

Spatio-Temporal Consistency as a Means to Identify Unlabeled Objects in a Continuous Data Field

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Abstract

Mesoscale ocean eddies are a critical component of the Earth System as they dominate the ocean's kinetic energy and impact the global distribution of oceanic heat, salinity, momentum, and nutrients. Therefore, accurately representing these dynamic features is critical for our planet's sustainability. The majority of methods that identify eddies from satellite observations analyze the data in a frame-by-frame basis despite the fact that eddies are dynamic objects that propagate across space and time. We introduce the notion of spatio-temporal consistency to identify eddies in a continuous spatio-temporal field, to simultaneously ensure that the features detected are both spatially and temporally consistent. Our spatio-temporal consistency approach allows us to remove most of the expert criteria used in traditional methods to reduce false negatives. The removal of arbitrary heuristics enables us to render more complete eddy dynamics by identifying smaller and longer lived eddies compared to existing methods.

1 Introduction

Our planet is more observable than ever thanks to earth-orbiting satellites, in-situ measurements, *etc.* This advanced coverage coincides with the increasing need to understand physical phenomena on a global scale. However, the global monitoring of dynamic phenomena from multiple data sources is relatively new and presents unique challenges that are rare in the traditional computer science literature. This is especially true when we consider the growing number of noisy, heterogeneous, and spatio-temporal datasets used in Earth Science. We present a novel method to identify objects in a continuous spatio-temporal field with an application to monitoring global ocean dynamics.

Mesoscale ocean eddies (herby eddies) are large (50-200km) rotating coherent features that dominate the ocean's kinetic energy. Eddies are *nonlinear* features (Chelton et al.

2007) as they not only rotate along their center but they also translate linearly. As such, the rotation of these features allows them to trap water (and associated properties) within their contour while their linear translation causes the trapped water to be transported up to several hundred kilometers. Thus, eddies play a critical role in the global vertical and horizontal distribution of heat, salinity, momentum, and nutrients across the globe.

Identifying eddies from satellite data has been an active field of research. The majority of studies identify eddies as instantaneous anomalies derived from satellite data, despite the fact that eddies are dynamic objects that propagate and evolve across space and time. Eddies are generally identified through two independent steps: First, eddy-like features are isolated in successive frames of satellite data. Second, the eddy-like features are tracked across time by associating each feature in one frame to another feature in the following time-step. Features that persist beyond a user-specified threshold are deemed significant. This approach has two major limitations: First, the identification step returns a large number of features, many of which are spurious. To reduce uncertainty, a set of expert-defined criteria are applied to each feature (such as minimum and maximum size) and those failing to meet any one of these criteria are removed from consideration. While such expert-criteria are necessary, they are also arbitrary and may cause quality features to be discarded (false negatives). Second, eddies are dynamic objects that propagate across space and time, yet most methods treat them as static by ignoring the temporal component of the phenomena.

We present a novel spatio-temporal pattern mining algorithm that is specifically designed for dynamic spatio-temporal phenomena. Our approach uses the notion of *spatio-temporal consistency* to identify objects. The intuition behind spatio-temporal consistency is that spatio-temporal phenomena leave distinct signature in both the spatial and temporal domains. Given the noise and uncertainty associated with more real-world applications, looking at any one signature alone is generally insufficient however inte-

grating both spatial and temporal information can provide a powerful object identification framework especially in unsupervised settings where ground truth data are unavailable. Within this framework, instead of using strict criteria to prune objects, only features that are simultaneously consistent in space and time are considered. Using space-temporal consistency instead of expert heuristics allows us to identify a non-trivial number of eddies that would fail the heuristic yet they contribute to global ocean dynamics.

2 Background

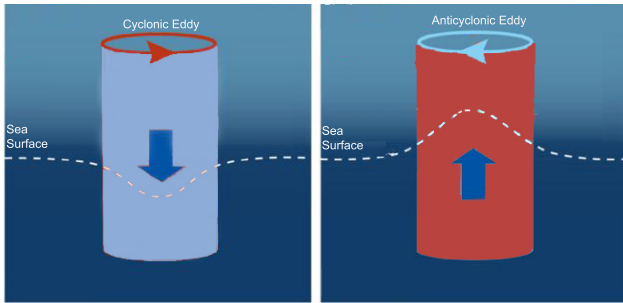


Figure 1: A cartoon of a cyclonic (left) and an anticyclonic eddy (right). The direction of rotation of the eddy causes the sea surface to either increase or decrease within the eddy’s contour. Some important eddy characteristics are its size (measured in pixels) and its amplitude which is the difference between the sea surface height extrema within the eddy’s interior and the mean surface height of the eddy’s perimeter.

