Data Assimilation to Improve Estimates of Hurricane Storm Surge

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Motivation

1. **Climate change amplifies storm surge risks**: Rising sea levels and changing hurricane climatology exacerbate storm surge threats to coastal regions in complex ways, necessitating advanced predictive tools.
2. **Surge models depend on wind accuracy**: Numerical models like the Advanced Circulation (ADCIRC) [5] model require precise wind field data to produce accurate storm surge simulations.
3. **Computational and accessibility barriers**: High-fidelity wind models are resource-intensive and not easily accessible, hindering real-time surge forecasting.
4. **Parametric wind models offer efficiency**: By using a few key parameters (namely $R_{\max}, V_{\max}, \Delta P$, and $\mathbf{u}$), parametric wind models (e.g. Holland [2]) are more computationally feasible but not as accurate.

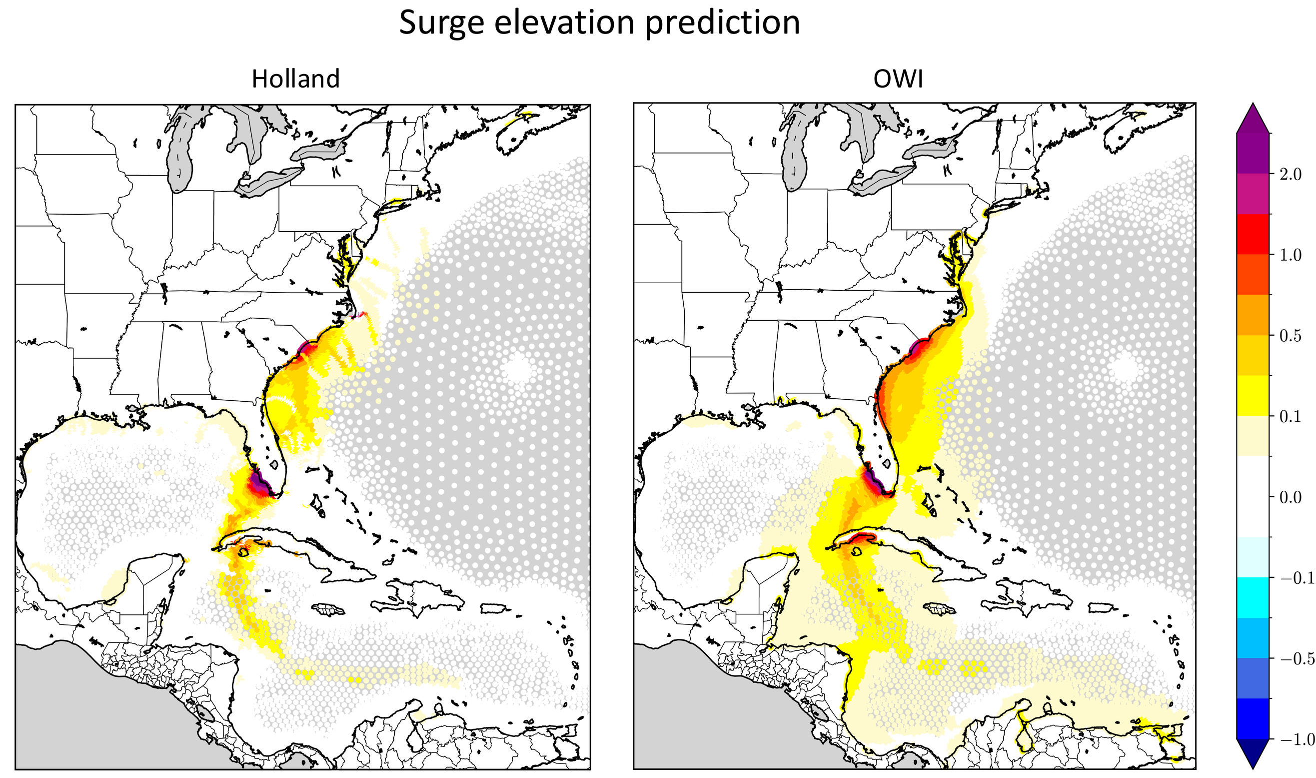
The problem: We need wind "everywhere" for good surge modeling – forecasting, hindcasting, and risk analysis – but must balance computational feasibility and accuracy for real-time surge predictions.

