

Accuracy of pathline predicates for flow visualization at the example of the benguela upwelling system

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[Abstract](#)

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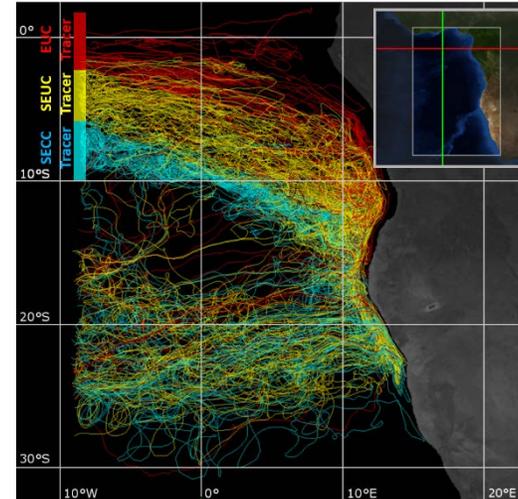
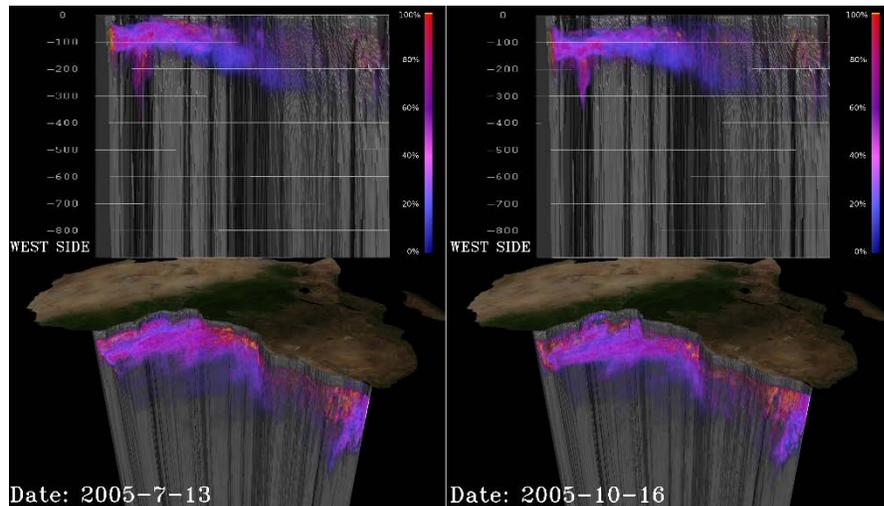
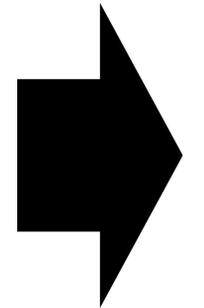
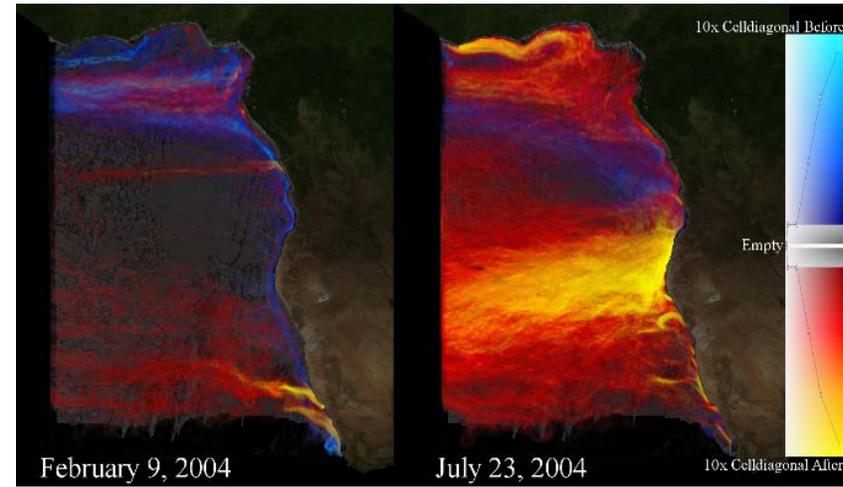
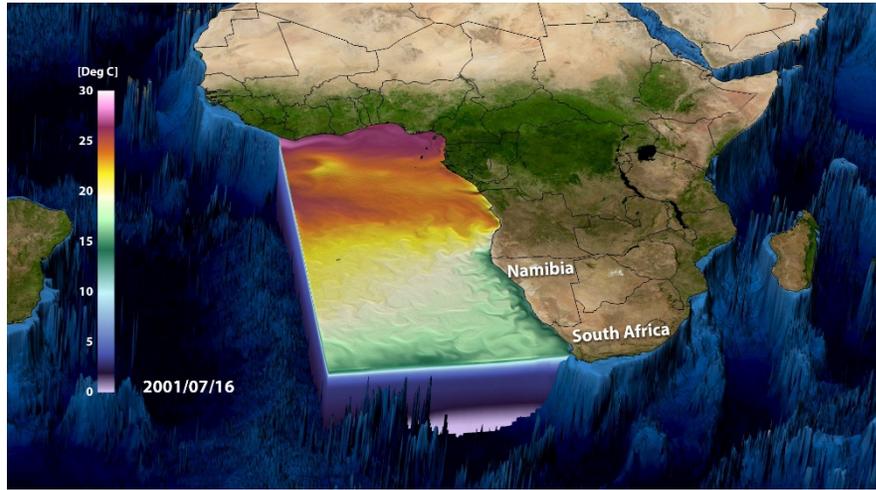
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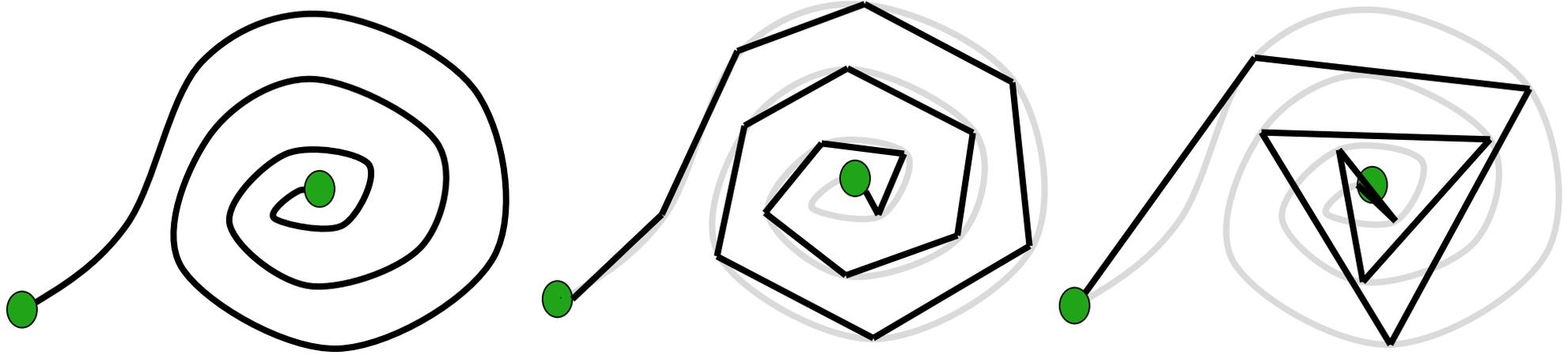
Image and Signal
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Visual Study of the Benguela Upwelling System using Pathline Predicates



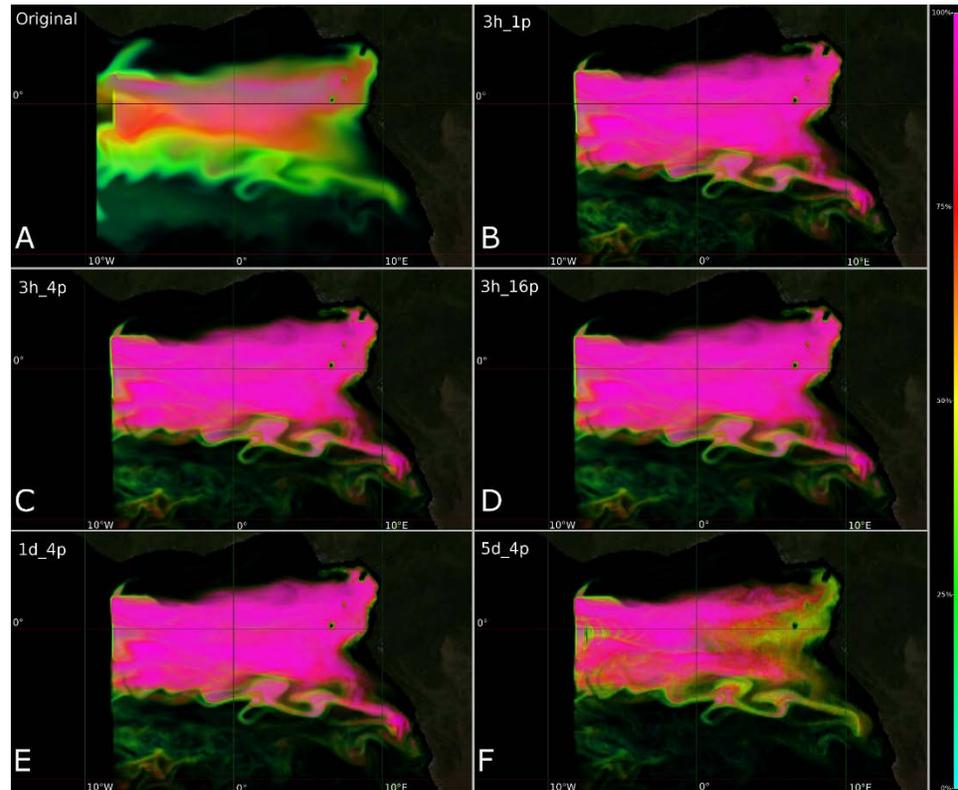
How accurate are Lagrangian techniques?



