

Cloud trails past Bermuda: a five-year climatology from 2012-2016

Article

Accepted Version

Johnston, M., Holloway, C. and Plant, R. S. (2018) Cloud trails past Bermuda: a five-year climatology from 2012-2016. *Monthly Weather Review*. ISSN 0027-0644 (In Press)
Available at <http://centaur.reading.ac.uk/79504/>

It is advisable to refer to the publisher's version if you intend to cite from the work.

Publisher: American Meteorological Society

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the [End User Agreement](#).

www.reading.ac.uk/centaur

CentAUR

Central Archive at the University of Reading

Reading's research outputs online



1 **Cloud Trails Past Bermuda: A Five-Year Climatology from 2012-2016**

2 Michael C. Johnston*, Christopher E. Holloway, and Robert S. Plant

3 *Department of Meteorology, University of Reading*

4 *Corresponding author address: Department of Meteorology, University of Reading, Reading, UK

5 E-mail: m.c.johnston@pgr.reading.ac.uk

ABSTRACT

6 Cloud trails are primarily thermally forced bands of cloud that extend down-
7 wind of small islands. A novel algorithm to classify conventional geostation-
8 ary visible-channel satellite images as Cloud Trail (CT), Non-Trail (NT), or
9 Obscured (OB) is defined. The algorithm is then applied to the warm season
10 months of five years at Bermuda comprising 16,400 images. Bermuda's low
11 elevation and location make this island ideal for isolating the role of the island
12 thermal contrast on CT formation.

13 CT are found to occur at Bermuda with an annual cycle, peaking in July, and a
14 diurnal cycle that peaks in mid-afternoon. Composites of radiosonde observa-
15 tions and ERA-interim data suggest that a warm and humid low-level environ-
16 ment is conducive for CT development. From a Lagrangian perspective, wind
17 direction modulates CT formation by maximizing low-level heating on local
18 scales when winds are parallel to the long axis of the island. On larger scales,
19 low-level wind direction also controls low-level humidity through advection.

20 **1. Introduction**

21 Bermuda is a small, flat island in the western North Atlantic Ocean with a total land area of
22 about 54 km² and topography not rising more than 76 m above sea level (CIA 2017). Bermuda is
23 also isolated, more than 1000 km away from the nearest land in North America to the west and the
24 Caribbean to the south. This situation, somewhat unique to Bermuda, helps to isolate the influence
25 of the island on the impinging flow.

26 Cloud trails are bands of cloud that extend downwind of small heated islands. This heating re-
27 sults in a thermal perturbation over and downwind of an island in the form of a turbulent plume
28 with associated thermally forced circulations that organize convection into one or more cloud
29 bands. These bands appear anchored to their parent island in animations of visible-channel satel-
30 lite imagery. Cloud trails are found to occur on ‘flat’ islands such as Nantucket (e.g. Malkus and
31 Bunker 1952; Malkus and Stern 1953); Anegada, British Virgin Islands (Malkus 1963); the Ba-
32 hamas Islands (Bhumralkar 1973); and Nauru (e.g. Nordeen et al. 2001; McFarlane et al. 2005;
33 Matthews et al. 2007). This phenomenon offers a somewhat simplified real-world setting to study
34 the behavior of convection associated with surface heterogeneities.

35 A similar phenomenon is also observed downwind of heated islands with significant topography:
36 for example, in The Lesser Antilles Islands (peaks near 1500 m) (e.g Garstang et al. 1975; Smith
37 et al. 2007; Kirshbaum and Fairman 2015); the Eastern Pacific Island of Guadalupe (1300 m)
38 (Dorman 1994); and Hawaii (over 4000 m) (e.g. Smolarkiewicz et al. 1988; Yang and Chen 2008;
39 Yang et al. 2008b,a). Such studies suggest that the topography plays a significant role in generating
40 flow perturbations. These perturbations are shown to be of greater magnitude but often with the
41 same sign as the thermal perturbations that result from solar heating (Crook and Tucker 2005;
42 Kirshbaum and Wang 2014). The topography also results in added downstream effects that can

43 interfere with or disrupt cloud trails. Drying due to downstream wave breaking was mentioned by
44 Kirshbaum and Fairman (2015), while vortex shedding could overwhelm any cloud trail signal.
45 These studies highlight the complicating role of topography, and motivates the focus on flat island
46 cases.

47 In addition to elevation, island size is important in determining the nature of convection that
48 develops in a heated flow. Williams et al. (2004) showed that the island signal in lightning flash
49 rates (a proxy for convective intensity) becomes indistinguishable from the background oceanic
50 regime for islands with an area less than 100 km^2 (small islands). Similar results were found for
51 the pattern of precipitation over tropical islands by Robinson et al. (2011) and Sobel et al. (2011).

52 One mechanism for the increase in convective intensity over larger islands is the convergence of
53 sea breeze fronts (e.g. Crook 2001). However, under no background flow and for a given heating
54 rate, two-dimensional simulations show that the strength of a sea breeze circulation decreases with
55 island/peninsula size (Savijarvi and Matthews 2004). Savijarvi and Matthews (2004) also found
56 that with some background flow, the windward cell of the weaker sea breezes for smaller islands
57 can be displaced and tilted downwind of the island - transforming the circulation into that of a
58 steady heat island like that in Estoque and Bhumralkar (1969).

59 Analysis of intensive field campaign observations on Nauru (as part of the Nauru Island Effect
60 Study - NIES (McFarlane et al. 2005)) revealed potential mechanisms for the initiation and main-
61 tenance of cloud trails there (Savijarvi and Matthews 2004; Matthews et al. 2007). These authors
62 propose that a thermal internal boundary layer forms and grows as oceanic air advects across the
63 heated island. This turbulent thermal layer then evolves into a warmer, cloud-topped plume down-
64 wind of the island. This idea of a warm plume is consistent with the observations at Barbados
65 discussed by Garstang et al. (1975). Matthews et al. (2007) also suggested that the warm plume

66 drives a thermal circulation that may be responsible for the maintenance of the cloud trails that
67 were found to extend on average 125 km downwind of Nauru (Nordeen et al. 2001) .

68 Cloud trail climatologies at Nauru and in the Lesser Antilles Islands were made using visible-
69 channel satellite imagery (Nordeen et al. 2001; Kirshbaum and Fairman 2015). Each hourly image
70 was manually classified by Nordeen et al. (2001) as either ‘Cloud Plume’ - a line of cloud is seen
71 extending downwind of and anchored to the island; ‘Non-plume’ - there is no evident band of
72 anchored cloud; or ‘Obscured’ - the island is obscured from view by larger scale cloud phenomena.
73 The current study will follow this definition, but referring to ‘Cloud Trail’ (CT), ‘Non-trail’ (NT),
74 and ‘Obscured’ (OB) scenes respectively.

75 Both Nordeen et al. (2001) and Kirshbaum and Fairman (2015) showed that strong surface
76 heating during the day was important for CT development. CT occurrence was seen to peak in
77 mid-afternoon both at Nauru and the Lesser Antilles Islands. At Nauru, this diurnal cycle in
78 CT occurrence combined with the low elevation of Nauru (only rising to 30 m above sea level)
79 reinforces the idea that cloud trails are primarily thermally driven by the difference in low-level
80 heating between the island and surrounding ocean (Nordeen et al. 2001).

81 In the following sections, a simple automated method for classifying visible-channel satellite
82 imagery at Bermuda as ‘Cloud Trail’, ‘Non-trail’, or ‘Obscured’ is outlined. The choice of an
83 automated classification scheme has the benefits of reproducibility, objectivity, and expedience
84 over manual classifications. Further, it has the potential to be quickly adapted for other locations
85 or similar problems.

86 This is applied to 16,400 images over five years to construct a climatology. We then use these
87 classifications in conjunction with radiosonde observations and European Re-Analysis Interim
88 (ERA-interim) data to describe the environments that coincide with each classification. Finally,

89 we discuss some cloud trail behaviour at Bermuda and why some environments appear more
90 favourable for CT formation.

91 **2. Methods**

92 *a. Data*

93 Imagery from the visible ($0.64\mu\text{m}$) channel of the Geostationary Operational Environmental
94 Satellite (GOES-13) is used to identify CT and thereby construct a climatology of their occur-
95 rence. GOES-13 is operated by the U.S. National Oceanographic and Atmospheric Administration
96 (NOAA) and National Aeronautics and Space Administration (NASA). Data with a nominal reso-
97 lution of 1 km and 30 mins used in this study is accessed through the Comprehensive Large Array-
98 Data Stewardship System (CLASS) archives at NOAA’s National Climate Data Center (NCDC)
99 (NOAA Office of Satellite and Product Operations and NOAA Center for Satellite Applications
100 and Research 1994).

101 Radiosonde observations taken at Bermuda, near 32.3°N , 64.8°W , are sourced from version
102 two of the Integrated Global Radiosonde Archive (IGRAv2). This dataset replaces the previous
103 version of IGRA (e.g. Durre et al. 2006, 2008). At Bermuda, radiosondes are regularly launched
104 once per day at 0900 LT (UTC - 0300). In this study, to compare radiosondes on different days, the
105 temperature, pressure, and relative humidity measurements are linearly interpolated to regularly
106 spaced pressure levels from 1000-hPa to 100-hPa with 5-hPa increments. After interpolation, the
107 potential temperature is calculated as follows:

$$\theta = T \left(\frac{p_0}{p} \right)^{\frac{R_d}{c_p}} \quad (1)$$

108 where θ is the potential temperature in Kelvin, T is the temperature in Kelvin, p_0 is a reference
109 pressure set to 1000-hPa, p is the pressure in hPa, R_d is the gas constant for dry air taken to be 287
110 $\text{J kg}^{-1} \text{K}^{-1}$, and c_p is the specific heat capacity of dry air at constant pressure, taken to be 1004 J
111 $\text{kg}^{-1} \text{K}^{-1}$.

112 Surface data at Bermuda are provided by the Bermuda Weather Service. Wind speed and direc-
113 tion measurements used in this study are 10 minute averages measured at 10 m above ground level
114 with observations every 10 minutes. These measurements are taken at Bermuda's L. F. Wade Inter-
115 national Airport, on runway 12 (at the northwest end of the airfield). Air temperature and relative
116 humidity at 1.5 m are also provided by the Bermuda Weather Service in hourly observations.

117 Finally, ERA-interim data (Dee et al. 2011) are used to investigate the large-scale environment.
118 Temperature, specific humidity, three dimensional wind components and mean sea level pressure
119 are used.

120 The period of interest for this study is May through October in the years 2012 through 2016.
121 May through October is referred to as the 'warm season' in this study. At Bermuda's latitude,
122 there is a stronger annual cycle in the large-scale environment than at Nauru or in the Caribbean
123 Sea. Further, the solar zenith angle is higher and therefore the diurnal surface heating is weaker
124 during the remaining months (November through April, or the 'cool season').

125 Reanalysis data shows that the North Atlantic Subtropical High (Bermuda-Azores High) is most
126 intense and extensive during the warm season - peaking in July. The cool season marks the period
127 where the Bermuda-Azores High is less influential or absent and so mid-latitude cyclones and
128 their fronts play a larger role in the local weather. It maintains largely settled weather across the
129 Western Atlantic. This is consistent with findings by Davis et al. (1997) on the variability of the
130 North Atlantic anticyclone. Given that large-scale disturbances can both obscure the island in

131 cloud and disrupt cloud trail formation with precipitation and sudden wind shifts, only the warm
132 season is considered for its more settled regime.

133 *b. Manual Classification Method*

134 Initially, a manual classification of the first warm season (May through October, 2012) is per-
135 formed to both aid in the design of an automated method for classification, and validate the auto-
136 mated classifications. Scenes are classified using the three categories (CT, NT, and OB) outlined
137 above. Here, a scene refers to a visible-channel satellite image cropped to a $4 \times 4^\circ$ domain cen-
138 tered on Bermuda. The surface wind direction is used to determine where the downwind side of
139 the island is in each scene.

140 Scenes are classified as CT if the area around the island is not covered in cloud and a band or
141 bands of cloud are seen downwind of and apparently anchored to Bermuda (e.g. Fig. 1a). If the
142 area around the island is not covered in cloud, but no band of cloud is seen anchored downwind
143 of the island, the scene is classified as NT (e.g. Fig. 1b). Finally, if the scene is mostly cloudy,
144 particularly in such a way that covers much of the island from view, it is classified as OB (e.g. Fig
145 1c).