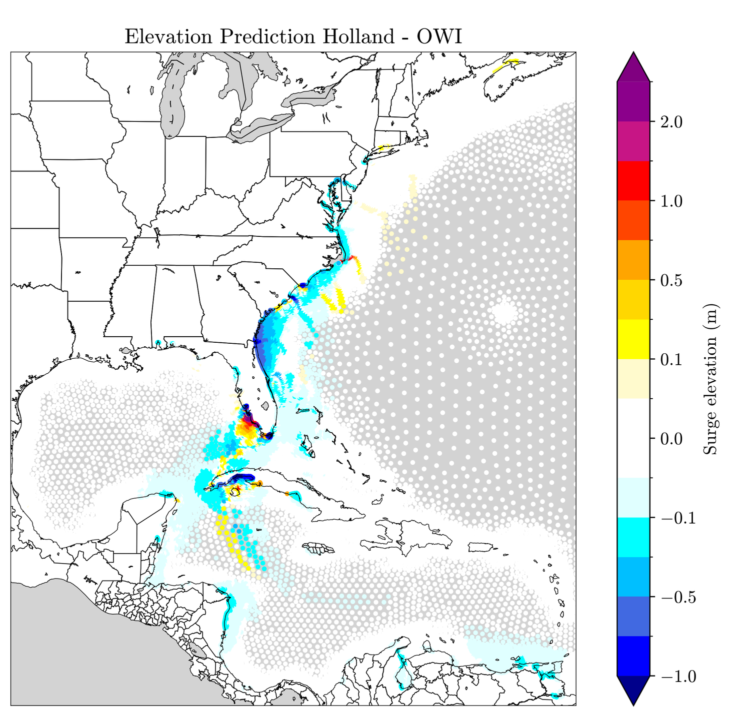
Our approach: Investigate whether data assimilation of the Holland parametric wind model improves ADCIRC wind field accuracy for storm surge forecasting/hindcasting.

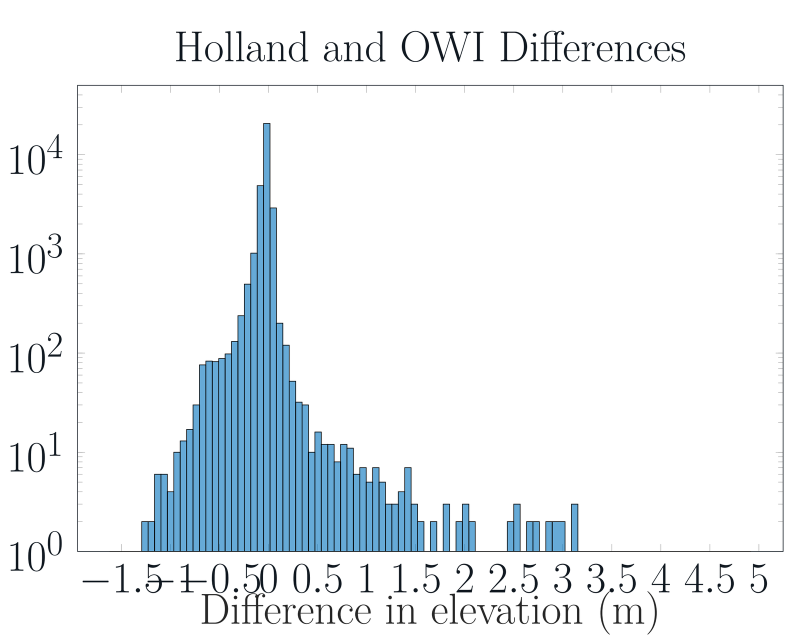
Key research questions

- How does the Holland wing model impact storm surge prediction accuracy (elevation/timing)?
- Can assimilating observed storm surge data be used to improve predictions made using the Holland wind model?

