Environment and Climate Change Canada

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Leveraging Radiance Observations & Deep Learning to Retrieve Atmospheric Profiles

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1. Introduction

- **Motivation:** Satellite brightness temperatures have a significant positive impact on atmospheric analyses and ensuing numerical weather predictions (NWP). However, much science potential remains untapped due to certain limitations. Data assimilation algorithms often assume spatially uncorrelated observation errors; it is common practice to perform spatial thinning of observations to minimize correlations between remaining observations (Figure 1). Also, only a subset of all available spectral channels is assimilated for NWP, especially for hyperspectral infrared sounders (e.g. IASI). From those, multiple spectral channels are also currently rejected in the presence of clouds and over land/sea-ice.

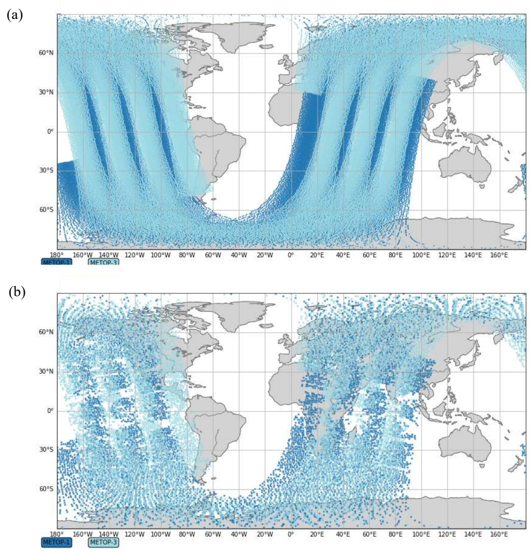

Figure 1: Distribution maps of IASI observations within a 6-hour window on 2025-03-02, as (a) captured by METOP-1 & METOP-3 (dark blue & light blue points respectively) and (b) operationally assimilated for NWP at ECCC.

- **Proposed solution:** ECMWF recently introduced a new Deep Learning (DL) approach to predict future weather parameters (e.g., surface temperature, wind) directly from level 1b radiance observations [1]. This proof-of-concept suggests that there may be predictive potential in an increased usage of satellite radiance observations and there is interest to build on this hypothesis from the perspective of NWP. **A methodology is being explored at ECCC to leverage DL to retrieve atmospheric profiles directly from level 1b radiance observations, without knowledge of the prior state.**

2. Methodology: RACCOONN

- A framework is being developed in Pytorch Lightning [2] for the **Retrieval of Atmospheric Conditions Computed using Only Observations & a Neural Network (RACCOONN).**
  - **Aim:** Assist NWP by enabling the assimilation of additional radiances $\vec{y}$ in the form of retrieved atmospheric profiles $\vec{x}$.
  - **Interpretation:** RACCOONN aims to approximate an inverse observation operator:

$$\text{If radiances } \vec{y} \approx H(\vec{x}, \vec{e}), \text{ then } RACCOONN(\vec{y}) \approx \vec{x}.$$

  - **How:** Train a neural network to learn the mapping between level 1b radiances and spatiotemporally co-located atmospheric conditions. Technical details include:
    - **Customizability:** Similarly to ECMWF's AnemoI suite [3], the Hydra library [4] is adopted to enable user customization of (a) data sources, (b) data preparation steps and (c) neural network architectures and training parameters to use.
    - **Workflow management:** From the Hydra configuration, the Snakemake tool [5] automates the pipeline based on dependencies between tasks (Figure 2).

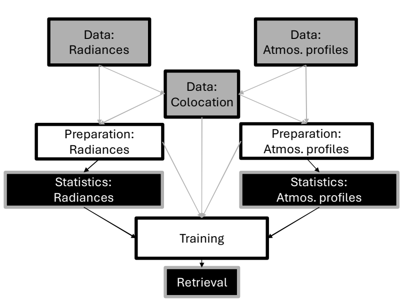

Figure 2: RACCOONN workflow, in the form of a Snakemake "directed acyclic" graph [5] that was constructed from Hydra configuration files [4]. The steps are summarized as follows:
(a) Acquisition & spatiotemporal colocation of both radiances and atmospheric profiles;
(b) Data preparation (preprocessing, dimensionality reduction/expansion, etc.) & statistics;
(c) Training of the neural network and retrieval of atmospheric profiles.

3. Proposed Plan

- **Idealized framework:** Modeled atmospheric profiles from known truth $\vec{x}_{\text{true}}$ are used in a radiative transfer model (i.e., RTTOV [6]) to generate simulated radiances $\vec{y}_{\text{true}}$.
  - Part of the generated dataset is used to learn a mapping between colocated synthetic radiances $\vec{y}$ & atmospheric profiles $\vec{x}$ (i.e., training and validation sets);
  - The rest is used as an independent dataset (i.e., test set) for evaluation and for comparison with existing retrieval schemes as references.