146 While this exercise is somewhat subjective, the majority of scenes were straightforward to clas-
147 sify. The biggest challenge was in distinguishing between downwind cloud bands that are CT
148 against those that are associated with other phenomena such as low-level convergence not linked
149 to the island, cold pools, etc. It is suspected that these features may be misclassified by an inten-
150 tionally simplistic automated approach.

151 *c. Algorithm for Automated Classification*

152 From our manual classification and the previous work discussed above, we know that (i) CT
153 are either absent or hidden from view by other large-scale cloud in OB scenes, and (ii) CT are
154 characterized by more cloud downwind of the island than upwind. These two ideas are used to
155 design an algorithm to automate the classification of scenes into our three categories.

156 First, cloudy and cloud-free pixels must be identified. Each pixel is nominally 1x1 km. The
157 albedo from the visible-channel satellite data is used to identify cloudy pixels. For simplicity we
158 create a binary cloud mask based on an albedo threshold. Pixels are called ‘cloudy’ and given
159 a value of ‘1’ if the albedo is greater than the albedo threshold. Remaining pixels with albedo
160 less than this threshold are given a value of ‘0’. Figure 2 shows an example of a visible-channel
161 satellite image in (a) and the cloud mask that results from this method in (b).

162 Sensitivity tests (not shown) on the choice of albedo threshold for a mostly cloud free day with
163 a cloud trail in the afternoon hours (according to observations from the L. F. Wade International
164 Airport (TXKF) and the manual classification) indicate that if the albedo threshold is lower than
165 0.10, the land area of Bermuda and the shallow water surrounding Bermuda is falsely masked as
166 cloud (e.g. Fig. 1b). Conversely, if the threshold is greater than 0.20, pixels containing smaller
167 cloud elements, or pixels that are part of regions of thin cloud might be falsely masked as not
168 cloudy. The albedo threshold is taken to be 0.15, as a compromise between these two limits and
169 the same value used in Yang and Chen (2008) and Kirshbaum and Fairman (2015).

170 A known issue with this simple masking method is that cloud cover over land and coastal regions
171 remains somewhat ambiguous. Land provides a higher background albedo than the ocean. Land
172 pixels may therefore still erroneously be masked as cloudy. Pixels over land, and one pixel away
173 from the coastline are therefore excluded from calculations to account for this issue.

174 Furthermore, for high solar zenith angles, spurious regions of high or low albedo can appear
175 depending on the cloud cover. For instance, individual towering clouds might cast shadows on
176 other cloudy regions - these shadowed areas are then falsely masked as cloud-free. Similarly, at
177 sunrise and sunset (when the solar zenith angle is 90°) there can be a very bright line through the
178 scene. Scenes must then be rejected if the maximum solar zenith angle is too high. To accomplish
179 this, five sample scenes that were obviously impacted by the above mentioned effects were chosen.
180 All scenes with solar zenith angle less than some threshold are then discarded. This threshold is
181 determined by taking a first guess of 90° and decreasing the threshold by 5° increments until
182 the five sample scenes are discounted. We find that scenes with a solar zenith angle $< 75^\circ$ are
183 sufficiently illuminated to avoid these high solar zenith angle issues.

184 Once a scene is subjected to this solar zenith angle test and converted to a cloud mask, it is then
185 assessed for the presence of a CT. In the algorithm, a scene is first classified as OB, or non-OB (i.e.
186 including both the CT and NT classifications). Then, the non-OB scenes are further subdivided
187 into CT or NT categories.

188 A circular region of interest with radius 0.25° (about 25 km) centered on Bermuda is considered.
189 This circle contains the entire island and the edges of this circle are at least 0.10° (10 km) away
190 from any land points (Fig. 2c). To determine how cloudy the scene is and therefore whether or not
191 to classify it as OB, the cloud fraction in that circular area is calculated. Here, the cloud fraction
192 is defined as the spatial mean of the cloud mask over a given area. Scenes with a cloud fraction
193 in the circular region greater than a threshold, α , are classified as OB. If the cloud fraction is less
194 than α , then the scene is non-OB and tested further.

195 The non-OB scenes are further sorted into NT and CT classifications. As seen in loops of
196 visible-channel satellite imagery and reported in the literature above, CT initiate at the island and
197 extend downwind, forming a band of cloud anchored to the island. Nordeen et al. (2001) used

198 cloud level (the mean over the 950 - 850-hPa layer) wind directions from once daily radiosondes
199 to manually identify CT at Nauru. However, while it may be reasonable to assume that there is
200 no significant change in wind direction during the day at Nauru because it is well embedded in
201 the tropical Pacific trade wind region, Bermuda is near the axis of the Bermuda-Azores high and
202 small changes in the position of this ridge axis could mean a reversal in the wind direction.

203 McFarlane et al. (2005) showed that at Nauru, the surface wind direction compares well with
204 the heading of identified CT. We have found that the 0900 LT pressure-weighted cloud level (950 -
205 850-hPa mean) wind direction from radiosonde ascents at Bermuda compare well with the surface
206 winds measured at the same time at Bermuda (not shown). For the purposes of this study, it there-
207 fore appears reasonable to use the half-hourly surface wind direction from TXKF to determine
208 where upwind and downwind directions are relative to Bermuda.

209 The same circular 0.25° area used to test for OB scenes is now divided into 10° sectors, thirty-
210 six in all (Fig. 2d). The first sector is centered on North. We expect the CT signal to be strongest
211 nearer to the island because of the anchoring described above. From sensitivity tests, if the radius
212 of the circle is too large, the sectors start to become broader than the CT and so the signal in sector
213 cloud fraction becomes damped (not shown). At distances of 0.25° , a sector is roughly 4.4 km
214 wide.

215 As a result of Bermuda's geometry, some sectors contain more non-land pixels than others.
216 Sensitivity to the number of pixels used for cloud fraction computations was tested by using sectors
217 of different lengths and shapes to make them contain more similar number of pixels. The results
218 are found to be generally insensitive to having a more equal pixel count in each sector.

219 Half-hourly 10 m wind direction observations are used to locate the upwind and downwind
220 sectors. To account for fluctuations in the wind direction, differences between wind direction and
221 CT heading, and CT occurring across two sectors, nine sectors centered on the wind direction are

222 considered. Next, the cloud fraction is calculated for each of nine sectors and the maximum cloud
223 fraction of those sectors is taken to represent the upwind or downwind cloud fraction (marked as
224 ‘U’ and ‘D’ respectively in Fig. 2d).

225 The difference between the downwind and upwind sector maximum cloud fractions (δF) is
226 taken. Since CT are characterized by organized cloudiness downwind of islands, it follows that
227 there should be a higher downwind cloud fraction than upwind cloud fraction. δF must be > 0 to
228 satisfy this condition. However, we also wish to exclude small differences which may be due to
229 random sampling of an undisturbed cloud field. Hence, δF must be compared to a threshold (β)
230 based on cloud fraction statistics for the chosen definition of upwind and downwind sectors.

231 Values chosen in our algorithm for α and β are discussed in Section 2d.

232 *d. Algorithm Parameters*

233 Assuming the manual classification is the ‘truth’, it is used to estimate optimal values for α
234 (the cloud fraction threshold above which a scene is classified as OB) and β (the δF difference
235 threshold above which a scene is classified as CT). For α , the cloud fraction is computed for
236 each manually classified scene as described in the above section for discriminating between OB
237 and non-OB scenes. We then consider the cumulative distribution of this cloud fraction for the
238 OB scenes, and the inverse cumulative distribution for the non-OB scenes. The cloud fraction at
239 which these two distributions intersect is taken to be the optimal value for α . With our manual
240 classifications, we find α to be 0.33.

241 To determine the value of β we again refer to the manual classification. We apply our above
242 method for discriminating between NT and CT scenes to all non-OB scenes. We then consider the
243 cumulative distribution of δF for CT scenes, and the inverse cumulative distribution of δF for the

244 NT scenes. Again, the δF where these two distributions intersect, 0.08, is taken as the value for
245 β . For more information on this process, please refer to the appendix.

246 Sensitivity tests (not shown) suggest that the overall patterns of the annual and diurnal cycle are
247 not very sensitive to the choice of α and β . We remark that $\alpha = 0.33$ is of a similar magnitude
248 to the mean cloud fraction for all days across the period of interest (0.342). A more conservative
249 (higher) value for β yields a more confident CT classification at the expense of rejecting the cases
250 with more complex background cloud.

251 3. Results and Discussion

252 a. Algorithm Validation

253 In effect, by our definitions for α and β , we are maximizing the Peirce Skill Score (PSS). This
254 score ranges from -1 to 1 where 1 indicates a perfect classification, and 0 indicates no skill in
255 classifying scenes. Peirce (1884) defines it as follows:

$$PSS = \left(\frac{H}{H+M} \right) - \left(\frac{F}{F+C} \right) \quad (2)$$

256 where PSS is the Peirce Skill Score, H is the number of hits, M is the number of misses, F is
257 the number of false alarms, and C is the number of correct negatives. This score describes the
258 match when there are two possible outcomes, ‘a’ (event occurs) or ‘b’ (event does not occur).
259 The corresponding algorithm-manual pairs are ‘aa’ for hit, ‘ba’ for miss, ‘ab’ for false alarm,
260 and ‘bb’ for correct negative. For α , ‘a’ refers to an OB classification, and ‘b’ refers to non-
261 OB classification. At this stage the algorithm has only made OB and non-OB classifications, the
262 manual NT and CT classifications both count toward non-OB. For β , we ask what classification

263 would the algorithm assign to the scenes that are manually classified as non-OB. In this case, ‘a’
264 refers to a CT classification and ‘b’ refers to an NT classification.

265 The PSS can then be applied to the individual categories. Following the ‘a’ and ‘b’ framework
266 above for CT classifications, ‘a’ refers to a CT classification, and ‘b’ refers to either NT or OB
267 classification. In these cases a correct negative (‘bb’) can be any combination of the two non-event
268 scenes (e.g. NT-NT, NT-OB, OB-NT, or OB-OB).

269 For CT, the PSS is 0.51. It is 0.46 for NT classifications, and 0.82 for OB classifications. Over-
270 all, the algorithm has a score of 0.60. The reader must be reminded that the manual classification
271 process is subjective, so while we take it to be the truth in determining our algorithm parameters
272 in the previous section, and for validation purposes here, it should be understood that it is sub-
273 ject to human error and interpretation differences. Despite this, the manual classification is still
274 instructive for building intuition for what to expect from the algorithm classifications.

275 However, the PSS does not describe every aspect of algorithm performance. Contingency tables
276 have been produced to further aid in quantifying the algorithm’s performance. Shown in Table 1(a)
277 are the contingency table results for the CT classification. Included in the table are the number
278 of ‘hits’, ‘misses’, ‘false alarms’, and ‘correct negatives’ as described above. The same four
279 categories are shown for NT and OB classifications in Table 1b and c.

280 In all cases, there are more hits than either false alarms or misses. Commonly used metrics
281 derived from such contingency tables are the ‘Hit Rate’ and ‘False Alarm Rate’ given by:

$$HR = 100 \times \frac{H}{H + M} \quad (3a)$$

$$FAR = 100 \times \frac{F}{F + C} \quad (3b)$$

283 respectively, and H , M , F , and C are as explained above.

284 Compared to the manual classification of the 2012 warm season, we find that the Hit Rate (Eq.
285 3a) is much higher than the False Alarm Rate (Eq. 3b) for each classification. These are 67.0% vs
286 15.6% for CT, 59.5% vs 13.1% for NT, and 91.0% vs 9.1% for OB.

287 Finally, we consider the bias score for each of our algorithm classifications. The bias score is
288 defined as:

$$BIAS = \frac{H + F}{H + M} \quad (4)$$

289 this quantity can range from 0 to ∞ , where a score of 1 represents a perfect classification, values
290 less than 1 indicates the algorithm is biased against making a classification, and values greater
291 than 1 indicate that the algorithm is biased toward making a given classification. Using the data
292 provided in Table 1 we find the bias to be 1.05 for cloud trail classifications, 0.82 for non-trail
293 classifications, 1.07 for obscured classifications, and 0.97 overall.

294 Taken all together, these scores suggest that the algorithm is skillful in making classifications as
295 compared to our subjective manual classification. Furthermore, it is not strongly biased toward or
296 against making any particular classification. We therefore apply the algorithm to subsequent data
297 to extend our analysis period to include May through October of 2012 through 2016.

