

Response to Reviewer #1 Comments for “Towards Objective Identification and Tracking of Convective Outflow Boundaries in Next-Generation Geostationary Satellite Imagery”

Authors: Jason Apke, Kyle Hilburn, Steven Miller, and David Peterson

Key:

Reviewer’s comments are in Red

Authors’ responses are in black italics.

Comments: It was particularly hard to find reviewers for this paper, and in my capacity of associate editor for this paper, I therefore decided to provide this review as a substitute for a review, given the timeline of the process.

Thank you for stepping in to review this paper, we appreciate the time and effort you have put in for us to get this manuscript published.

I do not have any major comments except:

1) The description of the optical flow methods could be a bit more detailed and possibly be supported with graphs. Improving the manuscript in this regard is not a requirement, but in my opinion the somewhat dense text does prevent some readers from fully appreciating the manuscript, and why in the end one method "won out" over the other.

Since so much progress has been made on the optical flow front without updates to satellite image motion tracking (e.g. AMVs), it is notably challenging to write a short and concise paper on the subject and connect it with the knowledge base of the typical meteorology and remote sensing researcher. In response to this comment, we have added a couple paragraphs to the background section 2.2 linking the current AMV optical flow approach (patch matching), which is a method most should understand, to the optical flow approach used here:

“Readers can contrast the HS method with the optical flow algorithm used in GOES AMVs, referred to as “patch matching” (PM; Fortun et al., 2015). In PM, a target (e.g. a 5x5 pixel box) identified as suitable for tracking is iteratively searched for in a sequential image within a reasonable search area (Fig. 1a). The motion is identified by which candidate target (e.g. another 5x5 pixel box displaced by the optical flow motion) in the sequential image best matches the initial target, typically by minimizing the sum-of-square error between the target and the candidate brightness values (Daniels et al., 2010; Nieman et al., 1997). The reader can draw similarities to the HS method by formulating the PM approach as an energy equation to be minimized,

$$E(\mathbf{U}) = \sum_{n \in T} |I(\mathbf{x}_n, t) - I(\mathbf{x}_n + \mathbf{U}, t + \Delta t)|^2 \quad (4)$$

where the minimum in E is found by computing Eq. (4) at every candidate target in the search region. As E is only minimized within the target area T , PM represents a local method.

Research and extensive validation has shown that, with quality control, PM provides a valuable resource to derive and identify winds in satellite imagery (Velden and Bedka, 2009). However, there are several types of motions where PM would fail (Fig. 1b), many of which occur

frequently in satellite OFB observations. AMVs found with Eq. (4) make two key assumptions, 1) that the brightness remains constant between sequential images at time t and $t + \Delta t$, and 2) that the motion \mathbf{U} is constant within the target. The first assumption, brightness constancy, fails when there are excessive illumination changes in a sector that are not due to motion. These illumination changes may be due to evaporation or condensation, or simply due to changes in solar zenith angle throughout the day in visible imagery. The HS method also uses assumption 1), though it is relaxed when combined with the smoothness constraint. Assumption 2), which is not made in the HS method or other global methods, implies the PM method has no way to handle rotation, divergence, or deformation in an efficient manner, unless it is known a priori. Assumption 2) also fails to account for motion discontinuities, such as those near cloud-edges or within transparent motions. Furthermore, as there is no other constraint aside from constant brightness, PM methods struggle when there is little to no texture in the target and candidates. Quality control schemes are thus necessary to remove sectors that are poorly tracked with Eq. (4) in most AMV approaches.

PM was a popular method for AMVs over other optical flow approaches prior to the GOES-R era due to its simplicity, computational efficiency, and capability to handle displacements common in low-temporal resolution satellite imagery (Bresky and Daniels, 2006). ...” (LINE 165-193)

We have also added a figure describing the patch matching approach, and a schematic of where it fails (see now Fig 1, at the end of this document for reference). This should clarify some of the nomenclature used on types of image motion.

We selected the Brox et al. (2004) optical flow approach due to its simplicity, capability to handle regions patch matching could not (e.g. Fig. 1b), available open-source information (e.g. from opencv.org), and effective documentation (from the cited Brox et al., 2004 and Brox 2005 documents). We do not want to convey that it is the best optical flow method for the task at hand, as those techniques are evolving each year, so we have now clarified the methodology text with citations to the current validation datasets (a.k.a. benchmarks) used by the computer vision community:

“As recently overviewed in Fortun et al., (2015), there are several optical flow approaches that provide dense motion estimates which account for the weaknesses highlighted in Fig. 1b. Many have their own advantages and drawbacks in terms of computational efficiency, flexibility, and capability to handle large displacements, motion discontinuities, texture-less regions, and turbulent scenes. We selected an approach here by Brox et al. (2004) (Hereafter B04), given its simplicity, current availability of open-source information, and excellent documentation. The reader is cautioned, however, that dense optical flow is a rapidly evolving field, and research is currently underway to improve present techniques. While dense optical flow validation for satellite meteorological applications research like OFB identification is taking place, the reader is referred to the Middlebury (Baker et al., 2011), the MPI Sintel (Butler et al., 2012), and the KITTI (Geiger et al., 2012) benchmarks for extensive validation statistics of the most recent techniques using image sequences for more general applications.” (LINE 229-240)

We feel a full validation of optical flow techniques for satellite motion tracking is beyond the scope of this research, though is almost certainly a topic of future work with the new capabilities of current generation geostationary satellite imagers. With this manuscript, we simply want to show that accounting for local optical flow method deficiencies can help improve our capabilities to track and identify operationally relevant meteorological features.

2) L247-250: These sentences are unclear. What is "calibrated to reflectance factor to isolate line features? First, "reflectance factor" should be clarified - is this simply reflectance in the native imagery? Second, what is calibrated to/by what, and how are line features actually isolated?

This section has been revised for clarity. To answer your first question, the term "Reflectance Factor" was borrowed from the ABI Product Users Guide (Schmit et al., 2010), which is the radiance times the Kappa factor. While they are not the same thing, reflectance factor can be converted to reflectance by dividing by the cosine of the solar zenith angle. Calibrated was not the correct word to use here, so the statement has been revised. Line features are then isolated by convolving the provided filters with the reflectance factor and isolating where the resulting field is ≥ 0.02 . To clarify this, we have added an additional equation step in the section. It now reads as follows:

"To handle the first step of line feature identification, a simple image line detection scheme was performed by convolving the original brightness field with a set of line detection kernels, so

$$L = \sum_{i=1}^4 a_i \star G(R) \quad (9)$$

where \star is the convolution operator, G is a gaussian smoothing function (using a 21x21 kernel and standard deviation of 5 pixels), R is the reflectance factor (radiance times the incident Lambertian-equivalent radiance, or the "kappa factor"; Schmit et al., 2010), L is the resulting line detection field, and a_i represents the two-dimensional line detection kernels, defined as

$$a_1 = \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix} a_2 = \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix} a_3 = \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} a_4 = \begin{bmatrix} -1 & -1 & 2 \\ -1 & 2 & -1 \\ 2 & -1 & -1 \end{bmatrix}$$

The resulting L field exhibits higher intensities where line features exist (Gonzalez and Woods, 2007). A threshold of $L \geq 0.02$ was used here to indicate a pixel contained a line feature. This method was compared to a subjective interpretation of boundary location for validation." (LINE 284-294)

3) L299: Use of "low correlation coefficient" in the reflectivity to identify dust – can you briefly explain and/or provide a reference? This does not appear to be common knowledge.

We have revised this sentence for clarity, and added citations to the relevant papers:

"The OFB was also captured in radar scans from KIWA at 2200 UTC (Fig. 4). The coincidence of low correlation coefficient ($< \sim 0.5$) and moderate to high reflectivity (near 20 dBZ) imply that the OFB contained non-meteorological scatterers (e.g. Zrnice and Ryzhkov, 1999). The radar

measurements are consistent with previous reported values of lofted dust (Van Den Broeke and Alsarraf, 2016).” (LINE 343-347)

4) L327: "Alternatively, storm-relative motion from optical flow..." What is the motion relative to - the convective core?

We used the motion relative to the 0-6 km storm motion vector (which is a density weighted average of the layer flow) produced by the Global Forecast System numerical model here. The sentence has been reworded for clarity:

“Alternatively, the storm-relative motion (here $> 15 \text{ m s}^{-1}$), or the motion relative to the 6 hr forecast field 0-6 km storm motion from the Global Forecast System (GFS) numerical weather prediction model run was used here to filter the false alarms (the red shading in Fig. 7b). The GFS forecast field was used over analysis to simulate what would be available globally in real-time.” (LINE 373-376)

5) L382-386: This statement is a bit hard to follow. What is "background", for example? (I think I know, but it would be good stating this explicitly.)

We changed the ambiguous term “background” to “surface,” and revised wording in this statement which should add clarity for readers. We were trying to state that convergence in the optical flow field only exists because there are stationary pixels ahead of the OFB. If this is the case, a faster OFB motion would then equal stronger convergence (so slower OFBs are less likely to be identified), which is undesirable for some types of products. We have revised this statement to:

“For this case study, it may have been possible to use convergence thresholding methods, analogous to radar-based objective OFB identification, to isolate the boundary. However, convergence as derived from the optical flow information here would only work because of local, stationary surface pixels ahead of the OFB. Thus, convergence would be stronger with faster OFB velocity, which is undesirable for an objective identification product as slow moving OFBs would be missed. The convergence would also be sensitive to nearby cloud structures ahead of the OFB which would exhibit different (non-stationary) motion from the surface.” (LINE 427-434)

6) Check that the grammar is correct - there are a few missing "the"s in a few places.

We have checked the grammar and cleaned up the manuscript where necessary.

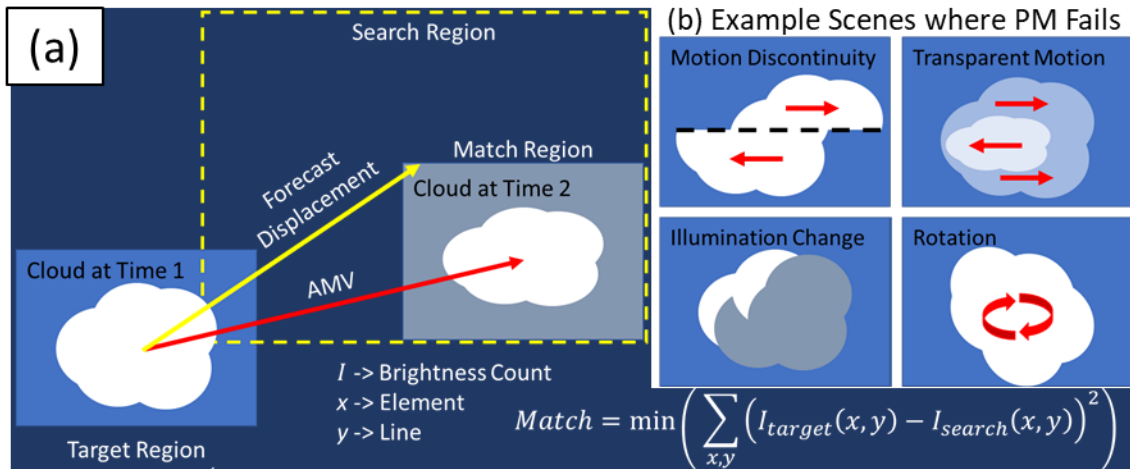


Figure 1. Schematic of a) the PM optical flow scheme used by AMVs (e.g. Bresky et al., 2012), which finds a suitable target to track (e.g. the cloud at time 1), forecasts the displacement with numerical models (yellow arrow/dash box), and iteratively searches for the target at time 2 minimizing the sum-of-square error to get the AMV (red arrow), and b) example cloud evolution types mentioned in-text where the approach shown in (a) fails.

Response to Reviewer #2 Comments for “Towards Objective Identification and Tracking of Convective Outflow Boundaries in Next-Generation Geostationary Satellite Imagery”

Authors: Jason Apke, Kyle Hilburn, Steven Miller, and David Peterson

“This work represents a unique application of an optical flow technique to high spatiotemporal geostationary imagery for the problem of identifying and tracking outflow boundaries. This paper is very well written and the work is well executed for the single case study described. Clearly, there is much more to be done and the author highlights these things, but I think this work is a great start and worthy of publication. Recommend publication with only minor updates needed.”

We would like to thank the reviewer for the kind words and feedback provided on this article. Below is a detailed list of comments made and the authors’ replies with details on modifications made to the first submission of the papers.

“Line 10: change 15 min full disk to 10 min full disk (ABI Mode 6 is now used operationally)”

This has been fixed. (see Line 79)

“Line 255: It is not clear to this reviewer how you define a “convective area”. The word, “area”, is used which would imply a group of pixels (presumably convective in this context). When working backwards toward this convection “area”, is the convective area found when coming to the first pixel meeting the brightness temperature threshold?”

In this paper, we define a convective area as any region within 50 km of a brightness temperature pixel $< -50\text{ }^{\circ}\text{C}$. This is not represented as a group of pixels here, rather a two-dimensional Haversine distance from all pixels below the brightness temperature threshold in the 10.3- μm image. This way, we can determine whether or not backward trajectories of targets we think are OFBs which are not forced to step along the pixel grid occur near deep convection.

To alleviate reader confusion, we have reworded the sentence at Line 298 to:

“If a back-traced pixel of the linear feature arrived within 50 km great-circle distance of a 10.35 μm brightness temperature ($BT_{10.35}$) pixel lower than 223 K ($-50\text{ }^{\circ}\text{C}$; using previous satellite imagery matched to the back-trajectory time), the original point was considered an OFB. The area subtended by the 50 km great circles derived from $BT_{10.35}$ is hereafter referred to as the “deep convection area.”

“- Technical Corrections The following references cited in the text were not found in the References section: Rotunno et al, 1988 Smalley et al 2007 Baker and Matthews, 2004 Van Den Broeke and Alsarraf, 2006”

Good catch. A problem with the citation management software used has since been fixed and these references have been added to the reference section. To ensure this is not repeated on the next draft, all other in-text citations have been double checked for accompanying references.

“Line 165: Remove “spatially” from this sentence: “Thus,most optical flow computations initially spatially subsample images to where all displacements 166 are initially less than 1-pixel (Anandan, 1989; discussed more in Section 3.1), which can cause fast moving small features to be lost.” ”

Removed spatially from the sentence.

