Tracking Low-Level Cloud Systems with Topology

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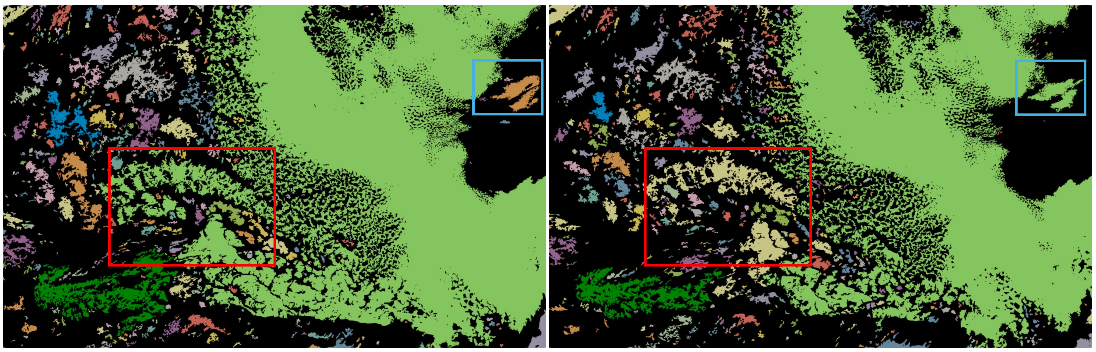

Figure 1: Topology-driven cloud tracking for a marine stratocumulus dataset over the ocean west of Africa. The two images show the detected cloud systems at 09:00 and 10:00 UTC on August 1, 2023. Color encodings indicate correspondences between cloud systems across the one-hour interval, allowing us to observe their evolution as they appear, disappear, merge, and split. Red and cyan boxes highlight examples of a splitting event and a merging event, respectively.

Abstract

Low-level clouds are ubiquitous in Earth's atmosphere. Their response to atmospheric conditions are essential to understanding the climate system and its sensitivity to anthropogenic influences. High-resolution geostationary satellites now resolve cloud systems with unprecedented detail, promoting cloud tracking as a vital research area for studying their spatiotemporal dynamics. It enables disentangling advective and convective components driving cloud evolution. This, in turn, provides deeper insights into the structure and lifecycle of low-level cloud systems and the atmospheric processes that govern them. In this paper, we propose a novel framework for tracking cloud systems using topology-driven techniques based on optimal transport. We first obtain a set of anchor points for the cloud systems based on the merge tree of the cloud optical depth field. We then apply topology-driven probabilistic feature tracking of these anchor points to guide the tracking of cloud systems. We demonstrate the utility of our framework by tracking clouds over the ocean and land to test for systematic differences in the two physically distinct settings. We further evaluate our framework through case studies and statistical analyses, comparing it against two leading cloud tracking tools and two topology-based general-purpose tracking tools. The results demonstrate that incorporating system-based tracking improves the ability to capture the evolution of low-level clouds. Our framework will inform low-level cloud characterization studies that fully profit from detailed satellite data.

Keywords: Feature tracking, merge tree, optimal transport, topology in data visualization, topological data analysis, applications

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1 Introduction

Low-level clouds (i.e., clouds with a base below 6,500 ft and limited vertical extend) are an important part of the atmosphere by transporting heat and moisture, and by interacting with radiation [58]. Understanding the structure and evolution of low-level clouds is key to improving our knowledge of atmospheric processes. Low-level clouds such as *shallow cumulus* clouds (colloquially known as *fair weather clouds* with their cotton-ball-like appearance) and *stratocumulus* clouds (gray or whitish cloud decks patterned by dark, cloud-free lines or cells [62]) significantly affect the Earth's radiative budget because they form cloud fields that can stretch over hundreds of kilometers. Due to their fine-scale structure, however, their accurate representation in climate models remains a significant challenge and a dominant contribution to the uncertainty in climate projections [36, 42]. Accurately describing these clouds in space as well as time is thus a prerequisite for their reliable representation in climate models. This emphasizes the importance of cloud characterization and tracking [44].

Cloud evolution is shaped by *convection* and *advection*. Convective motion, driven by buoyancy and atmospheric instability, especially governs local-scale vertical motion. These dynamics influence cloud growth, dissipation, and structural changes. In contrast, advection refers to the large-scale horizontal transport of clouds by prevailing winds, guided by atmospheric circulation patterns. Cloud tracking, therefore, helps differentiate convective and advective processes [1, 51], enabling studies on cloud dynamics [51], lifecycles [49], microphysical processes [14], and the evolution of cloud patterns [24]. What makes it interesting and different from classical computer vision problems is that clouds are a representation of a continuous process (such as condensation, evaporation, split, and merge) and cannot be treated as a fixed object [6]. Clouds occur in moist turbulent flow, which results in fractal characteristics of cloud boundaries, which in turn makes individual clouds difficult to identify and track. Recent progress in tracking methods, driven by growing satellite data records, has made it possible to study cloud characteristics in greater detail and improve our understanding of their behavior.

We present a novel topology-driven framework for tracking low-

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level clouds. We model low-level clouds as cloud systems that may consist of multiple cloud objects that are geometrically close, and use probabilistic feature tracking based on optimal transport to track them in a time-varying setting.

Our contributions are as follows:

- We present a new framework to track cloud systems using time-varying satellite image data. We first obtain a set of anchor points for the cloud systems based on the merge tree of the cloud optical depth field. We then apply merge-tree-based feature tracking of the anchor points to guide the tracking of cloud systems.
- We demonstrate the utility of our framework by tracking cloud systems from satellite data over both ocean and land, recognizing that cloud-tracking challenges may differ across these two physically distinct regimes.
- We further compare our framework with two leading cloud tracking tools and two topology-based general-purpose tracking tools via visualizations and statistical evaluations.

The source code is publicly available at https://github.com/tdavislab/cloud-tracking.

2 Related Work: Cloud Physics and Tracking

Clouds form and evolve across various spatiotemporal scales within Earth's atmosphere [31]. Low-level clouds in the warm regions of the lower latitudes are composed of liquid droplets, which makes them very effective at reflecting incoming sunlight back to space. This cooling effect is not strongly compensated for by a reduced emissivity of heat from the surface as low-level clouds re-emit absorbed long-wave radiation at cloud-top-temperature that are not much colder than the surface. Low-level clouds over land or ocean exhibit distinct characteristics. Over land convection is affected by surface inhomogeneities and strong surface heating, which leads to pronounced diurnal cycles. In contrast, oceanic convection is more organized and sustained, shaped by the ocean's high heat capacity, abundant moisture, uniform temperatures, and large-scale atmospheric circulation.

Advanced Geostationary Satellites (GS), such as Meteosat Third Generation (MTG [19]) and GOES-16's Advanced Baseline Imager (ABI [57]), provide high spatial and temporal resolution. However, they still do not resolve the fine-scale structure of low-level cloud systems [16, 17], which often span scales of hundreds of meters. Despite this limitation, treating the aggregation of these individual cloud objects—spanning hundreds of kilometers—as spatial distributions enables adequate resolution to capture their variability [4, 21].

