Object-Based Algorithm for the Identification and Tracking of Convective Outflow Boundaries in Numerical Models[✉]

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ABSTRACT

A novel object-based algorithm capable of identifying and tracking convective outflow boundaries in convection-allowing numerical models is presented in this study. The most distinct feature of the proposed algorithm is its ability to seamlessly analyze numerically simulated density currents and bores, both of which play an important role in the dynamics of nocturnal convective systems. The unified identification and classification of these morphologically different phenomena is achieved through a multivariate approach combined with appropriate image processing techniques. The tracking component of the algorithm utilizes two dynamical constraints, which improve the object association results in comparison to methods based on statistical assumptions alone. Special attention is placed on some of the outstanding challenges regarding the formulation of the algorithm and possible ways to address those in future research. Apart from describing the technical details behind the algorithm, this study also introduces specific algorithm applications relevant to the analysis and prediction of bores. These applications are illustrated for a retrospective case study simulated with a convection-allowing ensemble prediction system. The paper highlights how the newly developed algorithm tools naturally form a foundation for understanding the initiation, structure, and evolution of bores and convective systems in the nocturnal environment.

1. Introduction

Convectively generated outflow boundaries, such as density currents and bores, have an important contribution to the dynamics of mesoscale convective systems (MCSs). The theoretical importance of density currents is well established due to their critical role in the MCS evolution (e.g., Rotunno et al. 1988; Weisman and Rotunno 2004). On the other hand, atmospheric bores are still less familiar to the meteorological community, but these disturbances have received considerable attention recently, including being a focus of the Plains Elevated Convection at Night field campaign (PECAN; Geerts et al. 2017). The increasing interest in bores is largely driven by their ability to initiate and maintain nocturnal MCSs (Carbone et al. 1990;

Crook et al. 1990; Locatelli et al. 2002; Parker 2008; Blake et al. 2017; Parsons et al. 2018). Recent work has also shown that bores occur commonly in association with warm season nocturnal convection over the Great Plains (Haghi et al. 2017).

The dynamical significance of convective outflow boundaries has prompted the scientific community to create automated algorithms for identifying and tracking these features. The earliest algorithm developed for this purpose was entirely based on observational data and closely connected to the procurement plans for the Next Generation Weather Radar (NEXRAD) system (e.g., Crum and Alberty 1993). In particular, Uyeda and Zrnić (1986) as well as Smith et al. (1989) were the first to describe radar-based algorithms for gust front (density current) detection that relied on the velocity convergence along radials. Later enhancements to these algorithms included the addition of radar reflectivity in the Advanced Gust Front Algorithm (AGFA; Eilts et al. 1991) and the use of knowledge-based signal processing in the Machine Intelligent Gust Front Algorithm (MIGFA; Delanoy and Troxel 1993; Troxel et al. 1996; Smalley et al. 2005).

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Likewise, advances in computational resources have made it possible to identify and track convective outflow boundaries in high-resolution model outputs. Previous model-based algorithms have focused on detecting density currents by incorporating various physical parameters, such as temperature (Gentine et al. 2016), density potential temperature (Torri et al. 2015; Drager and van den Heever 2017), buoyancy (Tompkins 2001; Seigel 2014), wind (Langhans and Romps 2015), or a combination of several relevant parameters (Li et al. 2014).

Although the aforementioned methodologies have greatly enhanced our understanding of density current and gust front dynamics, they are somewhat restricted in their application, compared to the algorithm presented in this paper. On one hand, the approaches reviewed earlier on are not suitable for detecting multiple types of convective outflow boundaries. This limitation can be problematic with regard to typical nighttime environments in which density currents can trigger atmospheric bores upon their interaction with the stable boundary layer (White and Helfrich 2012). The frequent generation of bores during the nighttime hours (Haghi et al. 2017) and their important role in the maintenance of nocturnal MCSs (Parker 2008; Blake et al. 2017) necessitate the development of methods to detect and track bores as well as their parent density currents. The other limitation of earlier convective outflow algorithms is that they have been mostly applied in idealized modeling frameworks, which may make them inappropriate for real-time forecasting applications.

To understand the interplay between nocturnal outflow boundaries and convective systems in real-time high-resolution numerical weather prediction (NWP) models, this study presents a novel object-based algorithm that is capable of seamlessly identifying density currents and bores. The latter is achieved by employing a multivariate approach similar to the dryline identification algorithm of Clark et al. (2015). Rather than attempting to detect all convective outflow boundaries present in high-resolution model simulations, the objective of this algorithm is to isolate only those that provide sufficient lifting for the initiation and maintenance of nocturnal MCSs. The latter goal falls in line with the recent findings of Parker (2008), French and Parker (2010), and Parsons et al. (2018), who suggest that the primary lifting mechanism for nocturnal MCSs can change from a density current to an internal bore with the onset of nocturnal cooling.

Aside from the specific choice of identification parameters, the proposed algorithm differs from the previously discussed methods in terms of how it tracks the identified objects in time. Traditionally, object-tracking techniques rely on statistical methods to match objects

from two different model time steps (Lakshmanan 2012). By contrast, the object tracker proposed in this study accounts for the dynamics of convective outflow boundaries in an explicit manner. As will be shown later in the paper, imposing dynamical constraints in the algorithm yields more robust tracking results, compared to an algorithm based on statistical considerations alone. It is also worth remarking that developing algorithms with due regard to the dynamical aspects of the tracked objects was a key recommendation of Davis et al. (2009b)—one of the first studies focusing on object-based identification and verification using NWP data.

In addition to the technical details behind the algorithm framework, this paper also highlights a spectrum of additional algorithm applications relevant for bore research and operational forecasting of nocturnal storms. Generally speaking, these algorithm applications can be utilized in two different ways. The first pertains to the verification of numerically simulated convective outflow boundaries. With the advance of convection-allowing NWP models, object-based verification techniques like the Method for Object-Based Diagnostic Evaluation (MODE; Davis et al. 2006a) have become a popular choice for validating the accuracy of localized and spatially inhomogeneous fields such as precipitation (e.g., Davis et al. 2009a; Johnson et al. 2011a,b; Johnson and Wang 2012, 2013; Johnson et al. 2013; Clark et al. 2014). Unfortunately, the majority of these object-based methods cannot be readily extended to verify bore forecasts. MODE, for instance, relies on the presence of continuous observational datasets in order to verify model forecasts, which is not feasible in the case of convective outflow boundaries.

Second, the algorithm applications proposed in this paper can be also used to obtain a better understanding of the underlying bore dynamics, as well as the role of bores in initiating and maintaining nocturnal MCSs. To examine the characteristics of numerically simulated bores, previous studies (e.g., Martin and Johnson 2008; Koch et al. 2008) had to first identify their location by subjectively examining the appropriate model output fields. While this is a reasonable approach in terms of single case studies, analyzing the dynamical properties of bores in large datasets spanning a large number of numerical simulations is considerably more time consuming and, additionally, prone to human errors.

The algorithm framework and the attendant algorithm applications in this study are illustrated through a forecast experiment based on the 6 July 2015 PECAN case study. Using the Weather Research and Forecasting (WRF) Model (Powers et al. 2017), 40 ensemble members with a horizontal grid spacing of 1 km are run between 0300 and 0900 UTC. These high-resolution forecast members

are initialized with a Gridpoint Statistical Interpolation (GSI)-based convection-allowing ensemble data assimilation system (Johnson et al. 2015; Johnson and Wang 2017; Wang and Wang 2017) after assimilating both radar and conventional data over a time window of 3 and 12 h, respectively.

The rest of the paper is organized as follows. Sections 2 and 3 introduce the identification and tracking components of the algorithm. Section 4 describes several algorithm tools and their application to the 6 July 2015 case study. Finally, section 5 summarizes the main aspects of the algorithm, outlines some of its limitations, and suggests possible ways to overcome those in future work.

