# AUTOMATION IS ALL YOU NEED: FASTER EARTH SYSTEMS MODELS WITH AI/ML

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*Focal Area:* Data acquisition and assimilation enabled by machine learning (ML), artificial intelligence (AI) and advanced methods.

*Science Challenge:* Tropical cyclones can induce extreme water cycle events through dramatic precipitation and storm surge. More reliable models of intensity will translate into better prediction of the impact of extreme events in large scale Earth systems simulations. We demonstrate and describe AI/ML methodologies for rapid assimilation of new, in situ data products.

## 1. Rationale and Summary

The scale and complexity of Earth systems models inhibit interpretability and rapid design innovation. AI/ML can accelerate development and enhance impact of such systems by automating analysis and model development. We use cyclone modeling as a concrete example and explore the following themes.

**Automatic Analysis** The full cycle of development, execution, and forecasting from earth systems models can be decades long. Data output can be larger than is manageable by general compute or humans. We propose that automatic analysis of models that provide measurements useful for decision making is a crucial step for future earth systems.

**Automatic Modeling** First principle models can capture all relevant earth systems dynamics. But computational and data issues inhibit creation of models with a useful decision horizon. That is, we will face earth system changes before we can simulate or process them. AI/ML plus novel data collection can accelerate pure computational performance and parameterization of models.

## 2. Hurricane modeling from wave measurements: an example

Tropical cyclones induce extreme water cycle events with far reaching environmental impacts. Advances in numerical weather methodologies are credited with decades of improvements in tropical cyclone track prediction. However, meaningful improvements in intensity prediction have only come more recently with the introduction of certain dynamical models and consensus aids [4]. Future improvements in modeling of intensity associated phenomena will be realized by assimilating data at the air-sea interface of storms. interact. For instance, the DOE's Energy Exascale Earth System Model (E3SM) is incorporating wave models (e.g. NOAA's WAVEWATCH III) to simulate sea level rise and coastal inundation [7].

Incorporation of in situ, remotely sensed observations of oceanic currents and environmental factors improves intensity modeling in typically poorly initialized predictive models [9]. Deployed drifters with environmental sensing suites and real-time reporting capabilities can provide very valuable insight into

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the progress of a tropical cyclone by measuring factors that control storm intensity at the air-sea interface. These free-floating devices are distributed by the dynamics of the storm itself: the utility can be best realized by leveraging computational techniques to assimilate measures of currents and environmental parameters into dynamic cyclone models.

The DARPA Ocean of Things (OoT) program [6] has developed advanced ocean-going drifters that record and report via satellite a multitude of environmental variables. A 2020 OoT deployment coincided with Hurricane Sally in the Gulf of Mexico. Data collected from drifters and coastal weather stations (Figure 1) can be assimilated into a prototypical hurricane model [8] that has been used to simulate storm surge effects [13]. This model provides insight into both the particular storm's intensity profile and generalized relationships between ocean currents, wave dynamics, and atmospheric effects.

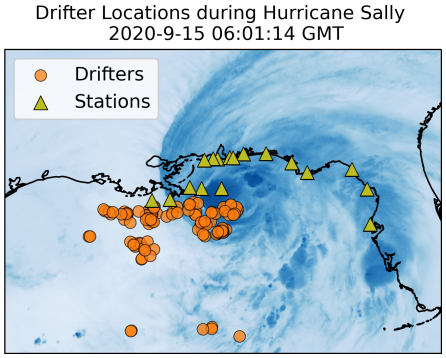


FIGURE 1. Location of drifters and weather stations with satellite imagery of Hurricane Sally.

The drifter sensor suite returned atmospheric pressure values but did not directly measure surface wind speed. Instead, the drifters reported peak wave period values, understood to be functionally related to wind speed. Explicit models of this functional relationship are dependent on physical assumptions that may be complicated under cyclonic conditions. Understanding the wind-wave relationship under these conditions is useful for modeling how wind-forcing drives inland inundation via storm surge. We selected a fitted wind-wave functional relationship from a set of candidate models incorporated into the hurricane model using a maximum likelihood estimator parameter fit and the Akaike information criterion (AIC) (Figure 2).

