J., Ramsay, B. H., and Bailey, A. A.: The multi-institution North American Land Data Assimilation System (NLDAS): Utilizing multiple GCIP products and partners in a continental distributed hydrological modeling system, *Journal of Geophysical Research: Atmospheres*, 109, n/a-n/a, 10.1029/2003JD003823, 2004.
- Moffett, K. B., and Gorelick, S. M.: A method to calculate heterogeneous evapotranspiration using submeter thermal infrared imagery coupled to a stomatal resistance submodel, *Water Resour Res*, 48, n/a-n/a, 10.1029/2011WR010407, 2012.
- Monson, R. K., Sparks, J. P., Rosenstiel, T. N., Scott-Denton, L. E., Huxman, T. E., Harley, P. C., Turnipseed, A. A., Burns, S. P., Backlund, B., and Hu, J.: Climatic influences on net ecosystem CO₂ exchange during the transition from wintertime carbon source to springtime carbon sink in a high-elevation, subalpine forest, *Oecologia*, 146, 130-147, 10.1007/s00442-005-0169-2, 2005.
- Monteith, J.: Evaporation and environment, *Symp. Soc. Exp. Biol.*, 1965, 4.
- Monteith, J. L.: Evaporation and surface temperature, *Quarterly Journal of the Royal Meteorological Society*, 107, 1-27, 10.1002/qj.49710745102, 1981.
- Mu, Q., Heinsch, F. A., Zhao, M., and Running, S. W.: Development of a global evapotranspiration algorithm based on MODIS and global meteorology data, *Remote Sensing of Environment*, 111, 519-536, <http://dx.doi.org/10.1016/j.rse.2007.04.015>, 2007.

- Mu, Q., Zhao, M., and Running, S. W.: Improvements to a MODIS global terrestrial evapotranspiration algorithm, *Remote Sensing of Environment*, 115, 1781-1800, <http://dx.doi.org/10.1016/j.rse.2011.02.019>, 2011.
- Myneni, R. B., Hoffman, S., Knyazikhin, Y., Privette, J. L., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G. R., Lotsch, A., Friedl, M., Morisette, J. T., Votava, P., Nemani, R. R., and Running, S. W.: Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data, *Remote Sensing of Environment*, 83, 214-231, [http://dx.doi.org/10.1016/S0034-4257\(02\)00074-3](http://dx.doi.org/10.1016/S0034-4257(02)00074-3), 2002.
- Norman, J. M., Kustas, W. P., and Humes, K. S.: Source approach for estimating soil and vegetation energy fluxes in observations of directional radiometric surface temperature, *Agricultural and Forest Meteorology*, 77, 263-293, [http://dx.doi.org/10.1016/0168-1923\(95\)02265-Y](http://dx.doi.org/10.1016/0168-1923(95)02265-Y), 1995.
- 10 Numata, I., Khand, K., Kjaersgaard, J., Cochrane, M. A., and Silva, S. S.: Evaluation of Landsat-Based METRIC Modeling to Provide High-Spatial Resolution Evapotranspiration Estimates for Amazonian Forests, *Remote Sensing*, 9, 46, 2017.
- Paul, G., Gowda, P. H., Vara Prasad, P. V., Howell, T. A., Aiken, R. M., and Neale, C. M. U.: Investigating the influence of roughness length for heat transport (zoh) on the performance of SEBAL in semi-arid irrigated and dryland agricultural systems, *Journal of Hydrology*, 509, 231-244, <http://dx.doi.org/10.1016/j.jhydrol.2013.11.040>, 2014.
- 15 Philip, R., and Novick, K.: AmeriFlux US-MMS Morgan Monroe State Forest, AmeriFlux; Indiana University, 2016.
- Priestley, C., and Taylor, R.: On the assessment of surface heat flux and evaporation using large-scale parameters, *Monthly weather review*, 100, 81-92, 10.1175/1520-0493(1972)100<0081:otaosh>2.3.co;2, 1972.
- Ramoelo, A., Majazi, N., Mathieu, R., Jovanovic, N., Nickless, A., and Dziki, S.: Validation of Global Evapotranspiration Product (MOD16) using Flux Tower Data in the African Savanna, South Africa, *Remote Sensing*, 6, 7406, 2014.
- 20 Raupach, M. R.: Influences of local feedbacks on land-air exchanges of energy and carbon, *Global Change Biology*, 4, 477-494, 10.1046/j.1365-2486.1998.t01-1-00155.x, 1998.
- Scott, R. L., Biederman, J. A., Hamerlynck, E. P., and Barron-Gafford, G. A.: The carbon balance pivot point of southwestern U.S. semiarid ecosystems: Insights from the 21st century drought, *Journal of Geophysical Research: Biogeosciences*, 120, 2612-2624, 10.1002/2015JG003181, 2015.
- 25 Shuttleworth, W., Gurney, R., Hsu, A., and Ormsby, J.: FIFE: the variation in energy partition at surface flux sites, *IAHS Publ*, 186, 1989.
- Shuttleworth, W. J., and Wallace, J. S.: Evaporation from sparse crops-an energy combination theory, *Quarterly Journal of the Royal Meteorological Society*, 111, 839-855, 10.1002/qj.49711146910, 1985.
- Simpson, I. J., Thurtell, G. W., Neumann, H. H., Den Hartog, G., and Edwards, G. C.: The Validity of Similarity Theory in the Roughness Sublayer Above Forests, *Bound-Lay Meteorol*, 87, 69-99, 10.1023/a:1000809902980, 1998.
- 30 Stoy, P. C., Mauder, M., Foken, T., Marcolla, B., Boegh, E., Ibrom, A., Arain, M. A., Arneth, A., Aurela, M., Bernhofer, C., Cescatti, A., Dellwik, E., Duce, P., Gianelle, D., van Gorsel, E., Kieley, G., Knohl, A., Margolis, H., McCaughey, H., Merbold, L., Montagnani, L., Papale, D., Reichstein, M., Saunders, M., Serrano-Ortiz, P., Sottocornola, M., Spano, D., Vaccari, F., and Varlagin, A.: A data-driven analysis of energy balance closure across FLUXNET research sites: The role of landscape scale heterogeneity, *Agricultural and Forest Meteorology*, 171, 137-152, <http://dx.doi.org/10.1016/j.agrformet.2012.11.004>, 2013.
- 35 Su, Z., Schmugge, T., Kustas, W. P., and Massman, W. J.: An Evaluation of Two Models for Estimation of the Roughness Height for Heat Transfer between the Land Surface and the Atmosphere, *J Appl Meteorol*, 40, 1933-1951, 10.1175/1520-0450(2001)040<1933:aeotmf>2.0.co;2, 2001.

- Su, Z.: The Surface Energy Balance System (SEBS) for estimation of turbulent heat fluxes, *Hydrol. Earth Syst. Sci.*, 6, 85-100, 10.5194/hess-6-85-2002, 2002.
- Sun, G., Noormets, A., Gavazzi, M. J., McNulty, S. G., Chen, J., Domec, J. C., King, J. S., Amatya, D. M., and Skaggs, R. W.: Energy and water balance of two contrasting loblolly pine plantations on the lower coastal plain of North Carolina, USA, *Forest Ecology and Management*, 259, 1299-1310, <http://dx.doi.org/10.1016/j.foreco.2009.09.016>, 2010.
- Suyker, A.: AmeriFlux US-Ne1 Mead-irrigated continuous maize site, AmeriFlux; University of Nebraska-Lincoln, 2016.
- Thomas, C. K., Law, B. E., Irvine, J., Martin, J. G., Pettijohn, J. C., and Davis, K. J.: Seasonal hydrology explains interannual and seasonal variation in carbon and water exchange in a semiarid mature ponderosa pine forest in central Oregon, *Journal of Geophysical Research: Biogeosciences*, 114, n/a-n/a, 10.1029/2009JG001010, 2009.
- 10 Timmermans, J., Su, Z., van der Tol, C., Verhoef, A., and Verhoef, W.: Quantifying the uncertainty in estimates of surface-atmosphere fluxes through joint evaluation of the SEBS and SCOPE models, *Hydrol. Earth Syst. Sci.*, 17, 1561-1573, 10.5194/hess-17-1561-2013, 2013.
- Troufleau, D., Lhomme, J. P., Monteny, B., and Vidal, A.: Sensible heat flux and radiometric surface temperature over sparse Sahelian vegetation. I. An experimental analysis of the kB-1 parameter, *Journal of Hydrology*, 188, 815-838, [http://dx.doi.org/10.1016/S0022-1694\(96\)03172-1](http://dx.doi.org/10.1016/S0022-1694(96)03172-1), 1997.
- 15 Tucker, C. J.: Red and photographic infrared linear combinations for monitoring vegetation, *Remote Sensing of Environment*, 8, 127-150, 1979.
- Twine, T. E., Kustas, W. P., Norman, J. M., Cook, D. R., Houser, P. R., Meyers, T. P., Prueger, J. H., Starks, P. J., and Wesely, M. L.: Correcting eddy-covariance flux underestimates over a grassland, *Agricultural and Forest Meteorology*, 103, 279-300, [http://dx.doi.org/10.1016/S0168-1923\(00\)00123-4](http://dx.doi.org/10.1016/S0168-1923(00)00123-4), 2000.
- 20 van der Kwast, J., Timmermans, W., Gieske, A., Su, Z., Olioso, A., Jia, L., Elbers, J., Karssenber, D., and de Jong, S.: Evaluation of the Surface Energy Balance System (SEBS) applied to ASTER imagery with flux-measurements at the SPARC 2004 site (Barrax, Spain), *Hydrol. Earth Syst. Sci.*, 13, 1337-1347, 10.5194/hess-13-1337-2009, 2009.
- van Dijk, A. I., Gash, J. H., van Gorsel, E., Blanken, P. D., Cescatti, A., Emmel, C., Gielen, B., Harman, I. N., Kiely, G., and Merbold, L.: Rainfall interception and the coupled surface water and energy balance, *Agricultural and Forest Meteorology*, 214, 402-415, 2015a.
- 25 van Dijk, A. I. J. M., Gash, J. H., van Gorsel, E., Blanken, P. D., Cescatti, A., Emmel, C., Gielen, B., Harman, I. N., Kiely, G., Merbold, L., Montagnani, L., Moors, E., Sottocornola, M., Varlagin, A., Williams, C. A., and Wohlfahrt, G.: Rainfall interception and the coupled surface water and energy balance, *Agricultural and Forest Meteorology*, 214-215, 402-415, <https://doi.org/10.1016/j.agrformet.2015.09.006>, 2015b.
- Velpuri, N. M., Senay, G. B., Singh, R. K., Bohms, S., and Verdin, J. P.: A comprehensive evaluation of two MODIS evapotranspiration products over the conterminous United States: Using point and gridded FLUXNET and water balance ET, *Remote Sensing of Environment*, 139, 35-49, <http://dx.doi.org/10.1016/j.rse.2013.07.013>, 2013.
- 30 Venturini, V., Islam, S., and Rodriguez, L.: Estimation of evaporative fraction and evapotranspiration from MODIS products using a complementary based model, *Remote Sensing of Environment*, 112, 132-141, <http://dx.doi.org/10.1016/j.rse.2007.04.014>, 2008.
- Verhoef, A., Bruin, H. A. R. D., and Hurk, B. J. J. M. V. D.: Some Practical Notes on the Parameter kB-1 for Sparse Vegetation, *J Appl Meteorol*, 36, 560-572, 10.1175/1520-0450(1997)036<0560:spnotp>2.0.co;2, 1997a.
- 35 Verhoef, A., De Bruin, H., and Van Den Hurk, B.: Some practical notes on the parameter kB-1 for sparse vegetation, *J Appl Meteorol*, 36, 560-572, 1997b.
- Verhoef, A., McNaughton, K. G., and Jacobs, A. F. G.: A parameterization of momentum roughness length and displacement height for a wide range of canopy densities, *Hydrol. Earth Syst. Sci.*, 1, 81-91, 10.5194/hess-1-81-1997, 1997c.