Surge elevation prediction







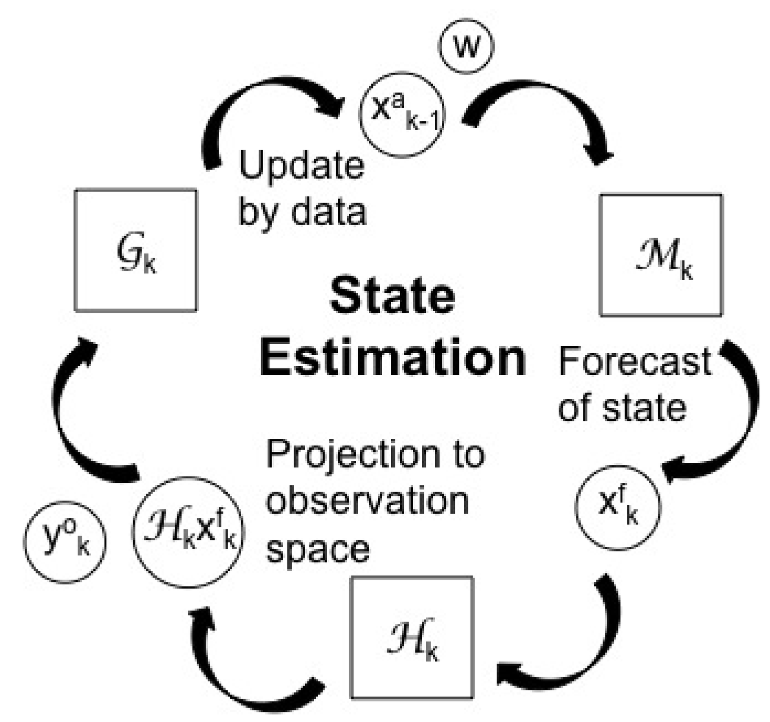
Methods

Twin Experiments

1. Generate synthetic "truth" surge data by forcing ADCIRC with Ocean Weather Inc (OWI) high-fidelity wind data at coordinates that recorded significant surge during Hurricane Ian.
2. Create a "baseline" case by simulating storm surge data with a Holland parameteric wind profile for the same time series, which is representative of what is available in real-time forecasting.
3. Assimilate the "truth" with the baseline to improve estimates of the mean state and the error covariance via Singular Evolutive Interpolated Kalman (SEIK) [3, 4, 1]

Data Assimilation

$\mathbf{x}_k^f, \mathbf{x}_k^a \in \mathbb{R}^n$	forecast and analyzed state, respectively	$\mathbf{y}_k^o \in \mathbb{R}^p$	true data available time k
$\mathcal{M}_k$	numerical forecast model (updates $\mathbf{x}_k^f$ iteratively)	$\mathbf{K}_k$	Kalman Gain weight matrix
$\mathcal{H}_k$	observation operator (projects $\mathbf{x}_k^f$ into observation space)	$\mathbf{P}_k^f, \mathbf{P}_k^a$	forecast analysis error covariance, respectively



Ensemble Kalman Filter (EnKF)

