Reconstruction of Submesoscale Velocity Fields

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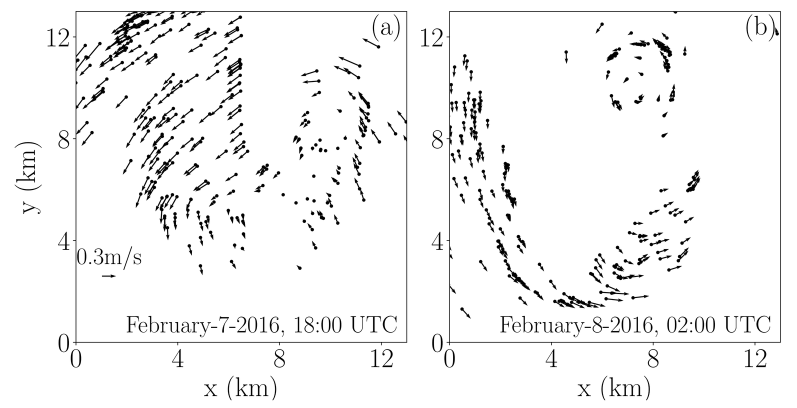
Submesoscale Ocean Structures

• Oceanic structures measuring 1 km - 20 km in size and lasting for periods < 48 hours[1]

• Believed to contribute to some of the energetic processes occurring routinely in the ocean with timescales of hours[2, 3]

• Important for local ocean mixing, which can impact the dispersion of pollutants and biological larvae in local marine ecosystems

• Difficult to observe and measure due to their small size and short duration[1], but are currently measured by deploying lagrangian drifters that record position through time while advected by oceanic currents



A submesoscale structure in the Gulf of Mexico was analyzed with drifters in early 2016. Figure supplied by Rafael Gonçalves.

Gaussian Process Regression

• A gaussian process is a collection of random variables such that any finite subset of those variables has a multivariate normal distribution.[4]

• Gaussian process regression (GPR) takes user provided observations that follow a gaussian process and a kernel function and interpolates data values at other previously unknown points.[4]

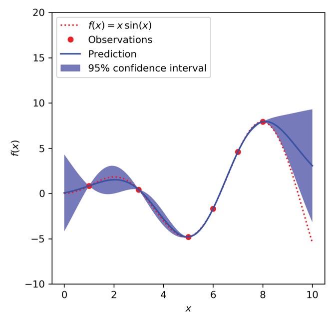
• The kernel or covariance function determines a degree of similarity between two points based on their distance.[4]

• GPR relies on the idea that points with high similarity should also have similar function values.

• For this experiment a radial-basis kernel function (RBF Kernel) was used:

