

1 Dear Dr Wang,

2

3 Thank you for handling our manuscript “BESS-STAIR: a framework to estimate daily, 30-meter,  
4 and all-weather crop evapotranspiration using multi-source satellite data for the U.S. Corn Belt”  
5 (hess-2019-376). We have tried our best to revise our manuscript in accordance with the comments  
6 and suggestions received from the two referees, and we added the necessary text and figures in the  
7 main text and appendix. We believe that all the comments have been addressed and thus our  
8 manuscript has been considerably improved. We are very grateful to you and the two referees, and  
9 we are hoping for the possibility to consider our manuscript as a potential contribution for HESS.

10

11 The major improvements we have made are:

- 12 ● We have added two figures about PET results.
- 13 ● We have added one table about LAI equations.
- 14 ● We have added example GPP maps in Appendix.
- 15 ● We have added relevant ET equations in Appendix.
- 16 ● We have replaced “LE” by “ET” throughout text, figures and tables.

17

18 Below are detailed responses:

19 **Response to reviewer #1:**

20 *1. The study “BESS-STAIR: a framework to estimate daily, 30-meter, and all-weather crop*  
21 *evapotranspiration using multi-source satellite data for the U.S. Corn Belt” used the BESS model*

22 *with 30-m fused inputs from a automated data fusion algorithm (STAIR) to simulate fine resolution*  
23 *cropland ET across the U.S. Corn Belt from 2000 to 2017. The results showed good performance*  
24 *compared with field measurement, indicating that BESS-STAIR is applicable for field scale ET*  
25 *simulations in the U.S. Corn Belt, which is useful and meaningful for agricultural water*  
26 *management and precision agriculture applications. The manuscript was well written and*  
27 *followed a good logic. Lots of work was done by the authors to explore applicable and reliable*  
28 *methods for agricultural management. It is good for the farmers and decision makers to know*  
29 *agricultural water demands. Thus, I think this study could be considered for publication in this*  
30 *journal.*

31 Dear reviewer: we greatly appreciate your positive summary on our manuscript.

32

33 *2. Please use only one term (ET or LE) consistently throughout the manuscript. It would be easier*  
34 *for people to read this manuscript.*

35 We have accepted your suggestion and made changes throughout text, figures and tables.

36

37 *3. In the section 2.1, please list the most important equations in the BESS model for ET*  
38 *calculations. And please list the full name of the variables before using the abbreviations (e.g.*  
39 *aVIS, Vcmax, etc.)*

40 We appreciate your suggestion.

41 The most important equations in the BESS model for ET calculations are now listed in Appendix  
42 1 in the revised version (L570).

43 Full names of LAI,  $\alpha$ VIS and  $\alpha$ NIR were listed in L90. Full name of Vcmax25 was shown in L120.

44

45 *4. Ln. 205, please show the equation for clear demonstration.*

46 We have followed your suggestion. We have added a Table 1 “Linear equations for LAI (y) as a

47 function of VI (x) for corn, soybean, and the combination of corn and soybean”.

VI	Corn	Soybean	Combination
WDRVI	$y = 6.288x + 4.631$	$y = 4.584x + 3.432$	$y = 5.745x + 4.288$
GWDRVI	$y = 8.964x + 5.875$	$y = 6.384x + 4.275$	$y = 8.110x + 5.395$
EVI	$y = 10.569x - 2.165$	$y = 8.116x - 1.936$	$y = 9.665x - 1.993$
LSWI	$y = 9.156x + 1.070$	$y = 7.553x + 0.888$	$y = 8.944x + 0.982$

48

49 *5. Ln. 254, CI could not be found in Eq. 6 or 7. Please check the manuscript clearly to correct this*

50 *kind of errors.*

51 Thanks for the suggestion. We have deleted this sentence. CI is not used.

52

53 *6. Fig. 6, is the irrigation measured in the field?*

54 Yes. The irrigation data at US-Ne1 and US-Ne2 are provided by FLUXNET2015 database.

55

56 *7. In Fig. 8 and 9, it would be good to point out flux tower sites.*

57 We have followed your suggestion by adding flux tower marks in all maps.

58

59 *8. I think Fig. 7 could be put in the supplementary materials, since Fig. 6 already showed good*  
60 *performance of BESS-STAIR ET.*

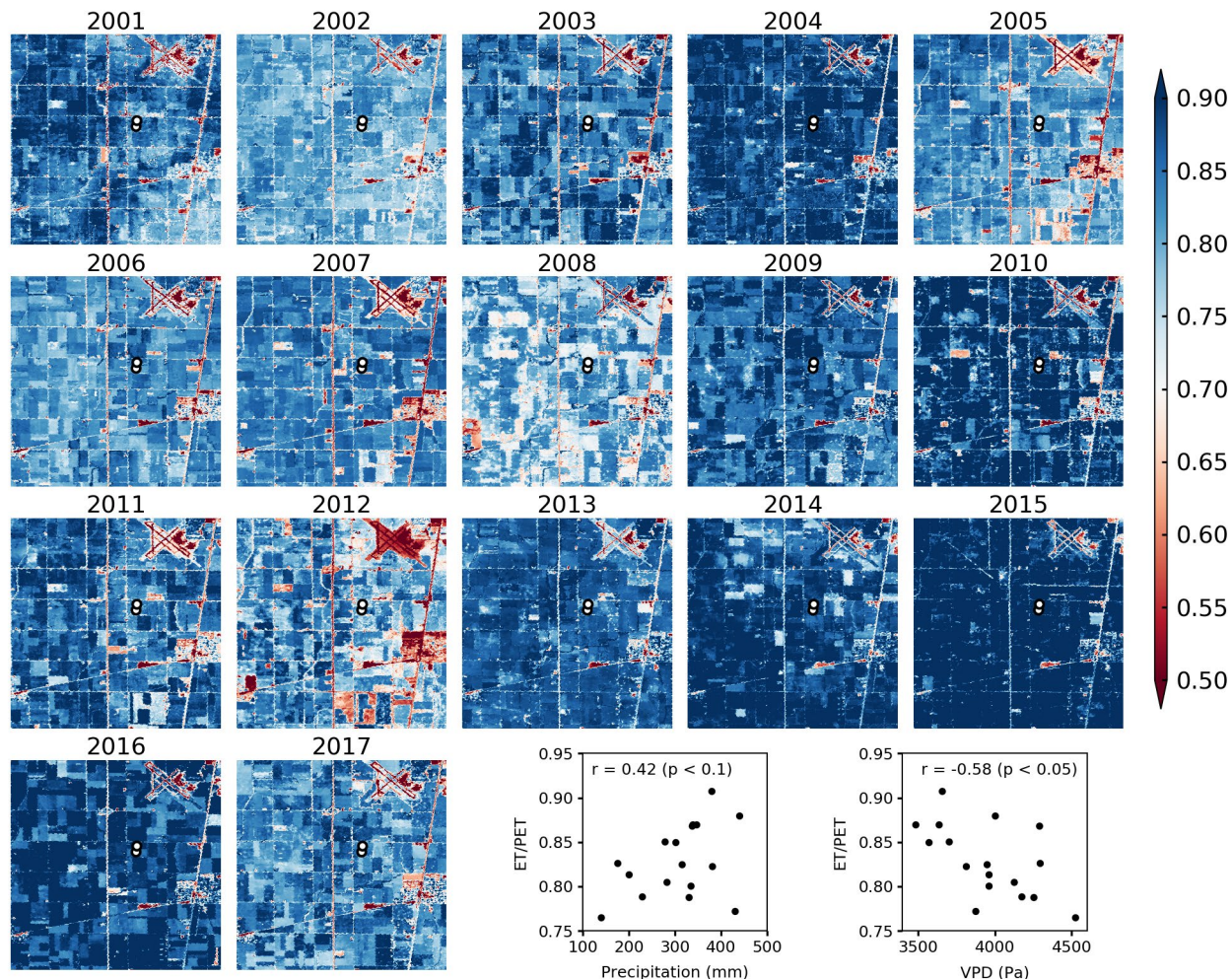
61 We agree that key information have already been shown in Fig. 6 so we have removed this figure.

62

63 *9. Ln.346-347, the authors said “measured daily LE do not show strong and fast response to*  
64 *precipitation and/or irrigation”, however, in Fig. 10, averaged ET showed significant correlations*  
65 *with precipitation. How did the author interpret this?*

66 We appreciate this important point. In most areas in the U.S. Corn Belt, atmospheric water demand  
67 dominates ET over soil water supply. In fact, the original Fig. 10 was special because that area-  
68 month has the highest correlation between ET and precipitation, thus that figure was not  
69 representative and misleading.

70 We have replaced it by another figure:



71

72 Figure 10. Peak growing season (June, July and August) BESS-STAIR ET/PET at Bondville  
 73 (39.95°N – 40.05°N, 88.25°W – 88.35°W) from 2001 throughout 2017, along with two scatter  
 74 plots between peak growing season precipitation and ET/PET and peak growing season VPD and  
 75 ET/PET over the 17 years. Precipitation and VPD data are from Daily Surface Weather Data  
 76 (Daymet) at Illinois Bondville, where VPD is derived using maximum air temperature and water  
 77 vapor pressure. Circles indicate flux towers in this region.

78 Accordingly, we have rewritten the paragraph (L398):

79 “BESS-STAIR is also able to produce long-term ET/PET estimation as an indicator of drought.

80 Figure 10 shows an example time series of peak growing season ET/PET at Bondville from 2001

81 through 2017. Overall substantial interannual variability is shown, with regional average ET/PET  
82 values ranging from the 0.76 in an extremely dry year 2012 to 0.91 in an extremely wet year 2015.  
83 A positive linear relationship ( $r = 0.42$ ,  $p < 0.1$ ) is observed between BESS-STAIR ET/PET and  
84 precipitation, and a negative linear relationship ( $r = -0.58$ ,  $p < 0.05$ ) is observed between BESS-  
85 STAIR ET/PET and VPD. The relative stronger relationship between ET/PET and VPD than that  
86 between ET/PET and precipitation indicates atmospheric water demand is likely to contribute  
87 more to drought than soil water supply in this area.”

88

89 **Response to reviewer #2:**

90 *1. The way I see it, this study provides a novel ET algorithm because of (1) the explicit treatment*  
91 *and modeling of stomatal conductance and canopy conductance; (2) the detailed representation*  
92 *of leaf architecture and inclination distribution; and (3) the ingenuity in gap filling cloudy days in*  
93 *the Midwest.*

94 Dear reviewer: we greatly appreciate your positive comments on our study.

95

96 *2. I think it is disingenuous of the authors to call this a coupled water-carbon-energy model. To*  
97 *me, this implies that there will be some sort of simulation of photosynthesis, NEP, NPP, and/or*  
98 *yields. I see that stomatal conductance was calculated using the Farquhar and Ball-Berry models.*  
99 *In order to make these calculations, there needed to be an estimate of net photosynthesis. Why are*  
100 *these estimates and maps not included as results in the study? If there is some limitation to*  
101 *simulating the carbon cycle, the authors should explain what that is or actually simulate some*  
102 *carbon components. I'm guessing there is some limitation here and I think that rather than calling*

103 *BESS-STAIR a water-carbon-energy model, that the authors should focus on the excellent strides*  
104 *that they have made by explicitly simulating the dynamic stomatal response, leaf inclination, and*  
105 *gap filling using surface albedo.*

106 We are glad that you see the water-carbon-energy integrated model as an innovation in high  
107 resolution ET estimation. Although the model estimates ET, GPP and Rnet simultaneously, the  
108 objective of this study is to demonstrate the performance of ET for water resource management.  
109 As a result, we purposely avoid putting too many GPP estimation results in the manuscript which  
110 might distract readers. Besides, GPP data is unavailable for many validation sites used in this study,  
111 and processing GPP measurements would take too much extra space, which would make the  
112 current manuscript too long. Even though, in the original manuscript, we still demonstrated good  
113 GPP estimation performance at three sites in Figure A1. We also showed that BESS-STAIR  
114 GPP~ET relationship is consistent with flux tower GPP~ET relationship at three sites in Table 3.  
115 Furthermore, readers can refer to our previous paper about BESS global GPP and ET products  
116 (Jiang and Ryu 2016). In the revised version, we have added several GPP maps in Figure A4 per  
117 your request.

118 Jiang, C., & Ryu, Y. (2016). Multi-scale evaluation of global gross primary productivity and  
119 evapotranspiration products derived from Breathing Earth System Simulator (BESS).  
120 *Remote Sensing of Environment*, 186, 528–547. <https://doi.org/10.1016/j.rse.2016.08.030>

121

122 *3. Line 21: “water-carbon-energy” coupled is a little disingenuous. To me this implies there will*  
123 *be a carbon budget or some carbon-related outputs from the model (e.g. Anet, NEP, NPP, yield).*

124 Please refer to the above response.

125

126 *4. Line 22: 'satellite' spelled incorrectly.*

127 We have corrected it.

128

129 *5. Line 37: Add "evaporation" to leaf transpiration.*

130 We have added it.

131

132 *6. Line 37: "ET at cropland is usually considered as crop water needs" is confusing. Please*  
133 *rephrase.*

134 We have rephrased it: "ET at cropland is usually considered as crop water use".

135

136 *7. Line 43: USDA, 1997 is an outdated reference. Please update, perhaps with some Midwest US*  
137 *specific references about precision irrigation.*

138 Thanks for the suggestion. We have replaced the reference by a recently published report by The  
139 U.S. Government Accountability Office.

140

141 *8. Line 44: You bring up the urgency of this need here. I ask you to follow up on this both in your*  
142 *computation and the discussion of the scalability of this model and also how it compares or*  
143 *outcompetes other similar models (e.g. STAR-FM).*

144 We appreciate this important suggestion. However, the purpose of this manuscript is to propose a  
145 new framework and to demonstrate its performance. We only would like to let the community



146 know that this framework differs from existing ones such as DisALEXI-STARFM with regards to  
147 methodology. We do not want to comment on or judge others' framework without careful  
148 investigation, especially considering their data are not publicly available. Meanwhile, we are open  
149 to share our data and welcome a third-party to conduct potential comparison studies and  
150 comprehensively evaluate the difference between frameworks in terms of performance,  
151 computation, scalability, etc.

152

153 *9. Line 48: "competitions" is an odd work to use here. Please rephrase.*

154 We have changed it to "balance".

155

156 *10. Line 113: Figure 1 is where I get confused about your use of coupled water-carbon-energy*  
157 *cycling to describe this model. If you have VCmax 25 and Ball-Berry parameters, what are you*  
158 *missing for Amax, and other carbon outputs?*

159 Thank you for your interests on the carbon part of our framework. Carbon output is not missed.  
160 Please refer to our response 2.

161

162 *11. Line 155: How is STAIR different from STAR-FM? (Semmens et al., 2015)*

163 When a single pixel suffers from gaps in two input snapshots of Landsat images, STARFM  
164 continues searching for the closest possible Landsat-MODIS image pair of a matching date, even  
165 if it is months away from the target prediction date. By comparison, STAIR utilizes the whole time  
166 series to conduct fusion.