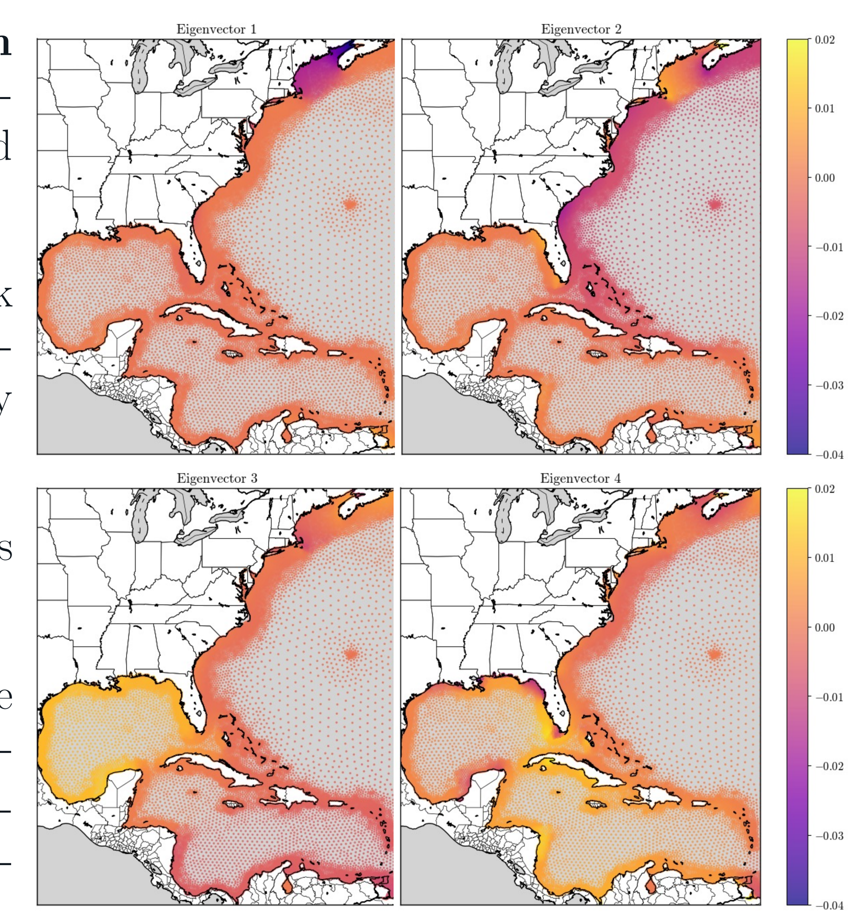
- state update produces an ensemble of updated states $\mathbf{x}_{i,k-1}^a, i = 1, \ldots r$:

$$\mathbf{x}_{i,k}^a = \mathbf{x}_{i,k}^f + \mathbf{K}_{k,e}(\mathbf{y}_{i,k}^o - \mathcal{H}_k \mathbf{x}_{i,k}^f)$$