“Line 285: replace “,etc.” with “,for example”.”

For clarity, we decided to just remove “etc.” all together, the sentence now reads:

“The combination of these model and observation datasets is employed to confirm the presence of a distinct convective OFB, rather than some other quasi-linear feature, such as a bore or elevated cloud layer.” (Line 328)

1 **Towards Objective Identification and Tracking of Convective Outflow Boundaries in Next-**
2 **Generation Geostationary Satellite Imagery**

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Abstract

Sudden wind direction and speed shifts from outflow boundaries (OFBs) associated with deep convection significantly affect weather in the lower troposphere. Specific OFB impacts include rapid variation in wildfire spread rate and direction, the formation of convection, aviation hazards, and degradation of visibility and air quality due to mineral dust aerosol lofting. Despite their recognized importance to operational weather forecasters, OFB characterization (location, timing, intensity, etc.) in numerical models remains challenging. Thus, there remains a need for objective OFB identification algorithms to assist decision support services. With two operational next-generation geostationary satellites now providing coverage over North America, high-temporal and spatial resolution satellite imagery provides a unique resource for OFB identification. A system is conceptualized here designed around the new capabilities to objectively derive dense mesoscale motion flow fields in the Geostationary Operational Environmental Satellite (GOES)-16 imagery via optical flow. OFBs are identified here by isolating linear features in satellite imagery, and back-tracking them using optical flow to determine if they originated from a deep convection source. This “objective OFB identification” is tested with a case study of an OFB triggered dust storm over southern Arizona. The results highlight the importance of motion discontinuity preservation, revealing that standard optical flow algorithms used with previous studies underestimate wind speeds when background pixels are included in the computation with cloud targets. The primary source of false alarms is incorrect identification of line-like features in the initial satellite imagery. Future improvements to this process are described to ultimately provide a fully automated OFB identification algorithm.

50 1. Introduction

51 Downburst outflows from associated deep convection (Byers and Braham Jr., 1949; Mitchell
52 and Hovermale, 1977) play a significant, dynamic role in modulation of the lower troposphere.
53 Their direct impacts to society are readily apparent—capsizing boats on lakes and rivers with
54 winds that seem to “*come out of nowhere*” (e.g. The Branson, MO duck boat accident; Associated
55 Press 2018), causing shifts in wildfire motion and fire intensity that put firefighters in harm’s way
56 (e.g. the Waldo Canyon and Yarnell Hill Fires; Hardy and Comfort, 2015; Johnson et al., 2014),
57 and threatening aviation safety at regional airports with sudden shifts from head to tail-winds and
58 turbulent wakes (Klinge et al., 1987; Uyeda and Zrnić, 1986). In the desert southwest, convective
59 outflows can loft immense amounts of dust, significantly reducing surface visibility and air quality
60 for those within the impacted area (e.g. Idso et al. 1972; Raman et al. 2014). These outflows are
61 commonly associated with rapid temperature, pressure, and moisture changes at the surface
62 (Mahoney III, 1988). Furthermore, the collision of outflows from adjacent storms can serve as the
63 focal point of incipient convection or the intensification of nascent storms (Mueller et al., 2003;
64 Rotunno et al., 1988).

65 Despite the understood importance of deep convection and convectively driven outflows, high
66 resolution models struggle to characterize and identify them (e.g. Yin et al. 2005). At present,
67 outflow boundaries (OFBs) are instead most effectively monitored in real-time at operational
68 centers around the world with surface, radar, and satellite data. Satellites often offer the only form
69 of observation in remote locations. The most common method for detecting outflows via satellite
70 data involves the identification of clouds formed by strong convergence at the OFB leading edge.
71 When the lower troposphere is dry, OFBs may be demarcated by an airborne “dust front”, after
72 passing over certain surfaces prone to deflation by frictional winds (Miller et al., 2008). The task

73 of identifying OFBs can prove quite challenging and would benefit greatly from an objective
74 means of feature identification and tracking for better decision support services.

75 The Advanced Baseline Imager (ABI), an imaging radiometer carried on board the
76 Geostationary Operational Environmental Satellite (GOES)-R era systems, offers a leap forward
77 in capabilities for the real-time monitoring and characterization of OFBs. Its markedly improved
78 spatial (0.5 vs. 1.0 km visible, 2 km vs. 4 km infrared), spectral (16 vs. 5 spectral bands), and
79 temporal (5 min vs. 30 min continental U.S., and 10 min vs. 3 hr full disk) resolution provides new
80 opportunities for passive sampling of the atmosphere over the previous generation (Schmit et al.,
81 2016). The vast improvement of temporal resolution alone (which includes mesoscale sectors that
82 refresh as high as 30 s) allows for dramatically improved tracking of convection (Cintineo et al.,
83 2014; Mecikalski et al., 2016; Sieglaff et al., 2013), fires and pyroconvection (Peterson et al., 2015,
84 2017, 2018), ice flows, and synoptic scale patterns (Line et al., 2016). This higher temporal
85 resolution makes identification of features like OFBs easier as well because of greater frame-to-
86 frame consistency.

87 The goal of this work is to use ABI information towards objective identification of OFBs. One
88 of the notable challenges in satellite identification of OFBs over radar or models is the lack of
89 auxiliary information. When working with a radar or a numerical model framework, for example,
90 additional information is available on the flow, temperature, and pressure tendency of the
91 boundary. Without that information, however, forecasters must rely on their knowledge of gust
92 front dynamics to identify OFBs in satellite imagery. Here, we introduce the concept of objectively
93 derived motion using GOES-16 ABI imagery for feature identification via an advanced optical
94 flow method, customized to the problem at hand. A case study of a convectively triggered OFB
95 and accompanying haboob dust front is presented in 5-min GOES-16 contiguous United States

96 (CONUS) sector information, as a way of evaluating and illustrating the potential of the
97 framework.

98 This paper is outlined as follows. The background for objective motion extraction and OFB
99 identification is presented in Section 2. The optical flow methods developed for this purpose are
100 discussed in Section 3. Section 4 presents the case study test of the current algorithm, and Section
101 5 concludes the paper with a discussion on plans for future work in objective feature identification
102 from next-generation geostationary imagers of similar fidelity to the GOES-R ABI, which are
103 presently coming online around the globe.

104

105 **2. Background**

106 *2.1 Previous Work in OFB Detection*

107 Objective identification of OFBs in meteorological data has been a topic of scientific inquiry
108 for more than 30 years. Uyeda and Zrnić (1986) and Hermes et al. (1993) use detections of wind
109 shifts in terminal Doppler radar velocity measurements to isolate regions of strong radial shear
110 associated with OFBs. Smalley et al. (2007) include the “fine line” reflectivity structure of
111 biological- and precipitation-sized particles to identify OFBs via image template matching.
112 Chipilski et al. (2018) considered the OFB objective identification in numerical models using
113 similar image processing techniques, but with additional dynamical constraints on vertical velocity
114 magnitudes and mean-sea level pressure tendency. Objective OFB identification has not been
115 demonstrated to date with the new ABI observations of the GOES-R satellite series. Identification
116 via satellite imagery would be valuable for local deep convection nowcasting algorithms which
117 use boundary presence as a predictor field (Mueller et al., 2003; Roberts et al., 2012), and for

118 operational centers around the world which may not have access to ground-based Doppler radar
119 data.

120 Traditionally, forecasters have identified OFBs in satellite imagery by visually identifying the
121 quasi-linear low-level cloud features and back-tracking them to an associated deep convection
122 source. Previous objective motion derivation algorithms are not designed to yield dense wind
123 fields, where motion is estimated at every image pixel, necessary for identifying and tracking
124 features such as OFBs (Bedka et al., 2009; Velden et al., 2005). In fact, the original image window-
125 matching atmospheric motion vector (AMV) algorithms produce winds only over targets deemed
126 acceptable for tracking by pre-processing checks on the number of cloud layers in a scene,
127 brightness gradient strength, and patch coherency. The targets are further filtered with post-
128 processing checks on acceleration and curvature through three-frame motion and deviation from
129 numerical model flow (Bresky et al., 2012; Nieman et al., 1997; Velden et al., 1997; More in
130 Section 2.2). These practices were followed for a very practical reason—AMV algorithms were
131 tailored for model data assimilation. In the formation of the model analysis, observational data
132 must be heavily quality-controlled, with outliers removed, to minimize data rejection. Here,
133 information such as OFBs would be rejected due to the detailed space/time structure of actual
134 convection which is typically poorly represented by the numerical model.

135 Deriving two-dimensional flow information at every point in the imagery would require either
136 modification of previous AMV schemes or post-processing of the AMV data via objective analysis
137 (e.g. Apke et al. 2018). The latter typically will not capture motion field discontinuities, resulting
138 in incorrect flows near feature edges (Apke et al., 2016). To capture such discontinuities in a dense
139 flow algorithm, new computer vision techniques, such as the gradient-based methods of optical
140 flow, must be adopted.

141 2.2 Optical Flow Techniques

142 Optical flow gradient-based techniques derive motion within fixed windows, thus eliminating
143 the reliance on models for defining a search region. A core assumption of many optical flow
144 techniques is brightness constancy (Horn and Schunck, 1981). Considering two image frames,
145 brightness constancy states that the image intensity I at some point $\mathbf{x} = [x, y]^T$ is equal to the
146 image intensity in the subsequent frame at a new point, $\mathbf{x} + \mathbf{U}$, where, with a translation model,
147 $\mathbf{U} = [u, v]^T$ represents the flow components of the image over the time interval (Δt) between the
148 two images:

$$I(\mathbf{x}, t) = I(\mathbf{x} + \mathbf{U}, t + \Delta t) \quad (1)$$

149 Eq. (1) can be linearized to solve for the individual flow components, u and v :

$$\nabla I \cdot \mathbf{U} + I_t = 0 \quad (2)$$

150 Where $\nabla I = [I_x, I_y]$ represents the intensity gradients in the x and y direction, and I_t represents
151 the temporal gradient of intensity. For one image pixel, Eq. (2) contains two unknowns with a
152 simple translation model for \mathbf{U} ; therefore, it cannot be solved pointwise. One well-known
153 approach to solving this so-called “aperture problem” is the Lucas-Kanade method, hereafter the
154 LK method, which considers a measurement neighborhood of the intensity space and time
155 gradients (e.g., Baker and Matthews, 2004; Bresky and Daniels, 2006). Use of neighborhoods, or
156 image windows, to derive optical flow are called *local* approaches. Another seminal approach was
157 introduced by Horn and Schunck (1981; HS Method) which solves the aperture problem by adding
158 an additional smoothness constraint to the brightness constancy assumption, and minimizing an
159 energy magnitude between two images:

$$E(\mathbf{U}) = \iint_{\Omega} (\nabla I \cdot \mathbf{U} + I_t)^2 + \alpha(|\nabla_2 u|^2 + |\nabla_2 v|^2) d\mathbf{x} \quad (3)$$

160 Where $E(\mathbf{U})$ represents an energy functional to be minimized over all image pixels Ω , α is a
 161 constant weight used to control the smoothness of the flow components $u(\mathbf{x})$ and $v(\mathbf{x})$, and $\nabla_2 =$
 162 $[\partial/\partial x, \partial/\partial y]^T$. This derivation is called a *global* approach, where the optical flow $u(\mathbf{x})$ and
 163 $v(\mathbf{x})$ at each pixel is found which minimizes the quantity of Eq. (3) by deriving the Euler-Lagrange
 164 equations, and numerically solving the linear system of equations with Gauss-Seidel iterations.

165 Readers can contrast the HS method with the optical flow algorithm used in GOES AMVs,
 166 referred to as “patch matching” (PM; Fortun et al., 2015). In PM, a target (e.g. a 5x5 pixel box)
 167 identified as suitable for tracking is iteratively searched for in a sequential image within a
 168 reasonable search area (Fig. 1a). The motion is identified by which candidate target (e.g. another
 169 5x5 pixel box displaced by the optical flow motion) in the sequential image best matches the initial
 170 target, typically by minimizing the sum-of-square error between the target and the candidate
 171 brightness values (Daniels et al., 2010; Nieman et al., 1997). The reader can draw similarities to
 172 the HS method by formulating the PM approach as an energy equation to be minimized,

$$E(\mathbf{U}) = \sum_{n \in T} |I(\mathbf{x}_n, t) - I(\mathbf{x}_n + \mathbf{U}, t + \Delta t)|^2 \quad (4)$$

173 where the minimum in E is found by computing Eq. (4) at every candidate target in the search
 174 region. As E is only minimized within the target area T , PM represents a local method.

175 Research and extensive validation has shown that, with quality control, PM provides a valuable
 176 resource to derive and identify winds in satellite imagery (Velden and Bedka, 2009). However,
 177 there are several types of motions where PM would fail (Fig. 1b), many of which occur frequently
 178 in satellite OFB observations. AMVs found with Eq. (4) make two key assumptions, 1) that the
 179 brightness remains constant between sequential images at time t and $t + \Delta t$, and 2) that the motion
 180 \mathbf{U} is constant within the target. The first assumption, brightness constancy, fails when there are
 181 excessive illumination changes in a sector that are not due to motion. These illumination changes

182 may be due to evaporation or condensation, or simply due to changes in solar zenith angle
183 throughout the day in visible imagery. The HS method also uses assumption 1), though it is relaxed
184 when combined with the smoothness constraint. Assumption 2), which is not made in the HS
185 method or other global methods, implies the PM method has no way to handle rotation, divergence,
186 or deformation in an efficient manner, unless it is known apriori. Assumption 2) also fails to
187 account for motion discontinuities, such as those near cloud-edges or within transparent motions.
188 Furthermore, as there is no other constraint aside from constant brightness, PM methods struggle
189 when there is little to no texture in the target and candidates. Quality control schemes are thus
190 necessary to remove sectors that are poorly tracked with Eq. (4) in most AMV approaches.