- Simulation calculated with 20 min steps
- Stored time intervals 5 day means

Evaluate the accuracy of pathline predicates for flow visualization

- **Pathline Error Estimation**
- **Trajectory Based Tracer Field**
 - Variations: number of particles
 - Variations: data resolution



Finish Teaser

Abstract

Coastal upwelling systems transport nutrient-rich water to the upper layer of the ocean. These regions are especially important for marine life and fishery. We are using pathline predicates to create visualizations of the spatio-temporal structure of the Benguela upwelling system. Based on a 3D flow field of a regional ocean model, we first derive space-filling trajectories covering the full model grid. With pathline predicates, we select trajectories related to upwelling. Next, we derive a 3D scalar field representing the pathline density, which is visualized using volume rendering techniques. Further analyses of the pathlines show a distinct annual cycle in the upwelling activity, which fits well to observation-based analyses found in literature. These techniques and their application are described in [1].

In this work, we focus on evaluating the accuracy of our techniques. Based on the 3D ocean flow field stored at relatively coarse time interval, we compute trajectories to emulate a retrospectively derived tracer field. For different source regions, our data set contains several synthetic tracer fields directly computed within the ocean model simulation using the original short time steps that we can compare with our trajectory-based tracer field. With our evaluation we aim at determining minimum requirements for the temporal resolution of flow data for retroactively applying particle pathline techniques or visual analyses. By analyzing the skill in reproducing a synthetic model tracer field, we can set up rules for using the particle pathline methods in general.

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2. Introduction

3. Method

4. Results

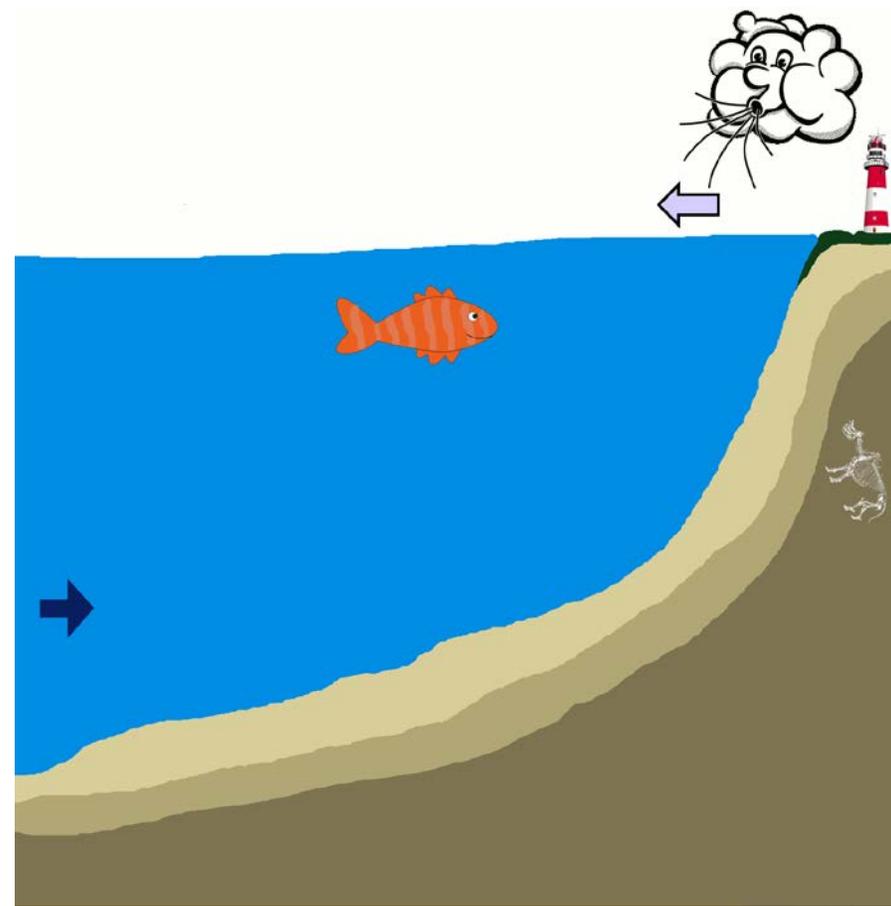
2.1 Upwelling Effect

2.2 Simulation Data

2.3 Analysis

2.4 Problem

- Wind stress at the sea surface cause transport of cool water from greater to shallower depths.
- Regions with cool nutrient-rich water, which "disproportionally contribute to the global primary production and host many of the major commercially used fish stocks" [1]
- High importance to marine life and fishery → focus of ongoing scientific observation campaigns and modeling activities.



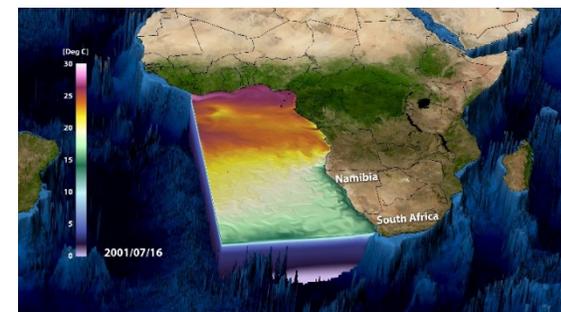
2.1 Upwelling Effect

2.2 Simulation Data

2.3 Analysis

2.4 Problem

- Using the **Benguela system** as an example (see simulation domain in image)
- **Simulation** based on the modular ocean model MOM version 5 [1,2,3].
- **Domain:** rectilinear grid of the size 261 x 351 x 62.
- **Simulation data** include:
 1. time-dependent flow fields (ocean current data)
 2. passive tracer fields



(Click on image for extension)

[1] GRIFFIES S. M., GNANADESIKAN A., DIXON K. W., DUNNE J. P., GERDES R., HARRISON M. J., ROSATI A., RUSSELL J. L., SAMUELS B. L., SPELMAN M. J., WINTON M., ZHANG R.: Formulation of an ocean model for global climate simulations. *Ocean Science* 1, 1 (2005), 45–79.

[2] HERZFELD M., SCHMIDT M., GRIFFIES S., LIANG Z.: Realistic test cases for limited area ocean modelling. *Ocean Modelling* 37, 1-2 (2011), 1–34.