2.1 Ocean Eddies: An Overview

Ocean eddies are coherent rotating structures of water that span tens to hundreds of kilometers and last for several weeks and up to years. Eddies are ubiquitous and during any given week nearly 4,000 eddies can be detected in satellite data (Faghmous et al. 2013).

Eddies are categorized based on their rotational direction. They are either *cyclonic* if they rotate counter-clockwise (in the Northern Hemisphere) or *anticyclonic* otherwise. Cyclonic eddies, like the one in Figure 1 (left), cause a decrease in sea surface height (SSH) and elevations in subsurface density surfaces. Anti-cyclonic eddies, such as the one depicted in Figure 1 (right), cause an increase in SSH and depressions in subsurface density surfaces. These characteristics allow us to identify ocean eddies in SSH satellite data. Anticyclonic eddies can be seen in ellipse-shaped regions of positive SSH anomalies, while cyclonic eddies are reflected in closed contoured negative SSH anomalies. The opposite rotation causes each type of eddy to have an opposite impact on various ocean properties. For simplicity, when we refer to the impact of an eddy we mean a cyclonic eddy with the understanding that an anticyclonic eddy would have the opposite effect. For instance, cyclonic eddies tend to have cold cores and we implicitly mean that anticyclonic have warm cores.

There are four major aspects that characterize eddies: their radius, amplitude, geodesic (rotational) speed, and their lifetime. The first three can be computed instantaneously from a single satellite snapshot, while life-time can only be computed once a feature is tracked. In this paper we will focus mainly on the eddy size as measured in pixels and their amplitude, which is the difference between the SSH of the eddy’s extrema and the mean SSH of the eddy’s periphery. The majority of studies consider a feature from satellite data to be significant if it has at least 9 pixels, more than 1cm in amplitude, and persists for a least 4 weeks.

2.2 Why Ocean Eddies Matter

Monitoring global ocean dynamics plays a critical role in ensuring future sustainability. Ocean eddies are a fundamental component of the ocean dynamics and have significant impacts on a wide range of atmospheric and oceanographic phenomena. Eddies have been shown to impact the atmosphere in their direct vicinity by influencing sea surface temperatures that in turn impact near-surface winds, clouds, and rainfall (Frenger et al. 2013). Eddies have also been shown to impact marine ecosystems by raising the deep nutrient-rich water to the surface, which renews the nutrient supply to phytoplankton and subsequently leads to increased fish production (Denman and Gargett 1983; Chelton et al. 2011). Additionally, eddies might interact with other large systems. For instance, one study found that a 7000-year-old coral reef was asphyxiated due to massive phytoplankton blooms, that were linked to a large eddy (Rahul et al. 2010). Similarly, some of the recent devastating hurricanes, including Hurricane Katrina, gained intensity in the Gulf of Mexico when passing over a warm-core eddy (Jaimes and Shay 2009). Finally, Southern Ocean eddies known as “Agulhas rings” may act as a moderating factor in global climate change when their warm and salty water reaches the upper arm of Atlantic Meridional Overturning Circulation (AMOC) where waters have become cooler and less salty because of Arctic ice melting (Beal et al. 2011).

2.3 Eddy Monitoring In Satellite Products

Until recently, ocean eddies were tracked using sea surface temperatures and ocean surface color. However many phenomena influence sea surface temperatures and color other than eddies. As a result, SSH are the most widely used data. Traditionally, eddies have been identified independently in a satellite snapshot without accounting for time. Some studies identified eddies based on a measure of rotation and deformation in fluid flow known as the Okubo-Weiss (W) parameter (Isern-Fontanet, García-Ladona, and Font 2003; Chelton et al. 2007). In such studies, eddies were defined as features where the W -parameter was below an expert-specified negative threshold. Other studies identified eddies through a wavelet-packet decomposition of the SSH field (Doglioli et al. 2007). Finally, more recent studies employed an iterative-threshold approach to isolate close-contour anomalies from the background (Chelton, Schlax, and Samelson 2011; Faghmous et al. 2012).

