



1 **A Bayesian model to correct underestimated 3D wind speeds from sonic anemometers**

2 **increases turbulent components of the surface energy balance**

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18 **Abstract**

19           Sonic anemometers are the principal instruments in micrometeorological studies of  
20 turbulence and ecosystem fluxes. Recent studies have shown that common designs underestimate  
21 vertical wind measurements because they lack a correction for transducer shadowing, with no  
22 consensus on a suitable correction. We reanalyze a subset of data collected during field  
23 experiments in 2011 and 2013 featuring two or four CSAT3 sonic anemometers. We introduce a  
24 novel Bayesian analysis with the potential to resolve the three-dimensional correction by  
25 optimizing differences between anemometers mounted both vertically and horizontally. A grid of  
26 512 points ( $\sim \pm 5^\circ$  resolution in wind location) is defined on a sphere around the sonic  
27 anemometer, from which the shadow correction for each transducer-pair is derived from a set of  
28 138 unique state variables. Using the Markov chain Monte Carlo (MCMC) method, the Bayesian  
29 model proposes new values for each state variable, recalculates the fast-response dataset,  
30 summarizes the five-minute wind statistics, and accepts the proposed new values based on the  
31 probability that they make measurements from vertical and horizontal anemometers more  
32 equivalent. MCMC chains were constructed for three different prior distributions describing the  
33 state variables: no shadow correction, the Kaimal correction for transducer shadowing, and  
34 double the Kaimal correction, all initialized with 10% uncertainty. The final posterior correction  
35 did not depend on the prior distribution and revealed both self- and cross-shadowing effects from  
36 all transducers. After correction, the vertical wind velocity and sensible heat flux increased  $\sim 10\%$   
37 with  $\sim 2\%$  uncertainty, which was significantly higher than the Kaimal correction. We applied the  
38 posterior correction to eddy covariance data from various sites across North America and found  
39 that the turbulent components of the energy balance (sensible plus latent heat flux) increased on  
40 average between 8-12%, with an average 95% credible interval between 6-14%. Considering this



41 is the most common sonic anemometer in the AmeriFlux network and is found widely within  
42 FLUXNET, these results provide a mechanistic explanation for much of the energy imbalance at  
43 these sites where all terrestrial/atmospheric fluxes of mass and energy are likely underestimated.  
44



## 45 **1. Introduction**

46           The eddy-covariance technique has become the most commonly used method for  
47 measuring the ecosystem exchange of mass and energy with the atmosphere. It is fundamental to  
48 the global network of flux towers that are central to quantifying terrestrial carbon sinks and  
49 sources (Baldocchi, 2003), to hydrological studies accounting for evapotranspiration and  
50 sublimation (Biederman et al., 2014; Reba et al., 2012), and to the energy balance through the  
51 turbulent fluxes of sensible and latent heat (Welch et al., 2015; Anderson and Wang, 2014).  
52 There is a growing consensus within the flux community that many sonic anemometers, the core  
53 instrument for all modern eddy-covariance systems, exhibit systematically biased underestimates  
54 of the vertical wind component (Frank et al., 2016; Horst et al., 2015; Kochendorfer et al., 2012).  
55 The ramifications for this are that all vertical fluxes (i.e., carbon dioxide, water vapor, latent  
56 heat, sensible heat, momentum) are similarly underestimated for any ecosystem. This is roughly  
57 consistent with the persistent energy balance closure problem across flux sites (Leuning et al.,  
58 2012; Stoy et al., 2013; Wilson et al., 2002) where a vast majority are assumed to be systematic  
59 biased towards low turbulent fluxes of sensible and latent heat.

60           Recent studies of Horst et al. (2015) and Frank et al. (2016) have shown that the error in  
61 at least two non-orthogonal sonic anemometer designs can be traced to transducer shadowing  
62 that remains uncorrected in the anemometer's firmware. In both studies, shadowing was  
63 described a priori by theoretical formulations based on the wind-tunnel tests of Kaimal (1979),  
64 yet there was no consensus on a correction. A shortcoming in the use of formulations derived for  
65 single transducer-pairs in laminar flow to describe turbulent flow distortions around more  
66 complex geometries (Fig. 1) is that shadowing between all transducers and structures cannot be  
67 accurately represented or incorporated. A second problem is that in turbulent flow fields there



68 are few standards available to use as a calibration reference. Advancements in Bayesian  
69 techniques (Gelman et al., 2004) have created the potential to resolve both of these issues by  
70 incorporating prior knowledge of transducer flow distortions with a model that evaluates the  
71 omnidirectionality of a sonic anemometer to produce a posterior 3D correction.

72 To quantify a 3D correction of the CSAT3 sonic anemometer, we reanalyze data from  
73 field experiments conducted by Frank et al. (2013) and Frank et al. (2016) where wind  
74 measurements from non-orthogonal anemometers mounted vertically and horizontally were  
75 significantly different. We develop a Bayesian hierarchical model to evaluate three hypotheses:

76 (1) A 3D shadowing correction based solely on wind location can make a non-orthogonal  
77 sonic anemometer omnidirectional.

78 (2) This correction increases vertical wind measurements more than expected from single  
79 transducer shadowing because it accurately represents all shadowing between transducers.

80 (3) In ecosystems where these instruments are deployed, the application of this correction  
81 will result in significantly higher turbulent components of the energy budget and improved  
82 surface energy budget closure.

83

## 84 **2 Methods**

### 85 **2.1 Reanalysis of field experiments**

86 We reanalyze data from field campaigns conducted by Frank et al. (2013) and Frank et al.  
87 (2016). To summarize them, experiments were conducted in 2011 and 2013 where multiple sonic  
88 anemometers were deployed in a horizontal array at 24.5 m height on the Glacier Lakes  
89 Ecosystem Experiments Site (GLEES) AmeriFlux scaffold above a subalpine forest in  
90 southeastern Wyoming, USA (Frank et al., 2014). The anemometers were initially mounted



91 vertically, oriented west, arranged south to north, staggered up and down, and located 0.50 m  
92 center-to-center from each other (Fig. 1). Periodically, some of the anemometers were rotated  
93 90° around their  $u$ -axis and mounted horizontally. In this study we focus only on the CSAT3  
94 sonic anemometer (Campbell Scientific, Inc., Logan, UT, USA) during times when both  
95 vertically and horizontally mounted anemometers were present (Table 1). It is conventional to  
96 describe the three dimensions of a sonic anemometer as the  $u$ ,  $v$ , and  $w$ -axes. To reduce  
97 confusion in describing horizontal anemometers, we refer to cardinal  $u$ ,  $v$ , and  $w$  where the  
98 measurements have been rotated to west-east ( $u$ ), south-north ( $v$ ), and down-up ( $w$ ), which are  
99 consistent with  $u$ ,  $v$ , and  $w$  for vertically mounted anemometers. Finally, because our Bayesian  
100 model is computationally intensive we reanalyze a subset of only 5% of the available data (see  
101 section 2.3).

## 102 **2.2 The Bayesian model**

103 Bayesian statistics are based on Bayes theorem (Bayes and Price, 1763), which in modern  
104 applications relates the posterior probability of a model parameter conditioned on data to the  
105 product of the likelihood of the data and the prior probability of that parameter (Gelman et al.,  
106 2004). In essence, the prior represents an initial educated guess or belief in the value of a model  
107 parameter, the likelihood is the probability of observing the data if it was deterministically  
108 generated from a model, and the posterior is an updated belief in the model parameter  
109 considering each the prior, the model, and the data. Analytical evaluation of the posterior is  
110 rarely possible, as is in our case, thus the posterior is commonly estimate through the Markov  
111 chain Monte Carlo (MCMC) method, Gibbs sampling (Appendix A.1), and the Metropolis-  
112 Hastings algorithm (Kruschke, 2010). The framework of our Bayesian model is to divide the  
113 sphere around the sonic anemometer into approximately equal grid points and to define a prior



114 probability distribution of the 3D shadowing correction for each transducer pair at each location.  
115 Then, the model proposes new corrections for each grid point, recalculates the fast-response  
116 dataset, summarizes new five-minute wind statistics, determines the probability that the updated  
117 measurements from vertical and horizontal anemometers are more equivalent using the proposed  
118 correction versus the old one (i.e., the ratio of Eq. A13 evaluated for the proposed versus old  
119 correction), and finally accepts/rejects the proposal probabilistically from this ratio to construct  
120 the posterior correction. The model recursively adjusts the distribution that generates the  
121 proposals to achieve between 25 and 50% acceptance rates. We define a grid of 512 points (~  
122  $\pm 5^\circ$  resolution of wind location) on a sphere around each of the three transducer pairs of the  
123 sonic anemometer. Neglecting the upper and lower mounting arms that extend back into the  
124 electronics housing and support block, the CSAT3 is symmetrical on either side of a transducer  
125 pair, between the upper and lower hemispheres, and for each of the three transducer pairs. To  
126 pool data and reduce computations, we make these assumptions of symmetry to describe all  
127 1,536 points from a set of 138 unique state variables.

128 We test three prior corrections: no shadow correction, the Kaimal correction (Kaimal,  
129 1979; Frank et al., 2016; Horst et al., 2015), and a doubling of the Kaimal correction (Frank et  
130 al., 2016). The Kaimal correction is defined as  $U_c = (1 - 0.16 + 0.16\theta/70)\hat{U}_c$  for  $\theta \leq 70^\circ$  and  
131  $U_c = \hat{U}_c$  for  $\theta > 70^\circ$ , where  $U_c$  and  $\hat{U}_c$  are the measured and corrected wind velocities and  $\theta$  is  
132 the angle between the wind and the acoustic path.

133 The model predicts the standard deviation of the data,  $\sigma_{f,i,c}$ , during each five-minute  
134 period,  $f$ , for each replicate sonic anemometer,  $i$ , in the three cardinal dimensions,  $c$  (Fig. 1),  
135 from a normal distribution with mean  $\hat{\sigma}_{f,i,c}$  and standard deviation  $\varepsilon$  (Eq. 1).

136 
$$\sigma_{f,i,c} \sim N(\hat{\sigma}_{f,i,c}, \varepsilon^{-2}) \quad (1)$$



137 The predicted mean is constructed in several steps. First, the state variable for the 3D correction,  
 138  $\vec{\alpha}_{T \times G}$ , is a matrix representing each of the three transducer axes,  $t$ , for each grid point,  $g$ . Here it  
 139 does not matter if each grid point is independent or that they linked together through symmetry.  
 140 It is given a normal prior probability distribution with mean equal to the prior correction,  $P_{t,g}$ ,  
 141 evaluated for each transducer-pair for wind blowing through the longitude,  $\lambda$ , and latitude,  $\varphi$ ,  
 142 associated with each grid point with a predefined standard deviation equal to 0.1, or  $\pm 10\%$   
 143 uncertainty (Eq. 2).

$$144 \quad \alpha_{T \times G, t, g} \sim N(P_{t, g}, 0.1) \quad (2)$$

145 The 3D correction is applied to every 20-Hz sample,  $j$ , of the original measured wind velocity  
 146 data in transducer coordinates,  $U_{T, t, f, i, j}$ . The multidimensional nominal predictor variable,  
 147  $\vec{x}_{G \times F \times I \times J, g, f, i, j}$ , selects the corresponding grid point that occurs with every 20-Hz sample. The  
 148 corrected 20-Hz wind velocity in transducer coordinates is  $\hat{U}_{T, t, f, i, j}$  (Eq. 3).

$$149 \quad \hat{U}_{T, t, f, i, j} = U_{T, t, f, i, j} \cdot \left( \vec{\alpha}_{T \times G} \vec{x}_{G \times F \times I \times J, g, f, i, j} \right) \quad (3)$$