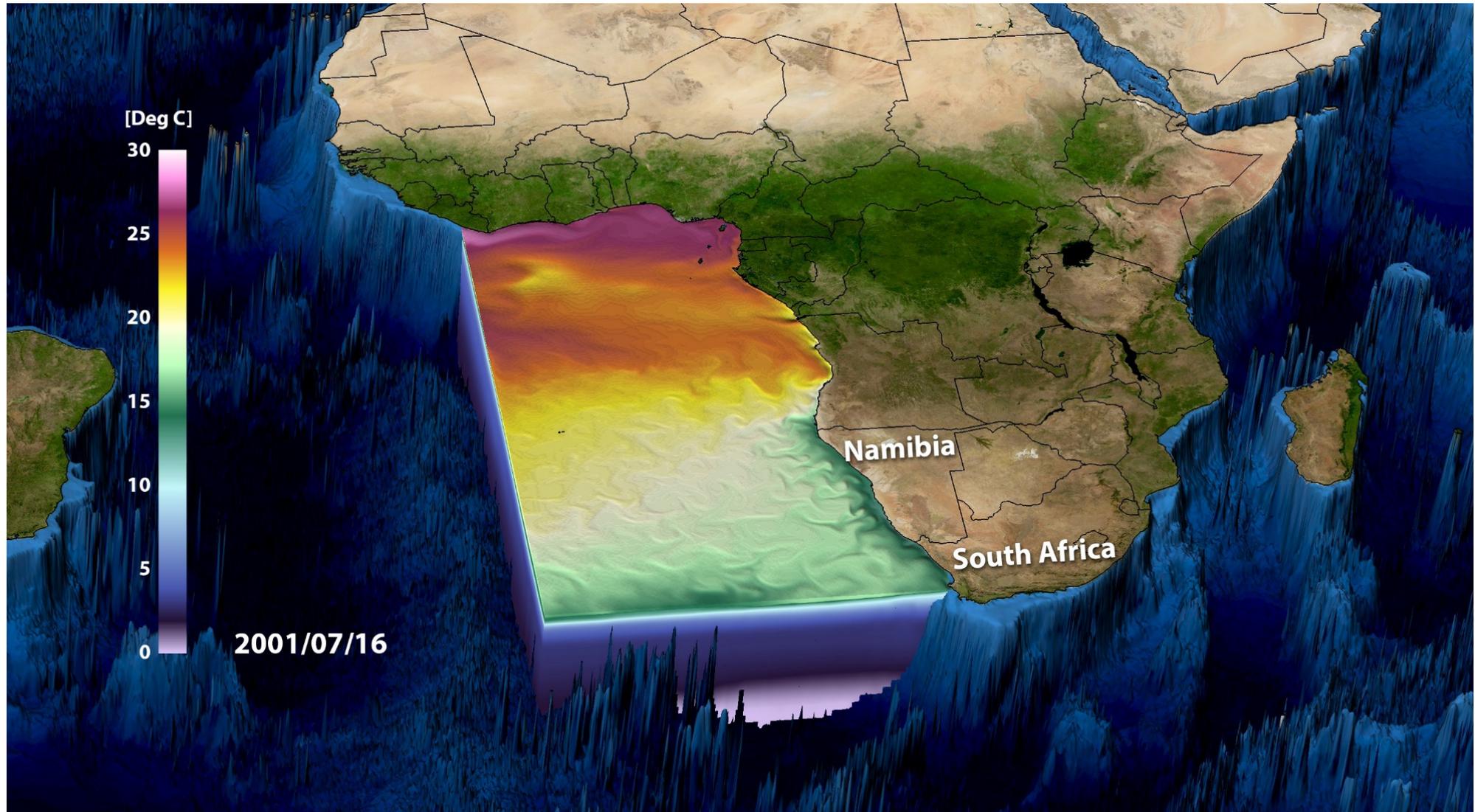
[3] SCHMIDT M., EGGERT A.: Oxygen cycling in the northern benguela upwelling system: Modelling oxygen sources and sinks.

1. Start

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(Click on image for shrinkage)

1. Start

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2.1 Upwelling Effect

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2.3 Analysis

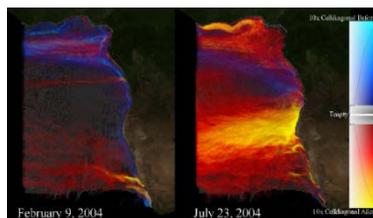
2.4 Problem

1. Compute a space and time filling set of trajectories for the entire model domain.
2. Use „upwelling-predicates“ to select trajectories related to upwelling.
3. Use the information of upwelling-trajectories for:
 - Determine a **upwelling time** for each upwelling-trajectories
 - Numeric analysis of upwelling depth or streng
 - Visual analysis „**Local Pathline Density (LPD)**“
 - Visual analysis „**Upwelling Particle Ratio (UPR)**“
 - Additional **specific filters**

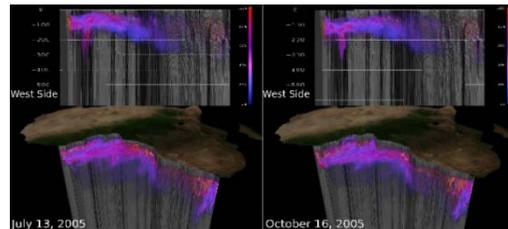
2.2

2.4

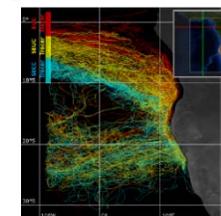
LPD



UPR



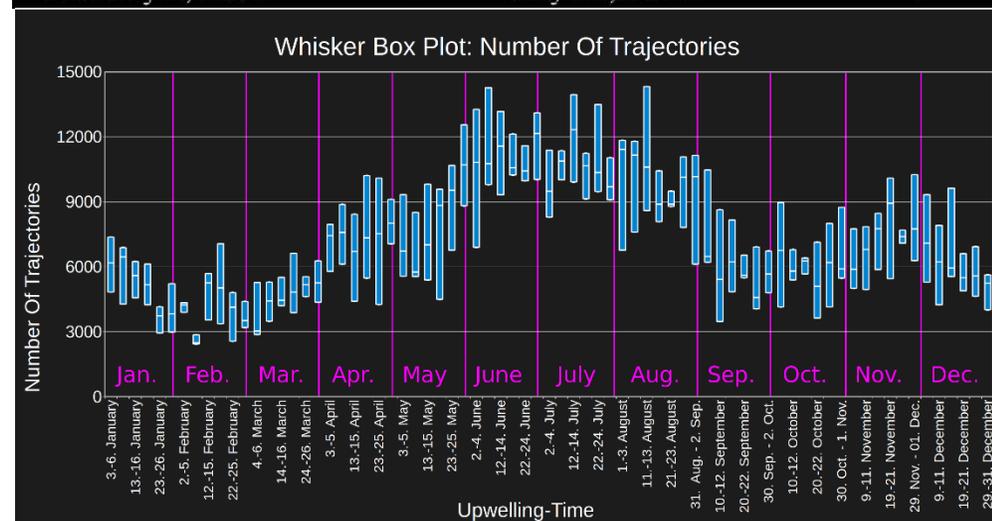
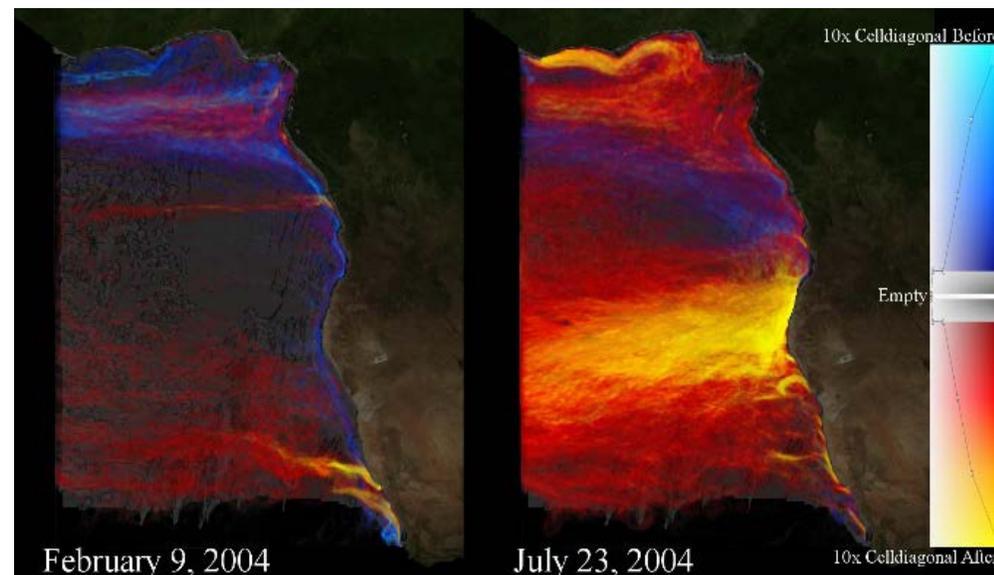
Specific Filters



(Click on an image for a close-up)

Local Pathline Density (LPD)

- Describes density of upwelling-trajectories in proportion to the cell diagonal.
- Coloring cell depending on LPD value.
- Figure (top): example of LPD visualization for strong and weak upwelling current. Coloring:
 - blue = before the upwelling
 - yellow-red = after the upwelling time.
- Identification of a distinct annual cycle in the upwelling activity
- Figure (bottom): numeric analysis of the number of upwelling trajectories.

