The HWRF Analog Ensemble: Results from the 2017 HFIP Real-Time Demo and other project developments

William E. Lewis*, Christopher Rozoff†, Luca delle Monache†, Stefano Alessandrini†

*Space Science and Engineering Center / University of Wisconsin-Madison
†Research Applications Laboratory / National Center for Atmospheric Research
• The Analog Ensemble (AnEn) method
  • why? what? how?
• The AnEn Intensity Model
  • Results with H215
• The AnEn Rapid Intensification Model
  • Results from the 2017 HFIP Demo
• Ongoing and Future Work
  • TC Track and Structure Forecasting
  • Neural network methods
  • more models?
The Analog Ensemble: Why?

The Analog Ensemble (AnEn) (delle Monache, 2013) is:

motivated by the observation that dynamical ensembles are both expensive to run (prohibitively so with the configurations used for the operational deterministic models) and tend to have problematic dispersion characteristics.

an inexpensive method for generating ensemble forecasts from any deterministic NWP model for which a library of historical forecasts is available.
The Analog Ensemble: What?

The Analog Ensemble (AnEn) (delle Monache, 2013) is:

an ensemble in which the PDF of the future state of the atmosphere is estimated with a set of observations that correspond to the best analogs of a deterministic NWP forecast.

The analogs for a particular forecast lead time are found by minimizing:

\[
\|F_t, A_r\| = \sum_{i=1}^{N_i} \frac{w_i}{\sigma_i} \sqrt{\sum_{i=-t}^{t} (F_{i,t+j} - A_{i,r+j})^2}
\]

F = forecast, A=potential analog, N=predictor (variable), w=predictor weight, \(\sigma\)=predictor historical stdev.
The Analog Ensemble: How?

The **Analog Ensemble (AnEn)** requires:

a **set of historical forecasts** which simulate the phenomenon of interest across a reasonably well sampled climatology, and thus provide reliable correlations between forecast outputs ($V_{\text{max}}$, $\Delta V_{\text{max}}$, etc.) known as predictors and readily available observations (observed $V_{\text{max}}$, $\Delta V_{\text{max}}$, etc.).
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The **Analog Ensemble (AnEn)** requires:

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The AnEn provides a naturally downscaled estimate of the atmospheric state with flow-dependent error characteristics.
The AnEn Intensity Model (Alessandrini et al., *MWR*, 2018)

- Developed with H215
- Predictors developed from synoptic ($\Delta s=18\text{km}$) and core ($\Delta s=2\text{km}$) grids
- 1110 and 1316 reforecasts from the HWRF pre-implementation test for the Atlantic and Eastern Pacific, respectively
- 63 predictors describing thermodynamic and kinematic properties of a TC’s environment and inner-core were computed and available for optimization
The AnEn Intensity Model (Alessandrini et al., *MWR*, 2018)

### Chosen Predictors

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Basins</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>H215 VMAX</td>
<td>ATL, EP</td>
<td>The predicted intensity from HWRF</td>
</tr>
<tr>
<td>LAT</td>
<td>ATL, EP</td>
<td>The latitude of the TC</td>
</tr>
<tr>
<td>MINSLP</td>
<td>EP</td>
<td>Minimum sea-level pressure from HWRF</td>
</tr>
<tr>
<td>TANG850</td>
<td>EP</td>
<td>Average 850-hPa tangential wind (r = 0 - 600) km</td>
</tr>
<tr>
<td>INRT</td>
<td>ATL, EP</td>
<td>The 850-500-hPa layer average of inertial stability in the radial region (r = 0 - 50) km, (0 - 100) km, (100 - 250) km</td>
</tr>
<tr>
<td>SHRD</td>
<td>EP</td>
<td>The 850-200-hPa vertical wind shear magnitude in the radial region (r = 0 - 500) km</td>
</tr>
<tr>
<td>COND</td>
<td>ATL</td>
<td>The total condensate averaged over the radial region (r = 100 - 250) km and (850 - 500) km.</td>
</tr>
<tr>
<td>RHLO</td>
<td>EP</td>
<td>The 850-700-hPa layer average of relative humidity in the radial region (r = 200 - 800) km</td>
</tr>
<tr>
<td>RHMD</td>
<td>ATL, EP</td>
<td>The 700-500-hPa layer average of relative humidity in the radial region (r = 200 - 800) km</td>
</tr>
<tr>
<td>IVCN VMAX</td>
<td>ATL, EP</td>
<td>The predicted intensity from the IVCN</td>
</tr>
</tbody>
</table>
The AnEn Intensity Model (Alessandrini et al., *MWR*, 2018)

Simulated 2015 forecast results (trained on 2011-2014)

AnEn IVCN superior through 24 hours, not as competitive after 48.
The AnEn Intensity Model (Alessandrini et al., *MWR*, 2018)

Simulated 2015 forecast results (trained on 2011-2014)

AnEn IVCN superior through 72 hours, competitive thereafter.
Objective: To develop new ensemble-based products that can be used by NHC forecasters.