- Vermote, E.: MOD09A1MODIS/Terra Surface Reflectance 8-Day L3 Global 500m SIN Grid V006, NASA EOSDIS Land Processes DAAC, 2015.
- Vinukollu, R. K., Wood, E. F., Ferguson, C. R., and Fisher, J. B.: Global estimates of evapotranspiration for climate studies using multi-sensor remote sensing data: Evaluation of three process-based approaches, *Remote Sensing of Environment*, 115, 801-823, 2011.
- 5 Wagle, P., Bhattarai, N., Gowda, P. H., and Kakani, V. G.: Performance of five surface energy balance models for estimating daily evapotranspiration in high biomass sorghum, *ISPRS Journal of Photogrammetry and Remote Sensing*, 128, 192-203, <https://doi.org/10.1016/j.isprsjprs.2017.03.022>, 2017.
- Wan, Z., and Li, Z. L.: Radiance-based validation of the V5 MODIS land-surface temperature product, *Int J Remote Sens*, 29, 5373-5395, 10.1080/01431160802036565, 2008.
- 10 Wan, Z., Hook, S., and Hulley, G.: MOD11A2 MODIS/Terra Land Surface Temperature/Emissivity 8-Day L3 Global 1 km SIN Grid V006, NASA EOSDIS Land Processes DAAC, USGS Earth Resources Observation and Science (EROS) Center. <https://lpdaac.usgs.gov> (accessed 16 June 2016): Sioux Falls, SD, doi, 10, 2015.
- Xia, Y., Mitchell, K., Ek, M., Sheffield, J., Cosgrove, B., Wood, E., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Lettenmaier, D., Koren, V., Duan, Q., Mo, K., Fan, Y., and Mocko, D.: Continental-scale water and energy flux analysis and validation for the North American
- 15 Land Data Assimilation System project phase 2 (NLDAS-2): 1. Intercomparison and application of model products, *Journal of Geophysical Research: Atmospheres*, 117, n/a-n/a, 10.1029/2011JD016048, 2012.
- Yang, J., Gong, P., Fu, R., Zhang, M., Chen, J., Liang, S., Xu, B., Shi, J., and Dickinson, R.: The role of satellite remote sensing in climate change studies, *Nature Climate Change*, 3, 875, 10.1038/nclimate1908 <https://www.nature.com/articles/nclimate1908#supplementary-information>, 2013.
- 20 Yang, Y., Long, D., Guan, H., Liang, W., Simmons, C., and Batelaan, O.: Comparison of three dual-source remote sensing evapotranspiration models during the MUSOEXE-12 campaign: Revisit of model physics, *Water Resour Res*, 51, 3145-3165, 10.1002/2014WR015619, 2015.
- Zhou, Y., Ju, W., Sun, X., Wen, X., and Guan, D.: Significant Decrease of Uncertainties in Sensible Heat Flux Simulation Using Temporally Variable Aerodynamic Roughness in Two Typical Forest Ecosystems of China, *Journal of Applied Meteorology and Climatology*, 51, 1099-1110, 10.1175/jamc-d-11-0243.1, 2012.

25

Table 1. An overview of the thirteen core AmeriFlux sites used for the validation of the STIC1.2 model.

Site Name	Latitude	Longitude	Elevation	Biome*	Average T_A (C)	Average Annual P (mm)	Climate**	Aridity Index (AI***)	Reference
US-Me2	44.4523	-121.557	1253	ENF	6.28	523	M	1.004	Thomas et al. (2009)
US-Ton	38.4316	-120.966	177	WSA	15.8	559	M	0.440	Baldocchi et al. (2004)
US-SRM	31.8200	-110.8700	1120	WSA	17.92	380	ASC	0.258	Scott et al. (2015)
US-SRG	31.7894	-110.828	1291	GRA	17	420	ASC	0.317	Scott et al. (2015)
US-Wkg	31.7365	-109.942	1531	GRA	15.64	407	ASC	0.225	Scott et al. (2015)
US-NR1	40.0329	-105.546	3050	ENF	1.5	800	SA	0.478	Monson et al. (2005)
US-Kon	39.0824	-96.5603	330	GRA	12.77	867	HS	0.674	Logan and Brunsell (2015)
US-KFS	39.0561	-95.1907	310	GRA	12	1014	HS	0.807	
US-ARM	36.6058	-97.4888	314	CRO	14.76	843	HS	0.551	Biraud (2002)
US-Ne1	41.1651	-96.4766	361	CRO	10.07	790	HC	0.645	Suyker (2016)
US-MMS	39.3232	-86.4131	275	DBF	10.85	1032	HS	0.984	Philip and Novick (2016)
US-NC1	35.8118	-76.7119	5	ENF	16.6	1320	HS	1.031	Domec et al. (2015), Sun et al. (2010)
US-NC2	35.8030	-76.6685	5	ENF	16.6	1320	HS	1.031	Domec et al. (2015), Sun et al. (2010)

* WSA = Woody savanna, GRA = Grassland, ENF = Evergreen needleleaf forest, DBF = Deciduous broadleaf forest, CRO=croplands

**M = Mediterranean, ASC= Arid steppe cold, SA= sub artic, HS = Humid subtropical, HC = Humid continental

5 *** AI = P/E_p (Food and Agriculture Organization, FAO, 2015). We categorized the sites into arid ($AI < 0.30$), semiarid ($0.50 > AI > 0.30$), subhumid ($0.65 > AI > 0.50$), and humid ($AI > 0.65$) zones, such that each -AI category contained at least two validation sites.

Table 2. Descriptions of MODIS and meteorological datasets used in this study.

Dataset Name	Variables	Spatial Resolution	Temporal	Source
MOD11A2	Land surface Temperature, emissivity	1 km × 1 km	8-day	Wan et al. (2015)
MOD09A1	Surface reflectance, Albedo, NDVI	1 km × 1 km	8-day	Vermote (2015)
MOD15A2/MCD15A2	LAI	1 km × 1 km	8-day	Myneni et al. (2002)
NLDAS	T_A , RH, R_s , u	<u>12.54</u> km × <u>12.54</u> km	hourly	Mitchell et al. (2004); Xia et al. (2009)
University of Idaho Gridded Surface Meteorological Data	T_A , RH, R_s , u	4 km × 4 km	Daily	Abatzoglou (2013)
PRISM	Precipitation	4 km × 4 km	Daily	PRISM Climate Group, Oregon State University

Table 3. Evaluation of 8-day cumulative ET from STIC1.2, SEBS, and MOD16 against observed ET from thirteen core AmeriFlux sites in the US combining data from one dry, one wet, and one normal year.

Model	R^2	RMSE (mm)	MAE (mm)	PBIAS (%)
STIC1.2	0.66	7.5	5.4	-3
SEBS	0.53	9.8	7.3	28
MOD16	0.59	8.9	6	-27

Table 4. Study years considered for regional-scale intercomparison of annual ETs from STIC1.2, SEBS, and MOD16

Zone (2001-2014 mean annual P, mm)	Dry year (annual P, mm)	Wet year (annual P, mm)	Normal year (annual P, mm)
W (838)	2013 (397)	2010 (1021)	2014 (856)
MW2 (403)	2012 (259)	2010 (428)	2005 (403)
MW1 (1037)	2012 (786)	2008 (1313)	2014 (1023)
E (1210)	2007 (915)	2003 (1643)	2010 (1220)

Table 5. Mean percentage difference in annual ET (standard deviation) between STIC1.2 vs. SEBS and MOD16 from all pixels within the bounding box of four study zones during dry, wet, and normal years.