Cloud tracking begins with the identification of individual clouds in the dataset, a process that depends on the type of cloud and the specific scientific objectives of the study. For instance, studies focusing on deep convective cells often rely on physical threshold-based approaches, such as brightness temperature [7, 12, 51, 52] or radar reflectivity [26, 41]. In the case of mixed-phase clouds, methods typically involve a combination of cloud mask (cloudy or non-cloudy pixel) and cloud optical depth [5]. Cloud optical depth (COD) quantifies the extent to which the cloud attenuates light primarily due to the scattering and absorption by cloud droplets. It is governed by cloud geometric thickness, cloud water mass, droplet concentration, and particle size distribution [39]. For shallow low-level clouds, cloud identification methods vary: [49] employs a cloud mask, while [25] applies a reflectivity threshold. However, shallow cumulus clouds, being inherently broken and scattered in nature, pose additional challenges. The resolution of the cloud mask, such as that provided by the CLAAS-2 product [37], may be insufficient to fully resolve these fragmented cloud structures.

The present and upcoming generations of geostationary satellites provide continuous, high spatiotemporal resolution observations, significantly advancing our ability to study rapidly evolving dynamic systems in the Earth's atmosphere. Historically, tracking approaches using geostationary satellite data have focused on mesoscale convective systems. Techniques for tracking clouds between successive observations range from manual methods [23,50,51] to automated approaches such as spatial correlation [2,8,48] and area-overlapping methods [35,59,61]. In some cases, a combination of correlation and overlapping techniques has been applied to improve accuracy [47]. Furthermore, fully automated tracking methods have been developed, primarily focusing on deep convective clouds to analyze mesoscale clusters [12] or to establish a generalized framework for diverse Earth system datasets, enhancing both adaptability and computational efficiency [33].

Individual clouds in a shallow cumulus cloud fields are not randomly distributed but organized into clustered patterns [21, 55]. Their broken structure leads to distinct patterns of cloud shadows and illuminations [15, 30]. [49] uses the Spinning Enhanced Visible and InfraRed Imager [57] on board the European geostationary Meteosat Second Generation (MSG) satellites and employs particle image velocimetry to track these clouds over the ocean but does not account for low-level clouds' splitting and merging behaviors. This phenomenon becomes particularly important when a cloud grows and merges with neighboring clouds, or when a complex cloud splits into smaller ones. Similarly, [25] uses the Advanced Himawari Imager (AHI) rapid scan onboard HIMAWARI-8 [22] and applies the Kalman filter as a motion prediction model to estimate the locations of cloud objects across successive time frames. However, their approach assumes a constant velocity field throughout the tracking process. Complementing observational studies, extensive research has been conducted to track simulated shallow cumulus clouds in large-eddy simulations [18, 56, 65], providing valuable insights into cloud lifecycle and dynamics.

3 Related Work: Topological Feature Tracking

Topology-based feature tracking for time-varying scalar fields is a two-step process: first, topological features are extracted at each time step; and second, these features are matched between adjacent time steps by solving a correspondence problem (or assignment problem in cloud science). Various topological descriptors—such as merge trees and persistence diagrams—have been used for feature tracking; see [64, Section 7.1] for a review. Soler et al. [34, 53] used persistence diagrams to perform topology tracking. They extracted points in a persistence diagram that encode homological features at each time step, and relied on lifted Wasserstein [53] or Wasserstein [34] matching between persistence diagrams at adjacent time steps to establish correspondences.

The main idea of merge-tree-based tracking is to follow the nodes of merge trees that represent critical points of the underlying scalar fields, using tree matching to establish correspondences. Doraiswamy et al. [7] combined merge trees with optical flow to track deep convective clouds. Pont et al. [40] extended the work on edit distance [54] and introduced a new Wasserstein metric between merge trees to support feature tracking. Yan et al. [63] used the labeled interleaving distance between merge trees to support geometric-aware feature tracking.

Most recently, Li et al. [29] introduced a probabilistic framework for tracking topological features using merge trees and optimal transport. They represented a merge tree as a measure network—a network associated with a probability distribution—and introduced a distance metric for comparing merge trees using partial optimal transport. This distance offers flexibility in capturing both intrinsic and extrinsic information of merge trees.

A traditional method for establishing correspondence between features is to calculate the overlap between regions surrounding the features. Lukasczyk et al. [20, 32] matched superlevel set components by measuring the overlap between their corresponding regions. Similarly, Saikia et al. [45, 46] performed topological feature tracking using merge trees. Their approach assesses the similarity of subregions segmented by merge trees at adjacent time steps, based on the overlap size between two regions and the similarity between histograms of scalar values within each region.

4 Technical Background

4.1 Merge Tree

Let $f : \mathbb{M} \to \mathbb{R}$ be a scalar field defined on a 2D domain $\mathbb{M} \subset \mathbb{R}^2$. A merge tree captures the connectivity among sublevel sets of f. We consider two points $x, y \in \mathbb{M}$ to be equivalent, denoted $x \sim y$, if $f(x) = f(y) = a$ and they belong to the same connected component of the sublevel set $f^{-1}(-\infty, a]$. Mathematically, the merge tree is a quotient space $T(\mathbb{M}, f) = \mathbb{M}/\sim$. For topology-based cloud tracking, f corresponds to the cloud optical depth (COD) field in a satellite image with a particular timestamp; it quantifies how much a ray of light is attenuated as it travels through a cloud. A higher optical depth indicates greater extinction of light within the cloud. Since we are interested in high-value areas of f, we work with the merge tree of $-f$, as shown in Fig. 2.

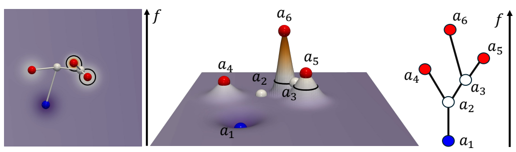

Figure 2: Left: a 2D visualization of a scalar field f with an embedded merge tree of $-f$. Middle: a 3D visualization of the graph of f. Right: an abstract visualization of the merge tree of $-f$. Local maxima are in red, saddles are in white, and the global minimum is in blue. The black contour passing through the saddle a_3 encloses two peak areas of the local maxima a_5 and a_6, respectively.

As illustrated in Fig. 2, we construct a merge tree as follows. We sweep the graph of f (middle) with a hyperplane at the function value a starting from the maximal value of f. As a decreases, we initiate a new branch of the merge tree each time we encounter a local maximum (e.g., at a_6, a_5, and a_4). Such a branch grows longer as a decreases, eventually merging with another branch at a saddle point. For instance, at the saddle a_3, the branch starting at a_6 merges with the branch starting at a_5. Given a simply connected domain, all branches eventually merge into a single connected component at the global minimum a_1. Leaves, internal nodes, and the root of the tree correspond to the local maxima, saddles, and the global minimum of f, respectively. With a slight abuse of notation, the merge tree $T = (V, E)$ is a rooted tree whose node set V is equipped with the scalar function f.

We define a mapping $\phi : \mathbb{M} \to T$ between points in the domain and the merge tree. The inverse image of an edge $e \in E$ under this mapping $\phi^{-1}(e)$ is called a *topological zone*. For example, the two peak areas enclosed by the black contour in Fig. 2 are the topological zones of the edges a_3a_6 and a_3a_5 in E, respectively. The area of a topological zone can serve as an *importance* measure for an edge in the merge tree [27], as it reflects the size of the peak in the domain. We may simplify branches with small topological zones during computation by employing this importance measure.

4.2 Feature Tracking with Optimal Transport

Li et al. [29] introduced topology-based feature tracking based on partial optimal transport. Our framework utilizes and significantly extends the work of Li et al. [29], making it suitable for cloud tracking. The key idea in [29] is the introduction of partial Fused Gromov-Wasserstein (pFGW) distance between merge trees. The pFGW distance generates a probabilistic matching between nodes in a pair of merge trees; such a matching serves as the starting point for deriving trajectories of the cloud systems in downstream analysis.

