Weekly Report – January 16, 2026

Cooperative Institute for Satellite Earth System Studies (CISESS)

NOAA/NESDIS/STAR

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SOCIAL MEDIA AND BLOG POSTS

Alaska's First Stormy Blast of the New Year

Alaska bore the brunt of another hurricane-force low-pressure system at the start of January 2026, blogs CISESS Scientist Christopher Smith, GOES-R Satellite Liaison for the National Weather Service Weather Prediction Center and Ocean Prediction Center. With wind speeds in the 40–50 kt range and with 60-kt gusts galore, significant wave heights approaching 40 feet were observed during a Jason-3/Poseidon altimeter pass, setting off a heavy freezing spray warning for the Bering Sea on 4 January 2026. These warnings were heeded by ships who for the most part avoided the Bering Sea.

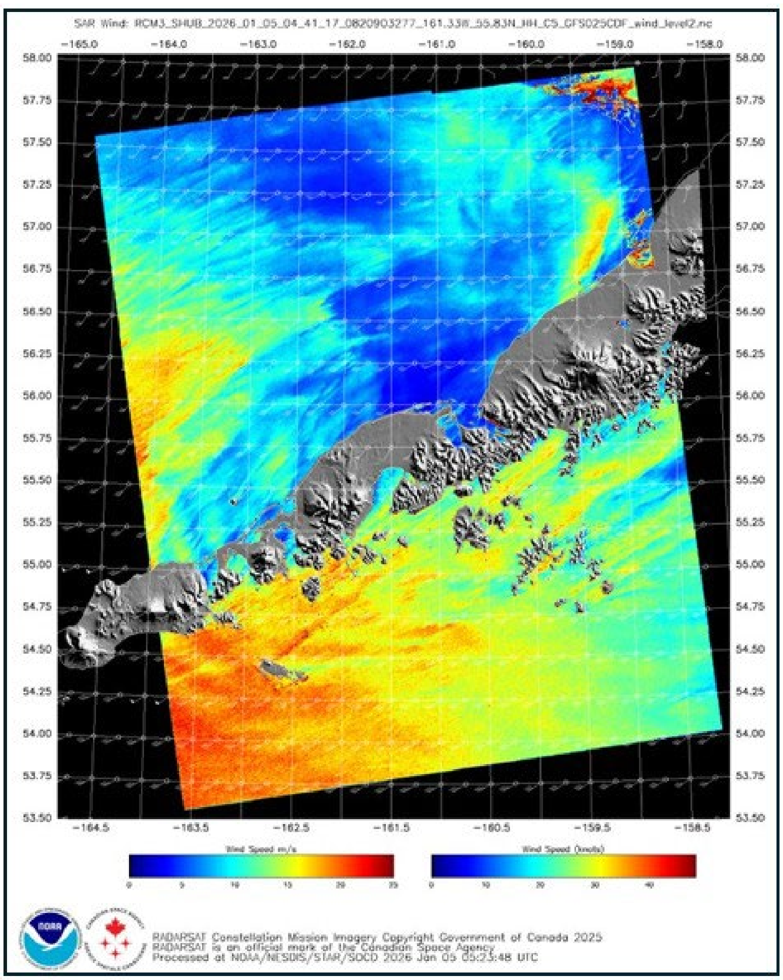

Figure: RADARSAT Constellation Mission-3 Synthetic Aperture Radar Winds Imagery valid at ~0440 UTC 05 January 2026 along the Alaska Peninsula. RADARSAT Constellation Mission Imagery Copyright Government of Canada 2025. RADARSAT is an official mark of the Canadian Space Agency. Credit: NESDIS/STAR

(Christopher Smith, CISESS, csmith70@umd.edu; Funding: GOES-R PGRR)