150 The non-orthogonal data is transformed via matrix multiplication into orthogonal coordinates,  
 151  $\hat{U}_{S, s, f, i, j}$ , with the three sonic dimensions,  $s$  (Eq. 4).

$$152 \quad \hat{U}_{S, s, f, i, j} = \vec{M}_{S \times T} \hat{U}_{T, t, f, i, j} \quad (4)$$

153 The matrix,  $\vec{M}_{S \times T}$ , is specific to the CSAT3 geometry (Eq. 5).

$$154 \quad \vec{M}_{S \times T} = \begin{bmatrix} -\frac{4}{3} & \frac{2}{3} & \frac{2}{3} \\ 0 & \frac{2}{\sqrt{3}} & -\frac{2}{\sqrt{3}} \\ \frac{2}{3\sqrt{3}} & \frac{2}{3\sqrt{3}} & \frac{2}{3\sqrt{3}} \end{bmatrix} = \begin{bmatrix} -1.333 & 0.667 & 0.667 \\ 0 & 1.155 & -1.155 \\ 0.385 & 0.385 & 0.385 \end{bmatrix} \quad (5)$$

155 In order for the model to predict data simultaneously from both vertical and horizontal  
 156 anemometers, a final corrected time series data set is produced in cardinal coordinates,  $\hat{U}_{C, f, i, c, j}$ .





$$157 \quad \dot{U}_{C_{f,i,c,j}} = \left( \vec{x}_{F \times I \times J \times O_{f,i,j,o}} \vec{N}_{O \times C \times S} \right) \dot{U}_{S_{s,f,i,j}} \quad (6)$$

158 The matrix  $\vec{N}_{O \times C \times S}$  is straightforward (Eq. 7), and the multidimensional nominal predictor  
 159 variable,  $\vec{x}_{F \times I \times J \times O_{f,i,j,o}}$ , selects the orientation,  $o$ , of every 20-Hz sample.

$$160 \quad \vec{N}_{O \times C \times S} = \begin{cases} \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, & o = 1 \text{ (i. e., vertical)} \\ \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}, & o = 2 \text{ (i. e., horizontal)} \end{cases} \quad (7)$$

161 Using the corrected time series data in cardinal coordinates, the model calculates the  
 162 average correction,  $\beta_{F \times I \times C_{f,i,c}}$ , for the five-minute standard deviation data for each anemometer  
 163 in each dimension (Eq. 8).

$$164 \quad \beta_{F \times I \times C_{f,i,c}} = \frac{\sqrt{\frac{1}{J-1} \sum_{j=1}^J \left( \dot{U}_{C_{f,i,c,j}} - \frac{1}{J} \sum_{j=1}^J \dot{U}_{C_{f,i,c,j}} \right)^2}}{\sqrt{\frac{1}{J-1} \sum_{j=1}^J \left( U_{C_{f,i,c,j}} - \frac{1}{J} \sum_{j=1}^J U_{C_{f,i,c,j}} \right)^2}} \quad (8)$$

165 Eq. 8 is equivalent to the ratio of the standard deviation of  $\dot{U}_C$  divided by the standard deviation  
 166 of  $U_C$  evaluated during each five-minute period for each sonic anemometer in each cardinal  
 167 dimension. The reference condition for every five-minute period,  $\vec{\sigma}_{F \times C}$ , is a state variable  
 168 representing the “true” standard deviation of wind velocity in each cardinal dimension. It is  
 169 assigned a uniform prior probability distribution that generously includes the “true” value by  
 170 allowing each  $\vec{\sigma}_{F \times C}$  to range from 0 to the maximum of all  $U_C$  measurements (Eq. 9).

$$171 \quad \vec{\sigma}_{F \times C_{f,c}} \sim \text{Unif}(0, \max(U_C)) \quad (9)$$

172 Finally, the model predicts the mean for the standard deviation data as the reference divided by  
 173 the correction (Eq. 10).

$$174 \quad \hat{\sigma}_{f,i,c} = \frac{\vec{\sigma}_{F \times C} \cdot \vec{x}_{F \times C_{f,c}}}{\beta_{F \times I \times C} \cdot \vec{x}_{F \times I \times C_{f,i,c}}} \quad (10)$$



175 The nominal predictor variable,  $\vec{x}_{F \times C_{f,c}}$ , selects the appropriate five-minute reference for each  
176 cardinal dimension while the other nominal predictor variable,  $\vec{x}_{F \times I \times C_{f,i,c}}$ , selects the five-minute  
177 correction for each sonic anemometer for that dimension.

178 To complete the Bayesian model definition, the model error is a state variable which is  
179 assigned a prior probability distribution with a gamma distribution (Eq. 11).

$$180 \quad \varepsilon \sim \text{Gamma}(1, \hat{b}) \quad (11)$$

181 The variance of the gamma distribution,  $\hat{b}$ , is assigned the same variance as the prior distribution  
182 for  $\tilde{\sigma}_{F \times C}$  which is a uniform distribution (Eq. 12).

$$183 \quad \hat{b} = \frac{\sqrt{12}}{\max(U_C) - 0} \quad (12)$$

184 Distributions are defined where normal distributions are  $\theta \sim N(a, b)$  with expected value  $E(\theta) = a$   
185 and variance  $\text{var}(\theta) = 1/b^2$ , gamma distributions are  $\theta \sim \text{Gamma}(a, b)$  with  $E(\theta) = a/b$  and  $\text{var}(\theta)$   
186  $= a/b^2$ , and uniform distributions are  $\theta \sim \text{Unif}(a, b)$  with  $E(\theta) = (a+b)/2$  and  $\text{var}(\theta) = (b-a)^2/12$ .

### 187 **2.3 Analysis**

188 Our Bayesian analysis was conducted using R (version 3.2.2, (R Core Team, 2015))  
189 within RStudio (version 0.99.486, (RStudio Team, 2015)). We constructed an MCMC chain of  
190 10,000 steps for each of the three priors. Because the Bayesian model estimates are relative and  
191 not an absolute correction (see discussion in section 4.1), we normalized each chain. This was  
192 done in post-processing by dividing each update to the 138 unique corrections by the average  
193 correction across all grid points. We inspected each chain and removed the first 500 steps for  
194 burn-in and kept 1 out of every 140 steps to eliminate autocorrelation between steps for most  
195 grid points (even after reducing to 138 state variables, a few of these were estimated from  
196 relatively little data which unavoidably led to high autocorrelation between steps). This reduced  
197 each MCMC chain to 68 steps, which we combined between the three priors to create a single



198 chain containing 204 independent samples of the posterior distribution of the normalized 3D  
199 correction. To define an absolute correction such that equatorial measurements (i.e.,  $(u^2 + v^2)^{1/2}$ )  
200 are unchanged (see discussion in section 4.1), we applied the normalized correction to the time  
201 series data of vertically mounted anemometers, calculated the corrected five-minute standard  
202 deviations for equatorial winds, performed linear regression without an intercept (i.e., model the  
203 average change in equatorial winds solely as a scaling factor) between these corrected and  
204 uncorrected standard deviations for each of the 204 posterior samples, and determined the  
205 scaling factor as the average of the 204 regression slopes. We divided all values in the  
206 normalized 3D correction by this scaling factor to produce our final posterior correction.

207 Computation of the Bayesian model was extremely intensive: completion of the three  
208 chains took upwards of two months of continuous computer processing (Windows 7, Intel®  
209 Core™ i7-3630QM CPU @ 2.40 GHz processor, 1 TB solid state hard drive, 20 GB RAM).  
210 During beta testing we attempted to estimate the 3D correction independently for all grid points  
211 and all transducer pairs, with a single MCMC chain requiring a half-year to complete. Likewise,  
212 we investigated increasing the number of grid points to obtain better resolution around the sphere  
213 as well as increasing the amount of sonic anemometer data used from the Frank et al. (2013) and  
214 Frank et al. (2016) datasets. In both cases we desired an order of magnitude better resolution or  
215 more data, but the time required to complete a single MCMC chain quickly made these  
216 improvements impractical. Instead, we determined that 512 grid points and 5% of the original  
217 data was optimal considering these processing constraints.

218 There is a slight distinction to be made between the prior corrections which are defined as  
219 a function,  $\alpha(\lambda, \varphi)$ , of the true longitude and latitude of the wind and the posterior correction  
220 which is a function,  $\alpha(\tilde{\lambda}, \tilde{\varphi})$ , where  $\sim$  represents the uncorrected sonic anemometer measurement



221 of wind location. This means the posterior correction can be applied directly to the uncorrected  
222 data whereas the prior should be applied recursively (i.e., determine the correction, update the  
223 wind location, update the correction). To directly compare the prior and posterior corrections, we  
224 also present our posterior correction with the wind locations recursively adjusted to approximate  
225 the “true” longitude and latitude. For these analyses, we smoothed the posterior with a spherical  
226 spline fit (Wahba, 1981) using R package *mgcv* (Wood, 2006).

227 We quantified the impact of shadowing on measurements of the standard deviations of  
228 winds in the three dimensions and the sensible heat flux ( $H$ ). This was done by applying the  
229 posterior correction to the time series data of vertically mounted anemometers, calculating the  
230 five-minute measurements, performing linear regression without an intercept between the  
231 corrected and uncorrected measurements for each of the 204 posterior samples, and defining the  
232 impact as a distribution composed of the 204 regression slopes. For  $H$ , the data was planar fit  
233 rotated (Lee et al., 2004), time lag adjusted, and vapor flux corrected (Massman and Lee, 2002)  
234 using ancillary data from the GLEES AmeriFlux site (Frank et al., 2014).

235 Finally, we quantified the impact of the 3D correction on the sum of the turbulent  
236 components of the energy balance (i.e., sensible and latent ( $LE$ ) heat flux) at various sites across  
237 North America (Table 2). Each site featured a CSAT3, a fast-response hygrometer, and ancillary  
238 meteorological data. Measurements of  $LE$  were calculated similar to  $H$  but including the Webb-  
239 Pearman-Leuning correction (Webb et al., 1980). The impact of the 3D correction was quantified  
240 as a distribution similar to above, except compiled from 30-minute time periods.

241

## 242 **3 Results**

### 243 **3.1 No correction**



244 Without any shadow correction applied, measurements between a vertically and a  
245 horizontally mounted anemometer were different, which becomes clear when the variance  
246 between two vertical anemometers is taken into account (Fig. 2b, d, f versus a, c, e). The root  
247 mean square error (RMSE) in the 5-minute standard deviation of wind along all cardinal  
248 dimensions ( $u$ ,  $v$ , and  $w$ ) combined was 9.4% between a vertical and a horizontal anemometer,  
249 whereas the same metric between two vertical anemometers was 3.9%. The largest discrepancy  
250 was along the cardinal  $v$ -axis, where the RMSE increased from 3.7% to 11.1% when comparing  
251 vertical and horizontal anemometers (Fig. 2c versus d).

### 252 **3.2 The Kaimal prior correction**

253 The Kaimal correction is symmetrical with respect to each sonic transducer path (Fig. 3a,  
254 c, e). Yet, the same correction when viewed in sonic coordinates reveals unique responses for  $u$ ,  
255  $v$ , and  $w$  (Fig. 3b, d, f). For small latitude winds, the corrections are small for  $u$  and  $v$   
256 measurements, while those for  $w$  are higher yet unstable around the equator (see discussion in  
257 section 4.2). When the Kaimal correction was applied to the vertically mounted anemometers,  
258 there were minor increases in the 5-minute standard deviations of  $u$  and  $v$  (0.8% and 2.9%) while  
259 the increases for  $w$  (5.6%) and  $H$  (5.5%) were more substantial. This correction explained some  
260 of the differences between vertically and horizontally mounted anemometers (Fig. 4) where the  
261 RMSE for all cardinal dimensions combined was 6.2%, or 1.60 times greater than the same error  
262 between two vertical anemometers. The discrepancy along the cardinal  $v$ -axis decreased to 6.6%,  
263 or 1.86 times greater than the same error for two vertical anemometers, though some bias is still  
264 apparent (Fig. 4c versus d). While the Kaimal correction is only one of three priors tested in our  
265 Bayesian model, it is perhaps the most accepted algorithm currently available to correct  
266 transducer shadowing in the CSAT3.