Co-leads:
- Ryan Torn (SUNY-Albany)
- Mark DeMaria (NHC)

Participants:
Eric Blake (NHC), Mike Brennan (NHC), Paul Kucera (NCAR), Will Lewis, Chris Rozoff, Stefano Alessandrini, Jon Moskaitis (NRL), Kate Musgrave (CSU-CIRA), Matt Onderlinde (NHC), Christopher Williams (NCAR)
### 2017 HFIP Demo / Ensemble Tiger Team Intercomparison

<table>
<thead>
<tr>
<th>Forecast Lead Time (hr)</th>
<th>Rapid intensification Threshold (kt)</th>
<th>Climatological Probability (1987-2016) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>24</td>
<td>30</td>
<td>5.9</td>
</tr>
<tr>
<td>48</td>
<td>55</td>
<td>3.9</td>
</tr>
<tr>
<td>72</td>
<td>65</td>
<td>6.8</td>
</tr>
</tbody>
</table>
2017 HFIP Demo / Ensemble Tiger Team Intercomparison

The AnEn Rapid Intensification Model

• Developed with H217
• Predictors developed from synoptic (Δs=18km) and core (Δs=2km) grids
• 860 and 1657 reforecasts from the HWRF pre-implementation test for the Atlantic and Eastern Pacific, respectively
• 65 predictors describing thermodynamic and kinematic properties of a TC’s environment and inner-core were computed and available for optimization
<table>
<thead>
<tr>
<th>Lead-time</th>
<th>Atlantic</th>
<th>Eastern Pacific</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 – 24 h</td>
<td>HWRF $\Delta v_{\text{max}}$</td>
<td>HWRF $\Delta v_{\text{max}}$</td>
</tr>
<tr>
<td></td>
<td>Symmetry of low-level inflow ($r = 0 -100\text{km}$)</td>
<td>Min SLP</td>
</tr>
<tr>
<td></td>
<td>IVCN $\Delta v_{\text{max}}$</td>
<td>IVCN $\Delta v_{\text{max}}$</td>
</tr>
<tr>
<td>0 – 48 h</td>
<td>HWRF $\Delta v_{\text{max}}$</td>
<td>Total condensate ($r = 0 – 100\text{ km}$)</td>
</tr>
<tr>
<td></td>
<td>CAPE ($r = 200 – 600\text{ km}$)</td>
<td>IVCN $\Delta v_{\text{max}}$</td>
</tr>
<tr>
<td></td>
<td>Latent Heat Flux ($r = 0 – 50\text{ km}$)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>IVCN $\Delta v_{\text{max}}$</td>
<td></td>
</tr>
<tr>
<td>0 – 72 h</td>
<td>HWRF $\Delta v_{\text{max}}$</td>
<td>HWRF $\Delta v_{\text{max}}$</td>
</tr>
<tr>
<td></td>
<td>Storm speed</td>
<td>Inertial stability ($r = 0 – 100\text{ km}$)</td>
</tr>
<tr>
<td></td>
<td>Latent Heat Flux ($r = 0 – 100\text{ km}$)</td>
<td>IVCN $\Delta v_{\text{max}}$</td>
</tr>
<tr>
<td></td>
<td>IVCN $\Delta v_{\text{max}}$</td>
<td></td>
</tr>
</tbody>
</table>
2017 HFIP Demo / Ensemble Tiger Team Intercomparison

Brier Skill Scores: Atlantic Basin

- 24 h, 30 kt
- 48 h, 55 kt
- 72 h, 65 kt

N cases: 169, 157, 265, 243, 303, 300, 145, 132, 221, 209, 251, 244, 127, 111, 183, 177, 211, 182

N RIs: 21, 21, 34, 28, 39, 37, 9, 9, 20, 16, 22, 22, 3, 3, 10, 11, 12, 11

HWRF: NCEP HWRF
HMON: NCEP HMON
COAMPS: Navy COAMPS-TC
HWAN: HWRF Analog
DTOPS: Deterministic to Probabilistic Statistical
SHIPS: SHIPS-RI
Brier Skill Scores: East-Pacific Basin