191 PM was a popular method for AMVs over other optical flow approaches prior to the GOES-R
192 era due to its simplicity, computational efficiency, and capability to handle displacements common
193 in low-temporal resolution satellite imagery (Bresky and Daniels, 2006). Linearizing the
194 brightness constancy assumption in Eq. (2) means that large and non-linear displacements
195 (typically > 1 pixel between images) will not be captured (Brox et al., 2004). Thus, most optical
196 flow computations initially subsample images to where all the displacements are initially less than
197 1-pixel (Anandan, 1989; discussed more in Section 3.1), which can cause fast moving small
198 features to be lost. Note that reducing the temporal resolution of GOES imagery (e.g. 10-min vs.
199 5-min scans) increases the displacement of typical meteorological features between frames.
200 Furthermore, constancy assumptions are more likely violated with reduced temporal resolution
201 since image intensity changes more through evaporation and condensation of cloud matter over
202 time. Thus, for the spatial resolution of ABI, it is impractical to consider optical flow gradient-
203 based methods at temporal resolutions coarser than 5-min for several mesoscale meteorological
204 phenomena, including OFBs. Very spatially coarse images do not need to be initially used with

205 faster scanning rates, such as super rapid scan 1-min information (Schmit et al., 2013), or the 30-
206 s temporal resolution mesoscale mode of ABI (Schmit et al., 2016).

207 While the HS method is designed for deriving dense flow in imagery sequences, it also does
208 not account for motion discontinuities in the flow fields. Hence, it suffers from incorrect flow
209 derivations near cloud edges, and would perform poorly for OFB detection and tracking. Black
210 and Anandan (1996) offer an intuitive solution to this problem, whereby the energy functional is
211 designed to minimize robust functions that are not sensitive to outliers:

$$E(\mathbf{U}) = \iint_{\Omega} \rho_d(\nabla I \cdot \mathbf{U} + I_t) + \rho_s(|\nabla_2 u|^2 + |\nabla_2 v|^2) d\mathbf{x} \quad (5)$$

212 The robust function data term for the HS method is simply $\rho_d(r) = r^2$, and smoothness $\rho_s(r) =$
213 r which implies that energy functionals increase quadratically for r outliers. Other robust
214 functions can also be minimized with similar gradient descent algorithms to Gauss-Seidel
215 iterations, while being less sensitive to outliers (Press et al., 1992; Black and Anandan, 1996).
216 Robust functions are popular in recent optical flow literature (Brox et al., 2004; Sun et al., 2010),
217 and a similar approach adopted here is discussed further in the methodology section. The reader
218 is referred to works by Barron et al. (1994), Fleet and Weiss (2005), Sun et al. (2010), and Fortun
219 et al. (2015) for more comprehensive reviews on optical flow background and techniques.

220 The relevance of optical flow in satellite meteorological research continues to increase now
221 that scanning rates of sensors such as the ABI are routinely at sub 5-min time scales, making
222 motion easier to derive objectively (Bresky and Daniels, 2006; Héas et al., 2007; Wu et al., 2016).
223 The dense motion estimation within fine-temporal resolution data has yet to be used for feature
224 identification. Optimizing optical flow for this purpose, and its specific application to OFBs, is the
225 aim of this study. The next section outlines our approach to this end.

226

227 3. Methodology

228 3.1 Optical Flow Approach

229 As recently overviewed in Fortun et al., (2015), there are several optical flow approaches that
230 provide dense motion estimates which account for the weaknesses highlighted in Fig. 1b. Many
231 have their own advantages and drawbacks in terms of computational efficiency, flexibility, and
232 capability to handle large displacements, motion discontinuities, texture-less regions, and turbulent
233 scenes. We selected an approach here by Brox et al. (2004) (Hereafter B04), given its simplicity,
234 current availability of open-source information, and excellent documentation. The reader is
235 cautioned, however, that dense optical flow is a rapidly evolving field, and research is currently
236 underway to improve present techniques. While dense optical flow validation for satellite
237 meteorological applications research like OFB identification is taking place, the reader is referred
238 to the Middlebury (Baker et al., 2011), the MPI Sintel (Butler et al., 2012), and the KITTI (Geiger
239 et al., 2012) benchmarks for extensive validation statistics of the most recent techniques using
240 image sequences for more general applications.

241 The B04 approach handles the drawbacks described in Fig. 1b and more, where the brightness
242 constancy assumption is no longer linearized, i.e.

$$\begin{aligned} E(\mathbf{U}) = \iint_{\Omega} \rho_d (|I(\mathbf{x} + \mathbf{U}, t + \Delta t) - I(\mathbf{x}, t)|^2 \\ + \gamma |\nabla_2 I(\mathbf{x} + \mathbf{U}, t + \Delta t) - \nabla_2 I(\mathbf{x}, t)|^2) \\ + \alpha \rho_s (|\nabla_2 u|^2 + |\nabla_2 v|^2) d\mathbf{x} \end{aligned} \quad (6)$$

243 Following B04, within the data robust function, we now have also included a gradient constancy
244 assumption, which is weighted by a constant γ to make the derived flow more resilient to changes
245 in illumination. Avoiding linearization of constancy assumptions improves the identification of

246 large displacements between images. The Charbonnier penalty is used for the data and smoothness
 247 robust functions following Sun et al. (2010),

$$\rho_d(r^2) = \rho_s(r^2) = \sqrt{r^2 + \epsilon^2} \quad (7)$$

248 with ϵ representing a small constant present to prevent division by zero in minimization, set to
 249 0.001. The values for \mathbf{U} are found by solving the Euler-Lagrange equations of Eq. (6) with
 250 numerical methods

$$E_u - \frac{dE_{u_x}}{dx} - \frac{dE_{u_y}}{dy} = 0 \quad (8)$$

$$E_v - \frac{dE_{v_x}}{dx} - \frac{dE_{v_y}}{dy} = 0 \quad (9)$$

251 with reflecting boundary conditions and subscripts that imply the derivatives. Eqs. (8) and (9) are
 252 solved with a nested-fixed point successive over-relaxation iteration scheme described in B04 and
 253 summarized in Fig. 2. The reader is referred to Chapter 4 of Brox (2005) for details on the full
 254 discretization of the derivatives in the successive over-relaxation scheme. Here, only the spatial
 255 dimensions are used for the smoothing term, though it is possible to include the time dimension
 256 with this system as well.

257 A difficulty in solving Eqs. (8) and (9) is that the successive over-relaxation scheme may
 258 converge on a local minimum of $E(\mathbf{U})$, rather than finding the global minimum. The typical
 259 approach to find the global minimum is to compute optical flow with coarse- to fine-scale warping
 260 iterations (e.g. Anandan, 1989). Coarse- to fine-scale warping iterations work by subsampling the
 261 initial image at the native resolution to a coarser spatial resolution and computing the flow initially
 262 at the coarsest resolution in the image pyramid. The \mathbf{U} results from the coarse image flow are then
 263 used as the first guess field for the next finest scale on the image pyramid (Fig. 3), and the second

264 image is warped accordingly. The warping step ensures that estimated displacements at every step
265 in the image pyramid remain small.

266 The B04 scheme includes coarse- to fine-scale warping iterations at every outer iteration k .
267 This means that the first iteration is run on a subsampled image, and the subsampling is reduced
268 by a scale factor at every k until the image reaches the native resolution at the final $k = nK$.
269 Images at every k in this subsampling are found using a gaussian image pyramid technique with
270 bicubic interpolation. The flow values of the image at $k - 1$ are upsampled accordingly at k also
271 with bicubic interpolation (the initial flow guess is $u = v = 0$ at $k = 0$). For improved
272 computation of spatial derivatives, the initial image is also smoothed with a 9x9 pixel kernel
273 gaussian filter with a standard deviation set to 1.5 pixels. The specific settings used for the coarse-
274 to fine- warped flow scheme here are shown in Table 1.

275 *3.2 Objective OFB identification*

276 There are two steps to the objective OFB identification process. First, a linear feature or sharp
277 boundary is identified in visible or infrared imagery. In some cases, the first step alone is enough
278 to identify OFBs subjectively. The second step is tracking that feature back in time to see where
279 it originated from (typically, near an area with deep convection). In the case of near stationary
280 convection and low-level flow, a forecaster might also use radial like propagation in this decision-
281 making process, however, since convection geometry and low-level flow varies from storm to
282 storm, only the first two steps are considered here. This approach aims to mirror the subjective
283 process, leveraging the information content of optical flow to do so.

284 To handle the first step of line feature identification, a simple image line detection scheme
285 was performed by convolving the original brightness field with a set of line detection kernels, so

$$L = \sum_{i=1}^4 a_i \star G(R) \quad (10)$$

286 where \star is the convolution operator, G is a gaussian smoothing function (using a 21x21 kernel and
 287 standard deviation of 5 pixels), R is the reflectance factor (radiance times the incident Lambertian-
 288 equivalent radiance, or the “kappa factor”; Schmit et al., 2010), L is the resulting line detection
 289 field, and a_i represents the two-dimensional line detection kernels, defined as

$$290 \quad a_1 = \begin{bmatrix} -1 & -1 & -1 \\ 2 & 2 & 2 \\ -1 & -1 & -1 \end{bmatrix} \quad a_2 = \begin{bmatrix} -1 & 2 & -1 \\ -1 & 2 & -1 \\ -1 & 2 & -1 \end{bmatrix} \quad a_3 = \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} \quad a_4 = \begin{bmatrix} -1 & -1 & 2 \\ -1 & 2 & -1 \\ 2 & -1 & -1 \end{bmatrix}$$

291

292 The resulting L field exhibits higher intensities where line features exist (Gonzalez and Woods,
 293 2007). A threshold of $L \geq 0.02$ was used here to indicate a pixel contained a line feature. This
 294 method was compared to a subjective interpretation of boundary location for validation.

295 To address the second step of the process, the constrained optical flow approach described in
 296 Section 3.1 was used to track the boundary pixels (both objectively and subjectively identified)
 297 back in time for three hours. The values of motion at each step in the backwards trajectory were
 298 determined with bilinear interpolation of the optical flow derived dense vector grid. If a back-
 299 traced pixel of the linear feature arrived within 50 km great-circle distance of a 10.35 μm brightness
 300 temperature ($\text{BT}_{10.35}$) pixel lower than 223 K (-50°C ; using previous satellite imagery matched to
 301 the back-trajectory time), the original point was considered an OFB. The area subtended by the
 302 50 km great circles derived from $\text{BT}_{10.35}$ is hereafter referred to as the “deep convection area.”
 303 While this brightness temperature threshold is subjective and can vary from case to case, it was
 304 found to produce a reasonable approximation of deep convection areas when compared to ground-
 305 based radar information for the case study described in the subsequent sections.

306 3.3 Data

307 The objective OFB identification methodology is tested using a case study from 5 July 2018
308 over the southwestern United States. This event featured a distinct OFB and associated dust storm
309 that was well-sampled by various ground- and space-based sensors. GOES-16 was in Mode-3,
310 generating one image over the study area every 5-min (continental U.S., or CONUS, ABI scan
311 domain). Optical flow computations employ the GOES-16 (GOES-East) ABI red band (0.64 μm ;
312 ABI channel 2), provided at a nominal sub-satellite spatial resolution of 500 m, but closer to 1 km
313 at the case study location. This channel is used at native resolution, though it can be subsampled
314 with a low-pass filter such that future versions can implement color information from the blue and
315 near-infrared bands (e.g. Miller et al. 2012). This means that the optical flow approach here is
316 daytime only. A similar B04 approach can be used on infrared data as well for day/night
317 independent information, though for detecting OFBs in the low levels, proxy visible products
318 would perform best. As described above, the clean longwave infrared band (10.35 μm ; ABI
319 channel 13) is used as first-order information on optically thick cloud-top heights and to assess the
320 convective nature of the observed scene ($\text{BT}_{10.35} < 223 \text{ K}$).

321 High frequency Automated Surface Observing Stations (ASOS; NOAA 1998), recording
322 temperature, pressure, wind speed and direction once every minute, complement the satellite
323 imagery. The Weather Surveillance Radar-1988 Doppler (Crum and Alberty, 1993) dual-
324 polarimetric data also sampled the OFB event from the KIWA radar near Phoenix, AZ. To
325 highlight the OFBs and the presence of dust, horizontal reflectivity and correlation coefficient are
326 used (Van Den Broeke and Alsarraf, 2016). Finally, for information on the full 3D dynamics of
327 the case study, a numerical model representation of the environment was collected from the High
328 Resolution Rapid Refresh system (HRRR, Benjamin et al. 2016). **The combination of these model**

329 and observation datasets is employed to confirm the presence of a distinct convective OFB, rather
330 than some other quasi-linear feature, such as a bore or elevated cloud layer.

331

332 4. Case Study Description

333 Convection was observed in south central Arizona on 5 July 2018 after 1800 UTC. A large
334 and well-defined linear structure emerged from below the convective cloud cover at 2200 UTC to
335 6 July 2018 0100 UTC propagating westward in GOES-16 imagery (Fig. 4). This linear structure,
336 demarcated by roll (arcus) clouds on the northern side and lofted dust on the southern side, was
337 apparent with strong visible reflectance contrast against the relatively dark surface and $BT_{10.35} \sim$
338 10 K cooler than the underlying surface. The dust lofted by this outflow produced low visibility
339 and hazardous driving conditions near Phoenix, AZ. Dust storm warnings were issued by the local
340 National Weather Service (NWS) forecast office by 2300 UTC. The structure's observed radial
341 propagation away from nearby deep convection and associated cloud and dust features lends to its
342 interpretation as a convective OFB.

343 The OFB was also captured in radar scans from KIWA at 2200 UTC (Fig. 5). The coincidence
344 of low correlation coefficient ($< \sim 0.5$) and moderate to high reflectivity (near 20 dBZ) imply that
345 the OFB contained non-meteorological scatterers (e.g. Zrnic and Ryzhkov, 1999). The radar
346 measurements are consistent with previous reported values of lofted dust (Van Den Broeke and
347 Alsarraf, 2016). Surface observations taken at the ASOS station reveal temperatures exceeding
348 317 K (44 °C) ahead of the OFB, with calm winds (Fig. 6). Temperatures dropped by 4 K, wind
349 speeds changed direction and increased sharply, and dew points increased rapidly as the OFB
350 crossed the station at ~ 2316 UTC. The rapid change in low-level meteorology is consistent with
351 convective OFBs sampled in previous studies (e.g. Mahoney III, 1988; Miller et al., 2008).