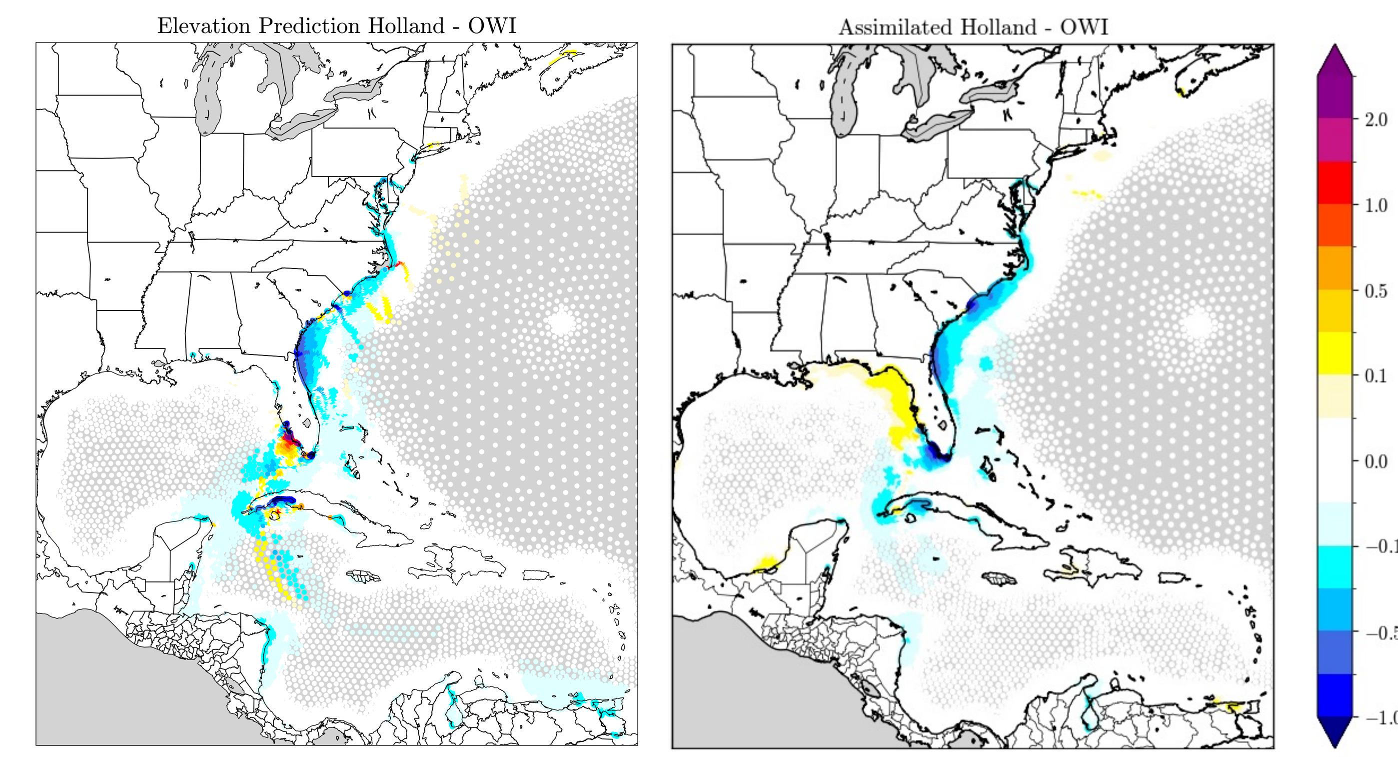
- $\mathbf{K}_{k,e}$ is constructed such that the error covariance $\mathbf{P}_k^a = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)\mathbf{P}_k^f$ is minimized
- EnKF is a good candidate for highly nonlinear models since ensembles allow better estimation of error covariance.

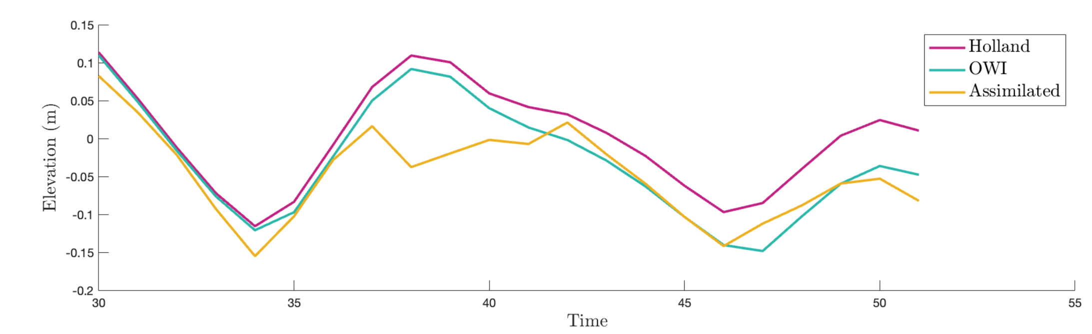
Single Evolutive Interpolated Kalman (SEIK): low-cost version of EnKF that minimizes the number of ensemble members needed to represent the $\mathbf{P}$