298 We have repeated much of the following analysis for the manual classifications and the algorithm
299 classifications for 2012 only to provide further confidence in our conclusions. See Appendix A for
300 details.

301 *b. Cloud Trail Climatology*

302 We have shown that for May through October of 2012, the algorithm compares well with the
303 manual classification. We can therefore confidently apply the algorithm to automate the clas-
304 sification of longer periods of satellite imagery and explore a longer climatology than previously

305 investigated in literature. From this climatology, it will then be possible to study the environmental
306 differences between days predominately in each classification.

307 The algorithm is used to classify visible-channel satellite imagery for May through October
308 of 2012-2016. These classifications are then sorted by time of day and by month. This aids in
309 exploring the annual and diurnal cycles (Fig. 3). As part of the annual cycle, the percentage of
310 OB scenes decreases to a local minimum in July - the same month in which the percentage of CT
311 scenes increases to a maximum. For all times of day, the percentage of CT scenes nearly doubles
312 from 24% in May to 44% in July, while OB scenes decrease from 45% to 22%. Meanwhile, the
313 percentage of NT scenes is steadier at between 29 and 35% (on the higher end in July and August).

314 Similarly, a diurnal cycle is evident when considering rows in Figure 3. The morning is char-
315 acterized by a higher percentage of NT than CT scenes, and this reverses in the afternoon and
316 evening. As a seasonal average, the percentage of NT scenes declines from near 38% in the morn-
317 ing to near 28% in the afternoon. Concurrently, CT scenes increase from near 24% in the morning,
318 to near 36% in the afternoon - offsetting the majority of the change in NT percentage. The percent-
319 age of OB scenes varies less through the day; between 40% in the early morning and late evening,
320 and 34% around 1100 LT. This local minimum in OB scenes occurs around the same time as the
321 decrease in the percentage of NT scenes and the increase in the percentage of CT scenes.

322 For days with CT scenes, the median first such scene is identified at 0945 LT and median final
323 scene at 1745 LT. The first CT scenes are identified earliest in the day in June and the last scene
324 is latest in the day in August. The first CT scene occurs later and the last occurs earlier in May
325 and October. In this part of the analysis, only days with two or more consecutive CT scenes
326 are considered. Cases in which CT occurred outside of the range of times with sufficiently low
327 solar zenith angles are expected, and such scenes cannot be classified by the algorithm. This
328 would result in a real start time that is earlier than detected in the algorithm. However, there is

329 a counteracting tendency for the algorithm to make more early morning CT classifications than
330 what was manually classified (see Appendix B).

331 More than one period of consecutive CT scenes may be classified on a given day. This is seen in
332 both the manual classification of just May through October 2012, and the algorithm classification
333 for the same period. Comparing the manual classification to just the algorithm classification for
334 months in 2012, we see that 59% of days have just one period in the manual classification, and
335 up to three periods occur per day. However, in the algorithm classification for 2012, only 23% of
336 days have one continuous period of CT scenes (an additional 31% have two periods, and there were
337 four days on which six periods were identified by the algorithm). Physically, we can explain more
338 than one CT period as occurring when the environment is marginal for CT formation. Changes
339 in the wind direction might then alter the strength of the island thermally driven lift by no longer
340 paralleling the long axis of the island, or a decrease in low-level humidity might make cloud
341 formation unobtainable by lift of the same strength. Either change, or some combination of both
342 might cause the CT to temporarily dissipate before conditions return to allow the CT to redevelop.
343 However, these may also be explained as artifacts of the algorithm. If the large scale cloudiness
344 is near the threshold for distinguishing between OB and non-OB scenes (α) a small increase in
345 cloud cover might fool the algorithm into classifying real CT as OB scenes. Similarly, if there is
346 an increase in the ambient upwind cloud (e.g. due to an advancing front), the algorithm might be
347 fooled into making an NT classification as the downwind-upwind cloud fraction difference is no
348 longer greater than our threshold β .

349 This climatology reveals that during the period of peak CT occurrence in July, there is also a
350 peak in their duration. The mean duration increases from 01:58 hours in May to a peak of 03:17
351 hours in July before decreasing to 01:34 hours in October when our period of study ends (not
352 shown). CT that persist for just one scene are taken to have a duration of half an hour here, and

353 those that persist for two or more consecutive scenes are considered to have one hour duration.
354 Each additional consecutive scene is counted as a further half hour of duration. On days in which
355 more than one period occurs, the longest duration is taken as the value for that day. Comparing
356 the manual and algorithm classifications for just 2012, we find that the manually classified CT last
357 roughly twice as long because of the increased intermittency in the algorithm classification.

358 For scenes that were manually classified as having CT (May through October of 2012), we
359 manually estimated the length of the CT in that scene by finding its end-point in the visible-
360 channel satellite imagery and calculating the distance between that point and the center-point of
361 the island (assuming that this is where the CT originated). This follows the methodology outlined
362 by Nordeen et al. (2001).

363 We then consider the half-hourly mean CT length estimated for the manually classified imagery.
364 First, there is a local maximum in CT length (78 km) at 0815 LT, and this then decreases to a
365 local minimum (41 km) by 0915 LT (not shown). This early morning CT is consistent with the
366 discussion above on the one or more short-lived CT.

367 Our second observation is that the CT length tends to increase through the remainder of the day.
368 CT on average grow from the local minimum length at 0915 LT, until 1515 LT when they are about
369 90 km in length. The mean length remains near 90-95 km through sunset. Using the 10 m wind
370 speed and the estimated length, we predict the length half an hour later (the time of the next scene)
371 assuming advection is the only factor controlling changes in length. We find these predictions to be
372 in generally good agreement with the manually estimated lengths with a correlation coefficient of
373 0.75 ($R^2 = 0.55$) on 109 length predictions (not shown). Additional factors, such as precipitation
374 or evaporation of cloud liquid due to entrainment of drier surrounding air might act against the
375 increase due to advection.

376 *c. Environmental Characteristics*

377 One goal of this study is to describe and highlight differences between CT, NT, and OB domi-
378 nated environments. To do this, we composite radiosonde data and ERA-interim reanalysis data
379 by classification. As there is an annual cycle at Bermuda in both the classifications and the envi-
380 ronmental conditions, we only consider the peak of the CT season June through August (JJA) to
381 avoid reproducing the signal of the annual cycle in our composites.

382 Most days are not completely in one single classification. However, the radiosonde data is
383 available once per day at 0900 LT. This presents the challenge of assigning a single classification
384 to a day made of several classifications.

385 To do this, the fraction of each day in each classification is calculated for all days in the period
386 May through October 2012-2016. Next, we evaluate the 75th percentile of these fractions for
387 each classification. If the fraction of a given day in a given classification is greater than its 75th
388 percentile, that day is assigned to that classification and included in that classification's composite.

389 For example, the 75th percentile for the fraction of day classified as CT is found to be 59%. If
390 at least 59% of the day's classified scenes are CT, then the data for that day is included in the CT
391 composite. The 75th percentiles for NT and OB are 50% and 59% respectively. The same day
392 cannot be assigned to more than one classification by this method since any two of the three 75th
393 percentile thresholds will always sum to greater than 100%.

394 The interpolated IGRAv2 data are used to consider the anomalies from the 0900 LT JJA 2012-
395 2016 mean potential temperature and relative humidity profiles. Radiosonde ascents that are in-
396 complete below 700-hPa are not included in the composites. The resulting radiosonde composites
397 for each classification are shown in Figure 4. The mean profile of potential temperature and com-
398 posite anomalies (top) and the mean profile of relative humidity and composite anomalies (bottom)

399 are shown for the layer between the surface and 700-hPa. With this method, about 25% of the JJA
400 days are assigned to each classification's composite - leaving about 25% of the days to be dis-
401 carded.

402 For each composite, we assume that the mean anomaly is the center of a normal distribution of
403 anomaly profiles. We then estimate this uncertainty as the standard error: $\frac{\sigma}{\sqrt{N}}$, where N is the
404 number of observations in a given composite.

405 CT-dominated days (dark grey dash-dot profiles in Fig. 4) have the highest surface potential
406 temperature of the three classifications. Potential temperature anomalies (Fig. 4b) decrease in
407 magnitude to near-zero above 950-hPa, indicating a less stable than normal boundary layer. The
408 anomalies then increase to become positive again by 700-hPa, indicating that the layer aloft is
409 slightly more stable than climatology for this period. These conditions have long been regarded as
410 favorable for shallow convection (e.g. Malkus 1952).

411 The composite profile of potential temperature anomalies for NT-dominated days (medium grey
412 dashed profiles in Fig. 4) has a similar shape to that for the CT-dominated days indicating a similar
413 pattern of stability anomalies. However, the NT anomalies are smaller than the CT anomalies
414 throughout the entire lower troposphere shown, and feature potential temperatures below normal
415 between 1000 and 850-hPa (Fig. 4b).

416 A very different potential temperature regime occurs for the OB-dominated days (the light grey,
417 dotted profiles in Fig. 4). The lowest 100-hPa is more stable than normal, while the profile
418 is less stable than normal aloft. This pattern is consistent with the idea that the OB days are
419 associated with large-scale cloudiness. Lower than normal near-surface potential temperatures are
420 an expected consequence of cloud-shading and possible evaporative cooling from precipitation.

421 Similarly, a clear separation between the classifications is evident in the relative humidity
422 anomaly composites (Fig. 4d). The OB-dominated days have the highest surface relative hu-

423 midity, but the OB- and CT-dominated days have similar, near normal relative humidity between
 424 1000 and 950-hPa. Above 950-hPa, the CT profile remains near normal, becoming slightly drier
 425 than normal while the OB profile becomes much more humid than normal. The NT profile again
 426 has a similar shape to the CT profile, but is drier than normal throughout this layer.

427 Overall, CT-dominated days are warmer than normal below 700-hPa with near normal relative
 428 humidity, while NT-dominated days are cooler and drier than normal below 700-hPa. The higher
 429 low-level relative humidity on CT-dominated days implies a lower lifting condensation level (LCL)
 430 than for NT-dominated days. However, the warmer low-levels on CT-dominated days implies a
 431 higher LCL than for the NT case. We therefore calculate the height of the LCL to further examine
 432 this relationship. We use Bolton (1980)'s formula for the temperature of the LCL:

$$T_{LCL} = \frac{1}{\frac{1}{T_D - 56} + \frac{\ln(\frac{T_K}{T_D})}{800}} + 56, \quad (5)$$

433 where T_D is the surface dew point temperature and T_K is the surface temperature (both temperatures
 434 are in Kelvin). This can then be used to find the pressure of the LCL as follows:

$$p_{LCL} = p_s \left(\frac{T_{LCL}}{T_K} \right)^{\frac{c_p}{R_d}}, \quad (6)$$

435 where p_{LCL} is the pressure of the LCL, p_s is the surface pressure, and c_p and R_d are as defined in
 436 the previous section.

437 The composite LCL pressure for each classification and the climatology are marked on Figure
 438 4c. We find that the mean composite LCL pressure for CT-dominated days is 955-hPa. This
 439 corresponds to a lower height than both climatology (949-hPa) and NT-dominated days (941-hPa).
 440 Lower LCL heights suggest cloud formation is more readily achievable and these results provide
 441 a plausible explanation for why cloud trail formation is sensitive to low-level humidity.

442 In addition to thermodynamic profiles, wind speed is expected to influence the types of circu-
443 lation that result from island surface heating by contributing to the organization of any cloud that
444 forms. In dry idealized two- and three- dimensional simulations, Savijarvi and Matthews (2004),
445 Kirshbaum (2013), and Kirshbaum and Wang (2014) show that for light or calm background wind
446 regimes, thermally induced circulations form over a surface heat source (reminiscent of pure sea
447 breezes). For stronger background winds, thermally induced circulations form a band of ascent
448 downwind of the heat source (reminiscent of CT).

449 The mean wind speed for each classified scene is shown in Table 2a. NT scenes are associated
450 with lighter winds and OB scenes are associated with stronger winds than both CT scenes and all
451 scenes. While lighter winds on NT days are possibly related to the turbulent generation of cloud
452 over the island, or instances of cloud related to sea breeze convergence rather than CT formation,
453 stronger winds associated with OB scenes are likely related to large-scale disturbances.