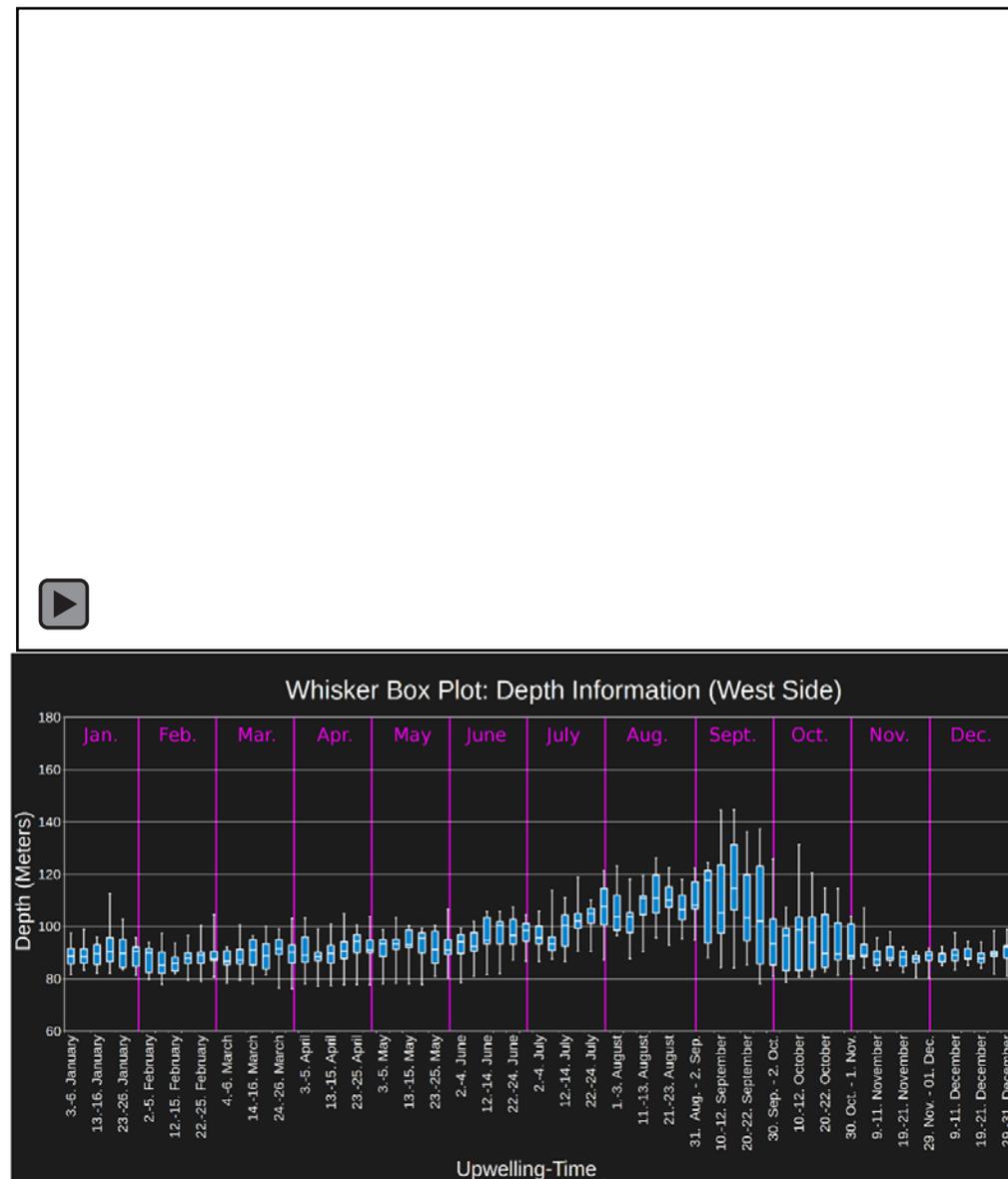


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Upwelling Particle Ratio (UPR)

- Describes for each cell the proportion of upwelling particles to non-upwelling particles.
- Video (top): visualization of the UPR values before the upwelling time.
(high extension of the z-axis)
- Identification of a distinct annual cycle in the upwelling source depth
- Figure (bottom): numeric analysis of the domain-
enter-depth of upwelling trajectories coming from
the west side.

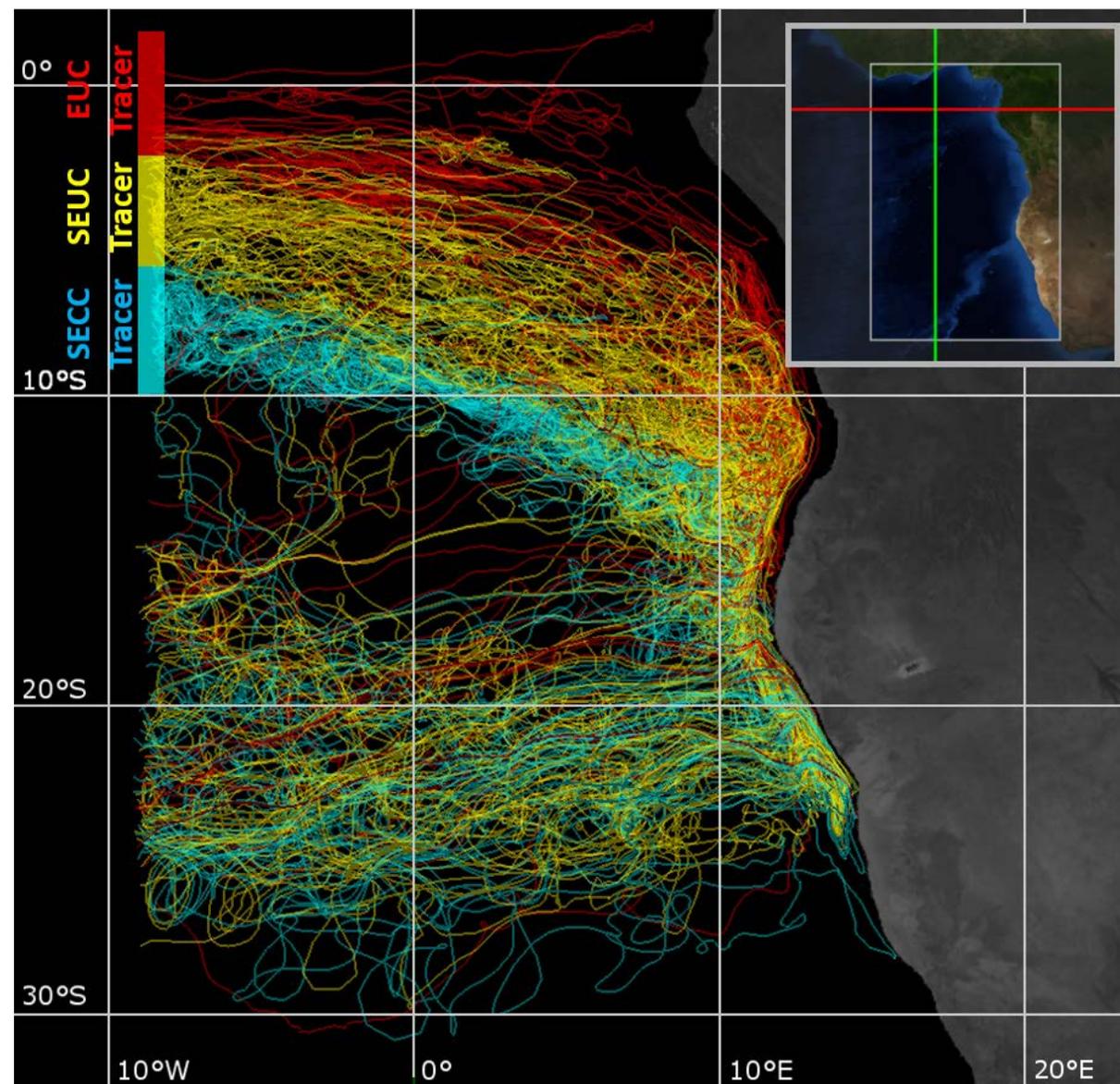
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Specific Filters

- Classify the upwelling trajectories by defined characteristics.
- using "predicates" in order to identify upwelling trajectories fulfilling user-defined requirements.
- **Example Figure** shows:
 - filtration of upwelling event between 15°S and 27°S .
 - additional classification into different source

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2.1 Upwelling Effect

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Problem:

- Stored time intervals are much larger than the model time step
- For our analysis: Simulation calculated with 20 minutes steps stored as 5-day mean data set ($\Delta t = 5d$).
- Question: how accurate Lagrangian techniques applied in a postprocessing step can be in spite of relatively coarse temporal sampling of flow field data.