167 STARFM requires users to manually select and specify clear reference images for the methods. It  
168 is possibly such semi-automatic feature leads to the fact that DisALEXI-STARFM has not been  
169 investigated at regional scale over long-term span. By comparison, STAIR is completely automatic  
170 and thus more scalable.

171 Detailed difference can be found in (Luo et al., 2018).

172 Luo, Y., Guan, K., & Peng, J. (2018). STAIR: A generic and fully-automated method to fuse  
173 multiple sources of optical satellite data to generate a high-resolution, daily and cloud-/gap-  
174 free surface reflectance product. *Remote Sensing of Environment*, 214(March), 87–99.  
175 <https://doi.org/10.1016/j.rse.2018.04.042>

176

177 *12. Lines 197-199: This is the first time that corn and soy are mentioned as the specific crops*  
178 *studied. It would be better if these were specified earlier in the manuscript.*

179 We have followed your suggestion. We have added one sentence in the first paragraph of the  
180 manuscript: “In the U.S. Corn Belt where more than 85% of corn and soybean are produced in the  
181 U.S. (Grassini et al., 2015) ...”

182

183 *13. Lines 235-235: Including the leaf inclination distribution is novel and interesting. It would be*  
184 *great to highlight this aspect of your work more in the abstract and also place it into context in*  
185 *the intro (I do not believe other satellite-based ET models characterize the canopy to this detail).*

186 Thank you for your positive comments. However, we set three fixed types of leaf inclination  
187 distribution "spherical", "planophile" and "plagiophile" for corn, soybean, and other biomes, and  
188 currently they are only used in the LAI estimation procedure. We think this contribution is not  
189 large enough to highlight.

190

191 *14. Line 255: Is soil albedo also estimated prior to canopy closure?*

192 Yes, we used “spectral reflectance in April when no crop is planted across the study area to derive  
193 representative soil spectral reflectance” (L238) and estimated visible and near-infrared albedo  
194 using Eq. (6) and (7) (L257).

195

196 *15. Line 322: I agree with Reviewer 1. Please make the necessary conversions and stick with ET.  
197 Introducing LH at this point in the paper is a distraction.*

198 We have accepted your suggestion.

199

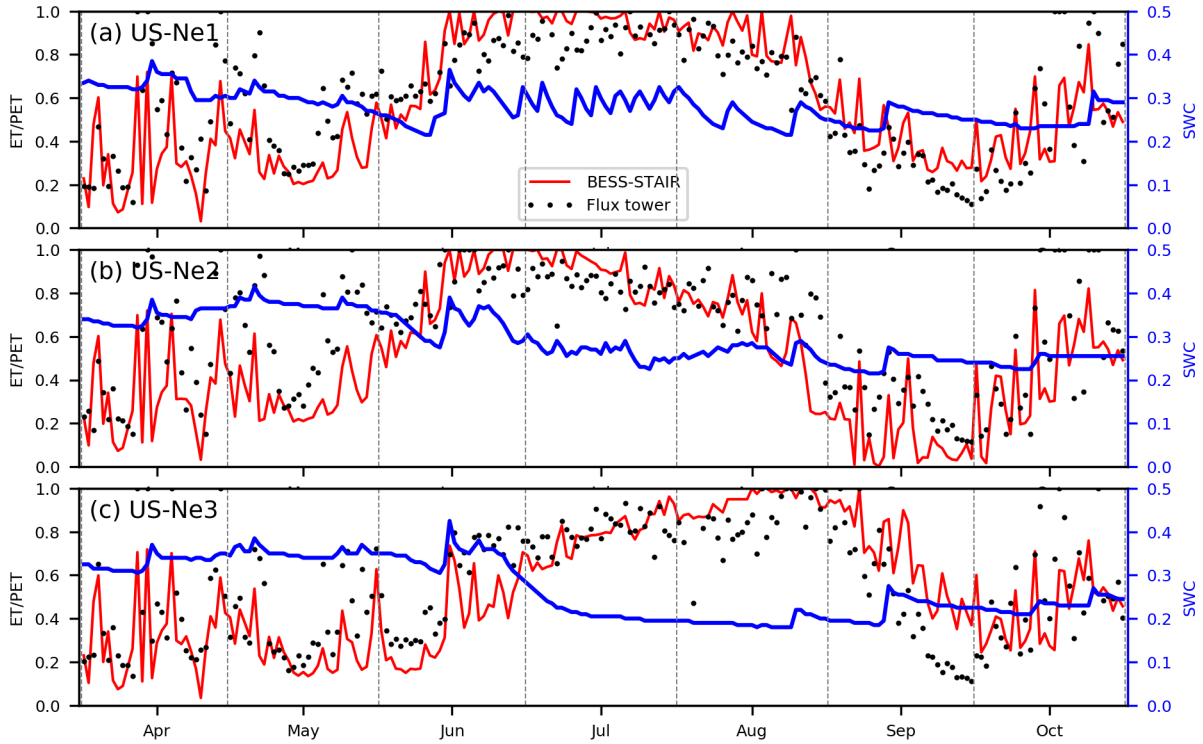
200 *16. Line 394: Please expand on the “high computational efficiency” of this model.*

201 This paragraph demonstrates interannual variations of BESS-STAIR ET, and computational  
202 efficiency is not key message we would like to convey here. Therefore, we have removed this  
203 statement to avoid distraction.

204

205 *17. Line 407: You mention PET here, but there are no PET maps. It would be interesting to  
206 compare PET to ET in a drought year (e.g. 2012).*

207 We appreciate and have followed your suggestion. In the revised manuscript, we have added two  
208 new figures about PET and corresponding paragraphs:

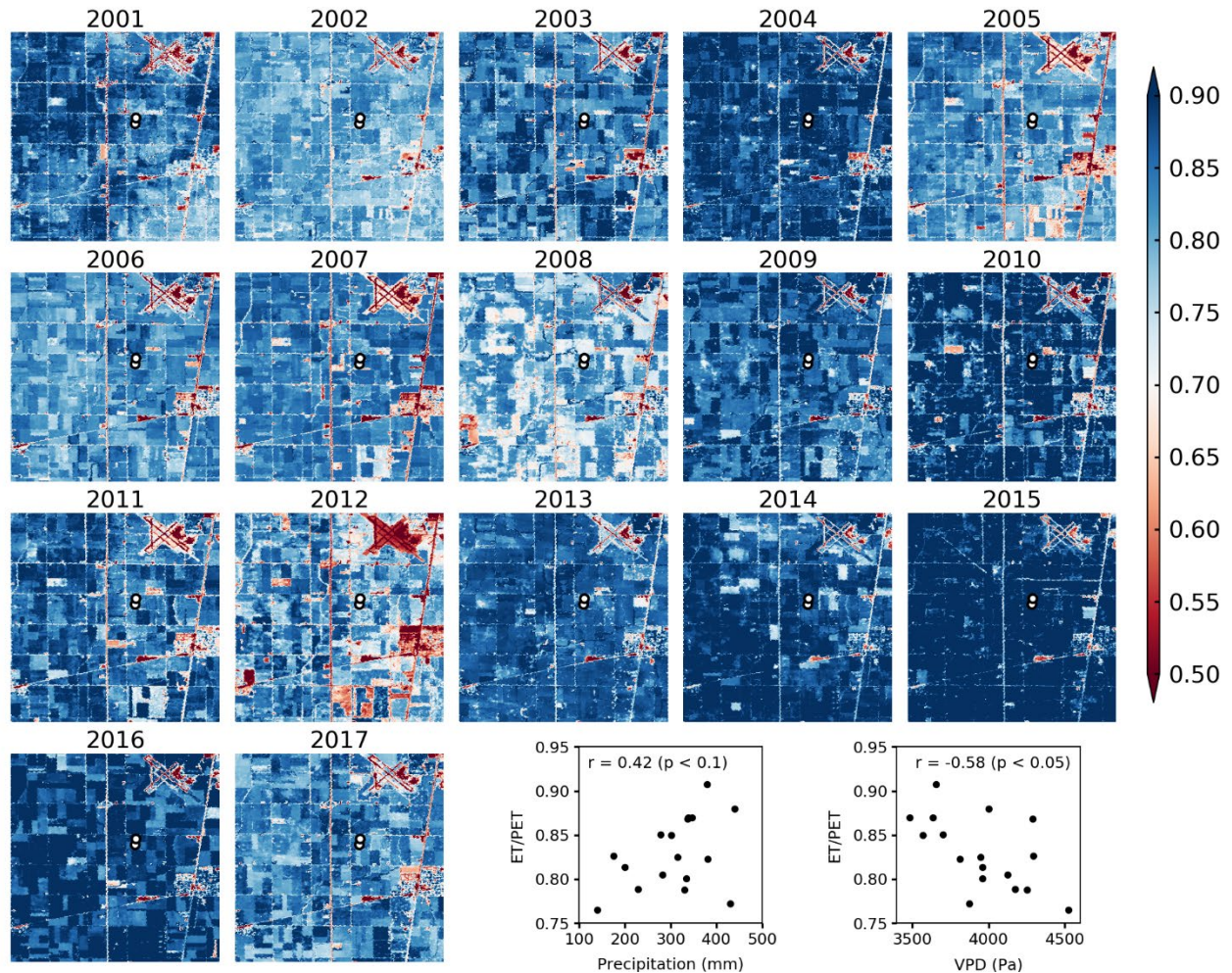


209

210 Figure 7. Seasonal time series of daily ET/PET derived from BESS-STAIR and flux tower for US-  
 211 Ne1, US-Ne2, and NS-Ne3 in 2012, along with measured daily mean soil water content (SWC).

212 “Figure 7 shows the comparison between BESS-STAIR ET/PET and flux tower ET/PET at three  
 213 sites (US-Ne1, US-Ne2, and NS-Ne3) at Mead, Nebraska. Overall, BESS-STAIR agrees well with  
 214 flux tower in both magnitude and seasonal cycle. Although 2012 is a severe drought year, soil  
 215 water content (SWC) at the rainfed site US-Ne3 still shows a relatively high level ( $> 0.2$ ). As a  
 216 result, ET/PET from both BESS-STAIR and flux tower are at the same level with the adjacent two  
 217 irrigated sites (US-Ne2 and US-Ne3).”

218



219

220 Figure 10. Peak growing season (June, July and August) BESS-STAIR ET/PET at Bondville  
 221 (39.95°N – 40.05°N, 88.25°W – 88.35°W) from 2001 throughout 2017, along with two scatter  
 222 plots between peak growing season precipitation and ET/PET and peak growing season VPD and  
 223 ET/PET over the 17 years. Precipitation and VPD data are from Daily Surface Weather Data  
 224 (Daymet) at Illinois Bondville, where VPD is derived using maximum air temperature and water  
 225 vapor pressure. Circles indicate flux towers in this region.

226 “BESS-STAIR is also able to produce long-term ET/PET estimation as an indicator of drought.  
 227 Figure 10 shows an example time series of peak growing season ET/PET at Bondville from 2001  
 228 through 2017. Overall substantial interannual variability is shown, with regional average ET/PET

229 values ranging from 0.76 in an extremely dry year 2012 to 0.91 in an extremely wet year 2015. A  
230 positive linear relationship ( $r = 0.42$ ,  $p < 0.1$ ) is observed between BESS-STAIR ET/PET and  
231 precipitation, and a negative linear relationship ( $r = -0.58$ ,  $p < 0.05$ ) is observed between BESS-  
232 STAIR ET/PET and VPD. The relative stronger relationship between ET/PET and VPD than that  
233 between ET/PET and precipitation indicates atmospheric water demand is likely to contribute  
234 more to drought than soil water supply in this area.”

235

236 *18. Line 443: You criticize other models for only focusing on the water cycle, but as it stands, this*  
237 *paper also only shares results related to the water cycle. I think you either should share some*  
238 *carbon cycle results or remove this type of language.*

239 We have shared some carbon cycle results in the manuscript. Please refer to our response 2.

240

241 *19. Lines 478-479: Traditionally, we do not introduce new figures in the discussion section. It*  
242 *would be better to move Figure 12 to the results section.*

243 While we greatly appreciate the reviewer’s suggestion, we feel that we have some different  
244 opinions on this point. We think that the Discussion section could have a figure, as long as the  
245 contents are to support interpreting findings, placing them in a bigger context, and relating them  
246 to other work, any measures. Here Figure 12 is to interpret WHY BESS-STAIR ET is advanced,  
247 whereas the whole results section is to show WHAT BESS-STAIR ET looks like. Therefore, we  
248 think putting it in the discussion section fits well for the overall discussion part. We are also aware  
249 that many papers in this journal and other top journals have new figures introduced in the  
250 discussion section, e.g.:

251 Guzinski, R., Nieto, H., Stisen, S., & Fensholt, R. (2015). Inter-comparison of energy balance  
252 and hydrological models for land surface energy flux estimation over a whole river  
253 catchment. *Hydrology and Earth System Sciences*, 19(4), 2017–2036.  
254 <https://doi.org/10.5194/hess-19-2017-2015>

255 Gerken, T., Bromley, G. T., Ruddell, B. L., Williams, S., & Stoy, P. C. (2018). Convective  
256 suppression before and during the United States Northern Great Plains flash drought of  
257 2017. *Hydrology and Earth System Sciences*, 22(8), 4155–4163.  
258 <https://doi.org/10.5194/hess-22-4155-2018>

259 Konings, A. G., & Gentine, P. (2017). Global variations in ecosystem-scale isohydricity. *Global*  
260 *Change Biology*, 23(2), 891–905. <https://doi.org/10.1111/gcb.13389>

261 Huemmrich, K. F., Campbell, P., Landis, D., & Middleton, E. (2019). Developing a common  
262 globally applicable method for optical remote sensing of ecosystem light use efficiency.  
263 *Remote Sensing of Environment*, 230(July 2018), 111190.  
264 <https://doi.org/10.1016/j.rse.2019.05.009>

265

266 *20. Line 505: Can you investigate drought and soil moisture using the 2012 drought year in your*  
267 *dataset?*

268 We have accepted your suggestion. Please refer to our response 17.

269

270 *21. Line 531-534: Back to your urgency point in the introduction: are we from real-time ET*  
271 *estimates at 30-m being freely available for irrigation management?*

272 No, we haven't achieved real-time ET estimations in this study. This is indeed our ultimate goal  
273 and still on the development. We are developing in-season classification of corn and soybean  
274 which is required by BESS as well as in-season STAIR fusion.