### 267 3.3 The Bayesian model

268 Figure 5 illustrates the approach of the Bayesian model. The model initializes the 512  
269 grid points with a prior, in this case the Kaimal correction. No matter the transducer pair or  
270 vertical versus horizontal mounting, the 3D correction for all cases are identical but rotated  
271 versions of a common correction based on 138 unique state variables. For a single instantaneous  
272 wind, the simultaneous corrections for all six combinations of transducer pairs and mounting  
273 orientations will be different. As the MCMC chains progress, the Bayesian model will  
274 continuously adjust each of the 138 unique state variables so that measurements from the  
275 vertically and horizontally mounted anemometers are most similar based on the univariate  
276 conditional posterior probability distribution (Eq. A13). Much of the predictive power of the  
277 model comes from resolving the inconsistencies along the cardinal  $v$ -axis (Fig. 2d) where  
278 vertically and horizontally mounted anemometers are likely to be most dissimilar. Specifically, a  
279 vertically mounted CSAT3 should measure reasonably correct cross winds which must flow  
280 across the entire transducer and support structure of a horizontally mounted CSAT3.

281 Each MCMC chain was initialized with the mean of each prior, yet after convergence  
282 their posterior corrections were remarkably similar regardless of the choice of prior correction,  
283 with one peculiarity (Fig. 6). There was a clear linear relationship between the prior correction  
284 averaged across all 512 grid points (1.000 for no correction, 1.040 for the Kaimal correction, and  
285 1.080 for the double-Kaimal correction) and the magnitude of the posterior correction (1.030,  
286 1.064, and 1.098, respectively) that relates to the Bayesian model estimating a relative and not  
287 absolute correction (see discussion in section 4.1). The posterior correction is more than an  
288 estimate of the optimal solution, as it intrinsically accounts for the uncertainty of the correction  
289 at each of the 512 grid points (Fig. 7). Whereas each prior was defined with 10% uncertainty



290 (Eq. 2), much of the posterior correction has much lower standard deviations, especially around  
291 the transducers where values were as low as 2.5% (Fig. 7a). These uncertainties can be expressed  
292 in sonic coordinates for the  $u$ ,  $v$ , and  $w$  components, which in general show that the posterior  
293 correction is most certain for winds along each of those axes, respectively (Fig. 7b-d), with the  
294 uncertainty along the  $w$  measurement ranging from 2.7-18.3%.

295 Figure 8 illustrates the completion of the Bayesian model where the same posterior  
296 correction is applied to all transducer pairs and both mounting orientations. For every  
297 instantaneous wind, application of these six different corrections ultimately results in the 5-  
298 minute standard deviations of wind along the cardinal  $u$ ,  $v$ , and  $w$  axis being most similar  
299 between the two mounting orientations.

### 300 **3.4 The posterior correction**

301 The posterior correction for each transducer pair is presented in Figure 9. These results  
302 take into account the recursive adjustment to the wind locations and have been smoothed with a  
303 spherical spline. Significantly more self-shadowing and cross-shadowing around the transducers  
304 is visible than compared to the Kaimal prior (Fig. 9a, c, e versus Fig. 3a, c, e, in locations near all  
305 transducers). These results are more certain (i.e., low standard deviations when compared to the  
306 original 10% assigned to the prior) near the transducers, poorly constrained near the equator (Fig.  
307 7a), and independent of the choice of prior correction (Fig. 6). Transforming the posterior  
308 correction into sonic coordinates reveals that similar to the Kaimal prior, minimal  $u$  and  $v$   
309 correction is required for small latitude winds (Fig. 9b, d versus 3b, d). But, the impact of the  
310 additional transducer shadowing impacts  $w$  measurements far more than was predicted (Fig. 9f  
311 versus Fig. 3f) where the posterior was fairly certain for latitudes greater than  $\pm 13.5^\circ$  (Fig. 7d);  
312 the high uncertainty for near-equatorial wind is discussed in Sect. 4.2. The posterior corrected



313 CSAT3 was the most omnidirectional between vertically and horizontally mounted anemometers  
314 (Fig. 10) where the RMSE for all cardinal dimensions combined was 5.3%, or 1.36 times greater  
315 than the same error between two vertical anemometers. The discrepancy along the cardinal  $v$ -axis  
316 was further reduced to 4.4%, which is only 1.20 times greater than the same error for two vertical  
317 anemometers, and the bias has been removed (Fig. 10d versus 4d). When the posterior correction  
318 was applied to the vertically mounted anemometers there were similar increases to the Kaimal  
319 correction in the 5-minute standard deviations of  $u$  and  $v$  ( $0.6 \pm 0.8$  [-1.0 2.2]%,  $2.7 \pm 0.7$  [1.5  
320 4.1]%, mean  $\pm$  standard deviation [95% credible interval], Fig. 11a-b). But, compared to the  
321 Kaimal correction, the increases in  $w$  ( $10.6 \pm 1.7$  [7.6 13.9]%) and  $H$  ( $9.9 \pm 1.6$  [7.2 12.6]%)  
322 were substantial and significantly higher (Fig. 11c-d). We provide the MCMC chain for the final  
323 posterior correction in the supplementary material as a tool for researchers to evaluate in other  
324 sonic anemometer studies, to examine the uncertainty in ecosystem flux measurements, and to  
325 investigate surface energy balance closure.

### 326 **3.5 Turbulent components of the ecosystem energy balance across a continent**

327 We applied the posterior correction to various sites across North America that deploy the  
328 CSAT3 in their eddy-covariance instrumentation (Table 2). The estimated increase in  $H + LE$  at  
329 these sites ranged from 8.1-11.6% with an average standard deviation and 95% credible interval  
330 of  $\pm 1.9\%$  and 6.1-13.8%. For all but one site, the increase in  $H + LE$  was significantly higher  
331 than the increase due to the Kaimal correction. At the 2 m Yuma, AZ site, the lack of  
332 significance is related to anomalously low instantaneous wind latitudes for which the  $w$   
333 correction is most uncertain (Fig. 7d).

334

## 335 **4 Discussion**





#### 336 **4.1 An omnidirectional standard**

337           Perhaps the most important shortcoming in almost every sonic anemometer study is the  
338 lack of a standard wind measurement to compare against. A fundamental problem is that the  
339 principle of sonic measurements (Barrett and Suomi, 1949; Kaimal and Businger, 1963) involves  
340 the observer effect, i.e. it is virtually impossible for sonic transducers to observe air parcels  
341 without influencing them (Buks et al., 1998). Thus, any method that relies on a sonic  
342 anemometer measurement as an absolute standard is flawed to an extent. And while we are  
343 justified to believe that some sonic anemometer measurements are more accurate than others  
344 (Frank et al., 2016) it is tenuous to choose any sonic anemometer measurement as a standard.  
345 Then, what are the alternatives? Wind tunnels are extremely useful (Horst et al., 2015; van der  
346 Molen et al., 2004) yet it is debatable that such laminar or quasi-laminar calibrations are  
347 transferrable to turbulent field conditions (Hogstrom and Smedman, 2004). And, while other new  
348 technologies such as Doppler Lidar exist (Sathe et al., 2011; Dellwik et al., 2015) their  
349 application as a field reference standard has been limited.

350           What we address is the general problem of determining a calibration given an unknown  
351 standard or nothing to compare against. Whether this problem exists in medicine (Lu et al.,  
352 1997), acoustics (MacLean, 1940; Monnier et al., 2012), or micrometeorology with respect  
353 calibrating sonic anemometry in turbulent flow fields, all approaches have a commonality of  
354 testing the relative consistency of a response to unknown signals. In our situation, we hold the  
355 3D sonic anemometer to an omnidirectional standard of relative consistency and contend that the  
356 correction that best achieves this standard is statistically the most likely 3D calibration. A  
357 CSAT3 without any 3D shadow correction is clearly not omnidirectional (Fig 2) as  
358 measurements depend on the instrument's orientation. A CSAT3 with the Kaimal transducer



359 shadow correction is better at meeting this standard (Fig 4). However, the posterior 3D  
360 correction is remarkably effective in making the CSAT3 omnidirectional (Fig. 10). Because the  
361 posterior correction closely achieves the omnidirectional standard, we support our first  
362 hypothesis and argue that it is the most accurate correction, in general, for the three dimensions  
363 of the CSAT3. Whether or not the posterior correction reveals meaningful information regarding  
364 vertical winds and turbulent fluxes is another matter discussed below.

365 A consequence of the omnidirectional standard is that implicitly this produces only  
366 relative results. Indeed, our Bayesian posterior has no meaning in an absolute sense without the  
367 additional constraint that equatorial winds should be unchanged by the correction. We do not  
368 specify the 3D correction at any of the grid points nor we do we specify a reference or “true”  
369 condition for the standard deviation of wind during any five minute period. Because of this, the  
370 parameter estimates for  $\vec{\sigma}_{F \times C}$  and  $\vec{\alpha}_{T \times G}$  only have meaning relative to each other. This issue is  
371 confounded by the choice of prior distributions which vary dramatically in shape, but produce  
372 similar posteriors except for differences in their absolute magnitudes (Fig. 6), i.e., higher  
373 magnitude priors produce higher magnitude posteriors. Which absolute magnitude is correct?  
374 Without specifying an absolute standard, the answer is none of them. To facilitate comparison  
375 and combination of the posteriors we normalized the three MCMC chains.

376 There is a clear need to specify an absolute standard to reference our results. Without  
377 one, our normalized posterior correction reduced the 5-minute standard deviations for equatorial  
378 winds (i.e., the  $u$ - $v$  plane) by 7%. Does this make physical sense? No. The idea that equatorial  
379 winds should not be changed is consistent with the expectation that the CSAT3 measures  
380 accurate equatorial winds, something that has been demonstrated in both wind tunnels and field  
381 campaigns (Yahaya and Frangi, 2004; Friebel et al., 2009). Even the Kaimal correction, which is



382 an absolute correction, predicts  $<0.1\%$  error in our measurements of equatorial winds. Because  
383 the omnidirectional standard is only relative, we impose an additional absolute standard by  
384 defining the average correction for equatorial winds to be zero, which is simply achieved by  
385 scaling the normalized posterior correction by 7%. While there certainly is some leeway in this  
386 constraint, if the normalized posterior correction were scaled by anything other than  $7 \pm 1.4\%$   
387 then the correction to horizontal winds would be significantly different (95% credible interval)  
388 than both zero and the Kaimal correction (Fig. 11a-b) and would run counter to our belief that  
389 the CSAT3 measures reasonable accurate horizontal winds.

#### 390 **4.2 Impact on vertical wind measurements and sensible heat flux**

391 Recent studies have questioned the accuracy of CSAT3 vertical wind velocity  
392 measurements (Frank et al., 2013; Kochendorfer et al., 2012) culminating with Horst et al.  
393 (2015) and Frank et al. (2016) who identified the anemometer's lack of transducer shadowing  
394 correction as the root cause. Quantifying the inaccuracy and determining how to fix this problem  
395 has been a challenge. While each of these studies estimated different errors in  $w$  at their field  
396 sites (3.5% (Horst et al., 2015), 6-10% (Frank et al., 2013), 5.5-12.5% (Frank et al., 2016), and  
397 14% (Kochendorfer et al., 2012)), it wasn't until Horst et al. (2015) proposed the application of  
398 the Kaimal correction (Kaimal, 1979) that a mechanistic explanation was used to quantify the  
399 underestimate. Whether or not the Kaimal correction is sufficient is a matter of debate, but it  
400 currently represents the best prior knowledge to explain the CSAT3's shortcomings.