2.3

This work:

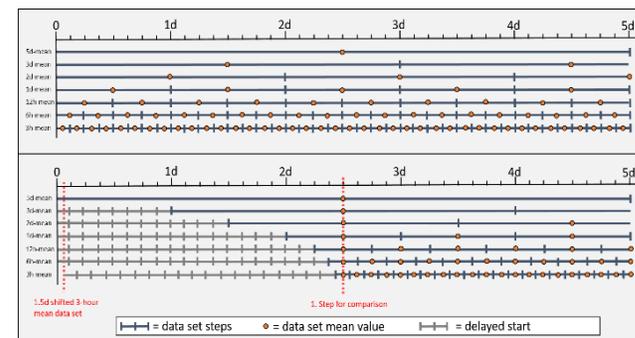
- Focus on evaluating the accuracy of our techniques by using data with **different temporal samplings** for:
 1. Compare pathlines with those derived for the fine data set with $\Delta t = 3h$.
 2. Compare emulated synthetic tracer fields (based on pathlines) with synthetic tracers computed within the ocean model simulation using $\Delta t = 20m$

3.1 Data Emulation

3.2 Pathline Error Estimation

3.3 Trajectory Based Tracer Field

- Using $\Delta t = 3\text{h}$ data to derive data sets with $\Delta t = 6\text{h}, 12\text{h}, 1\text{d}, 2\text{d}, 3\text{d}, 5\text{d}$ for comparison. The figure illustrates the scheme used for undersampling.
- For each data set with $\Delta t = 3\text{h}, 6\text{h}, 12\text{h}, 1\text{d}, 2\text{d}, 3\text{d},$ and 5d , we calculate a trajectory set with a minimum of n particles inside each cell with $n=\{1,4,16\}$. ([click for more information](#))



(Click on image for extension)

3.2

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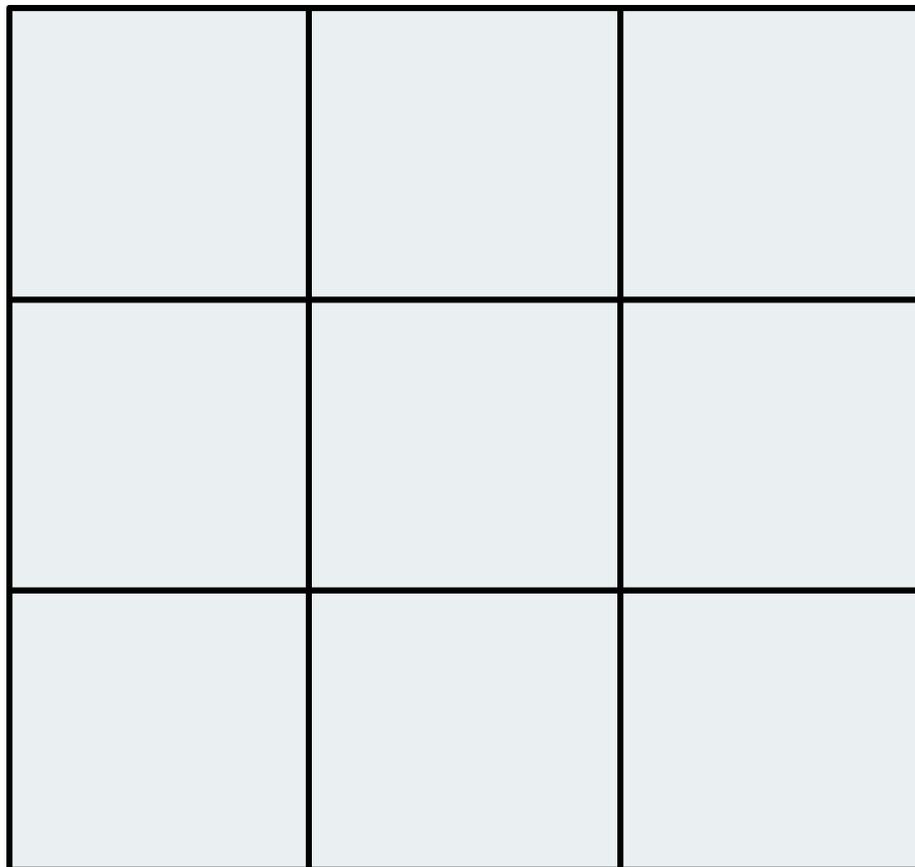
4. Results

3.1 Data Emulation

3.2 Pathline Error Estimation

3.3 Trajectory Based Tracer Field

Method to create the trajectory set



1. Initialization by seeding n particles at time $t = 0$ in each of the model's grid cells.
2. Integration of the pathlines (Runge-Kutta 4th-order scheme (RK), Euler).
3. Check at each time step the number of particles in each cell. Seed new particles if necessary.
4. Perform a backward integration for the new particles to use the information of previous time steps (until the very first timestep or until they leave the domain).

Example with two time steps and $n=4$

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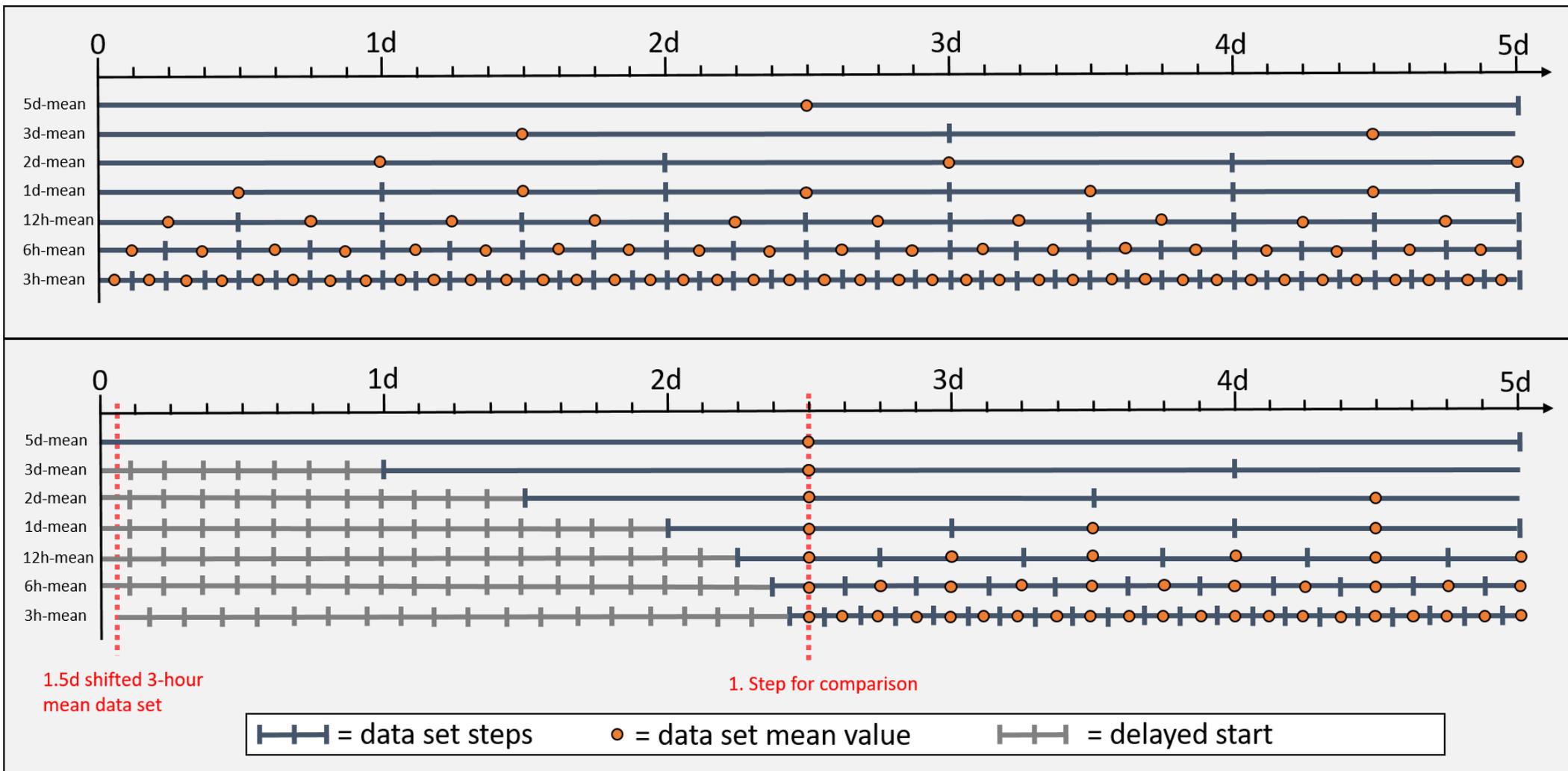
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3.1 Data Emulation

3.2 Pathline Error Estimation

3.3 Trajectory Based Tracer Field



(Click on image for shrinkage)