Optimal transport in a nutshell. To illustrate optimal transport, assume there are a number of factories with specific production capacities and a number of warehouses with prescribed storage capacities. Optimal transport aims to find the most efficient way to transport goods from the factories to the warehouses by minimizing the transportation cost while respecting the capacity constraints. For partial optimal transport, we allow losing a certain amount of goods during transportation.

Measure network. Following [29], we model merge trees as measure networks. That is, a merge tree can be represented as a triple $T = (V, p, W)$, where $p : V \to [0, 1]$ is a probability measure on the node set V (i.e., $\sum_{x \in V} p(x) = 1$ for all $x \in V$), and $W : V \times V \to \mathbb{R}$ denotes the pairwise intrinsic node relation.

A measure network $T = (V, p, W)$ may also be equipped with node attributes from an attribute space (A, d_A) that encodes extrinsic information. An example of a node attribute is the geometric location of its corresponding critical point in the domain. In this context, the attribute distance d_A is the Euclidean distance between critical points in the domain. We will discuss our choices for p, W, and (A, d_A) in the context of cloud tracking in Sec. 5.3.

Partial Fused Gromov-Wasserstein distance. The pFGW distance introduced by Li et al. [29] is based on the theory of partial optimal transport [3, 60]. Given two measure networks $T_1 = (V_1, p_1, W_1)$ and $T_2 = (V_2, p_2, W_2)$ equipped with node attributes, let $n_1 = |V_1|$ and $n_2 = |V_2|$ be the number of nodes. A coupling $C \in \mathbb{R}^{n_1 \times n_2}$ is a nonnegative matrix that encodes a joint probability measure between p_1 and p_2, with row and column marginals equal to p_1 and p_2, respectively. Formally, the set $\mathcal{C} = \mathcal{C}(p_1, p_2)$ of all couplings between T_1 and T_2 is

$$\mathcal{C}(p_1, p_2) = \{C \in \mathbb{R}_+^{n_1 \times n_2} \mid C\mathbf{1}_{n_2} = p_1, C^\top \mathbf{1}_{n_1} = p_2\}, \quad (1)$$

where $\mathbf{1}_n = (1, 1, ..., 1)^\top \in \mathbb{R}^n$. Following (1), optimal transport requires a coupling (matching) to preserve all measures p_1 and p_2.

On the other hand, partial optimal transport [3] allows partial coupling, thus partial matching between two measure networks. It relaxes the requirement for the coupling to sum to a number $m \le 1$ (i.e., $m \in [0, 1]$). The set $\mathcal{C}_m = \mathcal{C}_m(p_1, p_2)$ of the *relaxed couplings* is

$$\begin{aligned} &\mathcal{C}_m(p_1, p_2) \\ &= \{C \in \mathbb{R}_+^{n_1 \times n_2} \mid C\mathbf{1}_{n_2} \le p_1, C^\top \mathbf{1}_{n_1} \le p_2, \mathbf{1}_{n_1}^T C \mathbf{1}_{n_2} = m\}. \end{aligned} \quad (2)$$

The pFGW distance is defined on the set of relaxed couplings $\mathcal{C}_m$.

Given a pair of merge trees modeled as measure networks T_1 and T_2, the pFGW distance is defined as

$$\begin{aligned} d_q(T_1, T_2) = \min_{C \in \mathcal{C}_m} \sum_{i,j,k,l} \Big(&(1-\alpha)\, d_A(a_i, b_j)^q \\ &+ \alpha\, |W_1(i,k) - W_2(j,l)|^q \Big) C_{i,j} C_{k,l}. \end{aligned} \quad (3)$$

Here, $d_A(a_i, b_j)$ is the node attribute distance between $a_i \in V_1$ and $b_j \in V_2$. $|W_1(i,k) - W_2(j,l))|$ describes the *structural distortion* when we match pairs of nodes $(a_i, a_k) \in T_1$ with $(b_j, b_l) \in T_2$. The pFGW distance incorporates a parameter α to balance the weights between these two components. In the context of matching a pair of merge trees, the pFGW distance provides flexibility in preserving both the node properties (such as critical point locations in the domain) and the merge tree structure in the optimal coupling. It also allows the appearance and disappearance of new features.

In the "factory-warehouse" scenario, we are in the setting of optimal transport when $m = 1$ in (3). p_1 and p_2 prescribe the capacities of factories and warehouses, respectively, and the coupling C describes a transportation plan that respects these capacity constraints. The transportation cost is described by the attribute distances (e.g., Euclidean distances) between factories and warehouses as well as the structural relations among them (e.g., factories owned by a given company should transport goods to warehouses owned by the same company). Solving an optimization problem of (3) means finding the transportation plan with the lowest cost. On the other hand, we are in the setting of partial optimal transport when $0 < m < 1$ in (3), meaning that we allow $1 - m$ percent of goods to be lost/ignored during transportation.

5 Method

Cloud tracking faces three major challenges. First, clouds observed in satellite images are complex, time-varying phenomena involving numerous events, as cloud systems appear, disappear, merge, and split. Second, there is no consensus among domain scientists on the definition of cloud objects and cloud systems. Third, there are no ground-truth cloud tracking results available for satellite images supporting any form of supervised learning.

In this section, we describe our novel framework of topology-driven cloud tracking. Working closely with domain scientists, we first introduce the definition and detection of cloud objects (Sec. 5.1). We then describe our strategy of using critical points as anchor points for cloud objects (Sec. 5.2). Subsequently, we compute a matching between the anchor points using partial optimal transport (Sec. 5.3). We then generate trajectories for cloud systems formed by (possibly) multiple cloud objects (Sec. 5.4).

Compared to the work of Li et al. [29], our novel framework uses customized node probability with existing knowledge of the cloud data. Additionally, we propose the concept of tracking cloud systems and introduce a matching algorithm for cloud systems based on optimal transport. Our choice of merge-tree-based tracking is justified by its effectiveness in capturing the locality structure among local maxima.

5.1 Detecting and Simplifying Cloud Objects

In a cloud optical depth (COD) field f from a satellite image, regions with high function values usually indicate thicker clouds.

Cloud object detection. We use a thresholding strategy for the detection of cloud objects. We define each connected component of a superlevel set of f at a chosen threshold a (i.e., $f^{-1}[a, \infty)$) as a *cloud object*. Currently, there is no consensus on the threshold value a to detect low-level clouds. This results in a lack of widely accepted ground-truth data for cloud detection and tracking. Following established practices [33], we test a range of thresholds from 0.5 to 5.0 at a gap of 0.5 to analyze the impact of the threshold on (a) the number of cloud objects, and (b) their size distributions. We select $a = 2.0$ to mitigate both under- and over-segmentation; further details on threshold selection are provided in the supplement.

Cloud object simplification. We want to separate features from noise in our real-world cloud data. Stratocumulus clouds often cover large, continuous areas that can stretch hundreds of kilometers; therefore, we may consider removing smaller cloud objects that are deemed insignificant from stratocumulus clouds. On the other hand, shallow cumulus clouds are characterized by their small size (covering hundreds of meters across), relatively flat bases, and puffy tops; they could also grow into deeper convective systems depending on the available convective mass flux [10], as seen in their COD values. To handle these differences, we use different approaches to simplify the identification of cloud objects for stratocumulus and shallow cumulus, respectively.

For stratocumulus (typically over the ocean), we simplify by discarding small cloud objects based on area; see Fig. 3. By ignoring cloud objects smaller than 10 pixels, we can get rid of more than 70% of cloud objects from the field and still cover more than 97% of the total cloud area; see supplement for statistical details. Fig. 3 gives an example of area-based simplification. The cloud area maps show cloud objects in gray and the background in black. In the simplified cloud area map, cloud objects smaller than 10 pixels are ignored after simplification (cf. the green boxes).