352 The HRRR model captured the broad characteristics of this event (Fig. 7), showing moderate
353 low-level winds in excess of 10 m s^{-1} (Fig. 7a), cooler temperatures (Fig. 7b), and simulated
354 cumulus clouds from forced ascent (Fig. 7c). Model cross sections (Fig. 7d) indicated a moderate
355 increase in vertical motion ahead of the numerically derived boundary, and a sharp decrease in
356 virtual potential temperature behind the boundary. The shape of the virtual potential temperature
357 profile is consistent with other model observations of OFBs (e.g. Chipilski et al., 2018). The
358 observation and model data all show that the linear structure observed in Fig. 4 was modifying the
359 dynamics of the surface in a manner consistent with OFBs, and not some other linear cloud feature
360 type that is decoupled from the surface and may be misidentified by the satellite. Since such low-
361 level linear features are often obscured by cloud layers at higher altitudes, this case study in some
362 respects represents a best-case-scenario for evaluating optical flow capabilities towards identifying
363 OFBs.

364

365 5. Results

366 The first step in OFB identification requires identification of a feature that appears linear in
367 the imagery. Compared to the subjective boundary identification (considered as truth here; Fig 8a,
368 blue dots), the convolution method gives a reasonable approximation to where the OFB is located
369 within the higher intensity points in L (Fig. 8b). Unfortunately, the simply-applied convolution is
370 also sensitive to linear features associated with the deep convection itself (the blue shading in Fig.
371 8b). Hence, false alarms appear east of the boundary. These issues can be filtered out using either
372 cloud-top height or brightness temperature thresholding from separate infrared channels.
373 Alternatively, the storm-relative motion (here $> 15 \text{ m s}^{-1}$), or the motion relative to the 6 hr forecast
374 field 0-6 km storm motion from the Global Forecast System (GFS) numerical weather prediction

375 model run, was used here to filter the false alarms (the red shading in Fig. 8b). The GFS forecast
376 field was used over analysis to simulate what would be available globally in real-time.

377 The second step requires these linear fast-moving features to be traced backward to a deep
378 convection source using the optical flow computation (Fig. 9). To the west of the boundary, near
379 stationary optical flow vectors highlight the background (or ground) pixels. The boundary itself
380 exhibits a westward movement near $15\text{-}20\text{ m s}^{-1}$ ($\sim 30\text{-}40$ kts). The feature also appears to bow
381 outwards after faster motions are observed, near 33° N , -112° E during 2338-2358 UTC (Figs. 9b,
382 c). Similar westward motion is derived in the wake of the OFB, within the convective cold pool.
383 This results from the presence of airborne dust particles, which facilitate the computation of optical
384 flow vectors in this region.

385 The backwards trajectories of the subjectively and objectively identified OFB pixels in Figs.
386 8c and d (B04 method) show that many of the linear cloud features, particularly those associated
387 with the central arcus cloud, indeed originated near deep convection. However, when the
388 backwards trajectories of the B04 method were compared to other optical flow methods, such as
389 the approach by Wu et al. (2016), most were unsuccessful at obtaining coincidence between linear
390 cloud features along the OFB and a deep convection source. Wu et al. (2016) used an approach
391 introduced to the community by Farnebäck (2001), which is a *local* window method for optical
392 flow.

393 Example points 1–7 examined within the subjectively identified OFB backward trajectories
394 highlight an issue with *local* window approaches for this application (Fig. 10). The B04 approach
395 (Fig. 10, blue/yellow) produced motions that were relatively consistent with the true boundary
396 motion. Thus, many points that are lost in the *local* approaches are successfully backtracked to
397 the initial deep convection (e.g. points 3–5). With the Wu et al. approach (Fig. 10, orange/red),

398 OFB targets move slower than the actual boundary, and, over a three-hour tracking period,
399 eventually become stuck within the stationary background pixels. This tracking issue stems from
400 an assumption made in many *local* approaches that pixels within an image window all move in the
401 same direction with the same speed. When background pixels are included within an image
402 window containing clouds or dust, the resulting optical flow speed would then be underestimated.
403 The slow bias is observed in plots of optical flow speeds along the OFB (Fig. 11), where the Wu
404 et al. approach was $\sim 5\text{-}10\text{ m s}^{-1}$ slower than the B04 approach. While not shown, we found similar
405 backward trajectory issues using the LK approach. Full loops of the optical flow in Fig. 9 and
406 trajectories in Fig. 10 are included as supplementary material to this manuscript.

407 For all approaches tested, however, the methods struggled to backtrack the newly formed
408 cumulus to the north and the dust front to the south. With the cumulus to the north, the issues with
409 each algorithm appear to result from rapid cumulus development between frames (e.g. points 1
410 and 2 in Figs. 10a, b). Condensation like what is observed here is unfortunately not considered in
411 the brightness constancy assumption. Thus, condensing cloud features would only be tracked back
412 to when they initially form (after Fig. 10b) without additional dynamic constraints to Eq. (6). An
413 example can be seen when points 1 and 2 become stuck in Fig. 10c. This has important
414 implications on the limitations of backtracking OFB features to deep convection with optical flow
415 from imagery. If no cloud or dust feature exists to visualize an OFB in satellite imagery, some of
416 the feature propagation may be lost.

417 The dust to the south appears in the satellite imagery as early as 2200 UTC, though it was quite
418 transparent relative to the ground. It is therefore possible the stationary background pixels may be
419 dominant in the optical flow computation at points 6 and 7, resulting in slower wind speeds than
420 the true OFB propagation. Points 6 and 7 are also located near cumulus moving across the OFB

421 motion to the south. This dust front tracking could be improved using multispectral techniques
422 designed to highlight dust features over ground pixels, or by using additional color spectrum
423 information to discourage flow smoothness in Eq. (6) across the dust front from the cumulus to
424 the south (e.g. Sun et al., 2010).

425 Many line-like targets east of the OFB in Fig. 8d also originated from the deep convection,
426 which constitute false alarms. These false alarms can be reduced by further improving the OFB
427 targeting step in the objective process in future studies. For this case study, it may have been
428 possible to use convergence thresholding methods, analogous to radar-based objective OFB
429 identification, to isolate the boundary. However, convergence as derived from the optical flow
430 information here would only work because of local, stationary surface pixels ahead of the OFB.
431 Thus, convergence would be stronger with faster OFB velocity, which is undesirable for an
432 objective identification product as slow moving OFBs would be missed. The convergence would
433 also be sensitive to nearby cloud structures ahead of the OFB which would exhibit different (non-
434 stationary) motion from the surface. It is for this reason that a backwards trajectory approach was
435 elected instead of basing the detection on local horizontal convergence. The optical flow approach
436 used here does help highlight the OFB when storm motion alone was considered in addition to
437 convolution, showing how additional tools can be used in synergy to arrive at a more
438 comprehensive objective feature identification approach in future studies.

439

440 6. Conclusions and Future Outlook

441 A new method for the objective identification of outflow boundaries (OFBs) in GOES-16
442 Advanced Baseline Imager (ABI) data was developed using optical flow motion derivation
443 algorithms and demonstrated with provisional success on a dust storm case study. An optical flow

444 system constructed for this purpose shows promise in identifying and backtracking object events
445 to their source over traditional flow derivation methods, which can potentially be used to isolate
446 convective OFB features. To the best of the authors' knowledge, this study represents a first
447 attempt to objectively identify OFBs in geostationary satellite imagery.

448 The primary conclusions of this study are that optical flow approaches are now a viable option
449 to acquire meso-scale flows relevant to OFB tracking and detection in 5-min geostationary satellite
450 imagery, though the successful backtracking of OFB features requires use of flow algorithms that
451 can handle the presence of motion discontinuities and stationary background flow. The optical
452 flow algorithm tested in this study produced a dense motion field that was closer than other
453 methods to the true OFB motion and provided valuable information towards full objective OFB
454 identification in new products.

455 While several OFB related image pixels were successfully identified, the algorithm here is
456 relatively immature and remains fraught with false alarms where linear features are incorrectly
457 identified, and where correct features were not successfully backtracked to deep convection. The
458 algorithm is still limited by the assumptions made within optical flow, which only account for
459 changes in image brightness intensity resulting from pure feature advection. Therefore, if no
460 features (e.g. clouds) exist to highlight an OFB boundary within the imagery, the method proposed
461 here would not function properly. The method also struggles to resolve true OFB motions with
462 transparent dust movement, where a textured background beneath the dust may dominate the
463 motion estimate within a scene. Also, while infrared brightness temperature was enough to
464 identify deep convection in this case study, convection may be missed by brightness temperature
465 imagery if it is obscured by a higher cloud layer, or if the minimum cloud-top brightness
466 temperature exceeds an arbitrarily set threshold.

467 Given these limitations, future studies will explore more advanced systems for linear structure
468 identification to identify candidate features for tracking towards full objective OFB identification.
469 A machine learning system will be used to determine which linear characteristics of the image
470 should be backtracked instead of using two-dimensional convolution. Optical flow can be used to
471 precondition training information for a machine learning approach, if the motion or semi-
472 Lagrangian fields are needed. Furthermore, it will be prudent to use deep convection
473 correspondence through optical flow backtracking as one of many fields in future products, such
474 as radial propagation away from storms and near surface meteorological properties, to
475 probabilistically decide if an image pixel is associated with an OFB. To better identify deep
476 convection areas, the GOES Lightning Mapper (GLM) can be used, which provides information
477 on lightning location and energy at 8 km resolution with a 2 ms frame rate.

478 Feature identification with optical flow is not restricted to OFBs alone. For example, the
479 above-anvil cirrus plume (Bedka et al., 2018) over deep convection has been identified as an
480 important indicator of severe weather at the ground, yet no objective means of identification exists
481 today. The properties from optical flow could be used as an additional source of information in
482 such algorithm designs, allowing researchers to backtrack features to their apparent source (the
483 overshooting top in the case of the above-anvil cirrus plume) and monitor cloud temperature and
484 visible texture trends, or to simply use the dense motion itself to achieve better results. This
485 method will also be applicable to other cold pool outflow phenomena, such as bores, for which
486 new algorithms could utilize numerical model or surface observations for further clarification of
487 linear feature type.

488 Motion discontinuity preserving optical flow will also benefit several current algorithms for
489 monitoring deep convection in satellite imagery. Objective deep convection cloud-top flow field

490 algorithms (Apke et al., 2016, 2018) will benefit particularly when sharp cloud-edges and ground
491 pixels are present in an image scene. Systems that use infrared cloud-top cooling or emissivity
492 differences for deep convection nowcasting will also improve with better estimates of pre-
493 convective cumulus motion (Cintineo et al., 2014; Mecikalski and Bedka, 2006).

494 While the utility of a backwards trajectory approach was considered here, many other possible
495 methods exist for exploiting the semi-Lagrangian properties of time-resolved observations in
496 satellite imagery (e.g. Nisi et al., 2014). Use of fine-temporal resolution information will improve
497 optical flow estimates, and in turn the estimates of brightness temperature, reflectance, or cloud-
498 property changes in a moving frame of reference. We will explore these and other refinements in
499 ongoing and future work on this exciting frontier of next-generation ABI-enabled science.

500

501 **7. Data Availability**

502 Data used in this study are available upon request by contacting the lead author.

503

504 **8. Author Contributions**

505 JMA developed the primary code for the optical flow approach used here. He also co-
506 developed the objective outflow boundary identification techniques, and related Figs. (1, 2, 3, 4,
507 8-11) in the manuscript. He co-wrote much of the text and led the efforts of interpretation, analysis,
508 and presentation of the results.

509 KAH was responsible for case study identification, and collection of surface, radar, and HRRR
510 data relevant to this case study. He developed Figs. 5, 6 and 7. He also co-developed the objective
511 OFB identification process and co-wrote the text.

512 SDM was the PI of the Multidisciplinary University Research Initiative (MURI) research
513 project and was responsible for managing the development of the optical flow code and outflow
514 boundary case study information involved in Figs. (2, 3, 4, 8-11). He co-developed the objective
515 identification process and maintained and managed the satellite data necessary to complete the
516 study. He also co-wrote much of the text within the manuscript.

517 DAP co-developed the objective OFB identification scheme. He also co-developed the
518 conceptual Figs. 2 and 3 to add clarity to the optical flow process used here and co-wrote the text
519 within the manuscript.

520

521 **9. Competing Interests**

522 The authors declare that they have no conflicts of interest.

523

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531 **11. References**

- 532 Anandan, P.: A computational framework and an algorithm for the measurement of visual
533 motion, *Int. J. Comput. Vis.*, 2(3), 283–310, doi:10.1007/BF00158167, 1989.
- 534 Apke, J. M., Mecikalski, J. R. and Jewett, C. P.: Analysis of Mesoscale Atmospheric Flows
535 above Mature Deep Convection Using Super Rapid Scan Geostationary Satellite Data, *J. Appl.*
536 *Meteorol. Climatol.*, 55(9), 1859–1887, doi:10.1175/JAMC-D-15-0253.1, 2016.
- 537 Apke, J. M., Mecikalski, J. R., Bedka, K. M., McCaul Jr., E. W., Homeyer, C. R. and Jewett, C.
538 P.: Relationships Between Deep Convection Updraft Characteristics and Satellite Based Super
539 Rapid Scan Mesoscale Atmospheric Motion Vector Derived Flow, *Mon. Wea. Rev.*, 146, 3461–
540 3480 [online] Available from: <https://doi.org/10.1175/MWR-D-18-0119.1>, 2018.
- 541 Associated Press: Sheriff: 11 people dead after Missouri tourist boat accident, Assoc. Press
542 [online] Available from: <https://www.apnews.com/a4031f35b4744775a7f59216a56077ed>, 2018.
- 543 Baker, S. and Matthews, I.: Lucas-Kanade 20 years on: A unifying framework, *Int. J. Comput.*
544 *Vis.*, 56(3), 221–255, doi:10.1023/B:VISI.0000011205.11775.fd, 2004.
- 545 Baker, S., Scharstein, D., Lewis, J. P., Roth, S., Black, M. J. and Szeliski, R.: A database and
546 evaluation methodology for optical flow, *Int. J. Comput. Vis.*, 92(1), 1–31, doi:10.1007/s11263-
547 010-0390-2, 2011.
- 548 Barron, J. L., Fleet, D. J. and Beauchemin, S. S.: Performance of Optical Flow Techniques, *Int.*
549 *J. Comput. Vis.*, 12, 43–77, 1994.
- 550 Bedka, K. M., Velden, C. S., Petersen, R. A., Feltz, W. F. and Mecikalski, J. R.: Comparisons of
551 satellite-derived atmospheric motion vectors, rawinsondes, and NOAA wind profiler
552 observations, *J. Appl. Meteorol. Climatol.*, 48(8), 1542–1561, doi:10.1175/2009JAMC1867.1,
553 2009.
- 554 Bedka, K. M., Murillo, E., Homeyer, C. R., Scarino, B. and Mersiovski, H.: The Above Anvil
555 Cirrus Plume: The Most Definitive Severe Weather Indicator from Visible and Infrared Satellite
556 Imagery, *J. Appl. Meteor.*, In Prep, 2018.
- 557 Benjamin, S. G., Weygandt, S. S., Brown, J. M., Hu, M., Alexander, C., Smirnova, T. G., Olson,
558 J. B., James, E., Dowell, D. C., Grell, G. A., Lin, H., Peckham, S. E., Smith, T. L., Moninger, W.
559 R., Kenyon, J. and Manikin, G. S.: A North American Hourly Assimilation and Model Forecast
560 Cycle: The Rapid Refresh, *Mon. Weather Rev.*, 144(4), 1669–1694, doi:10.1175/MWR-D-15-
561 0242.1, 2016.
- 562 Black, M. J. and Anandan, P.: The robust estimation of multiple motions: Parametric and
563 piecewise-smooth flow fields, *Comput. Vis. Image Underst.*, doi:10.1006/cviu.1996.0006, 1996.
- 564 Bresky, W. C. and Daniels, J.: The feasibility of an optical flow algorithm for estimating
565 atmospheric motion, *Proc. Eighth Int. Wind. Work.*, 24–28, 2006.
- 566 Bresky, W. C., Daniels, J. M., Bailey, A. A. and Wanzong, S. T.: New methods toward
567 minimizing the slow speed bias associated with atmospheric motion vectors, *J. Appl. Meteorol.*
568 *Climatol.*, 51(12), 2137–2151, doi:10.1175/JAMC-D-11-0234.1, 2012.