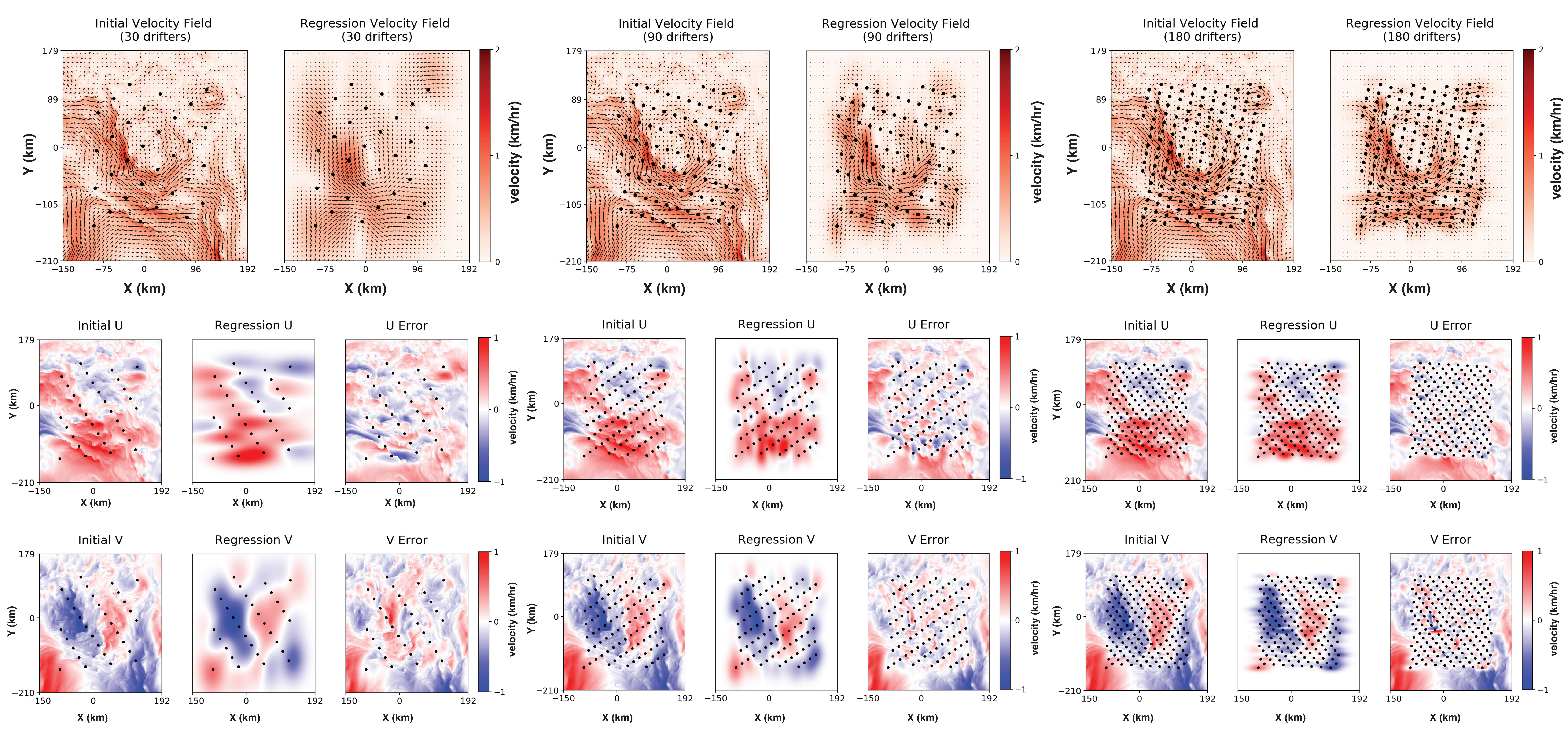
$$K(x, x') = \sigma^2 \exp\left(-\frac{(x-x')^2}{2l_x^2} - \frac{(y-y')^2}{2l_y^2} - \frac{(t-t')^2}{2l_t^2}\right)$$

where the parameters σ, l_x, l_y, and l_t are estimated by maximizing the log-likelihood of the data



As the distance from an observation point grows, the model becomes less accurate as the confidence level grows in size.

Figure and data are the output of the python scikit regression module.



Research Goal

Validate the ability of gaussian process regression to reconstruct velocity fields from known reference fields.

Methods

• Create a known vector field on a 389 km X 342 km X 24 hour (x, y, t) grid.

• Release n drifters and compute their trajectories through the vector field over the course of 24 hours, with positional and velocity data reported every 14.4 minutes.

• Perform GPR on the obtained drifter data.

• Compute regression output error as well as the curl and divergence at each point (x, y, t).

Conclusions

• Gaussian process regression (GPR) is able to accurately reproduce the velocity field of submesoscale structures using only positional data from deployed drifters.

• The GPR model increases in accuracy as the number observations increases.

• The accuracy of the GPR model is highly dependent on the field being tested, the length of time the drifters are left in the field, the frequency at which the drifters record data, and the initial drifter release pattern.

GPR is a useful tool in modeling submesoscale structures of reasonable complexity, provided that the data collection procedure is carefully attuned to the field being modeled.

The current modeling technique begins to break down where there is insufficeint observation coverage relative to the complexity of the field being observed.

Future Work

Future research in this area will center around finding optimal release patterns for drifters, optimizing the selection of one or more kernel functions to supply the gaussian process regression algorithm, and careful analysis of the optimized lengthscale parameters to better determine field collection methods.

We are also investigating the ability of GPR to model areas of high curl, divergence, and convergence.

Acknowledgements

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