401 Solely because the posterior correction makes the CSAT3 more omnidirectional does not  
402 imply that field measurements of vertical wind and turbulent fluxes are impacted, nor does this  
403 assure that these impacts would be due to anything more than chance. Even with the uncertainty  
404 in the posterior  $w$  correction explicitly quantified (Fig. 7d) it is difficult to foresee if  $w$  is



405 significantly impacted without applying the posterior correction to actual data. A powerful  
406 attribute of the Bayesian analysis is that the posterior correction can be applied to raw data to  
407 produce probability distribution estimates for  $w$  and  $H$  from which statistical inferences can be  
408 made. Using GLEES data, Fig. 11c-d confirms that to achieve an omnidirectional sensor (Fig.  
409 10) with minimal change to horizontal winds (Fig. 11a-b) the required correction will increase  
410 both  $w$  and  $H$  by an average of 10.6% and 9.9%, which is significantly more (>95% credible  
411 interval) than predicted by the Kaimal prior. We argue that this significant increase in the vertical  
412 wind occurs because the posterior correction more accurately accounts for all shadowing  
413 between transducers (Fig. 9 versus Fig. 3), therefore we support our second hypothesis.

414         Also of note, there are instabilities in the prior and posterior  $w$  corrections for near-  
415 equatorial winds that occur at latitudes less than  $\pm 4^\circ$  (6 inflection points around the equator, Fig.  
416 3f and 9f). The mathematical cause for these instabilities and the locations of the inflection  
417 points are derived in Appendix A.2, and unless the corrections for the three transducers are  
418 exactly equal everywhere around the equator these instabilities will exist. The existence of these  
419 instabilities should cause concern for eddy-covariance measurements. The ultimate impact of this  
420 phenomena is difficult to know, because on one hand,  $w$  for latitudes less than  $\pm 4^\circ$  are by  
421 definition very small, but on the other, these eddies constitute a large proportion of winds that  
422 exist under field conditions and their correction is currently unpredictable. For example, at  
423 GLEES 30% of winds occur at latitudes within  $\pm 4^\circ$  (unpublished analysis of Figure 4 from Frank  
424 et al. (2016)). It is unknown how aggressively the correction for these winds approaches  $\pm\infty$  or if  
425 more inflection points actually occur. For all non-orthogonal geometries, not just the CSAT3, if  
426 any transducer shadowing occurs at the equator, there will be instabilities in the  $w$  correction.

#### 427 **4.4 Impact across global flux networks**



428 Energy balance is a fundamental ecosystem concept where the flow of available energy  
429 into an ecosystem influences the microclimate, drives photosynthesis, and establishes trophic  
430 levels among the biota (Odum, 1957; Fisher and Likens, 1973; Teal, 1962). Yet, eddy covariance  
431 studies of ecosystem fluxes seldom delve into details of energy flow beyond the generation of  
432 sensible and latent heat. It is often stated that most eddy covariance sites underestimate these  
433 turbulent components of the energy balance by 10-20% when compared to the available energy  
434 (Wilson et al., 2002; Foken, 2008; Stoy et al., 2013; Leuning et al., 2012; Franssen et al., 2010).  
435 Even when sites thoroughly account for lesser components such as energy stored in the biomass  
436 or canopy air, the turbulent energy can still be 1-14% underestimated (Heilman et al., 2009;  
437 Oliphant et al., 2004; Barr et al., 2006; Wang et al., 2012). It is common for sites to deal with  
438 this problem by forcing energy balance closure by increasing  $H$  and/or  $LE$  (Heilman et al., 2009;  
439 Oliphant et al., 2004; Twine et al., 2000; Scott et al., 2004) or even carbon fluxes (Barr et al.,  
440 2006) by the percent of the energy imbalance. Is there a mechanistic reason why so many sites  
441 believe their turbulent fluxes are underestimated? While it is difficult to generalize for every site,  
442 one similarity among these studies (Heilman et al., 2009; Oliphant et al., 2004; Barr et al., 2006;  
443 Wang et al., 2012; Twine et al., 2000; Scott et al., 2004) is they all feature a CSAT3, as do ~60%  
444 of all sites in the AmeriFlux network (unpublished summary of 150 the 228 sites where  
445 anemometer information was available, list accessed at <http://ameriflux.lbl.gov/> in November  
446 2015) and numerous sites distributed across the world within FLUXNET  
447 (<http://fluxnet.fluxdata.org/>).

448 After applying the posterior correction to the CSAT3 at our site, measurements of one of  
449 the energy balance components,  $H$ , increased  $9.9 \pm 1.6\%$ , which is about twice the 5.5% increase  
450 predicted the Kaimal correction (Fig. 11) (note, the field experiments were conducted without a



451 co-located fast-response hygrometer, hence we do not estimate the impact on *LE* at our site).  
452 However, we must consider that our field site in Wyoming is unusual, with extreme wind and  
453 turbulence, and where summer friction velocity ( $u^*$ ) averages  $0.6 \text{ m s}^{-1}$  (Frank et al., 2016).  
454 While this made GLEES a good location to conduct the turbulent field experiments that led to  
455 the development of the posterior correction, do our results lead to similar impacts on ecosystem  
456 fluxes elsewhere? To answer this we applied the posterior correction to eddy covariance  
457 measurements at various sites across North America that employ the CSAT3 (Table 2). We  
458 found that the sum of the turbulent components of the energy balance (sensible plus latent heat  
459 flux) increased on average between 8-12% with the average 95% credible interval being 6-14%.  
460 At most sites this was significantly higher than applying the Kaimal correction. Thus, it is highly  
461 probable that at flux sites that employ the CSAT3 sonic anemometer the posterior correction will  
462 significantly increase the turbulent components of the energy budget and explain much of the  
463 ubiquitous energy imbalance problem; therefore we support our third hypothesis.

464 Are the results from this study applicable to the non-orthogonal sonic anemometers  
465 produced by other manufacturers? Possibly. Frank et al. (2016) showed that the Applied  
466 Technologies, Inc. A-probe shares a similar transducer geometry, a lack of a shadow correction  
467 algorithm, and similar differences between vertically and horizontally mounted anemometers, so  
468 it would be reasonable to expect a similar 3D correction for that instrument. But other  
469 manufacturers do apply wake corrections in their firmware that are traceable to wind tunnel  
470 calibrations. Are these adequate? Maybe not, as non-orthogonal anemometers from other  
471 manufacturers have been implicated to erroneously measure the vertical wind (Kochendorfer et  
472 al., 2012; Nakai et al., 2014; Nakai and Shimoyama, 2012). Without details of the calibrations or  
473 the wake corrections it is difficult to know. Regardless, for any non-orthogonal sonic



474 anemometer with vertically oriented transducers, equatorial instabilities are likely to exist  
475 (Appendix A.2) that would be extremely difficult to characterize with only a series of wind  
476 tunnel calibrations. One benefit of our methodology is that it allows an independent check on the  
477 sufficiency of these wake corrections. If such an instrument fails to consistently measure 3-  
478 dimensional winds (i.e., it responds like Fig. 2), then our methodology would estimate a  
479 posterior correction that could correct a wake-corrected anemometer. Because ~90% of all  
480 AmeriFlux sites use non-orthogonal sonic anemometers (Frank et al., 2013; Nakai et al., 2014), it  
481 would be appropriate to investigate this issue for all non-orthogonal sonic anemometer designs.

#### 482 **4.5 The next step**

483 While these results reveal much about the nature of shadowing in a non-orthogonal sonic  
484 anemometer, there is much more to be done. First, due to the intense computational burden of  
485 this analysis we never fully utilized our data. While we only analyzed 5% of the available data,  
486 limited the 3D correction to approximately  $\pm 5^\circ$  resolution and only 138 unique corrections, and  
487 terminated the Bayesian MCMC chains after only 10,000 steps, it still took months of continuous  
488 processing with extensive memory usage to produce these results. Obviously there is an  
489 opportunity to adapt this analysis to run on multiple cores or a supercomputer. As we developed  
490 our analysis it became apparent that with more data the standard deviations of the posterior  
491 distribution improved; we foresee that with 20 times more data the uncertainty in the posterior  
492 correction would be further reduced. Adaptation to a high-performance computer will allow for a  
493 more precise grid, longer MCMC chains, and a lower standard deviation of the posterior  
494 distribution.

495 Our results draw extensively on the symmetry of the CSAT3, which fails to account for  
496 the upper and lower mounting arms that extend back into the electronics housing and support



497 block. We beta tested our model to solve for the 3D correction independently for each transducer  
498 and for all grid points around the sphere. We abandoned this because winds at GLEES are fairly  
499 unidirectional causing many of the grid points to be poorly characterized. Plus with an order of  
500 magnitude more unique grid points to solve, the computation took over 5 months to complete  
501 just one MCMC chain! There is a middle ground between assuming symmetry and pooling data,  
502 i.e., the correction for the A transducer pair could be considered symmetrical along the  $u$ - $w$  plane  
503 and the corrections for transducer pairs B and C are mirror images of each other. In addition to  
504 solving the problem with less assumptions of symmetry, more experimental manipulations  
505 should be tested. We only tested a  $90^\circ$  rotation along the  $u$ -axis, but there are limitless other  
506 manipulations that would help characterize the shadowing around the entire 3D space  
507 surrounding an anemometer. Our model could easily be adapted to handle different  
508 manipulations using Eq. (7). This equation can be expanded to account for a limitless number of  
509 manipulations within the same analysis.

510 Our results using the posterior correction (Fig. 10) show that there is still unexplained  
511 residual error, though we expect some of this to be reduced with our suggestions above. While  
512 Horst et al. (2015) showed that to a first order that transducer shadowing is a function of the  
513 longitude and latitude of the instantaneous wind, the impact of other covariates such as wind  
514 velocity and turbulence may need to be considered. An advantage of performing our analysis in a  
515 Bayesian framework is that the model can be expanded to incorporate the effects of these  
516 covariates.

517 And finally, our posterior correction and methodology should be compared to other  
518 independent analysis of sonic anemometer shadowing such as wind tunnel data (Horst et al.,  
519 2015) or an independent Doppler Lidar system (Sathe et al., 2011). Care should be taken when





520 incorporating these results, as anemometers could respond differently under laminar flow in a  
521 wind tunnel versus under turbulent field conditions. Regardless, a key to resolving this problem  
522 will be to embrace new technologies, new experimental designs, and new analyses.

523

## 524 **5 Conclusion**

525         The non-orthogonal CSAT3 sonic anemometer produces different results (Fig. 2) when it  
526 is mounted horizontally instead of vertically (Fig. 1). Assuming that the primary source of this  
527 error is shadowing across the various transducers, a Bayesian model can estimate a posterior  
528 correction (Fig. 8) that ultimately makes measurements from vertically and horizontally mounted  
529 anemometers most similar (Fig. 10). Even when taking into account the uncertainty of the  
530 posterior correction (Fig. 7) the increases in vertical wind velocity and sensible heat flux  
531 measurements are significantly larger and are approximately twice the magnitude of the Kaimal  
532 correction (Fig. 11). When this posterior correction is applied to various eddy covariance sites  
533 across North America, the turbulent components of the ecosystem energy balance (sensible plus  
534 latent heat flux) increased between 8.1-11.6%, with an average 95% confidence that this increase  
535 was between 6.1-13.8% (Table 2). Considering this is the most common sonic anemometer in the  
536 AmeriFlux network and is found in all the regional networks that comprise FLUXNET, these  
537 results have major implications for countless studies that use the eddy-covariance technique to  
538 measure terrestrial/atmospheric exchange of mass and energy.