454 Furthermore, Bermuda is oriented such that its long axis runs approximately southwest-
455 northeast. From a Lagrangian perspective, surface heating is maximized for low-level flow par-
456 allel to the long axis of an island as an air parcel remains over the island heat source longer. For
457 southwesterly and westerly winds, more non-OB scenes are classified as CT (36-39%) than NT
458 (23-28%) (Table 2b). For all other wind directions, including northeasterly flow which is also
459 parallel to the long axis of the island, a greater proportion of non-OB scenes are classified as NT
460 than CT.

461 Examining the larger scale fields aids in explaining this result. We have already established
462 that low-level moisture is a dominant control on cloud trail formation. ERA-interim composites
463 of the 0900 LT 1000-hPa specific humidity for JJA in Figures 5a, c, and e show that Bermuda
464 lies in a moisture gradient pointing from northeast to southwest for all classifications. Given
465 this background moisture pattern, northeasterly flow results in advection of drier low-level air on

466 average. Such a flow therefore tends to make the environment less favorable for CT on average
467 despite maximizing low-level heating by maintaining a direction parallel to the long axis of the
468 island.

469 Indeed, these composites are consistent with the radiosonde and surface composites in Fig. 4.
470 They indicate that CT and OB days have similarly high low-level specific humidity while NT-
471 days have lower specific humidity. Additionally, the western part of the Bermuda-Azores High
472 (indicated by the 1020-hPa contour) is shown to extend its control on this region for much of JJA,
473 and it retreats to the east on OB days. This pressure pattern implies a wind field dominated by
474 westerlies and southwesterlies at Bermuda with lightest winds on NT days.

475 Finally, the composites show 500-hPa vertical motion between 0.00 and 0.01 Pa s⁻¹ near
476 Bermuda on CT-dominated days (Fig. 5b), about 0.01 Pa s⁻¹ on NT-dominated days (Fig. 5d), and
477 about -0.11 Pa s⁻¹ on OB-dominated days (Fig. 5f). Weak 500-hPa vertical motions or subsidence
478 seen on CT- and NT-dominated days is consistent with the expected lack of large-scale cloudiness
479 and favors shallow convection. This subsidence may also help to explain the drier and more stable
480 than normal layer seen in the sounding composites for NT-dominated days.

481 **4. Conclusions**

482 This study presents an algorithm to automate the classification of conventional visible-channel
483 satellite imagery into Cloud Trail, Non-Trail, and Obscured categories at Bermuda. The algorithm
484 first filters out morning and evening images with high solar zenith angles. It then masks cloudy
485 pixels using a simple binary threshold method. Next, the algorithm determines whether a scene is
486 obscured by cloud by considering the cloud fraction within 0.25° of the island. For non-obscured
487 scenes, the observed 10 m wind direction at the time of the satellite image is then used to define
488 an upwind and downwind region with respect to the island. A scene is then determined to include

489 a cloud trail by considering the difference between downwind and upwind cloud fractions. The
490 resulting classification is found to be consistent with a manual classification of a subset of the data
491 from May through October 2012.

492 The resulting classifications for the May through October 2012-2016 period from this algorithm
493 show both an annual and diurnal cycle in cloud trail occurrence at Bermuda. CT occurrence is
494 found to peak in July and between 1300 and 1500 LT. Between May and July CT occurrence
495 increases while OB occurrence decreases. This corresponds to the period in which the Bermuda-
496 Azores High enforces increasingly settled weather across Bermuda into July. From July to Octo-
497 ber, the fraction of OB scenes increases and the fraction of CT scenes decreases.

498 Similarly, CT occurrence increases during the day while the fraction of NT classifications de-
499 creases. This is likely in response to the stronger solar heating present in the afternoon, and
500 therefore stronger thermal forcing for the development of CT on otherwise non-OB days.

501 These classifications are then used to explore the characteristics of the environments present in
502 the morning of days in JJA on days predominately in each classification. Radiosonde compos-
503 ites show that CT-dominated days are characterized by conditions that are near the mean potential
504 temperature and relative humidity for the JJA period in 2012-2016. Surface observations and ERA-
505 interim data show that lower than normal low-level potential temperature and relative humidity,
506 lighter than normal 10 m winds, and 500-hPa subsidence are associated with NT-dominated days.
507 Lower than normal low-level potential temperature, higher than normal low-level relative humid-
508 ity, stronger than normal 10 m winds, and 500-hPa ascent are associated with OB-dominated days.

509 Differences in low-level humidity appear to be the most important factor in determining whether
510 or not a non-OB day will have a CT. Days with higher low-level humidity result in lower LCL and
511 therefore the level to which turbulent mixing must reach in order for condensation and cloud
512 formation is lower. Also of importance is the role of the low-level wind speed and direction which

513 controls the low-level heating following air across the island. Wind speed controls whether or not
514 the buoyant production of turbulence and the induced circulation is confined to the island in light
515 wind regimes, or whether thermally generated circulations are formed downwind of the island
516 in regimes with some background wind. Particularly for non-circular islands, wind speed and
517 direction control the residence time of air as it crosses the heated island and therefore the strength
518 of the thermally induced circulation.

519 Some additional insight into the behavior of cloud trails through the day is gained. We find
520 that more than one cloud trail can form per day, each lasting a few hours. Other times, a single
521 continuous cloud trail is observed. In an environment that is only marginally conducive for cloud
522 trail formation, this transient behavior might be explained by subtle changes in wind direction,
523 low-level humidity, or large-scale vertical motion through the day that periodically cut off activity
524 before allowing it to resume later in the day.

525 Composites based on days predominantly in each classification, and theory from past literature,
526 suggest that non-observed days are likely to have cloud trails given the following:

- 527 1. Sufficient low-level humidity and therefore relatively low LCL to support cloud formation
- 528 2. Maximised low-level heating from a Lagrangian perspective. This is achieved via long-axis
529 parallel low-level flow and low solar zenith angles.
- 530 3. Sufficiently strong low-level flow such that a pure sea breeze circulation isn't favoured over
531 a steady heat island circulation.

532 This study takes a step closer to fully characterizing the environments that are conducive for CT
533 formation, however, it presents further questions about their behavior. A future study might be able
534 to use multispectral satellite imagery to extend this analysis through the nighttime hours and this
535 could further our understanding of what happens to cloud trails after sunset. For instance, imagery

536 from the newly operational GOES-16 satellite includes a $3.9 \mu\text{m}$ channel at 2 km resolution that
537 might be appropriate for this purpose (Schmitt et al. 2017).

538 As operational numerical weather prediction systems are approaching the ability to resolve phe-
539 nomena on these scales, it is increasingly important to present a complete characterization of their
540 behavior. For instance, thermally driven circulations may still be present downwind of islands in
541 NT cases and incorrectly simulating the strength of this circulation might result in cloud forma-
542 tion where it should not exist. Therefore, future investigation is required to fully understand the
543 initiation, persistence/transience, and any potential transition from a shallow to deep convective
544 state. However, conventional observations like those presented are likely insufficient to describe
545 these characteristics, and high-resolution idealized simulations are therefore planned.

546 *Acknowledgments.* Surface station data for Bermuda were provided on behalf of the Government
547 of Bermuda Department of Airport Operations by the Bermuda Weather Service operated by CI²
548 Aviation, formerly BAS-Serco Ltd. Raw satellite data were downloaded from NOAA’s Compre-
549 hensive Large Array-Data Stewardship System (CLASS) and radiosonde data were obtained from
550 NCDC’s Integrated Global Radiosonde Archive version 2 (IGRAv2).

551 APPENDIX

552 *a. Choice of Algorithm Parameters*

553 The choice of α and β as described in section 2d is expanded upon here. Figure A1 shows the
554 cumulative distribution functions for the cloud fraction for scenes that were manually classified
555 as OB, and the inverse cumulative distribution function for the cloud fraction for scenes that were
556 manually classified as either NT or CT (i.e. non-OB). Similarly, Figure A2 shows the cumulative
557 distribution function for the difference between the sector with maximum cloud fraction in the

558 downwind quadrant and the sector with the maximum cloud fraction in the upwind quadrant for
559 scenes that were manually classified as CT, and the inverse cumulative distribution function for
560 scenes that were manually classified as NT.

561 In Figures A1 and A2, the point of intersection is taken to be the optimal value for distinguishing
562 between the two classifications - either OB or non-OB in the case of α , and either CT or NT in the
563 case of β . This maximizes the Peirce Skill Score and yields $\alpha = 0.33$ and $\beta = 0.08$.

564 *b. Algorithm vs Manual Classification for 2012 Warm Season*

565 In addition to the verification metrics presented in the text, and the contingency table in Table 1,
566 we also reproduce part of the analysis on the manually classified data from May through October
567 2012, and compare that to the analysis performed on the algorithm classifications for the same
568 period.

569 Figure A3 shows the variation of the percentage of classifications with time of day and month
570 of year. It is found that there is generally good agreement between the manual and algorithm
571 classifications, however, the biggest differences are between the CT and NT classifications in
572 Figure A3(a) and A3(b). In the algorithm, there are too many morning CT classifications and too
573 few morning NT classifications when compared to the manual classification. This is particularly
574 the case in the July through October timeframe. However, the algorithm reproduces both the
575 annual and diurnal cycles reasonably well, although the amplitude of the diurnal cycle is somewhat
576 lower in algorithm classifications compared to the manual classification because there are more
577 morning algorithm CT.

578 Similarly, the frequency of each classification by month also shows a high level of agreement
579 (Fig. A4). 51 more scenes were classified as CT by the algorithm than manually, 231 fewer scenes
580 were classified as NT by the algorithm, and 82 more scenes were classified as OB. As a percentage

581 of the corresponding manual classifications, this amounts to 5% more CT scenes in the algorithm,
582 18% fewer NT scenes in the algorithm, and 7% more OB scenes in the algorithm. Qualitative
583 characteristics (e.g. the timing of peak occurrence) of the annual cycle are largely preserved by
584 the algorithm.

585 Finally, Figure A5 shows the composite profiles on CT, NT, and OB days in JJA 2012. We
586 show that, again, the algorithm classification is able to adequately reproduce the results from
587 the manual classification. The composite sounding anomalies from the analysis performed using
588 the algorithm classifications is within the uncertainty ranges of the analysis performed using the
589 manual classifications for both the relative humidity and potential temperature anomalies. The two
590 classification methods are consistent in terms of the relationship between classifications and the
591 LCL - obscured days have the lowest LCL, followed by CT, and then NT days with the highest
592 LCL.

593 **References**

- 594 Bhumralkar, C. M., 1973: An Observational and Theoretical Study of Atmospheric Flow over a
595 Heated Island: Part I. *Mon. Wea. Rev.*, **101**, 719–730.
- 596 Bolton, D., 1980: The Computation of Equivalent Potential Temperature. *Mon. Wea. Rev.*, **108**,
597 1046 – 1053.
- 598 CIA, 2017: The CIA World Factbook: Bermuda. URL [https://www.cia.gov/library/publications/
599 the-world-factbook/geos/bd.html](https://www.cia.gov/library/publications/the-world-factbook/geos/bd.html).
- 600 Crook, N. A., 2001: Understanding Hector: The Dynamics of Island Thunderstorms. *Mon. Wea.*
601 *Rev.*, **129**, 1550–1563.
- 602 Crook, N. A., and D. F. Tucker, 2005: Flow over heated terrain. Part I: Linear theory and idealized
603 numerical simulations. *Mon. Wea. Rev.*, **133**, 2552–2564.

604 Davis, R. E., B. P. Hayden, D. A. Gay, W. L. Phillips, and G. V. Jones, 1997: The North Atlantic
605 Subtropical Anticyclone. *J. Climate*, **10**, 728–744.

606 Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: configuration and performance of
607 the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, **137**, 553–597.

608 Dorman, C. E., 1994: Guadalupe Island Cloud Trail. *Mon. Wea. Rev.*, **122**, 235–242.

609 Durre, I., R. S. Vose, and D. B. Wuertz, 2006: Overview of the Integrated Global Radiosonde
610 Archive. *J. Climate*, **19**, 53–68.

611 Durre, I., R. S. Vose, and D. B. Wuertz, 2008: Robust automated quality assurance of radiosonde
612 temperatures. *J. Appl. Meteor. Climatol.*, **47**, 2081–2095.

613 Estoque, M. A., and C. M. Bhumralkar, 1969: Flow over a localized heat source. *Mon. Wea. Rev.*,
614 **97**, 850–859.