2. Identification of convective outflow boundaries

a. Concept

As elucidated in section 1, the novelty of this algorithm comes from the unified description of density currents and bores, which is made possible by taking into account the *dynamical similarities* between these two convective outflow boundaries. Specifically, it is well known that (i) density currents and bores are characterized by high values of vertical velocity along their leading edge, and (ii) their passage leads to a sudden jump in pressure near the surface. The pressure rise in density currents is mostly hydrostatic in nature and arises due to the horizontal advection of cold air behind them, but it also contains a nonhydrostatic component associated with the deceleration of the density current relative inflow. This is to be contrasted with the pressure increase in a bore, which is caused by the net upward displacement and subsequent adiabatic cooling of near-surface stable air. The identification component of the algorithm parameterizes these effects through the 1-km above ground level (AGL) vertical velocity ($w^{1\text{km}}$) and the temporal change in mean sea level pressure (Δp), where Δ represents the model time step and is set to be 15 min in this study. Although the choice of a particular height level for the vertical velocity is somewhat arbitrary, the 1-km AGL vertical velocity was selected because it (i) marks the location where the prefrontal updraft of a convective outflow boundary is likely to be found (e.g., Rotunno et al. 1988) and (ii) has been used in some real-time NWP forecast products to assist the bore missions during the PECAN field campaign (Johnson et al. 2017). After carefully choosing representative threshold values for these two model variables (see section 2b for details), their corresponding binary fields are combined through a binary AND operation (1 and 0 for meeting or not meeting the criteria, respectively; see bottom-left side of Fig. 1). Later on, the algorithm utilizes the temporal change in the 2-m temperature (ΔT) to determine the morphology of

the identified objects. By definition, density currents cause a drop in the near-surface temperature [i.e., $\Delta T < 0^\circ\text{C} (15\text{ min})^{-1}$]. Nevertheless, the algorithm classifies the identified objects as density currents only if $\Delta T < \Delta T^{\text{DC}} = -1^\circ\text{C} (15\text{ min})^{-1}$, where the superscript DC denotes that the ΔT threshold refers specifically to density currents (see Table 1). The lower ΔT^{DC} value is chosen deliberately to ensure that the algorithm (i) captures only sufficiently strong density currents that are likely to have dynamic significance and (ii) accounts for the overall cooling of the nocturnal boundary layer. Since the passage of bores either does not change the 2-m temperature or leads to a slight near-surface warming (Koch and Clark 1999), a convective outflow object is classified as a bore only if $\Delta T \geq \Delta T^B = 0^\circ\text{C} (15\text{ min})^{-1}$, where the superscript B is shorthand for bores. It is namely these distinct surface temperature responses that permit the object-based algorithm to determine the morphology of the identified convective outflow boundaries.

The workflow associated with the identification component of the algorithm is further illustrated through the 1-km horizontal grid spacing simulation of the 6 July 2015 case study (Fig. 2), the details of which are summarized in section 1. In particular, the information contained within the Δp and $w^{1\text{km}}$ fields from Figs. 2a and 2b is used to create the convective outflow objects shown in Fig. 2c. The ΔT field from Fig. 2d emphasizes the heterogeneous morphology of the identified objects. For example, the southern portion of the tracked object (refer to the black contours in Fig. 2c) resembles an atmospheric bore (ΔT is neutral or positive), while the northern portion behaves like a density current (ΔT is mostly negative). As expected, the model-simulated reflectivity field in Fig. 2b suggests that the density current is located next to a convectively active region, in contrast to the bore, which has already propagated away from the parent MCS.

Additional evidence for the discriminating capabilities of the algorithm is provided in Fig. 3. The first column of this figure shows the algorithm output for two consecutive times, during which the tracked object splits into two additional objects, and the southern one changes its morphology from a density current to a bore. The objectively determined outflow classification results (Figs. 3a,c) verify successfully against the vertical cross sections for the corresponding forecast lead times (Figs. 3b,d). More specifically, the vertical cross section from Fig. 3b shows classical density current signatures, such as an enhanced prefrontal updraft and a sudden drop in the virtual potential temperature (θ_v) following the passage of the boundary. Contrastingly, there is an amplitude-ordered wave train in the wake of the first convective outflow boundary in Fig. 3d (for x between 0 and 10 km on the

FIG. 1. Workflow for the identification component of the algorithm. The variables p^{mslp} , w^{1km} , T^{2m} , $|\nabla p|$, and A^O refer to the mean sea level pressure, 1-km AG vertical velocity, 2-m temperature, magnitude of the horizontal mean sea level pressure gradient, and object area. Density currents and bores are abbreviated as DC and B, respectively. The current and previous algorithm processing times are denoted as t and $t - \Delta t$, while t_{sep} represents the separation time beyond which the numerical noise magnitude is significantly reduced (see text for more details). To simplify the notation, superscripts are removed upon taking temporal differences between variables (e.g., Δp is equivalent to Δp^{mslp}). Within this workflow, parallelograms represent data I/O, rectangles are the execution of algorithm routines, while rhombi denote specific decision-making processes. The parameter values associated with the identification component of the algorithm are summarized in the first half of Table 1.

TABLE 1. Parameter values for the identification and tracking components of the object-based algorithm. The identification thresholds refer to the smoothed and/or filtered model identification fields.

Parameter	Meaning	Value
Identification component		
Δp^-	Δp identification threshold for $t > t^{\text{sep}}$	$0.25 \text{ hPa (15 min)}^{-1}$
w_2^-	w^{1km} identification threshold for $t > t^{\text{sep}}$	0.2 m s^{-1}
$ \nabla p ^-$	$ \nabla p $ identification threshold for $t < t^{\text{sep}}$	0.2 hPa km^{-1}
w_1^-	w^{1km} identification threshold for $t < t^{\text{sep}}$	0.6 m s^{-1}
ΔT^{DC}	ΔT threshold for identifying density currents	$-1^\circ\text{C (15 min)}^{-1}$
ΔT^{B}	ΔT threshold for identifying bores.	$0^\circ\text{C (15 min)}^{-1}$
t_{sep}	Separation time	150 min
λ_{sep}	Separation wavelength for the DCT	150 km
$\sigma_{\Delta p}$	Standard deviation for smoothing the Δp field	1.5 km
σ_w	Standard deviation for smoothing the w^{1km} field	3 km
$\sigma_{ \nabla p }$	Standard deviation for smoothing the $ \nabla p $ field	2 km
$\sigma_{\Delta T}$	Standard deviation for smoothing the ΔT field	5 km
i^{bo}	Number of iterations for the binary opening operation	1
i^{bc}	Number of iterations for the binary closing operation	10
A^-	Minimum object size at the end of object identification	360 km^2
Tracking component		
CC^-	Minimum allowed cross-correlation coefficient threshold	0.3
CC^+	Maximum allowed cross-correlation coefficient threshold	1.0
β^+	Maximum allowed angle deviation from the PGF direction	90°
V_o^+	Maximum allowed object propagation speed	30 m s^{-1}
δ	Maximum allowed $\mathbf{V}_o^{\text{TM}} - \mathbf{V}_o^{\text{CD}}$ difference	3 m s^{-1}

cross section), which is typical for the passage of an undular bore. It is worth remarking that the bore in Fig. 3d is immediately followed by its parent density current. The latter is located around $x = 0 \text{ km}$ on the cross section and appears to be considerably shallower in comparison to the previously shown forecast lead time (Fig. 3b). Note that the significantly weaker vertical velocities at the leading edge of the shallow density current prevent the object-based

algorithm from identifying it. This example portrays the algorithm's objective to only detect convective outflow boundaries that provide sufficient lifting for the initiation and maintenance of nocturnal convection. The scenario depicted in Fig. 3 corresponds quite well to the idealized simulations of Parker (2008), wherein the primary lifting mechanism required for the sustenance of a nocturnal squall line changes from a density current to a bore following the stabilization of the underlying boundary layer.

b. Implementation

All variables used in the identification component of the algorithm are modified in order to yield meaningful identification results. As far as the w^{1km} and ΔT fields are concerned, Gaussian filters with standard deviations of $\sigma_w = 3 \text{ km}$ and $\sigma_{\Delta T} = 5 \text{ km}$ are applied to remove any small-scale noise (Table 1). The alteration of Δp is slightly more involved due to the presence of numerical noise for short forecast lead times. Specifically, the use of data assimilation (DA) in the numerical simulations from this study introduces spurious inertia-gravity waves due to the imbalance between mass and wind fields (Lynch and Huang 1992; Wang et al. 2013). Although it is possible to remove this spurious numerical noise by exploiting initialization techniques such as the nonlinear normal mode initialization (Baer and Tribbia 1977) and digital filter initialization (Lynch and Huang 1992), this work proposes an alternative technique to remove the numerical noise within the formulation of the algorithm itself. In particular, the discrete cosine transform (DCT; Ahmed et al. 1974) is applied to the pressure tendency field Δp in an attempt to filter out the spurious inertia-gravity waves whose wavelength is considerably larger than the wavelength of the Δp signal defining the convective outflow boundaries. The choice of DCT was guided by the study of Denis et al. (2002), which emphasized the suitability of the method for limited-area models with aperiodic model fields. Although the choice of a scale separation wavelength λ_{sep} is somewhat arbitrary, tuning experiments over three diverse case studies showed that $\lambda_{\text{sep}} = 150 \text{ km}$ is optimal. To filter out the large-scale Δp features, the spectral coefficients corresponding to $\lambda_{\text{sep}} > 150 \text{ km}$ are set to 0 before inverting the Δp field back to physical space. Finally, since the filtered Δp field still contains small-scale features that can degrade the identification capabilities of the algorithm, a Gaussian filter with $\sigma_{\Delta p} = 1.5 \text{ km}$ is applied to the filtered Δp field. The relatively small value of $\sigma_{\Delta p}$ allows the object-based algorithm to detect dissipating bore objects, in which the Δp signature is weak.

