Forecasts of Tropical Cyclone Vortex Initialization using an LSTM Network

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BACKGROUND

- Tropical cyclones (**TCs**) pose great risks to life and property such as wind damage, inland flooding, and loss of life.
- Numerical model forecasts of tropical cyclones have improved over the past several decades, resulting in reduced track and intensity errors.
- One main limitation of numerical model forecasts of TCs is a course model grid resolution relative to the scale of TC genesis (**TCG**) processes. This can result in an inadequately resolved mass and wind fields.
- Vortex initialization (**VI**) is one technique to resolve the mass and wind fields. Some methods involve insertion of a false vortex or data assimilation (DA) to resolve the dynamics of TCG.[1, 2, 3]
- Emerging machine learning (**ML**) methods have demonstrated skill in improving TC forecast track and intensity errors.[4, 5]

Can a ML method help extend a numerical model forecast to predict when VI occurs?

METHODS

- ML model is a network with two long short term memory (**LSTM**) layers.
- **WRF/EnKF** data[6] is used for testing and training. It contains **80 ensemble members** with **6 hourly** data.
  - The dataset combines Advanced Research Weather Research and Forecasting model (WRF) and an ensemble Kalman filter (EnKF) and assimilates observational data.
- **Training data**: 6 hourly 80 ensemble members for 09/18/2018 12:00 UTC to 09/30/2018 18:00 UTC from WRF/EnKF. Data is reduced into principal components (PCs) using singular value decomposition (SVD) for the first 10 eigenmodes, and PCs are used to train.
  - Input data: surface pressure & winds, lower and upper troposphere winds
  - Output data: surface pressure & surface windspeeds with **24 h lag**
- **Testing data**: Three TC cases from WRF/EnKF are used to test a 24 h forecast with 24 h of past data input into the network. The storms, with their min surface pressure (PSFC), and max wind speed at first date of occurrence (TCG): **Trami** (1003 hPa, 13 m/s), "**Twenty-Nine**" (1004 hPa, 13 m/s), **Kong-Rei** (1000 hPa, 13 m/s)

RESULTS

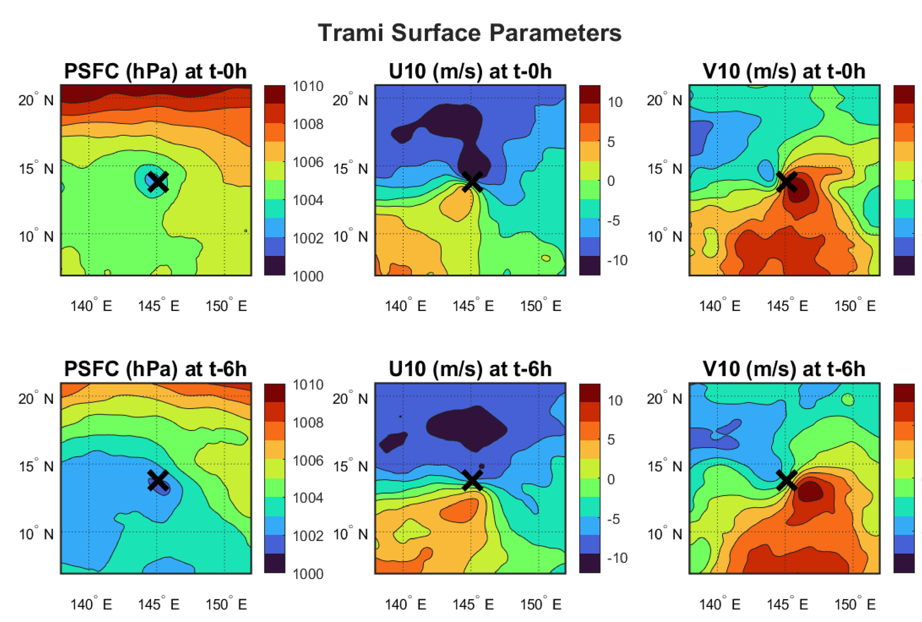

Figure 1: Trami ensemble mean WRF/EnKF surface pressure and 10 meter and windspeeds at time of TCG and 6h prior. X denotes the location of min PSFC at time of TCG from TC Vitals.