Although each approach is slightly different with various tradeoffs, these methods share one common pitfall: they all

rely on expert criteria to identify objects and reduce the risk of false positive. In fact some of these methods are so sensitive to parameterization that they report a 50% difference in results depending on the threshold used (Souza, de Boyer Montégut, and Le Traon 2011).

2.4 Challenges

Monitoring eddies presents stimulating computer science challenges that generalize to numerous problems that deal with spatio-temporal data. There are several conceptual and computational challenges when trying to mine objects in a continuous spatio-temporal field. First, the very notion of objects is subjective and uncertain. This is due to the fact that the objects are not directly observable (compared to identifying a clear object such as a car in an image). Instead, we must rely on proxy data to infer the presence or absence of an object. For our application, we cannot directly observe the actual eddies unless we were able to measure subsurface information (eddies can span tens of meters vertically into deep waters), thus we rely on an imprecise estimate of an eddy’s impact of the observable sea surface height field. Furthermore, the spatio-temporal autocorrelation within the field (some from post-processing) makes the data smooth and as a result it is difficult to identify the object’s exact boundaries. Second, the proxy data tend to be extremely variable, which makes developing parameter-free methods challenging. Some of the variability is due to natural variability in the Earth System., while other sources of variability include measurement error and our incomplete understanding the processes that drive many natural phenomena (model representation). Finally, a growing number of domains lack ground truth data for evaluation. In the case of eddies, the majority of algorithms use anecdotal field studies to validate their methods. Thus there is a need for novel objective evaluation methods for unsupervised learning algorithms in science. For a deeper discussion of the challenges and opportunities in spatio-temporal data mining see (Faghmous and Kumar 2013).

2.5 Data and Research Objectives

In this study, we identify spatio-temporal objects (eddies) in continuous SSH anomaly data. We use the Version 3 dataset of the Archiving, Validation, and Interpretation of Satellite Oceanographic (AVISO) which contains 7-day averages of SSH on a 0.25° grid from October 1992 through January 2011¹. In addition to identifying spatially consistent features (*i.e.* their physical contour), we wish to analyze how consistent they are in time and use such consistency as a measure of certainty that could replace the strict heuristics commonly used in the literature.

3 Methods

The majority of eddy detecting algorithms focus primarily on identifying features independently in space, and use strict criteria concerning a feature’s physical attributes as means to reduce false positives. Thus, despite the fact that eddies are

¹Available at <http://www.aviso.oceanobs.com/es/data/products/sea-surface-height-products/>

coherent features across space and time, existing methodologies fail to take advantage of such structure and introduce unnecessary uncertainty by analyzing four-dimensional data (latitude, longitude, time, and sea surface height) as three dimensional.

Instead of relying on a static view coupled with arbitrary parameters, we take inspiration from the physical world to identify spatio-temporal objects. In the physical world, we generally think of an object existing or not based on whether it is spatio-temporally consistent. For instance, an object can only exist if its body is spatially consistent – all its molecules are tightly packed in the proper form, *etc.* Additionally an object must be temporally consistent – it can only be at one place at a time. We call this insight that objects have distinct and complimentary signatures in space and time as *spatio-temporal consistency*.

We use this general notion of spatio-temporal consistency to identify eddies in the continuous spatio-temporal field based on known signals they leave in spatial and temporal domains. We define an eddy feature as a group of spatio-temporally consistent SSH anomalies:

Spatial consistency: Depending on their rotational direction, eddies can be seen as closed-contour positive or negative anomalies. Furthermore, (Chelton, Schlax, and Samelson 2011) showed that mesoscale eddies can be approximated in space as axially symmetric Gaussian structures of the form

$$h(r) = A \exp(-r^2/L_e^2) \quad (1)$$

where h is SSH, r is the radial distance from the eddy centroid, A is the eddy amplitude, and L_e is the e-folding scale for the eddy. (Chelton, Schlax, and Samelson 2011) estimated for a mesoscale eddy in the AVISO dataset $L_e \approx 0.4^\circ$. That is, given that an eddy’s center is its local extrema, the remaining pixels in the eddies contour should obey axisymmetric Gaussian change². Here we use the iterative thresholding method introduced by (Faghmous et al. 2013) to identify spatially consistent SSH anomalies. Due to space limitations, we will focus on the novel temporal component of our algorithm.