3.1 Data Emulation

3.2 Pathline Error Estimation

3.3 Trajectory Based Tracer Field

- All initial particles calculated with the data sets with $\Delta t = 3h, 6h, 12h, 1d, 2d, 3d,$ and $5d$ have the same start position and the same starting time.
- Idea: compare pathlines of initial particles and use the best available temporal resolution $\Delta t = 3h$ with a standard RK integration as reference.
- As values for comparison we are using:

- **mean absolute distance (MAD)**

$$MAD(m,t) = \frac{\sum_{i=1}^n \sqrt{\|pos_{3h}^t(i) - pos_m^t(i)\|}}{n}$$

- **mean squared distance (MSD)**

$$MSD(m,t) = \frac{\sum_{i=1}^n \|pos_{3h}^t(i) - pos_m^t(i)\|^2}{n}$$

- **mean line difference (MLD)**

$$MLD(m,t) = \frac{\sum_{i=1}^n |\sqrt{\|pos_{3h}^0(i) - pos_{3h}^t(i)\|} - \sqrt{\|pos_m^0(i) - pos_m^t(i)\|}|}{n}$$

3.1

3.3

1. Start

2. Introduction

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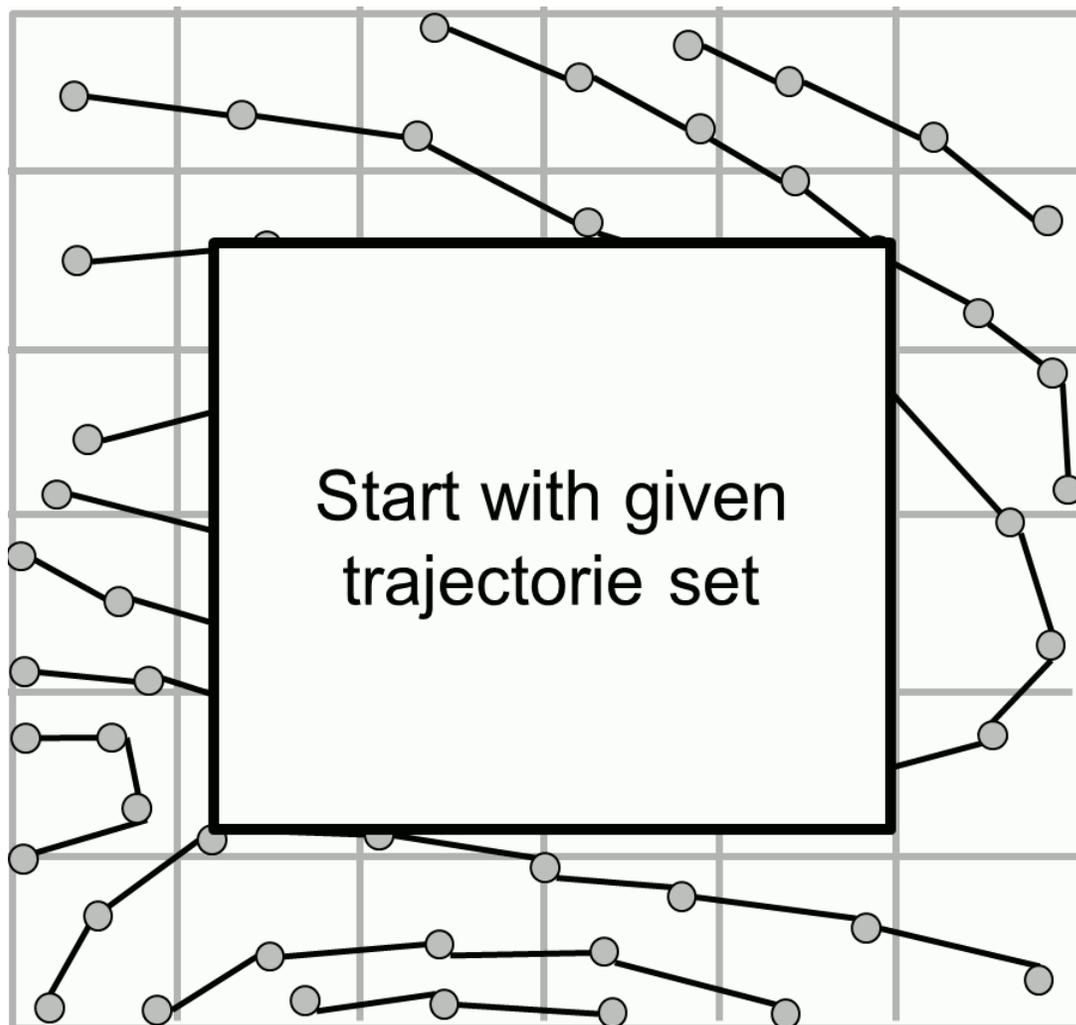
4. Results

3.1 Data Emulation

3.2 Pathline Error Estimation

3.3 Trajectory Based Tracer Field

3.2



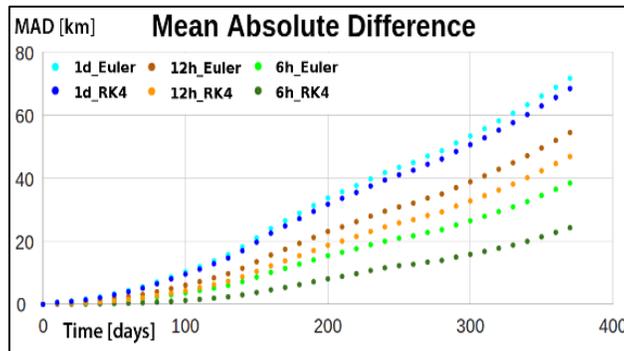
The following steps explain how we created our simulated tracer field for the comparison with the original tracer.

1. Check each trajectory for intersection points with a defined tracer source area and mark them.
2. Determine all particles for each cell and point in time.
3. Calculate tracer concentration ratio as simulated tracer value.

4.1 Pathline Error Estimation

4.2 Trajectory Based Tracer Field

MAD-Plot



(Click on image for a close-up)

- All three values show nearly the same result (MAD example in left figure).
- The graphs show that the error grows with time.
- As expected, the lowest MAD is achieved by using the RK integration using the $\Delta t = 6h$ data.
- **BUT:** Even with the $\Delta t = 6h$ data, the average error after one year is around 40 kilometers (equivalent to a deviation of about four cells)

➔ Any storage intervals larger than the model time step lead to an error. The larger the difference, the larger the error.

4.1 Pathline Error Estimation

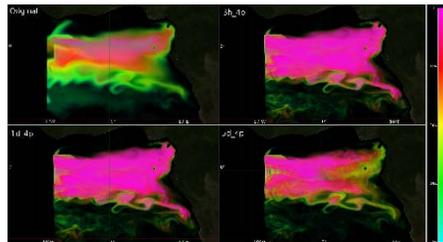
4.2 Trajectory Based Tracer Field

Pattern Analysis:

- Figure (left): good agreement of the shape of the emulated tracer cloud with that of the original tracer, even with the coarse data set with $\Delta t = 5d$.

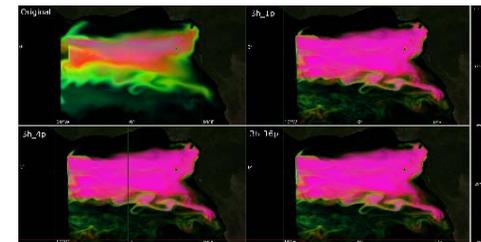
Despite the unsatisfying results of the Pathline Error Estimation, the shape of the emulated synthetic tracer pattern matches reasonably well.