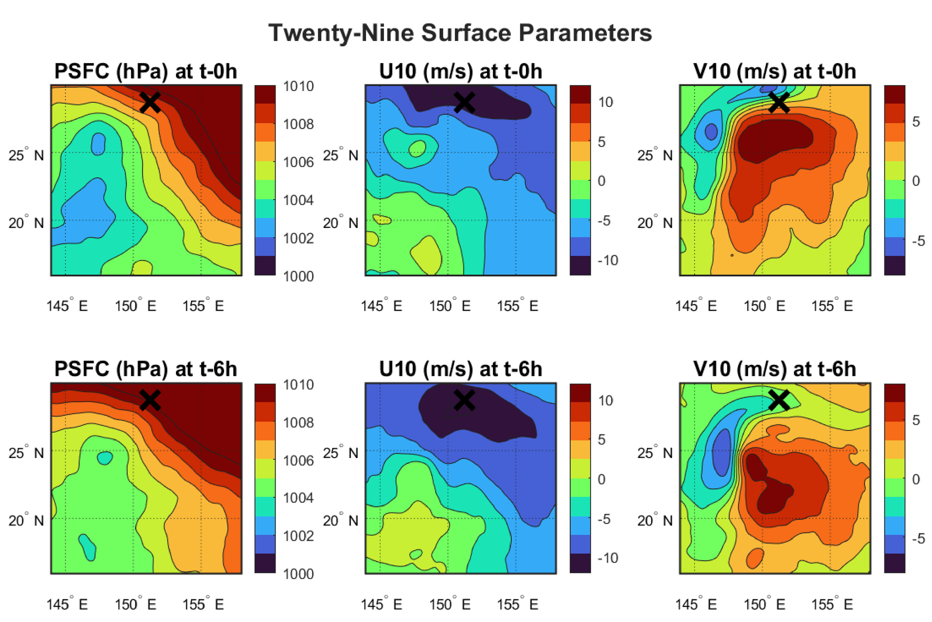

Figure 2: Twenty-Nine ensemble mean WRF/EnKF surface pressure and 10 meter and windspeeds at time of TCG and 6h prior. X denotes the location of min PSFC at time of TCG from TC Vitals.

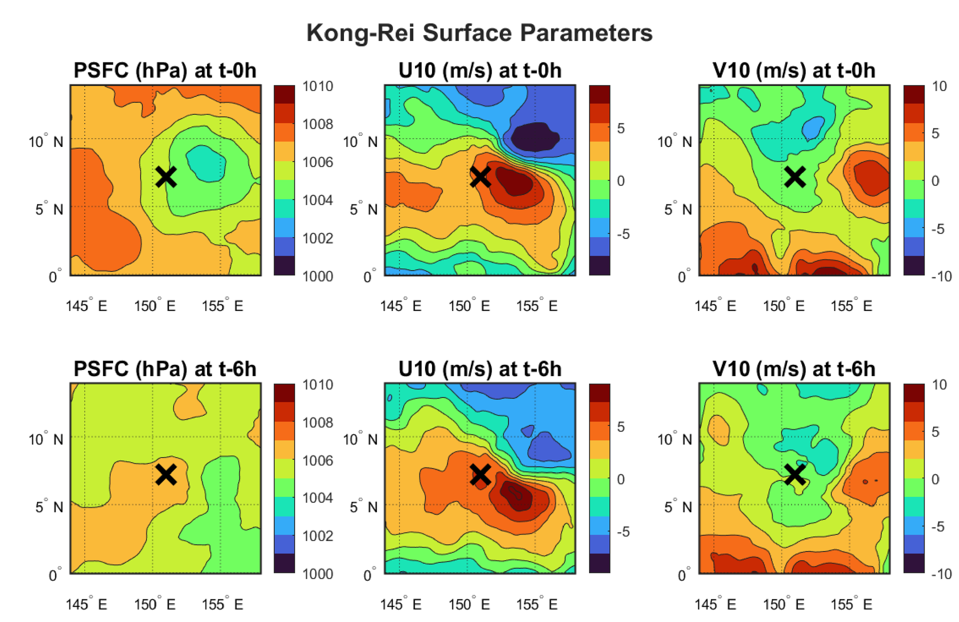

Figure 3: Kong-Rei ensemble mean WRF/EnKF surface pressure and 10 meter and windspeeds at time of TCG and 6h prior. X denotes the location of min PSFC at time of TCG from TC Vitals.

- Figures 1-3 show the surface pressure (PSFC), 10m zonal windspeed (U10), & 10m meridional windspeed (V10) at the time of TCG and 6h prior for each test case.
- Existing WRF/EnKF track error can be seen through difference in location from the center of minimum PSFC and the X of real TC location at time of TCG.