It is worth mentioning that the DCT filter may be not as effective during the first hour or two of model integration when the spurious gravity wave activity is

FIG. 2. Illustrating the identification component of the algorithm. The 15-min changes in the (a) mean sea level pressure Δp and (d) 2-m temperature ΔT after these fields have been smoothed and/or filtered with the DCT. (b) The 1-km AGL vertical velocity ($w^{1\text{km}}$; color shaded) and the 35-dBZ contour of simulated radar reflectivity (dark cyan contours). (c) All convective outflow boundaries identified by the object-based algorithm; the target objects tracked in this particular algorithm run are plotted in black, while the rest of the convective outflow objects detected at the current model time step (0645 UTC 6 Jul 2015) are in gray.

prolific and spans a larger spectrum of wavelengths. To address this issue, the algorithm has the option to substitute the Δp field with the magnitude of the horizontal mean sea level pressure gradient $|\nabla p|$ close to the model initialization time (upper-left portion of Fig. 1). Similar to Δp , the $|\nabla p|$ field is smoothed via a Gaussian filter with $\sigma_{|\nabla p|} = 2$ km. The time at which the pressure identification variable changes from $|\nabla p|$ back to Δp is referred to as a separation time t_{sep} and is defined to be the forecast lead time beyond which the absolute value of the

domain-averaged $|\Delta p|$ does not show significant temporal trends ($t^{\text{sep}} = 2$ h 30 min for the numerical simulation used in this study). Algorithm tests comparing its performance with the two pressure identification variables confirmed that $|\nabla p|$ is a reasonable substitute of Δp for very short forecast lead times, but degrades the object identification results in the absence of significant numerical noise. Further note that the threshold value of $w^{1\text{km}}$ for $t < t^{\text{sep}}$ is 3 times larger, compared to its counterpart value for $t > t^{\text{sep}}$ (i.e., $w_1^- = 3w_2^-$; refer to Table 1).

FIG. 3. Example of classifying convective outflow objects for two different forecast times: (top) 0400 UTC and (bottom) 0630 UTC. (a),(c) Location of the identified objects. The color shading corresponds to the object morphology as determined by the identification component of the algorithm: blue represents density currents (DC), red is bores (B), and gray marks those parts of the convective outflow objects whose morphology cannot be determined unambiguously (CO). The final shape of the objects is additionally modified with the medial axis transform. (b),(d) Cross sections are taken along the line segment AA' and show the vertical velocity (w ; color shading) as well the virtual potential temperature (θ_v ; black lines). The thick black contours embedded within the cross sections outline the subjectively determined density current and bore, while the stippled gray shading represents the terrain height.

The latter is intended to help the algorithm identify decaying convective outflow objects with weak vertical motions. Alternative approaches for optimally defining the threshold values of the identification parameters are examined in [section 5](#).

Last, we discuss the application of morphological image processing techniques within the identification component of the object-based algorithm. These techniques aim to address the discontinuous nature of the convective outflow

objects produced as a result of merging the $w^{1\text{km}}$ and Δp (or $|\nabla p|$) fields through the binary AND operation. More specifically, the algorithm incorporates the so-called *open-close filter* ([Dougherty 1992](#)), defined as the sequential application of 1 binary opening and 10 binary closing iterations (see [Table 1](#)). This filter was chosen because of its restoration property, which removes both union and subtractive noises ([Dougherty and Lotufo 2003](#)). In particular, binary opening removes small-scale objects

identified incorrectly by the algorithm, while binary closing fills the gaps between adjacent outflow objects, making their structure more coherent. Note that binary opening is applied first in order to prevent the spurious growth of small-scale objects. The choice of binary iterations (i^{bo} and i^{bc} ; Table 1) was based on several tuning experiments, in which the structure of the identified outflow objects was assessed qualitatively. To ensure that only sufficiently large objects are considered by the algorithm, an additional size thresholding is applied ($A^O > A^-$; bottom-left corner of Fig. 1 and Table 1 for the value of A^-) prior to the classification of the identified convective outflow boundaries as density currents or bores.

c. Grid spacing considerations

Apart from the need to choose appropriate model parameters, the identification of convective outflow boundaries in the algorithm is ultimately dependent on the ability of NWP models to correctly represent their dynamical characteristics (e.g., surface warming, pressure rise). Past studies (Koch et al. 2008; Martin and Johnson 2008; Johnson et al. 2017) along with additional analyses based on the 6 July 2015 simulations (see Fig. S1 in the online supplemental material) have concluded that the adequate representation of atmospheric bores in NWP models requires a horizontal grid spacing of less than 4 km. This, in turn, implies that the object-based algorithm should be used only in conjunction with data from higher-resolution convection-permitting NWP models. With a view of making our algorithm applicable to a broader range of model configurations, the remainder of this section discusses how changes in the horizontal resolution of convection-allowing models impact its identification capabilities. In particular, we comment on the key modifications required to successfully adapt the algorithm to a coarser 3-km model output, which is more typical of currently operational convection-allowing NWP systems such as the High-Resolution Rapid Refresh model (HRRR; Smith et al. 2008).

It is well known that coarser-resolution model simulations tend to have a smoothing effect on the underlying model fields, which can, in turn, have downstream impacts on the number and/or extent of objects identified by the algorithm. Nonetheless, the application of a Gaussian filter implicitly circumvents this problem as it smooths the identification variables from different model resolutions to the same spatial scale. This statement is supported both by Table 2 and Figs. S2a and S2b, which show that the median and interquartile range (IQR) values associated with the smoothed identification variables are nearly identical on the 1- and 3-km model domains (i.e., their ratio is ~ 1). The only exception is the magnitude of the mean sea level pressure gradient $|\nabla p|$, for which the

median and IQR values on the 3-km domain are lower than their respective values on the 1-km domain (refer to Figs. S2c,d). The aforementioned discrepancy arises because the Gaussian filter is applied to model variables with different statistical characteristics: $|\nabla p| \in [0, \infty)$, while $\{w^{1\text{km}}, \Delta p, \Delta T\} \in (-\infty, \infty)$. To use the pressure gradient magnitude as an identification variable on the coarser 3-km model output, the threshold value $|\nabla p|^-$ from Table 1 needs to be scaled accordingly. In this study, the latter was achieved via the quantile mapping (QM) technique (e.g., Reiter et al. 2018). The QM results summarized in Table 2 indicate that the scaling factor for the $|\nabla p|^-$ threshold is $\alpha_{|\nabla p|}^{1 \rightarrow 3} \cong 0.6$; that is, the $|\nabla p|^-$ value needs to be reduced by 40% on the 3-km grid in order for the algorithm to provide equivalent object identification results. As expected, the scaling factors for the other identification variables are ~ 1 , suggesting that their corresponding thresholds do not need to be changed if the algorithm is to be run on numerical simulations with a horizontal grid spacing of 3 km.

Another important consequence of using coarser convection-allowing model simulations with the object-based algorithm is the requirement to adjust the number of iterations in the open-close filter (i.e., i^{bo} and i^{bc} in Table 1). Assuming there is a one-to-one correspondence between the binary fields on two different model domains with a horizontal grid spacing of Δ_1 and Δ_2 , it can be shown that

$$(i_{\Delta_2}^{\text{bo}}, i_{\Delta_2}^{\text{bc}}) \Delta_2 = (i_{\Delta_1}^{\text{bo}}, i_{\Delta_1}^{\text{bc}}) \Delta_1, \quad (1)$$

that is, the number of open-close iterations on the new domain is inversely proportional to the change in model resolution. To account for the fact that the number of iterations must be an integer number (i.e., $i_{\Delta}^{\text{bo}}, i_{\Delta}^{\text{bc}} \in \mathbb{Z}$), the relationship from Eq. (1) is further approximated as

$$(i_{\Delta_2}^{\text{bo}}, i_{\Delta_2}^{\text{bc}}) = (i_{\Delta_1}^{\text{bo}}, i_{\Delta_1}^{\text{bc}}) \frac{\Delta_2}{\Delta_1}, \quad (2)$$

where $\backslash$ represents an integer division operator. Applying Eq. (2) and using the information from Table 1 gives $i_{3\text{km}}^{\text{bo}} = 0$ and $i_{3\text{km}}^{\text{bc}} = 3$, insinuating that the algorithm should not use any binary opening iterations if it is run on model data with a horizontal grid spacing of 3 km.