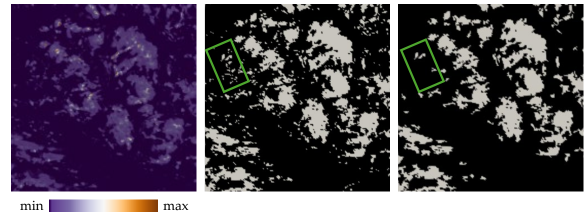

Figure 3: Apply area-based simplification to stratocumulus clouds. From left to right: the COD field, the cloud area map, and the simplified map by excluding cloud objects smaller than 10 pixels.

For Shallow cumulus (typically over land), instead of filtering by size, we apply a higher COD threshold to remove regions with low values, focusing only on the prominent clouds.

5.2 Attaching Anchor Points to Cloud Objects

We need to associate cloud objects with topological features to perform topology-driven tracking. To that end, we use nodes of merge trees that correspond to the critical points of the COD field f as anchor points for cloud objects.

To attach anchor points, we could associate a subtree of the merge tree to each cloud object. For example, Fig. 4(a) shows five cloud objects enclosed by the white contours. The tree structure within each cloud object is a subtree of the global merge tree. We use the local maxima in this subtree as the anchor points of the cloud object. These anchor points' trajectories are subsequently used to derive the trajectory of cloud objects. In practice, we may reduce the number of anchor points for computational efficiency; see Fig. 4(b) for an example and the supplement for technical details.

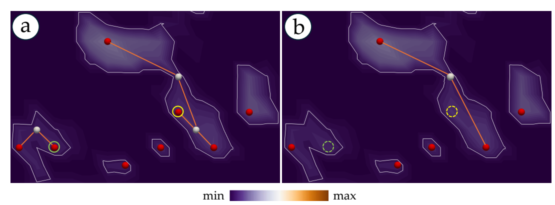

Figure 4: (a) A set of cloud objects enclosed by white contours; each contains a subtree of the global merge tree. Local maxima (a.k.a., anchor points) are in red, and saddles are in white. (b) Simplifying subtrees by removing the highlighted anchor points (inside green or yellow circles) and their parent saddles.

5.3 Anchor Point Tracking with Partial Optimal Transport

We adapt the work of Li et al. [29] to track anchor points with partial optimal transport. Building on prior knowledge of the characteristics of the COD field, we enhance this work by incorporating a tailored probability distribution for critical points.

Model merge trees as measure networks. We first model a merge tree T of the COD field f as an attributed measure network $T = (V, p, W)$ with node attributes (A, d_A). We modify the framework of [29] to focus on tracking local maxima of a merge tree, which act as anchor points for cloud systems.

For each local maximum $x \in V$, we set its probability as $p(x) = 1/n$, where n is the number of local maxima in T. For saddles and the global minimum, we assign a probability of 0 due to the high complexity and uncertainty of the COD field [43], which causes their locations to be highly unstable. This instability makes it challenging to find suitable matchings for these nodes. Furthermore, disregarding the probability of saddles and the global minimum enables us to preserve more anchor points without compromising computational efficiency, ultimately enhancing the robustness of tracking.

We use the pairwise node relation matrix W to encode the tree distance. Recall that each node $v \in V$ is equipped with a function value

$f(v)$. The tree distance between two adjacent nodes in T (i.e., the edge weight) is $W(a,b) = |f(a) - f(b)|$, whereas the tree distance between two nonadjacent nodes is the shortest path distance between them. Previous works [28,29] show that the tree distance can encode the scalar field topology via merge tree structures. Specifically, in the context of cloud tracking, the tree distance reflects the locality among the anchor points: anchor points attached to the same cloud object belong to the same subtree. Our framework captures anchor point locality inherently, regardless of whether saddles or the global minimum are preserved in the optimal transport.

We encode the locations of critical points as the node attributes. Given a pair of merge trees $T_1 = (V_1, p_1, W_1)$ and $T_2 = (V_2, p_2, W_2)$, the node attribute for $a_i \in V_1$ is (x_i, y_i), in which x_i and y_i denote the coordinates of the critical point. Similarly, the node attribute for $b_j \in V_2$ is (x_j, y_j). The attribute distance d_A between a_i and b_j is

$$d_A(a_i, b_j) = d_E\big((x_i, y_i), (x_j, y_j)\big) \tag{4}$$

d_E in Eq. (4) represents the Euclidean distance, and our framework prevents the matching of anchor points that are far apart.

Matching critical points with partial optimal transport. By computing the pFGW distance between a pair of merge trees T_1 and T_2 following (3), we obtain an optimal coupling C between their nodes. We interpret the coupling as a probabilistic matching between critical points from adjacent time steps. The sub-matrix of the coupling matrix, consisting only of rows and columns corresponding to local maxima, represents the matching between anchor points.

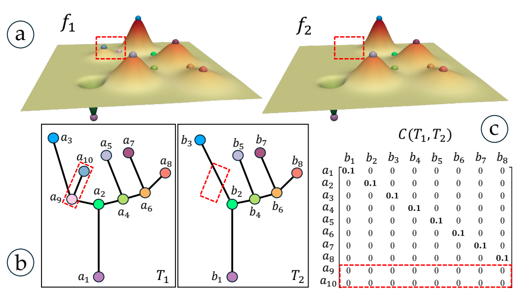

Figure 5: Partial optimal transport. We match the merge trees of $-f_1$ and $-f_2$ (b) using pFGW with $m = 0.8$, producing a coupling matrix C (c). Matched nodes in the two trees share the same color (a-b).

We provide a simple example in Fig. 5. Let f_1 and f_2 in (a) be the scalar fields of adjacent time steps. T_1 and T_2 in (b) are the merge trees of $-f_1$ and $-f_2$, respectively. Let p_1 and p_2 be uniform measures on all the nodes, including local maxima, saddles, and the global minimum. Based on structural similarity between T_1 and T_2, it is natural to match nodes $a_i \in T_1$ with $b_i \in T_2$ for $i \in [1, 8]$. On the other hand, nodes a_9 and a_{10} in T_1 are missing from T_2 (c.f., the red boxes). Ideally, we want to ignore a_9 and a_{10} during the matching process. Based on these intuitions, setting $m = 0.8$ in the pFGW distance produces the desired transportation plan captured by $C = C(T_1, T_2)$ in (c).

Each entry $C_{i,j}$ in C denotes the probability of matching $a_i \in T_1$ with $b_j \in T_2$. We see that $C_{i,i} = 0.1$, which aligns well with our expectations. Meanwhile, $C_{9,j} = C_{10,j} = 0$ for $j \in [1, 8]$, indicating that $a_9, a_{10} \in T_1$ are not matched to any nodes in T_2. A sub-matrix of C, with rows corresponding to a_3, a_5, a_7, a_8, a_{10} and columns corresponding to b_3, b_5, b_7, b_8, represents the probabilistic matching between anchor points. While this example shows a one-to-one node matching, our framework generally allows multiple nonzero entries in a row or column, which distinguishes our framework from other topology-based frameworks that produce one-to-one matchings.

5.4 Computing Trajectories for Cloud Systems

Constructing cloud systems. We first merge cloud objects into cloud systems. A cloud system may consist of multiple cloud objects that are geometrically close. Eytan et al. [9] suggested that most of the radiative effect of a cloud is confined within ~4km around the cloud. Therefore, we merge cloud objects within 4km away from each other as a cloud system and identify cloud objects farther than 4km as different cloud systems. The set of anchor points for each cloud system is the collection of anchor points for all cloud objects within the system.

