

NOAA ROSES Semi-Annual Report

Reporting Period: March 2021 – September 2021 (2nd report)

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Project Title: Probabilistic Nowcasting of Aviation Turbulence Using Deep Learning Applied to Advanced Geostationary Imagery

Executive Summary (1 paragraph max)

In spite of the progress made by numerical models in forecasting aviation turbulence, major hazards remain undetected. Today's geostationary imagery provides an alternate approach, with high spatial precision and low latency that reveal structures associated with turbulence not captured by numerical models alone. Processing this geostationary imagery with deep learning offers a new and *comprehensive* way to quantify the hazards posed by turbulence-forming atmospheric structures that surpasses the skill of previous heuristic methods. During this period, we did a critical assessment of the new online version of the turbulence estimation model and began compiling WRF-modeled cases studies of mountain-wave turbulence.

Progress toward FY20 Milestones and Relevant Findings

Evaluation of new algorithm: We have continued monitoring the latest version of the aviation turbulence product online. This is necessary in order to evaluate the effects of the major changes made in the algorithm during the last reporting period. Overall, the product demonstrates the same high skill in real time as observed in the historical validation.

After examining the algorithm in so many conditions and becoming more familiar with its shortcomings, we began in August to dive deeper into the conditions leading to weaker performance. Two examples organized by NWS forecaster Sean Campbell demonstrate the range of conditions being examined. The first example (Figure 1) shows below-average model skill in predicting a large turbulence event. In the area from southern Illinois to southern West Virginia, the estimated probability of Moderate-or-Greater turbulence is around 10%, sometimes lower. However, nine aircraft reported Moderate turbulence in this area and even more reported Light-to-Moderate turbulence. The second example (Figure 2) has a similar number of turbulence reports but in an area of 10-50% modeled probability of Moderate-or-Greater turbulence, demonstrating much higher model skill. Comparing the two cases shows the pattern in the atmospheric observations that is beginning to emerge: Turbulence is of course strongly associated with atmospheric inversions, as observed in the corresponding atmospheric soundings. However, the inversions usually do not appear in the model's GFS input data. Rather, the model uses other features in the model fields that correlate with inversions (as well as other sources of instability), such as high wind and vertical wind shear. When these associated features are absent in the GFS fields, the model estimates low turbulence probability. Thus, the skill of the model may depend heavily on whether inversions can be

inferred by the GFS and neural network. We will examine more cases during the next reporting period to confirm this hypothesis.

Modeling mountain wave turbulence: We are beginning to compile a set of WRF-modeled examples of mountain wave turbulence events. These will serve both as deep-dive comparisons for model accuracy, and as a training data set for future capabilities. Many algorithms, including ours, struggle to estimate mountain wave turbulence, and the purpose of this effort is to find where a neural network can exploit the unique features within mountain waves to improve the network’s skill. Figures 3 and 4 demonstrate a case of MRF-modeled turbulent mountain waves over Colorado that we will use in our study.

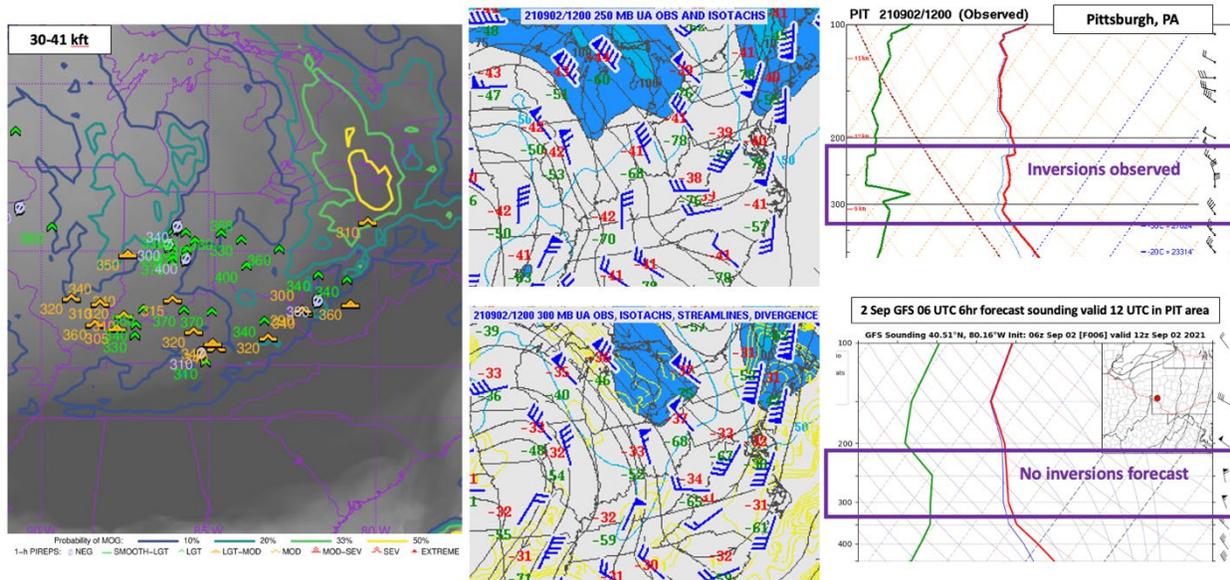


Figure 1. Left: CruiseNet 2.1 turbulence estimation product for 2 Sept 2021 1220 UTC. Contours indicate probability of turbulence and symbols represent pilot reports of turbulence; Middle: Corresponding GFS windfield; Right: Observed and GFS-modeled vertical transect in the area of turbulence.