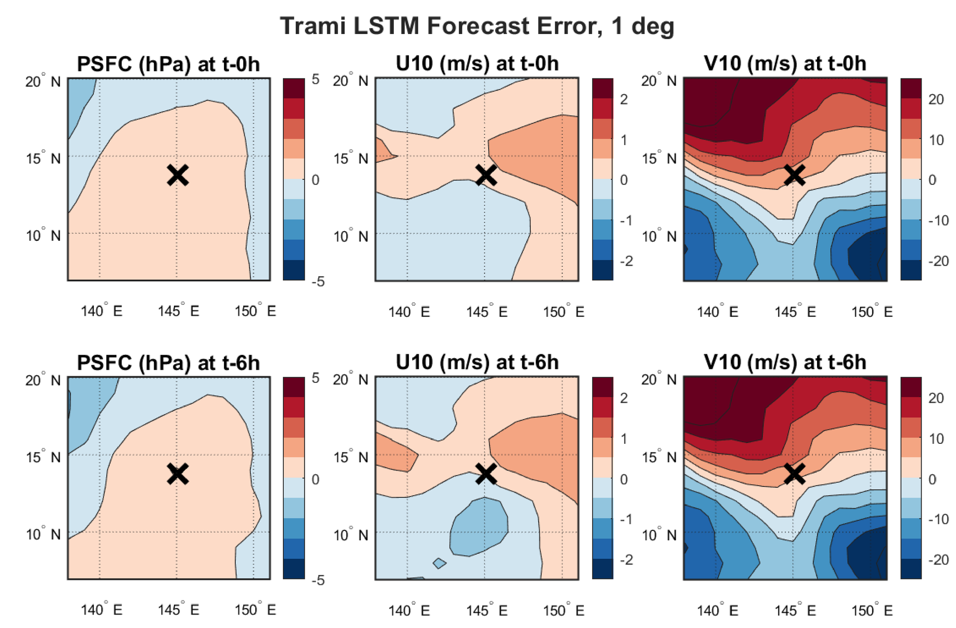

Figure 4: Trami LSTM forecast error for surface pressure and 10 meter windspeeds at time of TCG and 6h prior. X denotes the location of min PSFC at time of TCG from TC Vitals.

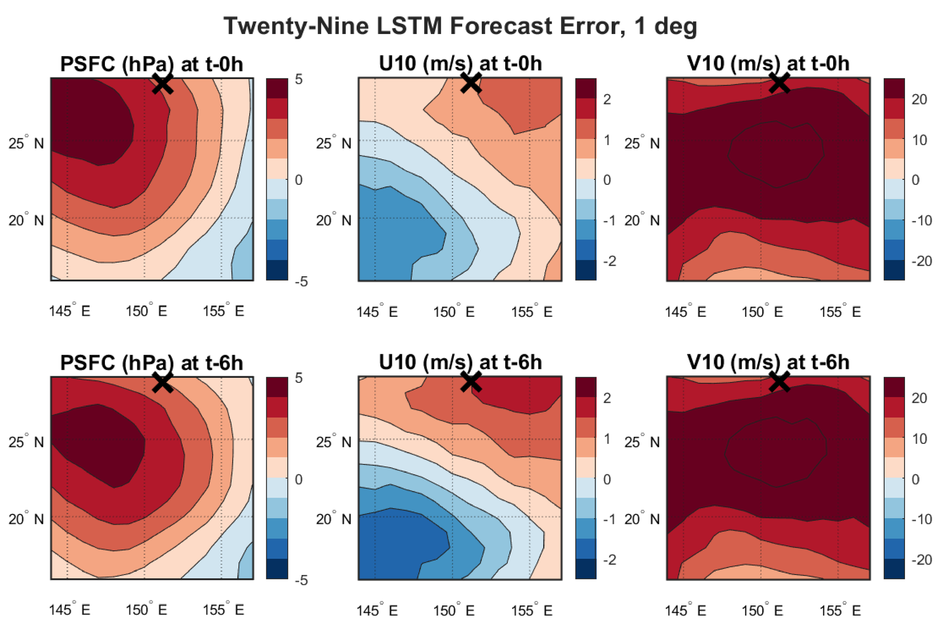

Figure 5: Twenty-Nine LSTM forecast error for surface pressure and 10 meter windspeeds at time of TCG and 6h prior. X denotes the location of min PSFC at time of TCG from TC Vitals.