Tracking cloud systems. As described in Sec. 5.2, each cloud system contains one or more local maxima as its anchor point. We can use the matching between the anchor points (see Sec. 5.3) to compute the trajectory for cloud systems.

We introduce a matching score between cloud systems at adjacent time steps. We denote the set of anchor points for a cloud system X as P_X. The matching probability from the optimal coupling between an anchor point v_1 at time step t and v_2 at time step $(t+1)$ is $C_t(v_1, v_2)$. Then, for the cloud systems X (at time step t) and Y (at time step $(t+1)$), the matching score between them is

$$S_t(X,Y) = \sum_{x \in P_X, y \in P_Y} C_t(x,y). \tag{5}$$

Informally, this score is the probability of mass transportation from X to Y. The higher this score is, the more likely the two are matched.

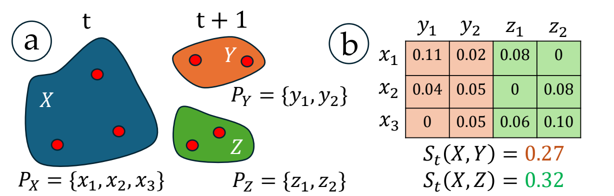

Figure 6: Cloud system matching score. (a) Cloud system X at time t and cloud systems Y and Z at time $(t+1)$ with their set of anchor points. (b) Selected rows and columns of the coupling matrix C.

Fig. 6 gives an example of matching scores involving cloud systems X, Y, and Z. In (a), there are three anchor points for X at time step t, and two for Y and Z at time step $(t+1)$, respectively. The coupling matrix C for the anchor point matching probability is in (b). For example, the matching probability between anchor point x_1 from X and y_1 from Y is 0.11. The matching score $S_t(X,Y)$ equals the sum of the first two (orange) columns for anchor points y_1 and y_2, which is 0.27. Similarly, $S_t(X,Z)$ equals the sum of the last two (green) columns for anchor points z_1 and z_2, which is 0.32.

With the matching scores, we can match the cloud systems via a bipartite graph matching algorithm. Let H_t denote the set of cloud systems at time step t. We use $S_t(X,\cdot) = \sum_{h \in H_{t+1}} S_t(X,h)$ to denote the total outgoing probability for a cloud system $X \in H_t$ and $S_t(\cdot,Y) = \sum_{h \in H_t} S_t(h,Y)$ the total incoming probability for $Y \in H_{t+1}$. A matching between the cloud system X and Y is *valid* if $S_t(X,Y)$ is nonzero and satisfies one of the two conditions:

1. $Y = \arg\max_{h \in H_{t+1}} S_t(X,h)$, and $X = \arg\max_{h \in H_t} S_t(h,Y)$;
2. $S_t(X,Y) \geq \max\{S_t(X,\cdot), S_t(\cdot,Y)\} \times r$.

Condition (1) means that X and Y are mutually the best match; otherwise, condition (2) implies that the matching score must exceed a threshold proportional to the maximum cumulative score of both X and Y. The proportionality factor is governed by the parameter r, which controls the strictness of the matching criteria. In practice, we set $r = 0.1$. We justify this parameter choice in the supplement.

Among valid matchings, we search for a one-to-one cloud system matching strategy that prioritizes the pairing of cloud systems with larger areas. We implement this process using a greedy algorithm.

1. **Sorting by area.** First, we sort all cloud systems $X \in H_t$ in descending order based on their areas, ensuring that larger cloud systems are processed first.
2. **Greedy matching.** For each cloud system X in the sorted list, we evaluate all candidate cloud systems $Y \in H_{t+1}$ that satisfy matching conditions (1) or (2) and choose the one with the largest area to be matched to X.
3. **Handling unmatched systems.** For all remaining cloud systems that are unmatched, we mark them as terminated (for $X \in H_t$) or newly formed (for $Y \in H_{t+1}$).

By combining all the selected matchings across adjacent time steps, we generate a set of trajectories for the cloud systems. We do not match clouds across non-adjacent time steps, so a cloud that disappears and later reappears is recorded as separate trajectories.

Merge and split events. Cloud systems often merge and split as they evolve, providing weather scientists with insights into their evolution. Our framework supports computing and visualizing these events. Following the tracking algorithm outlined above, we have computed all valid matchings, with one labeled as the main trajectory and the others identified as secondary trajectories. In the example in Fig. 6, we let the main trajectory of the cloud system X go to Z if the area of Z is larger than Y. However, the trajectory from X to Y can also be considered secondary due to the high matching score between X and Y. Including this secondary trajectory allows us to interpret the scenario as follows: at time step t, cloud system X splits into two systems, Y and Z, at time step $t+1$, with Z continuing along the main trajectory.

6 Experimental Results

In this section, we experiment with two datasets from geostationary satellites. The first **Marine Cloud** dataset focuses on marine stratocumulus clouds over the ocean west of Africa during August 2023, whereas the second **Land Cloud** dataset covers shallow cumulus cloud systems over central Europe from April to September between 2018 and 2019; see supplement for details on these datasets. We review and compare against two state-of-the-art cloud tracking tools (Sec. 6.1), with parameter justifications (Sec. 6.2). We then perform statistical evaluations (Sec. 6.3) and discuss our tracking results in Secs. 6.4 and 6.5. Additionally, we compare our approach with two topology-based general-purpose tracking tools in Sec. 6.6.

6.1 Two Leading Cloud Tracking Tools

We report the results from two state-of-the-art open-source cloud tracking tools for comparative analysis: tobac [13,33] and PyFLEXTRKR [11]. We refer to our tool as the pFGW framework.

We briefly compare the two cloud tracking frameworks with ours. All three tools involve superlevel thresholds for cloud detection. The tool tobac applies the Watershed algorithm [38] with the threshold, whereas PyFLEXTRKR and pFGW use superlevel set components to identify cloud objects. For cloud tracking, tobac tracks the centroids of cloud objects and computes the matching plan with the minimum sum of the Euclidean distances between matched cloud centroids. PyFLEXTRKR computes the region overlap for cloud tracking. In comparison, pFGW combines topological and geometric information of anchor points and summarizes the tracking results for all anchor points within a cloud system. Furthermore, instead of tracking cloud objects, pFGW considers multiple cloud objects as a cloud system and tracks the system as a whole. For simplicity, we use *cloud entity* to refer to either cloud object or cloud system for the rest of the paper. We report other algorithmic details of tobac and PyFLEXTRKR in the supplement.

6.2 Parameter Configurations

Computing the pFGW distance requires two parameters α and m (see Sec. 4.2). We intend to put a higher weight on preserving the geometric location of nodes while still considering the intrinsic merge tree structure, leading to $\alpha \leq 0.5$. We set $\alpha = 0.4$ for the **Marine Cloud** dataset and $\alpha = 0.2$ for the **Land Cloud** dataset. We adopt the strategy of [29] to tune m. Specifically, we impose a threshold on the maximum distance between matched nodes across adjacent time steps and select the largest m such that no matches exceed this threshold. This approach preserves high-probability couplings while avoiding clearly spurious matches. For a fair comparison, we use the same superlevel set threshold for cloud detection for all three methods. See the supplement for other parameters of the three methods and a discussion about parameter choices.