615 Garstang, M., P. D. Tyson, and G. D. Emmitt, 1975: The Structure of Heat Islands. *Rev. Geophys.*
616 *Space*, **13**, 139–165.

617 Kirshbaum, D. J., 2013: On Thermally Forced Circulations over Heated Terrain. *J. Atmos. Sci.*,
618 **70**, 1690–1709.

619 Kirshbaum, D. J., and J. G. Fairman, 2015: Cloud Trails Past the Lesser Antilles. *Mon. Wea. Rev.*,
620 **143**, 995–1017.

621 Kirshbaum, D. J., and C.-C. Wang, 2014: Boundary Layer Updrafts Driven by Airflow over Heated
622 Terrain. *J. Atmos. Sci.*, **71**, 1425–1442.

623 Malkus, J. S., 1952: Recent Advances in the Study of Convective Clouds and their Interaction
624 with the Environment. *Tellus*, **4:2**, 71–87.

625 Malkus, J. S., 1963: Tropical Rain Induced by a Small Natural Heat Source. *J. Appl. Meteor.*, **2**,
626 547–556.

627 Malkus, J. S., and A. F. Bunker, 1952: Observational Studies of the air flow over Nantucket Island
628 During the Summer of 1950. *Pap. Phys. Oceanogr. Meteor.*, **12**, 1–50.

629 Malkus, J. S., and M. E. Stern, 1953: The Flow of a Stable Atmosphere Over a Heated Island, Part
630 I. *J. Meteor.*, **10**, 30–41.

631 Matthews, S., J. M. Hacker, J. Cole, J. Hare, C. N. Long, and R. M. Reynolds, 2007: Modification
632 of the Atmospheric Boundary Layer by a Small Island: Observations from Nauru. *Mon. Wea.*
633 *Rev.*, **135**, 891–905.

634 McFarlane, S. A., C. N. Long, and D. M. Flynn, 2005: Impact of Island-Induced Clouds on
635 Surface Measurements: Analysis of the ARM Nauru Island Effect Study Data. *J. Appl. Meteor.*,
636 **44**, 1045–1065.

637 NOAA Office of Satellite and Product Operations and NOAA Center for Satellite Applications and
638 Research, 1994: NOAA GOES 8-15 Series Imager Level 1b Data. Channel 1. NOAA National
639 Centers for Environmental Information.

640 Nordeen, M. K., P. Minnis, D. R. Doelling, D. Pethick, and L. Nguyen, 2001: Satellite Observa-
641 tions of Cloud Plumes Generated by Nauru. *Geophys. Res. Lett.*, **28**, 631–634.

642 Peirce, C. S., 1884: The numerical measure of the success of predictions. *Science*, **4**, 453–454.

643 Robinson, F. J., S. C. Sherwood, D. Gerstle, C. Liu, and D. J. Kirshbaum, 2011: Exploring the
644 Land-Ocean Contrast in Convective Vigour Using Islands. *J. Atmos. Sci.*, **68**, 602–618.

645 Savijarvi, H., and S. Matthews, 2004: Flow over Small Heat Islands: A Numerical Sensitivity
646 Study. *J. Atmos. Sci.*, **61**, 859–868.

647 Schmitt, T. J., P. Griffith, M. M. Gunshor, J. M. Daniels, S. J. Goodman, and W. J. Lebar, 2017:
648 A Closer Look at the ABI on the GOES-R Series. *Bull. Amer. Meteor. Soc.*, **98**, 681–698.

649 Smith, R. B., A. C. Gleason, P. A. Gluhosky, and V. Grubisic, 2007: The Wake of St. Vincent. *J.*
650 *Atmos. Sci.*, **54**, 606–623.

- 651 Smolarkiewicz, P. K., R. M. Rasmussen, and T. L. Clark, 1988: On the dynamics of Hawaiian
652 Cloud bands: Island forcing. *J. Atmos. Sci.*, **45**, 1872–1905.
- 653 Sobel, A. H., C. D. Burleyson, and S. E. Yuter, 2011: Rain on Small Tropical Islands. *J. Geophys.*
654 *Res.*, **116**, D08 102.
- 655 Williams, E., T. Chan, and D. Boccippio, 2004: Islands as Miniature Continents, Another Look at
656 the Land-Ocean Lightning Contrast. *J. Geophys. Res.*, **109**, D16 206.
- 657 Yang, Y., and Y.-L. Chen, 2008: Effects of Terrain Heights and Sizes on Island-Scale Circulations
658 and Rainfall for the Island of Hawaii during HaRP. *Mon. Wea. Rev.*, **136**, 120–146.
- 659 Yang, Y., S.-P. Xie, and J. Hafner, 2008a: The Thermal Wake of Kauai Island: Satellite Observa-
660 tions and Numerical Simulations. *J. Clim.*, **21**, 4568–4586.
- 661 Yang, Y., S. P. Xie, and J. Hafner, 2008b: Cloud patterns lee of Hawaii Island: A synthesis of
662 satellite observations and numerical simulation. *J. Geophys. Res. Atmos.*, **113**, D15 126.

663 **LIST OF TABLES**

664 **Table 1.** Contingency tables for (a) CT classifications, (b) NT classifications, and (c)
665 OB classifications. Using the CT classification as an example: top left are ‘hits’
666 where the algorithm and the manual classifications are both CT; top right are
667 ‘false alarms’ where the algorithm classification is CT but the manual classifi-
668 cation is not CT; bottom right are ‘Correct Negatives’ where the algorithm and
669 the manual classifications are both not CT; and bottom left are ‘misses’ where
670 the algorithm classification is not CT but the manual classification is CT. . . . 33

671 **Table 2.** (a) Mean 10 m wind speed (m/s) at Bermuda’s L. F. Wade International Airport
672 by algorithm classification. The number of observations in each classification
673 is included in brackets. (b) The percent of scenes in each classification and the
674 total number of classified scenes by wind direction. . . . 34

675 TABLE 1. Contingency tables for (a) CT classifications, (b) NT classifications, and (c) OB classifications.
 676 Using the CT classification as an example: top left are ‘hits’ where the algorithm and the manual classifications
 677 are both CT; top right are ‘false alarms’ where the algorithm classification is CT but the manual classification
 678 is not CT; bottom right are ‘Correct Negatives’ where the algorithm and the manual classifications are both not
 679 CT; and bottom left are ‘misses’ where the algorithm classification is not CT but the manual classification is CT.

Class		(a) CT		(b) NT		(c) OB	
hits	false alarms	649	371	743	275	1117	193
misses	correct negatives	320	2008	506	1824	111	1927

680 TABLE 2. (a) Mean 10 m wind speed (m/s) at Bermuda's L. F. Wade International Airport by algorithm
 681 classification. The number of observations in each classification is included in brackets. (b) The percent of
 682 scenes in each classification and the total number of classified scenes by wind direction.

(a) Mean Speed	CT	NT	OB	All
	5.27 (5191)	4.83 (5196)	6.18 (6013)	5.46 (16400)
(b) Wind DIR	CT	NT	OB	All
N	27%	44%	29%	1197
NE	26%	39%	35%	1318
E	23%	31%	46%	1578
SE	27%	32%	41%	2000
S	33%	33%	34%	2747
SW	36%	23%	41%	2861
W	39%	28%	33%	3399
NW	29%	40%	31%	1300

683

LIST OF FIGURES

684 **Fig. 1.** GOES-13 visible-channel satellite imagery showing example scenes. (a) CT scene where
 685 clouds organize into a band downwind of Bermuda as indicated by a southwest-northeast
 686 oriented band of higher albedo. (b) NT scene in which there are few clouds and some of
 687 the higher albedo near and over the island might be shallow water and land showing up
 688 rather than cloud. (c) OB scene where the island (and much of the surroundings) is obscured
 689 from view by widespread cloud as indicated by high albedo throughout the scene. In each
 690 example, a wind barb is plotted showing 10 m wind direction and speed in knots at TXKF
 691 provided by the Bermuda Weather Service. 37

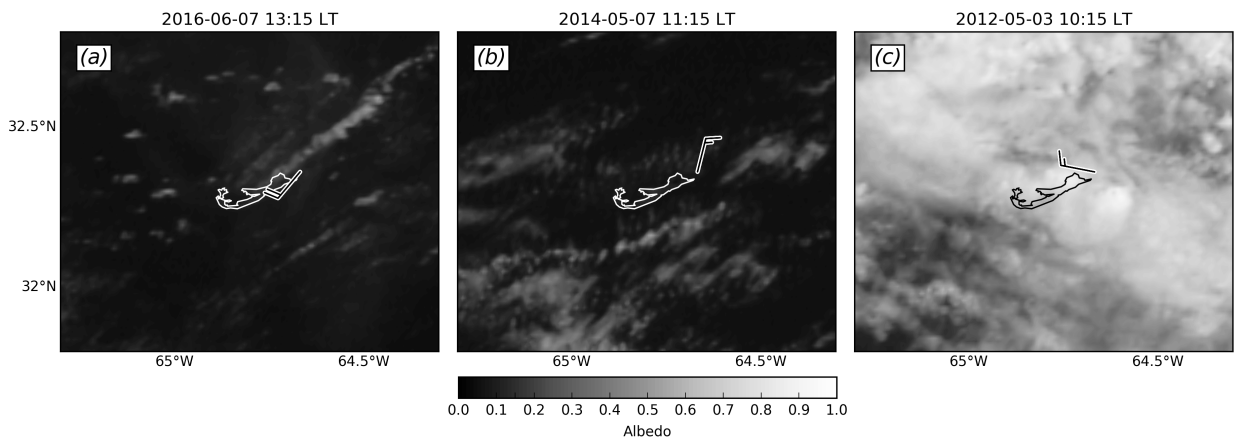
692 **Fig. 2.** A walkthrough of the steps taken to classify each scene. (a) GOES-13 visible-channel satel-
 693 lite imagery. (b) Cloud mask applied to (a), cloudy pixels are shown in grey. (c) The cloud
 694 fraction in the circular area centered on 32.3°N, 64.8°W with a radius of 0.25° (dark grey
 695 shaded region) is used to determine if the scene is OB. In this example, the cloud fraction is
 696 0.071 which is less than $\alpha = 0.33$ and so the scene is non-OB. (d) Since the scene is non-OB,
 697 the same circular area from (c) is split into 10° wide sectors, thirty-six in total. The 10 m
 698 wind direction at TXKF is used to find the upwind and downwind quadrant (i.e. nine sectors
 699 in each direction). The cloud fraction is calculated for each sector of the upwind quadrant
 700 (light grey) and the downwind quadrant (dark grey). The difference between the maximum
 701 downwind cloud fraction (arrow marked with ‘D’) and the maximum upwind cloud fraction
 702 (arrow marked ‘U’) has to be greater than $\beta = 0.08$ for the scene to be classified as CT. 38

703 **Fig. 3.** The fraction of total scenes in each classification arranged by local time and month for the
 704 (a) CT, (b) NT, and (c) OB categories. For example the top left cell of the panel (a) represents
 705 the percent of all scenes in May between 0800 and 0900 local time that are classified as CT.
 706 The three panels sum to 100%. The diurnal cycle progresses from left (morning) to right
 707 (evening), and the annual cycle progresses from top (May) to bottom (October) on each
 708 panel. The cells with an ‘X’ in them represent times when all images are rejected due to
 709 high solar zenith angles. 39