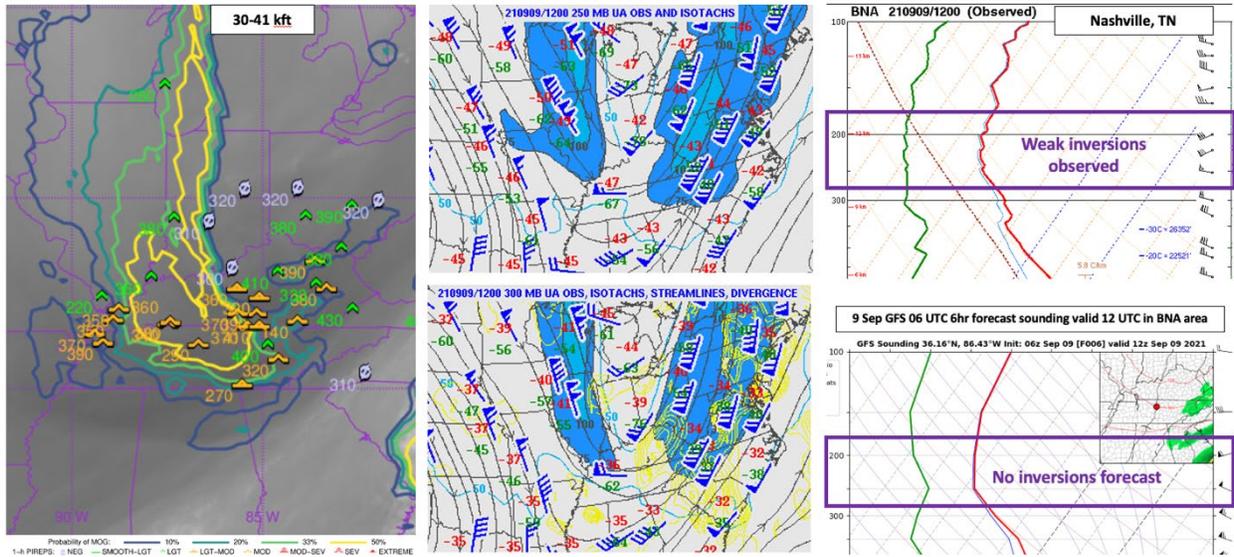


Figure 2. Left: CruiseNet 2.1 turbulence estimation product for 2 Sept 2021 1220 UTC. Contours indicate probability of turbulence and symbols represent pilot reports of turbulence; Middle: Corresponding GFS windfield; Right: Observed and GFS-modeled vertical transect in the area of turbulence.

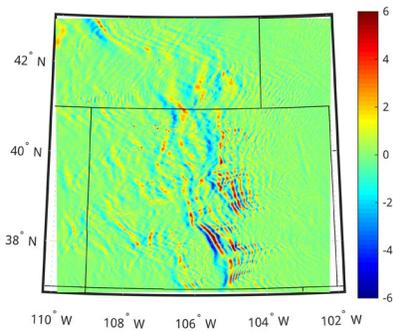


Figure 3. Vertical wind (m/s) at 500 hPa for case study at 28 Apr 2019 1600 UTC.

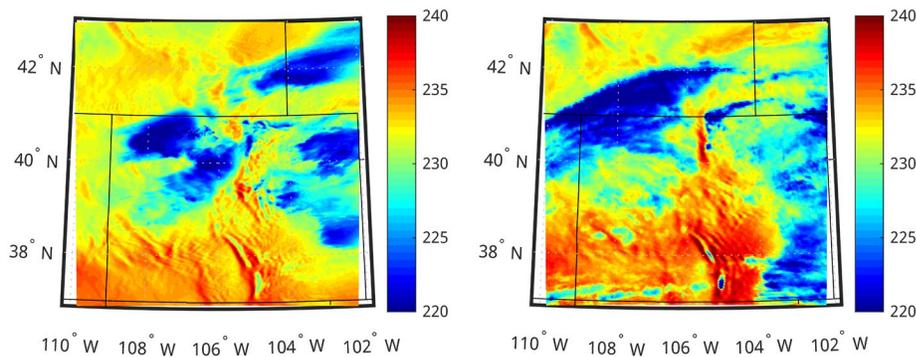


Figure 4. GOES-16 Channel 8 brightness temperature from the same case. Left: Simulated, Right: Observed.

Plans for Next Reporting Period

For the next six-month period we plan to

- Continue examining online cases of weak performance
- Continue producing model fields of mountain wave turbulence cases
- Adapt the model to additional GOES ABI channels and the GLM
- Improve the model with multi-image temporal data