6.3 Evaluation Metrics

Tracking clouds over time using satellite observations is challenging due to their dynamic nature, including their appearances, disappearances, splitting, merging, and transformation. Based on earlier studies in cloud science [12,26], we utilize three evaluation metrics to assess the tracking results.

First, we study the distribution of **timespans** for cloud entities (cloud objects or cloud systems). The timespan is the duration of time (i.e., the number of time steps) a cloud entity travels along its trajectory. This metric indicates how consistently a tracking method monitors cloud entities. However, we do not postulate that every cloud entity should be long-lived.

Second, we investigate the distribution of the standard deviation of a cloud property (e.g., mean COD value of a cloud entity at a given time step) along trajectories, referred to as the **SD of mean COD**. The physical properties of a cloud entity are expected to remain fairly stable over time, with no significant deviations. A mismatch is likely to result in an increase in the standard deviation along the trajectory. We consider only trajectories with a timespan longer than the median timespan and at least three time steps, as the standard deviation is highly sensitive to small sample sizes.

Third, we examine the distribution of the **linearity loss** of trajectories. The linearity loss of a trajectory is the root mean square error (RMSE) of the centroids of cloud entities from the line of best fit. Given the momentum of clouds, it is reasonable to expect short-lived trajectories to be nearly linear without abrupt jumps. However, longer trajectories are more likely to follow the mean flow, which can vary across time and space and lead to curved paths not captured by this metric. For consistency, we evaluate this metric on the same set of trajectories used in the mean mean COD study.

6.4 Case Study: Marine Cloud Dataset

We first examine the **Marine Cloud** dataset, which focuses on marine stratocumulus clouds over the ocean west of Africa. We highlight our topology-driven tracking results in Fig. 1 using two time steps on Aug 1, 2023, at 09:00 and 10:00 UTC, respectively. We then perform a detailed analysis of the cloud tracking results using a subregion from the same dataset also on Aug 1, 2023 in Fig. 7. There are 28 time steps within the day from 09:00 to 15:45 UTC with 15-minute intervals.

Cloud detection and tracking. We first compare the cloud detection results across the three cloud tracking tools: pFGW, PyFLEXTRKR, and tobac. All three methods successfully identify cloud entities from the COD fields, with small discrepancies due to the minor differences between watershed-based (used by tobac) and superlevel-set-based (used by PyFLEXTRKR and to some extent pFGW) strategies.

Meanwhile, we highlight the differences between tracking *cloud objects* versus *cloud systems* in Fig. 7. For PyFLEXTRKR (3rd column), at 09:45 UTC, the central green object (magenta box) splits into two distinct objects (green and gray). At 10:00 UTC, these two

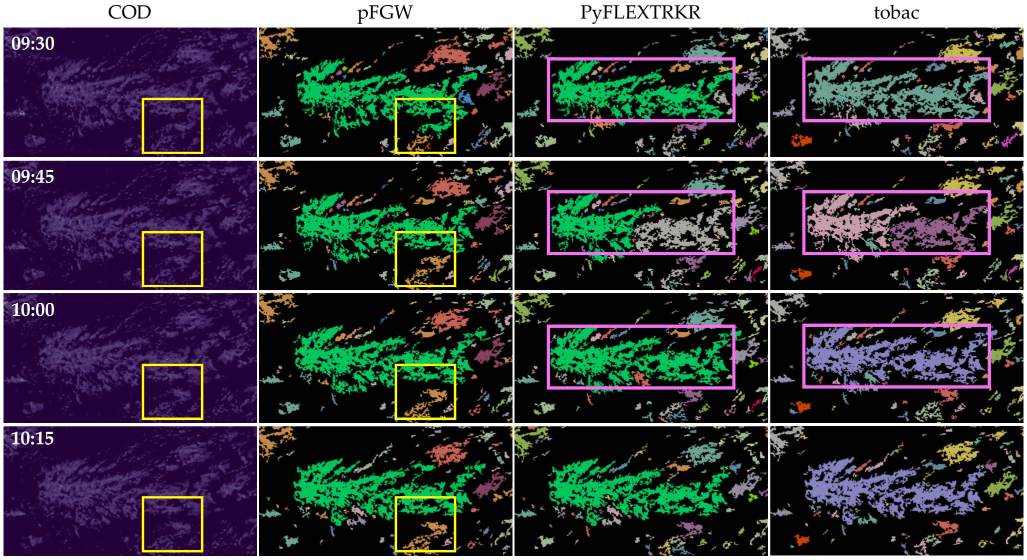

Figure 7: Tracking results of a region in the **Marine Cloud** dataset on Aug 1, 2023, at 9:30, 9:45, 10:00, and 10:15 UTC, respectively. Cloud entities are colored by feature correspondences. From left to right: visualizations of COD fields, tracking results for pFGW, PyFLEXTRKR, and tobac, respectively. For pFGW, yellow blocks from top to bottom showcase a cloud transition process from the green cloud system to the orange one. For PyFLEXTRKR and tobac, magenta boxes highlight suboptimal tracking results due to the transient splitting and merging of cloud objects.

objects merge back together, and the trajectory of the newborn gray object terminates. For tobac (4th column), we observe similar cloud splitting and merging events at 09:45 and 10:00 UTC, respectively; however, tobac considers the objects (magenta boxes) at 9:45 and 10:00 UTC to be new entities, giving rise to three new trajectories. However, the cloud-splitting event at 09:45 UTC is not obvious in the COD field. In contrast, at 09:45 UTC, pFGW does not split the same green cloud system in the center, as our tracking method aggregates nearby cloud objects into a single cloud system.

Previous studies report significant COD uncertainties outside the 5-50 range [43]. With a detection threshold of 2.0, such uncertainties can blur cloud boundaries, leading to transient splits and merges. Tracking cloud systems (instead of cloud objects) with pFGW mitigates this by avoiding numerous short-lived trajectories for these transient events.

As shown in Fig. 7, we gain additional insights by tracking cloud systems instead of cloud objects using pFGW. The yellow boxes in the 1st and 2nd columns highlight a cloud transition process, where a part of the central green system splits and merges into the bottom orange system. In contrast, PyFLEXTRKR and tobac track all cloud objects individually in this region, thus it is harder to infer the change in proximity between clouds.

Statistical evaluation. We statistically evaluate the **Marine Cloud** dataset from Aug 1 to Aug 8, 2023. The observed time period for each day is from 09:00 to 15:45 UTC with a 15-minute interval. We calculate the tracking results for each day separately and then aggregate the statistics from all eight days to evaluate the overall performance for each method. For pFGW, we include statistics involving tracking cloud systems (*pFGW-system*) and tracking cloud objects (*pFGW-object*).

Fig. 8 shows the distributions of trajectory timespan. These distributions are comparable across all three methods. The distributions of pFGW for tracking cloud objects and tracking cloud systems are also similar. Specifically, PyFLEXTRKR generates more short-lived trajectories (primarily those lasting less than 15 minutes); tobac generates fewer longer-lived trajectories compared to the other two methods. In comparison, pFGW preserves long-term trajectories while reducing the number of short-lived ones.