PUBLICATIONS

Earth's Ever-changing Carbon Budget: the Latest Update
Citation: Friedlingstein, Pierre; Michael O'Sullivan, Matthew W. Jones, Robbie M. Andrew, Judith Hauck, Peter Landschützer, Corinne Le Quéré, Hongmei Li, Ingrid T. Luijkx, Are Olsen, Glen P. Peters, Wouter Peters, Julia Pongratz, Clemens Schwingshackl, Stephen Sitch, Josep G. Canadell, Philippe Ciais, Robert B. Jackson, Simone R. Alin, Almut Arneth, Vivek Arora, Nicholas R. Bates, Meike Becker, Nicolas Bellouin, Carla F. Berghoff, Henry C. Bittig, Laurent Bopp, Patricia Cadule, Katie Campbell, Matthew A. Chamberlain, Naveen Chandra, Frédéric Chevallier, Louise P. Chini, Thomas Colligan, Jeanne Decayeux, Laique M. Djeutchouang, Xinyu Dou, Carolina Duran Rojas, Kazutaka Enyo, Wiley Evans, Amanda R. Fay, Richard A. Feely, Daniel J. Ford, Adrianna Foster, Thomas Gasser, Marion Gehlen, Thanos Gkritzalis, Giacomo Grassi, Luke Gregor, Nicolas Gruber, Özgür Gürses, Ian Harris, Matthew Hefner, Jens Heinke, George C. Hurtt, Yosuke Iida, Tatiana Ilyina, Andrew R. Jacobson, Atul K. Jain, Tereza Jarníková, **Annika Jersild**, Fei Jiang, Zhe Jin, Etsushi Kato, Ralph F. Keeling, Kees Klein Goldewijk, Jürgen Knauer, Jan Ivar Korsbakken, Xin Lan, Siv K. Lauvset, Nathalie Lefèvre, Zhu Liu, Junjie Liu, Lei Ma, Shamil Maksyutov, Gregg Marland, Nicolas Mayot, Patrick C. McGuire, Nicolas Metzl, Natalie M. Monacci, Eric J. Morgan, Shin-Ichiro Nakaoka, Craig Neill, Yosuke Niwa, Tobias Nützel, Lea Olivier, Tsuneo Ono, Paul I. Palmer, Denis Pierrot, Zhangcai Qin, Laure Resplandy, Alizée Roobaert, Thais M. Rosan, Christian Rödenbeck, Jörg Schwinger, T. Luke Smallman, Stephen M. Smith, Reinel Sospedra-Alfonso, Tobias Steinhoff, Qing Sun, Adrienne J. Sutton, Roland Séférian, Shintaro Takao, Hiroaki Tatebe, Hanqin Tian, Bronte Tilbrook, Olivier Torres, Etienne Tourigny, Hiroyuki Tsujino, Francesco Tubiello, Guido van der Werf, Rik Wanninkhof, Xuhui Wang, Dongxu Yang, Xiaojuan Yang, Zhen Yu, Wenping Yuan, Xu Yue, Sönke Zaehle, Ning Zeng, and Jiye Zeng, 2025. Global carbon budget 2024. *Earth Syst. Sci. Data*, **17**(3), 965–1039, https://doi.org/10.5194/essd-17-965-2025.
Summary: An international team of researchers, including CISESS Scientist Annika Jersild, presents a rigorous overview of the most recent state of Earth's carbon budget in a paper published in the journal *Earth System Science Data*. Here, they quantify the five major components of the global carbon budget, namely, fossil carbon dioxide (CO_2) emissions, emissions from land-use change, CO_2 removal not based on vegetation, total anthropogenic emissions, and atmospheric CO_2, along with their uncertainties, with a strong focus on the recent period (since 1958, the onset of robust atmospheric CO_2 measurements), the last decade

(2014–2023), and the years 2023 and 2024. Ocean and land CO_2 sinks are also analyzed. The authors report that the global atmospheric CO_2 concentration averaged over 2023 reached 419.31±0.1 ppm. Of interest given the recent high fire activity in both North America and South America, global fire CO_2 emissions in 2024 have been 11–32% higher than the 2014–2023 average. A slew of other statistics are offered, with results disseminated to the broad stakeholder community via [spreadsheets published by the Integrated Carbon Observation System Carbon Portal].