275

276 Chongya Jiang and Kaiyu Guan, on behalf of all the authors.

# BESS-STAIR: a framework to estimate daily, 30-meter, and all-weather crop evapotranspiration using multi-source satellite data for the U.S. Corn Belt

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**Abstract.** With increasing crop water demands and drought threats, mapping and monitoring of cropland evapotranspiration (ET) at high spatial and temporal resolutions becomes increasingly critical for water management and sustainability. However, estimating ET from satellite for precise water resources management is still challenging due to the limitations in both existing ET models and satellite input data. Specifically, the process of ET is complex and difficult to model, and existing satellite remote sensing data could not fulfill high resolutions in both space and time. To address the above two issues, this study presented a new high spatiotemporal resolution ET mapping framework, i.e., BESS-STAIR, which integrates a satellite-driven water-carbon-energy coupled biophysical model BESS (Breathing Earth System Simulator) with a generic and fully-automated fusion algorithm STAIR (SaTellite dAta IntegRation). In this framework, STAIR provides daily 30-meter multispectral surface reflectance by fusing Landsat and MODIS satellite data to derive fine-resolution leaf area index and visible/near-infrared albedo, all of which, along with coarse-resolution meteorological and CO<sub>2</sub> data, are used to drive BESS to estimate gap-free 30-m resolution daily ET. We applied BESS-STAIR from 2000 through 2017 in six areas across the U.S. Corn Belt, and validated BESS-STAIR ET estimations using flux tower measurements over 12 sites (85 site-years). Results showed that BESS-STAIR daily ET achieved an overall  $R^2 = 0.75$ , with RMSE = 0.93 mm d<sup>-1</sup> and relative error = 27.9% when benchmarked with the flux measurements. In addition, BESS-STAIR ET estimations well captured the spatial patterns, seasonal cycles, and interannual dynamics in different sub-regions. The high performance of the BESS-STAIR framework is primarily resulted from: (1) the implementation of coupled constraints on water, carbon, and energy in BESS, (2) high-quality daily 30-m data from STAIR fusion algorithm, and (3) BESS's applicability under all-sky conditions. BESS-STAIR is calibration-free and has great potentials to be a reliable tool for water resources management and precision agriculture applications for the U.S. Corn Belt, and even for worldwide given the global coverage of its input data.



## 1 Introduction

35 Accurate field-level management of water resources urgently demands reliable estimations of evapotranspiration (ET) at  
high spatial and temporal resolutions. ET is the sum of water loss from soil surface through evaporation and that from plant  
components through leaf transpiration and evaporation, and ET at cropland is usually considered as crop water needs-use  
(Allen et al., 1998). ET consumes up to 90% of total water inputs (precipitation plus irrigation) in agro-ecosystems in the  
Western and Midwestern United States (Irmak et al., 2012). In the U.S. Corn Belt where more than 85% of corn and soybean  
40 are produced in the U.S. (Grassini et al., 2015), increasing vapor pressure deficit (VPD) and drought sensitivity has been  
recognized as severe threats to future crop security (Lobell et al., 2014; Ort and Long, 2014). The vulnerability to drought in  
this region is further exacerbated by elevated rates of grass-to-crop conversion and expansion of irrigated areas (Brown and  
Pervez, 2014; Wright and Wimberly, 2013). Furthermore, precision water resources management requires capacity to  
account for spatial heterogeneity and to guide real-time decision-making (GAO, 2019) (~~USDA, 1997~~). Accordingly, reliable  
45 tools are urgently needed to estimate, map and monitor the total amount and spatial and temporal variations of cropland ET.

One critical requirement for the accurate estimations of ET at high spatiotemporal resolutions is reliable and advanced  
satellite-based models. This is challenging because the process of ET is complex and difficult to model. ET results from  
competitions-balance between atmospheric water demand and soil water supply, and it is also regulated by plants through  
50 canopy development and stomatal behaviors in order to optimize their water, carbon and energy use strategies (Katul et al.,  
2012; Wang and Dickinson, 2012). A large number of satellite-based ET estimation methods have been developed based on  
different theories and techniques. In general, they can be grouped into many categories: statistical or machine learning  
methods (Jung et al., 2010; Lu and Zhuang, 2010), water balance methods (Pan et al., 2012; Wan et al., 2015), energy  
balance methods (Anderson et al., 1997; Su, 2002), triangular or trapezoid space methods (Jiang and Islam, 1999; Li et al.,  
55 2009), Priestley–Taylor methods (Fisher et al., 2008; Miralles et al., 2011), and Penman–Monteith methods (Mu et al., 2011;  
Yebera et al., 2013). Kalma et al. (2008), Li et al. (2009) and Zhang et al. (2016) have provided detailed reviews on the pros  
and cons of different remote sensing approaches.

Given the complexity of the ET process, we argue that a reliable ET model should include both necessary biophysical  
60 processes and high-quality multi-source observations to constrain ET estimations (Loew et al., 2016). While remote sensing-  
based approaches tend to focus on constraints from various satellite data, land surface models (LSMs) are proficient to  
include processes that account for interactions between environment and plant structure and functions. Given the gaps  
between remote sensing and LSMs, a distinct ET model, the Breathing Earth System Simulator (BESS), was developed  
(Jiang and Ryu, 2016; Ryu et al., 2011). Different from the above-mentioned remote sensing models, BESS is a biophysical  
65 model, which adopts modules commonly-implemented in land surface models but uses various satellite remote sensing data  
as direct inputs. Specifically, BESS is a two-leaf water-carbon-energy coupled model driven by environmental and  
vegetation variables derived from multi-source satellite data. As the energy cycle, carbon cycle and water cycle are jointly

modeled and mutually constrained in BESS, it has produced a series of high-quality global long-term (2000-2017) products, including the 5-km resolution global radiation (R<sub>g</sub>) and photosynthetically active radiation (PAR) and diffuse PAR products (Ryu et al., 2018), and 1-km resolution gross primary productivity (GPP) and ET products (Jiang and Ryu, 2016), which enables tracking crop growth and yields too (Huang et al., 2018). In particular, the 1-km resolution BESS ET product is able to capture the total amount and spatial and temporal variations in arid/semi-arid areas like Australia (Whitley et al., 2016, 2017), California (Baldocchi et al., 2019) and Northwestern China (Wei et al., 2019). The fidelity of coarse-resolution BESS ET product suggests its potential at fine resolutions.

75

The other critical requirement for accurate estimations of ET at high spatiotemporal resolutions is satellite input data at high resolutions in both space and time. This is challenging because existing satellite missions cannot satisfy the two conditions simultaneously. Data fusion techniques, which take multi-sensor data to generate fusion data with high resolutions in both space and time, provide a possible and scalable solution. Several such algorithms have been developed over the past decade (Gao et al., 2006; Houborg and McCabe, 2018; Zhu et al., 2010), and they have been successful for localized applications (Gao et al., 2017; Gómez et al., 2016; Wu et al., 2015). Notably, energy balance and thermal-based ET models such as ALEXI/DisALEXI and SEBS have been combined with the fusion algorithm such as STARFM and ESTARFM to generate daily 30-m ET estimations with favourable performance at several sites (Anderson et al., 2018; Cammalleri et al., 2013; Li et al., 2017; Ma et al., 2018).

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Here we propose and present a new ET estimation framework that combines BESS with a novel fusion algorithm SaTallite dAta IntegRation (STAIR) (Luo et al., 2018), for accurate ET estimation at both high resolution in time and space. BESS has demonstrated its high performance in estimating ET at medium to coarse resolutions, but the major obstacle of moving BESS's ET estimation to finer resolutions is the lack of key vegetation status variables at higher spatial resolutions, including leaf area index (LAI), and visible and near-infrared albedo ( $\alpha_{vis}$  and  $\alpha_{nir}$ ). In BESS, these surface information are critical to resolving spatial heterogeneity, while environmental information such as radiation, temperature, humidity and CO<sub>2</sub> concentration are relatively homogeneous. To cope with the absence of high spatiotemporal resolution vegetation data, we propose to couple STAIR with BESS. STAIR is a genetic and fully-automated fusion algorithm to generate cloud-/gap-free surface reflectance product in high spatiotemporal resolution (Luo et al., 2018). Instead of manually selecting image pairs adopted by most other data fusion algorithms, STAIR automatically takes full advantage of time-series of daily coarse-resolution images and fine-resolution but less frequent images. Moreover, STAIR's high efficiency in computation allows scalability for large scale productions, which enable this new framework to deliver daily 30-m ET at regional and decadal scales.

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100 The objective of this study is to address a fundamental issue in agro-ecological science and applications: lack of high spatiotemporal gap-free ET data for decision-making. We implemented a new ET estimation framework BESS-STAIR and

tested it at six study areas across the U.S. Corn Belt from 2000 to 2017. This is the first attempt to couple a satellite-driven LSM with data fusion technique to provide daily 30m-resolution ET estimations at regional and decadal scales. While existing frameworks retrieve clear-sky ET from satellite-observed LST and fill ET gaps for cloudy-sky days, BESS-STAIR simulates all-sky ET and LST as a result of crop biophysical properties. This manner has more referential significance for crop modeling studies and has potential of breaking a new path to agro-ecological science and applications. We conducted comprehensive evaluation on the BESS-STAIR ET estimations with regards to the overall performance, spatial patterns, seasonal cycles and interannual dynamics, benchmarked on the ET observations from 12 eddy-covariance flux towers across the U.S. Corn Belt. The paper also discussed on the performance, advantages, limitations and potential improvements of the BESS-STAIR ET framework.

## 2 Materials and methods

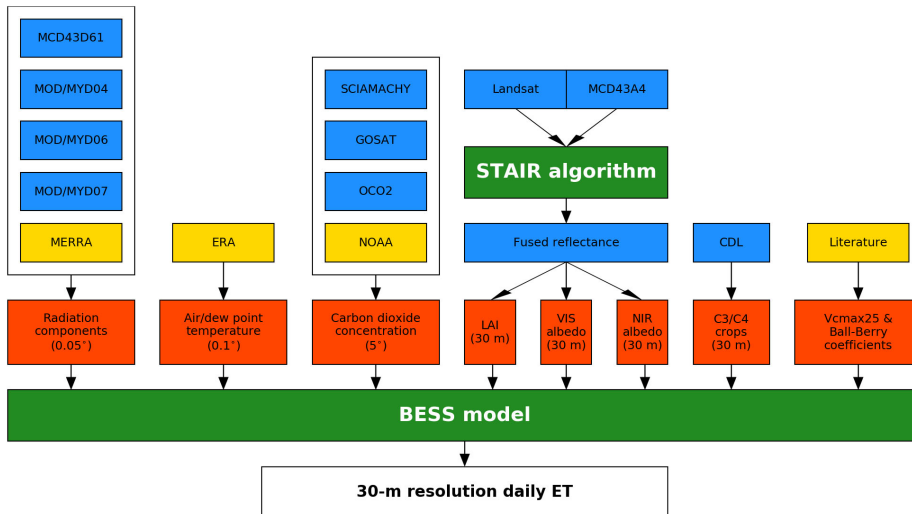


Figure 1. The BESS-STAIR framework. The BESS ET estimation model and the STAIR data fusion algorithm are highlighted in green boxes. Blue boxes are satellite data, yellow boxes are ancillary data, and red boxes are key inputs to BESS. The output of BESS-STAIR is the 30-m resolution daily ET highlighted in white box.

BESS-STAIR estimates cropland ET at 30-m resolution at daily interval (Figure 1). BESS is driven by environmental variables (radiation, temperature, humidity, and CO<sub>2</sub> concentration), plant structural variables (LAI,  $\alpha_{VIS}$  and  $\alpha_{NIR}$ ), and plant functional variables (peak maximum carboxylation rate at 25 °C (peak  $V_{cmax25}$ ) and Ball-Berry coefficients, for C3 and C4

plants, respectively). Among these key inputs, LAI,  $\alpha_{VIS}$  and  $\alpha_{NIR}$  characterize crop canopy structure, which are usually very heterogeneous. In the global BESS ET product (Jiang and Ryu, 2016), these vegetation variables are derived from MODIS satellite data at 1-km resolution; while in BESS-STAIR, they are derived from 30-m resolution surface reflectance fused from high spatial resolution Landsat data and high temporal resolution MODIS data by STAIR.

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### 2.1 The ET estimation model: BESS

BESS is a sophisticated satellite-driven water-carbon-energy coupled biophysical model designed to continuously monitor and map water and carbon fluxes (Jiang and Ryu, 2016; Ryu et al., 2011). It is a simplified land surface model, including an atmosphere radiative transfer module (Kobayashi and Iwabuchi, 2008; Ryu et al., 2018), a two-leaf canopy radiative transfer module (De Pury and Farquhar, 1997), and an integrated carbon assimilation – stomatal conductance – energy balance module. Specifically, the Farquhar model for C3 and C4 plants (Collatz et al., 1992, 1991), the Ball-Berry model (Ball et al., 1987), and the quadratic form of the Penman-Monteith equation (Paw U and Gao, 1988) are used for the simulation of carbon assimilation, stomatal conductance and energy balance, respectively. This carbon-water integrated module employs an iterative procedure to solve intercellular CO<sub>2</sub> concentration, stomatal conductance and leaf temperature for sunlit and shade canopy. Instantaneous sunlit/shade GPP and sunlit/shade/soil ET and net radiation at Terra and Aqua overpass times are simultaneously estimated, followed by a temporal upscaling procedure to derive daily GPP and ET using semi-empirical cosine functions (Ryu et al., 2012). The Priestley-Taylor equation is used to compute daily potential ET (PET) based on estimated daily net radiation and meteorological data inputs.

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A unique feature of BESS is that BESS takes full advantages of atmospheric and land products derived from multi-source satellite data. By using MOD/MYD 04 aerosol products (Sayer et al., 2014), MOD/MYD 06 cloud products (Baum et al., 2012), MOD/MYD 07 atmospheric profile products (Seemann et al., 2003), along with gap-free atmospheric data provided by MERRA-2 reanalysis products (Gelaro et al., 2017), BESS calculates direct/diffuse visible/near-infrared radiation components at 0.05° resolution. By coupling CO<sub>2</sub> concentration derived from SCIAMACHY and GOSAT satellite data (Dils et al., 2014) with those from OCO-2 satellite data (Hammerling et al., 2012), as well as NOAA long-term field observations ([www.esrl.noaa.gov/gmd/ccgg/trends/](http://www.esrl.noaa.gov/gmd/ccgg/trends/)), BESS derives long-term continuous monthly CO<sub>2</sub> concentration maps. Finally, in this study BESS uses air temperature and dew point temperature provided by ERA5 reanalysis products at 0.1° resolution (Hersbach and H., 2016). In addition to these environmental variables, BESS also highly relies on vegetation structural and functional variables. By using satellite-derived LAI,  $\alpha_{VIS}$  and  $\alpha_{NIR}$ , BESS quantifies the absorption of ultraviolet/visible/near infrared radiation by sunlit/shaded canopy through a canopy radiative transfer model. This model also upscales leaf level ( $V_{\text{cmax25}}$ ) to sunlit/shade canopy, which is used in the Farquhar photosynthesis model.  $V_{\text{cmax25}}$  is a parameter depending on the plant functional type (Bonan et al., 2011; Kattge et al., 2009), and its seasonal variation is empirically parameterized by LAI (Ryu et al., 2011).

155 **2.2 The data fusion algorithm: STAIR**

STAIR is a generic and fully-automated method for fusing multi-spectral satellite data to generate high spatiotemporal resolution and cloud-/gap-free data (Luo et al., 2018). It fully leverages the complementary strengths in the high temporal resolution MCD43A4 nadir reflectance (daily but 500 m resolution) (Schaaf et al., 2002) and the high spatial resolution Landsat L2 nadir reflectance (30-m resolution but 16-day revisiting frequency) (Masek et al., 2006) time series data. STAIR first imputes the missing pixels using an adaptive-average correction procedure, and then employs a local interpolation model to capture finer spatial information provided by Landsat data, followed by a time-series refinement step that incorporates the temporal patterns provided by MODIS data. This strategy allows higher efficiency in missing-data interpolation as well as greater robustness against concurrently missed MODIS and Landsat observation, which is a common situation during continuous cloudy/snowy days.