539

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547

## 548 **Appendix**

### 549 **A.1 Univariate conditional posterior distribution functions for Gibbs sampling**

550 For the univariate conditional posterior distribution functions there is a distinction  
 551 between independent grid points versus those linked together through symmetry. In the case of  
 552 the former, these functions can be evaluated for each unique grid point,  $g$ , for each transducer  
 553 pair,  $t$ . In the case of the latter,  $g$  and  $t$  refer to the sets of all grid points and transducers that  
 554 share the same unique state variable for their shadow correction, and these functions can be  
 555 applied to each of these unique sets.

556 First, using Bayes Theorem, the joint posterior distribution of the model parameters can  
 557 be expressed as being proportional to the product of the likelihood of the data and the joint prior  
 558 distribution of the model parameters (Eq. A1).

$$559 \quad p\left(\tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon \mid \sigma_{f,i,c}\right) \propto p\left(\sigma_{f,i,c} \mid \tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon\right) p\left(\tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon\right) \quad (\text{A1})$$

560 Because the prior distributions for three model parameters are independent, the joint prior  
 561 distribution can be written as the product of the individual probabilities (Eq. A2).

$$562 \quad p\left(\tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon \mid \sigma_{f,i,c}\right) \propto p\left(\sigma_{f,i,c} \mid \tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon\right) p\left(\tilde{\sigma}_{F \times C_{f,c}}\right) p\left(\alpha_{T \times G_{t,g}}\right) p(\varepsilon)$$

563 (A2)

564 The likelihood of the data is normally distributed (Eq. A3).

$$565 \quad p\left(\sigma_{f,i,c} \mid \tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon\right) = \frac{1}{\sqrt{2\pi\varepsilon}} e^{\left(-\frac{1}{2\varepsilon^2}(\sigma_{f,i,c} - \hat{\sigma}_{f,i,c})^2\right)} \quad (\text{A3})$$



566 Because  $\hat{\sigma}_{f,i,c}$  is both a function of  $\tilde{\sigma}_{F \times C f,c}$  and  $\alpha_{T \times G t,g}$  the likelihood is indeed a function of all  
 567 three model parameters. The individual prior distributions for  $\tilde{\sigma}_{F \times C f,c}$ ,  $\alpha_{T \times G t,g}$ , and  $\varepsilon$  are  
 568 uniformly (Eq. A4), normally (Eq. A5), and gamma (Eq. A6) distributed, respectively.

$$569 \quad p\left(\tilde{\sigma}_{F \times C f,c}\right) = \begin{cases} \frac{1}{\max(U_c)}, & 0 \leq \tilde{\sigma}_{F \times C f,c} \leq \max(U_c) \\ 0, & \text{otherwise} \end{cases} \quad (\text{A4})$$

$$570 \quad p\left(\alpha_{T \times G t,g}\right) = \frac{1}{\sqrt{2\pi}(0.1)} e^{\left(-\frac{1}{2(0.1)^2}(\alpha_{T \times G t,g} - P_{t,g})^2\right)} \quad (\text{A5})$$

$$571 \quad p(\varepsilon) = b e^{-b\varepsilon} \quad (\text{A6})$$

572 Gibbs sampling for each model parameter is based on the univariate conditional posterior  
 573 distribution which assumes that all other model parameters plus the data are given (in the case of  
 574 sampling within a multidimensional array, all other parameters within that array are given except  
 575 the one at the index being evaluated). For  $\tilde{\sigma}_{F \times C f,c}$  the univariate conditional posterior distribution  
 576 can be expressed as a form of Bayes Theorem (Eq. A7).

$$577 \quad p\left(\tilde{\sigma}_{F \times C f,c} \mid \tilde{\sigma}_{F \times C -f,c}, \alpha_{T \times G}, \varepsilon, \underline{\sigma}\right) = \frac{p\left(\tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \varepsilon \mid \underline{\sigma}\right) p(\underline{\sigma})}{p\left(\tilde{\sigma}_{F \times C -f,c}, \alpha_{T \times G}, \varepsilon, \underline{\sigma}\right)} \quad (\text{A7})$$

578 The under-bar denotes all elements within a multidimensional array, while the notation  $\tilde{\sigma}_{F \times C -f,c}$   
 579 means all elements of  $\tilde{\sigma}_{F \times C}$  except for  $\tilde{\sigma}_{F \times C f,c}$ . On right side of Eq. A7, both the second term in  
 580 the numerator and the denominator are assumed given and can be omitted if the equal sign is  
 581 changed to a proportional sign. The first term in the numerator,  $p\left(\tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \varepsilon \mid \underline{\sigma}\right)$ , is the joint  
 582 posterior distribution summed across all parameters (Eq. A8).

$$583 \quad p\left(\tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \varepsilon \mid \underline{\sigma}\right) \propto$$

$$584 \quad \prod_{f=1}^F \prod_{c=1}^3 \left\{ \left[ \prod_{i=1}^I p\left(\sigma_{f,i,c} \mid \tilde{\sigma}_{F \times C f,c}, \alpha_{T \times G t,g}, \varepsilon\right) \right] p\left(\tilde{\sigma}_{F \times C f,c}\right) \right\} \prod_{t=1}^3 \prod_{g=1}^G p\left(\alpha_{T \times G t,g}\right) p(\varepsilon) \quad (\text{A8})$$



585 Assuming that all but  $\tilde{\sigma}_{F \times C f, c}$  is given plus requiring that the proposed value for  $\tilde{\sigma}_{F \times C f, c}$  is  
 586 within the valid range (i.e.,  $p(\tilde{\sigma}_{F \times C f, c})$  is constant and can be omitted) Eq. A7 simplifies to Eq.  
 587 A9.

$$588 \quad p\left(\tilde{\sigma}_{F \times C f, c} \mid \underline{\tilde{\sigma}_{F \times C}_{-f, c}}, \underline{\alpha_{T \times G}}, \varepsilon, \underline{\sigma}\right) \propto \prod_{i=1}^I p\left(\sigma_{f, i, c} \mid \tilde{\sigma}_{F \times C f, c}, \alpha_{T \times G_{t, g}}, \varepsilon\right) \quad (\text{A9})$$

589 Substituting in the likelihood from Eq. A3 and simplifying gives the univariate conditional  
 590 posterior distribution for  $\tilde{\sigma}_{F \times C f, c}$  (Eq. A10).

$$591 \quad p\left(\tilde{\sigma}_{F \times C f, c} \mid \underline{\tilde{\sigma}_{F \times C}_{-f, c}}, \underline{\alpha_{T \times G}}, \varepsilon, \underline{\sigma}\right) \propto e^{\left(-\frac{1}{2\varepsilon^2} \sum_{i=1}^I (\sigma_{f, i, c} - \tilde{\sigma}_{f, i, c})^2\right)} \quad (\text{A10})$$

592 The univariate conditional posterior distribution for  $\alpha_{T \times G_{t, g}}$  can be expressed as Bayes Theorem  
 593 (Eq. A11).

$$594 \quad p\left(\alpha_{T \times G_{t, g}} \mid \underline{\tilde{\sigma}_{F \times C}}, \underline{\alpha_{T \times G}_{-t, g}}, \varepsilon, \underline{\sigma}\right) = \frac{p(\underline{\tilde{\sigma}_{F \times C}}, \underline{\alpha_{T \times G}}, \varepsilon \mid \underline{\sigma}) p(\underline{\sigma})}{p(\underline{\tilde{\sigma}_{F \times C}}, \underline{\alpha_{T \times G}_{-t, g}}, \varepsilon, \underline{\sigma})} \quad (\text{A11})$$

595 Again, only the first term in the numerator must be evaluated while assuming that all but  $\alpha_{T \times G_{t, g}}$   
 596 are given (Eq. A12).

$$597 \quad p\left(\alpha_{T \times G_{t, g}} \mid \underline{\tilde{\sigma}_{F \times C}}, \underline{\alpha_{T \times G}_{-t, g}}, \varepsilon, \underline{\sigma}\right) \propto \prod_{f=1}^F \prod_{i=1}^I \prod_{c=1}^3 p\left(\sigma_{f, i, c} \mid \tilde{\sigma}_{F \times C f, c}, \alpha_{T \times G_{t, g}}, \varepsilon\right) p\left(\alpha_{T \times G_{t, g}}\right)$$

$$598 \quad (\text{A12})$$

599 Substituting in both the likelihood of the data (Eq. A3) and the prior distribution for  $\alpha_{T \times G_{t, g}}$  (Eq.  
 600 A5) and simplifying yields the univariate conditional posterior distribution for  $\alpha_{T \times G_{t, g}}$  (Eq. A13).

$$601 \quad p\left(\alpha_{T \times G_{t, g}} \mid \underline{\tilde{\sigma}_{F \times C}}, \underline{\alpha_{T \times G}_{-t, g}}, \varepsilon, \underline{\sigma}\right) \propto e^{\left(-\frac{1}{2\varepsilon^2} \sum_{f=1}^F \sum_{i=1}^I \sum_{c=1}^3 (\sigma_{f, i, c} - \tilde{\sigma}_{f, i, c})^2 - \frac{1}{2(0.1)^2} (\alpha_{T \times G_{t, g}} - P_{t, g})^2\right)}$$

$$602 \quad (\text{A13})$$



603 An important issue is that  $\hat{\sigma}_{f,i,c}$  is a function of  $\alpha_{T \times G_{t,g}}$  and must be evaluated for every proposed  
 604 change to the 3D correction. This is computationally intensive and causes a bottleneck in the  
 605 analysis. Finally, the univariate conditional posterior distribution for  $\varepsilon$  can be expressed as Bayes  
 606 Theorem (Eq. A14).

$$607 \quad p\left(\varepsilon \mid \tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \underline{\sigma}\right) = \frac{p\left(\tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \varepsilon \mid \underline{\sigma}\right) p(\underline{\sigma})}{p\left(\tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \underline{\sigma}\right)} \quad (\text{A14})$$

608 Only the first term in the numerator must be evaluated while assuming that all but  $\varepsilon$  are given  
 609 (Eq. A15).

$$610 \quad p\left(\varepsilon \mid \tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \underline{\sigma}\right) \propto \prod_{f=1}^F \prod_{i=1}^I \prod_{c=1}^3 p\left(\sigma_{f,i,c} \mid \tilde{\sigma}_{F \times C_{f,c}}, \alpha_{T \times G_{t,g}}, \varepsilon\right) \quad (\text{A15})$$

611 Substituting in the likelihood from Eq. A3 and simplifying yields the univariate conditional  
 612 posterior distribution for  $\varepsilon$  (Eq. A16)

$$613 \quad p\left(\varepsilon \mid \tilde{\sigma}_{F \times C}, \alpha_{T \times G}, \underline{\sigma}\right) \propto \varepsilon^{-3FI} e^{\left(-\frac{1}{2\varepsilon^2} \sum_{f=1}^F \sum_{c=1}^3 \sum_{i=1}^I (\sigma_{f,i,c} - \hat{\sigma}_{f,i,c})^2\right)} \quad (\text{A16})$$

## 614 **A.2 Instability in the $w$ correction for near equatorial winds**

615 For a CSAT3, the amount of correction applied to the vertical wind velocity, expressed as  
 616 the individual corrections  $\alpha_A(\lambda, \varphi)$ ,  $\alpha_B(\lambda, \varphi)$ , and  $\alpha_C(\lambda, \varphi)$  for the three transducer pairs  $A$ ,  $B$ ,  
 617 and  $C$  as functions of longitude,  $\lambda$ , and latitude,  $\varphi$ , is:

$$618 \quad \frac{w_{corrected}}{w_{uncorrected}} = \frac{2}{3\sqrt{3}} \left[ \left( -\frac{\cos \lambda}{2 \tan \varphi} + \frac{\sqrt{3}}{2} \right) \alpha_A(\lambda, \varphi) + \left( \frac{\cos \lambda + \sqrt{3} \sin \lambda}{4 \tan \varphi} + \frac{\sqrt{3}}{2} \right) \alpha_B(\lambda, \varphi) + \left( \frac{\cos \lambda - \sqrt{3} \sin \lambda}{4 \tan \varphi} + \right. \right. \\ 619 \quad \left. \left. \frac{\sqrt{3}}{2} \right) \alpha_C(\lambda, \varphi) \right] \quad (\text{A17})$$

