Using Machine Learning to improve 1-h Low-level Rotation Forecasts

Montgomery L. Flora¹,³,⁴, Corey Potvin¹,³,⁴, Amy McGovern¹,², Patrick Skinner³,⁴

¹School of Meteorology, University of Oklahoma, Norman, OK; ²School of Computer Science, University of Oklahoma, Norman, OK;
³Cooperative Institute for Mesoscale Meteorological Studies, Norman, OK; ⁴NOAA/OAR/National Severe Storms Laboratory, Norman, OK

BACKGROUND

NOAA Warn-on-Forecast (WoF): a promising effort to improve warning lead times by providing rapid-update probabilistic guidance to human forecasters (Stensrud et al. 2009, 2013).

Low-level rotation on 3-km grid may potentially discriminate well between tornadic and non-tornadic (Wheatley et al. WAF 2015; Sobash et al. WAF 2016; Skinner et al. WAF 2016)

Current storm-scale forecasting techniques rely on uncalibrated probability of exceedance (PoE; # of ensemble members > threshold / ensemble size)

However, CAMs often contain large errors in storm intensity, timing, and location.

Machine learning can leverage ensemble uncertainty, incorporate several model variables, and mitigate forecast bias to produce calibrated probabilistic forecasts (McGovern et al. BAMS 2017)

DATA SOURCES

NSSL Experimental WoF System for ensembles (NEWS-e) model output
- 18-member ensemble forecast with 3-km grid spacing
- Initialized every 30 minutes starting at 1900 UTC until 0300 UTC
- Generated during the 2016 & 2017 NOAA Hazardous Weather Testbed Spring Forecasting Experiments (total of 30 dates)

NSSL Multi-Radar Multi-Sensor low-level (0-2 km AGL) azimuthal shear
- Azimuthal shear ~ ½ vorticity
- Quality-checked and remapped to the NEWS-e grid

PREDICTORS

6 ensemble statistics are calculated for 21 variables (see below)
- 0 (min), 25, 50, 75, 100 (max) percentiles and standard deviation
- Both for raw and gradient magnitude fields
- Maximized in 1-window

<table>
<thead>
<tr>
<th>Thermodynamics</th>
<th>Kinematics</th>
<th>Storm</th>
</tr>
</thead>
<tbody>
<tr>
<td>*ML LCL</td>
<td>2 m Tɛ</td>
<td>0-1 km SRH</td>
</tr>
<tr>
<td>*ML CAPE</td>
<td>*ML θɛ</td>
<td>0-3 km SRH</td>
</tr>
<tr>
<td>*ML CIN</td>
<td>2 m Temp</td>
<td>0-1 km U shear</td>
</tr>
<tr>
<td>SFC Pressure</td>
<td>2 m Qs</td>
<td>0-6 km U shear</td>
</tr>
<tr>
<td>2 m θ</td>
<td>*ML Qv</td>
<td>0-1 km V shear</td>
</tr>
</tbody>
</table>

*ML: 0-75 mb Mixed layer

DEFINING SIGNIFICANT LOW-LEVEL ROTATION

Maximize 2*Azimuthal Shear in 1-h window
Spatial Maximum in 3 grid point radius
Convolve with Gaussian Kernel (2 grid point radius)
Significant low-level rotation > 0.01 s⁻¹

Smart Sampling
- Balanced training datasets improve model performance
- For each date and initialization time, extract all data from regions within the significant low-level rotation
- Randomly extract from outside in equal portion

Climatological Sampling
- Needed for calibrating the probabilities
- Randomly sample 3% of domain with 3.5% of points coming from within the low-level rotation regions

DATA EXTRACTION

2330-0030 UTC May 17, 2016
0100-0200 UTC May 17, 2016

Random Forest
PoE
Random Forest
PoE

NEXT STEPS...

- Employing an object-matching forecast verification approach
- Employing additional algorithms such as logistic regression and gradient-boosted trees
- Removing storm predictors to evaluate the discrimination ability of environment variables

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