3. Tracking convective outflow boundaries

a. Concept

The concept behind the object tracker is presented in Fig. 4. This schematic shows how a convective outflow boundary might evolve in a typical nighttime environment

TABLE 2. Dependence of the algorithm's identification component on the horizontal resolution of convection-allowing NWP models. The second and third columns show the median and IQR ratios of the coarser 3-km identification variables to the original 1-km ones. To obtain these ratios, the median and IQR values from one of the ensemble members are averaged throughout the 6-h model integration period used in the 6 Jul 2015 case study. The fourth column shows the scaling factor $\alpha^{1 \rightarrow 3}$ that needs to be applied to the identification thresholds corresponding to the 3-km model output so that the algorithm results from the 1- and 3-km model outputs match. As explained in the text, $\alpha^{1 \rightarrow 3}$ is derived using the quantile mapping (QM) technique. The asterisk next to one of the $\alpha_{w^{\text{ikm}}}^{1 \rightarrow 3}$ values indicates that the scaling factor for w^{ikm} refers to both of its thresholds: $w_1^- = 0.6 \text{ ms}^{-1}$ and $w_2^- = 0.2 \text{ ms}^{-1}$.

Identification variable	Median ratio	IQR ratio	Threshold scaling factor ($\alpha^{1 \rightarrow 3}$)
w^{ikm}	1.00	0.97	0.97*
Δp	1.00	0.97	0.99
$ \nabla p $	0.74	0.63	0.59

and also highlights the key processes that the object tracker is expected to handle. Suppose that the leftmost object in Fig. 4 is one of the many objects identified by the algorithm at some initial time t_0 . Throughout its evolution, the aforementioned object could undergo various changes including (i) translation ($t_0 \rightarrow t_0 + \Delta t$), (ii) splitting ($t_0 + \Delta t \rightarrow t_0 + 2\Delta t$), (iii) merging ($t_0 + 3\Delta t \rightarrow t_0 + 4\Delta t$), and (iv) morphology transformation ($t_0 + 2\Delta t \rightarrow t_0 + 3\Delta t$; blue to red color shading). The purpose of the object tracker is to recognize all of these changes by associating objects between two consecutive image frames (separated by the model time step Δt).

b. Implementation

Association of objects from two neighboring image frames is a challenging problem, particularly in cases of object splitting, merging, or rapid evolution (all of which are common for convective outflow boundaries). Past work on multiobject tracking has examined several techniques with a varying degree of complexity (Lakshmanan 2012). Those methods range from a simple minimization of object distances (greedy approach; Dijkstra 1959) to Kalman filter applications (Kalman 1960). Nevertheless, the aforementioned tracking techniques are prone to errors, especially when the identified objects undergo rapid structural changes. To address these problems, Lakshmanan et al. (2003) developed a hybrid tracking approach that exhibits superior performance over the aforementioned methods. In this work, we use a variation of the hybrid tracking approach to formulate our object tracker.

The components of the object tracker are summarized by the block diagram in Fig. 5 and further illustrated in Fig. 6 through a representative case scenario, in which a

target object

FIG. 4. A schematic showing the concept behind the tracking component of the algorithm as well as the typical evolution of a convective outflow boundary in the nighttime environment starting from an analysis time t_0 . The blue (red) objects represent density currents (atmospheric bores), while the arrows denote the objects' motion vectors.

target object (black shading) splits into two smaller objects (1 and 2; gray shading) at the current model time step. In addition to these two objects, the binary field in Fig. 6 contains an additional third object (3), which is not physically related to the target object. Ideally, the tracking component of the algorithm should only associate objects 1 and 2 with the target object. Within the framework of the object tracker, this is achieved through a sequential application of three different constraints, the technical details of which are explained in the remainder of this section.

The first constraint is purely statistical in nature and utilizes the template matching technique (Brunelli 2009). Template matching calculates the 2D cross correlation between an image $I(x, y)$ and a kernel $K(x, y)$; that is,

$$I(x, y) \circ K(x, y) = \sum_{i=-w/2}^{i=w/2} \sum_{j=-h/2}^{j=h/2} I(x+i, y+j) K(i, j), \quad (3)$$

where (x, y) is a coordinate pair from the model domain, while w and h denote the width and height of the kernel, respectively. The purpose of template matching is to measure the degree of statistical similarity between a candidate object¹ from the current image frame and a target object identified in the previous image frame.

Template matching is performed on each target-candidate object pair for a given algorithm analysis time. We let the smaller of those objects be the kernel $K(x, y)$, while the larger one is the image $I(x, y)$ (refer to splitting and merging scenarios in Fig. 5). To account for different kernel shapes and sizes, the result from Eq. (3) is normalized by the sum of the kernel values to yield the 2D cross-correlation coefficient CC; that is,

¹ A candidate object is an object to be associated with the target object.

FIG. 5. Workflow for the tracking component of the algorithm that illustrates the association procedure between a target object identified in a previous image frame (T) and a candidate object from the current image frame (O). The meaning of different diagram blocks remains the same as in Fig. 1. The superscripts TM/CD refer to the template matching/closest distance approaches used in calculating the candidate object's motion vector $\mathbf{V}_O$; $-\nabla \Pi$ is the PGF, and $\angle \beta(\mathbf{V}_O, -\nabla \Pi)$ denotes the angle between $\mathbf{V}_O$ and $-\nabla \Pi$. The parameter values associated with the tracking component of the algorithm are summarized in the second half of Table 1.

$$CC = \frac{\sum_{i=-w/2}^{i=w/2} \sum_{j=-h/2}^{j=h/2} I(x+i, y+j) K(i, j)}{\sum_{i=-w/2}^{i=w/2} \sum_{j=-h/2}^{j=h/2} K(i, j)}. \quad (4)$$

The object tracker assumes that two objects are statistically related to each other for sufficiently large values of the maximum correlation coefficient ($CC^{\max}$). The value of 0.72 for $CC^{\max}$ in Fig. 6b implies there is a high likelihood that candidate object 1 is associated with the target object. Furthermore, the location of $CC^{\max}$ suggests that object 1 originates from the southern portion of the target object. Both of these inferences are consistent with the object splitting scenario depicted in Fig. 6a.

Apart from measuring the statistical similarity between candidate and target objects, the template matching procedure provides an estimate for the motion vector $\mathbf{V}_O$ (denoted as $\mathbf{V}_O^{\text{TM}}$; see Fig. 5). In particular, $\mathbf{V}_O^{\text{TM}}$ is calculated by dividing the Euclidian distance between the location of the central kernel point² K_{00} ($X_{K_{00}}$) and the location of $CC^{\max}$ ($X_{CC^{\max}}$) (i.e., the distance between the two object centroids) through the model time step Δt . Mathematically,

$$\mathbf{V}_O^{\text{TM}} = \frac{\text{dl}[X_{CC^{\max}}, X_{K_{00}}]}{\Delta t} = \frac{\sqrt{(x_{CC^{\max}} - x_{K_{00}})^2 + (y_{CC^{\max}} - y_{K_{00}})^2}}{\Delta t}. \quad (5)$$

Past algorithm tests have shown that the $\mathbf{V}_O^{\text{TM}}$ estimates can be impacted negatively if objects undergo rapid structural changes. To address this issue, the tracker incorporates a second estimate of $\mathbf{V}_O$ ($\mathbf{V}_O^{\text{CD}}$; see Fig. 5), which is based on the “greedy approach” of Dijkstra (1959) and measures the shortest distance between the center of the kernel $X_{K_{00}}$ and the collection of image points $\mathbf{l} = \{(x_l, y_l) | I(x, y) = 1\}$ corresponding to the coordinates of the larger object; that is,

$$\mathbf{V}_O^{\text{CD}} = \frac{\min\{\text{dl}[X_{K_{00}}, \mathbf{l}]\}}{\Delta t}. \quad (6)$$

As indicated in Fig. 5, $\mathbf{V}_O = \mathbf{V}_O^{\text{TM}}$ only if $|\mathbf{V}_O^{\text{TM}} - \mathbf{V}_O^{\text{CD}}| < \delta = 3 \text{ m s}^{-1}$.