24 h, 30 kt

48 h, 55 kt

72 h, 65 kt

HWRF: NCEP HWRF

COAMPS: Navy COAMPS-TC

HWAN: HWRF Analog

DTOPS: Deterministic to Probabilistic Statistical

SHIPS: SHIPS-RI

N cases: 4 25 131 60 262 244

N R: 0 0 5 6 28 26

2 19 96 42 200 192

1 15 72 30 159 28

2017 HFIP Demo / Ensemble Tiger Team Intercomparison
The HFIP Demo began on 1 AUG, but due to technical problems, the RI version of the AnEn did not go online until 30 Aug.

To assess the performance of the RI AnEn over the full demo period, we computed forecasts for all Atlantic and East Pacific TCs from 1 AUG to 30 NOV.*

Comparison was made with operational HWRF only using homogenous samples.

* Forecast evaluation began with the 2AUG 12UTC cycle in accordance with the EOD of H217.
Atlantic Basin

\[
\begin{align*}
\Delta V_{\text{max}} \geq 30 \text{kt} & : 362, 39 \\
\Delta V_{\text{max}} \geq 55 \text{kt} & : 309, 23 \\
\Delta V_{\text{max}} \geq 65 \text{kt} & : 263, 17
\end{align*}
\]
Hurricane Harvey (AL09)
Hurricane Harvey (AL09)

# Forecasts

<table>
<thead>
<tr>
<th>$\Delta V_{\text{max}} \geq 30 \text{kt}$</th>
<th>$\Delta V_{\text{max}} \geq 55 \text{kt}$</th>
<th>$\Delta V_{\text{max}} \geq 65 \text{kt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>49</td>
<td>45</td>
<td>41</td>
</tr>
</tbody>
</table>

# RI events

<table>
<thead>
<tr>
<th>$\Delta V_{\text{max}} \geq 30 \text{kt}$</th>
<th>$\Delta V_{\text{max}} \geq 55 \text{kt}$</th>
<th>$\Delta V_{\text{max}} \geq 65 \text{kt}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>5</td>
<td>5</td>
</tr>
</tbody>
</table>

Brier Skill Score

Forecast Lead Time (hr)

- 24
- 48
- 72

# Forecasts

# RI events

HWRF

AnEn
Hurricane Irma (AL11)
Hurricane Irma (AL11)

Forecast Lead Time (hr)

<table>
<thead>
<tr>
<th>Forecast Lead Time (hr)</th>
<th>HWRF</th>
<th>AnEn</th>
</tr>
</thead>
<tbody>
<tr>
<td>24</td>
<td>-0.6</td>
<td>-0.4</td>
</tr>
<tr>
<td>48</td>
<td>-0.7</td>
<td>-0.6</td>
</tr>
<tr>
<td>72</td>
<td>-0.8</td>
<td>-0.7</td>
</tr>
</tbody>
</table>

Brier Skill Score

- For $\Delta V_{max} \geq 30$ kt:
  - 47 forecasts, 8 RI events

- For $\Delta V_{max} \geq 55$ kt:
  - 43 forecasts, 5 RI events

- For $\Delta V_{max} \geq 65$ kt:
  - 39 forecasts, 3 RI events

# Forecasts
# RI events
Hurricane Maria (AL15)
Hurricane Maria (AL15)

- $\Delta V_{\text{max}} \geq 30\text{kt}$
  - # Forecasts: 53
  - # RI events: 7
- $\Delta V_{\text{max}} \geq 55\text{kt}$
  - # Forecasts: 49
  - # RI events: 7
- $\Delta V_{\text{max}} \geq 65\text{kt}$
  - # Forecasts: 45
  - # RI events: 4

Brier Skill Score

Forecast Lead Time (hr)

HWRF
AnEn
Eastern Pacific Basin

<table>
<thead>
<tr>
<th>ΔV_{max} ≥ 30kt</th>
<th>ΔV_{max} ≥ 55kt</th>
<th>ΔV_{max} ≥ 65kt</th>
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</thead>
<tbody>
<tr>
<td># Forecasts</td>
<td># RI events</td>
<td></td>
</tr>
<tr>
<td>94</td>
<td>11</td>
<td>48</td>
</tr>
<tr>
<td>65</td>
<td>6</td>
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Brier Skill Score

Forecast Lead Time (hr)

- 24
- 48
- 72

HWRF  AnEn
Hurricane Kenneth (EP13)
Hurricane Kenneth (EP13)

![Graph showing Brier Skill Score for different forecast lead times and intensity thresholds.]