Temporal consistency: As moving objects, eddies impact a wide range of regions. When an eddy passes over a region, their slow transitional speed of 10km/week (Frenger et al. 2013) causes them to leave a unique signal in the temporal profile of regions they pass through. Figure 2 demonstrates such impact. As an eddy approaches a region, the SSH gradually decreases and will reach a local (temporal) minima when the eddy is on top of that region. The SSH will then gradually return to its initial height as the eddy moves away.

To quantify how likely an eddy passed by a given location, we analyze each grid location which can be characterized by an SSH time-series denoting that location’s SSH temporal evolution. Each location is susceptible to interact with a cyclonic eddy, an anticyclonic one, or neither. As mentioned above, the presence of an eddy causes that location to have a local extrema in time, thus we search for all local extrema (minima and maxima for cyclonic and anticyclonic

²See figure 15 in (Chelton, Schlax, and Samelson 2011)

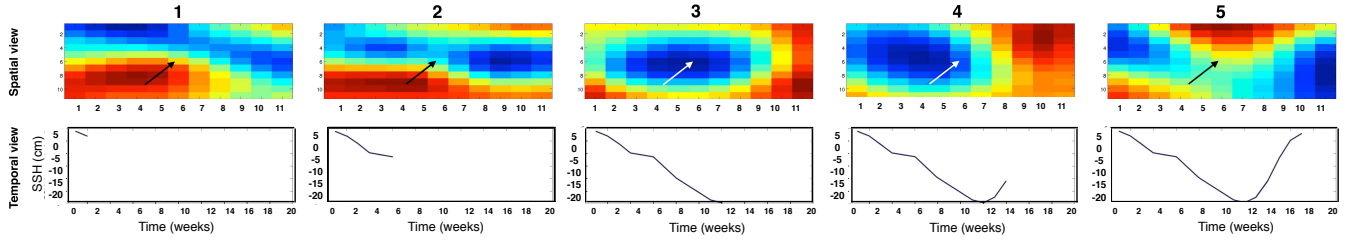


Figure 2: An eddy’s footprint on a location’s temporal SSH profile. Top row: a spatial view of the SSH anomalies as a cyclonic eddy moves from right to left. The eddy can be seen as the large negative (blue) ellipse propagating through the field. Bottom row: The temporal view of the SSH anomalies at the location highlighted by the arrow in the top row (center pixel in the spatial view). The SSH anomalies are near +5cm before the eddy reaches the location of interest. As the eddy draws nearer the SSH anomalies gradually decrease until they reach a minimum when the eddy’s passes through that pixel. The eddy’s passing through this location causes a 30cm change in SSH over 14 weeks. The slow and gradual impact on SSH is the temporal footprint eddies have on SSH.

eddies respectively) along the 954 week time-series (nearly 20 years). To test how significant the imprint of the eddy was, we compute the area above the curve (for cyclonic eddies) as a measure of the strength of the signal. We expect stronger eddies to leave a larger area or a deeper imprint on locations it passes by. For any pixel p_i in a satellite snapshot at time t_i we can score it as a function of how far (in time) is t_i from the time the nearest temporal extrema occurred at p_i and how deep was the temporal imprint at p_i . Formally, we assign a score $s_i^{t_j}$ for each pixel p_i at time t_j :

$$s_i^{t_j} = \frac{A_{ext}}{|t_j - t_{ext}| + 1} \quad (2)$$

where A_{ext} is the area over/under the curve for the nearest local extrema and t_{ext} is the time at which the nearest extrema occurred at p_i . Thus, $s_i^{t_j}$ will be high when both the area created by the extrema is high and when the current time t_j is close to the time when the nearest extrema occurred (t_{ext}). We take the absolute value of the distance in time to avoid negative quantities. We add one to the time difference to avoid dividing by zero when $t_j = t_{ext}$.