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The algorithm starts from the imputation of the missing pixels (due to cloud cover or Landsat 7 Scan Line Corrector failure) in satellite images. For MODIS images, a Savitzky-Golay filter is first applied to reconstruct continuous time series. For Landsat images, a two-step approach is employed using both temporal and spatial information from clear-sky observations. First, a temporal interpolation through a linear regression is applied as the initial gap-filling, based on the whole time series of images throughout a year. Second, an adaptive-average correction procedure is applied to remove inharmonic spatial patterns between gap-filled and original data. The target image is partitioned into multiple segments, each of which contains one type of homogeneous pixels. The relative difference between a gap pixel and neighbourhood pixels of it within the same segment is calculated using clear-sky observations acquired in several dates close to the target image acquisition date. Based on the assumption that the relative difference remains roughly the same across different dates in a short time period (e.g., < 2–3 weeks), such difference is used to correct the filled values of the gap pixel derived from temporal interpolation so that the spatial relationship between the gap-filled pixel and its neighbourhood pixels within the same segment is consistent with those in clear-sky observations.

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The STAIR fusion algorithm fully exploits the spatial and temporal information in the time series of gap-filled MODIS and Landsat images throughout the growing season (April - October). A nearest neighbour sampling is conducted for all the MODIS images to achieve the same image size, pixel resolution and projected coordinate system with Landsat images. Difference image is calculated for each pair of Landsat and resampled MODIS images, and a linear interpolation is applied to reconstruct the difference image for any given date when no Landsat image is available. Such difference image is used to correct the resampled MODIS image on that date and to generate a fused Landsat image. In this manner, the fused image captures the most informative spatial information provided by the high spatial resolution Landsat data and incorporates the temporal patterns provided by the high temporal resolution MODIS data without any user interference. The fusion algorithm is applied to the six Landsat bands: blue, green, red, near-infrared (nir), shortwave infrared 1 (swir1), and shortwave infrared-2 (swir2).

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190 **2.3 Derivation of BESS inputs from STAIR data**

At global scale, LAI,  $\alpha_{VIS}$  and  $\alpha_{NIR}$  can be obtained from MODIS and other satellite data, but for field-scale agricultural applications high spatial resolution data are needed to account for the spatial heterogeneity between fields or within a field. At this point, we employed two approaches to estimate 30-m resolution daily LAI from STAIR fused surface reflectance data: an empirical approach based on linear relationship with vegetation indices (VIs) and a mechanic approach based on inversion of a canopy radiative transfer model (RTM).  
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First, we estimated LAI using the empirical approach, because of availability of field LAI measurements in the study area. We calculated four VIs calculated from STAIR-derived spectral reflectance: Wide Dynamic Range Vegetation Index (WDRVI), Green Wide Dynamic Range Vegetation Index (GWDRCVI), Enhanced Vegetation Index (EVI), and Land Surface Water Index (LSWI) for corn and soybean, respectively (Eq. (1) – (3)). These four ~~VIs~~ VIs were chosen because they utilized information from different band combinations.  
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$$WDRVI = \frac{0.1\rho_N - \rho_R}{0.1\rho_N + \rho_R} \quad (1)$$

$$GWDRCVI = \frac{0.1\rho_N - \rho_G}{0.1\rho_N + \rho_G} \quad (2)$$

$$EVI = 2.5 \frac{\rho_N - \rho_R}{\rho_N + 6\rho_R - 7.5\rho_B + 1} \quad (3)$$

$$LSWI = \frac{\rho_N - \rho_{SW1}}{\rho_N + \rho_{SW2}} \quad (4)$$

where  $\rho_B$ ,  $\rho_G$ ,  $\rho_R$ ,  $\rho_N$ , and  $\rho_{SW1}$  refer to the surface reflectance at blue, green, red, near-infrared, the first shortwave-infrared band, respectively. Subsequently, we used field measured LAI data collected using destructive method at Mead, Nebraska from 2001 through 2007 to build VI-LAI relationships (Gitelson et al., 2007). For each of the four VIs we build a linear regression between time series of VI and LAI for corn, soybean, and the combination of corn and soybean, respectively  
205 (Table 1). At this point, the equation derived from the combination of corn and soybean was used for vegetation cover other than corn and soybean. Although this might cause bias for forest LAI estimation, it is not a concern in this study as we focused on crop ET only. We applied linear regressions to four VIs separately and averaged the four derived LAI as the final LAI estimation, with the expectation that such average would reduce uncertainty caused by individual VI-LAI relationship.  
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Table 1. Linear equations for LAI (y) as a function of VI (x) for corn, soybean, and the combination of corn and soybean.

<u>VI</u>	<u>Corn</u>	<u>Soybean</u>	<u>Combination</u>
<u>WDRVI</u>	<u>y = 6.288x + 4.631</u>	<u>y = 4.584x + 3.432</u>	<u>y = 5.745x + 4.288</u>
<u>GWDRCVI</u>	<u>y = 8.964x + 5.875</u>	<u>y = 6.384x + 4.275</u>	<u>y = 8.110x + 5.395</u>

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$$\begin{aligned} \underline{EVI} & \quad y = 10.569x - 2.165 & y = 8.116x - 1.936 & y = 9.665x - 1.993 \\ \underline{LSWI} & \quad y = 9.156x + 1.070 & y = 7.553x + 0.888 & y = 8.944x + 0.982 \end{aligned}$$

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Second, we inversed PROSAIL RTM using a look-up table (LUT) method. PROSAIL is an efficient and widely-used model to simulate canopy reflectance given a set of sun-object-view geometry, canopy structure, leaf biochemical, and soil optical parameters (Jacquemoud et al., 2009). It is a combination of the PROSPECT leaf hyperspectral properties model (Jacquemoud et al., 1996; Jacquemoud and Baret, 1990) and the SAIL canopy bidirectional reflectance model (Verhoef, 1984, 1985). PROSAIL is particularly suitable for grasslands and croplands (Darvishzadeh et al., 2008; Xu et al., 2019), and therefore used in this study. LUT is a robust and easy method to retrieve model parameters from observed canopy reflectance (Verrelst et al., 2018). It is based on the generation of simulated canopy reflectance database for a number of plausible combinations of model parameter value ranges, and the identification of parameter values in the database leading to the best agreement between simulated and observed canopy reflectance. LUT is particularly suitable for big data processing (Myneni et al., 2002), and therefore used in this study.

We established a database by running PROSAIL with sampled parameter values listed in Table 42. For computation efficiency, we only sampled varied values for four parameters while others were fixed. These four free parameters, including LAI (10 values), fraction of vegetation cover (6 values), soil brightness (5 values) and chlorophyll content (4 values), were chosen because they have been identified as the most sensitive parameters in canopy radiative transfer models (Bacour et al., 2002; Mousivand et al., 2014). Leaf inclination distribution function is also sensitive but we set fixed types "spherical", "planophile" and "plagiophile" for corn, soybean, and other biomes, respectively (Nguy-Robertson et al., 2012; Pisek et al., 2013). The fixed values of other parameters were set according to literature (Baret et al., 2007; Feret et al., 2008; Jacquemoud et al., 2009). Solar zenith angle at satellite overpass time can be calculated so we did not set it as a free parameter. Instead, we built a set of databases with solar zenith angle values (°) of 20, 25, 30, 35, 40, 45 and 50, respectively, representing the range during growing season in the study area. In PROSAIL, specific absorption coefficients and refractive index of leaf material are pre-measured hyperspectral data from 400 to 2500 nm with 1 nm interval (Feret et al., 2008), we averaged them over wavelengths to match Landsat 7 bands and assumed differences of spectral ranges between Landsat 5, Landsat 7 and Landsat 8 have marginal influence on LAI retrieval. We did not use default soil spectrum in PROSAIL, but spatiotemporally averaged all cropland pixels spectral reflectance in April when no crop is planted across the study area to derive representative soil spectral reflectance.

Table 42. Parameter values needed to establish the canopy reflectance database by PROSAIL.

Parameters	Values
LAI (m <sup>2</sup> m <sup>-2</sup> )	0, 0.5, 1, 2, 3, 4, 5, 6, 7, 8

Fraction of vegetation cover (m <sup>2</sup> m <sup>-2</sup> )	0, 0.2, 0.4, 0.6, 0.8, 1
Soil brightness (a.u.)	0.01, 0.4, 0.8, 1.2, 1.6
Chlorophyll content (ug cm <sup>-2</sup> )	0, 20, 40, 60
Leaf inclination distribution function	spherical for corn, planophile for soybean, plagiophile for others
Structure coefficient (a.u.)	1.75
Carotenoid content (ug cm <sup>-2</sup> )	0
Equivalent Water Thickness (cm)	0.015
Leaf Mass per area (g cm <sup>-2</sup> )	0.0075
Brown pigment content (a.u.)	0
Hot spot parameter (a.u.)	0.1
View zenith angle (°)	0
Azimuth angle (°)	0

To retrieve LAI, we compared STAIR-derived surface reflectance ( $R_{STAIR}$ ) with records in the canopy reflectance database simulated by PROSAIL ( $R_{PROSAIL}$ ) pixel by pixel. We used root mean square error (RMSE) as the cost function which was defined as:

$$RMSE = \sqrt{\frac{1}{l} \sum_{\lambda=1}^l [R_{STAIR}(\lambda) - R_{PROSAIL}(\lambda)]^2}, \quad (5)$$

where  $\lambda = 1, 2, \dots, l$  indicates band number and  $l = 6$  for STAIR. Ideally, the simulated reflectance in the database yielding the smallest RMSE can be considered as the best simulation, and the corresponding LAI value can be considered as the solution for the satellite pixel. However, in reality the solution might not be unique, because different parameter combinations could derive similar reflectance simulations and errors in both satellite and model could further amplify this problem (Verrelst et al., 2018). For this reason, we chose top 10% small RMSE simulations in the database and considered the average of corresponding LAI values as the final solution. The threshold 10% was decided by evaluating LUT-retrieved LAI against field-measured LAI at three Mead sites, and it was within a reasonable range from top 50 records to top 20% records suggested by previous studies (Duan et al., 2014; Weiss et al., 2000).

We further employed semi-empirical equations to calculate  $\alpha_{VIS}$  and  $\alpha_{NIR}$  (Liang, 2001) from STAIR-derived spectral reflectance in six Landsat bands:

$$\alpha_{VIS} = 0.443\rho_B + 0.317\rho_G + 0.240\rho_R \quad (6)$$

$$\alpha_{NIR} = 0.693\rho_N + 0.212\rho_{SW1} + 0.116\rho_{SW2} - 0.003 \quad (7)$$

where  $\rho_{SW2}$  is the surface reflectance at the second shortwave-infrared band. ~~CI was set 0.75 for herbaceous and 0.70 for woody plants according to the global mean value of different plant functional types (He et al., 2012).~~ For C3 crops/grasses, forests, and C4 crops/grasses, peak  $V_{\text{max}25}$  values were set 180, 60 and 45, respectively (Kattge et al., 2009; Zhang et al.,



2014). Ball-Berry slope and intercept are another two important parameters used in the stomatal conductance model, and their values were set 13.3 and 0.02 for C3 crops/grasses, 9.5 and 0.005 for forests, and 5.8 and 0.04 for C4 crops, respectively (Miner et al., 2017). Distributions of C3 and C4 crops were obtained from Crop Data Layer (CDL) data (Boryan et al., 2011).

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#### 2.4 Evaluation of BESS-STAIR ET

The BESS-STAIR ET estimations were evaluated against flux tower ET measurements in the U.S. Corn Belt. The U.S. Corn Belt (Figure 2) generally refers to a region in the Midwestern United States that has dominated corn and soybean production in the United States (Green et al., 2018), which currently produces about 45% and 30% of the global corn and soybean, respectively (USDA, 2014). The region is characterized by relatively flat land, deep fertile soils, and a high soil organic matter (Green et al., 2018). Most part of the U.S. Corn Belt has favorable growing conditions of temperature and rainfall. A majority of the croplands in the U.S. Corn Belt are rainfed, with a small portion in the west part relying on irrigation.

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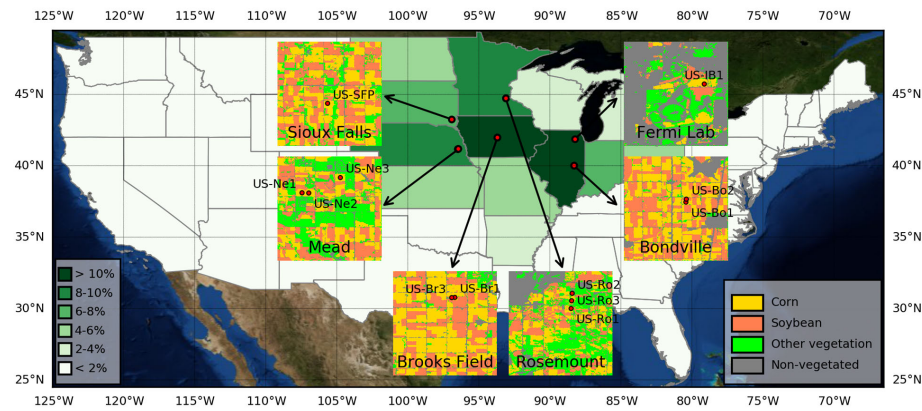


Figure 2. Study areas. Red dots indicate 12 flux tower sites scattered in six areas across the U.S. Corn Belt. The background map indicates the percent each state contribute to the total national corn and soybean plantation area (USDA, 2018).

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A total of 12 cropland sites scattered in six areas across the U.S. Corn Belt are registered in the AmeriFlux or FLUXNET network with publicly-available ET data (Figure 2 and Table 23). These sites include both corn only and corn/soybean rotation sites and both rainfed and irrigated sites, covering typical cropping patterns in the U.S. Corn Belt. All of them were used in this study to ensure the representativeness of the validation for the precision agriculture applications in this region. For six sites: US-Bo1 (Meyers and Hollinger, 2004), US-Bo2 (Bernacchi et al., 2005), US-Br1 (Prueger et al., 2003), US-Br3 (Prueger et al., 2003), US-Ro2 (Turner et al., 2016) and US-SFP (Wilson and Meyers, 2007), level 2 half-hourly data

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were downloaded from the AmeriFlux website (<http://ameriflux.lbl.gov/>). For three sites: US-IB1 (Matamala et al., 2008), US-Ro1 (Griffis et al., 2010) and US-Ro3 (Griffis et al., 2010), standardized gap-filled level 4 daily mean data were downloaded from the Carbon Dioxide Information Analysis Center data archive website (<https://mirrors.asun.co/climate-mirror/cdiac.ornl.gov/pub/ameriflux/>). For the other three sites (Suyker et al., 2004): US-Ne1, US-Ne2 and US-Ne3, standardized high-quality gap-filled daily mean data were downloaded from the FLUXNET2015 website (<http://fluxnet.fluxdata.org/data/fluxnet2015-dataset/>).