Years	West		Mid-West 2		Mid-West 1		East	
	STIC 1.2 - SEBS	STIC1.2- MOD16	STIC 1.2 - SEBS	STIC1.2- MOD16	STIC 1.2 - SEBS	STIC1.2- MOD16	STIC1.2- SEBS	STIC1.2- MOD16
Dry	-69 (58)	15 (23)	-85 (37)	55 (23)	-22 (9)	26 (13)	-12 (7)	11 (17)
Wet	-66 (53)	11 (20)	-73 (34)	43 (23)	-33 (13)	-8 (14)	-13 (7)	-1 (14)
Normal	-72 (58)	21 (21)	-78 (34)	43 (24)	-25 (8)	6 (12)	-13 (7)	6 (15)

5 **Table 6. Mean percent difference in annual ET (standard deviation) between STIC1.2 vs SEBS and MOD16 within the bounding box of the four study zones considering all pixels and five vegetation types based on MCD12Q1 products (Friedl et al., 2010).**

Zones	STIC1.2 - SEBS						STIC1.2 – MOD16					
	All	ENF	DBF	WSA	GRA	CRO	All	ENF	DBF	WSA	GRA	CRO
W	-93	-59	NA	-55	-135	-49	24	26	NA	16	30	18
	(62)	(34)	(NA)	(35)	(60)	(19)	(23)	(24)	(NA)	(23)	(22)	(17)
MW2	-86	-49	-47	-61	-94	-58	42	32	13	44	44	25
	(34)	(24)	(30)	(23)	(31)	(31)	(23)	(20)	(35)	(19)	(23)	(36)
MW1	-29	-17	-13	-22	-31	-31	15	25	-1	6	18	17
	(11)	(11)	(9)	(10)	(9)	(9)	(10)	(17)	(17)	(22)	(20)	(19)
E	-15	-9	-11	-15	-17	-19	7	5	-3	5	19	18
	(7)	(9)	(7)	(7)	(6)	(6)	(6)	(21)	(12)	(15)	(14)	(12)

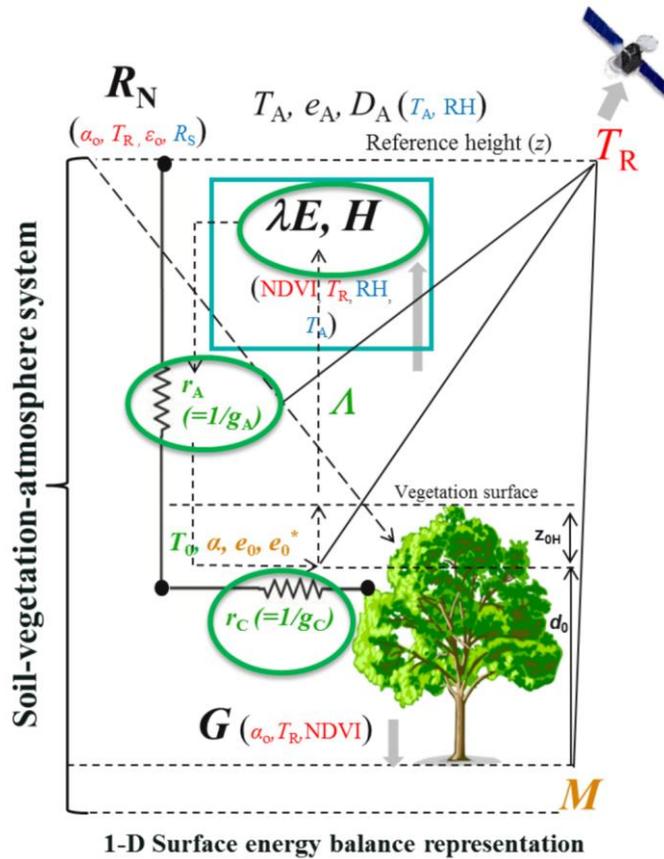
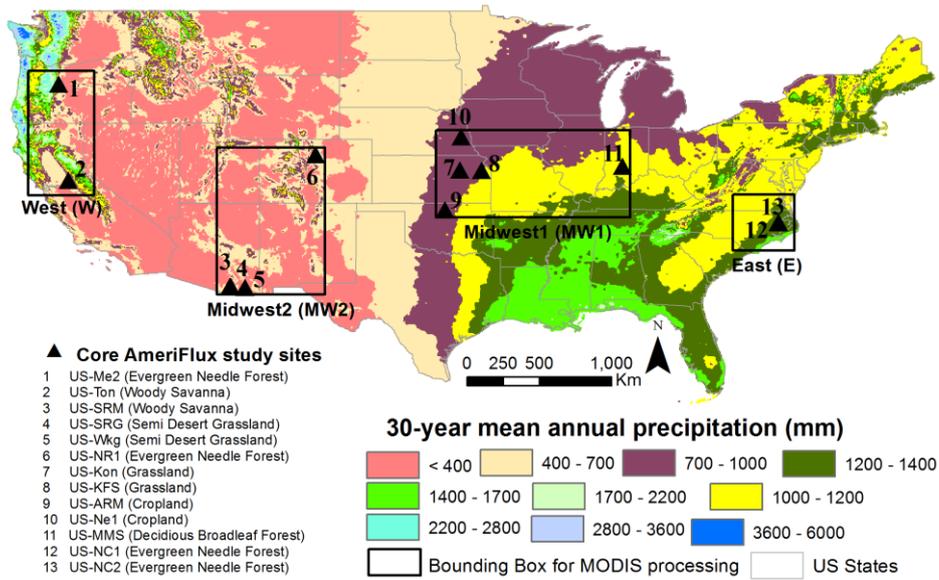


Figure 1: Schematic representation of one-dimensional description of STIC1.2 showing how a feedback is established between the surface layer evaporative fluxes and source/sink height mixing and coupling (dotted arrows between e_0 , e_0^* , g_A and g_C , and λE). Here r_A and r_C (g_A and g_C) are the aerodynamic and canopy resistances (conductances); e_0^* is the saturation vapour pressure at the source/sink height; T_0 is the source/sink height temperature (i.e. aerodynamic temperature) that is responsible for transferring the sensible heat (H); e_0 and e_s are the vapour pressure at the source/sink height and the surface, respectively; z_{0H} is the roughness length for heat transfer, d_0 is the displacement height; T_R is the radiometric surface temperature; M is the surface moisture availability or evaporation coefficient; R_N and G are net radiation and ground heat flux; T_A , e_A , and D_A are temperature, vapour pressure, and vapour pressure deficit at the reference height (z); and λE and H are latent and sensible heat fluxes, respectively. Inputs from MODIS land surface products and gridded weather datasets for the regional implementation of STIC1.2 in this paper are shown in red and blue fonts, respectively. Texts in green font represent the state variables for which analytical solution was obtained by solving the 'state equations' (Eqs. ~~(7)-(10)~~(10)). Texts in burnt orange are the variables that were obtained iteratively along with the state variables.

Formatted: Font: 9 pt, Bold

Formatted: Font: 9 pt, Bold



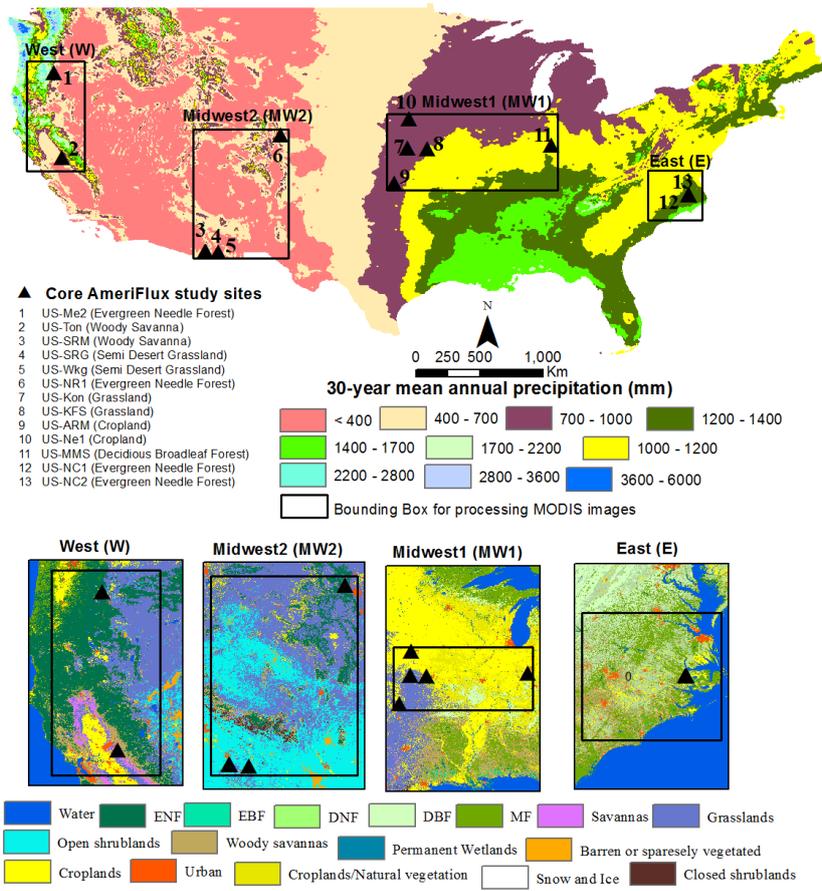


Figure 2: Distribution of core AmeriFlux sites (13) used in this study shown over 30-year (1980-2010) mean annual precipitation of the US and the processing grids (MODIS subsets) used to estimate regional-scale ET from MODIS datasets. MODIS Land cover maps for each processing grid represents the year 2013 and shows IGBP level 1 classes. EBF, DNF, and MF represent evergreen broadleaf forest, deciduous needle forest, and mixed forest respectively.

