

Weekly Report

CIRA
STAR/NESDIS
National Oceanic and Atmospheric Administration (NOAA)

Submitted by: Maranda Hutson
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Prepared by: CIRA and STAR contributors

Products and Applications

Publications (Citation: followed by a short Summary: (Why & so what), & detailed summary):

Citation: Imme Ebert-Uphoff, Lander Ver Hoef, John S. Schreck, Jason Stock, Maria J. Molina, Amy McGovern, Michael Yu, Bill Petzke, Bill, Kyle Hilburn, David M. Hall, David J. Gagne, William F. Campbell, Jacob T. Radford, Jebb Q. Stewart, and Sam Scheuerman. Measuring Sharpness of AI-Generated Meteorological Imagery. *Artificial Intelligence for the Earth Systems*. Early online release: 09 June 2025. <https://doi.org/10.1175/AIES-D-24-0083.1>

Short summary: AI-based estimates of meteorological images, e.g., for forecasting applications, often lack sharpness, but there are no well established metrics to measure sharpness of meteorological imagery. This manuscript seeks to close this gap by exploring sharp-ness metrics for meteorological imagery, analyzing their properties, and providing guidelines for their interpretation. We hope that the tools provided here will aid the development of AI algorithms that provide more realistic meteorological imagery.

Detailed summary: AI-based algorithms are emerging in many meteorological applications that produce imagery as output, including for global weather forecasting models. However, the imagery produced by AI algorithms, especially by convolutional neural networks (CNNs), is often described as too blurry to look realistic, partly because CNNs tend to represent uncertainty as blurriness. This blurriness can be undesirable since it might obscure important meteorological features. More complex AI models, such as Generative AI models, produce images that appear to be sharper. However, improved sharpness may come at the expense of a decline in other performance criteria, such as standard forecast verification metrics. To navigate any trade-off between sharpness and other performance metrics it is important to quantitatively assess those other metrics along with sharpness. While there is a rich set of forecast verification metrics

available for meteorological images, none of them focus on sharpness. This paper seeks to fill this gap by 1) exploring a variety of sharpness metrics from other fields, 2) evaluating properties of these metrics, 3) proposing the new concept of Gaussian Blur Equivalence as a tool for their uniform interpretation, and 4) demonstrating their use for sample meteorological applications, including a CNN that emulates radar imagery from satellite imagery (GREMLIN) and an AI-based global weather forecasting model (GraphCast). (POC: I. Ebert-Uphoff, L. Ver Hoef, and K. Hilburn, CIRA; iebert@colostate.edu, Lander.Ver_Hoef@colostate.edu, kyle.hilburn@noaa.gov. Funding: NSF AI institute, NOAA GOES-R Program.)

Title:
Measuring Sharpness of AI-Generated Meteorological Imagery

Authors:
Imme Ebert-Uphoff, Lander Ver Hoef, John S. Schreck, Jason Stock, Maria J. Molina,
Amy McGovern, Michael Yu, Bill Petzke, Kyle Hilburn, David M. Hall, David J. Gagne,
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Affiliations:

Academia: Colorado State University (CIRA, ECE, CS, MATH)
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Federally funded research center:
National Center for Atmospheric Research (NCAR)

Government labs:
US Naval Research Laboratory
NOAA-GSL

Private sector: NVIDIA

Figure: Authors and affiliations of sharpness paper (<https://doi.org/10.1175/AIES-D-24-0083.1>), illustrating that the work was a broad collaboration of members from academia, a federally funded research center, government labs, and the private sector.

Awards and Recognition

Media Interactions and Request

Blog Posts and Social Media

Travel, Workshops, Conferences, and Meeting Reports

Training and Education activities

GREMLIN Briefing to NWS: On July 8, K. Hilburn provided a virtual briefing to the National Weather Service on GREMLIN (GOES Radar Estimation via Machine Learning to Inform NWP). The briefing covered a description of GREMLIN, provided examples of strengths and limitations, discussed the applicability to NWS, and the path forward. (POC: Kyle Hilburn, CIRA, kyle.hilburn@noaa.gov; Funding: GOES-R).

Future Meetings and Events (dates, meeting/event, location, staff involved)

Other