620 If the individual corrections for the three transducer pairs never approach 0 or  $\pm\infty$ , which is a  
 621 safe assumption considering they are always around 1 (Figs. 3a, c, e and 9a, c, e), the limit of this  
 622 as the latitude approaches the equator is:



$$\lim_{\varphi \rightarrow 0} \frac{w_{corrected}}{w_{uncorrected}} = \frac{1}{3} (\alpha_A(\lambda, \varphi) + \alpha_B(\lambda, \varphi) + \alpha_C(\lambda, \varphi)) +$$

$$\frac{2}{3\sqrt{3}} \left[ \left( -\frac{\cos \lambda}{2} \right) \alpha_A(\lambda, \varphi) + \left( \frac{\cos \lambda + \sqrt{3} \sin \lambda}{4} \right) \alpha_B(\lambda, \varphi) + \left( \frac{\cos \lambda - \sqrt{3} \sin \lambda}{4} \right) \alpha_C(\lambda, \varphi) \right] \lim_{\varphi \rightarrow 0} \frac{1}{\tan \varphi} \quad (\text{A18})$$

This approaches  $\pm\infty$  unless the terms associated with the limit of the tangent exactly cancel. This is achieved if  $\alpha_A(\lambda, 0^\circ) = \alpha_B(\lambda, 0^\circ) = \alpha_C(\lambda, 0^\circ)$ , which includes the special case where  $\alpha_A(\lambda, 0^\circ) = \alpha_B(\lambda, 0^\circ) = \alpha_C(\lambda, 0^\circ) = 1$ . Based on our assumptions of symmetry with the CSAT3,  $\alpha_B(\lambda, \varphi) = \alpha_A(60^\circ - \lambda, -\varphi)$  and  $\alpha_C(\lambda, \varphi) = \alpha_A(60^\circ + \lambda, -\varphi)$ . Therefore, the  $w$  correction for near equatorial winds is unstable unless:

$$\alpha_A(\lambda, 0^\circ) = \frac{1 + \sqrt{3} \tan \lambda}{2} \alpha_A(60^\circ - \lambda, 0^\circ) + \frac{1 - \sqrt{3} \tan \lambda}{2} \alpha_A(60^\circ + \lambda, 0^\circ) \quad (\text{A19})$$

This is satisfied by  $\lambda = 30^\circ, 90^\circ, 150^\circ, 210^\circ, 270^\circ$ , and  $330^\circ$ . Eq. A19 shows that if the weighted average of  $\alpha_A(60^\circ - \lambda, -\varphi)$  and  $\alpha_A(60^\circ + \lambda, -\varphi)$  cancel  $\alpha_A(\lambda, 0^\circ)$  then the correction will be stable. This cannot be achieved if the correction  $\alpha_A(\lambda, 0^\circ)$  is monotonic between  $0^\circ \leq \lambda \leq 90^\circ$ . Because the  $w$  correction is symmetric every  $30^\circ$ , any solution besides  $\lambda = 30^\circ, 90^\circ, 150^\circ, 210^\circ, 270^\circ$ , and  $330^\circ$  will be mirrored 12 times.

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- 791  
792



793 Table 1. Summary of the subset of data from Frank et al. (2013) and Frank et al. (2016)  
 794 reanalyzed in this study listing the four CSAT3 anemometers (A-D), their location within the  
 795 five-position horizontal array, and if mounted horizontally (\*). Because processing the Bayesian  
 796 model is extremely intensive, only 5% of the available data was reanalyzed.

Dates	Position					Number of 5-min periods	
	1	2	3	4	5	Available	Reanalyzed
5-19 July 2011	A*	B	-	C	D*	2,520	126
19-26 July 2011	A	B*	-	C*	D	1,992	100
9-16 August 2011	B*	A	-	D	C*	1,974	98
16-22 August 2011	B	A*	-	D*	C	1,620	81
26-30 July 2013	A*	-	B	-	-	906	46
23-27 August 2013	-	-	A	-	B*	1,050	52
6-24 September 2013	-	-	B	D*	-	498	25

797



798 Table 2. Increase in  $H + LE$  (sum of the turbulent components of the energy balance, i.e. sensible  
 799 and latent heat flux) at various sites across North America after applying shadow correction to  
 800 the CSAT3 time series data.

Site	Coordinates	Dates	Height (m)	Percent change after applying shadow correction	
				Kaimal correction	Posterior correction mean $\pm$ standard deviation [95% credible interval]
Yuma, AZ, USA	33° 5' N 114° 32' W	6-15 June 2008	8.25	5.1%	9.8 $\pm$ 2.3% [5.1% 14.8%]
Yuma, AZ, USA	33° 5' N 114° 32' W	5-14 June 2009	2.00	4.5%	9.4 $\pm$ 2.8% [3.1% 16.1%]
Fraser, CO, USA	39° 53' 48.23" N 105° 53' 33.87" W	5-14 April 2015	27.50	5.6%	9.9 $\pm$ 1.4% [7.4% 12.2%]
Fraser, CO, USA	39° 53' 48.23" N 105° 53' 33.87" W	5-14 April 2015	6.40	6.8%	11.6 $\pm$ 1.2% [9.4% 13.9%]
Beltsville, MD, USA	39° 1' 51.23" N 76° 50' 39.40" W	16-31 July 2014	4.00	5.5%	10.4 $\pm$ 2.1% [6.3% 14.8%]
Glacier Peak, WY, USA	41° 22' 52" N 106° 15' 47" W	August-8 September 2015	3.20	5.3%	11.3 $\pm$ 3.1% [4.6% 19.2%]
Agua Salud, Panama	9° 13' 31.65" N 79° 45' 36.41" W	6-16 November 2015	5.00	4.7%	8.1 $\pm$ 1.6% [5.3% 10.8%]

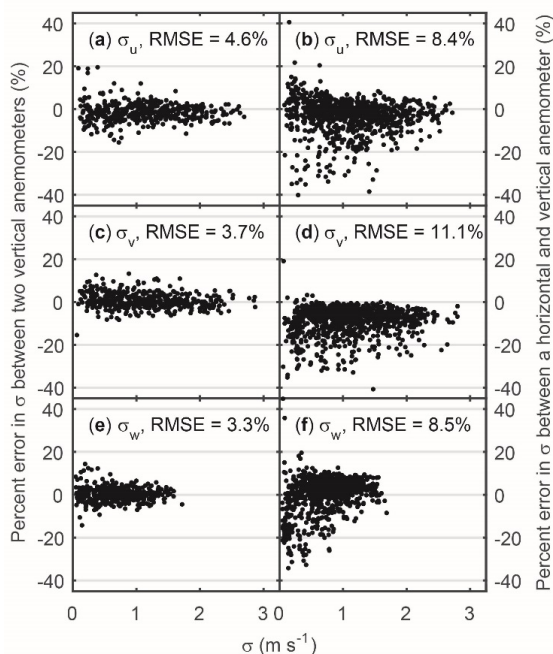
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802

803 Fig. 1. Photograph of the 2011 experiment with two CSAT3 sonic anemometers mounted  
804 vertically and two horizontally. The cardinal  $u$ ,  $v$ , and  $w$  axes are shown in light blue near one of  
805 the vertical instruments. Figure from Frank et al. (2013).

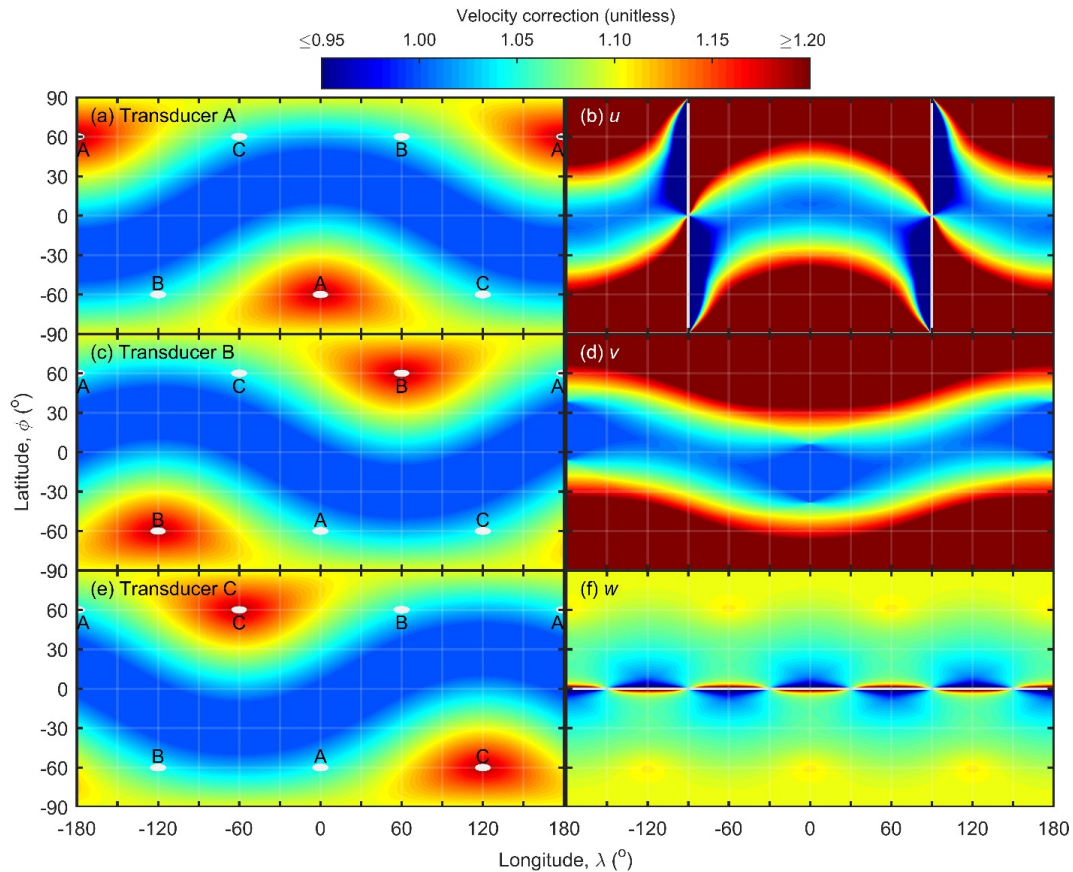
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808 Fig. 2. Uncorrected measurements of the 5-minute standard deviation of wind ( $\sigma$ ) along the  
809 cardinal **(a, b)**  $u$ , **(c, d)**  $v$ , and **(e, f)**  $w$  axes are not equivalent between vertically and horizontally  
810 mounted CSAT3 sonic anemometers. Data from an ideal 3D anemometer would have similar  
811 percent errors between a horizontal and a vertical anemometer **(b, d, f)** as found between two  
812 anemometers mounted vertically **(a, c, e)**. The data are from 2011 and 2013 field experiments at  
813 the GLEES AmeriFlux site (Frank et al., 2016; Frank et al., 2013). The 2011 data in panels **b, d,**  
814 and **f** are randomly paired between the two anemometers in different orientations. Results are  
815 summarized as root mean square error (RMSE).

