Estimating Winds with Multistatic Meteor Radar Data and Helmholtz Decomposition



Abstract

This project aims to simulate winds in the mesosphere and lower thermosphere (MLT), a region that often presents a challenge due to its limited observable materials and phenomena. Utilizing meteor position data and projected wind velocities detected with a multistatic radar network, we were able to construct a Gaussian process (GP) kernel using a Helmholtz decomposition. This approach yields a posterior distribution that enables us to model the wind velocities in a given region. The technique is beneficial because it accounts for dependence between two dimensions of the vector field, rather than assuming independence of all components, and includes statistical uncertainty information by its nature. Further enhancements to this method could involve the incorporation of three-dimensional dependencies between components.

Introduction

- Mesosphere and lower thermosphere (MLT) ranges from 60-110 km and is difficult to study
- Radio waves detect meteor trails, which move with the wind to give Doppler shifts and projected wind velocities
- SIMONe campaign data using multistatic radar network with multiple transmitters and receivers for best meteor detection
- Method is useful for improving dynamic simulations/understanding of this region

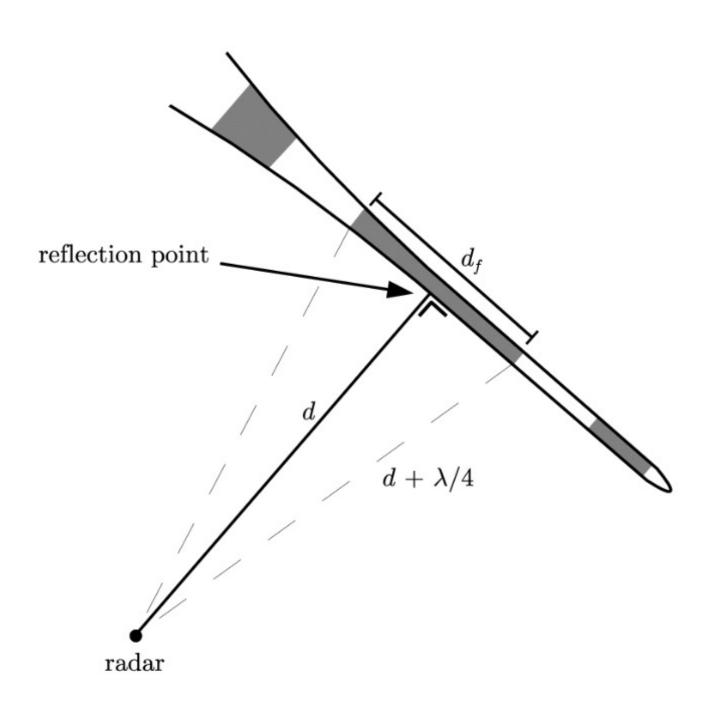


Figure 1. Compact meteor plasma trails reflect radar pulses, and their movements with the wind impart detectable Doppler shifts.

Hannah Isbell^{1,2}

*Mentor: Ryan Volz*¹

Methodology

Gaussian process regression (GPR)

- General idea: "Interpolation with error bars"- predicts values at points with no data and includes uncertainty
- Steps:
 - Set mean and covariance function/kernel of a dataset
 - Assume Gaussian distribution
 - Form likelihood function and adjust hyperparameters
 - Produce posterior distribution, which then makes predictions for chosen test points

Helmholtz decomposition

• Assume vector/wind field F can be broken into two components: $F = -\nabla \phi + \nabla \times \psi$

where ϕ is called the potential function and ψ the stream function

Velocity Method (old):

• Assume GP priors for each wind component u, v, and w

Helmholtz Method (new):

- Assume GP priors for both scalar potentials, ϕ and ψ
- Construct new Helmholtz kernel to incorporate 4D:

$$K_{uu} = \frac{\partial^2 k_{\phi}(x, x')}{\partial x \partial x'} + \frac{\partial^2 k_{\psi}(x, x')}{\partial y \partial y'} \qquad K_{vv} = \frac{\partial^2 k_{\phi}(x, x')}{\partial y \partial y'} + \frac{\partial^2 k_{\psi}(x, x')}{\partial x \partial x'}$$

$$K_{vu} = \frac{\partial^2 k_{\phi}(x, x')}{\partial y \partial x'} - \frac{\partial^2 k_{\psi}(x, x')}{\partial x \partial y'} \qquad K_{uv} = \frac{\partial^2 k_{\phi}(x, x')}{\partial x \partial y'} - \frac{\partial^2 k_{\psi}(x, x')}{\partial y \partial x'}$$

$$K_{\phi}\left(\vec{x}, \vec{x'}\right) = \sigma_{\phi}^2 K_{\phi_z}(z, z') K_{\phi_t}(t, t') K_{\phi_{xy}}\left(\begin{bmatrix}x\\y\end{bmatrix}, \begin{bmatrix}x'\\y'\end{bmatrix}\right)$$