Storage Step Size Analysis

Magnitude Analysis:

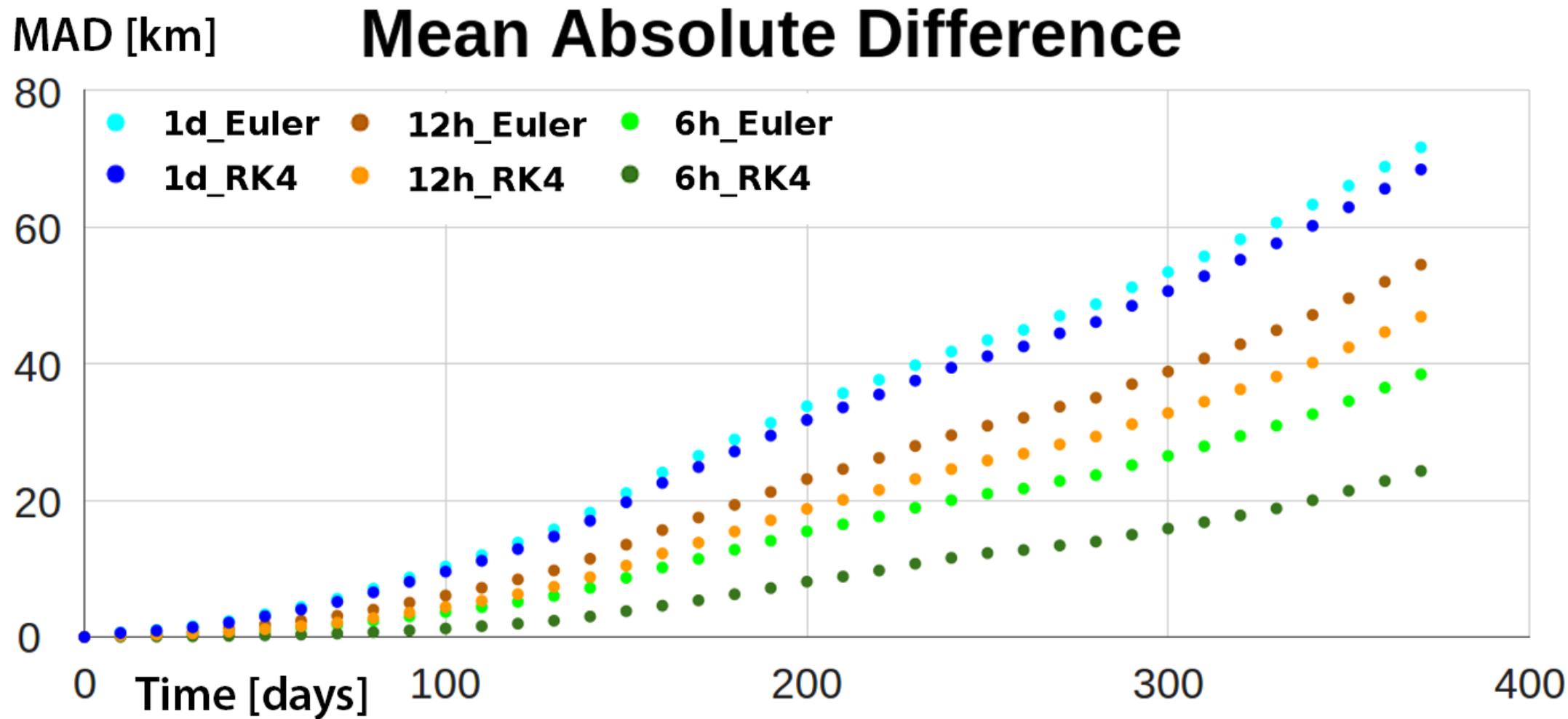
- Figure (left): For all temporal samplings our method overestimates the tracer concentration.
 - Figure (right): Even with a larger number of particles we could not improve the results
- ➔ Further analysis and improvement of our method is necessary

Number of Particles Analysis



(Click on images for close-up)

4.1

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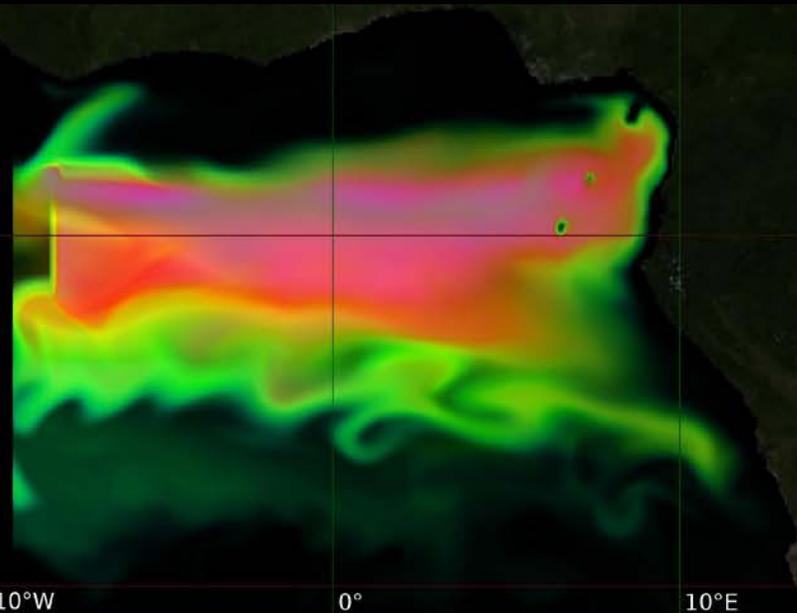
1. Start

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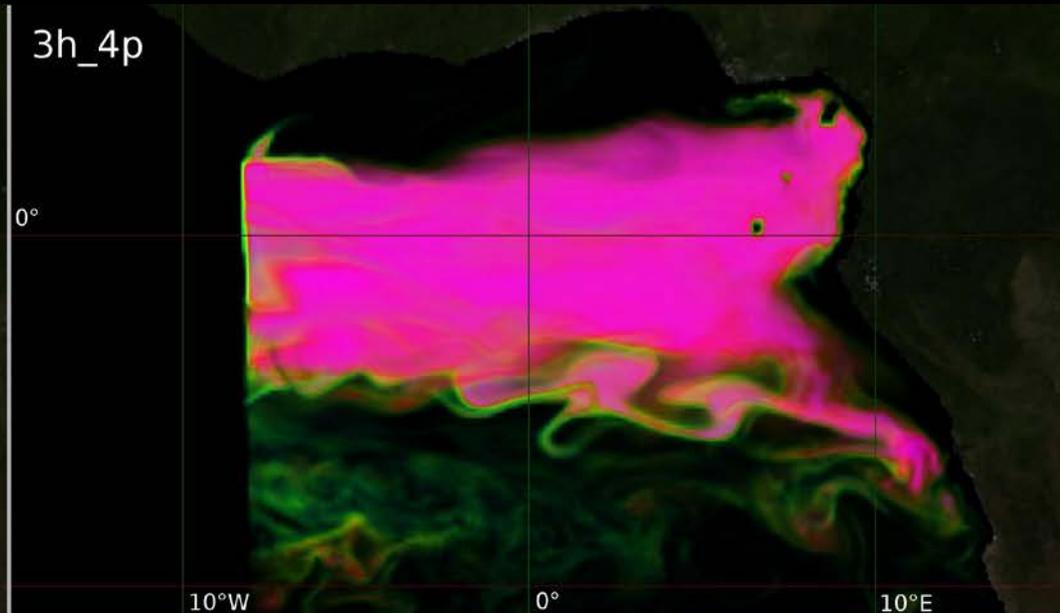
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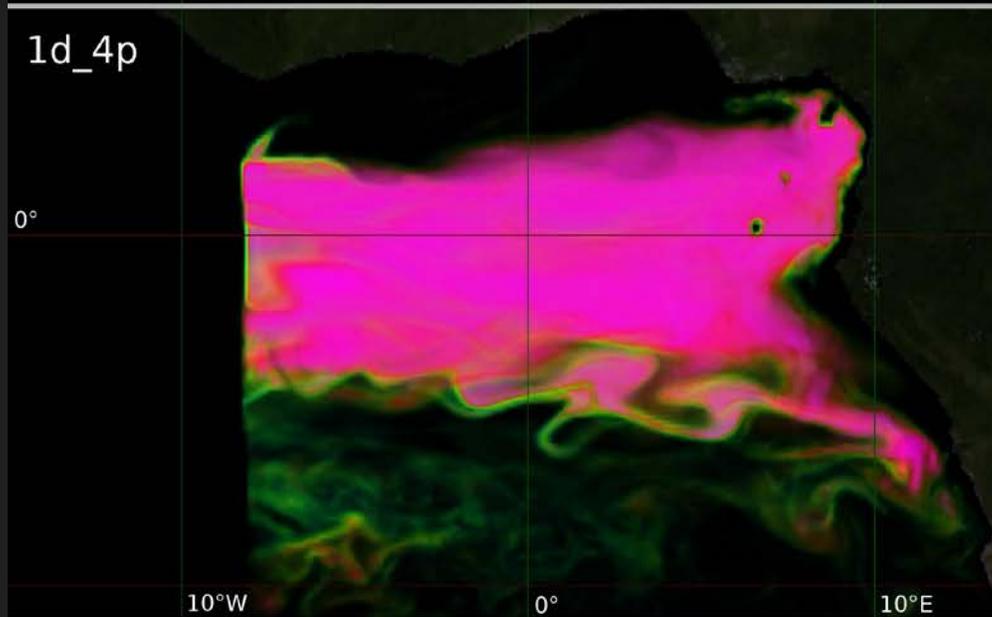
Original



