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Predicting surface solar irradiance from satellite imagery with deep learning radiative transfer emulation

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Short-term solar irradiance forecasts are becoming increasingly important as power grid operators have to deal with the uncertainty in incoming surface solar irradiance (SSI) and the expected photovoltaic (PV) power production. Geostationary satellites are an excellent source of spectral imagery of SSI-relevant atmospheric components over large geographical regions. The spectral measurements of the Spinning Enhanced Visible and Infrared Imager (SEVIRI) onboard the geostationary Meteosat Second Generation satellite form the basis of many SSI estimation and forecasting techniques [3], [4], [6]. These forecasting techniques usually rely on level 2 products to estimate SSI from reflectance but this induces a significant delay in the forecasting cycle. We demonstrate that using a deep learning regressor to estimate surface solar irradiance can drastically reduce this delay.

Previous machine learning-based methods for estimating SSI from geostationary reflectance imagers show great promise and can outperform state-of-the-art radiative transfer retrieval methods at the ground stations used as training sites [1], [2], [5]. Previous methods only use ground station SSI to train on, but point-wise estimators trained on a group of ground stations do not generalize well to out-of-sample ground stations, possibly because of changes in surface albedo [5].

To improve the generalization, we introduce a deep learning spatial convolution operator which is trained to emulate radiative-transfer SSI retrievals from spectral satellite imagery. Our SSI estimator model is fine-tuned on an extensive network of ground stations as a second training set. In this contribution, we will demonstrate the performance of the radiative transfer emulator, its applications and latency based on independent measurements from ground stations across Europe.

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