Figure 3 demonstrates how we score each location (or pixel p_i) for a given time t_j . First, all maxima and minima the 20-year time-series are identified (in red and green respectively). Then for a given time t_j we search for the nearest temporal extrema t_{ext} . In this case, let’s assume we are looking for the imprint of cyclonic eddies, thus we are interested in sustained depressions (*i.e.* minima) in SSH³. In this example, t_j is at 20 weeks and the nearest minima is at $t_{ext} = 18$ weeks. The area above the local minima at t_{ext} is A_{ext} and is computed as the area between the dashed line and the time-series curve. A_{ext} is approximately 80. Thus the score for the pixel p_i at t_j is $s_i^{t_j} = \frac{80}{(20-18)+1} = 26.6$ We assign the temporal score of an entire eddy by averaging the temporal scores of all pixels within the contour of the eddy as identified in space.

Using these two definitions, we can now have a space-time consistency model for ocean eddies in SSH: features

³for anticyclonic eddies we would analyze the increases in SSH and their maxima

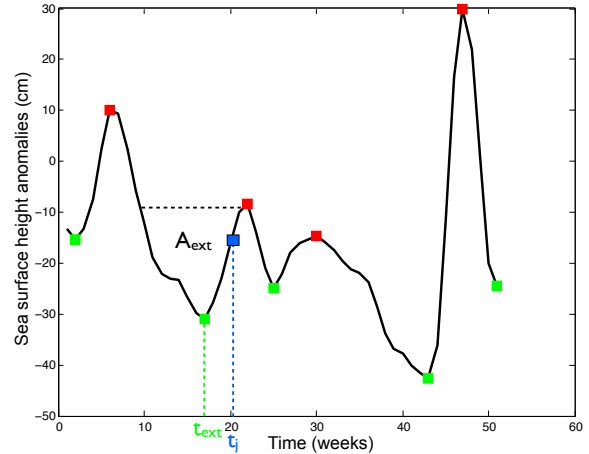


Figure 3: An SSH time-series at a single pixel. Each green and red square denote a local minimum and maximum respectively. We search for all “U” shaped segments by simply ascending to the left and right of each local minimum. Once the two maxima surrounding the local minimum are identified, we compute the area over the curve (for cyclonic eddies) between the SSH time-series and a horizontal dashed line drawn from the smallest of the two maxima.

must be a closed-contour local anomalies and those regions that make the eddy’s interior must have a slowly decreasing (increasing) SSH profile in the temporal domain. Figure 4 shows the complimentary spatio-temporal view of the data. Notice that each view is imperfect but together they provide a more certain view of the object.

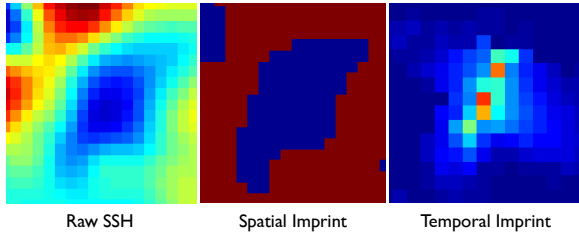


Figure 4: The different and complimentary views of the data. *Left*: raw SSH where a cyclonic eddy can be seen as close contour negative anomaly. *Center*: the resulting connected component from the iterative thresholding method. *Right*: The score of each pixel based our temporal scoring method.

The source code along with an interactive eddy viewer are available for download and to contribute to as an Open-Source project at: www.ucc.umn.edu/eddies

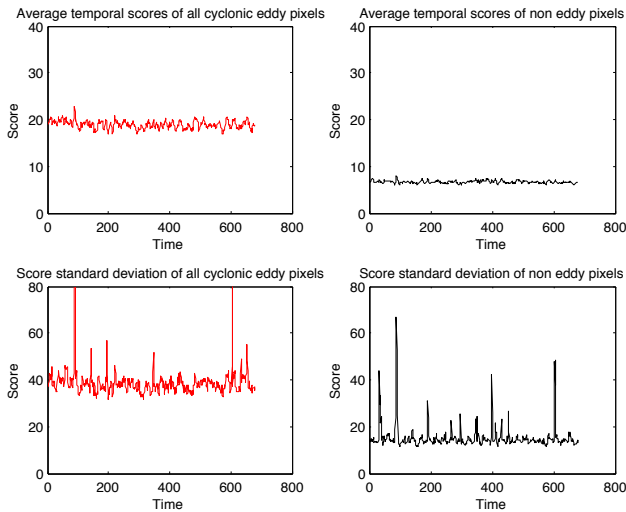


Figure 5: Variation over time (in weeks) of mean temporal scores of pixels within eddies (eddy pixels) and pixels outside eddies (non-eddy pixels). The bottom row shows the standard deviations of the scores. The scores for eddy pixels are significantly higher than those of pixels that are not within an eddy.