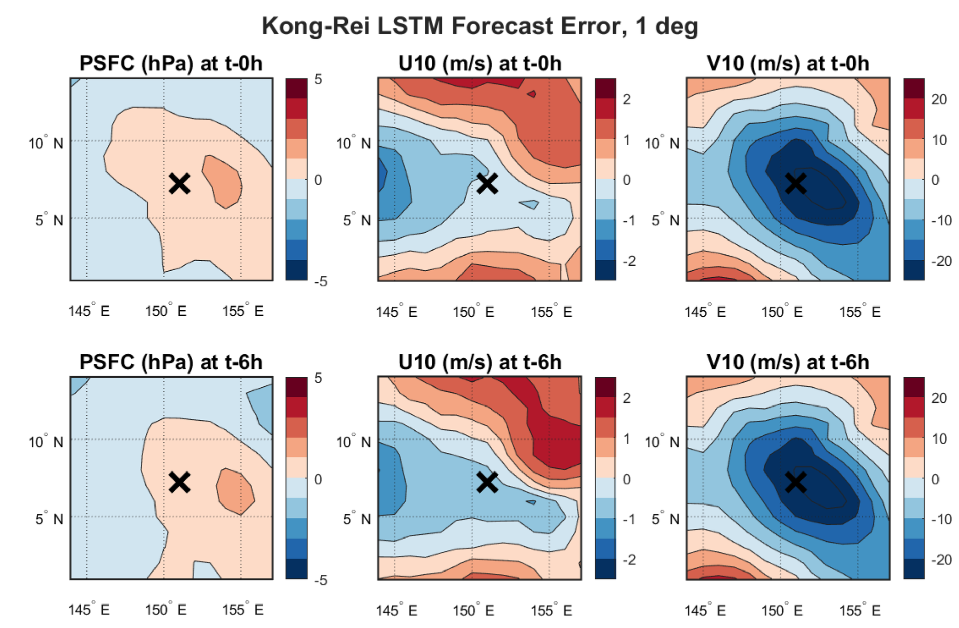

Figure 6: Kong-Rei LSTM forecast error for surface pressure and 10 meter windspeeds at time of TCG and 6h prior. X denotes the location of min PSFC at time of TCG from TC Vitals.

- Figures 4-6 show the error of LSTM forecast minus expected value from WRF/EnKF with the training data domain of 100E-180E, 0N-30N at 1 degree resolution.
- All three cases predict a greater min PSFC than expected, & smaller zonal windspeed than expected. The model did not accurately forecast meridional windspeeds.
- LSTM forecast retains the same track error as the WRF/EnKF data it was trained on.
- "Twenty-Nine" was located at the northern boundary of the training data and had the greatest PSFC error.

DISCUSSION

- Impact of model biases on network training:
  - The location and intensity errors in WRF/EnKF were also seen in LSTM forecast.
  - The LSTM network learned the model biases of WRF/EnKF.
  - The limits of WRF/EnKF limit LSTM learning (e.g. processes over terrain).
- Limitations of training and testing data:
  - Regional latitude and longitude limits of LSTM network limit representation of global processes, and LSTM network did not learn latitudinal effects on dynamics.
  - Testing the LSTM network model on the same data it had been trained results in greater forecast success than in-situ applications.

Exclusion of moisture variables:

- The selected input variables represent dynamic parameters required for TCG, but excludes moisture variables to represent convective processes.
- Future research could include input variables to represent convective available potential energy (CAPE) or mid tropospheric relative humidity (RH).

CONCLUSIONS

- Summary:

  A long short term memory model was trained on 80 members from WRF/EnKF which is a 6h DA cycled dataset at 1-degree resolution from 100E-180E, 0N-30N. Three TC cases were tested and compared to the ensemble mean surface parameters (PSFC, 10 m winds).
- The LSTM network forecasted VI for test cases from within the training dataset. This success may not be replicated for other time periods. The limited training dataset would not capture decadal, seasonal, and sub-seasonal variability affecting TCG.
- Opportunities for future work:
  - Expand training data set and number of test cases. Refine the spatial domain of training data to expand northward and southward, remove values over land to focus on ocean processes.
  - Add a variable to training data to represent latitudinal effects better (i.e. Coriolis parameter or absolute vorticity)
  - Improve selection of number of eigenmodes for each variable for PCs

KEY REFERENCES

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