Unlike other approaches, the tracker presented in this paper prioritizes the dynamics of convective outflow boundaries by adding two dynamical constraints as part of the object association procedure. The first one makes use of the pressure gradient force [PGF; $-\nabla \Pi$, where $\Pi \equiv -(1/\rho_0)p^{\text{mslp}}$ is the mean sea level pressure normalized by the reference density value] in an attempt to restrict the direction toward which objects are allowed to propagate. Given that density currents and bores are associated with jumps in the surface pressure, one should expect them to

² Note that the center of the kernel K_{00} is taken to be the closest point to $K(0, 0)$ where $K = 1$.

FIG. 6. (a) Application of the object tracker to a splitting case scenario. The black and gray color shading shows the position of the target and candidate objects, respectively. Their centroids are marked with a blue dot and used to estimate the candidate object's motion vector $\mathbf{V}_o$ (green arrow). The red arrows show the direction of the PGF ($-\nabla\Pi$) computed from the cluster of red points along the target object. The yellow boxes to the right of each candidate object summarize the output from the object tracker. (b) The cross-correlation coefficient (CC) field between the target object and candidate object 1. The red star and the boxed text in the lower-left corner show the location and value of the maximum cross-correlation coefficient $CC^{\max}$. (c) The mean sea level pressure (p^{mslp} ; blue color shading) and the direction of the PGF ($-\nabla\Pi$; red arrows) along the target object.

move approximately in the direction of the PGF (red arrows in Fig. 6c). Having said that, a candidate object can be associated with a target object only if the angle between the object's motion vector and the PGF [i.e., $\angle\beta(\mathbf{V}_o, -\nabla\Pi)$] is sufficiently small. The second dynamical constraint imposes an upper limit on the object's propagation speed and is denoted as V_o^+ . Ideally, V_o^+

should be derived from theoretical considerations regarding either the density current speed [e.g., Eq. (2) in Koch et al. (1991)] or the bore speed [e.g., Eqs. (2.4) and (3.1) in Rottman and Simpson (1989)]. However, to assess the overall feasibility of the second dynamical constraint in the initial algorithm tests, V_o^+ was assumed to remain constant throughout the algorithm runs. A similar

approach was undertaken by Davis et al. (2006b) in their definition of “rain systems.”

Association between a target and a candidate object occurs only if the following three conditions are met simultaneously: $[CC^{\max} \in (CC^-, CC^+)] \wedge [\angle\beta(\mathbf{V}_o, -\nabla\Pi) < \beta^+] \wedge [|\mathbf{V}_o| < V_o^+]$ (refer to the second half of Table 1 for the values of CC^- , CC^+ , β^+ , and V_o^+). According to the object splitting scenario in Fig. 6a, all candidate objects are able to pass the template matching threshold of $CC^- = 0.3$. However, only candidate objects 1 and 2 successfully meet the additional dynamical requirements regarding the object’s propagation speed and direction. Therefore, this example shows how the tracker is able to handle the complex dynamical behavior of convective outflow boundaries by exploiting their statistical and dynamical properties simultaneously.

The addition of dynamical constraints in the object tracker is beneficial for several reasons. First, the simultaneous fulfillment of three different conditions relaxes the prescribed threshold values used for object association (Table 1). Tracking objects only with the aid of template matching [e.g., the hybrid tracking approach of Lakshmanan et al. (2003)] would have required a significantly higher value of CC^- in order to avoid spurious object associations. While a higher CC^- would decrease the number of false alarms, it can also lower the probability of detection, especially when convective outflow objects undergo significant structural changes.

Another benefit of incorporating dynamical constraints in the algorithm’s tracker is to make the search area (i.e., the area within which target and candidate objects are associated) flow dependent (dynamic). This idea is illustrated in the schematic from Fig. 7, where all three candidate objects are perfectly correlated with the target object ($CC^{\max} = 1.0$), but only the first one is physically associated. In this example, both the statically and dynamically defined search areas correctly discard object 3 from the association process. Nevertheless, due to its isotropic search radius ($R = R_s$), the static method will spuriously associate object 2 with the target object despite the aforementioned candidate object being located upstream of the target’s propagation direction. This result is contrasted by our flow-dependent tracking method, which would shrink the search area in accordance to the PGF direction and correctly disassociate candidate object 2 from the target object. It is also worth noting that a tracking method using a static search radius will underperform in cases featuring extreme environmental conditions for which convective outflow boundaries propagate faster than usual. For instance, candidate object 1 in Fig. 7 fails to pass the object association test for the static approach since it moves beyond $R = R_s$ in a single model time step. Provided that

V_o^+ is defined according to theory, the model-derived environmental information should increase the value of V_o^+ and, as a result, extend the search radius $R = V_o^+ \Delta t$ of the tracker. As revealed by the schematic example in Fig. 7, object 1 falls within this extended search area and will be correctly associated with the target object.

The use of dynamical constraints is also important when candidate objects are perfectly correlated with the target object (i.e., $CC^{\max} = 1$; e.g., all candidate objects in Fig. 7). While a perfect match between a candidate and a target object is certainly possible, these situations typically occur if one of the objects is so small that it can fit entirely into the other one. In such cases, the additional dynamical information provided by $\angle\beta$ and V_o^+ is essential in determining whether the two objects are physically related to one another.

4. Applications of the object-based algorithm

The intention of this section is to discuss the development of specific algorithm tools relevant for both research and operational forecasting applications. Special emphasis is placed on using the algorithm in conjunction with convection-allowing ensemble prediction systems.

a. Theoretical prediction of bores based on environmental profiles from NWP models

One application of the object-based algorithm is to use hydraulic and linear wave theories in order to determine whether a density current can trigger a bore and whether this bore will be maintained in the nighttime environment. Predicting the development and longevity of bores is needed due to their potential role in modifying convective instability and initiating deep convection (Carbone et al. 1990; Karyampudi et al. 1995; Koch and Clark 1999; Locatelli et al. 2002; Wilson and Roberts 2006). During the PECAN field campaign, such theoretical predictions were made by manually picking two environmental profiles on both sides of a numerically simulated density current (Haghi et al. 2015; Geerts et al. 2017). Despite the encouraging results from such a forecasting approach, its application is highly subjective and time consuming. In the context of ensemble prediction systems where information from multiple ensemble members is integrated to provide probabilistic bore forecasts, an automated objective method is much more desirable. As a result, the algorithm introduced in sections 2 and 3 is extended to objectively determine whether the nighttime environment can support convectively generated bores using environmental profiles from NWP models.

The method for extracting environmental profiles of meteorological variables on both sides of a density

FIG. 7. A schematic illustration highlighting the benefits of using dynamical constraints in the object tracker. The black-filled shape represents a target object from a previous image frame, while the three gray-filled shapes (numbered 1, 2 and 3) are candidate objects identified in the current image frame. The black arrow indicates the direction of the PGF ($-\nabla\Pi$), while the meaning of the blue dots is the same as in Fig. 6. The red circle and green semicircle correspond to the static and dynamic tracker search areas whose radii is given by $R = R_s$ and $R = V_o^+ \Delta t$, respectively.

current will be referred to as a *four-dimensional (4D) distance minimization* and is schematically portrayed in Fig. 8a. The key variable in this method is the user-defined reference point $R = (x_r, y_r)$ (blue dot in Fig. 8a), which indicates where the theoretical bore analysis is to be performed. For the sake of explaining the minimization procedure, Fig. 8a considers a collection of three target objects identified by the algorithm for the first three algorithm time steps (i.e., $\mathbf{T} = \{\mathbf{T}_0, \mathbf{T}_{\Delta t}, \mathbf{T}_{2\Delta t}\}$). Here, the set $\mathbf{T}_t = \{T_s^{\mathbf{T}_t} = (x_s^{\mathbf{T}_t}, y_s^{\mathbf{T}_t}) | 1 < s < N^{\mathbf{T}_t} \wedge s \in \mathbb{Z}\}$ represents the target coordinates at time t , while $N^{\mathbf{T}_t}$ is the total number of points associated with $\mathbf{T}_t$. Let the Euclidian distance between R and a point located within target $\mathbf{T}_t$ be defined as $d_s^{\mathbf{T}_t} = \mathbb{d}[T_s^{\mathbf{T}_t}, R]$. Analogous to the previous definitions, we now define the corresponding set $\mathbf{D} = \{\mathbf{D}_0, \mathbf{D}_{\Delta t}, \mathbf{D}_{2\Delta t}\}$, where $\mathbf{D}_t = \{d_s^{\mathbf{T}_t} | 1 < s < N^{\mathbf{T}_t} \wedge s \in \mathbb{Z}\}$ represents the collection of Euclidian distances between the reference point R and the coordinate points comprising $\mathbf{T}_t$. The objective of the 4D minimization procedure is to find the smallest distance from point R to