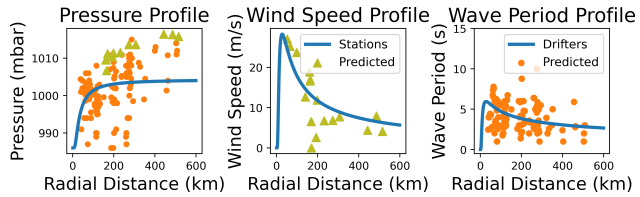


FIGURE 2. Drifter and weather station data alongside model predicted profiles.

We observed poor fitting to pressure observed further from the center of the storm. We suspect these skewed residuals result from both model deficiencies and absent geospatial context. We trained a feed-forward neural-network against the residuals of the modeled pressure profile and observed data, using as input the coordinates of sensor locations (Figure 3). The resulting correction model contextualized the cylindrical storm model as situated in a broader north-northeast pressure gradient, which is locally consistent with contemporaneous isobar maps [11].

This vignette illustrates the utility of ML approaches for augmenting physical models of earth systems by inferring requisite quantities from in situ drifters.

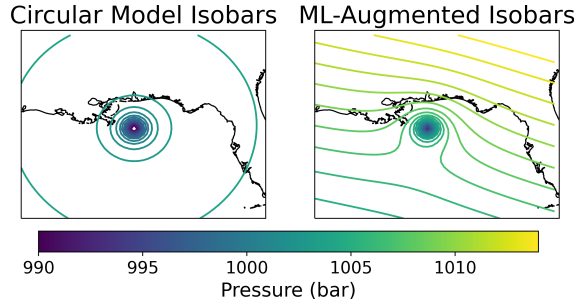


FIGURE 3. Isobars of pressure from a prototypical, circularly symmetric model and an ML-augmented model.

## 3. AI/ML automation frontiers for hurricane modelings

We have provided a canonical data driven hurricane model at a single time-slice. We reflect on how to include more variables and how AI/ML automation helps us.

A hurricane involves multiple fluids, thermodynamics, and fluid structure interactions. They are coupled to other similarly complex atmospheric events. First principle models exist for many atmospheric conditions which reduce the problem by making ideal assumptions for numerical computations or theory. One must trade precision for speed and this is done by providing simplified models of subgrid phenomena to close the model. As these systems will be used for decision support it is useful to quantify which aspects or systems in the problem contribute the most to the uncertainty—this could point to the data or model or both.

3.1. **AI/ML for correcting and closing models.** To enhance the utility of Lagrangian drifter data described herein, one can model the floats as particles in the ocean flow using the Maxey–Riley equations [12, 3]. This is a problem of closure where data and machine learning can help. The Maxey–Riley equations give the dynamics of particles in a fluid (or at the interface of two fluids in the Lagrangian drifter case). The dynamics depend on ocean and atmospheric forces, as well as the shape and mass distribution of the particles. Using data from Lagrangian drifters it is possible to make a data driven model for the dynamics where a kinematic correction term is learned as a deep neural network (DNN) [1]. Closure issues like this also arise in turbulence modeling and recent work has applied DNN [2, 5]. Modeling discrepancy or error between a first principle model and observed data has similar considerations and therefore provide a path to novel assimilation techniques. These observations could be used to enhance the vignette in Section 2

3.2. **Recovery of parameters from data.** A functional relationship between drifter motion and wind and water forcing may also be useful in recovering these sources from data in an inverse problems sense. Here, we can exploit DNN for their speed and generalization abilities. Recent work has highlighted that one can learn not only dynamics (giving a single solution), but also solution operators (giving an entire family of solutions) [10]. Moreover, the structure of neural networks allows the execution speed-up given by highly parallel computations. Combining these facts accelerates by orders of magnitude the many forward computations required for inverse problem computations.

3.3. **End-to-end capability.** The enormous data size and run times often prevent use of earth systems models for forecasting. Neural network can be used to automate tasks and build end-to-end pipelines from data to forecast and even possibly decision. Moreover, AI/ML can be used to compress models for distribution and reuse (for example [10]).

3.4. **Conclusion.** We have illustrated the ability to combine first principle modeling with AI/ML tools to close models where in the past expert knowledge was required and the structural advantages of tools such as deep neural networks for faster computation. This approach applies more broadly in the earth systems context in the same way. Earth systems will require a hierarchy of models which must be combined to close the total system—we suggest that a path to accelerating this modeling is closure through learned models. The tradespace of speed vs. accuracy is ever present in HPC, where learning tools, in particular deep neural networks, offer orders of magnitude speed ups.

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