$$K_{\psi}\left(\vec{x}, \vec{x'}\right) = \sigma_{\psi}^2 K_{\psi_z}(z, z') K_{\psi_t}(t, t') K_{\psi_{xy}}\left(\begin{bmatrix}x\\y\end{bmatrix}, \begin{bmatrix}x'\\y'\end{bmatrix}\right)$$

with $K_{\psi_z}, K_{\psi_t}, K_{\psi_{xy}}$ all having internal length scales (Ex: $K_{\psi_z}(z, z') = (1 + \sqrt{5}r + \frac{5}{3}r^2) e^{-\sqrt{5}r}$ with $r = \left\|\frac{z-z'}{\delta}\right\|_2$)

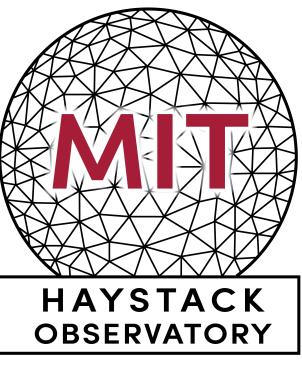
Note: scalar potentials from above related to velocities

• Accounts for dependence of x and y components

Model Refinement:

- Initialized parameters, did not optimize
- Not sensitive to length scales
- Assumed zero vertical wind and common z and t kernels to decrease unknowns
- Found xy stream parameter should be larger than xy potential





Simulated Winds

t: 2018-11-05 06:00:00Z

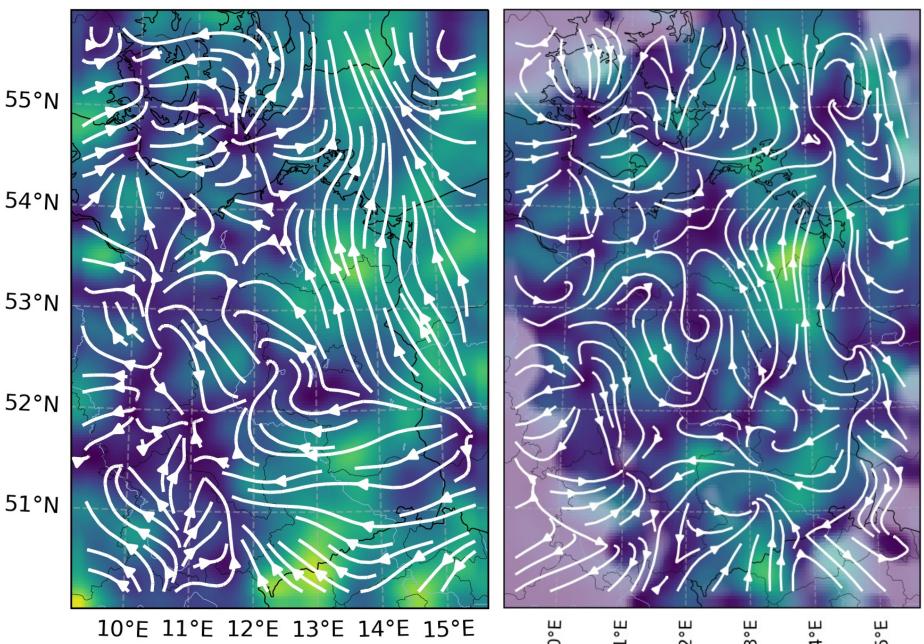


Figure 2. Left: randomly simulated wind field. Right: Helmholtz method simulation. Streamlines show wind direction and background colors represent horizontal speed, fading where uncertainty is high.

Analysis:

- Graphs look qualitatively similar (except regions with no meteors)
- Parameters for Helmholtz plot:
 - potential amplitude = stream amplitude = 25
 - t scale = 1800 s, z scale = 5 km
- xy potential= 35 km, xy stream= 30 km (not real data)
- Note: consistent with parameters used to create the plots

Conclusion

- Resulting wind fields are at least as good as previous method's
- Still needs adjustments before we can confidently say Helmholtz method is better

Future Work:

- Automate optimization of parameters to improve accuracy
- Trying different kernels, which may incorporate 3D dependencies

References

Berlinghieri, R., et al. (2023). Gaussian processes at the Helm(holtz): A more fluid model for ocean currents. In Proceedings of the 40th International Conference on Machine Learning (Vol. 202). Proceedings of Machine Learning Research.

Volz, R., et al. (2021). Four-dimensional mesospheric and lower thermospheric wind fields using Gaussian process regression on multistatic specular meteor radar observations. Atmospheric Measurement Techniques, 14, 7199–7219.