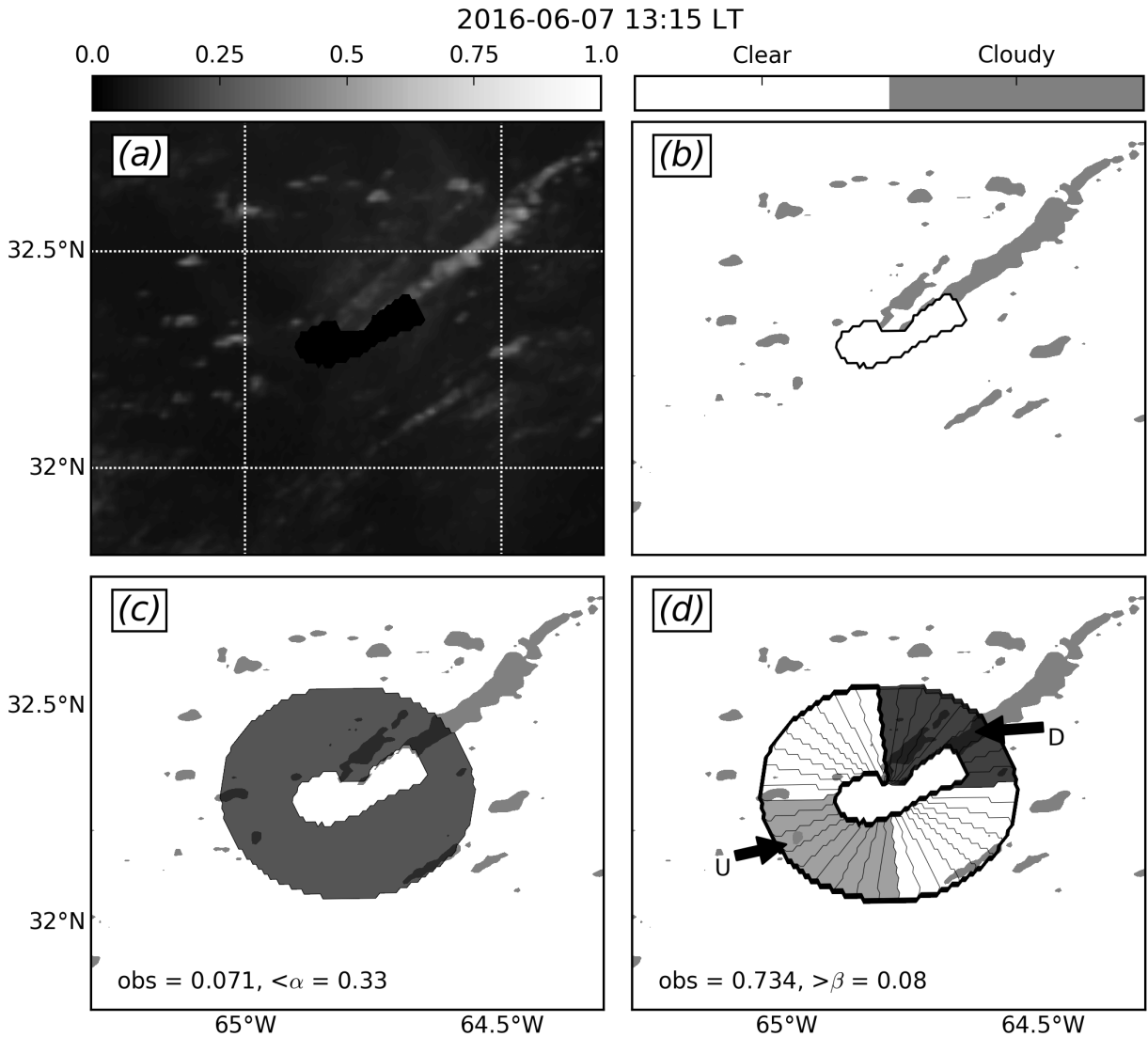
710 **Fig. 4.** (a) The climatological potential temperature (θ) profile. The mean surface θ is marked with
 711 a black dot. (b) The composite θ anomalies for CT (dash-dot line with dark grey shading),
 712 NT (dashed line with grey shading), and OB (dotted line with light grey shading). The
 713 shaded region represents the uncertainty about the mean anomaly: $\pm \frac{\sigma}{\sqrt{N}}$. The surface θ for
 714 each classification is shown by dots with the corresponding shade of grey. The range on the
 715 surface values is again $\pm \frac{\sigma}{\sqrt{n}}$. (c) The mean climatological relative humidity profile as in (a).
 716 The mean LCL for each classification, and for the climatology are shown as horizontal line
 717 segments with corresponding line styles. (d) The composite relative humidity anomalies.
 718 Composites are for the 0900 LT radiosondes for JJA in 2012-2016. In each case, only
 719 data between the surface and 700-hPa are shown. LCL pressures are calculated using the
 720 temperature and dew point of the lowest altitude reported by the radiosonde and equations 5
 721 and 6. 40

722 **Fig. 5.** JJA, 2012-2016 ERA-interim reanalysis composites centered on Bermuda. (a) and (b) are
 723 composites for Cloud Trails, (c) and (d) are composites for Non-Trails, and (e) and (f) are
 724 composites for Obscured. The left-hand column shows the mean sea-level pressure in hPa
 725 (solid black contours), 1000-hPa temperature in °C (dashed grey contours), and 1000-hPa
 726 specific humidity in g kg⁻¹ (shading). The right-hand column shows the 500-hPa vertical
 727 velocity in Pa s⁻¹, ascent and subsidence are shown in dashed and solid contours respec-
 728 tively. 41

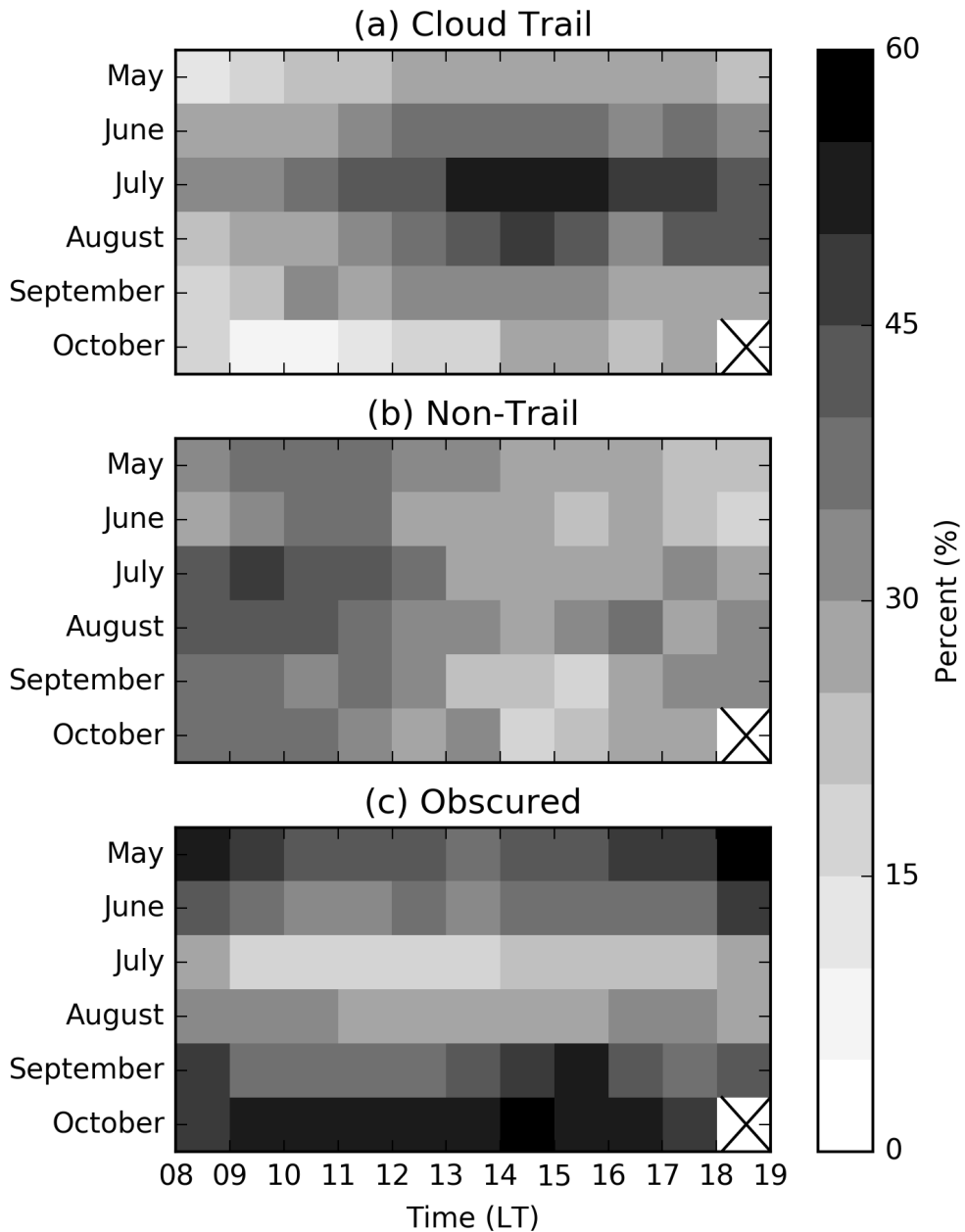
729	Fig. A1. Cumulative distribution function of the cloud fraction for OB scenes and the inverse cumulative distribution function of the cloud fraction for non-OB scenes. The cloud fraction value at the intersection of these two distributions, 0.33, is taken as the value of our parameter α	42
730		
731		
732	Fig. A2. Cumulative distribution function of the difference in maximum downwind and upwind cloud fraction, δF , for CT scenes compared to δF for NT scenes. The difference at the intersection of these two distributions, 0.08, is taken as the value of our parameter β	43
733		
734		
735	Fig. A3. As in Figure 3, but for the classifications from May through October 2012. Algorithm classifications are on the left, to be compared with the manual classifications on the right. . . .	44
736		
737	Fig. A4. The percentage of all scenes in each month from May through October 2012 that are classified as cloud trail (solid line), non-trail (dotted line), and obscured (dashed line). This analysis is done for the algorithm classification on the left, and the manual classifications on the right.	45
738		
739		
740		
741	Fig. A5. As in Figure 4, but for the classifications for May through October 2012. Note that these are anomalies with respect to the 2012-2016 JJA climatology. These profiles are made for the algorithm classifications on the left and the manual classifications on the right.	46
742		
743		



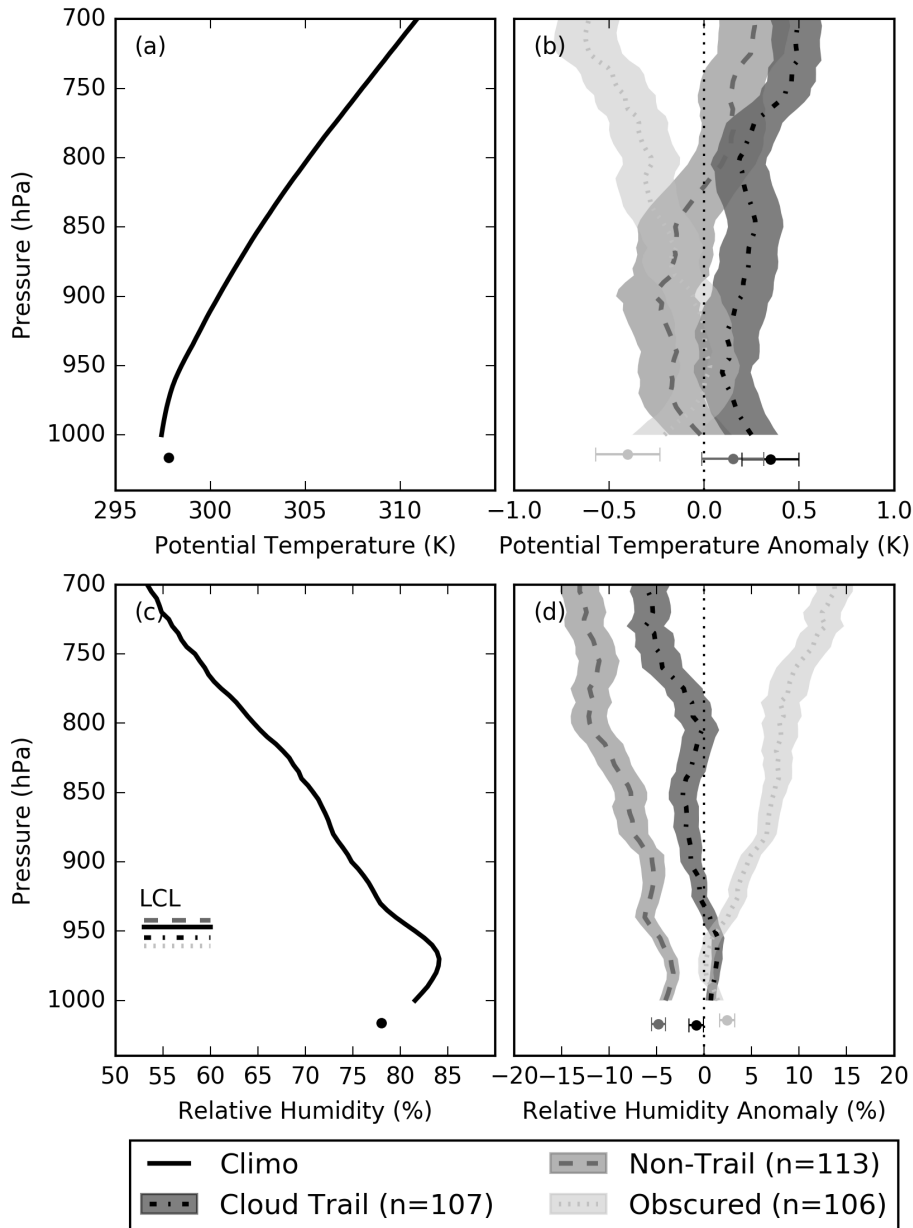
744 FIG. 1. GOES-13 visible-channel satellite imagery showing example scenes. (a) CT scene where clouds
 745 organize into a band downwind of Bermuda as indicated by a southwest-northeast oriented band of higher
 746 albedo. (b) NT scene in which there are few clouds and some of the higher albedo near and over the island
 747 might be shallow water and land showing up rather than cloud. (c) OB scene where the island (and much of the
 748 surroundings) is obscured from view by widespread cloud as indicated by high albedo throughout the scene. In
 749 each example, a wind barb is plotted showing 10 m wind direction and speed in knots at TXKF provided by the
 750 Bermuda Weather Service.