- **Description of preliminary idealized experiments:**

1. **"Inverse" radiative transfer operator for a <u>single</u> profile:** Train RACCOONN to directly retrieve an atmospheric profile ($\vec{x}$), from radiances ($\vec{y}$) synthetized using a radiative transfer model ($H(\vec{x})$). The aim of this experiment is not to be realistic, but rather to be an assessment of the fundamental capabilities and limitations of DL using an idealized framework with uniform atmospheric conditions.
   - Reference $\vec{x}_{\text{true}}$: Single atmospheric profile (temperature, wind components, humidity) over eta levels (i.e., pressure-based, terrain-following) computed by ECCC's Innovation Cycle-3 global deterministic prediction system [GDPS: 8] using the Modular and Integrated Data Assimilation System [MIDAS: 9] software.
   - Setup:
     - Atmospheric profiles $\vec{x}_{\text{train}}$: Based on the methodology established in [7] to produce a set of state vectors $\vec{x}_{\text{train}}$, random perturbations consistent with estimated state error covariances are added to $\vec{x}_{\text{true}}$ to generate multiple realizations with consistent atmospheric conditions:

$$\vec{x}_{\text{train}} = \vec{x}_{\text{true}} + \mathbf{B}^{1/2}\,\vec{\delta},$$

       where perturbations $\vec{\delta}$ are generated from a standard normal distribution and **B** is a static climatological state error covariance matrix [7, 10].
     - Radiances $\vec{y}_{\text{train}}$: Radiances are simulated using the RTTOV radiative transfer model H and the simulated atmospheric profiles $\vec{x}_{\text{train}}$,

$$\vec{y}_{\text{train}} = H(\vec{x}_{\text{train}}).$$

   - RACCOONN training experiments:
     - Dimensionality: Assess the number & selection of spectral channels needed to perform the "inversion" of an atmospheric profile with increased dimensionality (e.g., varying the information content in the vertical).
     - Spatiotemporal dependency: After evaluating its "inversion" capabilities for clear sky conditions over the ocean, assess the method at different retrieval locations in space (e.g., in the presence of clouds, over land/sea-ice) and time.
     - Initial neural network architecture exploration.

2. **"Inverse" radiative transfer operator for <u>various</u> profiles:** Enhanced realism with respect to experiment #1 by using diverse atmospheric conditions.
   - Reference: Similar to experiment #1, but for various profiles $\vec{x}_{\text{true}}$.
   - Setup:
     - Atmospheric profiles $\vec{x}_{\text{train}}$: Based on $\vec{x}_{\text{true}}$ for various time and locations to generate realizations with diverse atmospheric conditions.
     - Radiances $\vec{y}_{\text{train}}$: Same methodology as in experiment #1.
   - RACCOONN training experiments: Refinement of neural network architecture.

3. **"Inverse" radiative transfer operator with perturbed observations:**
   - Scheme for comparison: 1D-VAR retrievals ($\vec{x}_{1\text{D}}$) computed using MIDAS [7].
   - Reference: Same as in experiment #2.
   - Setup:
     - Atmospheric profiles $\vec{x}_{\text{train}}$: Based on $\vec{x}_{\text{true}}$ at various time and locations.
     - Background state $\vec{x}_{\text{b}}$: Perturbed states are generated as in experiment #1 to serve as a-priori estimates for 1D-Var, with state error covariance matrix **B**.
     - Radiances $\vec{y}_{\text{train}}$: Based on the methodology established in [7] to produce a set of state vectors $\vec{y}_{\text{train}}$, random perturbations consistent with observation error covariances are added to the true state in observations space,

$$\vec{y}_{\text{train}} = H(\vec{x}_{\text{true}}) + \mathbf{R}^{1/2}\,\vec{\delta},$$

       where perturbations $\vec{\delta}$ are generated from a standard normal distribution and **R** is the observation measurement error covariance matrix.

4. Summary

- **RACCOONN:** Ongoing development of a flexible DL framework to directly retrieve atmospheric profiles from radiance observations. The inferred profiles could be assimilated as substitutes to currently unassimilated radiances.
- **Proposed plan:** Initially use simulated atmospheric conditions and corresponding forward-modeled radiances to train & evaluate RACCOONN against known truths. Then increase gradually the complexity & realism of idealized experiments to approach observations.

5. References

[1] Alexe *et al.* (2024): https://doi.org/10.48550/arXiv.2412.15687;
[2] Falcon *et al.* (2019): https://doi.org/10.5281/zenodo.7469930;
[3] ECMWF – AnemoI: https://github.com/ecmwf/anemoi-core;
[4] Yadan (2019): https://github.com/facebookresearch/hydra;
[5] Mölder *et al.* (2021): https://doi.org/10.12688/f1000research.29032.1;
[6] Saunders *et al.* (2018): https://doi.org/10.5194/gmd-11-2717-2018;
[7] Wang, Buehner, & Huang (2025): https://doi.org/10.1002/qj.4948;
[8] Buehner *et al.* (2015): https://doi.org/10.1175/MWR-D-14-00354.1;
[9] Buehner *et al.* (2025): https://doi.org/10.5194/gmd-18-1-2025;
[10] Gauthier *et al.* (1999): ECMWF Workshop on Diagnosis of Data Assimilation Systems.

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