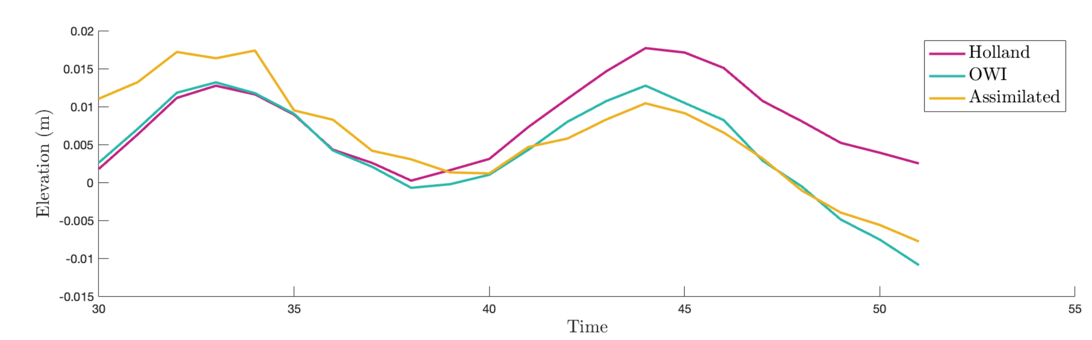
- covariance matrix is decomposed as r-rank $\mathbf{P}_a^k = \mathbf{L}_k \mathbf{U}_k \mathbf{L}_k^T$ using empirical orthogonal function (EOF) analysis such that only $\mathbf{U}$ is updated
- $\mathbf{L}$ is a matrix of eigenvectors of $\mathbf{P}$ and $\mathbf{U}$ is a diagonal matrix of the eigenvalues of $\mathbf{P}$
- Using an error tolerance of 0.99, we choose r using the ratio $\sum_{j>r} \lambda_j / \mathrm{Tr}(\mathbf{P})$, the relative error in the square L^2 norm of using approximations to the state in the r-dimensional feature space



Results







The assimilated results above show a reduction in the differences between Holland and OWI runs, especially in areas around Cuba, South Florida, and North Carolina. In some areas, the differences increased, which warrants further investigation.

The time series for a previous experiment on a coarser mesh (above) also shows the potential for data assimilation to increase accuracy of parametric wind representation.

References

[1] T. Butler et al. "Data Assimilation within the Advanced Circulation (ADCIRC) Modeling Framework for Hurricane Storm Surge Forecasting". In: *Monthly Weather Review* 140.7 (2012), pp. 2215–2231. DOI: 10.1175/MWR-D-11-00118.1. URL: https://journals.ametsoc.org/view/journals/mwre/140/7/mwr-d-11-00118.1.xml.

[2] Greg J Holland, James I Belanger, and Angela Fritz. "A revised model for radial profiles of hurricane winds". In: *Monthly weather review* 138.12 (2010), pp. 4393–4401.

[3] L. Nerger et al. "Data assimilation with the Ensemble Kalman Filter and the SEIK filter applied to a finite element model of the North Atlantic". In: *Journal of Marine Systems* 65.1 (2007). Marine Environmental Monitoring and Prediction, pp. 288–298. ISSN: 0924-7963. DOI: https://doi.org/10.1016/j.jmarsys.2005.06.009. URL: https://www.sciencedirect.com/science/article/pii/S0924796306002971.

[4] Dinh Tuan Pham, Jacques Verron, and Marie Christine Roubaud. "A singular evolutive extended Kalman filter for data assimilation in oceanography". In: *Journal of Marine Systems* 16.3 (1998), pp. 323–340. ISSN: 0924-7963. DOI: https://doi.org/10.1016/S0924-7963(97)00109-7. URL: https://www.sciencedirect.com/science/article/pii/S0924796397001097.

[5] Joannes J Westerink, Richard Albert Luettich, Norman W Scheffner, et al. "ADCIRC: an advanced three-dimensional circulation model for shelves, coasts, and estuaries. Report 3, Development of a tidal constituent database for the western North Atlantic and Gulf of Mexico". In: (1993).