Table 23. Information of 12 flux tower sites used for validation.

ID	Site	Location	Latitude	Longitude	Plant	Irrigation	Years	Source
1	US-Bo1	Bondville, IL	40.0062	-88.2904	corn/soybean	N	2000-2008	AmeriFlux L2
2	US-Bo2	Bondville, IL	40.0090	-88.2900	corn/soybean	N	2004-2006	AmeriFlux L2
3	US-Br1	Brooks Field, IA	41.9749	-93.6906	corn/soybean	N	2005-2011	AmeriFlux L2
4	US-Br3	Brooks Field, IA	41.9747	-93.6936	corn/soybean	N	2005-2011	AmeriFlux L2
5	US-IB1	Fermilab, IL	41.8593	-88.2227	corn/soybean	N	2005-2007	AmeriFlux L4
6	US-Ne1	Mead, NE	41.1651	-96.4766	corn	Y	2001-2012	FLUXNET2015
7	US-Ne2	Mead, NE	41.1649	-96.4701	corn/soybean	Y	2001-2012	FLUXNET2015
8	US-Ne3	Mead, NE	41.1797	-96.4397	corn/soybean	N	2001-2012	FLUXNET2015
9	US-Ro1	Rosemount, MN	44.7143	-93.0898	corn/soybean	N	2004-2006	AmeriFlux L4
10	US-Ro2	Rosemount, MN	44.7288	-93.0888	corn/soybean/clover	N	2008-2016	AmeriFlux L2
11	US-Ro3	Rosemount, MN	44.7217	-93.0893	corn/soybean	N	2004-2006	AmeriFlux L4
12	US-SFP	Sioux Falls, SD	43.2408	-96.9020	corn	N	2007-2009	AmeriFlux L2

By comparing with eddy covariance ET, we evaluated three ET estimations: BESS-STAIR with VIs-based LAI, BESS-STAIR with RTM-based LAI, and BESS-STAIR with MODIS LAI. MODIS LAI refers to MCD15A3H 500m resolution 4-day composite LAI product downloaded from <https://lpdaac.usgs.gov/tools/data-pool/>. Since eddy covariance technique used by flux towers provides water flux observations in term of latent heat (LE) rather than ET, evaluations were conducted by comparing BESS-STAIR daily LE estimates with flux tower measurements. At this point, water flux can be simply converted from energy unit (LE, MJ m<sup>-2</sup> d<sup>-1</sup>) to water unit (ET mm d<sup>-1</sup>) by dividing latent heat of vaporization which is a function of daily temperature (Henderson-Sellers, 1984). Flux tower measurements usually have an irregular and dynamic footprint at scales from 100-m to 1-km (Fu et al., 2014), but for simplicity, only 30-m resolution BESS-STAIR pixels containing the flux tower were used for the direct comparison. With regard to flux towers, measurements data were directly used without energy closure adjustment. For AmeriFlux level 2 data, half-hourly data were averaged to daily LE-ET only if no gaps exist during the day to avoid sampling bias caused by missing data. For AmeriFlux level 4 data and FLUXNET2015 data, gap-filled daily LE-ET were used directly.

### 3 Results

#### 3.1 Performance of STAIR LAI

LAI is the key input of BESS. The accuracy of high-resolution LAI estimations determine the validity of high-resolution ET estimations. We evaluated Vis-based LAI and RTM-based LAI estimations derived from 30-m resolution STAIR fused surface reflectance data against field measurements. We also compared them with 500-m resolution MODIS LAI. Overall, STAIR-derived LAI agree well with measured LAI, with  $R^2 > 0.85$ ,  $RMSE < 0.8$  and mean bias error (MBE)  $\approx 0$  (Figure 3). The RTM-based method which is calibration free yields same performance with Vis-based method which requires substantial field measurements to build empirical relationships. Misclassification of CDL data between corn and soybean is an important uncertainty source since both methods rely on crop types. During 2001 – 2007, 4 out of 21 site years (19%) over the three Mead sites were misclassified. By using the correct classification (not shown), the accuracy of LAI estimations reach  $R^2 = 0.90$  and  $RMSE = 0.62$  for Vis-based method and  $R^2 = 0.89$  and  $RMSE = 0.68$  for RTM-based method. By comparison, coarse-resolution MODIS LAI has relatively large errors, especially a negative bias ( $R^2 = 0.55$ ,  $RMSE = 1.68$  and  $MBE = -0.97$ ).

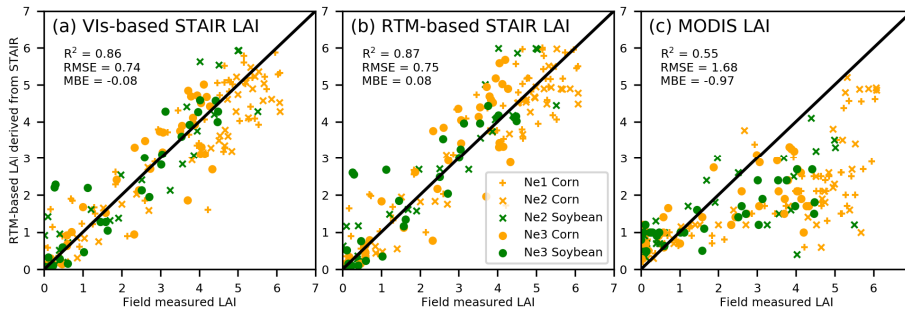


Figure 3. Scatter plots between LAI measurements and LAI estimations. LAI measurements are destructively collected at three Mead sites. (a) – (b) STAIR-derived daily 30m-resolution LAI using Vis-based method and RTM-based method, respectively. (c) 500m-resolution MODIS LAI.

#### 3.2 Performance of BESS-STAIR ET

BESS-STAIR daily LE-ET estimations are in a highly aligned agreement with ground truth from the 12 flux-tower measurements (Figure 4). Across all of the 12 sites, BESS-STAIR LE-ET with RTM-based LAI achieves an overall coefficient of determination ( $R^2$ ) of 0.75, root-mean-square error (RMSE) of  $2.29 \text{ MJ m}^{-2} \text{ d}^{-1}$ , relative error ( $E(|X_{\text{estimation}} - X_{\text{measurement}}|)/E(X_{\text{measurement}})$ ), RE) of 27.9%, and no overall bias. Figure 5 further exhibits its performance over all of the 12 flux tower sites.  $R^2$  values range from 0.68 to 0.94 for corn, and 0.65 to 0.81 for soybean, highlighting the robustness of

BESS-STAIR ET in the U.S. Corn Belt. BESS-STAIR  $\overline{LE-ET}$  with VIs-based LAI has similar performance ( $R^2 = 0.75$ , RMSE = 2.24 MJ m<sup>-2</sup> d<sup>-1</sup>, and RE = 27.4%). Considering relatively small difference between BESS-STAIR using RTM-based LAI and that using VIs-based LAI, only the former one which is calibration-free is demonstrated in the following parts of this paper. By comparison, BESS  $\overline{LE-ET}$  with MODIS LAI shows larger errors ( $R^2 = 0.65$ , RMSE = 2.50 MJ m<sup>-2</sup> d<sup>-1</sup>, and RE = 30.2%) comparing to BESS-STAIR.

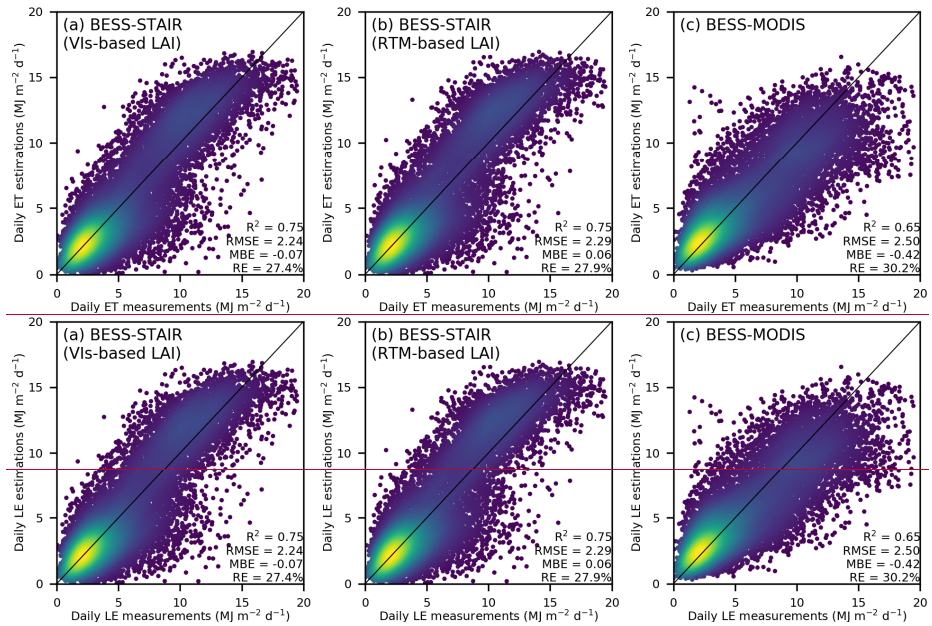


Figure 4. Density scatter plots between  $\overline{LE-ET}$  measurements and  $\overline{LE-ET}$  estimations.  $\overline{LE-ET}$  measurements are from eddy covariance data collected at 12 flux towers. (a) and (b) BESS-STAIR  $\overline{LE-ET}$  with VIs-based LAI and RTM-based LAI, respectively. (c) 500m-BESS  $\overline{LE-ET}$  with MODIS LAI.

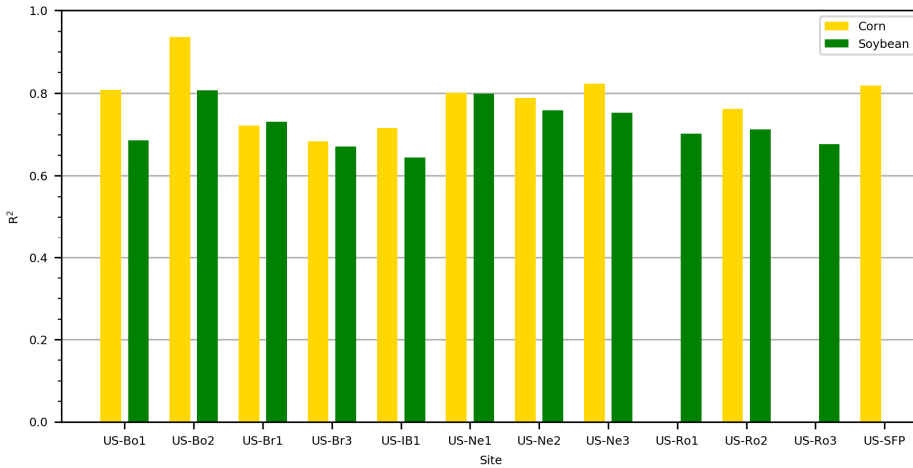
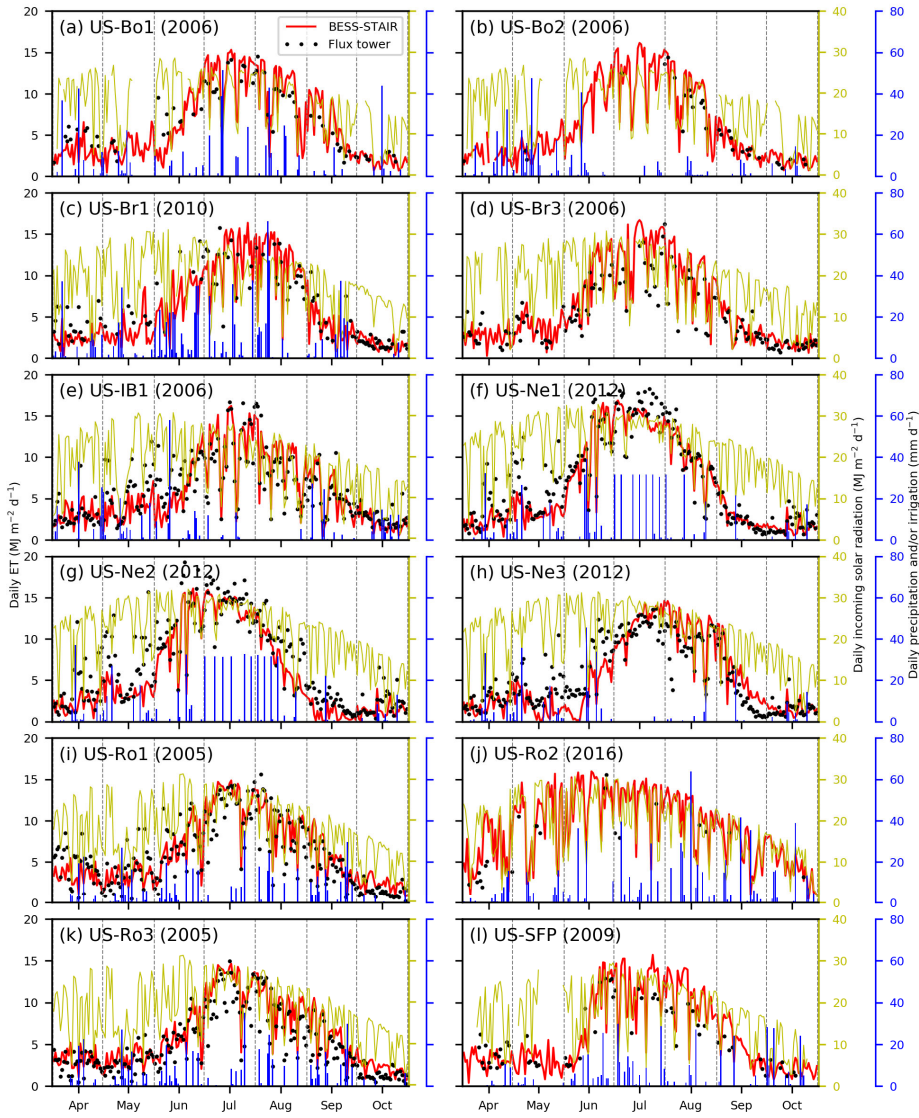


Figure 5. Site-by-site  $R^2$  between flux tower measured and BESS-STAIR estimated daily  $LE-ET$  for corn and soybean, respectively. Crop type is from CDL data.

Figure 6 shows the comparison between BESS-STAIR  $daily LE$  estimations and flux tower measurements over site years with least data gaps in measurements. Across all of the 12 sites, BESS-STAIR well captures the seasonal characteristics of  $LEET$  observation from flux towers, as they exhibit generally consistent variations over the growing season. During the peak growing season (June, July and August), the radiation displays a dominant impact on measured  $daily LE$ , and it is reasonably estimated by BESS-STAIR  $LE$  as well. In most cases, measured  $daily LE$  do not show strong and fast response to precipitation and/or irrigation, possibly due to the plentiful water storage in soil. Two exceptions are US-IB1 (2006) and US-Ne3 (2012). In case of US-IB1, no precipitation is available in August and little in July. As a result,  $daily LE$  measurements drop slightly quicker in August than other cases. Such anomaly is also depicted by BESS-STAIR  $LE$ . In case of US-Ne3, the severe drought in 2012 summer causes ~~much slightly~~ lower  $LEET$  values than the two adjacent irrigation sites (US-Ne1 and US-Ne2). BESS-STAIR  $LE$  also captures this considerable reduction, although a slight bias is observed in July. Figure 7 further demonstrates that the seasonal cumulative ET at three Mead sites calculated for both the flux tower measurements and BESS-STAIR estimations overall agree well throughout the peak growing season (June—September).