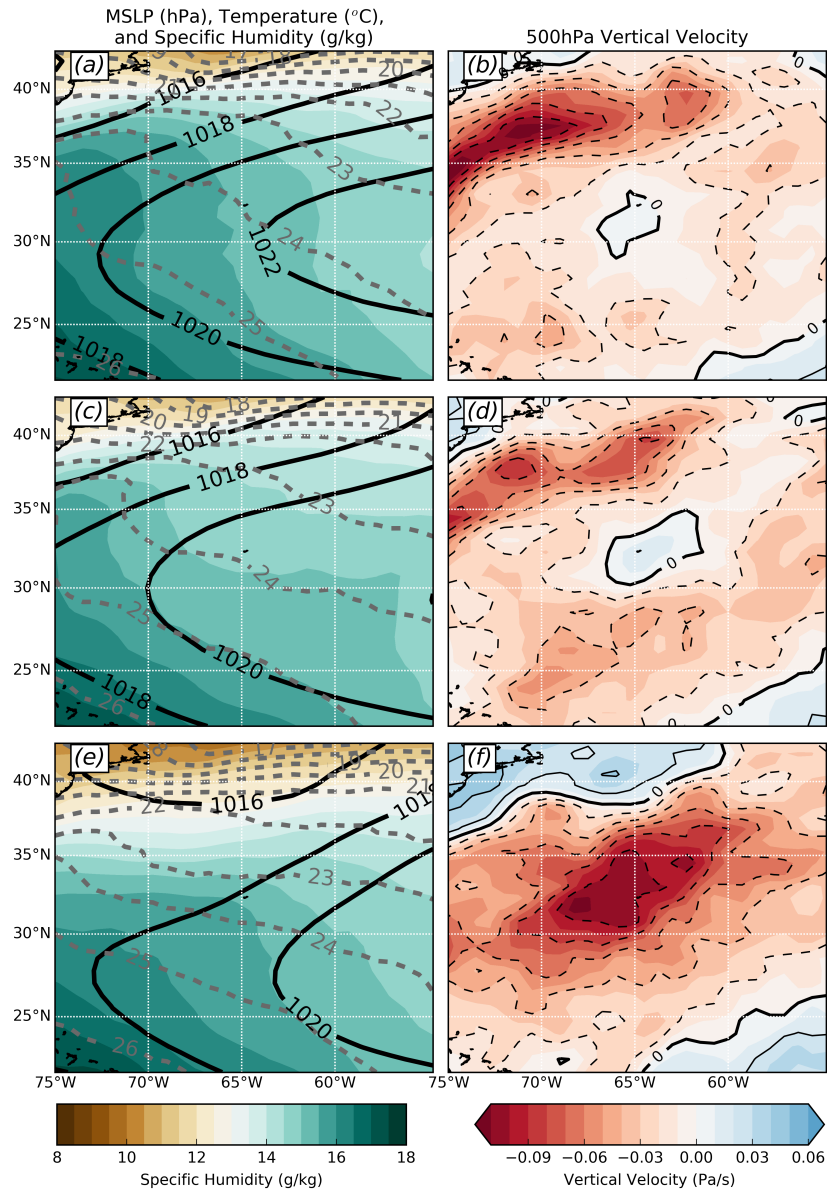
751 FIG. 2. A walkthrough of the steps taken to classify each scene. (a) GOES-13 visible-channel satellite
 752 imagery. (b) Cloud mask applied to (a), cloudy pixels are shown in grey. (c) The cloud fraction in the circular
 753 area centered on 32.3°N, 64.8°W with a radius of 0.25° (dark grey shaded region) is used to determine if the
 754 scene is OB. In this example, the cloud fraction is 0.071 which is less than $\alpha = 0.33$ and so the scene is non-OB.
 755 (d) Since the scene is non-OB, the same circular area from (c) is split into 10° wide sectors, thirty-six in total.
 756 The 10 m wind direction at TXKF is used to find the upwind and downwind quadrant (i.e. nine sectors in each
 757 direction). The cloud fraction is calculated for each sector of the upwind quadrant (light grey) and the downwind
 758 quadrant (dark grey). The difference between the maximum downwind cloud fraction (arrow marked with 'D')
 759 and the maximum upwind cloud fraction (arrow marked 'U') has to be greater than $\beta = 0.08$ for the scene to be
 760 classified as CT.



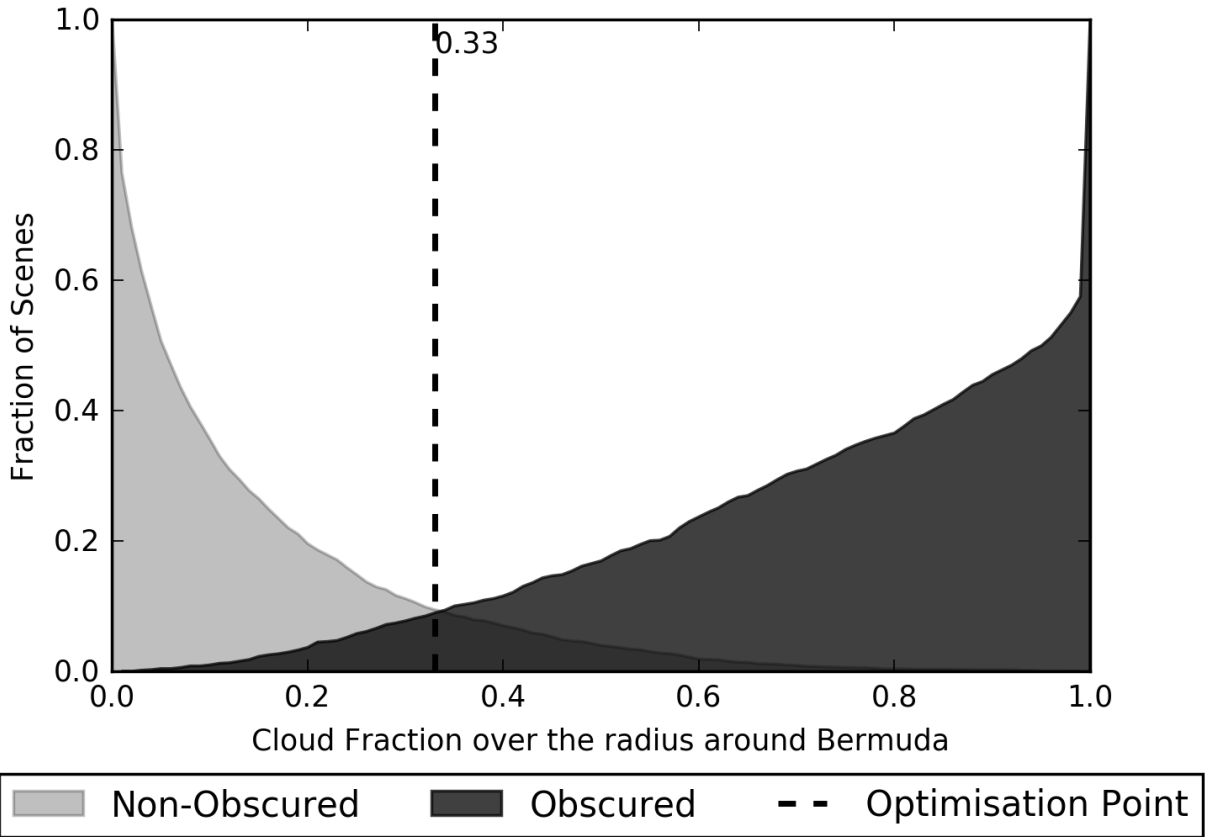
761 FIG. 3. The fraction of total scenes in each classification arranged by local time and month for the (a) CT, (b)
 762 NT, and (c) OB categories. For example the top left cell of the panel (a) represents the percent of all scenes in
 763 May between 0800 and 0900 local time that are classified as CT. The three panels sum to 100%. The diurnal
 764 cycle progresses from left (morning) to right (evening), and the annual cycle progresses from top (May) to
 765 bottom (October) on each panel. The cells with an 'X' in them represent times when all images are rejected due
 766 to high solar zenith angles.



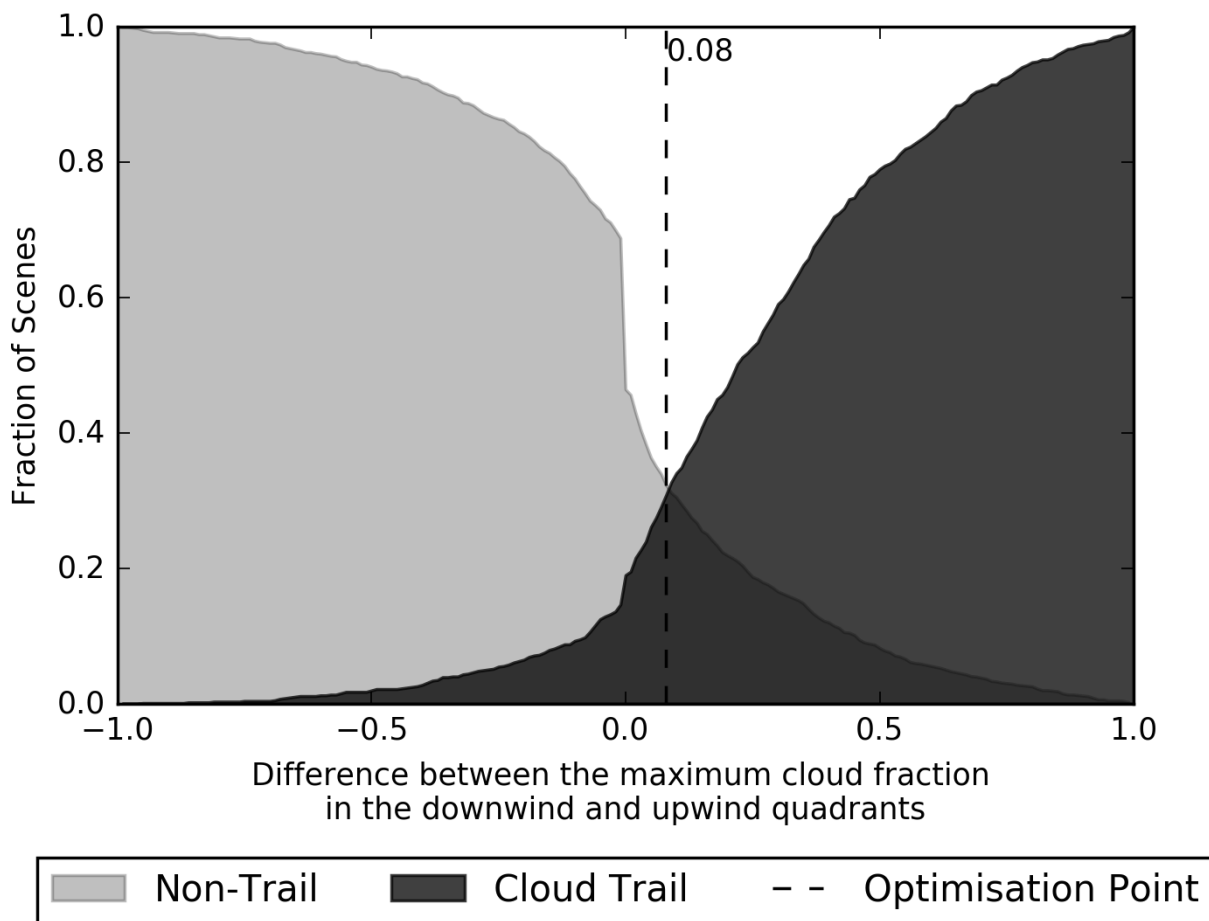
767 FIG. 4. (a) The climatological potential temperature (θ) profile. The mean surface θ is marked with a black
 768 dot. (b) The composite θ anomalies for CT (dash-dot line with dark grey shading), NT (dashed line with grey
 769 shading), and OB (dotted line with light grey shading). The shaded region represents the uncertainty about the
 770 mean anomaly: $\pm \frac{\sigma}{\sqrt{N}}$. The surface θ for each classification is shown by dots with the corresponding shade of
 771 grey. The range on the surface values is again $\pm \frac{\sigma}{\sqrt{n}}$. (c) The mean climatological relative humidity profile as
 772 in (a). The mean LCL for each classification, and for the climatology are shown as horizontal line segments
 773 with corresponding line styles. (d) The composite relative humidity anomalies. Composites are for the 0900 LT
 774 radiosondes for JJA in 2012-2016. In each case, only data between the surface and 700-hPa are shown. LCL
 775 pressures are calculated using the temperature and dew point of the lowest altitude reported by the radiosonde
 776 and equations 5 and 6.