3.1 The Significance of The Temporal Scores

We begin our analysis by verifying that the temporal consistency score has a meaningful signal on a global scale. To do so, for any global snapshot of weekly data, we classify pixels as either within an eddy or outside an eddy based on whether that pixel was labeled as part of an eddy from

the spatial consistency step. Each pixel at time t_i is given a score as a function of the area over/under the curve closest to the current time-step using equation 2. We then average the scores of the “inside eddy” pixels and the “outside eddy” pixels for each week. Figure 5 shows the weekly mean of the temporal scores of the pixels contained in an eddy (top red curve) and those that are outside an eddy (top black curve). The bottom row in Figure 5 shows the weekly standard deviation of eddy and non-eddy pixels respectively. We see that pixels that are within an eddy tend to have a significantly higher temporal score than those that do not.

Not only does our temporal score provide a meaningful signal about the presence or absence of eddies, it also carries information about the potential lifetime of an eddy (via how strong the eddy is when passing by a location). Figure 6 segments the eddy pixels from the red curve in the top left panel of Figure 5 by the lifetime of the eddy the pixel was in. The scores get progressively better as the eddies live longer. The bottom row in Figure 6 shows the standard deviations of the scores and highlights that the variability decreases for longer lived eddies.

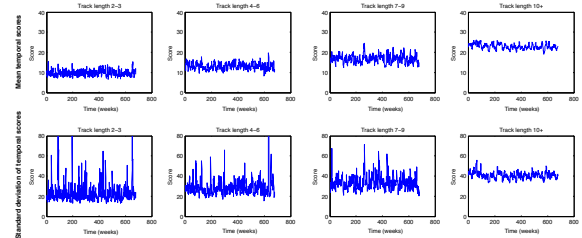


Figure 6: The mean scores of pixels that are within an eddy from Figure 5 but further segmented by the lifetime of the eddy in question. For shorter lived eddies (leftmost and second from left panels) the scores tend to be lower than the average score of an eddy pixel. However, as the quality of the eddies increase as seen by longer lifetimes, the temporal scores become higher and are less variable. This is an indication that our proposed temporal score has both a signal for the likelihood of the presence of an eddy at any given location as well as the potential lifetime of eddy passing by a location.

3.2 The Impact of Expert Heuristics

While heuristics are necessary to ensure significant features are discovered, their strict and arbitrary nature make them prone to discarding real features that fall below certain thresholds. Using the temporal scores as an alternative, we removed all expert criteria used in previous studies (*e.g.* (Chelton, Schlax, and Samelson 2011)) such as the minimum feature size of 9 pixels. Once all features we discovered using the iterative thresholding method described in (Faghmous et al. 2013) were identified in space, we applied our proposed temporal scoring mechanism to those features and added the features that did not meet the traditional 9 pixel minimum size criteria as well as those that has a sub-centimeter amplitude to the candidate features to be tracked.

We restricted the newly added features to those with top 50% scores regardless of size and tracked the features across space and time using the tracking algorithm described in (Chelton, Schlax, and Samelson 2011).

Based on this setup, the heuristics method identified 146,336 features in one year of data (2009). Our spatio-temporal consistency method identified nearly thirty percent more features during the same period with 195,967. This is because we do not throw away features that fail any of the expert heuristics. Figure 7 shows the ratio of total features that went on to live a certain amount of weeks. Notice that the ratio of untracked features are higher for our method because, as the experts suggested, removing the heuristics will introduce many spurious features. That being said, our method then performs very similarly to the heuristic-based algorithm as we get to longer lived and thus more significant features. Note that the ratio of long-lived tracks are similar while we detect a third more eddies. This suggests that expert heuristics remove a significant number of high quality features from the analysis.