569 Van Den Broeke, M. S. and Alsarraf, H.: Polarimetric Radar Observations of Dust Storms at C-
570 and S-Band, *J. Oper. Meteor.*, 4(9), 123–131, 2016.

571 Brox, T.: From Pixels to Regions: Partial Differential Equations in Image Analysis, Ph.D. thesis,
572 Saarland University, Saarbrücken, Germany., 2005.

573 Brox, T., Bruhn, A., Papenberg, N. and Weickert, J.: High accuracy optical flow estimation
574 based on a theory for warping, 2004 *Eur. Conf. Comput. Vis.*, 4(May), 25–36, 2004.

575 Butler, D. J., Wulff, J., Stanley, G. B. and Black, M. J.: A naturalistic open source movie for
576 optical flow evaluation, *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell.*
577 *Lect. Notes Bioinformatics)*, 7577 LNCS(PART 6), 611–625, doi:10.1007/978-3-642-33783-
578 3_44, 2012.

579 Byers, H. R. and Braham Jr., R. R.: *The Thunderstorm*, U.S. Thund., U.S. Gov't. Printing Office,
580 Washington D.C., 1949.

581 Chipilski, H. G., Wang, X. and Parsons., D. P.: An Object-Based Algorithm for the Identification
582 and Tracking of Convective Outflow Boundaries, *Mon. Weather Rev.*, 1–57, doi:10.1175/MWR-
583 D-18-0116.1, 2018.

584 Cintineo, J. L., Pavolonis, M. J., Sieglaff, J. M. and Lindsey, D. T.: An Empirical Model for
585 Assessing the Severe Weather Potential of Developing Convection, *Weather Forecast.*, 29(3),
586 639–653, doi:10.1175/WAF-D-13-00113.1, 2014.

587 Crum, T. D. and Alberty, R. L.: *The WSR-88D and the WSR-88D Operational Support Facility*,
588 *Bull. Am. Meteorol. Soc.*, 74(9), 1669–1687, doi:10.1175/1520-0477, 1993.

589 Daniels, J. M., Bresky, W. C., Wanzong, S. T., Velden, C. S. and Berger, H.: GOES-R Advanced
590 Baseline Imager (ABI) Algorithm Theoretical Basis Document for Derived Motion Winds.
591 [online] Available from: <https://www.goes-r.gov/products/baseline-derived-motion-winds.html>,
592 2010.

593 Farnebäck, G.: Two-Frame Motion Estimation Based on Polynomial Expansion, in *Proceedings:*
594 *Eighth IEEE International Conference on Computer Vision*, vol. 1, pp. 171–177., 2001.

595 Fleet, D. and Weiss, Y.: Optical Flow Estimation, *Math. Model. Comput. Vis. Handb.*, 239–257,
596 doi:10.1109/TIP.2009.2032341, 2005.

597 Fortun, D., Bouthemy, P., Kervrann, C., Fortun, D., Bouthemy, P. and Kervrann, C.: Optical
598 flow modeling and computation : a survey To cite this version : Optical flow modeling and
599 computation : a survey, *Comput. Vis. Image Underst.*, 134, 1–21 [online] Available from:
600 https://hal.inria.fr/hal-01104081/file/CVIU_survey.pdf, 2015.

601 Geiger, A., Lenz, P. and Urtasun, R.: Are we ready for autonomous driving? the KITTI vision
602 benchmark suite, *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, 3354–3361,
603 doi:10.1109/CVPR.2012.6248074, 2012.

604 Gonzalez, R. C. and Woods, R. E.: *Digital Image Processing (3rd Edition)*., 2007.

605 Hardy, K. and Comfort, L. K.: Dynamic decision processes in complex, high-risk operations:
606 *The Yarnell Hill Fire*, June 30, 2013, *Saf. Sci.*, 71(Part A), 39–47,

607 doi:10.1016/j.ssci.2014.04.019, 2015.

608 Héas, P., Mémin, E., Papadakis, N. and Szantai, A.: Layered estimation of atmospheric
609 mesoscale dynamics from satellite imagery, *IEEE Trans. Geosci. Remote Sens.*, 45(12), 4087–
610 4104, doi:10.1109/TGRS.2007.906156, 2007.

611 Hermes, L. G., Witt, A., Smith, S. D., Klinge-Wilson, D., Morris, D., Stumpf, G. and Eilts, M.
612 D.: The Gust-Front Detection and Wind-Shift Algorithms for the Terminal Doppler Weather
613 Radar System, *J. Atmos. Ocean. Technol.*, 10, 693–709, 1993.

614 Horn, B. K. P. and Schunck, B. G.: Determining optical flow, *Artif. Intell.*, 17(1–3), 185–203,
615 doi:10.1016/0004-3702(81)90024-2, 1981.

616 Idso, S. B., Ingram, R. S. and Pritchard, J. M.: An American Haboob, *Bull. Am. Meteorol. Soc.*,
617 53(10), 930–935, doi:10.1175/1520-0477(1972)053<0930:AAH>2.0.CO;2, 1972.

618 Johnson, R. H., Schumacher, R. S., Ruppert, J. H., Lindsey, D. T., Ruthford, J. E. and
619 Kriederman, L.: The Role of Convective Outflow in the Waldo Canyon Fire, *Mon. Weather*
620 *Rev.*, 142(9), 3061–3080, doi:10.1175/MWR-D-13-00361.1, 2014.

621 Klinge, D. L., Smith, D. R. and Wolfson, M. M.: Gust Front Characteristics as Detected by
622 Doppler Radar, *Mon. Weather Rev.*, 115(5), 905–918, doi:10.1175/1520-
623 0493(1987)115<0905:gfcadb>2.0.co;2, 1987.

624 Line, W. E., Schmit, T. J., Lindsey, D. T. and Goodman, S. J.: Use of Geostationary Super Rapid
625 Scan Satellite Imagery by the Storm Prediction Center*, *Weather Forecast.*, 31(2), 483–494,
626 doi:10.1175/WAF-D-15-0135.1, 2016.

627 Mahoney III, W.: Gust front characteristics and the kinematics associated with interacting
628 thunderstorm outflows, *Mon. Weather Rev.*, 116(7), 1474–1492 [online] Available from:
629 [http://journals.ametsoc.org/doi/abs/10.1175/1520-](http://journals.ametsoc.org/doi/abs/10.1175/1520-0493(1988)116%3C1474%3AGFCATK%3E2.0.CO%3B2)
630 [0493\(1988\)116%3C1474%3AGFCATK%3E2.0.CO%3B2](http://journals.ametsoc.org/doi/abs/10.1175/1520-0493(1988)116%3C1474%3AGFCATK%3E2.0.CO%3B2), 1988.

631 Mecikalski, J. R. and Bedka, K. M.: Forecasting Convective Initiation by Monitoring the
632 Evolution of Moving Cumulus in Daytime GOES Imagery, *Mon. Weather Rev.*, 134, 49–78,
633 doi:10.1175/MWR3062.1, 2006.

634 Mecikalski, J. R., Jewett, C. P., Apke, J. M. and Carey, L. D.: Analysis of Cumulus Cloud
635 Updrafts as Observed with 1-Min Resolution Super Rapid Scan GOES Imagery, *Mon. Wea.*
636 *Rev.*, 144(2015), 811–830, doi:10.1175/MWR-D-14-00399.1, 2016.

637 Miller, S. D., Kuciauskas, A. P., Liu, M., Ji, Q., Reid, J. S., Breed, D. W., Walker, A. L. and
638 Mandoos, A. Al: Haboob dust storms of the southern Arabian Peninsula, *J. Geophys. Res.*
639 *Atmos.*, 113(1), 1–26, doi:10.1029/2007JD008550, 2008.

640 Miller, S. D., Schmidt, C. C., Schmit, T. J. and Hillger, D. W.: A case for natural colour imagery
641 from geostationary satellites, and an approximation for the GOES-R ABI, *Int. J. Remote Sens.*,
642 33(13), 3999–4028, doi:10.1080/01431161.2011.637529, 2012.

643 Mitchell, K. E. and Hovermale, J. B.: A Numerical Investigation of the Severe Thunderstorm
644 Gust Front, *Mon. Weather Rev.*, 105(5), 657–675, doi:10.1175/1520-
645 0493(1977)105<0657:aniots>2.0.co;2, 1977.

646 Mueller, C., Saxen, T., Roberts, R., Wilson, J., Betancourt, T., Dettling, S., Oien, N. and Yee, J.:
647 NCAR Auto-Nowcast System, *Weather Forecast.*, 18(4), 545–561, doi:10.1175/1520-
648 0434(2003)018<0545:NAS>2.0.CO;2, 2003.

649 Nieman, S. J., Menzel, W. P., Hayden, C. M., Gray, D., Wanzong, S. T., Velden, C. S. and
650 Daniels, J.: Fully automatic cloud drift winds in NESDIS operations, *Bull. Am. Meteorol. Soc.*,
651 78(6), 1121–1133, 1997.

652 Nisi, L., Ambrosetti, P. and Clementi, L.: Nowcasting severe convection in the Alpine region:
653 The COALITION approach, *Q. J. R. Meteorol. Soc.*, 140(682), 1684–1699, doi:10.1002/qj.2249,
654 2014.

655 NOAA: Automated Surface Observing System user’s guide. National Oceanic and Atmospheric
656 Administration, 61 pp + appendixes. [Available online at
657 <http://www.nws.noa.gov/asos/pdfs/aum-toc.pdf>.], 1998.

658 Peterson, D. A., Hyer, E. J., Campbell, J. R., Fromm, M. D., Hair, J. W., Butler, C. F. and Fenn,
659 M. A.: The 2013 Rim Fire: Implications for predicting extreme fire spread, pyroconvection,
660 smoke emissions, *Bull. Am. Meteorol. Soc.*, 96(2), 229–247, doi:10.1175/BAMS-D-14-00060.1,
661 2015.

662 Peterson, D. A., Fromm, M. D., Solbrig, J. E., Hyer, E. J., Surratt, M. L. and Campbell, J. R.:
663 Detection and inventory of intense pyroconvection in western North America using GOES-15
664 daytime infrared data, *J. Appl. Meteorol. Climatol.*, 56(2), 471–493, doi:10.1175/JAMC-D-16-
665 0226.1, 2017.

666 Peterson, D. A., Campbell, J. R., Hyer, E. J., Fromm, M. D., Kablick, G. P., Cossuth, J. H. and
667 DeLand, M. T.: Wildfire-driven thunderstorms cause a volcano-like stratospheric injection of
668 smoke, *NPJ Clim. Atmos. Sci.*, 1(1), 1–8, doi:10.1038/s41612-018-0039-3, 2018.

669 Press, W. H., Flannery, B. P., Teukolsky, S. A. and Vetterling, W. T.: *Numerical recipes in C:*
670 *the art of scientific programming.*, 1992.

671 Raman, A., Arellano, A. F. and Brost, J. J.: Revisiting haboobs in the southwestern United
672 States: An observational case study of the 5 July 2011 Phoenix dust storm, *Atmos. Environ.*, 89,
673 179–188, doi:10.1016/j.atmosenv.2014.02.026, 2014.

674 Roberts, R. D., Anderson, A. R. S., Nelson, E., Brown, B. G., Wilson, J. W., Pocerlich, M. and
675 Saxen, T.: Impacts of Forecaster Involvement on Convective Storm Initiation and Evolution
676 Nowcasting, *Weather Forecast.*, 27(5), 1061–1089, doi:10.1175/WAF-D-11-00087.1, 2012.

677 Rotunno, R., Klemp, J. B. and Weisman, M. L.: A theory for strong, long-lived squall lines, *J.*
678 *Atmos. Sci.*, 45, 463–485, 1988.

679 Schmit, T. J., Gunshor, M. M., Fu, G., Rink, T., Bah, K. and Wolf, W.: GOES-R Advanced
680 Baseline Imager (ABI) Algorithm Theoretical Basis Document for Cloud and Moisture Imagery
681 Product. Version 2.3., 2010.

682 Schmit, T. J., Goodman, S. J., Lindsey, D. T., Rabin, R. M., Bedka, K. M., Gunshor, M. M.,
683 Cintineo, J. L., Velden, C. S., Scott Bachmeier, A., Lindstrom, S. S. and Schmidt, C. C.:
684 Geostationary Operational Environmental Satellite (GOES)-14 super rapid scan operations to
685 prepare for GOES-R, *J. Appl. Remote Sens.*, 7(1), 073462–073462,

686 doi:10.1117/1.JRS.7.073462, 2013.