5

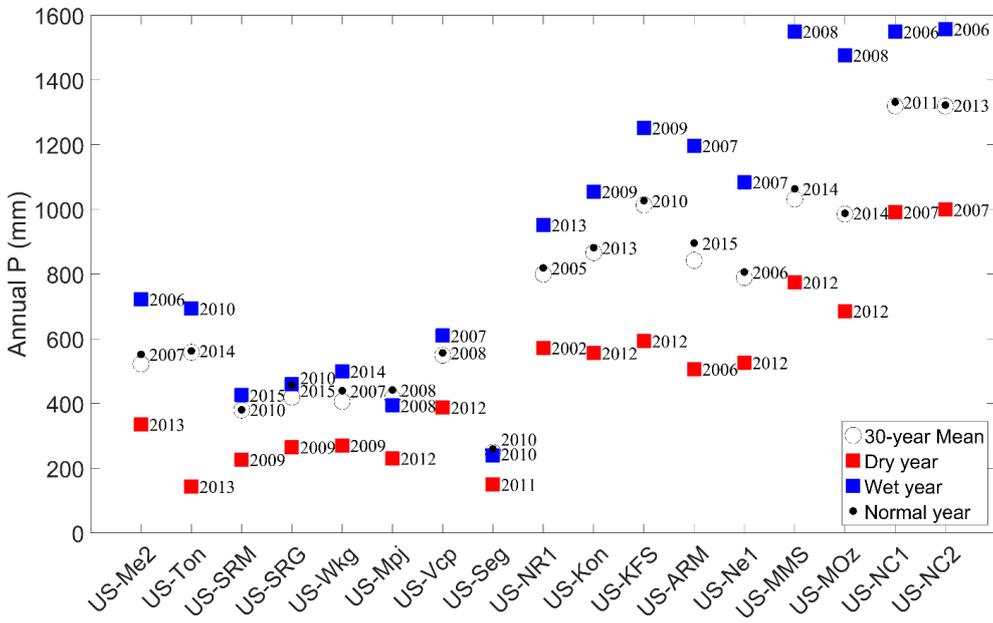
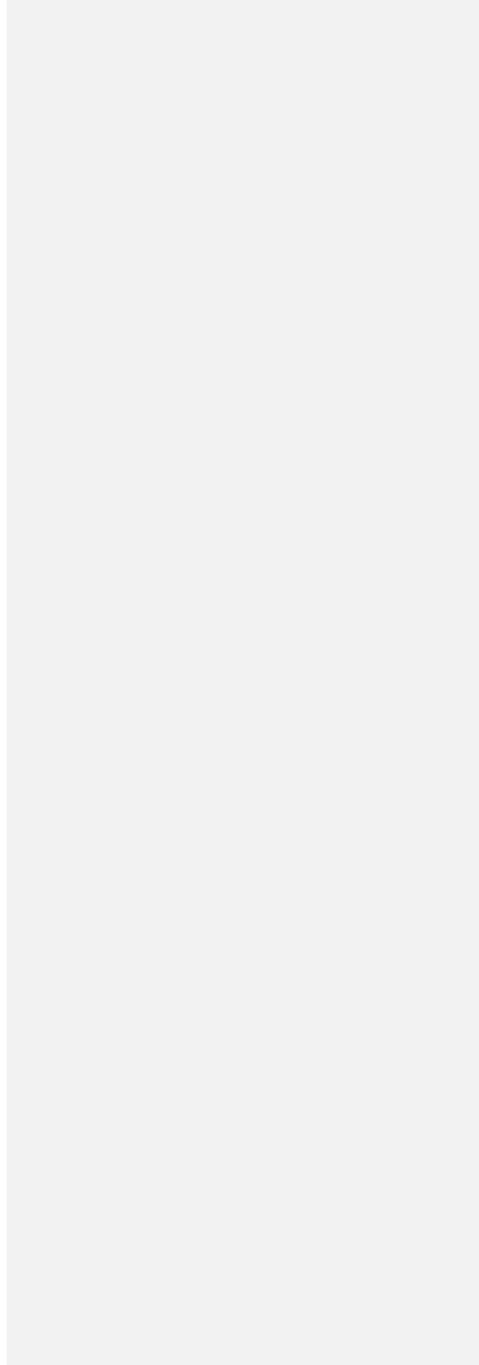
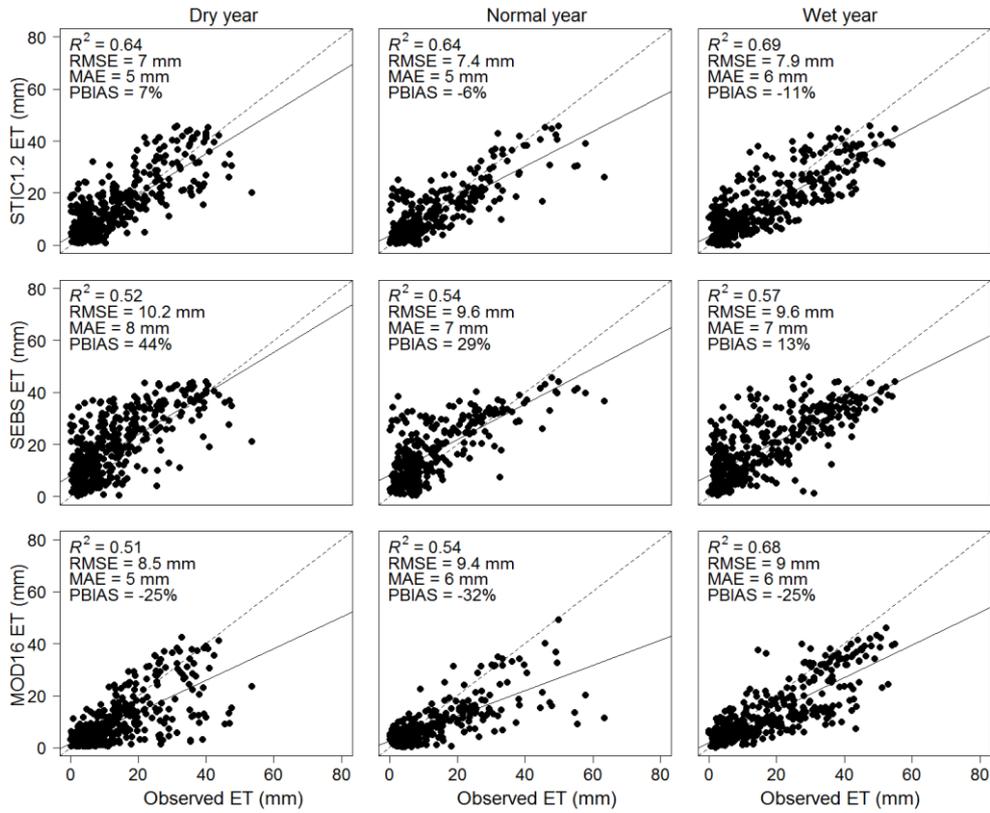


Figure 3: Distribution of annual precipitation during dry, wet, and normal years considered for ET evaluation at each site corresponding to its 30-year mean annual precipitation from the PRISM data.





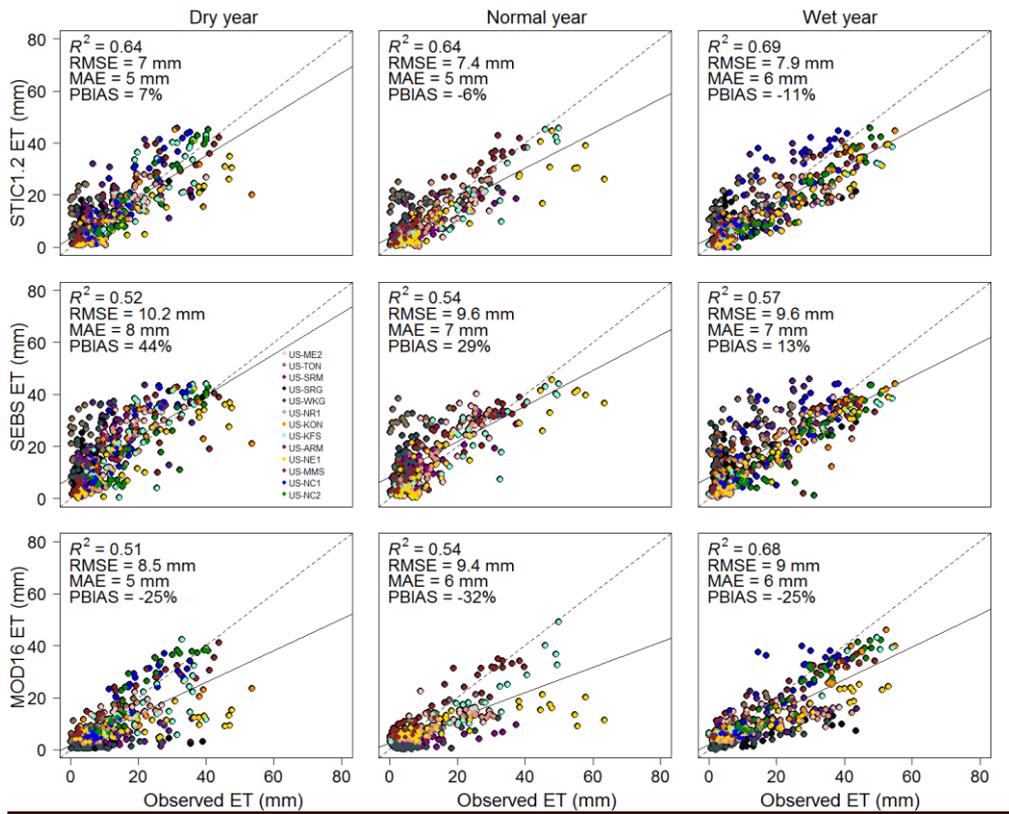
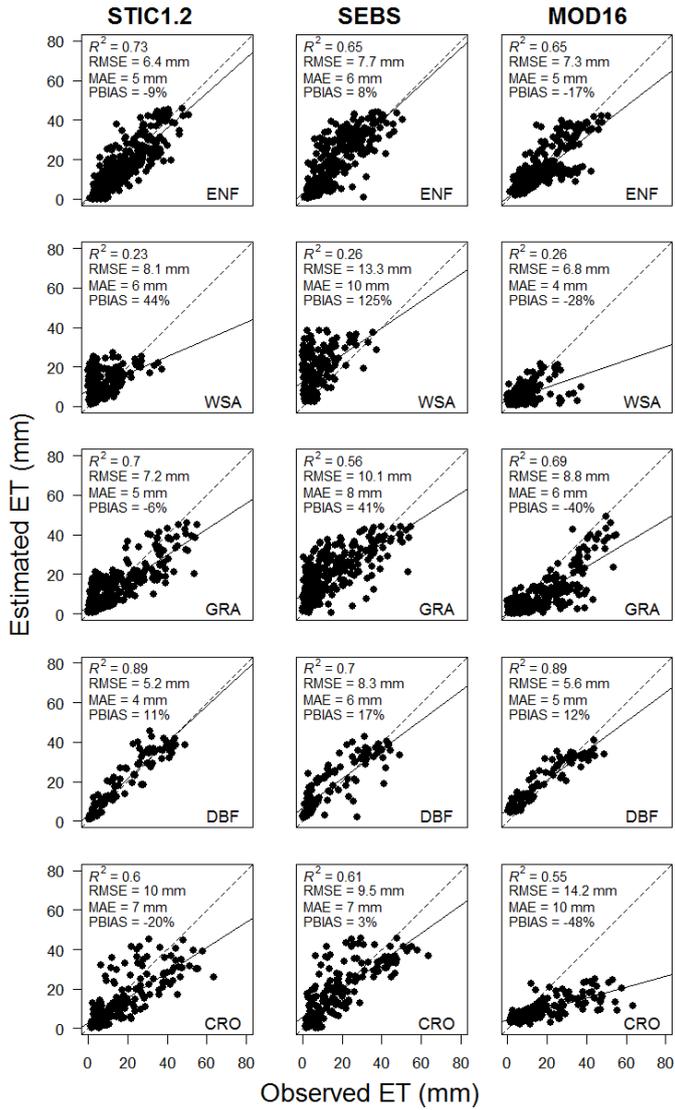


Figure 4: Evaluation of 8-day cumulative ET from STIC1.2, SEBS, and MOD16 against observed ET from thirteen core AmeriFlux sites in the US during dry, wet, and normal years.