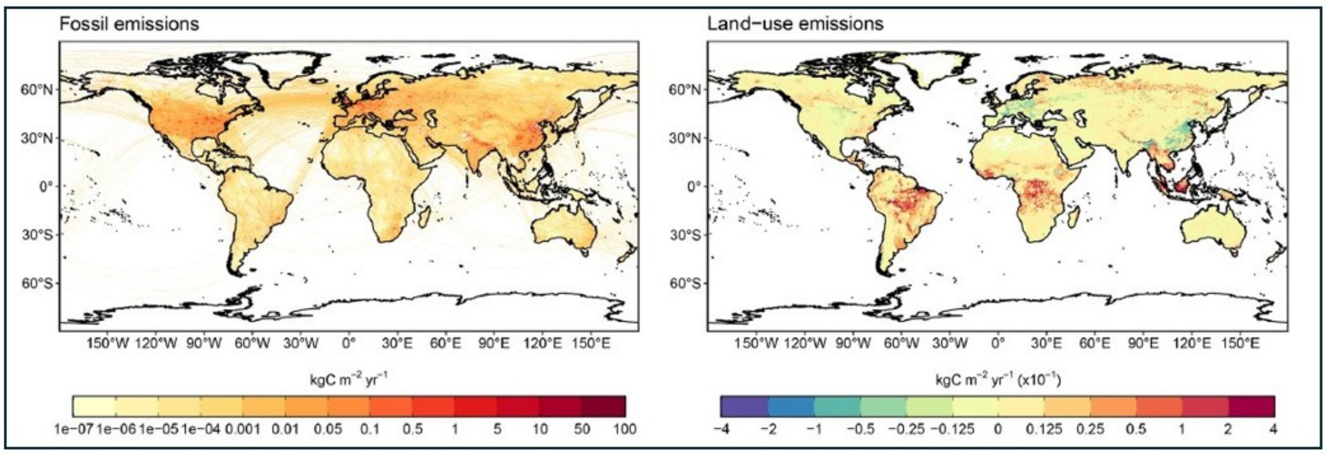

Figure: The 2014–2023 decadal mean components of the global carbon budget, presented for (left) fossil CO_2 emissions and (right) land-use change emissions.

(Annika Jersild, CISESS, ajersild@umd.edu; Funding: GOMO)

Using Machine Learning to Identify Data Contamination
Citation: Arulraj, Malarvizhi, **Veljko Petkovic**, Huan Meng, and Ralph R. Ferraro, 2025: Lessons learned: Can machine learning model expose dataset contamination? *Artif. I. Earth Syst.*, accepted, https://doi.org/ 10.1175/AIES-D-25-0030.1.
Summary: When working with large quantities of multi-dimensional data from multiple sources, dataset contamination is inevitable. Many methods have been developed to diagnose such contamination. However, unforeseen errors can sometimes sneak in, a topic discussed by CISESS Scientists Malarvizhi Arulraj and Veljko Petkovic and colleagues, based on something they noticed while doing research. Using simulated observations of a future space-borne passive microwave sensor to develop a convolutional neural network (CNN)-based model that would predict Total Column Water Vapor (TCWV), they discovered an oversight in time matching that led to contamination of a small part of their TCWV dataset. This prompted the authors to study how changing the amount of contaminated data used for training affects how well the model performs and detects errors. They found that CNN model output does not identify data issues when trained only on contaminated data (see Figure). As the percentage of contaminated samples in the training datasets decreased, though, the model's ability to pick up

the data issue increased. They conclude that since some level of data contamination is unavoidable, users, especially benchmark dataset developers, should carefully examine the data going into their models to understand its quality.

