New machine learning approaches for tropospheric profiling based on COSMIC-2 data over Taiwan

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INTRODUCTION

Earth's atmosphere is a complex, inhomogeneous and highly variable environment, which is indispensable to life and the main place of human activity. Hence, there is a demand of accurate and reliable prediction of weather and climate, which take advantages of meteorological parameters (such as temperature, pressure, water vapour) derived from different sensors i.e. Radio Occultation (RO). RO refractivity profiles can be straightforwardly transformed to dry temperature and dry pressure profiles using reduced refractivity equation in the regions where water vapour is negligible (above around 8-12 km altitude) and ideal gas and equilibrium assumptions can be applied. However, in the lower troposphere, this assumption is no longer valid due to the presence of abundant water vapour. Hence, ancillary information about temperature, pressure or water vapour pressure is required to calculate the physical atmospheric parameters. To overcome this problem, in this study, I tested different machine learning algorithms (artificial neural network and random forest regression) applied to the COSMIC-2 bending angle/refractivity to derive tropospheric profiles of pressure, temperature and water vapour.

DATA

- Study area: western North Pacific in the vicinity of Taiwan (110-130°E, 10-30°N)
- 6535 RO profiles from the FORMOSAT-7/COSMIC-2 for a period between 1 October 2019 and 31 May 2020.
- ERA5 reanalysis meteorological profiles as the target during training.
- External validation: 56 radiosonde observations from 17 stations.
- INPUT RO bending angle/refractivity profiles, latitude, hour and month of the event.
- OUTPUT: temperature, pressure and water vapour partial pressure
- All profiles interpolated between 1 and 20 km with 0.1 km spacing

METHODOLOGY

1. Dataset split
2. Co-location RO with RAOB (2h-time window and 70 km spatial distance)
3. MinMax scaler
4. Hyperparameter tuning – random search
5. Hyperparameter tuning – grid search
6. Final models
7. Testing and evaluation

TESTING RESULTS

<table>
<thead>
<tr>
<th>Neural Network</th>
<th>Random Forest</th>
<th>CDAAC wePf2</th>
<th>ERA5</th>
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</thead>
<tbody>
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<td><strong>INPUT</strong></td>
<td><strong>OUTPUT</strong></td>
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<td><strong>OUTPUT</strong></td>
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<tr>
<td>Temperature [K]</td>
<td>MAE</td>
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<td>0.79</td>
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<tr>
<td>Pressure [hPa]</td>
<td>MAE</td>
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<tr>
<td>Water vapour [hPa]</td>
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<td><strong>RMSE</strong></td>
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<td>Temperature [K]</td>
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