- $\Delta V_{\text{max}} \geq 30\text{kt}$
  - # Forecasts: 18
  - # RI events: 5
- $\Delta V_{\text{max}} \geq 55\text{kt}$
  - # Forecasts: 14
  - # RI events: 4
- $\Delta V_{\text{max}} \geq 65\text{kt}$
  - # Forecasts: 10
  - # RI events: 2

Forecast Lead Time (hr)

- 24 hours
- 48 hours
- 72 hours

 HWRF
 AnEn
HWRF AnEn RI Model Conclusions

• Demonstrates skill relative to climatological baseline at all lead times in the AL and at 48 and 72 hours in the EP.

• Robust 40-50% skill increase over deterministic HWRF in AL, 20-30% in EP.

• Reasons for lagging performance in EP still under investigation (EP training set was larger than AL, but verification set was significantly smaller, so could be as simple as sampling issue).
Ongoing Work

AnEn Track Model

- Based in a Lagrangian framework following the TC trajectory
- $\triangle \text{lon}(t,t_0)$ and $\triangle \text{lat}(t,t_0)$ are predicted by AnEn independently
- They are coupled by Schaake Shuffle (SS) technique to build displacement vectors (from the storm location at forecast lead time=0)
- Each displacement member can be used to have realistic member trajectories
Ongoing Work

AnEn Track Model

Promising: MDE very similar to HWRF up to about lead time=20 (60 hours ahead) and very good spread/skill relationship of the ensemble

Stefano’s presentation on the TC Track AnEn at the 33rd AMS Hurricane Conference: Monday, 16 April 2018 at 9:45am
Ongoing Work

AnEn Structure Model

• Goal: Predict 4 parameters: RMW, R34, R50, and R64 by quadrant

• Two implementation strategies
  1. Direct AnEn models for structure parameters
  2. Parameterized wind curves using the modified Rankine vortex

\[ v(r, \theta) = a \cos(\theta - \theta_a) + b \cos[2(\theta - \theta_b)] + (v_{\text{max}} - a - b) \left( \frac{r}{r_{\text{max}}} \right) \]

\[ \left\{ \begin{array}{ll}
   \left( \frac{r}{r_{\text{max}}} \right) & \text{for } r < r_1, \\
   \left( \frac{r}{r_{\text{max}}} \right)^a & \text{for } r \geq r_1.
\end{array} \right. \]

3. Predictors follow similarly to AnEn intensity model

Please visit Chris’ Poster at the 33rd AMS Hurricane Conference: Tuesday, 17 April 2018
Neural Networks

- **Simple NN** trained on H217 pre-implementation forecast set
- NEW: AL and EP no longer segregated (basin becomes a predictor)
- Competitive with OFCL, superior to HWRF at all lead times.
- Out to 36 hr, most important predictor is initial operational $V_{\text{max}}$ estimate

VMAX MAE

GARSON VARIABLE IMPORTANCE

Acknowledgement: Brian Reich (NSCU)
Neural Networks

• **Convolutional NNs (CNNs)** offer the ability to work directly with 2D model output
• Already widely used for biometric and geospatial imagery analysis applications, and recently in “Dvorak-like” TC intensity estimation (Pradhan et al., 2018)
• Ability to scan 2D fields for predictors (rather than rely on traditional feature extraction) is a major advantage
• Deep learning method, so free of bias imposed by prior assumptions
• Given HWRF’s increasing resolution and skill in simulating realistic convective structures in the TC core and rainband regions, **CNNs** offer the promise of identifying and using important, heretofore unutilized information from the model.
Upcoming Work

• Completion of AnEn Track and Structure models
• Preparations for 2018 HFIP Demo:
  • Processing H218 Pre-Implementation Forecast Set (Early Christmas Wishlist: LOTS of forecasts)
  • H218 AnEn RI model
  • H218 AnEn intensity / track / structure models
• Machine Learning enhancements (simple and convolutional Neural Networks) which preliminarily look very promising.
  • Convolutional Neural Networks (CNN) in particular offer the possibility of a significant leap in the identification and use of new predictors.
• Potential application of AnEn to other models (e.g. GFS) which have training / reforecast datasets available.