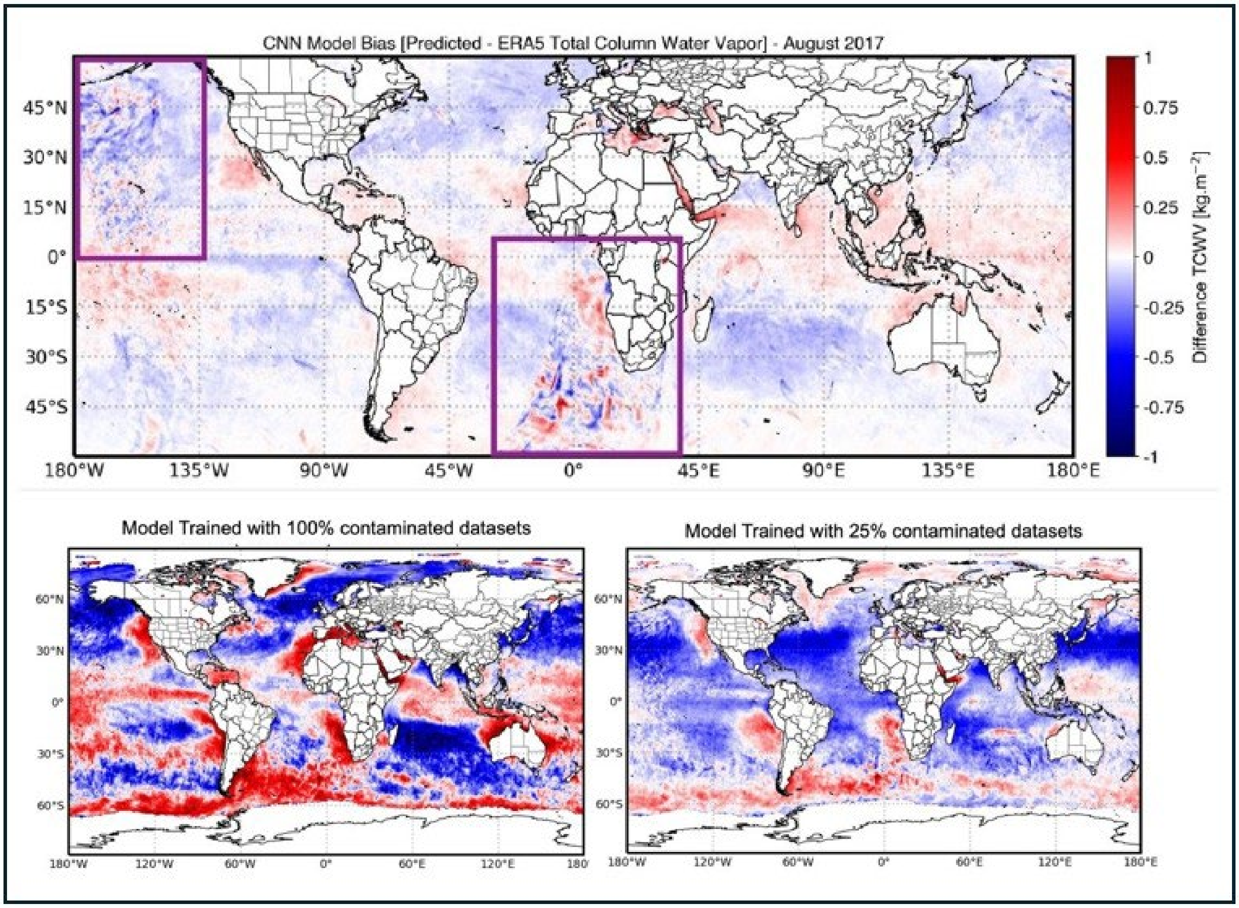

Figure: (Top) Root-mean-square error between predictions (from the model trained with both contaminated and non-contaminated data) and ERA5-derived TCWV. The purple boxes highlight areas with artifacts resembling satellite orbit patterns. (Bottom) Same as the top figure but with predictions from the CNN model trained with 100% and 25% contaminated data. Spatial artifacts in the top figure are not as noticeable here.

(Malarvizhi Arulraj, CISESS, marulraj@umd.edu, Funding: JSTAR, JSTAR GCOM & METOP-SG; Veljko Petkovic, CISESS, veljko@umd.edu, Funding: JSTAR, JSTAR GCOM & LEO)

(Maureen Cribb, CISESS, mcribb@umd.edu, Funding: CISESS Task I)