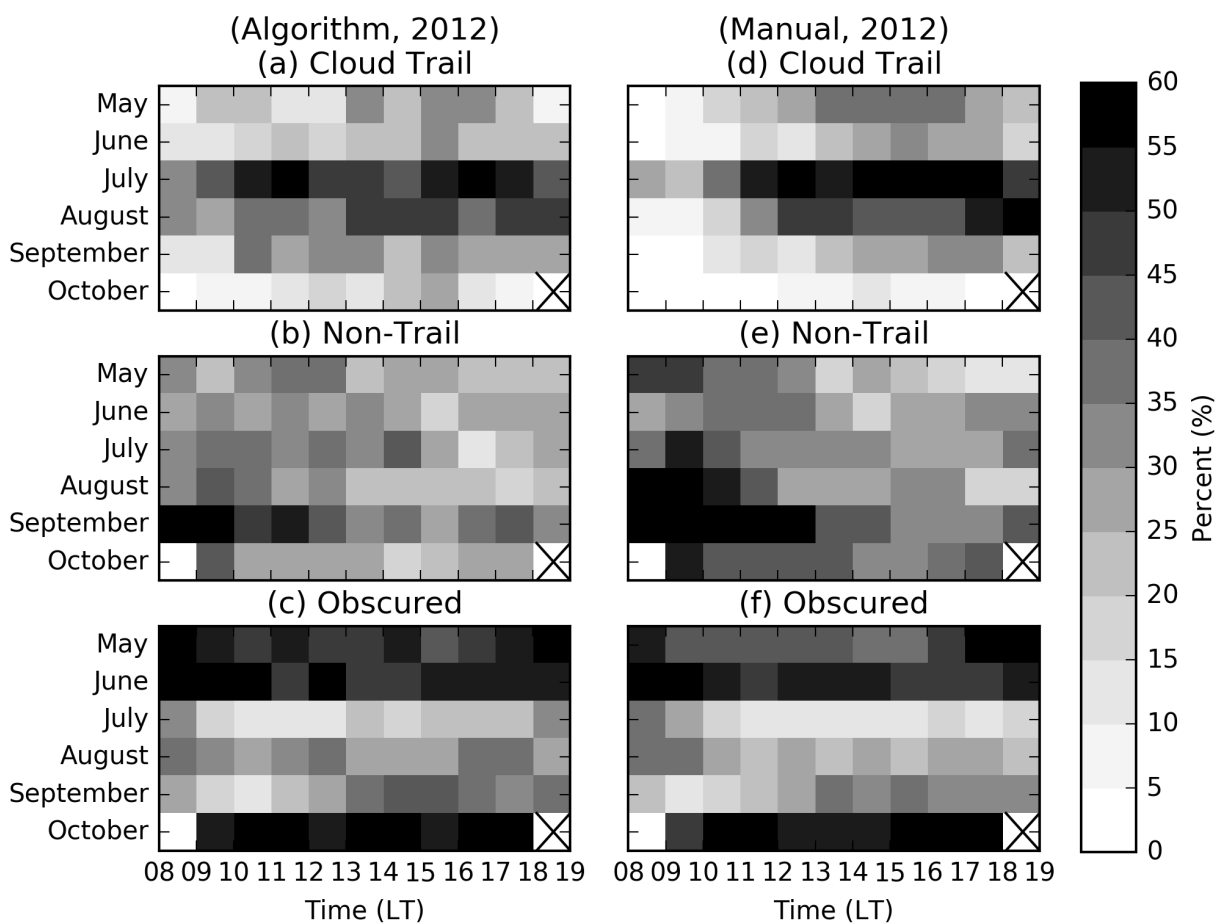
777 FIG. 5. JJA, 2012-2016 ERA-interim reanalysis composites centered on Bermuda. (a) and (b) are composites
 778 for Cloud Trails, (c) and (d) are composites for Non-Trails, and (e) and (f) are composites for Obscured. The
 779 left-hand column shows the mean sea-level pressure in hPa (solid black contours), 1000-hPa temperature in °C
 780 (dashed grey contours), and 1000-hPa specific humidity in g kg^{-1} (shading). The right-hand column shows the
 781 500-hPa vertical velocity in Pa s^{-1} , ascent and subsidence are shown in dashed and solid contours respectively.



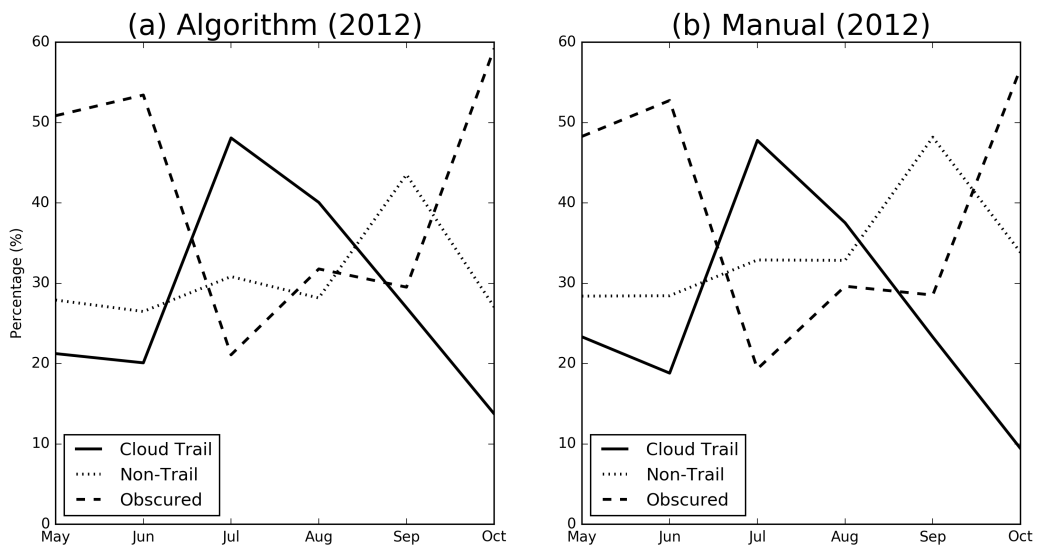
782 Fig. A1. Cumulative distribution function of the cloud fraction for OB scenes and the inverse cumulative
 783 distribution function of the cloud fraction for non-OB scenes. The cloud fraction value at the intersection of
 784 these two distributions, 0.33, is taken as the value of our parameter α .



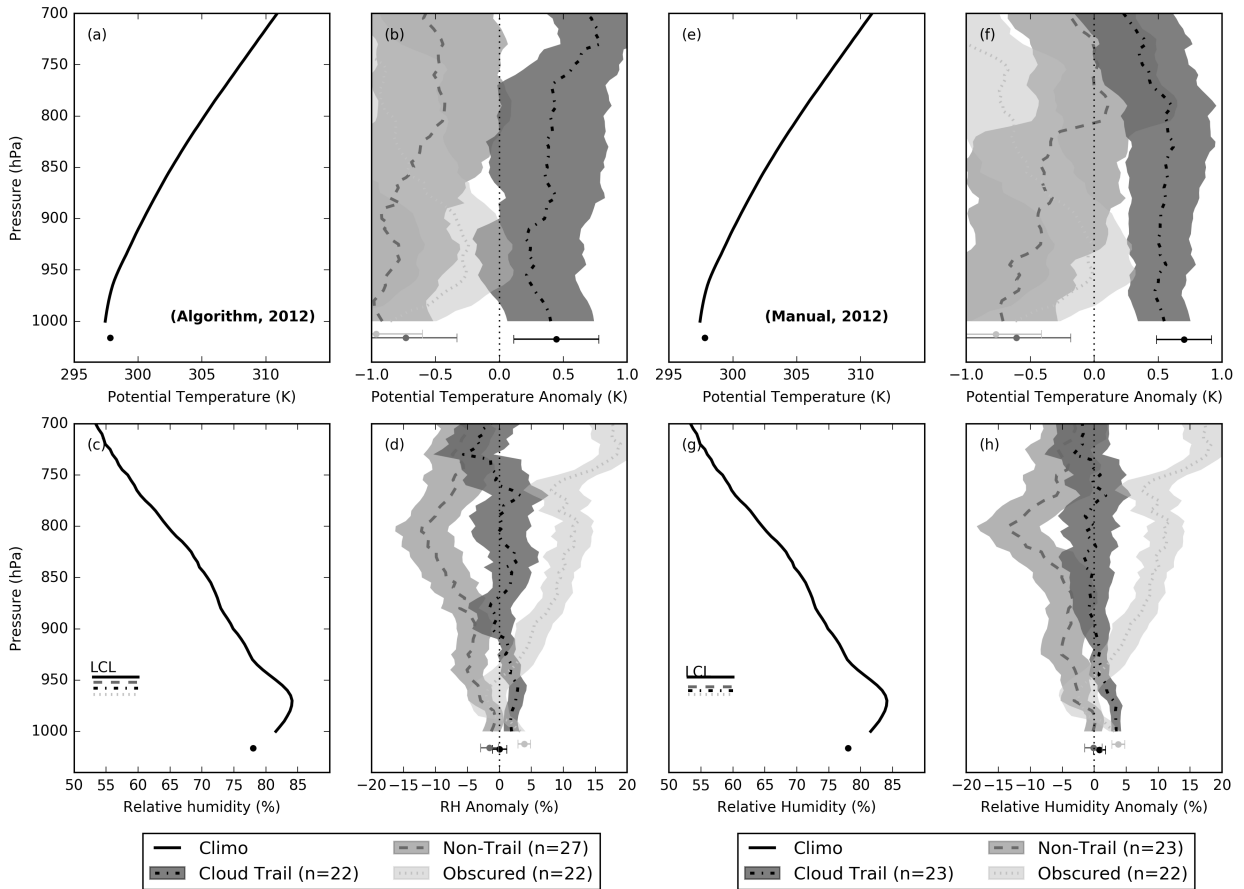
785 Fig. A2. Cumulative distribution function of the difference in maximum downwind and upwind cloud fraction,
 786 δF , for CT scenes compared to δF for NT scenes. The difference at the intersection of these two distributions,
 787 0.08, is taken as the value of our parameter β .



788 Fig. A3. As in Figure 3, but for the classifications from May through October 2012. **Algorithm** classifications
 789 are on the left, to be compared with the **manual** classifications on the right.



790 Fig. A4. The percentage of all scenes in each month from May through October 2012 that are classified as
 791 cloud trail (solid line), non-trail (dotted line), and obscured (dashed line). This analysis is done for the **algorithm**
 792 classification on the left, and the **manual** classifications on the right.



793 Fig. A5. As in Figure 4, but for the classifications for May through October 2012. Note that these are anomalies
 794 with respect to the 2012-2016 JJA climatology. These profiles are made for the **algorithm** classifications on
 795 the left and the **manual** classifications on the right.