any of the three target objects $\mathbf{T} = \{\mathbf{T}_0, \mathbf{T}_{\Delta t}, \mathbf{T}_{2\Delta t}\}$ considered in this example [i.e., $d_{\min} \equiv d_{s_{\min}}^{\mathbf{T}_{t_{\min}}} = \min(\mathbf{D})$]. The previous expression indicates that the distance $d_{\min}$ is uniquely associated with the positional index $s_{\min}$ from the nearest target object $\mathbf{T}_{t_{\min}}$. The latter positional index defines the so-called pivot point $P = T_{s_{\min}}^{\mathbf{T}_{t_{\min}}}$ (light blue dot in Fig. 8a). In the schematic diagram from Fig. 8a, $t_{\min} = \Delta t$, and the pivot point P is located in the middle parts of $T_{\Delta t}$. The main purpose of point P is to mark the center of the pivot line (PL) segment AA' (red line in Fig. 8a), which intersects the density current needed for the theoretical bore analysis. Note that the orientation of AA' is parallel to the direction of the PGF ($-\nabla\Pi$) (i.e., approximately in the direction of density current propagation).

The 4D minimization procedure is typically applied throughout the entire time period for which the algorithm is run, such as in the example from Fig. 8b. The time series showing the minimal distances for different time steps suggests that the objects from most of the ensemble members pass over the user-selected reference point $R \sim 4$ h after the numerical model is initialized. It is worth pointing out that the time of passage $t_{\min}$ is not necessarily identical between different ensemble members. The latter results from the inherent ensemble diversity with regard to the simulated density currents and highlights the ability of the 4D minimization framework to analyze those density currents in a dynamically consistent way (i.e., at the time of their passage over the reference point R).

An example of a probabilistic bore prediction using theoretical considerations is shown in Fig. 9 and refers to a specific choice of R with a latitude of 43.4° and a longitude of -97.7° . The two environmental profiles needed for the theoretical bore forecasts are extracted from the end points of the PL segment AA' . The total length of AA' is relatively large (80 km) to ensure that the aforementioned profiles are taken sufficiently away from the nonhydrostatic density current head. The first part of this analysis uses the two-layer hydraulic theory of Rottman and Simpson (1989) in order to determine the likelihood of bore development. According to this theory, the development of a bore is dependent upon the value of the Froude number F and nondimensional height H (see more details in Rottman and Simpson 1989). The analysis of the vertical profiles from points A and A' allows us to calculate the flow regime for each of the ensemble members and plot their distribution in the parameter space of F and H . For instance, the ensemble forecast results shown in Fig. 9a suggest a partially blocked flow regime, in which an atmospheric bore is expected to form ahead of the analyzed density current. Moreover, the mode of the ensemble distribution reveals that the most

FIG. 8. The 4D distance minimization of convective outflow objects with respect to a user-defined reference point. (a) The minimization procedure for an idealized example in which a convective outflow boundary propagates in the positive x direction at a constant speed C . The minimum distance ($d_{\min}$) between the reference point (R ; dark blue dot) and the pivot point within the convective outflow object (P ; cyan dot) occurs during the second image frame at $t = \Delta t = t_{\min}$. The red line segment AA' , parallel to the PGF ($-\nabla\Pi$), displays the position of the vertical cross section required for the theoretical and explicit object analyses. (b) The application of the 4D minimization method to the ensemble forecast experiment from 6 Jul 2015, with point R prescribed to have a latitude of 42.4° and a longitude of -96.4° . The gray lines show the minimum distance between R and the convective outflow object at a particular forecast lead time [i.e., $\min(\mathbf{D}_t)$]. The red circles mark the values of $(d_{\min}, t_{\min})$ for each ensemble member, while the black triangles indicate where the trajectory of a particular ensemble member is terminated.

likely bore strength is $S = 2.2$, which corresponds to a weakly turbulent atmospheric bore.

The second part of the probabilistic bore prediction utilizes linear wave theory and estimates whether the environmental conditions are favorable for maintaining the convectively generated atmospheric bore. In particular, the algorithm calculates the ensemble distribution of the Scorer parameter ℓ^2 (Scorer 1949) ahead of the density current (i.e., at point A'). The example ℓ^2 distribution from Fig. 9b shows a sharp decrease in ℓ^2 from the surface to 1 km AGL, where ℓ^2 approaches 0 m^{-2} . The latter condition insinuates that waves originating in the subcritical region of the bore are likely to be trapped³ (i.e., maintain the bore for a longer time). This example also highlights the enhanced variability in the ensemble forecasts of ℓ^2 near the surface, which possibly results from the inherent difficulty of numerical models to describe the nocturnal boundary layer structure. The increased range of ℓ^2 values near the surface is likely to

yield different wave trapping characteristics (Haghi et al. 2017).

b. Analysis of object attributes based on explicitly resolved convective outflow boundaries

The ability of convection-allowing NWP models to explicitly simulate convective outflow boundaries provides a unique opportunity for the object-based algorithm to extract dynamically relevant density current and bore attributes. One of them is the propagation speed C , which has been routinely analyzed in previous work (e.g., Goff 1976; Koch et al. 1991). Although the object-based algorithm already utilizes motion vector estimates for the purposes of object tracking (see discussion on $\mathbf{V}_O$ in section 3b), we propose an alternative method to estimate C in the neighborhood of the user-defined reference point R (i.e., C_R). Such a consideration takes into account the scarcity of bore observations and allows the algorithm to perform model verification only in regions where such data are readily available.

To calculate C_R , we consider the target object containing the pivot point P at time $t = t_{\min}$ ($\mathbf{T}_{t_{\min}}$; black color shading in Fig. 10a) and the target objects from the two neighboring time steps ($\mathbf{T}_{t_{\min}-\Delta t}$ and $\mathbf{T}_{t_{\min}+\Delta t}$; gray color shading in Fig. 10a). Prior to estimating C_R , the three target objects are skeletonized using the medial axis

³ If k is a horizontal wavenumber, then the square of the vertical wavenumber $m^2 = \ell^2 - k^2$ becomes negative for $\ell^2 \rightarrow 0 \text{ m}^{-2}$ and finite values of k . According to linear wave theory, if m^2 transitions from positive to negative values, wave trapping will occur in the layer characterized by positive m^2 values (like in the example from Fig. 9b).

FIG. 9. Theoretical bore predictions performed over a reference point R with a latitude of 43.4° and a longitude of -97.7° . (a) The ensemble flow regime distribution upstream of a density current. Forecast results are plotted in the parameter space of the Froude number (F ; y axis) and the nondimensional height (H ; x axis). The solid black curves separate different flow regimes, while the dashed black curves represent lines of constant bore strength $S = h_1/h_0$. The partially blocked regime is located between the thick solid black curves. The red color shading displays the ensemble probability of a particular flow regime; probability contours (blue lines) are plotted at intervals of 0.3, starting from 0.05. The green dot indicates the position of the most likely flow regime (i.e., the mode of the ensemble distribution). (b) The ensemble forecast results associated with the vertical Scorer parameter (ℓ^2) profile; the black line refers to the median Scorer profile, while the gray-shaded region shows the IQR of ℓ^2 at a given height. The dashed blue line corresponds to $\ell^2 = 0$.

transform (MAT; Lakshmanan 2012), that is, $\mathbf{T}_t \xrightarrow{\text{MAT}} \mathbf{T}_t^{\text{sk}}$ for some time t . This transform intends to increase the accuracy of the C_R estimate due to its property to simplify the shape of the objects. Since the pivot point P may no longer belong to $\mathbf{T}_t^{\text{sk}}$ as a result of the MAT, we define a new pivot point P^{sk} , which minimizes the distance between P and $\mathbf{T}_t^{\text{sk}}$ (i.e., $P^{\text{sk}} = \min\{\mathcal{D}[P, \mathbf{T}_t^{\text{sk}}]\}$). Then, using the direction of the PGF ($-\nabla\Pi$) at point P^{sk} and the closest nine neighboring points, we define a total of 10 PL segments (colored lines in Fig. 10a), each having a length of 80 km. If the set of coordinates for a particular PL is denoted as $\mathbf{L}$, then $\{X_{t_{\min}-\Delta t}^{\text{sk}}, X_{t_{\min}+\Delta t}^{\text{sk}}\} = \{\mathbf{L} \cap \mathbf{T}_{t_{\min}-\Delta t}^{\text{sk}}, \mathbf{L} \cap \mathbf{T}_{t_{\min}}^{\text{sk}}, \mathbf{L} \cap \mathbf{T}_{t_{\min}+\Delta t}^{\text{sk}}\}$ is the set of three points where the PL intersects the objects considered in this analysis. Therefore, the propagation speed of the object associated with the i th pivot line (C_R^i) is defined as the Euclidian distance between the $X_{t_{\min}-\Delta t}^i$ and $X_{t_{\min}+\Delta t}^i$ points divided over twice the model time step (Δt); that is,

$$C_R^i = \frac{\mathcal{D}[X_{t_{\min}-\Delta t}^i, X_{t_{\min}+\Delta t}^i]}{2\Delta t}. \quad (7)$$