687 Schmit, T. J., Griffith, P., Gunshor, M. M., Daniels, J. M., Goodman, S. J. and Lehair, W. J.: A
688 Closer Look at the ABI on the GOES-R Series, *Bull. Am. Meteorol. Soc.*, doi:10.1175/BAMS-
689 D-15-00230.1, 2016.

690 Sieglaff, J. M., Hartung, D. C., Feltz, W. F., Counce, L. M. and Lakshmanan, V.: A satellite-
691 based convective cloud object tracking and multipurpose data fusion tool with application to
692 developing convection, *J. Atmos. Ocean. Technol.*, 30(3), 510–525, doi:10.1175/JTECH-D-12-
693 00114.1, 2013.

694 Smalley, D. J., Bennett, B. J. and Frankel, R.: MIGFA : The Machine Intelligent Gust Front
695 Algorithm for Nexrad, in *32nd Conf on Radar Meteorology/11th Conf. on Mesoscale Processes*,
696 p. 10, Amer. Meteor. Soc., Albuquerque, NM. [online] Available from:
697 https://ams.confex.com/%0Aams/32Rad11Meso/techprogram/paper_96098.htm, 2007.

698 Sun, D., Roth, S. and Black, M. J.: Secrets of optical flow estimation and their principles, in
699 *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern*
700 *Recognition.*, 2010.

701 Uyeda, H. and Zrnić, D. S.: Automatic Detection of Gust Fronts, *J. Atmos. Ocean. Technol.*, 3,
702 36–50, 1986.

703 Velden, C. S. and Bedka, K. M.: Identifying the uncertainty in determining satellite-derived
704 atmospheric motion vector height attribution, *J. Appl. Meteorol. Climatol.*, 48(3), 450–463,
705 doi:10.1175/2008JAMC1957.1, 2009.

706 Velden, C. S., Hayden, C. M., Nieman, S. J., Menzel, W. P., Wanzong, S. and Goerss, J. S.:
707 Upper-Tropospheric Winds Derived from Geostationary Satellite Water Vapor Observations,
708 *Bull. Am. Meteorol. Soc.*, 78(2), 173–195, 1997.

709 Velden, C. S., Daniels, J., Stettner, D., Santek, D., Key, J., Dunion, J., Holmlund, K., Dengel, G.,
710 Bresky, W. and Menzel, P.: Recent-innovations in deriving tropospheric winds from
711 meteorological satellites, *Bull. Am. Meteorol. Soc.*, 86(2), 205–223, doi:10.1175/BAMS-86-2-
712 205, 2005.

713 Wu, Q., Wang, H.-Q., Lin, Y.-J., Zhuang, Y.-Z. and Zhang, Y.: Deriving AMVs from
714 Geostationary Satellite Images Using Optical Flow Algorithm Based on Polynomial Expansion,
715 *J. Atmos. Ocean. Technol.*, 33(8), 1727–1747, doi:10.1175/JTECH-D-16-0013.1, 2016.

716 Yin, D., Nickovic, S., Barbaris, B., Chandy, B. and Sprigg, W. A.: Modeling wind-blown desert
717 dust in the southwestern United States for public health warning: A case study, *Atmos. Environ.*,
718 39(33), 6243–6254, doi:10.1016/j.atmosenv.2005.07.009, 2005.

719 Zrnic, D. S. and Ryzhkov, A. V.: Polarimetry for Weather Surveillance Radars, *Bull. Am.*
720 *Meteorol. Soc.*, 80(3), 389–406, doi:10.1175/1520-0477(1999)080<0389:PFWSR>2.0.CO;2,
721 1999.

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723 **12. List of Tables**

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726 **13. List of Figures**

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729 numerical models (yellow arrow/dash box), and iteratively searches for the target at time 2
730 minimizing the sum-of-square error to get the AMV (red arrow), and b) example cloud evolution
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735 displacements are found in the initial coarse grid (yellow arrow at the top of the pyramid), which
736 are used as initial displacements for the next levels (red and blue arrows). The final
737 displacement is the sum of each displacement estimate (white arrow). In this schematic, an
738 example scale factor of 0.5 was used over 3 pyramid levels, in this work, a scale factor of 0.95
739 for 77 levels was used.

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741 (bottom) over south-central AZ, centered on an OFB of interest.

742 **Figure 5.** The KIWA Radar 2244 UTC 0.5° horizontal reflectivity (top) in dBZ and correlation
743 coefficient (bottom). Range rings in grey indicate every 30° azimuth and 50 km in range.

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747 located at (32.95 °N -111.77 °E). The red line indicates the approximate time of boundary
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756 backtracking the c) subjectively and d) objectively identified OFB features are also shown,
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762 (knots). Circles represent motion < 5 kts, which commonly occur over ground pixels.

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765 and the Wu et al. (2016) approach (orange/red) at a) 0023 UTC, b) 2358 UTC, c) 2338 UTC and
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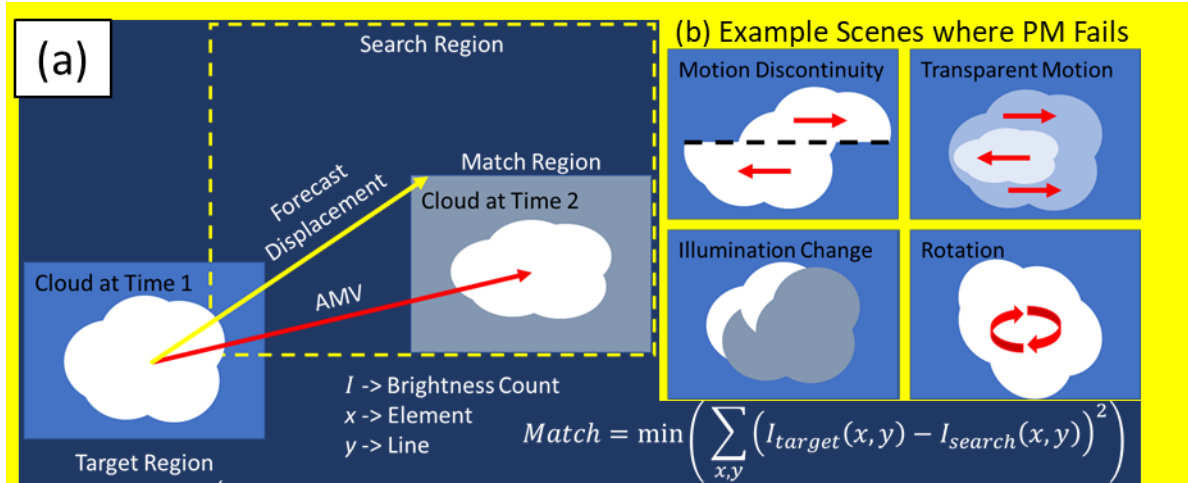
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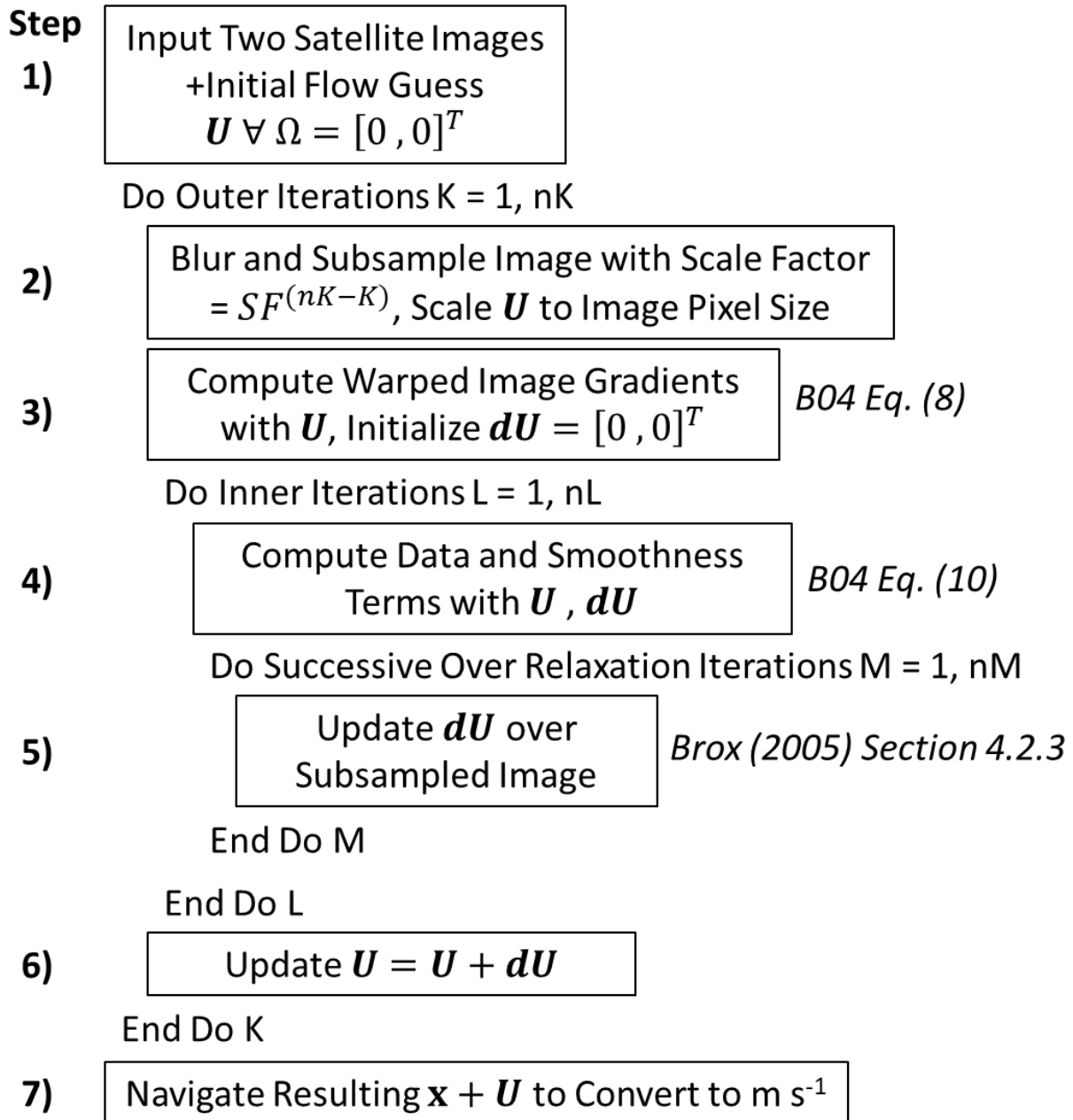
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Parameter	Value
Outer Iterations (Pyramid Levels, nK)	77
Inner Iterations (nL)	10
Successive Over-Relaxation Iterations (nM)	5
Successive Over-Relaxation Parameter	1.99
Pyramid Scale Factor (SF)	0.95
γ	10
α	50