Fig. 9 presents the overall statistics for comparison and displays the *trajectory timespan* distribution in the form of a box plot (1st column). PyFLEXTRKR generates more short-lived trajectories

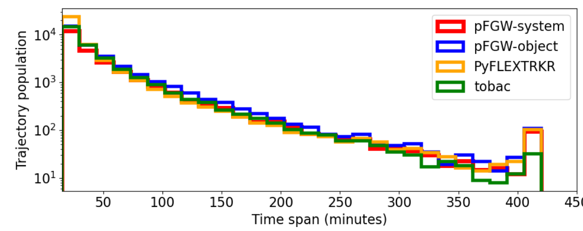

Figure 8: **Marine Cloud** dataset: distribution of trajectory timespans in log-scale for pFGW tracking cloud systems (red) and objects (blue), PyFLEXTRKR (orange), and tobac (green); data aggregated over eight days (Aug 1-8, 2023).

compared to the other two methods, with the median trajectory timespan being just 15 minutes (one timestep). In contrast, pFGW and tobac exhibit a higher median value of 30 minutes (two timesteps), whereas pFGW has a higher interquartile range and mean. It shows that pFGW performs the best at preserving the trajectory duration among the three approaches.

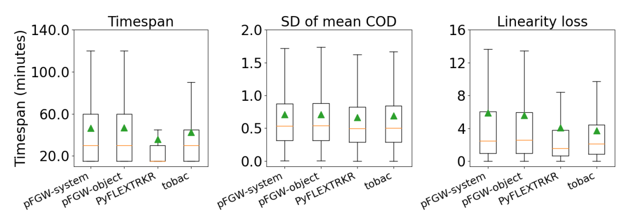

Figure 9: **Marine Cloud** dataset: box plots showing the median (orange line), mean (green triangle), and interquartile range (box boundary) of the distribution for three evaluation metrics.

We compute the standard deviation of mean COD and the linearity loss for trajectories that last for at least 45 minutes (three timesteps); see the 2nd and 3rd columns of Fig. 9. Three methods have similar performance in preserving the mean COD of cloud entities along the trajectory. On the other hand, pFGW has a higher linearity loss compared to the other two methods. This is anticipated as cloud merging and splitting events have been observed to introduce undesirable shifts in the centroid position of the cloud system along the main trajectory. In particular, such position shifts can be drastic for large cloud systems, which are often long-lived for stratocumulus clouds. In contrast, tobac is less effective at identifying cloud merging and splitting events for large cloud entities (see Fig. 7 4th column); PyFLEXTRKR performs worse in maintaining the trajectory timespan. As a result, both tools generate fewer trajectories with high linearity loss.

6.5 Case Study: Land Cloud Dataset

The **Land Cloud** dataset is collected above central Europe, where the complex land-driven convection strongly affects the low-level cloud systems. As the land warms up during the day, shallow cumulus often initiates in the morning, grows mature over time, and reaches its peak in the late afternoon. Hence, during its life cycle, the optical depth of shallow cumulus changes over time. Therefore, we divide the data into three periods for each day: 06:00 to 09:00 UTC for the *morning*, 09:05 to 15:00 for the *midday* period, and 15:05 to 17:55 for the *late afternoon*. In particular, we are interested in the morning and midday periods, as these are typically when the initiation and maturation of shallow cumulus occur, respectively.

For the morning period, we set the superlevel set threshold to 9.0, and for the midday period, we set it to 10.0. This decision is based on the observed quality of cloud segmentation using superlevel set components, as outlined in [12], and the parameter sensitivity analysis described in Sec. 5.1, with further details in the supplement. We do not simplify cloud entities by area because shallow cumulus clouds (particularly during the initiation stage) are smaller and have more gaps between individual cloud objects.

Cloud detection and tracking. We use the data from May 1, 2018, for our case study. We check the transition from 08:30 to 08:35 UTC for data in the morning. For data in the midday, we check the transition from 12:05 to 12:10 UTC. We color all the new cloud entities in magenta at 8:35 UTC and 12:10 UTC, respectively. These new entities may arise from the formation of shallow cumulus, the splitting of a cloud entity, or the loss of cloud tracking.

The morning period reveals a cluster of shallow cumulus clouds developing near the center of the COD field, as illustrated in the first two rows of Fig. 10. These shallow cumulus clouds are identified as a set of small cloud entities in the tracking results. When comparing the performance of pFGW and PyFLEXTRKR, it becomes evident that PyFLEXTRKR loses a significant number of trajectories for these tiny cloud entities; see the cyan box in the 3rd column. This limitation stems from the region-overlap-based approach used by PyFLEXTRKR to track clouds. In small clouds, even slight positional shifts can lead to insufficient overlaps, causing the tracker to lose these clouds. In comparison, pFGW is based on the clouds' geometric location and topological information, making it more robust when tracking small shallow cumulus clouds.

As the day progresses towards midday, the shallow cumulus system and many small cumulus cells evolve, growing thicker and merging into large cloud entities. In the bottom two rows, we observe large cloud entities in the top half of the image (red box), and clusters of small cloud entities in the bottom half (orange box). Both pFGW and PyFLEXTRKR exhibit similar performance in tracking the large cloud entities. However, for the small clouds, PyFLEXTRKR generates numerous new cloud entities (see magenta cloud entities in the orange box), showing its limitations in tracking smaller clouds consistently. In comparison, pFGW exhibits a better capability in consistently tracking small shallow cumulus clouds.

tobac shows better performance in preserving the trajectories for small cloud objects than PyFLEXTRKR (c.f. 3rd and 4th column). However, we observe that the large cloud objects at 8:30 UTC (1st row, pink boxes) are not tracked by tobac during the morning period. These two objects merge into one at 8:35 UTC, which is treated as a new object by tobac, similar to what we have observed in Sec. 6.4. Furthermore, tobac also fails to track the large objects during the midday transition (3rd and 4th row, yellow box).

Statistical evaluation. We perform the statistical evaluation similar to Sec. 6.4. We collect statistics for the datasets for three days on May 1, Jun 23, 2018, and May 12, 2019, respectively in Fig. 12. The 1st row shows the distribution of evaluation metrics for the morning period, and the 2nd row shows the distribution for the midday period.

We start with the trajectory timespan distribution. Among the three methods, PyFLEXTRKR performs the worst on tracking small shallow cumulus, which constitutes the majority of the cloud entity population. Therefore, for both morning and midday periods, most trajectories from the PyFLEXTRKR last for less than five minutes (one time step); see Fig. 11 and Fig. 12 1st column. Meanwhile, tobac does not generate trajectories with a lifetime above 300 minutes in the midday period as the other two methods do; see Fig. 11 2nd row. This reflects our previous observation in Fig. 10 4th column that tobac performs worse than the other two methods in tracking large cloud entities, many of which are persistent in the **Land Cloud** dataset. In contrast, pFGW performs the best on maintaining trajectories for small shallow cumulus in the morning and has a similar trajectory lifetime distribution to tobac in tracking cloud objects during the midday period; see Fig. 12 1st column. By merging nearby cloud objects into cloud systems, pFGW may get fewer trajectories with a long lifetime. However, pFGW still performs better than tobac in maintaining long-term trajectories in the midday period; see Fig. 11 2nd row.

We compute the standard deviation of mean COD and the linearity loss for trajectories that last for at least 15 minutes (three timesteps). When evaluating the ability to preserve mean COD along the same trajectory, all three methods have comparable performances during both morning and midday; see the 2nd column of Fig. 12.

Lastly, because there are fewer large cloud entities in the **Land Cloud** dataset, the linearity loss of pFGW trajectories is similar to that of tobac. On the other hand, it is anticipated that PyFLEXTRKR generates trajectories with the least linearity loss because PyFLEXTRKR often loses track of cloud entities on the **Land Cloud** dataset.

6.6 Comparison with Topology-based Tracking Tools

For completeness, we further compare pFGW against two topology-based general-purpose tracking tools: the Lifted Wasserstein Matcher (LWM) [53] and the Wasserstein distance between merge trees (MTW) [40].