Figure 10b shows the distribution of the propagation speeds from all quality-controlled ensemble members and neighboring points ($32 \times 10 = 320$ points in total) in proximity to point R , which has a latitude of 41.7° and a

longitude of -97.4° in this example. For this particular choice of R , the median and interquartile range values turn out to be 17.6 m s^{-1} and 2.1 m s^{-1} , respectively. Similar to the theoretical bore analysis, the ensemble distribution of C_R does not refer to a single model time, but rather corresponds to the time when a convective outflow object associated with a particular ensemble member passes over the reference point R .

There are at least two advantages of calculating C_R via the aforementioned neighborhood method. On one hand, this approach takes into account the inherent uncertainty of the C_R estimate (indicated by the coloring of the PLs in Fig. 10a), which can arise both due the differential propagation of the tracked objects as well as the algorithm's inability to calculate the exact location of the three intersection points $\{X_{t_{\min}-\Delta t}^{\text{sk}}, P^{\text{sk}}, X_{t_{\min}+\Delta t}^{\text{sk}}\}$ used in the calculation of C_R . The box-and-whisker diagram inset in Fig. 10a reveals that the velocity in the neighborhood of point R can vary by more than 2 m s^{-1} , making the single-valued estimates of C_R not representative of the object's propagation speed. On the other hand, the neighborhood approach also leads to a significant increase in the sample size of the C_R ensemble (Fig. 10b) and, as a result, improves the overall representation of ensemble uncertainty with respect to the object's propagation speed. In particular, sensitivity experiments indicated that the ensemble

FIG. 10. Evaluating the propagation speed C_R of a convective outflow object in proximity of the user-defined reference point $R = (41.7^\circ, -97.4^\circ)$. (a) The methodology for calculating C_R based on the length of the PLs (purple to red colors indicating increasing PL lengths) as well as the variability of C_R in the neighborhood of R (box-and-whisker diagram in the figure inset). The meaning of the other symbols is summarized in the legend at the bottom right-hand side of the figure. (b) The ensemble distribution of C_R . The values associated with the first, second, and third quartiles (q_1 , q_2 , and q_3) of this distribution are shown at the top-left corner of the figure. The second quartile (the median) is additionally plotted as a dashed red line.

distribution of C_R becomes more Gaussian after including the additional speed estimates from the neighboring points (not shown).

The second explicit analysis tool concerns the evaluation of bore amplitude and lifting in the vicinity of the reference point R ; that is,

$$S_R = \left[\frac{h_1}{h_0} \right]_R, \quad (8)$$

and

$$\Delta h_R = [h_1 - h_0]_R, \quad (9)$$

where h_0 and h_1 denote the height of the stable boundary layer (SBL) prior to and after the passage of the bore. Calculating S_R and Δh_R rests on the assumption that the virtual potential temperature θ_v is conserved when air parcels undergo bore lifting. Note that the accuracy of this approach will decrease in the presence of convectively induced latent heating, whereby θ_v surfaces can no longer be treated as material surfaces.

The procedure for estimating S_R and Δh_R starts with constructing a cross section over the central PL segment from Fig. 10a. The length of the resulting cross section (Fig. 11a) is the same as in the theoretical bore analysis from section 4a (80 km) and restricts the algorithm to only sample the undisturbed environment away from the bore front. Here, we utilize one of the theoretical bore analysis routines in order to get a first estimate of the inversion height upstream of the approaching bore

($\hat{h}_0$; gray diamond shape). More specifically, $\hat{h}_0$ is defined as the depth over which the environmental lapse rate exceeds the moist adiabatic lapse rate [see Haghi et al. (2017) for more details]. The height of the stable layer downstream of the bore ($\hat{h}_1$; gray diamond shape) is then defined as the maximum height of the $\theta_v(z = \hat{h}_0)$ surface (gray dotted line).

It is worth remarking that the definition of $\hat{h}_1$ in this object-based algorithm differs from previous studies, wherein $\hat{h}_1$ is typically calculated as the average stable layer height in the wake of the bore. The rationale behind our definition of $\hat{h}_1$ is based on qualitatively analyzing the diverse bore structures in our ensemble simulations. Specifically, examination of certain ensemble members revealed that bores may either (i) not show a semipermanent increase in the SBL height or (ii) be characterized by a rather shallow θ_v slope owing to more pronounced dispersion effects. The atypical bore characteristics in such cases meant that it is not appropriate to artificially divide a bore into subcritical and supercritical regions and then estimate the average postbore height in the subcritical region. By letting the postbore SBL height $\hat{h}_1$ be the maximum height of the $\theta_v(z = \hat{h}_0)$ surface, the algorithm is able to better capture the intrinsic bore diversity and provide more consistent ensemble results. With these considerations in mind, our first estimates of the effective bore amplitude and lifting nearby point R can be written as $\hat{S}_R = [\hat{h}_1/\hat{h}_0]_R$ and $\hat{\Delta h}_R = [\hat{h}_1 - \hat{h}_0]_R$, respectively.

Analogous to the estimation of the propagation speed C , we also give first-order accounts to the accuracy of the

FIG. 11. Evaluating the effective bore amplitude $S_R = [h_1/h_0]_R$ in proximity of the user-defined reference point $R = (41.7^\circ, -97.4^\circ)$. (a) The methodology for finding S_R is illustrated with the aid of a cross section showing the vertical velocity (w ; color shading) and the virtual potential temperature (θ_v ; black solid lines) along the central PL from Fig. 10a. The gray dots show the original SBL height estimate provided by the theoretical bore analysis. The minimum and maximum heights of the original SBL height estimate ($\hat{h}_0$ and $\hat{h}_1$) are marked with the two gray diamonds, while its uncertainty range is marked with the two dashed gray lines. The green dots refer to the optimal SBL height (i.e., the θ_v surface experiencing maximum bore lifting). The minimum and maximum values of this optimal SBL height define h_0 and h_1 (green diamonds), which are used in the S_R estimate. Note that the gray and the green diamonds in this example overlap due to their similar location along the cross section. (b) The ensemble distribution of S_R . The meaning of the symbols in this histogram is the same as in Fig. 10b.

retrieved SBL height $\hat{h}_0$, which is a traditionally challenging variable to estimate (Vickers and Mahrt 2004). In particular, model results have indicated that neighboring θ_v surfaces can differ significantly with respect to their postbore displacement heights. To alleviate this sensitivity, the deterministic value of $\theta_v(z = \hat{h}_0)$ is perturbed by ± 2 K to create a broad range of stable boundary layer heights (dashed gray lines in Fig. 11a) that accounts for errors in the retrieval technique as well as the underlying ambiguity in terms of defining the SBL height. Within this envelope of possible SBL heights, the algorithm searches for the θ_v surface with the highest vertical displacement (green dotted line in Fig. 11a), which is then used to get optimal estimates of h_0 and h_1 (green diamond shapes). In particular, h_0 and h_1 are defined to be the minimum and maximum of the aforementioned θ_v surface. These optimal SBL heights are then used to redefine the bore amplitude and lifting from Eqs. (8) and (9).