775



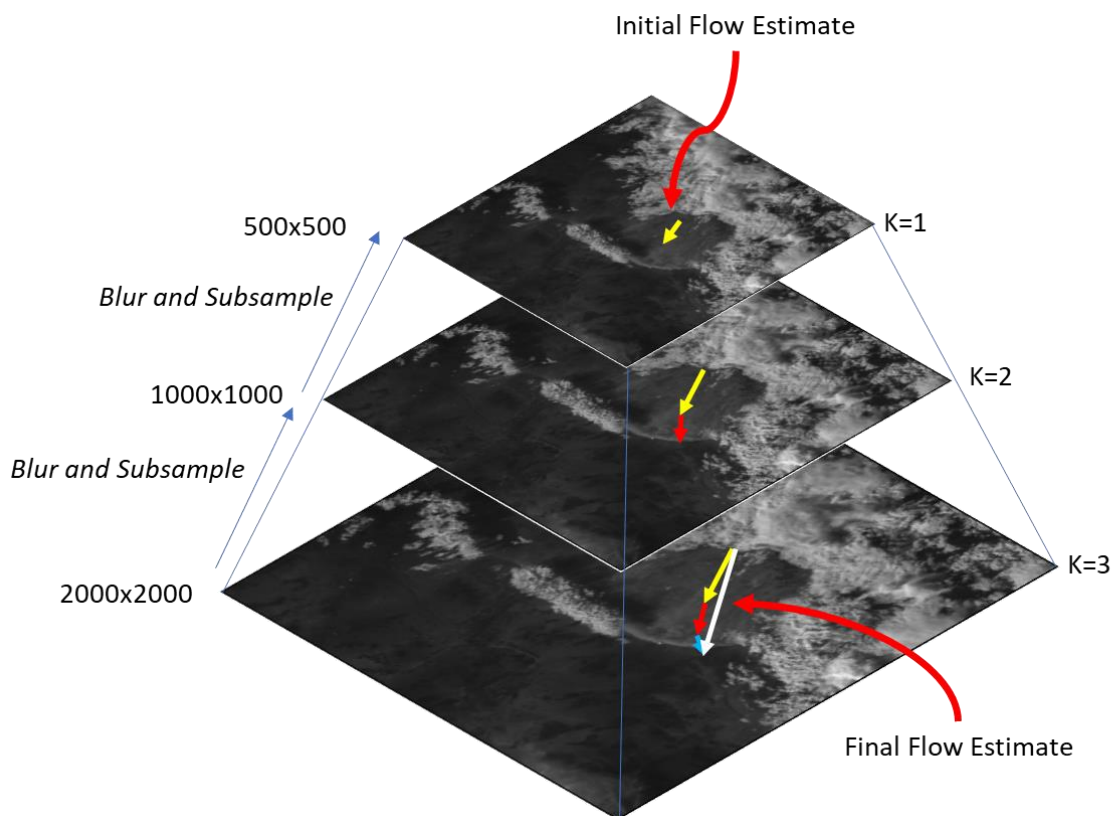
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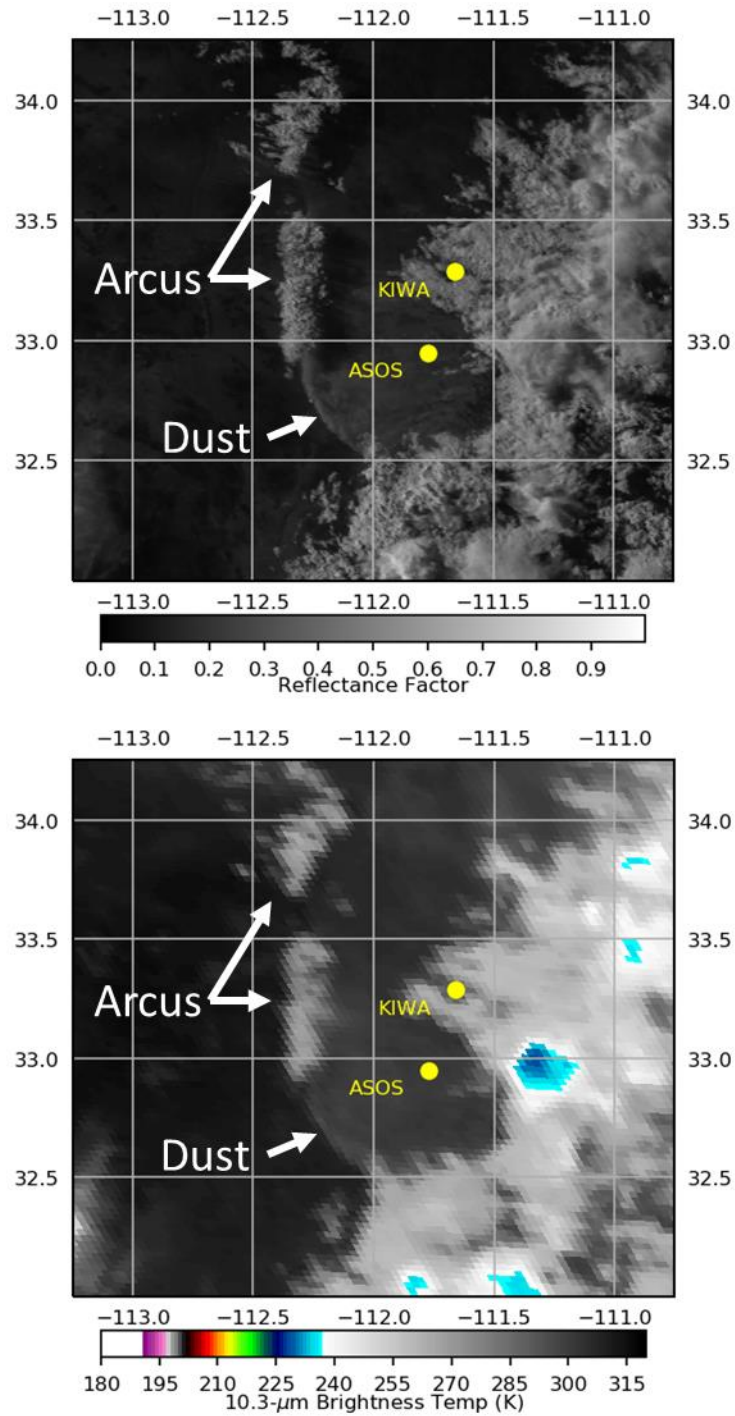
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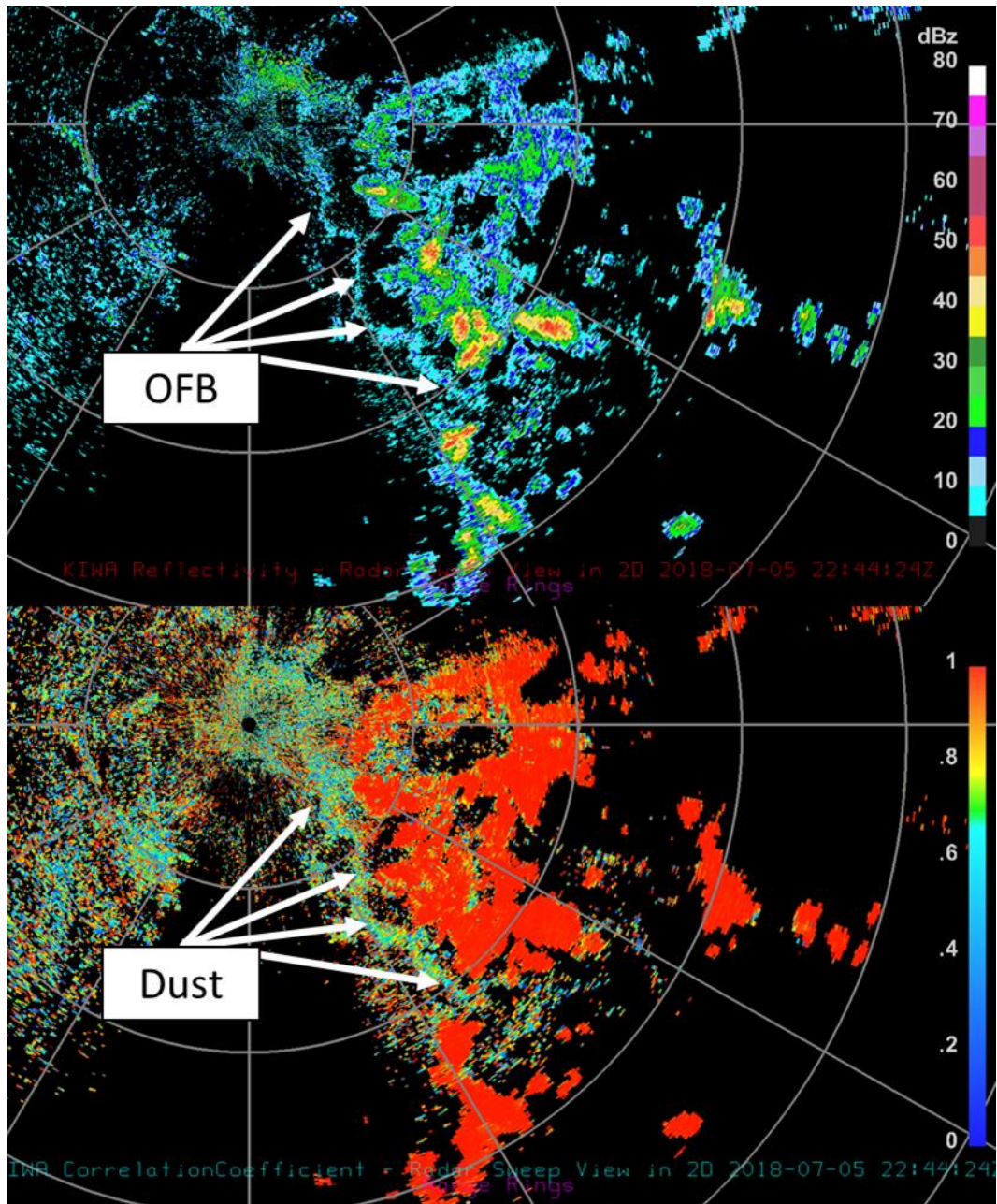
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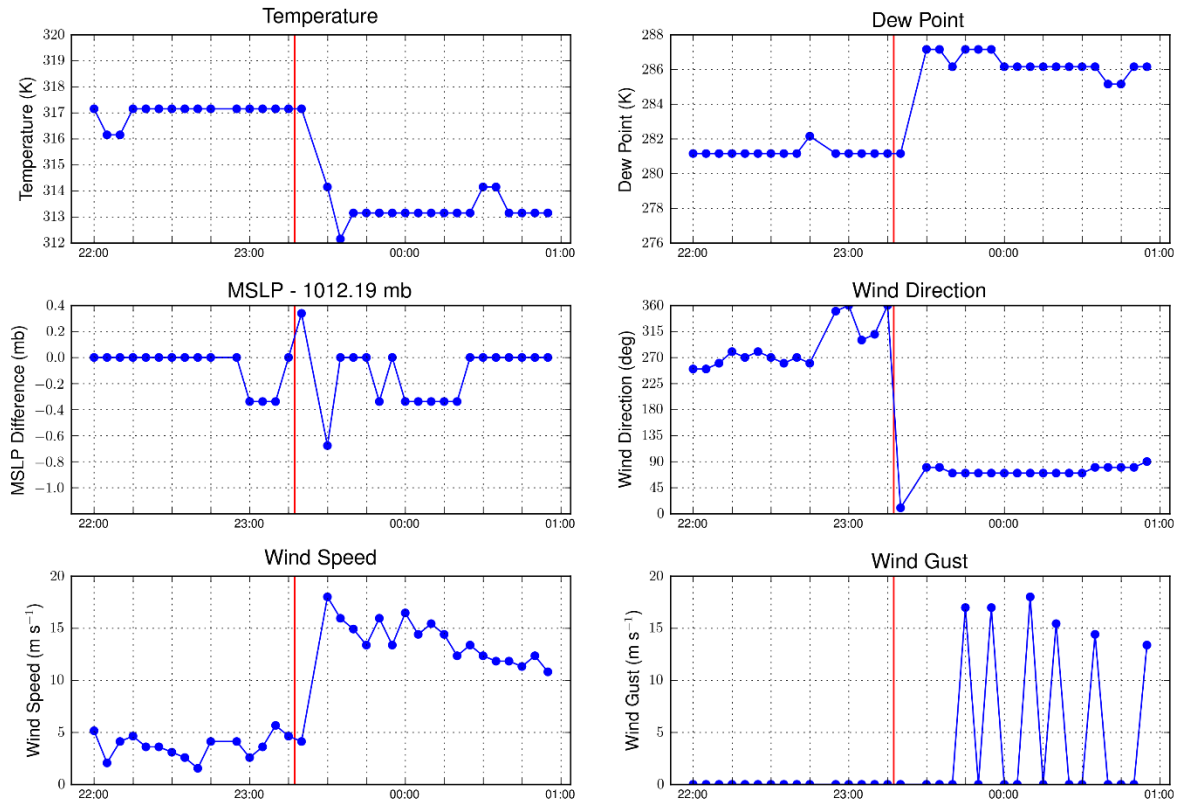
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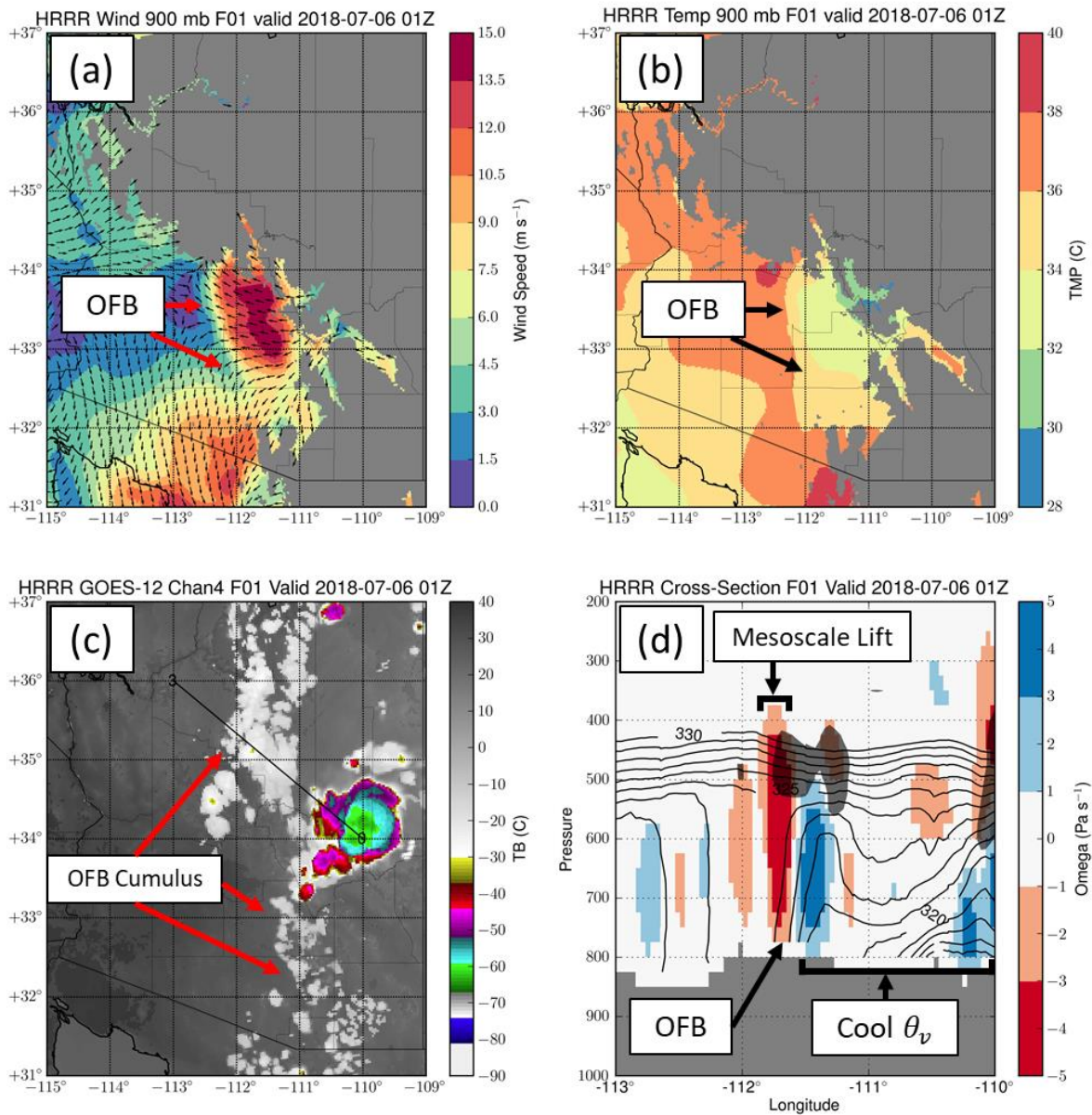
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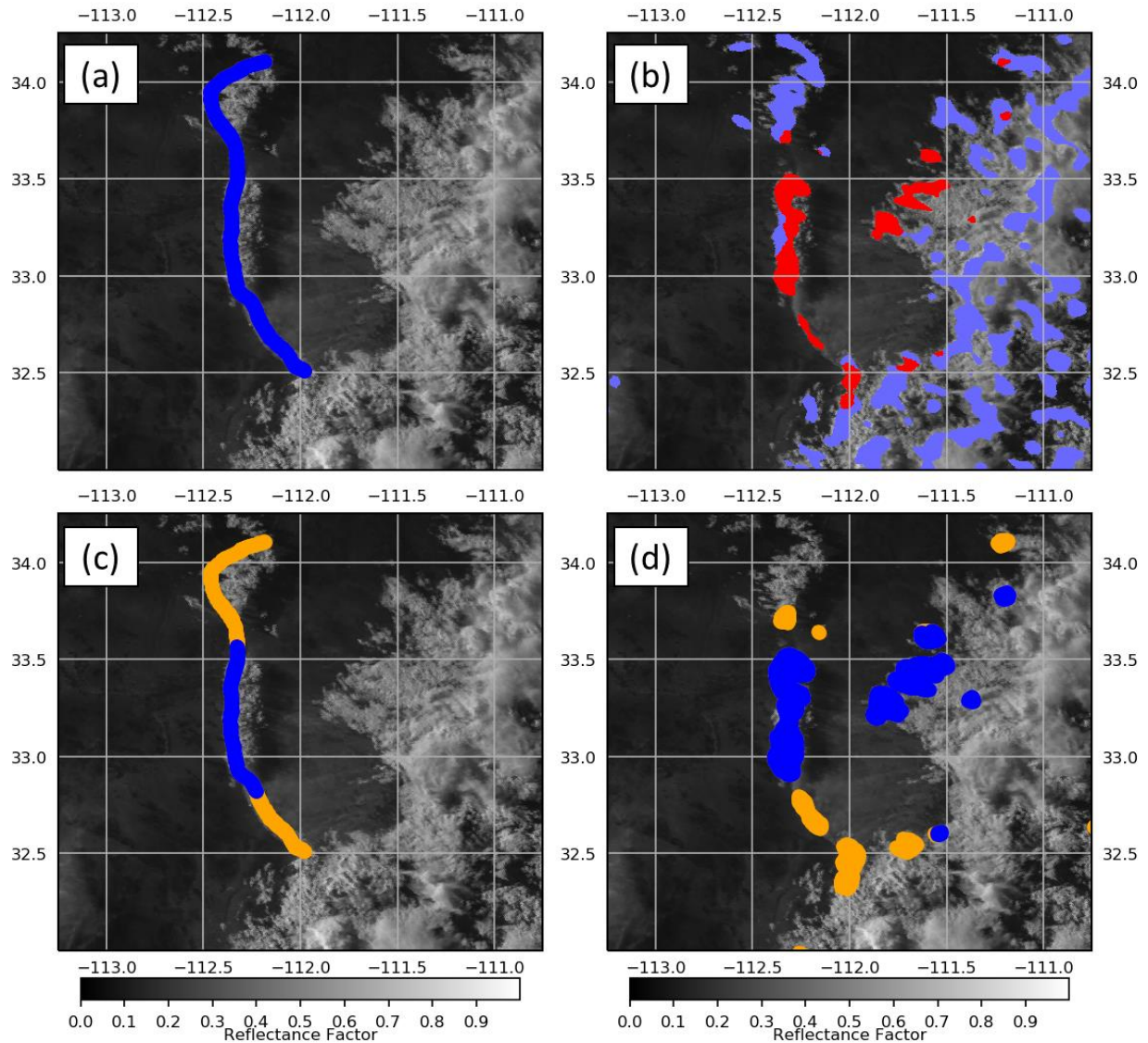
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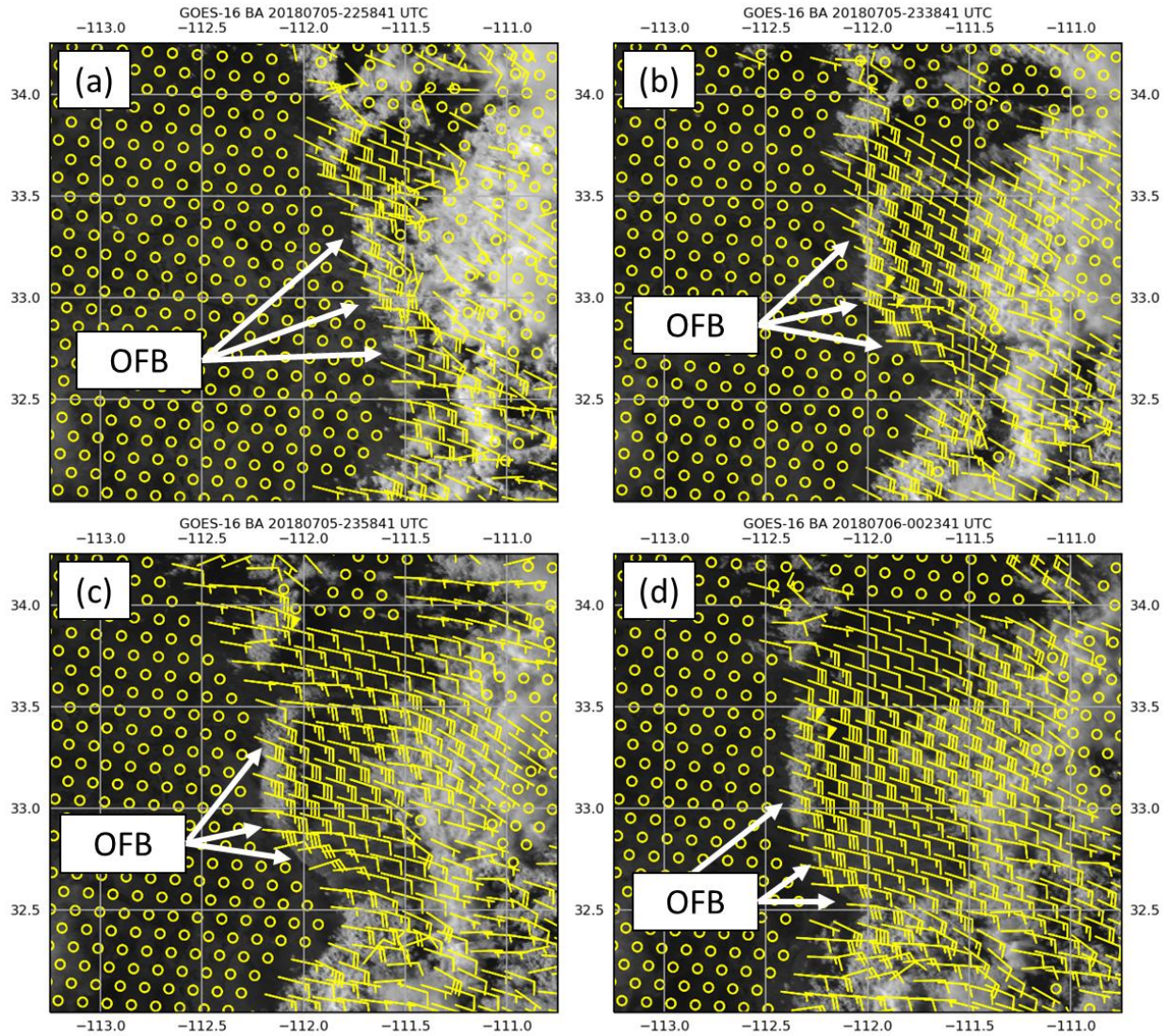
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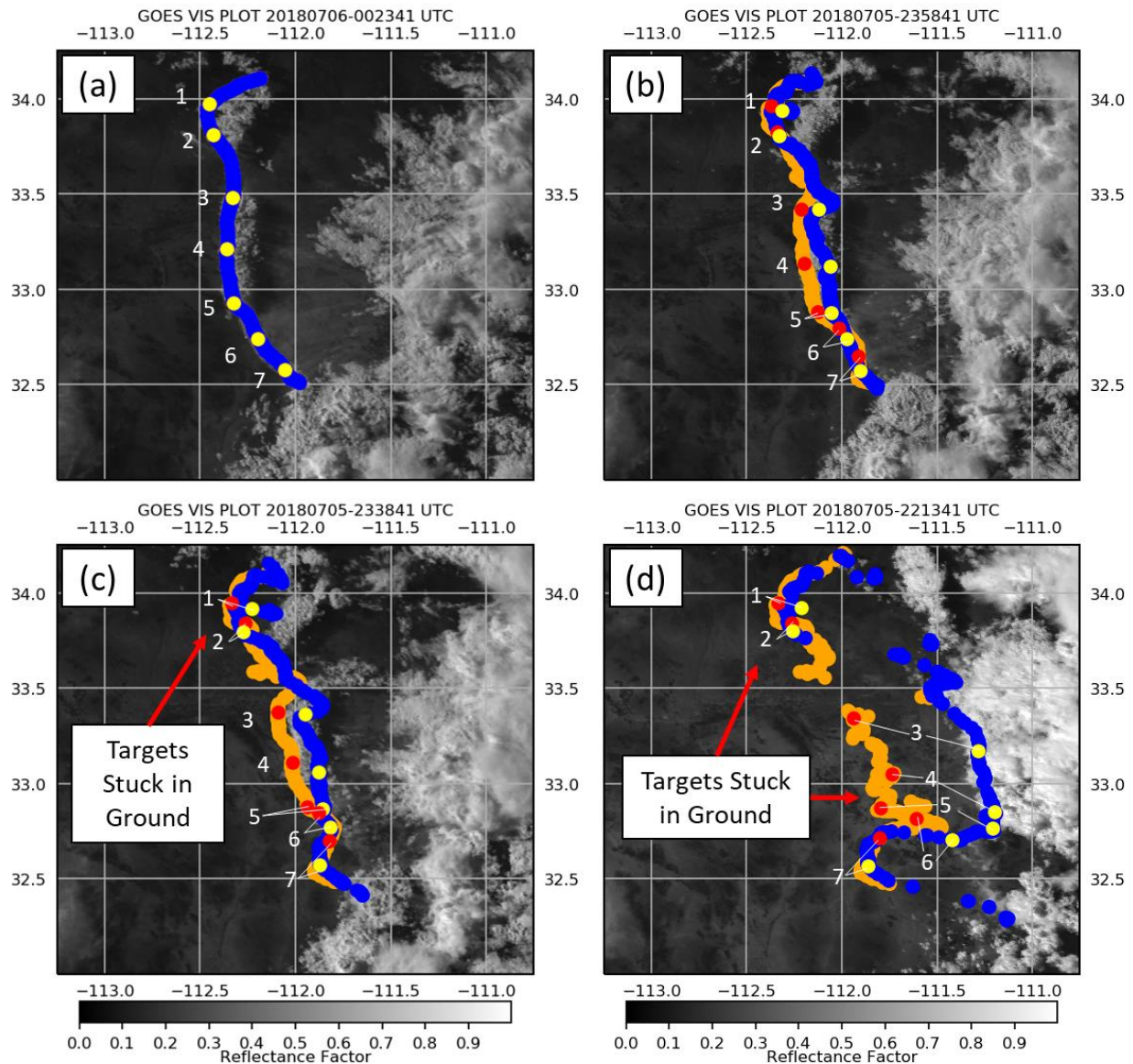