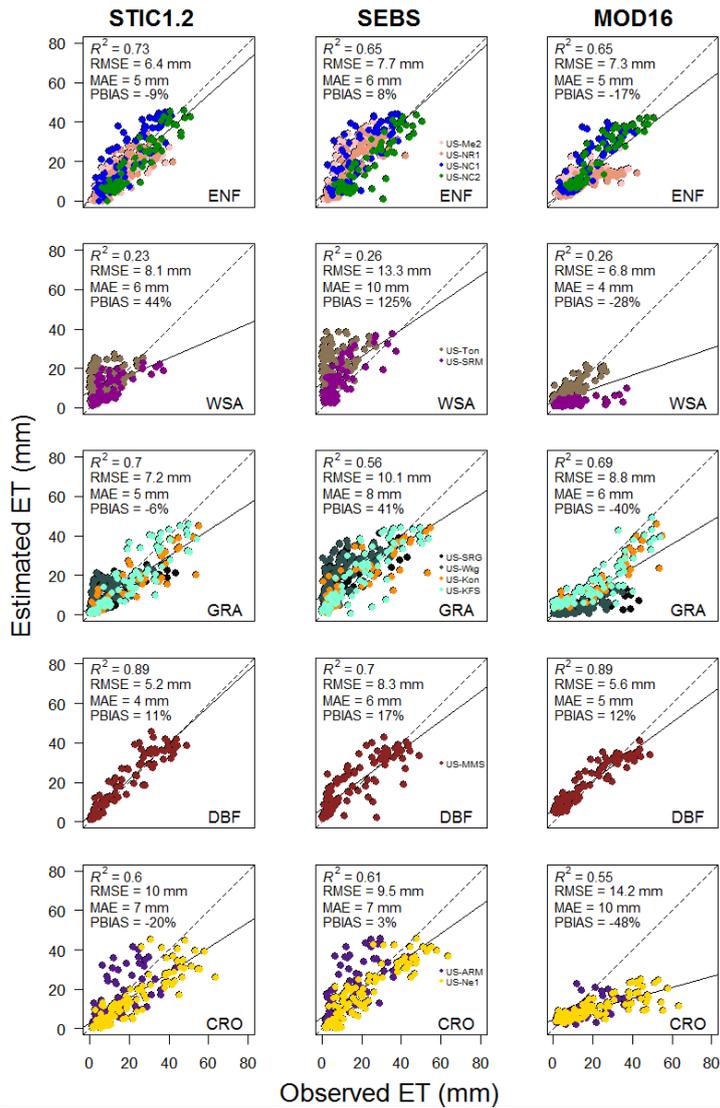


Figure 5: Validation of 8-day cumulative ET from STIC1.2, SEBS, and MOD16 for each biome type.

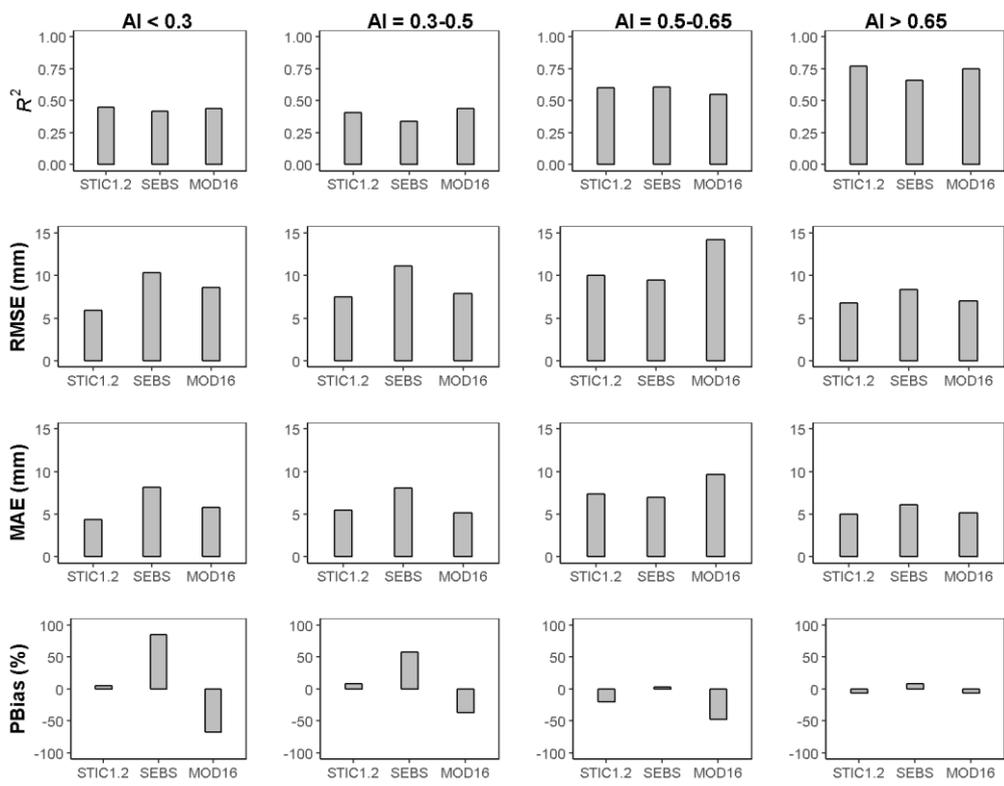
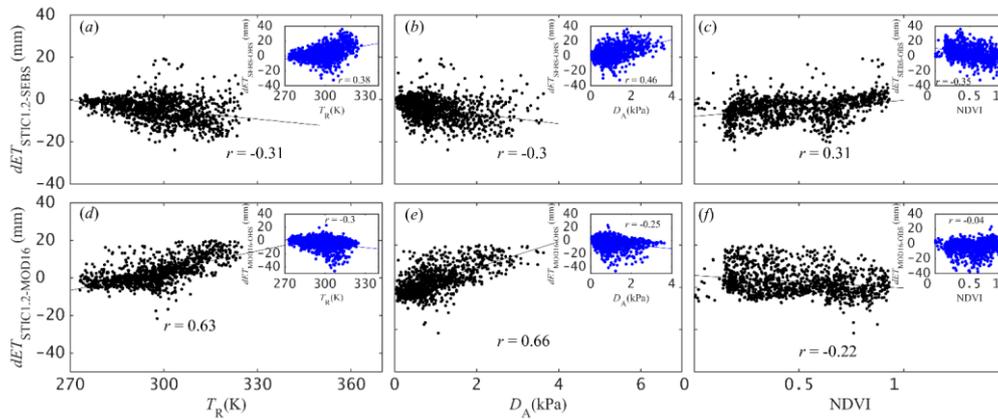
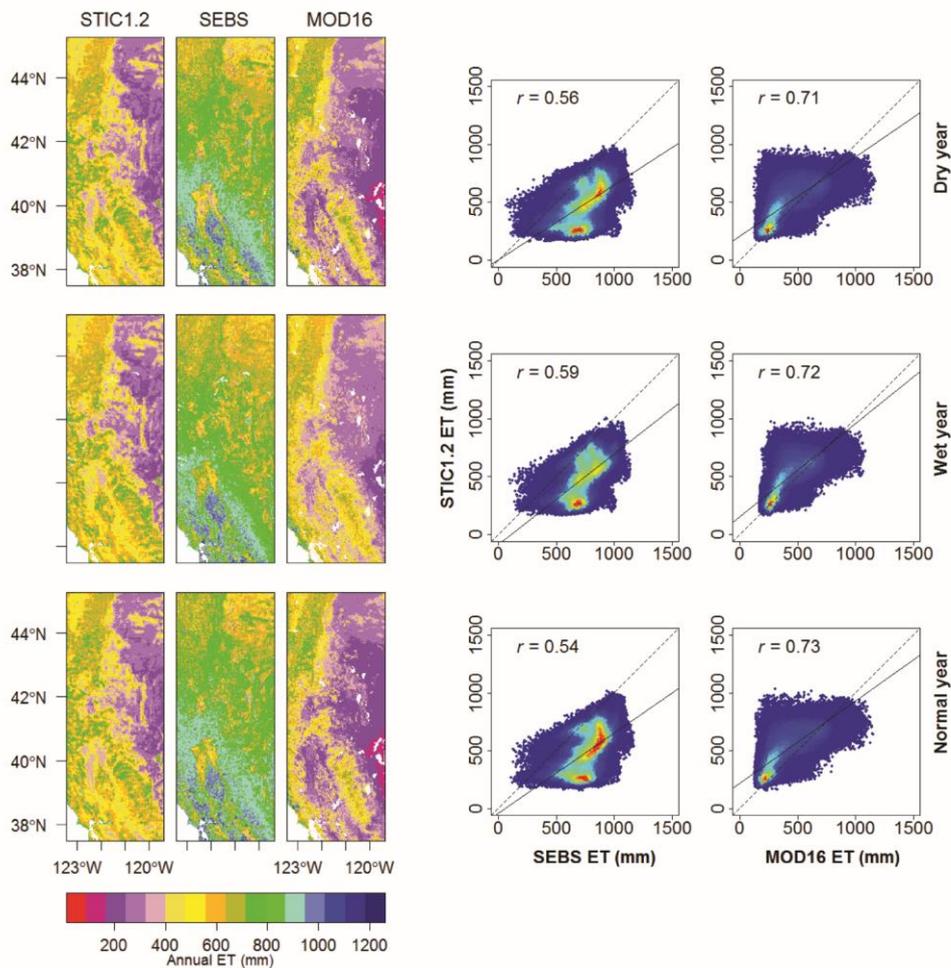


Figure 6: Evaluation of 8-day cumulative ET from STIC1.2, SEBS, and MOD16 for each long-term aridity index (AI) category.



5

Figure 7: Scatter plots of differences in STIC1.2 and (top row) SEBS and (bottom row) MOD16 ET estimates against input land surface variables used in these models (T_R , D_A , and NDVI). The **pearson-Pearson** correlation coefficient, r (p -value was < 0.005 for all cases except $dET_{MOD16-obs}$ vs. NDVI relationship), is also shown in each plot.



