Data Assimilation with Machine Learning Surrogate Models: A Case Study with FourCastNet

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Overview

- **Issue**: Data-driven weather forecasting surrogate models give accurate short-term predictions, but inaccurate long-term forecasts
- **Our work**: Online weather prediction using learned surrogates supplemented with low-resolution observations.
- **Case study**: Integrate FourCastNet [1] within a 3DVar [2] data assimilation framework using noisy, low-resolution ERA5 [3] data as a proxy for observational data.
- **Results**: Filtering estimates are accurate over a long time horizon & provide effective initial conditions for forecasting tasks, including extreme event prediction.

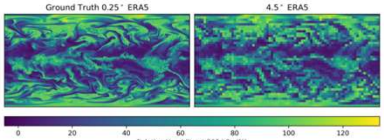

Figure 1. 0.25˚ ERA5 data for relative humidity at 500 hPa versus 4.5˚ ERA5 data.

Methodology

For our data assimilation task, we implement **3DVar**

$$x_t^s = (I - KH)\mathcal{F}_s(x_{t-1}^s) + Ky_t, \quad t \geq 1$$

$$\mathcal{F}_s = S \circ \mathcal{F}_{\mathrm{FCN}}$$

$$K = CH^{\mathrm{T}}(HCH^{\mathrm{T}} + R)^{-1}$$

$C = qBB^{\mathrm{T}}$, and B is a 2D convolution with a Gaussian kernel like in **Figure 2.**

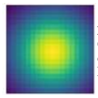

Figure 2. Gaussian convolution kernel.

- x_t^s : surrogate 3DVar analysis at time t
- $\mathcal{F}_{\mathrm{FCN}}$: weather surrogate, FourCastNet
- C : background covariance
- S : 2D smoothing convolution
- R : measurement error covariance
- H : linear observation operator
- y_t : low-resolution observations, time t

Stability Theory of 3DVar Errors [4,5].

Suppose we collect sparse, noisy, and unbiased observations over time of the true dynamical system $\mathcal{F}$.

Assumption 1. Observability with true dynamics

$$||(I - KH)D\mathcal{F}(x)|| \leq \lambda \quad \forall x \in \mathbb{R}^{d_x}$$

for some $\lambda \in (0, 1)$.

Assumption 2. Short-term surrogate accuracy

$$||(I - KH)(\mathcal{F}_s(x) - \mathcal{F}(x))|| \leq \varepsilon \quad \forall x \in \mathbb{R}^{d_x}$$

for some $\varepsilon \in \mathbb{R}^+$.

Then, $\exists c > 0$ such that $\displaystyle\lim_{t\to\infty} \sup \mathbb{E}||x_t^s - x_t^{\mathrm{true}}|| \leq c\left(\frac{\gamma + \varepsilon}{1 - \lambda}\right)$

Results

3DVar Assimilation with 4.5˚ Observations and FourCastNet

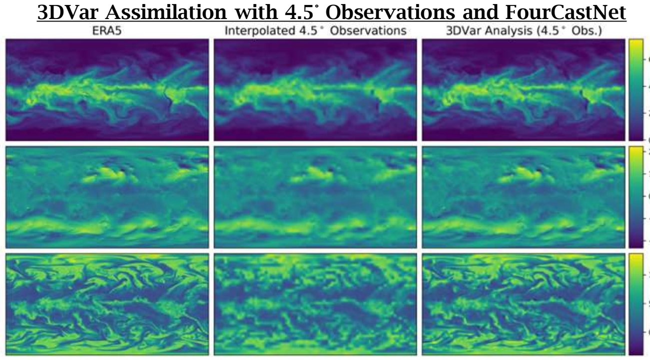

Figure 3. Ground truth ERA5 data, interpolated 4.5˚ observations, and our 3DVar analysis based on 4.5˚ for total column water vapor (TCWV), U-component wind speed at 10m above the surface (U 10m), and relative humidity at 500 hPa (RH 500hPa) on December 31, 2023 18:00 UTC. Our 3DVar analysis is constructed from initializing on January 1, 2023 at 00:00 UTC and assimilating 4.5˚ observations every 6 hours.