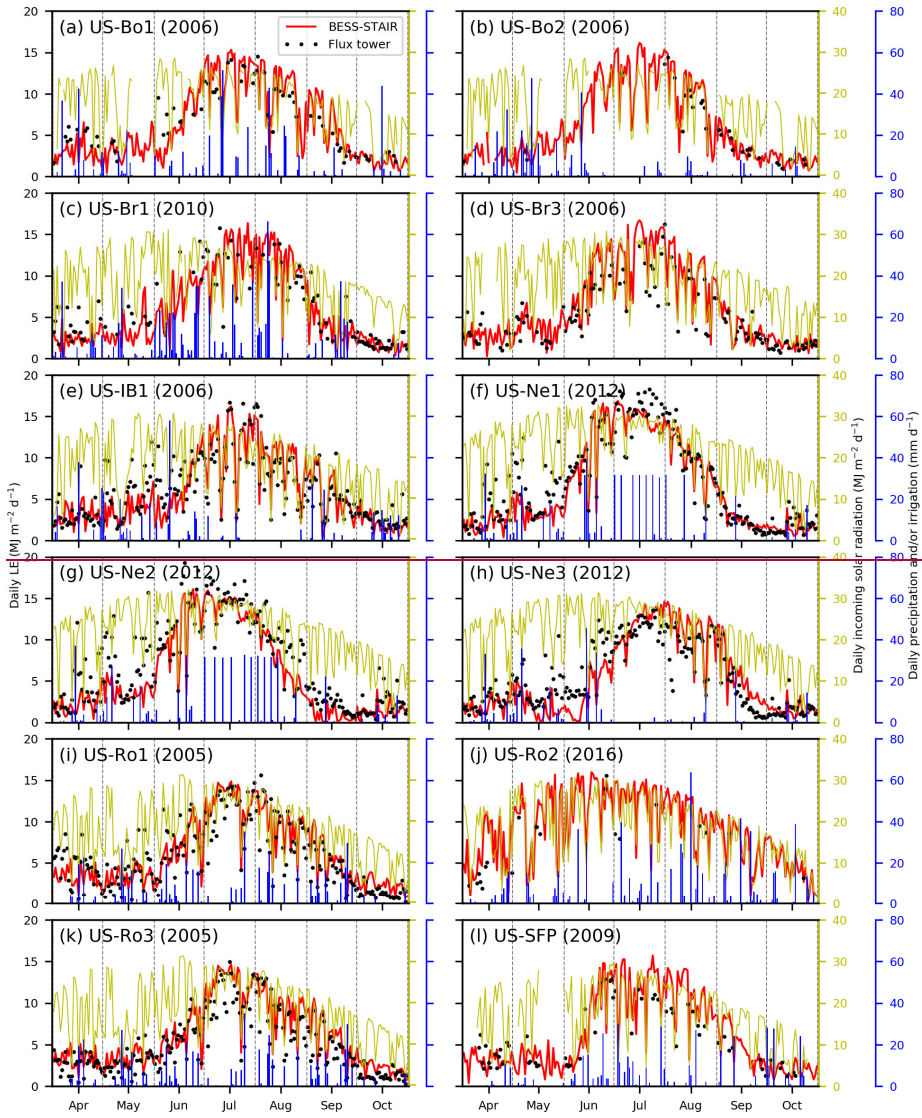
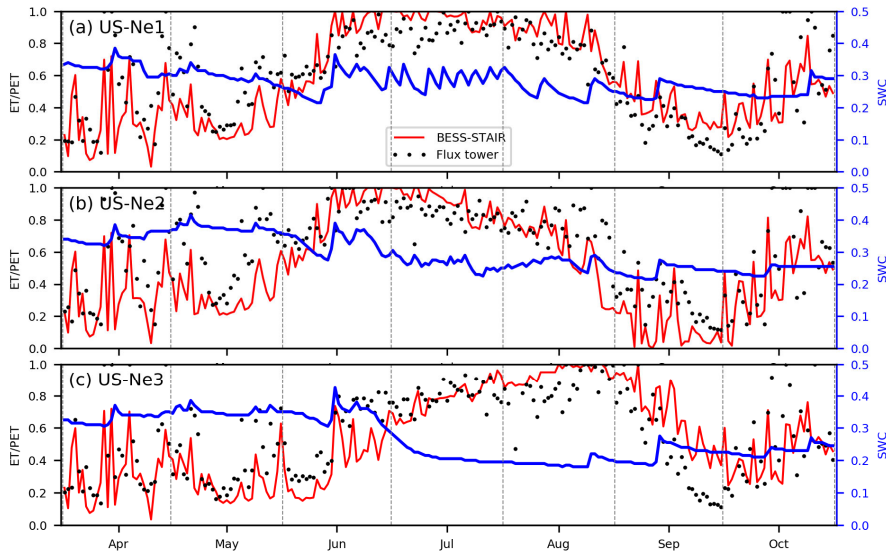


Figure 6. Seasonal time series of flux tower measured and BESS-STAIR estimated  $\text{daily } L E_{\text{daily ET}}$  for 12 selected site years. Daily radiation and precipitation/irrigation are overlaid except for US-Br3.



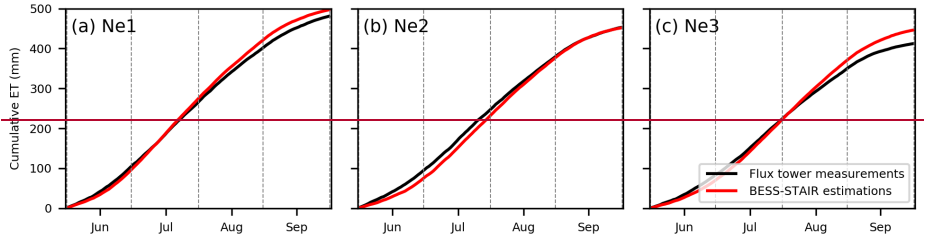
365

Figure 7. Seasonal time series of daily ET/PET derived from BESS-STAIR and flux tower for US-Ne1, US-Ne2, and NS-Ne3 in 2012, along with measured daily mean soil water content (SWC).

370

Figure 7 shows the comparison between BESS-STAIR ET/PET and flux tower ET/PET at three sites (US-Ne1, US-Ne2, and NS-Ne3) at Mead, Nebraska. Overall, BESS-STAIR agrees well with flux tower in both magnitude and seasonal cycle. Although 2012 is a severe drought year, soil water content (SWC) at the rainfed site US-Ne3 still shows a relatively high level ( $> 0.2$ ). As a result, ET/PET from both BESS-STAIR and flux tower are at the same level with the adjacent two irrigated sites (US-Ne2 and US-Ne3).





375 **Figure 7. Multi year mean cumulative ET for flux tower measurements and BESS-STAIR estimations at three Mead sites from 2001 through 2012.**

### 3.3 Spatiotemporal variations of BESS-STAIR ET

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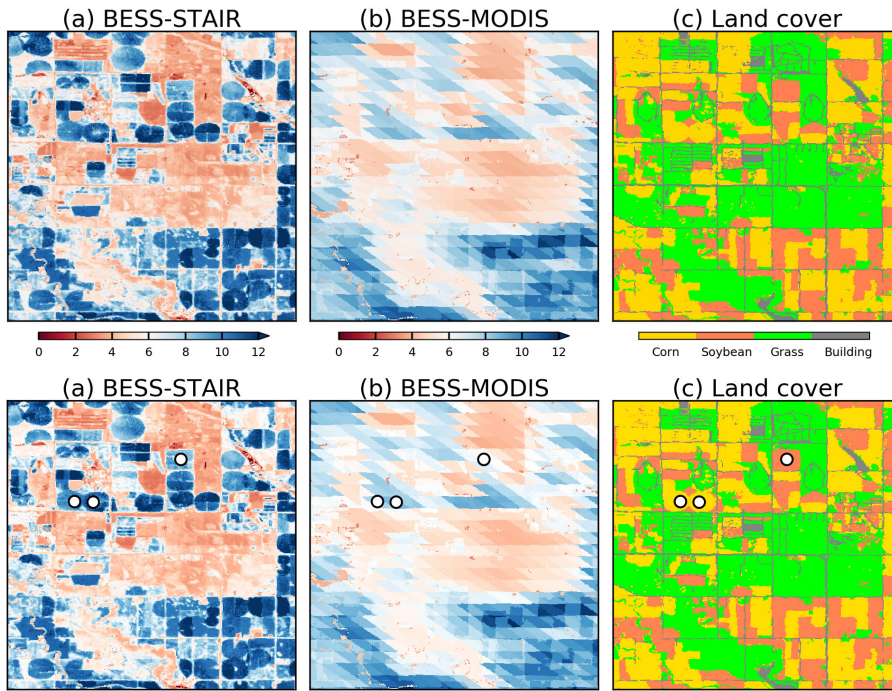
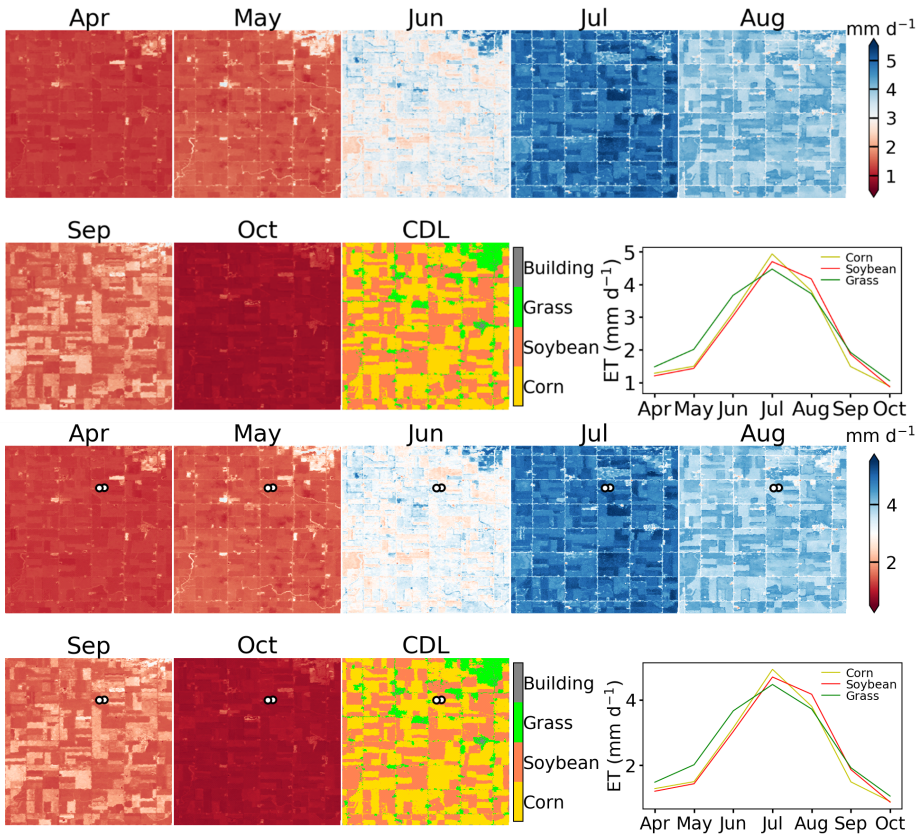


Figure 8. Daily LEDaily ET (MJ m<sup>-2</sup> d<sup>-1</sup>) derived from (a) BESS-STAIR and (b) BESS-MODIS at Mead (41.1°N – 41.2°N, 96.4°W – 96.5°W) on August 1, 2012. Circles indicate flux towers in this region.

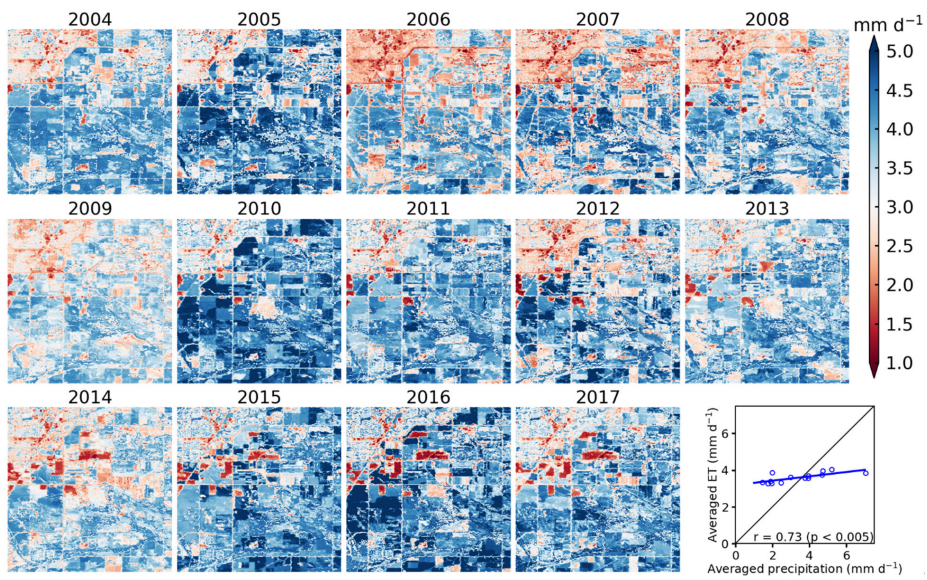
385 BESS-STAIR daily ET demonstrates prominent spatial variations within the 0.1° × 0.1° area near the Mead site in Nebraska  
(Figure 8). Because of the impact of drought, central pivot irrigated fields characterized by round-shaped plots generally  
display higher values than surrounding croplands, and croplands have much higher values than grasslands. Variabilities of  
ET between different crop fields and within individual crop fields are also observable. Such variabilities might be attributed  
to different irrigation strategies, varieties and/or other management. By comparison, though 500m-resoluition BESS-  
390 MODIS ET is able to capture the general spatial pattern, it has many mixed pixels and is unable to demonstrate gradients  
across field boundaries.



395 Figure 9. Monthly mean BESS-STAIR ET at Brooks Field (41.9°N – 42.0°N, 96.65°W – 96.75°W) during the growing  
 400 season of 2000, along with a CDL land cover map. The last subplot shows the average time series of corn, soybean and  
 grass. Circles indicate flux towers in this region.

Reasonable seasonal cycles for different land cover types are revealed by BESS-STAIR monthly ET averaged from gap-free  
 400 daily estimations. An example time series of monthly ET maps at Brooks Field during the growing season of 2000 is shown  
 in Figure 9. BESS-STAIR ET clearly captures the temporal dynamics throughout the growing season. All vegetation show  
 low values (e.g., < 2 mm d<sup>-1</sup>) in April, May, September and October, but high values in June, July and August (JJA), with  
 their peaks in July. Different seasonal cycles for corn, soybean and grass are also captured. Grass has the highest ET among

the three vegetation types from April through June. Corn has higher ET than soybean in June and July, and decreases quickly  
405 since August. Soybean has the lowest ET from April through June, but has the highest ET in August.