Repeating the outlined procedure for the entire ensemble of 36 quality-controlled members provides the ensemble distribution of bore amplitudes in Fig. 11b. For this specific choice of $R = (41.7^\circ, -97.4^\circ)$, S varies between 1.5 and 2.7 and has a median value of 2.1. The interquartile ensemble range implies that $\sim 1/4$ of the ensemble members predict the development of a bore with laminar characteristics, while the remaining $\sim 3/4$ of them anticipate a weakly turbulent bore. Further

analysis also revealed that there is a positive correlation between C_R and S_R for the ensemble forecasts used in this study (not shown). The latter is consistent with the two-layer hydraulic theory presented by Rottman and Simpson (1989) [refer to their Eqs. (2.4) and (3.1)] and suggests that the explicit bore routines provide physically sound results.

c. Object-based probabilities of explicitly resolved convective outflow boundaries

Apart from its ability to objectively analyze the characteristics of explicitly resolved convective outflow boundaries, the algorithm presented herein can also provide probabilistic information regarding their representation in convection-allowing ensemble prediction systems. Given that each member in the ensemble forecast is associated with two distinct binary fields corresponding to the location of the simulated density currents and bores, object-based probabilities can be generated by simply calculating the relative frequency of the aforementioned binary fields over different model grid points. An example application of the outlined procedure is shown in Fig. 12 and illustrates how the object-based probabilities that are linked to the largest convective outflow object identified close to the model initialization time (0315 UTC; refer to Figs. 12a,c) evolve after more than 3 h of model integration (Figs. 12b,d). Note that the object-based probabilities evaluated with

FIG. 12. Object-based (a),(b) density current and (c),(d) bore probabilities computed with respect to the largest convective outflow boundary in the 1-km ensemble forecasts of the 6 Jul 2015 case study. (left) The first set of probabilities is generated for 0315 UTC and coincides with the time when the largest convective outflow object is initialized by the algorithm. (right) The second set of probabilities is plotted for 0630 UTC or after the algorithm has tracked the largest convective outflow boundary for 3 h 15 min. Probability fields are additionally smoothed with a Gaussian kernel ($\sigma = 2$ km). The 35%, 65%, and 95% probability values are plotted with solid lime contours.

respect to the other target objects are not shown in Fig. 12 for clarity.

The sequence of images in Fig. 12 suggests that the largest convective outflow boundary initialized in our numerical simulations is expected to move east-southeast and that the main lifting mechanism associated with this particular boundary is very likely to change from a density current to a bore in the later forecast hours. Although a similar evolution is also evident in the deterministic forecast from Fig. 3, the algorithm-derived probabilities in this example contain additional information that could be potentially useful to operational forecasters. For instance, Figs. 12b and 12d reveal that the bore (density current) probabilities in the southern portion of the tracked outflow boundary are higher (lower), compared to its northern parts. Given a hypothetical scenario in which the ensemble members predict the development

of convection in the vicinity of the highest bore probabilities, operational forecasters would have an additional physical insight about the forcing mechanism behind the model-simulated convection. If the radar and surface observations collected later on do (or do not) confirm the presence of a bore, these operational forecasters will have strong evidence that the NWP products used as part of their analysis are accurate (inaccurate) and would be able to adjust their forecasts accordingly. This idealized example suggests that the ability of the object-based algorithm to discriminate between density currents and bores could serve as useful guidance for the operational forecasting of nocturnal convection.

It is important to add that the object-based probabilities calculated with respect to the initial target objects are not the only means of utilizing the ensemble information contained in convection-allowing NWP

models. In particular, density current and bore probabilities can be produced by independently considering all objects identified at a given model time step. However, since the latter approach does not make use of the algorithm's tracker, operational forecasters would be unable to follow the evolution of convective outflow boundaries that are of particular interest to them. By contrast, the object-based probabilities in the example from Fig. 12 do not only add a temporal component to the algorithm's output, but are also quite relevant in the context of short-range and rapidly updating NWP systems (e.g., the HRRR; Smith et al. 2008), wherein convective outflow boundaries are commonly present in the model's initial conditions.

5. Conclusions and discussion

This study describes the development of an object-based algorithm for the automatic identification and tracking of convectively generated outflow boundaries. While object-based techniques to analyze density currents have been developed previously (Li et al. 2014; Drager and van den Heever 2017), a unique aspect of this algorithm is its ability to simultaneously account for both density currents and atmospheric bores. The detection of these morphologically different convective outflow boundaries is possible only after combining several model fields. Although the use of multiple identification variables is not a new concept (e.g., Clark et al. 2015), the specific parameter choice made in this algorithm is fundamentally different from past studies and is designed to target only those convective outflow boundaries that provide sufficient lifting for the initiation and maintenance of nocturnal MCSs. It is important to note that some of the identification variables are challenging to use without additional preprocessing steps. In particular, the spatial inhomogeneity of vertical velocity (w^{1km}) and the contamination of mean sea level pressure tendencies (Δp) with spurious numerical noise require the application of carefully tuned image processing/filtering techniques in order to obtain physically meaningful results.

Another novel feature of the proposed algorithm is its object tracker. Following the suggestion of Davis et al. (2009b), the object tracker is formulated to explicitly account for the dynamics of convective outflow boundaries. The inclusion of the pressure gradient force direction ($\angle \beta$) and the maximum translational velocity (V_{ϕ}^+) as dynamical constraints for object association is especially important if objects experience rapid structural and/or morphological changes. In these cases, traditional statistical methods such as template matching are likely to provide erroneous tracking results.

Likewise, the incorporation of dynamical information provides a better link between the algorithm and the underlying model data. For instance, it should be possible to relate differences in the speed or direction of object propagation back to the pressure gradient force used in the formulation of the algorithm.

To address the growing interest in atmospheric bores among researchers and operational forecasts (e.g., during the PECAN field campaign; Geerts et al. 2017), the second objective of the paper was to describe several algorithm applications relevant to the analysis and prediction of bores in NWP models. These applications were shown in the context of a convection-allowing ensemble forecast experiment from 6 July 2015. To the authors' best knowledge, this is the first time a dedicated methodology for describing the ensemble distribution of specific bore parameters is presented. Such ensemble estimates are expected to provide valuable information for assessing the predictability of the studied phenomenon.

The four-dimensional minimization procedure, which lies at the heart of the suggested algorithm tools, allows algorithm users to automatically sample convective outflow boundaries and perform various diagnostics pertinent to their own research objectives. The specification of user-defined verification (reference) points through the aforementioned minimization procedure obviates the need for a spatially continuous verification dataset, which is required in other object-based verification methods (e.g., MODE; Davis et al. 2006a). The postprocessing tools developed as part of this object-based algorithm represent a natural extension of previous PECAN efforts to forecast the development and maintenance of bores based on manual input from model-derived environmental profiles (Haghi et al. 2015; Geerts et al. 2017). Apart from completely automating the routines needed for the theoretical bore analysis, the ability of the algorithm to determine the likelihood of bore occurrence could prove especially beneficial to operational forecasters by guiding them where the initiation of nocturnal convection is more likely.

Despite the encouraging performance of the newly developed object-based algorithm, it is also important to point out some of its limitations. The algorithm weaknesses are largely associated with its identification component. Most evidently, the static threshold values used to define convective outflow boundaries in the model domain are global in nature and only valid over relatively short periods of time. Within this study, the aforementioned problem is addressed by introducing two different sets of threshold values dependent upon the forecast lead time and the magnitude of the spurious numerical noise. One way to improve the identification

capabilities of the algorithm is to use adaptive thresholding methods (e.g., through utilizing image histograms; Tobias and Seara 2002). Alternatively, introducing more sophisticated techniques such as marker-controlled watershed segmentation (Soille 2003) could completely remove the need for prescribing threshold values. Past experience related to the development of methods for detecting and tracking convective outflow boundaries in radar data can be also helpful in bolstering the identification results of our object-based algorithm. For instance, Delanoy and Troxel (1993) show how tracking gust fronts and anticipating their location in future radar scans improves the overall identification results. Another potentially useful concept incorporated in the aforementioned study is the application of functional template correlation (FCT) filters (Delanoy et al. 1992). In particular, this type of matched filters can be designed to describe the topological characteristics of model-simulated convective outflow boundaries and, hence, reduce the number of spuriously identified objects.

Finally, it is hoped that this paper will serve as a foundation for future studies aiming at advancing the algorithm's capabilities as well as developing other relevant algorithm applications. A particularly interesting line of research would be to determine whether the classification of convective outflow boundaries can be extended to more complex features such as solitons and deep tropospheric gravity waves. Future work should also take advantage of the algorithm's capability to objectively analyze some of the dynamical aspects of convective outflow boundaries. In line with the observational study of Toms et al. (2017), the algorithm could offer a convenient framework to examine the temporal evolution of the wave trapping characteristics following a model-simulated bore. Such an analysis could lend important insights into the two-way interactions between atmospheric bores and the ambient environment in which they develop and maintain. Moreover, a data assimilation study utilizing the proposed algorithm to objectively evaluate the forecast impact of assimilating novel PECAN observations is already being carried out by the authors of this work and will be reported in an upcoming paper.

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