816



817

818 Fig. 3. The Kaimal correction, one of three priors tested in this study, for the (a) A, (c) B, and (e)

819 C transducer pairs, each represented by a white dot, of a CSAT3 sonic anemometer accounts for

820 self-shadowing but not cross-shadowing between transducers. The same correction expressed in

821 sonic anemometer coordinates (b)  $u$ , (d)  $v$ , and (f)  $w$  shows that for near-equatorial winds,

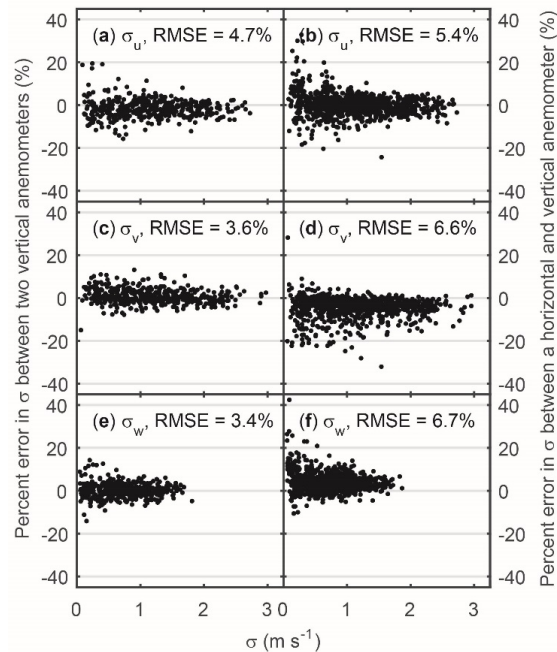
822 minimal correction is required for the horizontal wind components while significant correction

823 and instability exist in the vertical wind component  $w$ . Longitude and latitude are relative to the  $u$

824 axis (Fig. 1).

825



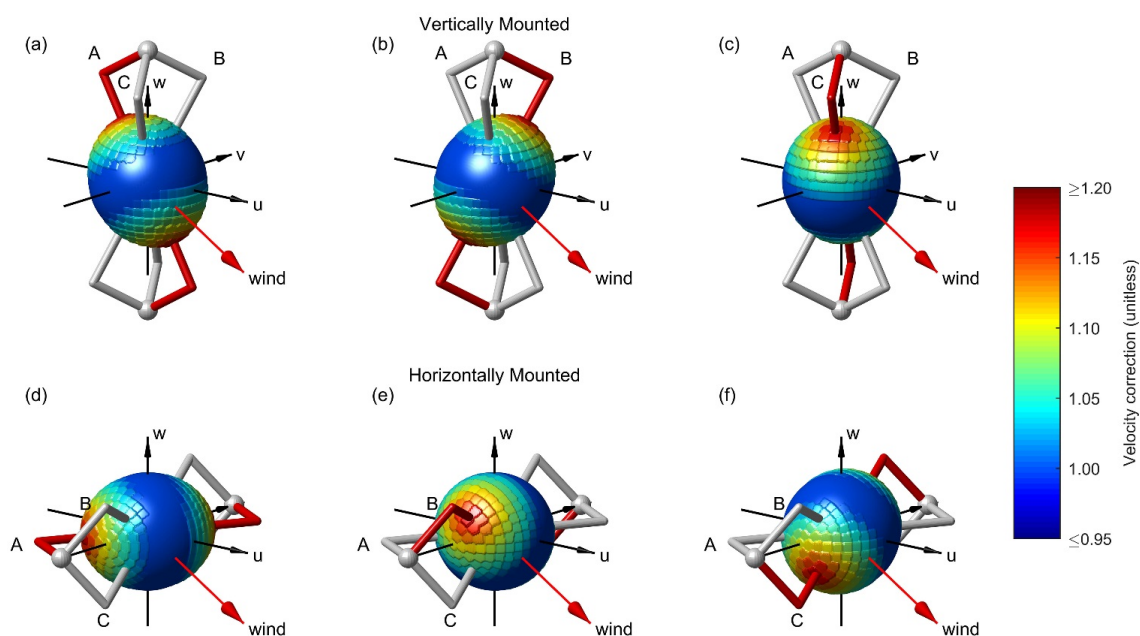


826

827 Fig. 4. Kaimal corrected measurements (i.e. one of three priors tested) of the 5-minute standard  
828 deviation of wind ( $\sigma$ ) along the cardinal **(a, b)**  $u$ , **(c, d)**  $v$ , and **(e, f)**  $w$  axes are more equivalent  
829 between vertically and horizontally mounted sonic anemometers. The percent errors between a  
830 horizontal and a vertical anemometer **(b, d, f)** are smaller for all three cardinal dimensions than it  
831 was for the uncorrected data (Fig. 2) being more similar to those found between two  
832 anemometers mounted vertically **(a, c, e)**. The data are from 2011 and 2013 field experiments at  
833 the GLEES AmeriFlux site (Frank et al., 2016; Frank et al., 2013). The 2011 data in panels **b, d,**  
834 and **f** are randomly paired between the two anemometers in different orientations. Results are  
835 summarized as root mean square error (RMSE).

836





837

838 Fig. 5. The Kaimal correction, one of three priors tested in this study, evaluated among 512 cells

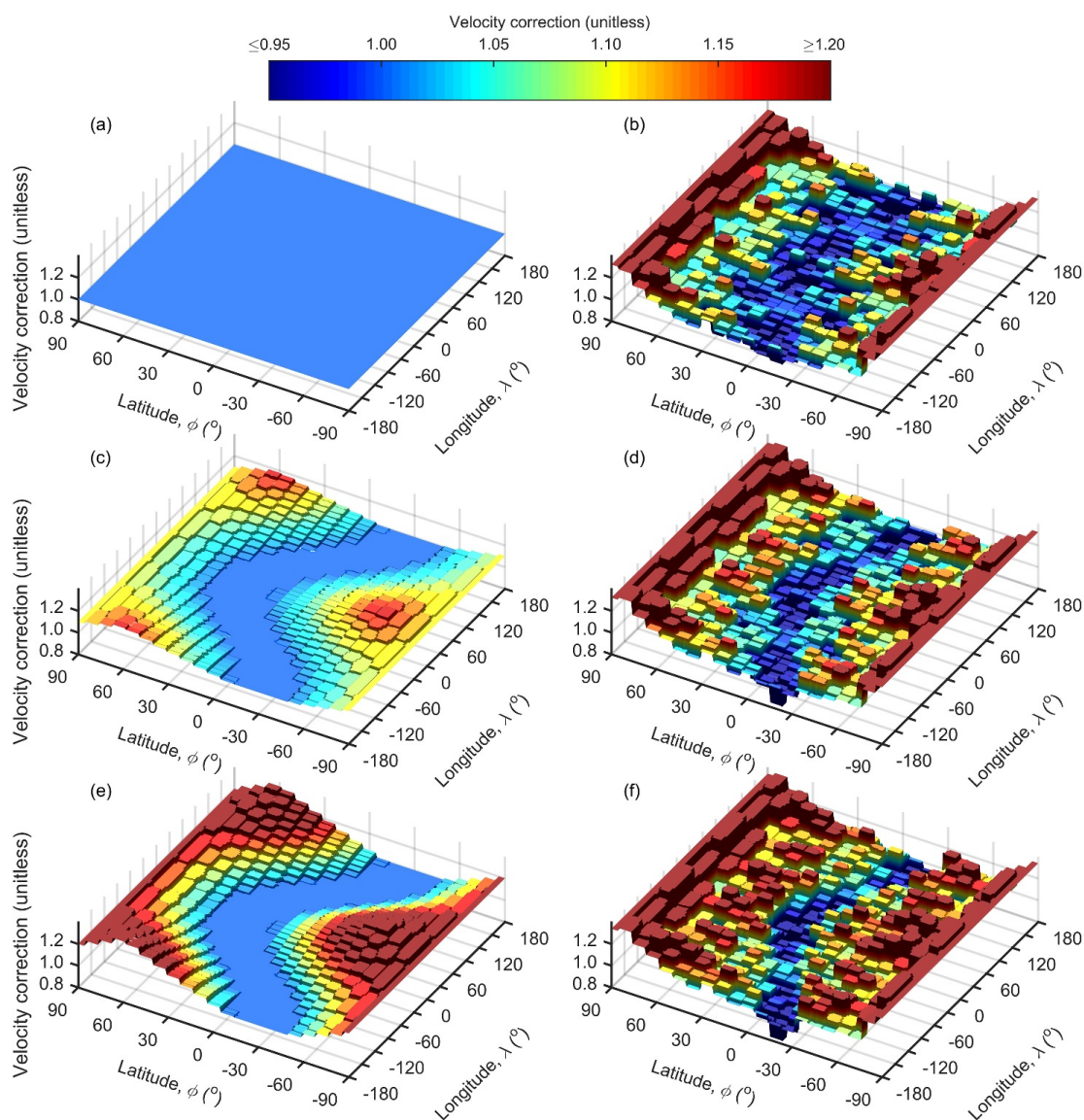
839 for the (a, d) A, (b, e) B, and (c, f) C transducer pairs of the CSAT3 sonic anemometer mounted

840 either in the (a-c) typically vertical or (d-f) experimentally horizontal orientations. Though the

841 correction is identical relative to all transducer pairs, the same instantaneous wind results in

842 different corrections depending on the transducer pair and the orientation.

843



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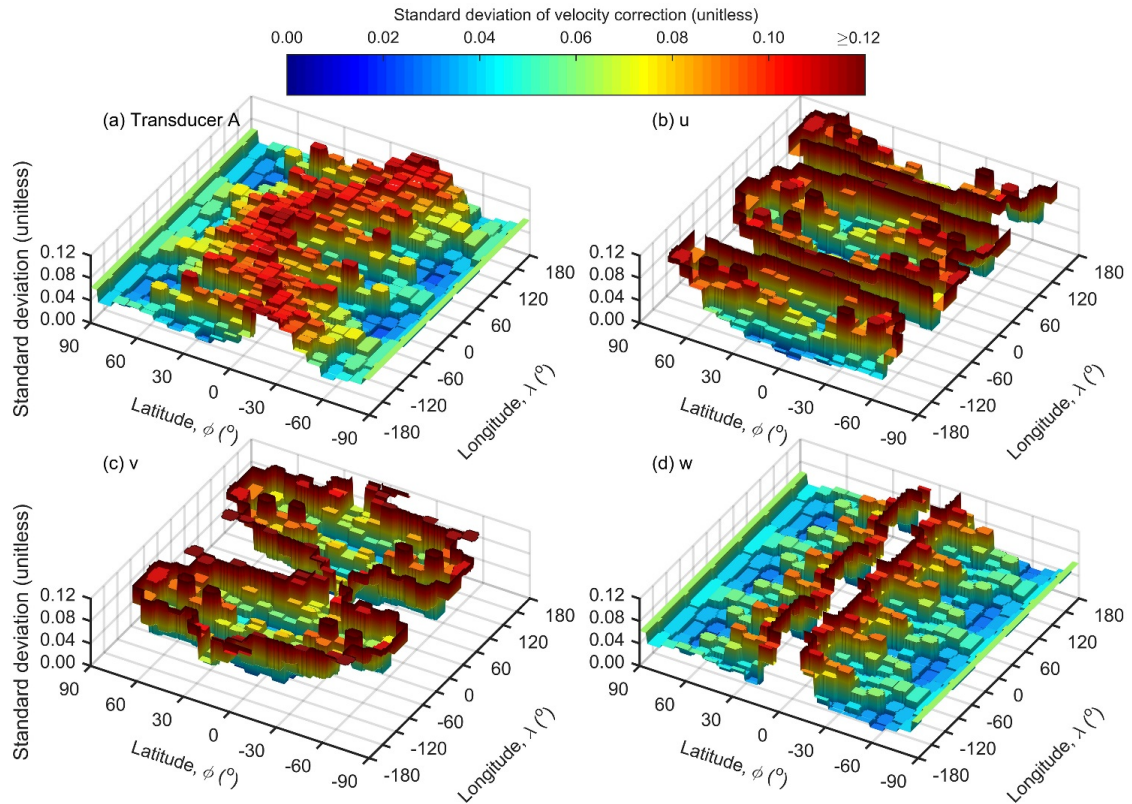
845 Fig. 6. The A transducer pair correction evaluated among 512 cells for the three prior corrections  
846 tested in this study, (a) flat, (c) Kaimal, and (e) double-Kaimal, with their corresponding  
847 unnormalized posterior corrections (b), (d), and (f), respectively. All posteriors have similar  
848 relative topography. They differ in absolute scaling where priors with higher absolute magnitude



849 result in posteriors with higher absolute magnitude, which is apparent from the different

850 colorings.