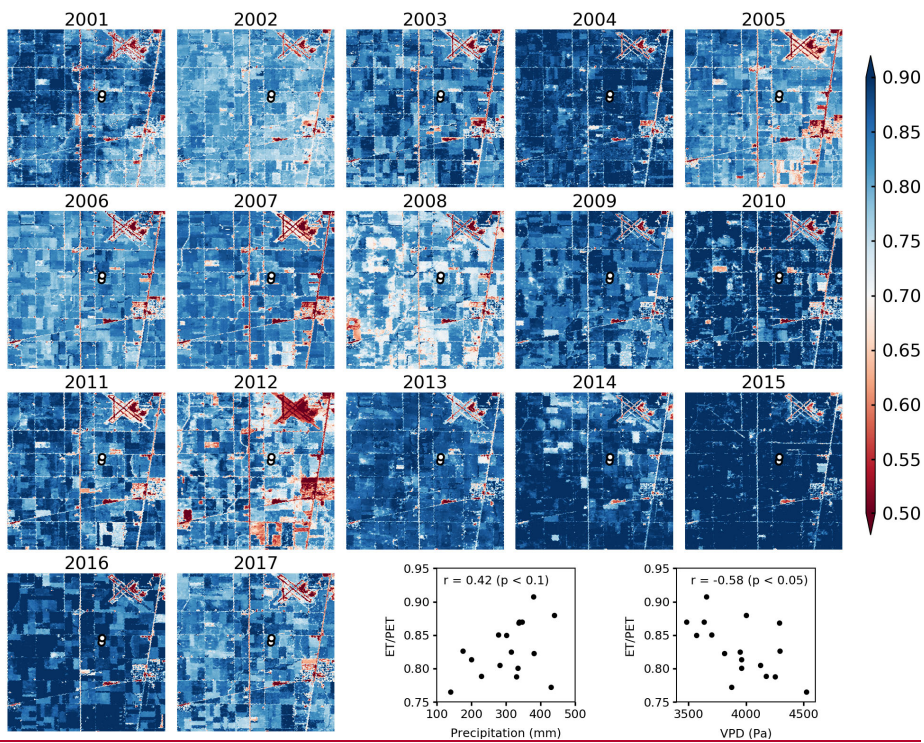


Figure 10. Peak growing season (June, July and August) Monthly-mean BESS-STAIR ET/PET in July at Rosemount Bondville (4439.6595°N – 4440.7505°N, 9388.0525°W – 9388.1535°W) from 2004-2001 throughout 2017, along with a two scatter plots between regional-averaged monthly-mean peak growing season precipitation and ET/PET and peak growing season VPD and ET/PET in July over the 14-17 years. Monthly precipitation maps are from PRISM (<http://www.prism.oregonstate.edu/historical/>) Precipitation and VPD data are from Daily Surface Weather Data (Daymet) at Illinois Bondville ([https://modis.ornl.gov/cgi-bin/sites/site/?id=us\\_illinois\\_bondville&product=Daymet](https://modis.ornl.gov/cgi-bin/sites/site/?id=us_illinois_bondville&product=Daymet)), where VPD is derived using maximum air temperature and water vapor pressure. Circles indicate flux towers in this region.

BESS-STAIR is also able to produce long-term ET/PET estimation as an indicator of droughts due to its high computational efficiency. Figure 10 shows an example time series of peak growing season ET/PET at Bondville from 2001 through 2017. Overall substantial interannual variability is shown, with regional average ET/PET values ranging from the 0.76 in an extremely dry year 2012 to 0.91 in an extremely wet year

2015, observable, although much smaller than seasonal variability (Figure 10). In this case, time series of a positive linear relationship ( $r = 0.42$ ,  $p < 0.1$ ) is observed between BESS-STAIR ET/PET and precipitation, and a negative linear relationship ( $r = -0.58$ ,  $p < 0.05$ ) is observed between BESS-STAIR ET/PET and VPD. The relative stronger relationship between ET/PET and VPD than that between ET/PET and precipitation indicates atmospheric water demand is likely to contribute more to drought than soil water supply in this area, is in line with that of precipitation, as indicated by a significant linear correlation  $r = 0.73$  ( $p < 0.005$ ). It is also noted that ET is relatively steady given the high interannual variation in precipitation, and BESS-STAIR enables the investigation of such response at field scales.

## 4 Discussions

### 4.1 Performance of BESS-STAIR ET

In this study, we have presented BESS-STAIR, a new framework for estimating croplands ET at field and daily scale, and we have demonstrated its high performance in the U.S. Corn Belt. The process-based biophysical model BESS, driven by 30-m resolution vegetation-related variables derived from STAIR fused surface spectral reflectance data (Figure 3) and medium resolution environmental inputs derived from MODIS and other satellite data (Figure 1), is able to produce gap-free ET and PET estimations on field-scale and at daily interval across space and time (Figure 4-7). Over the 12 sites across the U.S. Corn Belt (Figure 2), BESS-STAIR explains 75% variations in flux tower measured ~~daily LE~~ daily ET (Figure 4), with an overall RMSE of  $2.29 \text{ MJ m}^{-2} \text{ d}^{-1}$  (equivalent to  $0.93 \text{ mm d}^{-1}$  or  $26 \text{ W m}^{-2}$ ), a 27.9% relative error, and stable performance across sites (Figure 5), as well as consistent seasonal dynamics with respect to flux tower measurements (Figure 6-7).

The error statistics of BESS-STAIR are commensurate with previous high resolution croplands ET mapping studies. Typical RMSE values include  $25 \text{ W m}^{-2}$  by TSEB-DTD (Guzinski et al., 2014),  $35 \text{ W m}^{-2}$  by METRIC (Irmak et al., 2011),  $62 \text{ W m}^{-2}$  by SEBS (McCabe and Wood, 2006),  $0.60 \text{ mm d}^{-1}$  by SSEBop (Senay et al., 2016), and  $1.04 \text{ mm d}^{-1}$  by SEBAL (Singh et al., 2008). Nevertheless, it is worth mentioning that those studies used original Landsat data and therefore suffered from considerably large data gaps. In contrast, BESS-STAIR uses daily Landsat-MODIS fusion data free from any gaps, which leads to temporally continuous ET estimation at the field level, thus can meet the requirements of precision agriculture. In addition, it is worth mentioning that BESS-STAIR is calibration-free and therefore is scalable. It also indicates that the accuracy of BESS-STAIR ET is likely to further improve by using locally optimized driving force or parameter values.

BESS-STAIR is also comparable to other croplands ET mapping studies utilizing data fusion techniques. For example, DisALEXI-STARFM daily ET estimates were validated against the flux tower measurements over the three Mead sites (Yang et al., 2018). They reported error statistics around  $1.2 \text{ mm d}^{-1}$  RMSE and 29% relative error. BESS-STAIR's performance at these three same sites shows an average of  $0.89 \text{ mm d}^{-1}$  RMSE and 25.3% relative error (Figure 11). At monthly scale, the average RMSE and relative errors are only  $0.48 \text{ mm d}^{-1}$  and 14.3% (Figure A1). In addition, BESS-STAIR

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has a potential to apply to any croplands around the world back to 1984 when both high spatial resolution data (e.g., Landsat/TM) and high temporal resolution data (e.g., NOAA/AVHRR) were available.

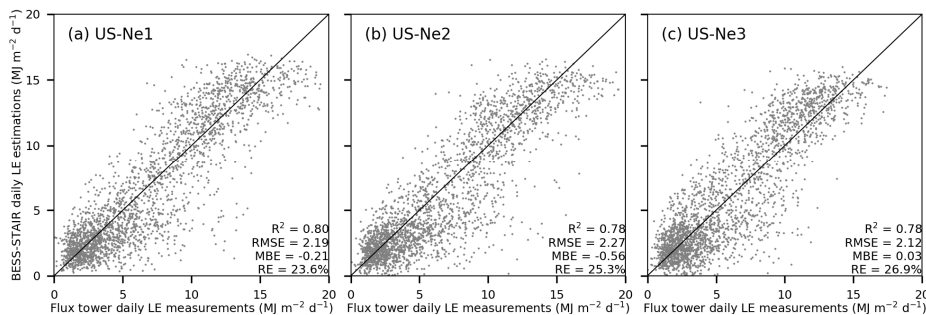


Figure 11. Scatter plots between  $\overline{LEET}$  measurements and  $\overline{LEET}$  estimations at three sites US-Ne1, US-Ne2 and US-Ne3.

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#### 4.2 Scientific advantages of BESS-STAIR ET

The efficacy of BESS-STAIR lies in several aspects. First, BESS is a water-carbon-energy coupled biophysical model. BESS employs atmospheric and canopy radiative transfer modules, carbon assimilation module, stomatal conductance module, and energy balance module (Jiang and Ryu, 2016; Ryu et al., 2011). BESS integrates the simulation of carbon cycle, water cycle and energy cycle in the same framework. Such carbon-water-energy coupling strategy realistically and coherently simulates plant physiology and their response to the environment, specifically the carbon uptake and water loss by plants have been simulated synchronously through environmental constraints on stomatal conductance, with further constraints by available energy (Baldocchi and Meyers, 1998; Leuning et al., 1995). Many land surface models have already adopted such strategy and have successfully simulated the evolution of terrestrial ecosystems (Ju et al., 2006; Sellers, 1997; Tian et al., 2010). However, this is not the case in commonly-used remote sensing models. Empirical methods, water balance methods, and Priestley–Taylor methods only focus on the water cycle. Energy balance methods, triangular space methods, and Penman–Monteith methods couple water cycle and energy cycle and consider ET in the context of energy partitioning. BESS, unlike these remote sensing models, constrains ET with regards to both energy requirement and carbon requirement, thanks to explicit modeling of radiative transfer and stomatal behavior processes. For above reasons, BESS-STAIR ET does not only achieve high accuracy (Figure A1 – A3), but also accurately capture responses to GPP, radiation, temperature, and humidity at daily scale (Table 34). Thus, BESS-STAIR has the potential to advance the understanding of crop responses to climate change through bridging remote sensing data and land surface models, which was first suggested by Sellers et al. (1997) more than 20 years ago.



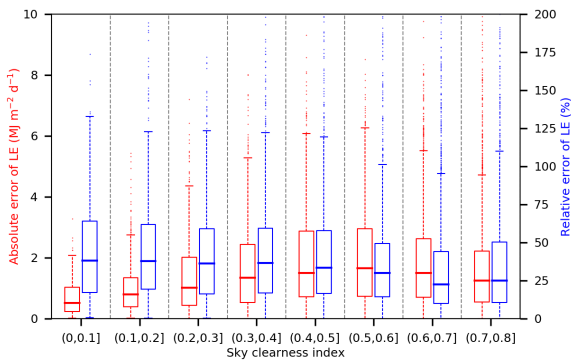
480 Table 34. BESS-STAIR captures the correct response of ~~daily-LE~~daily ET to GPP, radiation (Rg), temperature (Ta) and  
 485 humidity (VPD) as compared to flux tower measurements over the three Mead sites from 2001 through 2012. The linear  
 equation slopes and correlation coefficients between ~~LE~~ET and other factors are similar in flux tower measurements and  
 BESS-STAIR estimations, for both the whole growing season (April – October) or only peak growing season (June, July and  
 August). For “flux tower” columns, Rg, Ta and VPD are from site measurements, while for “BESS-STAIR” columns, they  
 are from satellite-derived coarse resolution inputs.

Time period	Relationship	Flux tower		BESS-STAIR	
		Equation	Correlation	Equation	Correlation
Growing season (April – October)	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ GPP (gC m <sup>-2</sup> d <sup>-1</sup> )	y = 0.44x + 3.19	r = 0.86 (p < 0.01)	y = 0.65x + 2.60	r = 0.90 (p < 0.01)
	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ Rg (MJ m <sup>-2</sup> d <sup>-1</sup> )	y = 0.33x - 0.07	r = 0.56 (p < 0.01)	y = 0.29x + 0.28	r = 0.51 (p < 0.01)
	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ Ta (°C)	y = 0.44x - 1.60	r = 0.67 (p < 0.01)	y = 0.43x - 1.64	r = 0.54 (p < 0.01)
	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ VPD (hPa)	y = 0.32x + 4.10	r = 0.31 (p < 0.01)	y = 0.44x - 2.50	r = 0.68 (p < 0.01)
JJA (June, July, August)	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ GPP (gC m <sup>-2</sup> d <sup>-1</sup> )	y = 0.35x + 4.85	r = 0.76 (p < 0.01)	y = 0.39x + 6.36	r = 0.63 (p < 0.01)
	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ Rg (MJ m <sup>-2</sup> d <sup>-1</sup> )	y = 0.36x + 1.79	r = 0.58 (p < 0.01)	y = 0.36x + 3.40	r = 0.77 (p < 0.01)
	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ Ta (°C)	y = 0.52x - 2.20	r = 0.46 (p < 0.01)	y = 0.15x + 9.40	r = 0.28 (p < 0.01)
	<del>LE</del> ET (MJ m <sup>-2</sup> d <sup>-1</sup> ) ~ VPD (hPa)	y = 0.28x + 7.61	r = 0.32 (p < 0.001)	y = 0.28x + 4.37	r = 0.30 (p < 0.001)

The second strength is that BESS-STAIR is designed most sensitive to the variables which can be well-quantified from  
 remote sensing data. BESS ET is most sensitive to solar radiation, followed by LAI (Ryu et al., 2011), as BESS ET is mainly  
 constrained by net radiation and GPP. In most cases, solar radiation is the predominant component of net radiation, while  
 490 LAI determines the capacity of radiation absorption and subsequently determines GPP. BESS explicitly computes radiation  
 components in high accuracy by driving an atmosphere radiative transfer model FLiES using MODIS cloud, aerosol and  
 atmospheric profile products. Globally, BESS-estimated solar radiation has its R<sup>2</sup> about 0.85 and 0.95 for MODIS snapshots  
 and 4-day averages, respectively (Ryu et al., 2018). On the other hand, BESS-STAIR calculates high spatiotemporal  
 resolution LAI and albedo from fused surface reflectance data. Since Landsat and MODIS surface reflectance products are  
 495 publicly-available and highly-reliable (Claverie et al., 2015; Masek et al., 2006), spatial heterogeneity and temporal  
 dynamics of crop growing conditions are well captured (Figure 8). This study only uses reflectance data fused from Landsat  
 and MODIS, but STAIR can be easily extended to further incorporate other types of data, such as Sentinel-2 (10 m  
 resolution) and Planet Lab CubeSats (3 m resolution) (McCabe et al., 2017). By incorporating more high resolution  
 observations, the relevance of reconstructed high resolution image series can be further improved.