5 **Figure 8:** Annual ET (mm) maps for the dry, wet, and normal years derived from STIC1.2, SEBS, and MOD16 for the western (W) bounding box covering US-Ton and US-Me2 flux sites (Fig. 1). Scatterplots between annual ET estimates from STIC1.2 vs. SEBS and MOD16 are shown on the right.

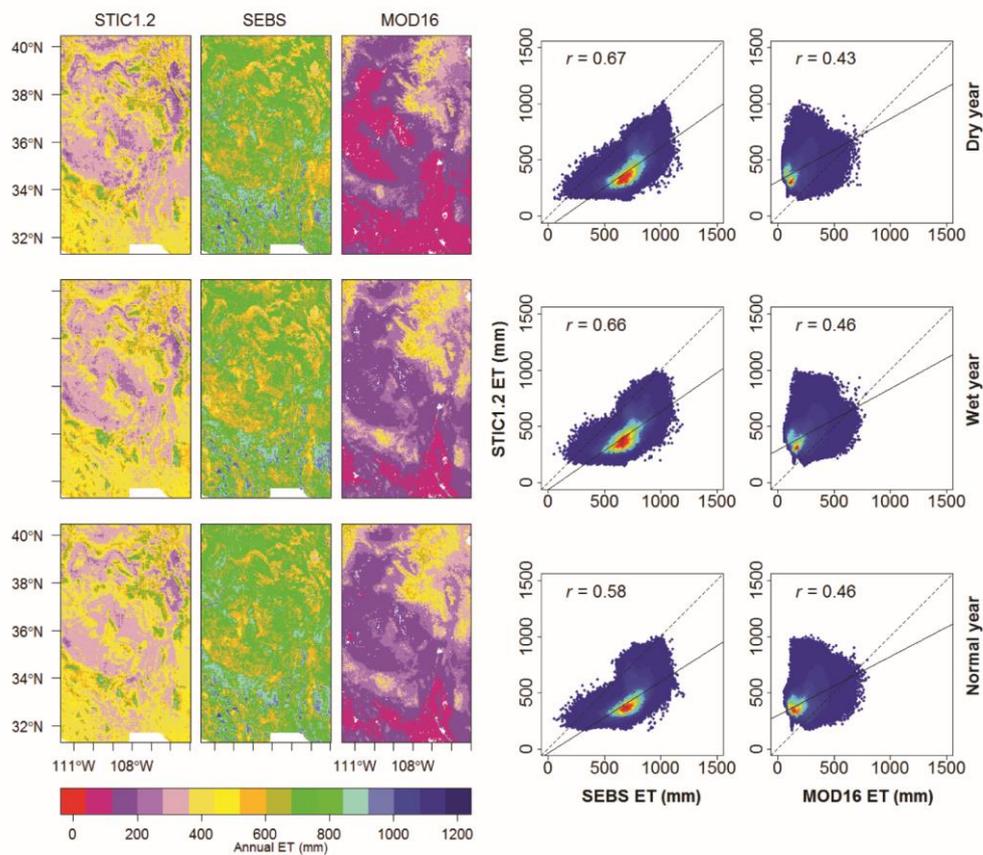


Figure 9: Annual ET (mm) maps for the dry, wet, and normal years derived from STIC1.2, SEBS, and MOD16 for the mid-western 2 (MW2) bounding box covering US-ARM, US-SRG, US-Wkg, and US-NR1 flux sites (Fig. 1). Scatterplots between annual ET estimates from STIC1.2 vs. SEBS and MOD16 are shown on the right.

5

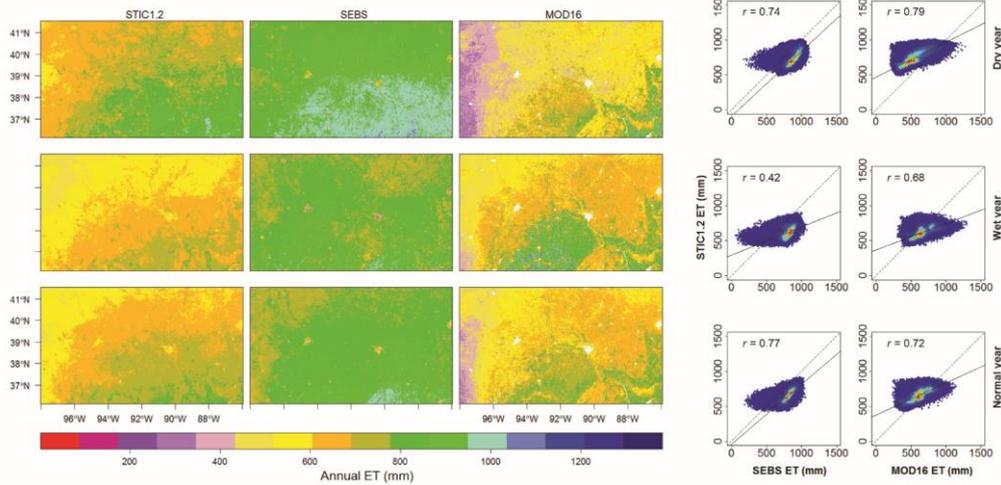


Figure 10: Annual ET (mm) maps for the dry, wet, and normal years derived from STIC1.2, SEBS, and MOD16 for mid-western 1 (MW1) bounding box covering US-Kon, US-KFS, US-ARM, US-Ne1, and US-MMS flux sites (Fig. 1). Scatterplots between annual ET estimates from STIC1.2 vs. SEBS and MOD16 are shown on the right.

5

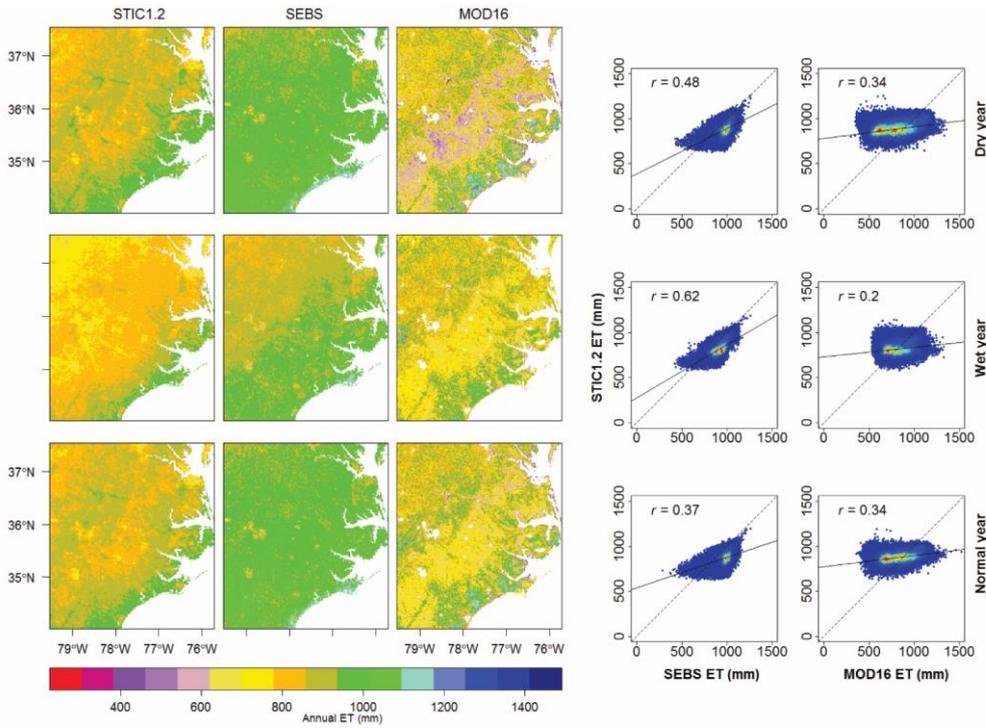


Figure 11: Annual ET (mm) maps for the dry, wet, and normal years derived from STIC1.2, SEBS, and MOD16 for the eastern (E) bounding box covering US-NC1 and US-NC2 flux sites (Fig. 1). Scatterplots between annual ET estimates from STIC1.2 vs. SEBS and MOD16 are shown on the right.

5

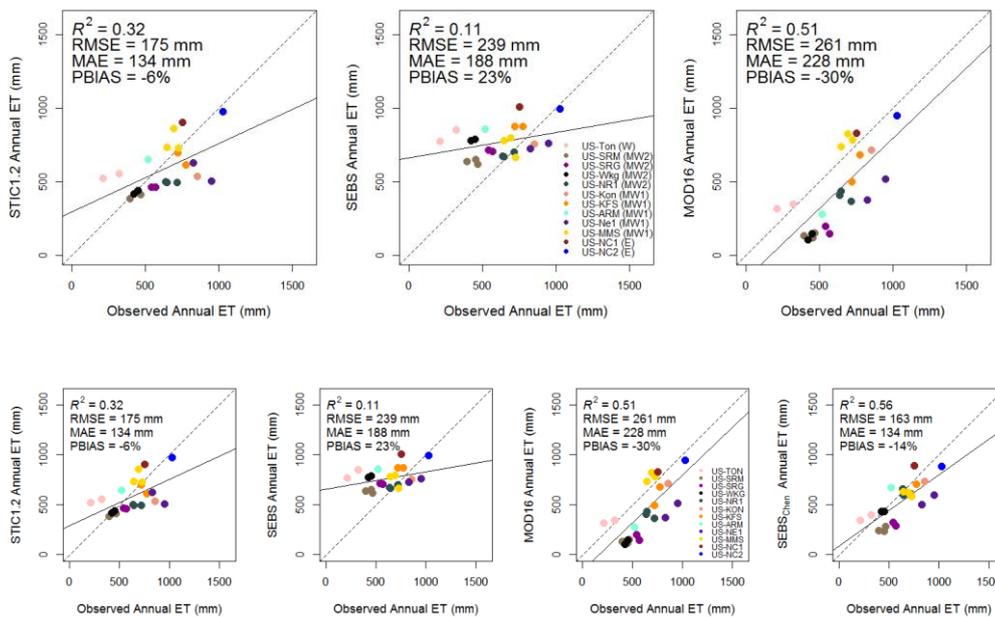


Figure 12: Comparison of annual ET from STIC1.2, SEBS, and MOD16, and SEBS_{chen} against observed annual ET from the core AmeriFlux sites. Missing daily observed ET at the flux sites were filled using linear interpolation between available days. Missing 8-day cumulative ET from STIC1.2 and SEBS were filled using constant EF approach. Annual ET from the models and flux sites are compared when at least 38 (out of 46) 8-day cumulative ET were available for computation of annual ET and at least 300 days of observed λE were available at the flux tower sites. SEBS_{chen} is a recently developed global monthly SEBS ET product based on improved kB^{-1} parametrization outlined in Chen et al. (2013).

