Deep Learning Based Convective Boundary Layer Determination for Aerosol and Wind Profiles observed by Wind LIDAR

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The height of planetary boundary layer (PBL) and convective boundary layer (CBL) are key parameters in regional air quality models to determine turbulence mixing, vertical diffusion, convective transport, cloud/aerosol entrainment, and deposition of pollutants. The conventional methods for identification of PBL pattern from lidar aerosol backscatter profiles in general require some criteria to be matched. Whereas, the CBLH can be easily determined from the variance of vertical wind speed measured by Doppler lidar/radar wind profiler. However, it is difficult define a criterion to identify the height of CBL from aerosol backscatter profile, especially when the CBL is too shallow in the night-time.

To overcome this issue, a deep-learning model is used to build non-supervised packages to identify the CBLH from aerosol and wind products measured by Doppler wind lidar. The machines are trained by a convolutional neural network (NN) in a supervised way and be forced to learn how to retrieve CBLH on real and non-ideal conditions in fully automated and unsupervised manners.

The Doppler wind lidar profiles of vertical wind, radial wind speeds in 4 directions (north, east, south, west) and aerosol backscatter (SNR) are separated into two kinds of 2D spatio-temporal maps (wind with backscatter and backscatter only) at 15-minute intervals with a sampling rate about 4 seconds. The CBL height determined from the variance of vertical wind speed measured by wind lidar and validated with co-launched radiosonde data is used to initially train the machine. The stacked hourglass network has been modified to capture the height of CBL from radial wind speed and aerosol backscatter, respectively. We collected a year's lidar data and generated over 30,000 maps for training. The Mean Absolute Error (MAE) of the CBLH estimated by the proposed deep learning method using 4 directional wind speeds and aerosol backscatters (without vertical component) is about 56 m. However, if only aerosol backscatter is used to train the model, the MAE of CBLH are about 91 m and 86 m for day-time and night-time measurements, respectively.

Unlike the conventional algorithms used to derive PBLH from lidar backscatter profiles, the deep-learning based method can efficiently find the feature of CBLH from Doppler wind lidar products without any prior assumption, and even only backscatter is used as the training data set. Our results also indicate that might be possible to derive CBLH from backscatter profiles measured by Mie-scatter based aerosol/cloud lidars.