500 The third strength is that BESS-STAIR is able to perform under all-weather conditions. BESS-STAIR fills data gaps in  
 surface reflectance, which has a smooth day-to-day variation even with changes in sky conditions (Liu et al., 2017). Based  
 on filtered surface reflectance, LAI and albedo time series are well-reconstructed, and subsequently BESS-STAIR could

505 directly work under all-weather condition. In this manner, BESS-STAIR has no need to fill cloudy-sky ET using clear-sky ET estimations, which is error prone because the empirically-filled ET estimations usually lack sophisticated process-level model constraints and thus can have large uncertainties. Figure 12 shows that the estimation errors of BESS-STAIR ET do not change significantly under different sky conditions, with low to high “sky clearness index” referring more cloudy to more clear sky conditions.



510 Figure 12. BESS-STAIR estimated ~~daily LE~~ daily ET has similar performance with varying sky clearness index (the ratio of incoming radiation on surface to that on top-of-atmosphere). The lower and upper boundaries of boxes refer to the first and third quartile of error statistics. The bars inside boxes refer to median values. The whiskers indicate 1.5 times of distance between the first and third quartiles.

515 **4.3 Limitations and future improvements of BESS-STAIR ET**

In this study, several inputs used by BESS have some limitations in terms of generality and accessibility. First, three plant functional parameters, peak  $V_{cmax25}$ , Ball-Berry slope and intercept are obtained from literatures, assuming constant given C3 or C4 plant type. Other land surface models tend to use the similar strategy by assigning fixed values to a given plant functional type (PFT) (Bonan et al., 2011; Kattge et al., 2009; Miner et al., 2017). The drawback of this strategy is the overlook of within-PFT variations and the feedback mechanisms between vegetation and its environment (Van Bodegom et al., 2014). These limitations might be mitigated by incorporating innovative leaf trait estimation techniques emerged in recent years, such as imaging spectroscopy (Serbin et al., 2015), sun-induced fluorescence (Zhang et al., 2018), and plant optimization theory (Walker et al., 2017; Wang et al., 2017). Second, BESS-STAIR in this study uses CDL data which is only available in United States. Fortunately, BESS does not require specific crop types but only C3/C4 distributions, and the separation of the major C4 crop maize from other crops is practical using time-series satellite data (Cai et al., 2018; Zhong et

al., 2016). It is noted that misclassification of C4 and C4 crops are likely to cause large bias in GPP, but relatively small bias in ET (Fig. A1 – A3).

530 Though BESS-STAIR is able to capture water stress impact on ET in the U.S. Corn Belt where atmospheric demands play a major role, its applicability to regions where soil supply dominates needs further investigation. Some studies suggest that optical signal as an indicator of drought performs at a longer time scale than thermal signal does (Otkin et al., 2017). Drought first decreases soil moisture content due to enhanced ET induced by high atmospheric demand, then decreases ET due to low soil moisture content, and finally causes damage to plants which changes surface reflectance. Accordingly, LAI  
535 may not serve as a relevant early warning of droughts. Furthermore, severe soil moisture stress may cause physiological deterioration in addition to structural damage that has been reflected in LAI. To address this issues for dry regions, we acknowledge that LST observations may provide essential adding values. At this point, the capacity of BESS-STAIR in estimating LST leads to a possibility of optimizing BESS-STAIR using satellite-derived LST. Recent advances of innovative thermal observation platforms such as ECOSTRESS (Hulley et al., 2017), GOES-R (Schmit et al., 2017), and Sentinel-3  
540 (Zheng et al., 2019) have provide great opportunity to integrate satellite-derived LST with the BESS-STAIR.

The BESS model itself in essence estimates instantaneous ET. The ratio of snapshot potential solar radiation to daily potential solar radiation is adopted as a scaling factor for the temporal upscaling of ET (Ryu et al., 2012). In this study, BESS runs two times per day, utilizing radiation components derived from Terra/MODIS (around 11:00 AM) and  
545 Aqua/MODIS (around 1:00 PM) data, respectively. The two instantaneous ET estimates are separately upscaled to daily estimates and averaged. In spite of robustness of the upscaling algorithm (Ryu et al., 2012), bias cannot be avoided if the sky conditions at two overpass times are not representative for that day, which is natural and common in the presence of moving cloud. Since BESS is a time-independent model and can perform at any time during daytime, adding more snapshots to account for the diurnal variations of radiation can solve this problem. Unfortunately, fine-resolution polar-orbiting satellite  
550 usually have similar overpass times (10:00 AM – 11:00 AM and 1:00 PM – 2:00 PM), so even adding more satellites is likely to bring redundant information only. Reanalysis radiation data covering diurnal cycle have limited accuracy and coarse resolution (Babst et al., 2008; Zhang et al., 2016b), so they may be unable to provide much added values as well. Next-generation geostationary satellites, acquiring data with both high spatial and high temporal resolutions such as GOES-R and GaoFen-4 (Goodman et al., 2012; Xu et al., 2017), are expected to enable BESS-STAIR ET in hourly or sub-hourly  
555 interval and subsequently generate more realistic daily ET estimates.

## 5 Conclusions

In this study we presented BESS-STAIR, a new framework to estimate high spatiotemporal resolution ET that can be used for field-level precision water resources management. BESS-STAIR couples a satellite-driven water-energy-carbon coupled  
560 biophysical model BESS with a generic and fully-automated fusion algorithm STAIR to generate gap-free 30-m resolution

daily ET estimations. Comprehensive evaluation of BESS-STAIR ET estimations revealed: 1) reliable performance over 12 flux tower sites across the U.S. Corn Belt, and 2) reasonable spatial patterns, seasonal cycles and interannual dynamics. The proposed BESS-STAIR framework has demonstrated its ability to provide significant advancements with regard to daily field-level estimations of ET at regional and decadal scales. We expect BESS-STAIR to become a solid tool for precision water resources management and other precision agriculture applications for the U.S. Corn Belt as well as other agricultural areas around the world, thanks to the global coverage of input data.

Data availability. The data generated in this study are available upon request.

Competing interests. The authors declare that they have no conflict of interest.

Author contribution. C.J. and K.G. designed the study, C.J. conducted the modeling and analysis, M.P. and B.P. provided research inputs during the analysis, Y.R. and S.W. provided guidance in the BESS model and the STAIR algorithm, respectively. All the authors contributed to the writing of the manuscript.

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#### Appendix

[Appendix 1. Key equations for energy balance in BESS. Subscript  \$i\$  represents sunlit or shaded canopy.](#)

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595 Canopy conductance  $G_{c,i}$  for sunlit/shade canopy is calculated as (Ball, 1988):

$$G_{c,i} = m \frac{RH}{C_a} A_{c,i} + b \quad (A1)$$

where  $m$  and  $b$  are Ball-Berry coefficients, RH is relative humidity,  $C_a$  is ambient  $CO_2$  concentration,  $A_{c,i}$  is carbon assimilation by sunlit/shaded canopy.

Canopy net radiation  $R_n$  for sunlit/shade canopy is calculated as (Kowalczyk et al., 2006):

$$R_{n,i} = Q_{s,i} + Q_{l,i} - \epsilon_p G_r (T_{l,i} - T_a) \quad (A2)$$

where  $Q_{s,i}$  and  $Q_{l,i}$  are net shortwave and longwave radiation for sunlit/shaded canopy,  $T_{l,i}$  is leaf temperature for sunlit/shaded canopy,  $T_a$  is air temperature,  $\epsilon_p$  is specific heat,  $G_r$  is canopy conductance for radiation:

$$G_r = 4\sigma\epsilon_l T_a^3 / \epsilon_p \quad (A3)$$

At this point,  $A_{c,i}$  is calculated by the Farquhar photosynthesis model for C3 (Collatz et al., 1991) and C4 (Collatz et al., 1992) crops,  $Q_{s,i}$  and  $Q_{l,i}$  are calculated by radiative transfer models for shortwave (Ryu et al., 2011) and longwave (Kowalczyk et al., 2006), respectively.  $T_{l,i}$  is solved through an iterative procedure (Jiang and Ryu, 2016). Subsequently, latent heat flux  $\lambda E_i$  for sunlit/shaded canopy is calculated by the quadratic form of the Penman-Monteith equation :

$$a\lambda E_i^2 + b\lambda E_i + c = 0 \quad (A4)$$

605 where  $\lambda$  is latent heat of vaporization, and

$$a = \frac{1}{2} \frac{d^2 e_s(T_a)}{dT_a^2} \frac{r_a^2}{\rho C_p \gamma (r_a + r_{c,i})} \quad (A5)$$

$$b = -1 - \frac{de_s(T_a)}{dT_a} \frac{r_a}{\gamma (r_a + r_{c,i})} - \frac{d^2 e_s(T_a)}{dT_a^2} \frac{R_{n,i} r_a^2}{\rho C_p \gamma (r_a + r_{c,i})} \quad (A6)$$

$$c = \frac{\rho C_p}{\gamma (r_a + r_{c,i})} D + \frac{de_s(T_a)}{dT_a} \frac{r_a}{\gamma (r_a + r_{c,i})} R_n + a R_{n,i}^2 \quad (A7)$$

where  $e_s(T_a)$  is saturated vapour pressure,  $r_a$  is aerodynamic resistance,  $\rho$  is air density,  $\gamma$  is psychrometric constant,  $D$  is vapour pressure deficit,  $r_{c,i}$  is canopy resistance, the reciprocal of  $G_{c,i}$ .

Soil evaporation is calculated as (Fisher et al., 2008):

$$\lambda E_i = \frac{\frac{de_s(T_a)}{dT_a}}{\frac{de_s(T_a)}{dT_a} + \gamma} (R_{n,soil} - G) RH^{D/1000} \quad (A8)$$

610 where  $R_{n,soil}$  is net radiation for soil, and  $G$  is ground heat storage calculated as  $0.3 \times R_{n,soil}$ .

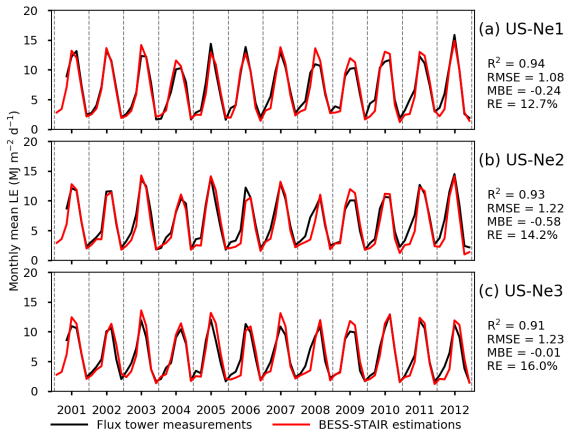
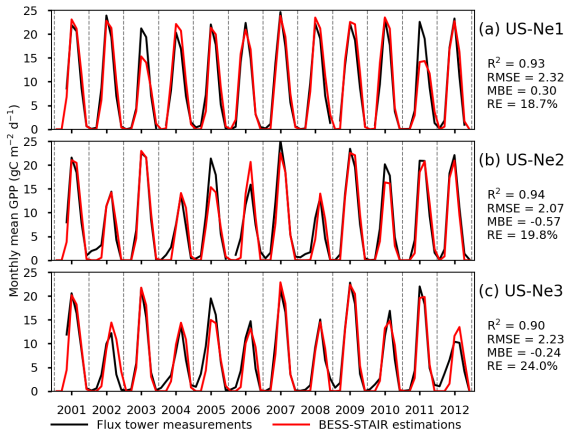
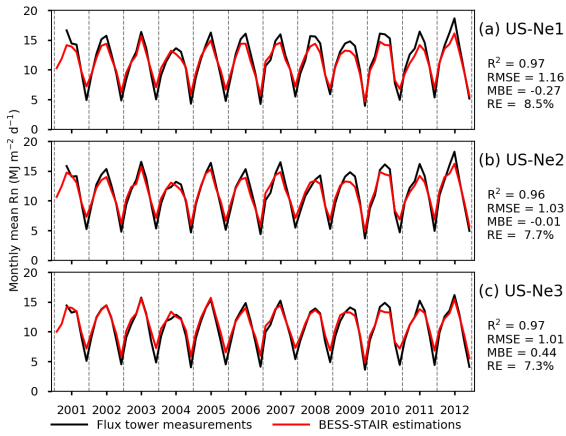


Figure A1. Time series of monthly mean  $\overline{LEET}$  from flux tower measurements and BESS-STAIR estimations.



615 Figure A2. Time series of monthly mean GPP from flux tower measurements and BESS-STAIR estimations. Significant underestimations in 2003 and 2011 for Ne1, in 2005 for Ne2, and in 2005 for Ne3 are due to misclassification of corn as soybean in CDL. Significant overestimations in 2006 for Ne2 are due to misclassification of soybean as corn in CDL.



620 Figure A3. Time series of monthly mean Rn from flux tower measurements and BESS-STAIR estimations.

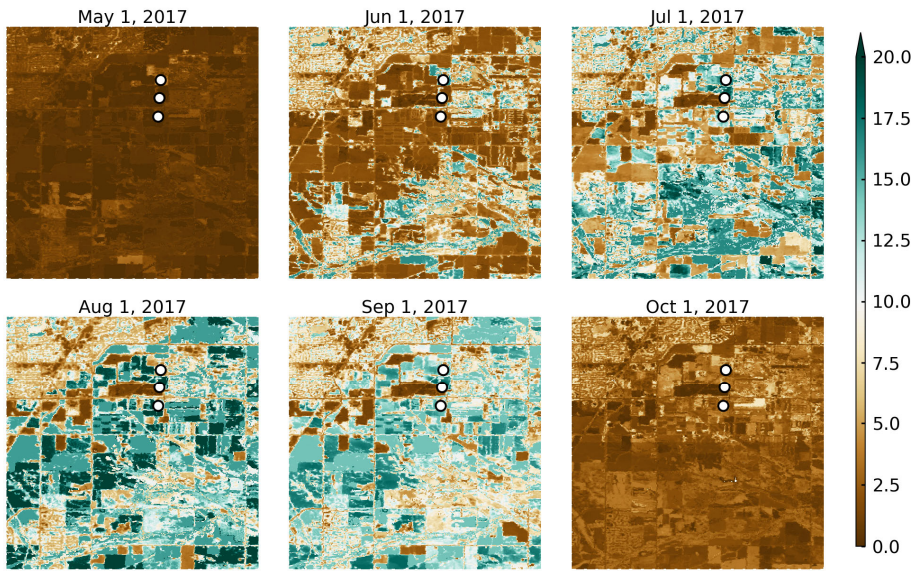


Figure A4. Examples of daily GPP ( $\text{GC m}^2 \text{d}^{-1}$ ) derived from BESS-STAIR at Rosemount ( $44.65^\circ\text{N} - 44.75^\circ\text{N}$ ,  $93.05^\circ\text{W} - 93.15^\circ\text{W}$ ) in 2017. Circles indicate flux towers in this region.

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- 630 [disposition=inline%3B filename%3DAllen\\_FAO1998.pdf](https://s3.amazonaws.com/academia.edu.documents/40878584/Allen_FAO1998.pdf?AWSAccessKeyId=AKIAIWOWYYGZ2Y53UL3A&Expires=1527634764&Signature=GkL44Ekv1zkaqSV04%2F4EwT99LEk%3D&response-content-disposition=inline%3B filename%3DAllen_FAO1998.pdf), 1998.
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**Figure 1:** The logo of Copernicus Publications.

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