Application of a Deep Learning Nested U-Net for Reflectivity Inpainting in Spaceborne Radar Blind-Zones

FRASER KING,[1] CLAIRE PETTERSEN,[1] AND CHRISTOPHER G. FLETCHER[2]

ABSTRACT

CloudSat's Cloud Profiling Radar (CPR) is one of the few observation-based systems for remotely monitoring high-latitude snowfall. However, the CPR is unable to observe hydrometeor activity within the lowest 1.2 km of the atmosphere due to ground-clutter contamination. This radar "blind-zone" limits CloudSat's ability to detect and measure the intensity of shallow snowfall processes occurring near Earth's surface, leading to increased uncertainty in CloudSat-derived snowfall estimates. Here, we develop a deep learning U-Net++-style convolutional neural network (i.e. blindpaint) for predicting reflectivity within a radar blind-zone. By relating latent information encoded in blind-zone-aloft clouds with additional context from collocated atmospheric climate variables, blindpaint learns to predict the presence and intensity of near surface reflectivities. Blindpaint demonstrates a higher proof of detection and lower false alarm rate to traditional inpainting methods, indicating an improved ability to predict the presence of near surface hydrometeors. The pixel-level accuracy of the inpainted blind-zone reflectivity values from blindpaint also demonstrate mean absolute error performance improvements that are an order of magnitude lower than traditional inpainting techniques. Additionally, by training blindpaint on a combination of CPR-calibrated KaZR surface radar datasets at multiple locations (along with collocated ERA-5 atmospheric data), and simulating the blind-zone, we are able to produce a generalized model which can then be applied to spaceborne observations from CloudSat. Machine learning inpainting techniques like those explored in this work demonstrate a compelling utility in enhancing current and future spaceborne remote sensing missions by revealing important connections between the blind-zone and the surrounding atmospheric state.

[1] Climate and Space Sciences and Engineering, University of Michigan, Ann Arbor, MI, USA
[2] Department of Geography & Environmental Management, University of Waterloo, Waterloo, ON, Canada
Corresponding author: kingfr@umich.edu