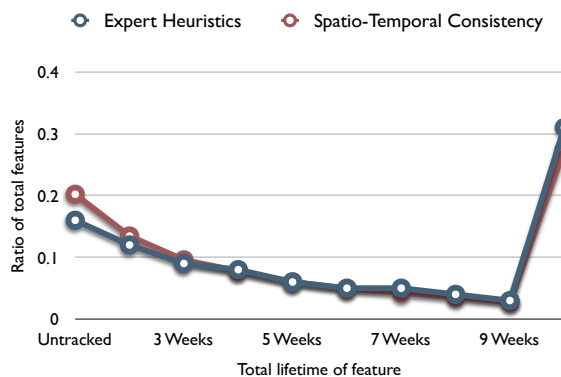


Figure 7: The ratio of total features that lived a certain lifetime. Imposing the expert heuristics results in 146,336 features. Relaxing such constraints and using spatio-temporal consistency instead allows us to identify 195,967 features. Despite identifying nearly thirty percent more features, the percentage of features that persist for a certain lifetime remain very similar between the two methods, especially when we move into the longer lived eddies (4+ weeks). This shows that the expert heuristics remove a large number of high quality eddies.

3.3 What the Heuristics Hide

One of the main limitations of applying strict heuristics is that eddies with certain properties tend to be highly concentrated in certain regions in the world. For instance, eddies decrease monodically in size from the equator to the poles, thus high latitude eddies tend to be smaller than their equatorial counterparts (Fu et al. 2010). Here we show that when we visualize the density of the tracks associated with features that the strict heuristic approaches would not consider we quickly see the impact of such heuristics on our understanding of global ocean dynamics. Due to space limitations,

we focus on the minimum size heuristic.

Figure 8 shows the track density for 2009⁴ of tracks that lasted longer than 4 weeks yet contained a feature that had fewer than 9 pixels. We only included the highest scoring small features as described in the previous section. One can notice a clear concentration of significant tracks with small eddies near the poles as well as along the major currents in the North West Atlantic and North West Pacific oceans. This analysis demonstrates the value of introducing spatio-temporally consistent features despite them not meeting the strict heuristics of traditional eddy monitoring algorithms.

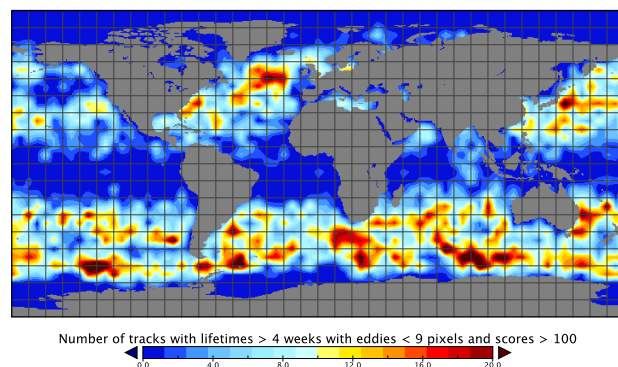


Figure 8: Track density for tracks that lasted at least 4 weeks and contained a feature smaller than 9 pixels that was temporally consistent according to our temporal scoring mechanism. Notice the high density regions near the poles and along the major currents in the North Western Atlantic and North Western Pacific oceans. These tracks would have been completely missed if one used the strict minimum eddy size of 9 pixels. Only one year of data was used (2009) to highlight the high density regions with small eddies.

4 Conclusion and Future Work

The majority of eddy identification algorithms rely on necessary yet arbitrary heuristics to reduce the risk of false discovery. We introduced an alternative approach that objectively identifies eddies by simultaneously monitoring a feature’s consistency in space and time. The introduction of the concept of temporal consistency allows us to give a confidence score to each feature identified in space without the need of completely discarding it because it might have failed to meet an arbitrary threshold. Keeping features that are spatio-temporally consistent yet fail to meet certain heuristics allows us to observe richer ocean dynamics. Now that we have shown that spatio-temporal consistency can be used as a confidence metric, new eddy identification and tracking algorithms can be more robust by re-imagining the way eddy tracks are constructed.

In the traditional approach, all eddy-like features are first identified without any temporal information. Any feature

⁴Due to the high number of such tracks we show only a single year of data to easily highlight regions of high “small eddy” density

that fails to meet the expert heuristics is discarded and the remaining features are tracked from one time-step to the next by attaching each feature at time t with its nearest spatial neighbor in $t + 1$. However, we have shown that not all features are created equal and instead of starting the tracking with all available features our temporal score would allow us to first track the most certain (*i.e.* highest quality) features first, and gradually insert less certain features to simply complement high quality tracks (by extending them or connecting them). This would allow for higher quality tracks while giving the power to the researcher to select which level of uncertainty she is willing to accept.

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