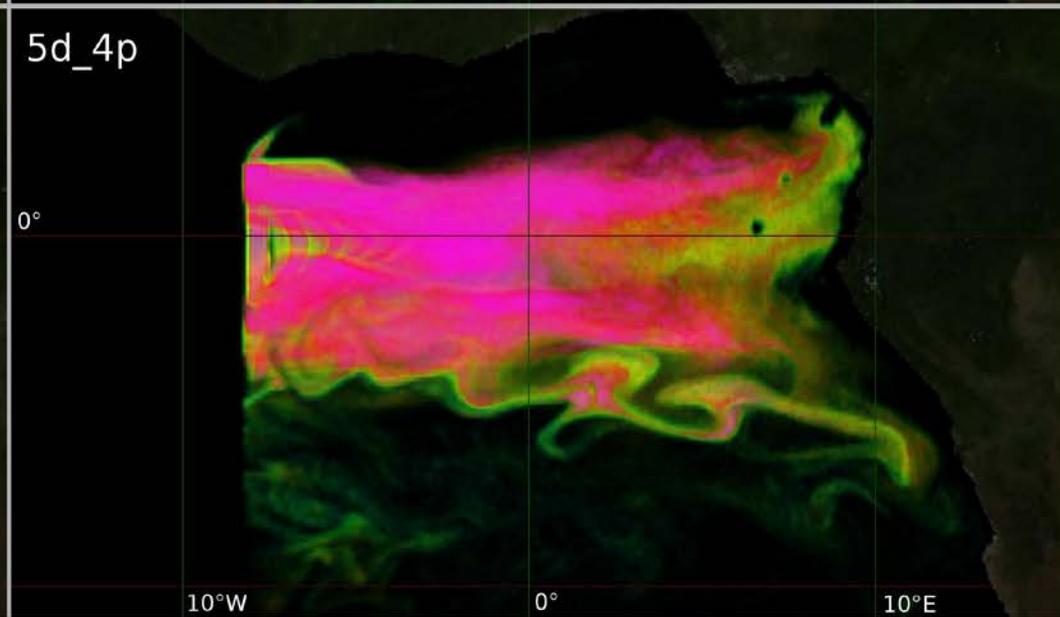
3h_4p



1d_4p



5d_4p



100%

75%

50%

25%

0%

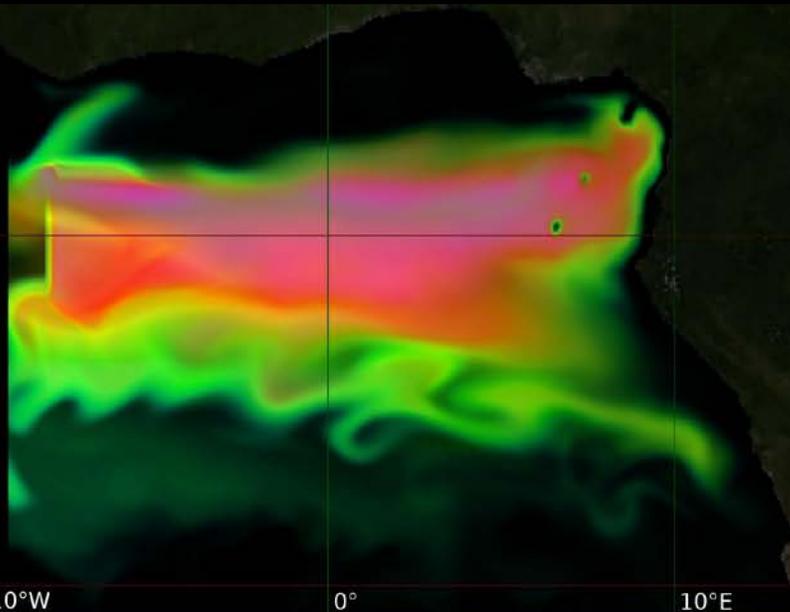
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Original



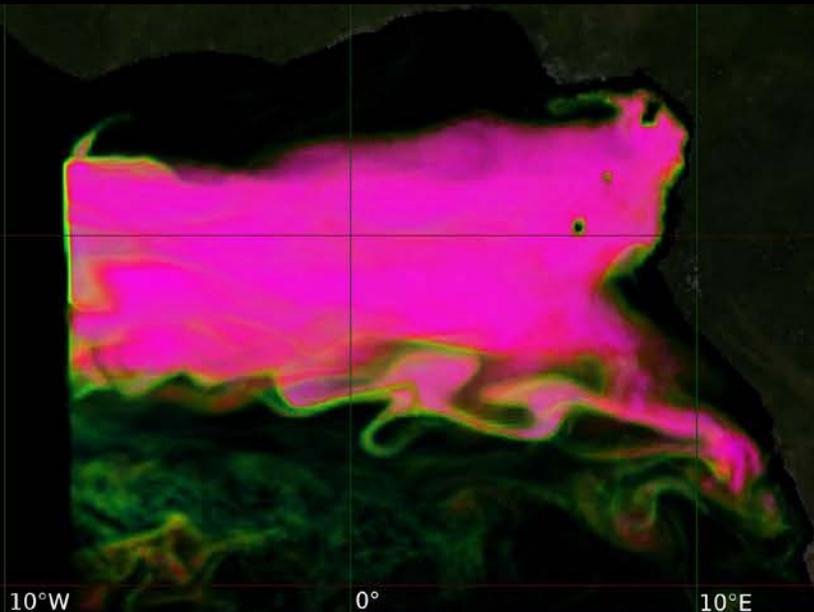
0°

10°W

0°

10°E

3h_1p



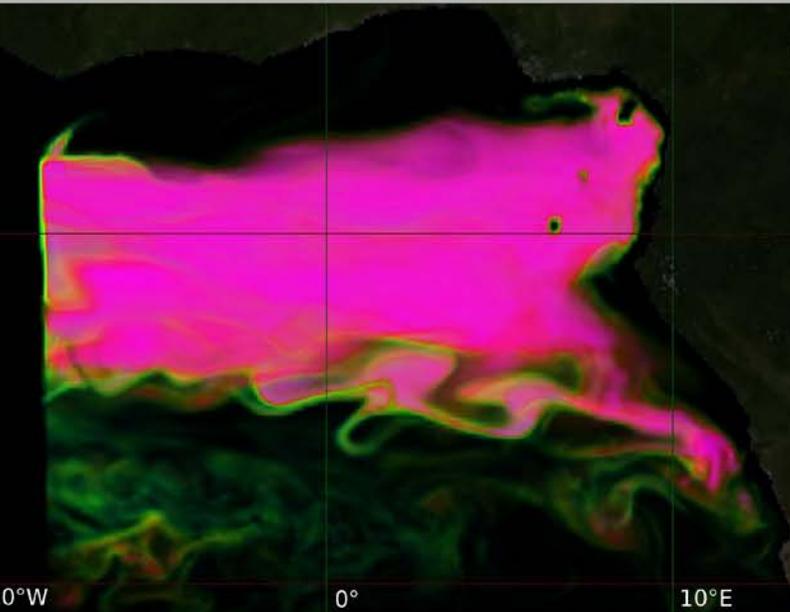
0°

10°W

0°

10°E

3h_4p



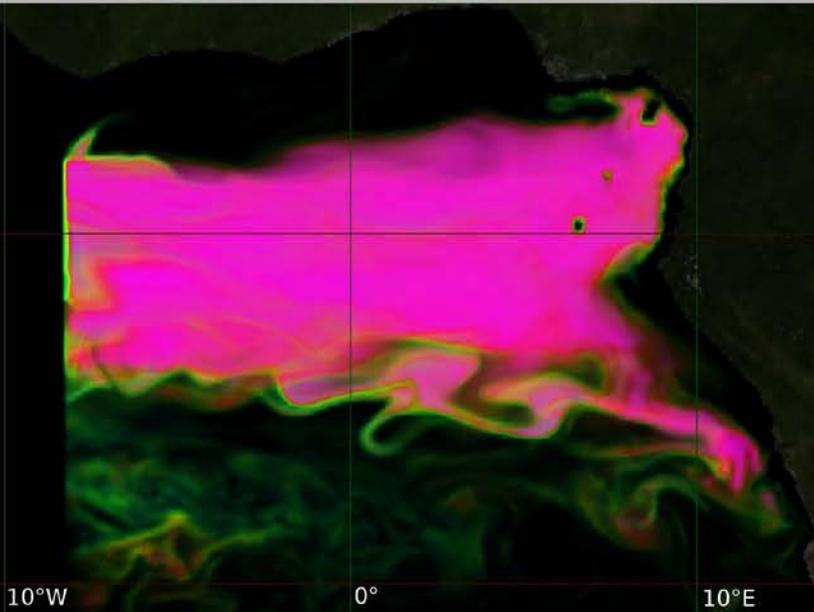
0°

10°W

0°

10°E

3h_16p



0°

10°W

0°

10°E

100%

75%

50%

25%

0%