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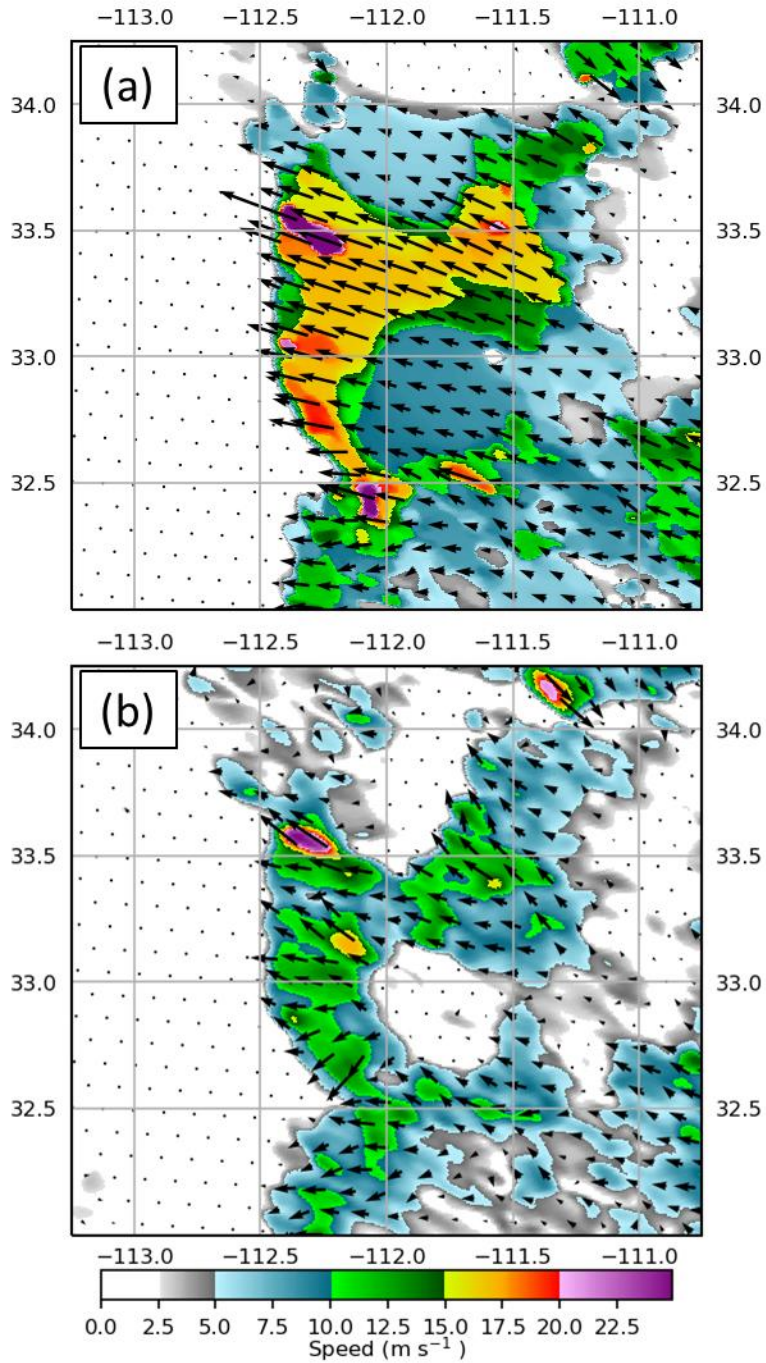
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