We first compute the critical point trajectories using LWM and MTW, respectively. Next, we compute the cloud system trajectories for LWM and MTW using a postprocessing pipeline similar to that of pFGW. We use the parameter settings that generate the best critical point matching results for statistical evaluation; see the supplement for justifications. We compare the cloud system tracking performance using the statistics described in Sec. 6.3. Additional experimental details are in the supplement.

Statistical evaulation. Fig. 13 shows the distribution of cloud trajectory statistics (in Sec. 6.3) for the three topology-based methods.

We start with the trajectory timespan in Fig. 13 left. Among the three methods, MTW performs the worst in maintaining trajectory continuity. The mean and median trajectory timespan for MTW tracking results are the lowest. In comparison, pFGW and LWM have similar performance, while LWM has a slightly higher mean timespan for trajectories. For the standard deviation of mean COD, all three approaches demonstrate similar distributions for their results. This indicates that all three methods perform similarly in matching cloud systems with similar COD distributions, which are partly reflected by the anchor point COD values. Lastly, pFGW achieves the lowest linearity error on average, with LWM performing slightly worse, while MTW performs substantially worse; see Fig. 13 right (where the boxplot of MTW goes beyond the boundary). This is expected because MTW does not consider geometric locations when matching anchor points.

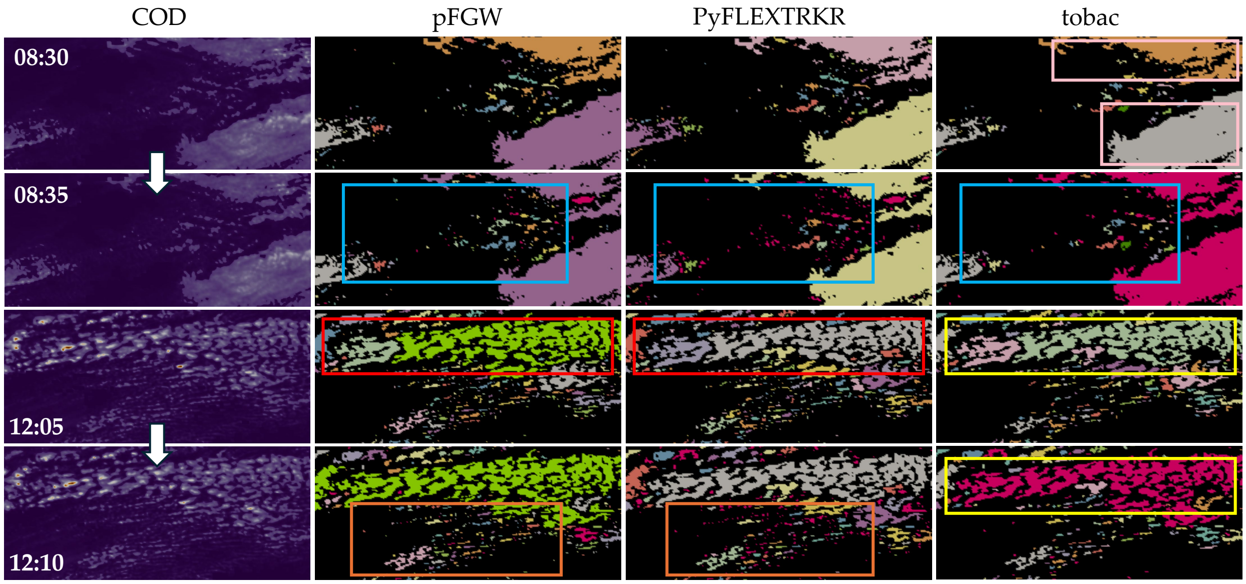

Figure 10: Tracking results of a region in the **Land Cloud** dataset on May 1, 2018. From left to right: visualizations of COD fields, tracking results for pFGW, PyFLEXTRKR, and tobac, respectively. The top two rows (resp. bottom two rows) are for the transition during the morning (resp. midday) period. All new cloud entities in the 2nd and 4th rows are colored magenta; others are colored by correspondences. Cyan and orange boxes (3rd column) highlight the areas where PyFLEXTRKR fails to track many small shallow cumulus clouds (shown as new entities in magenta). Yellow and pink boxes (4th column) emphasize the suboptimal tracking results from tobac when two large cloud objects merge.

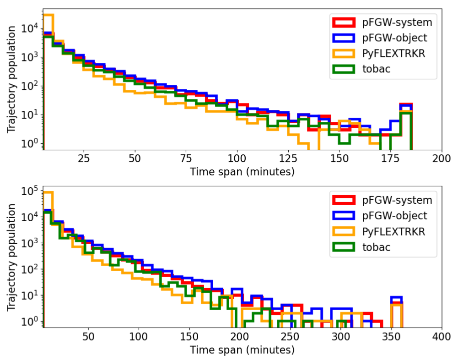

Figure 11: **Land Cloud** dataset: distributions of trajectory timespans in log-scale for pFGW tracking cloud systems (red) and objects (blue), PyFLEXTRKR (orange), and tobac (green); data aggregated over three days (May 1 and Jun 23 in 2018, and May 12 in 2019). The top row is for the morning period, and the bottom is for the midday.

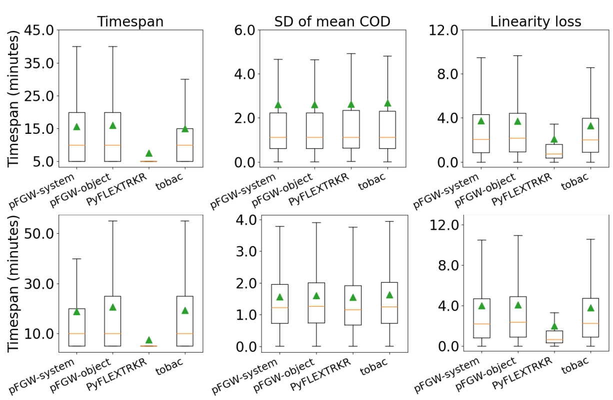

Figure 12: **Land Cloud** dataset: statistical evaluation for the morning data (1st row, 06:00–09:00 UTC) and midday data (2nd row, 09:05–15:00 UTC). Box plots show the median (orange line), mean (green triangle), and interquartile range (box boundary) for three evaluation metrics.

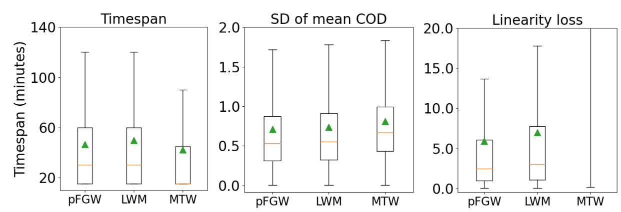

Figure 13: **Marine Cloud** dataset: box plots showing the median (orange line), mean (green triangle), and interquartile range (box boundary) of the distribution for three topology-based tracking methods. The box for the linearity loss for MTW exceeds the plot's upper bound.

7 Conclusion and Discussion

The case studies and statistical evaluations provide several important takeaways. First, our framework operates with cloud systems instead of cloud objects, reducing sensitivity to threshold selection and producing fewer short-lived cloud trajectories. Tracking low-level clouds as systems offers deeper insights into their proximity and evolution. Second, our framework demonstrates strong performance in tracking clouds compared to two state-of-the-art cloud tracking methods. Notably, it is the most consistent in tracking small shallow cumulus clouds over land as well as large stratocumulus over the ocean. In future work, we aim to enhance tracking quality by integrating additional cloud variables, such as cloud fraction, cloud liquid water path, and cloud top height [44].

Acknowledgments

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