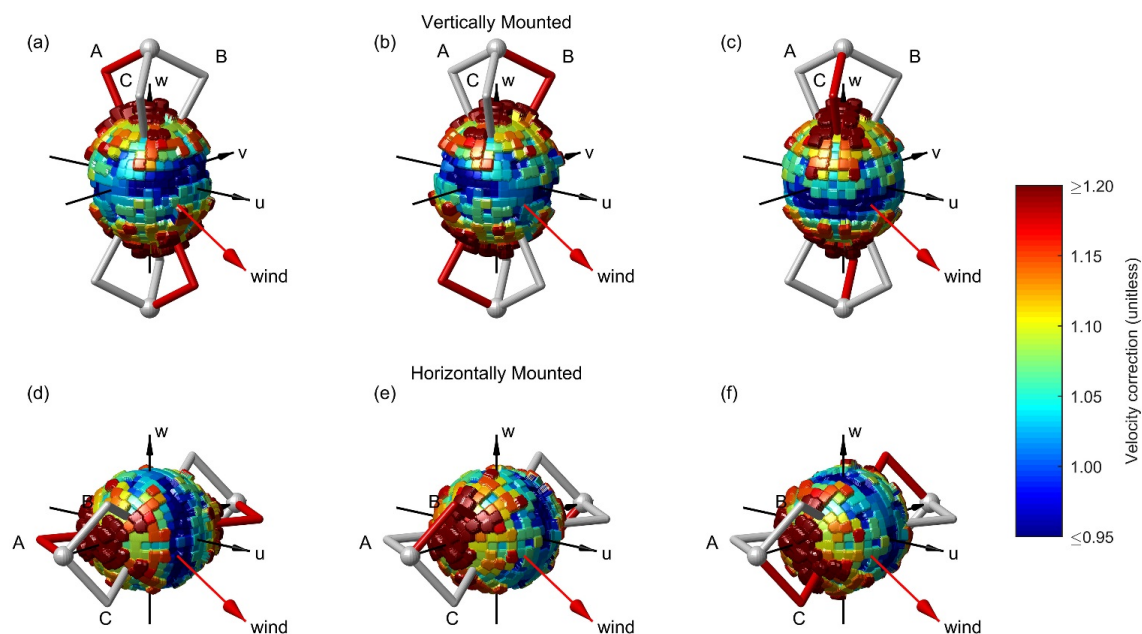
851



852

853 Fig. 7. Standard deviations of the posterior correction for (a) the A transducer pair and the  
854 wind velocities (b)  $u$ , (c)  $v$ , and (d)  $w$ . When compared to the standard deviation of the prior which  
855 was defined as 0.1, the transducer correction is more certain in regions with higher topography  
856 (Fig. 6). The results in CSAT3 sonic coordinates reflect both the uncertainty in the transducer  
857 correction plus cancelation and amplification of errors due to the coordinate transformation. The  
858 posterior correction for  $u$ ,  $v$ , and  $w$  is most certain for winds along the  $u$ ,  $v$ , and  $w$ -axes,  
859 respectively.

860

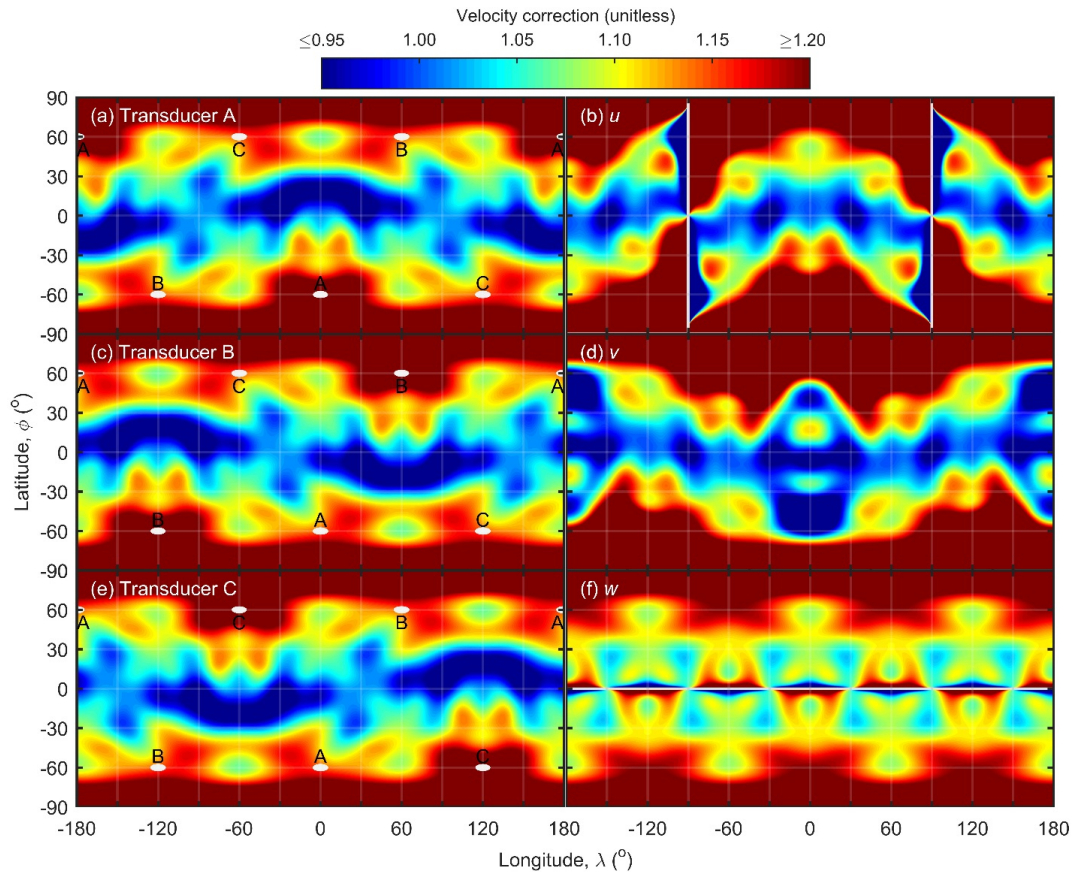


861

862 Fig. 8. The posterior correction evaluated for the (a, d) A, (b, e) B, and (c, f) C transducer pairs  
863 of the CSAT3 sonic anemometer mounted either in the (a-c) typically vertical or (d-f)  
864 experimentally horizontal orientations. The correction is identical relative to all transducer pairs  
865 and is constructed from 512 cells with 138 unique values. The Bayesian model adjusts these  
866 values to simultaneously correct the same instantaneous wind measured from different  
867 transducer pairs and orientations in order to produce similar cardinal  $u$ ,  $v$ , and  $w$  wind statistics  
868 (Fig. 10).

869

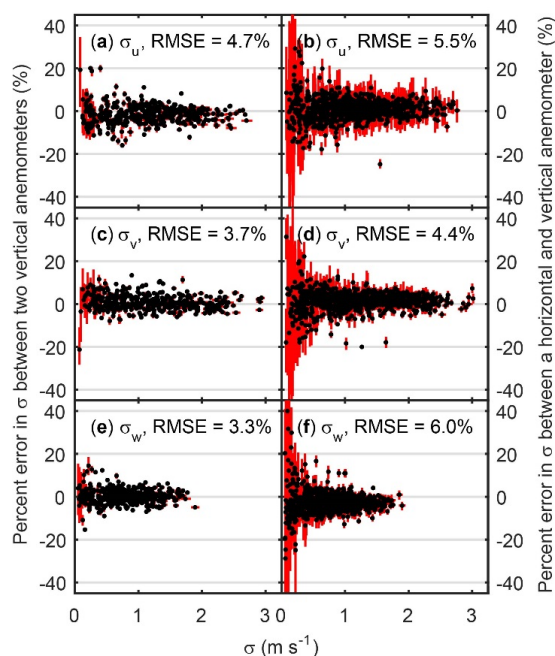




870

871 Fig. 9. The posterior correction for the (a) A, (c) B, and (e) C transducer pairs, each represented  
 872 by a white dot, of a CSAT3 sonic anemometer accounts for both self-shadowing and cross-  
 873 shadowing between transducers. The same correction expressed in sonic anemometer  
 874 coordinates (b)  $u$ , (d)  $v$ , and (f)  $w$  shows that for near-equatorial winds, minimal correction is  
 875 required for the horizontal wind components while even more correction exists in the vertical  
 876 wind component  $w$  than was present with the Kaimal correction (Fig. 3f). Longitude and latitude  
 877 are relative to the  $u$  axis (Fig. 1).

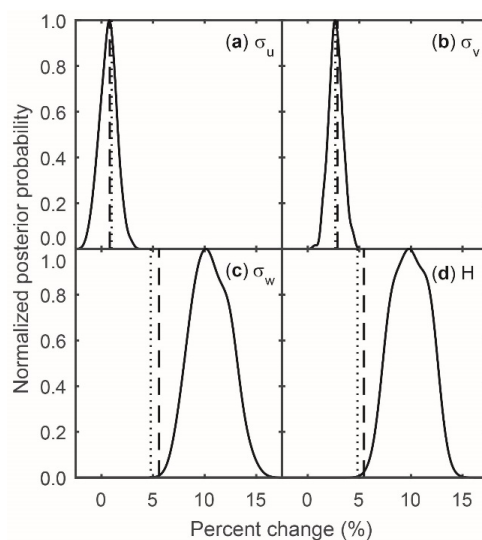
878



879

880 Fig. 10. Posterior corrected measurements of the 5-minute standard deviation of wind ( $\sigma$ ) along  
881 the cardinal **(a, b)**  $u$ , **(c, d)**  $v$ , and **(e, f)**  $w$  axes are most equivalent between vertically and  
882 horizontally mounted sonic anemometers than with either the uncorrected (Fig. 2) or Kaimal  
883 corrected data (Fig. 4). The percent errors between a horizontal and a vertical anemometer are  
884 small **(b, d, f)**, especially for the cardinal  $v$ -dimension **(d)**, and are similar to those found  
885 between two anemometers mounted vertically **(a, c, e)**. The data are from 2011 and 2013 field  
886 experiments at the GLEES AmeriFlux site (Frank et al., 2016; Frank et al., 2013). The 2011 data  
887 in panels **b, d, and f** are randomly paired between the two anemometers in different orientations.  
888 Results are summarized as root mean square error (RMSE). The red lines are 95% credible  
889 intervals.

890



891

892 Fig. 11. Though application of the Kaimal (dashed lines) and posterior (solid lines) corrections  
893 result in similar changes to the 5-minute standard deviations of wind ( $\sigma$ ) along the (a)  $u$  and (b)  $v$   
894 axes, application of the posterior correction results in significantly higher (95% credible interval)  
895 (c) winds along the  $w$  axis and (d) sensible heat flux ( $H$ ). The dotted lines are an alternate  
896 formulation of the Kaimal correction proposed by Wyngaard and Zhang (1985) and used in  
897 Horst et al. (2015). Data are for vertically mounted anemometers only.

898