5
10
15

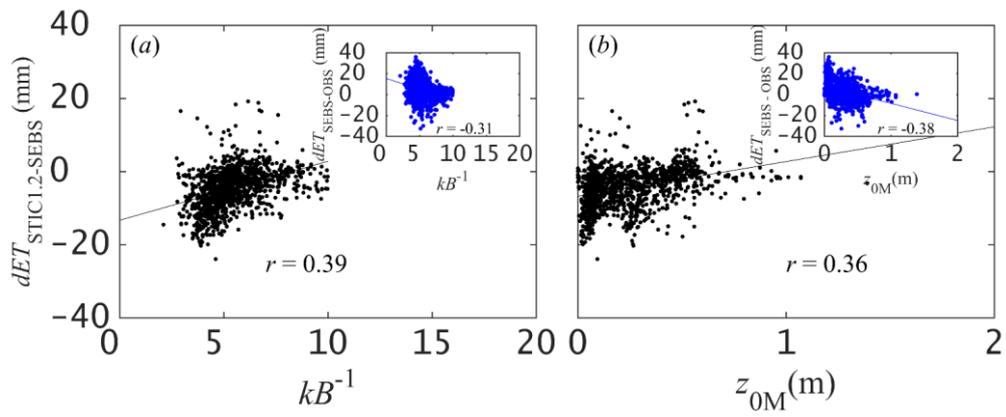


Figure 13: Scatterplots of the residual differences in cumulative 8-day ET estimates from STIC1.2 and SEBS and the residual errors from SEBS (versus the observations) against kB^{-1} and z_{0M} . Pearson correlation coefficient, r (p -value was < 0.005 for all relationships shown above), are also shown in each plot. z_{0M} was estimated from NDVI (van der Kwast et al., 2009) using no prior canopy height information.

20

Formatted: Tab stops: 2.13", Left

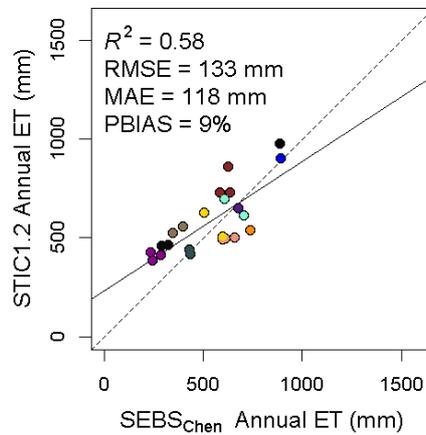
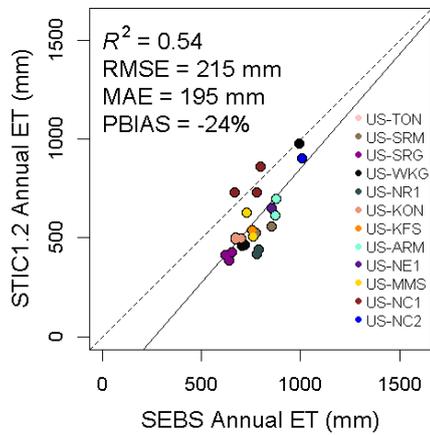
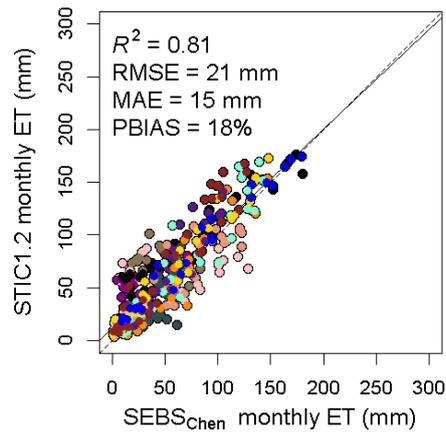
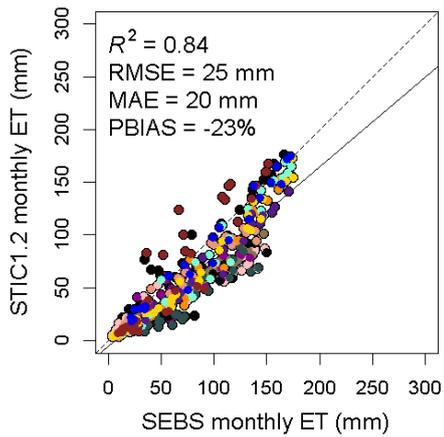
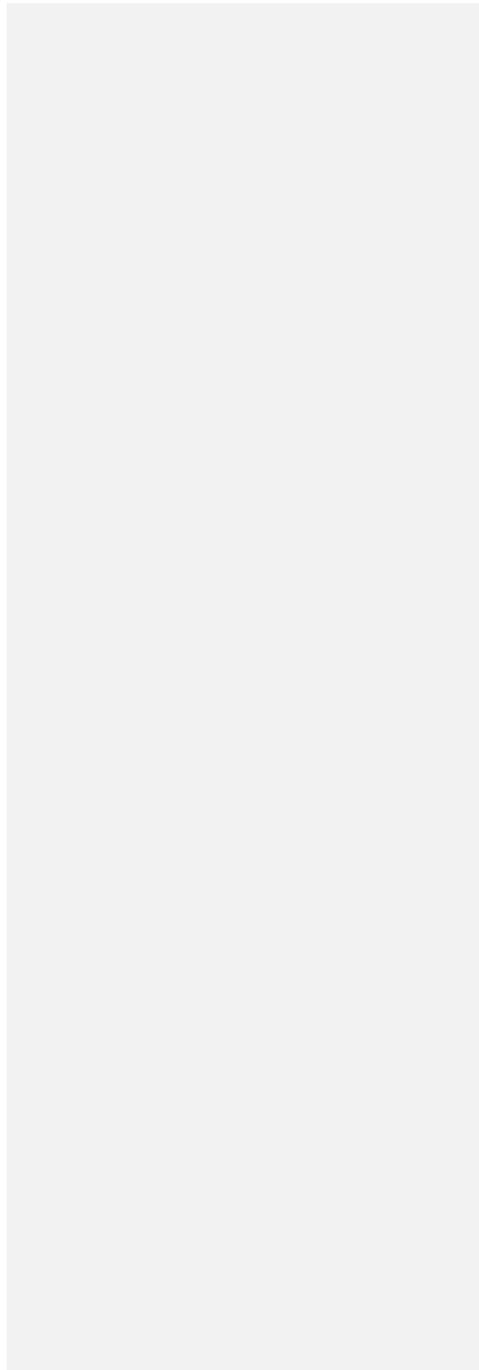


Figure 14: Scatterplots of monthly and annual ET estimates from STIC1.2 against those from SEBS and a recently developed global SEBS products (Chen et al., 2013) with improved k_B^{-1} characterization. Monthly SEBS and STIC1.2 ET estimates were produced using an aggregation of 8-day average EF multiplied by monthly total net radiation (similar to Eq. 17).

|



APPENDIX

Appendix A:

A1. Table of symbols and their description used in the study.

Symbol	Description
λ	Latent heat of vaporization of water ($\text{J kg}^{-1} \text{K}^{-1}$)
H	Sensible heat flux (W m^{-2})
R_N	Net radiation (W m^{-2})
R_S	Shortwave radiation (W m^{-2})
R_{ld}	Incoming longwave radiation (W m^{-2})
R_{lu}	Outgoing longwave radiation (W m^{-2})
G	Ground heat flux (W m^{-2})
ϕ	Available energy (W m^{-2})
ET	Evapotranspiration (evaporation + transpiration) as depth of water (mm)
λE	Latent heat flux (W m^{-2})
E_p	Potential evaporation as depth of water (mm)
g_A	Aerodynamic conductance (m s^{-1})
g_C	Canopy (or surface) conductance (m s^{-1})
r_A	Aerodynamic resistance (s m^{-1})
r_C	Canopy (or surface) resistance (s m^{-1})
M	Aggregated surface moisture availability (0–1)
T_A	Air temperature ($^{\circ}\text{C}$)
T_D	Dewpoint temperature of the air ($^{\circ}\text{C}$)
T_R	Radiometric surface temperature ($^{\circ}\text{C}$)
T_{SD}	Dew point temperature at the source/sink height ($^{\circ}\text{C}$)
T_0	Aerodynamic surface temperature ($^{\circ}\text{C}$)
RH	Relative humidity (%)
e_A	Atmospheric vapour pressure (hPa) at the level of T_A measurement
D_A	Atmospheric vapour pressure deficit (hPa) at the level of T_A measurement
e_S	Vapour pressure at the surface (hPa)
e_S^*	Saturation vapour pressure at surface (hPa)
e_0^*	Saturation vapour pressure at the source/sink height (hPa)
e_0	Saturation vapour pressure at the source/sink height (hPa)

s	Slope of saturation vapour pressure versus temperature curve (hPa K ⁻¹)
s_1	Slope of saturation vapour pressure and temperature between ($T_{SD} - T_D$) versus ($e_0 - e_A$), approximated at T_D (hPa K ⁻¹)
s_2	Slope of saturation vapour pressure and temperature between ($T_R - T_D$) versus ($e_S^* - e_A$), estimated according to Mallick et al. (2015) (hPa K ⁻¹)
γ	Psychrometric constant (hPa K ⁻¹)
ρ_A	Density of air (kg m ⁻³)
c_p	Specific heat of dry air (MJ kg ⁻¹ K ⁻¹)
A	Evaporative fraction
A_R	Relative evaporation (-)
θ	Surface (0–5 cm) soil moisture (m ³ m ⁻³)
LAI	Leaf area index (m ² m ⁻²)
NDVI	Normalized difference vegetation Index (-)
β	Bowen ratio (-)
θ_v	Virtual potential temperature near the surface (K)
ϵ_0	Surface emissivity (-)
α_0	Surface albedo (-)
u^*	Friction velocity (m s ⁻¹)
R_{N24}	Daily net radiation (W m ⁻²)
$R_{N24,8\text{-day}}$	8-day net radiation (W m ⁻²)
kB^{-1}	Excess resistance to the heat transfer parameter (-)
λE_{wet}	λE at wet limits (W m ⁻²)
H_{wet}	H at wet limits (W m ⁻²)
H_{dry}	H at dry limits (W m ⁻²)
L	Monin–Obukhov length (m)
g	Acceleration due to gravity (9.8 m s ⁻²)
d_0	Zero plane displacement height (m)
Ψ_H	Atmospheric stability correction for heat transport (-)
Ψ_M	Atmospheric stability correction for momentum transfer (-)
z_{0M}	Roughness length for momentum transfer (m)
z_{0H}	Roughness length for heat transfer (m)
z	Reference height (m)

z_b	Blending Height (m)
k	von Karman constant (-)