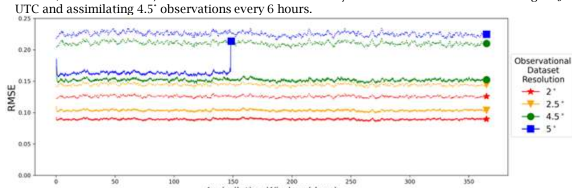

Figure 4. 3DVar assimilation error (solid lines), and interpolation error (dotted lines) over 2023. These errors are standardized and averaged across 20 atmospheric features. Using 5˚ observations in our 3DVar leads to filter divergence.

Forecasting with Ground Truth ERA5, Climatology, Interpolated 4.5˚ Observations, and Our 3DVar Analysis (4.5˚ Obs.)

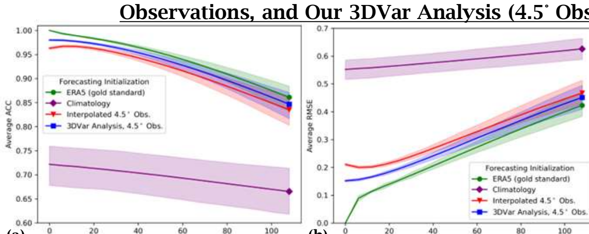

Figure 5. Week-long forecasting RMSE **(a)** and ACC **(b)** based on ground truth ERA5 data using four types of forecasting initializations. Week-long forecasting statistics are computed based on initializations across 2023. The shaded regions denote the 5% and 95% percentiles of forecasting statistics.

Extreme Event Forecasting: Typhoon Mawar 2023

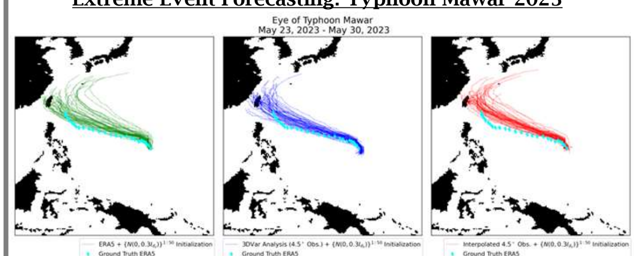

Figure 6. Forecasts beginning on May 23, 2023 00:00 UTC of the eye of Typhoon Mawar for three initialization types. Ensemble members were created at initialization by adding independent standardized $N(0, 0.3)$ noise. In each plot, we show the ground truth eye of Typhoon Mawar from May 23 to May 30, 2023 characterized by the minimum mean sea level pressure.

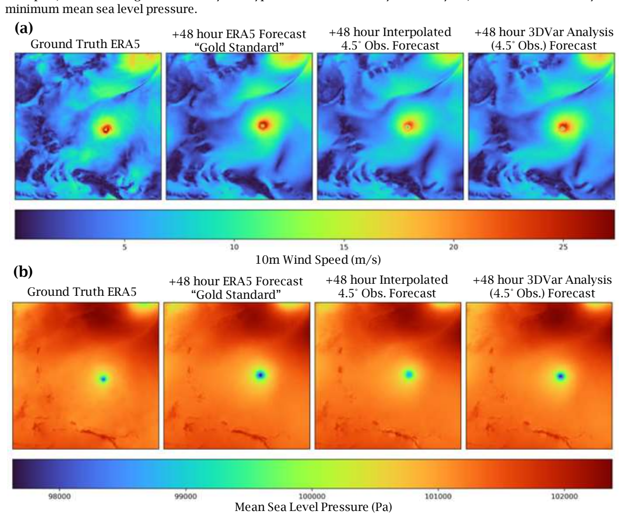

Figure 7. Forecasts 48 hours after initialization for wind speed at 10m above the surface **(a)** and mean sea level pressure **(b)** for three different initializations (far right three) and the ground truth ERA5 (far left).

Conclusions

Integrating FourCastNet into a 3DVar data assimilation algorithm can produce analyses that:

1. closely resemble the high-resolution ground truth, even in low-resolution observation regimes.
2. remain accurate over long time horizons when given sufficiently rich observations.
3. outperform in forecasting tasks when used as an initial condition compared to more naïve initializations, such as interpolating low-resolution observations and climatology.
4. when used as an initial condition for Typhoon Mawar forecasting, produced predictions that better characterized the intensity in terms of (1) the trajectory of the typhoon, (2) minimum mean sea level pressure at the eye, and (3) maximum 10m wind speed.

Future work includes assimilating real observational data with data-driven weather models, which is irregularly sampled throughout the space and requires a nonlinear observation operator *H*.

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