A2. Derivation of ‘state equations’ in STIC 1.2

After neglecting the horizontal advection and energy storage, the surface energy balance equation is written as:

$$\phi = \lambda E + H \quad (\text{A1})$$

While H is controlled by a single aerodynamic resistance (r_A) (or $1/g_A$); λE is controlled by two resistances in series, the canopy (or surface) resistance (r_C) (or $1/g_C$) and the aerodynamic resistance to vapour transfer ($r_C + r_A$). For simplicity, it is implicitly assumed that the aerodynamic resistance of water vapour and heat are equal (Raupach, 1998), and both the fluxes are transported from the same level from near surface to the atmosphere. The sensible and latent heat flux can be expressed in the form of aerodynamic transfer equations (Boegh et al., 2002; Boegh and Soegaard, 2004) as follows:

$$H = \rho_A c_P g_A (T_0 - T_A) \quad (\text{A2})$$

$$\lambda E = \frac{\rho_A c_P}{\gamma} g_A (e_0 - e_A) = \frac{\rho_A c_P}{\gamma} g_C (e_0^* - e_0) \quad (\text{A3})$$

Where T_0 and e_0 are the air temperature and vapour pressure at the source/sink height (i.e., T_0 and vapour pressure) and represent the vapour pressure and temperature of the quasi-laminar boundary layer in the immediate vicinity of the surface level. T_0 can be obtained by extrapolating the logarithmic profile of T_A down to z_{0H} .

By combining Eqs. (A1), (A2), and (A3) and solving for g_A , we get the following equation.

$$g_A = \frac{\phi}{\rho_A c_P \left[(T_0 - T_A) + \left(\frac{e_0 - e_A}{\gamma} \right) \right]} \quad (\text{A4})$$

Combining the aerodynamic expressions of λE in Eq. (A3) and solving for g_C , we can express g_C as a function of g_A and vapour pressure gradients.

$$g_C = g_A \frac{(e_0 - e_A)}{(e_0^* - e_0)} \quad (\text{A5})$$

In Eqs. (A4) and (A5), two more unknown variables (e_0 and T_0) are introduced resulting into two equations and four unknowns. Hence, two more equations are needed to close the system of equations. An expression for T_0 is derived from the Bowen ratio (β) (Bowen, 1926) and evaporative fraction (A) (Shuttleworth et al., 1989) equation as:

$$\beta = \left(\frac{1 - A}{A} \right) = \frac{\gamma (T_0 - T_A)}{(e_0 - e_A)} \quad (\text{A6})$$

$$T_0 = T_A + \left(\frac{e_0 - e_A}{\gamma} \right) \left(\frac{1 - A}{A} \right) \quad (\text{A7})$$

The expression for T_0 introduces another new variable (A); therefore, one more equation that describes the dependence of A on the conductances (g_A and g_C) is needed to close the system of equations. In order to express A in terms of g_A and g_C , STIC1.2 adopts the advection – aridity (AA) hypothesis (Brutsaert and Stricker, 1979) with a modification introduced by

Mallick et al. (2015). The AA hypothesis is based on a complementary connection between the potential evaporation (E_p), sensible heat flux (H), and ET; and leads to an assumed link between g_A and T_0 . However, the effects of surface moisture (or water stress) were not explicit in the AA equation and Mallick et al. (2015) implemented a moisture constraint in the original advection-aridity hypothesis while deriving a ‘state equation’ of A (Eq. A8). A detailed derivation of the ‘state equation’ for A is described in Mallick et al. (2014, 2015, and 2016).

$$A = \frac{2\alpha s}{2s + 2\gamma + \gamma \frac{g_A}{g_C} (1 + M)} \quad (\text{A8})$$

A3. Estimating e_0 , e_0^* , M , and α in STIC 1.2

In the early versions of STIC (Mallick et al., 2014; Mallick et al., 2015), no distinction was made between the surface and source/sink height vapour pressures and hence e_0^* was approximated as the saturation vapour pressure at T_R . e_0 was estimated from M with an assumption that the vapour pressure at the source/sink height scales between extreme wet–dry surface conditions. However, the level of e_0^* and e_0 should be consistent with the level of T_0 from which the sensible heat flux is transferred (Lhomme and Montes, 2014). To use the PM equation predictively, it is imperative to consider the feedback between the surface layer evaporative fluxes and source/sink height mixing and coupling (McNaughton and Jarvis, 1984). Therefore, STIC1.2 uses physical expressions for estimating e_0^* and e_0 followed by estimating T_{SD} and M as described below.

15 An estimate of e_0^* is obtained by inverting the aerodynamic transfer equation of λE .

$$e_0^* = e_A + \left[\frac{\gamma \lambda E (g_A + g_C)}{\rho_A c_p g_A g_C} \right] \quad (\text{A9})$$

Following Shuttleworth and Wallace (1985) (SW), the vapour pressure deficit (D_0) ($=e_0^* - e_0$) and e_0 at the source/sink height are expressed as follows.

$$D_0 = D_A + \left[\frac{\{s\phi - (s + \gamma)\lambda E\}}{\rho_A c_p g_A} \right] \quad (\text{A10})$$

$$e_0 = e_0^* - D_0 \quad (\text{A11})$$

A physical equation of α is derived by expressing A as a function of the aerodynamic equations H and λE .

$$A = \frac{\lambda E}{H + \lambda E} \quad (\text{A12})$$

$$A = \frac{\frac{\rho_A c_p}{\gamma} \frac{g_A g_C}{g_A + g_C} (e_0^* - e_A)}{\rho_A c_p g_A (T_0 - T_A) + \frac{\rho_A c_p}{\gamma} \frac{g_A g_C}{g_A + g_C} (e_0^* - e_A)} \quad (\text{A13})$$

$$A = \frac{g_C (e_0^* - e_A)}{[\gamma (T_0 - T_A) (g_A + g_C) + g_C (e_0^* - e_A)]} \quad (\text{A14})$$

Combining Eqs. (A14) and (A8) (eliminating A), α can be expressed as:

$$\alpha = \frac{g_C(e_0^* - e_A) \left[2s + 2\gamma + \gamma \frac{g_A}{g_C} (1 + M) \right]}{2s[\gamma(T_0 - T_A)(g_A + g_C) + g_C(e_0^* - e_A)]} \quad (\text{A15})$$

Following Venturini et al. (2008), and the theory of psychrometric slope of saturation vapour pressure versus temperatures, M is expressed as the ratio of the dewpoint temperature difference between the source/sink height and air to the temperature difference between T_R and dewpoint temperature of the air (T_D).

$$M = \frac{s_1(T_{SD} - T_D)}{\kappa s_2(T_R - T_D)} \quad (\text{A16})$$

Where T_{SD} is the dewpoint temperature at the source/sink height; s_1 and s_2 are the psychrometric slopes of the saturation

5 vapour pressure and temperature between $(T_{SD} - T_D)$ versus $(e_0 - e_A)$ and $(T_R - T_D)$ versus $(e_S^* - e_A)$ relationship (Venturini et al., 2008); and κ is the ratio between $(e_0^* - e_A)$ and $(e_S^* - e_A)$. Despite T_0 drives the sensible heat flux, the comprehensive dry-wet signature of the underlying surface due to soil moisture variations is directly reflected in T_R (Kustas and Anderson, 2009). Therefore, using T_R in the denominator of Eq. (A16) tends to give a direct signature of the surface moisture availability (M).

10 In Eq. (A16), both s_1 and T_{SD} are unknowns, and an initial estimate of T_{SD} is obtained using Eq. (6) of Venturini et al. (2008) where s_1 was approximated in T_D . From the initial estimates of T_{SD} , an initial estimate of M is obtained as $M = s_1(T_{SD} - T_D)/s_2(T_R - T_D)$. However, since T_{SD} also depends on λE , an iterative updating of T_{SD} (and M) is carried out by expressing T_{SD} as a function of λE as described below (also in Mallick et al., 2016). By decomposing the aerodynamic equation of λE , T_{SD} can be expressed as follows.

$$\lambda E = \frac{\rho_A C_P}{\gamma} g_A (e_0 - e_A) = \frac{\rho_A C_P}{\gamma} g_A s_1 (T_{SD} - T_D) \quad (\text{A17})$$

$$T_{SD} = T_D + \frac{\gamma \lambda E}{\rho_A C_P g_A s_1} \quad (\text{A18})$$

15 An initial value of α is assigned as 1.26 and initial estimates of e_0^* and e_0 are obtained from T_R and M as $e_0^* = 6.13753 e^{\frac{17.27 T_R}{(T_R + 237.3)}}$ and $e_0 = e_A + M(e_0^* - e_A)$. Initial T_{SD} and M were estimated from Eq. (6) of Venturini et al. (2008) and Eq. (A16), respectively. With the initial estimates of these variables; initial estimate of the conductances, T_0 , Λ , and λE are obtained. This process is then iterated by updating e_0^* (using Eq. A9), D_0 (using Eq. A10), e_0 (using Eq. A11), T_{SD} (using Eq. A18 with s_1 estimated at T_D), M (using Eq. A16), and α (using Eq. A15), with the initial estimates of g_C , g_A , and λE , and
 20 recomputing g_C , g_A , T_0 , Λ , and λE in the subsequent iterations with the previous estimates of e_0^* , e_0 , T_{SD} , M , and α until the convergence λE is achieved. Stable values of λE , e_0^* , e_0 , T_{SD} , M , and α are obtained within ~25 iterations.