

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 live 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 However, in the lower troposphere, this assumption is no longer valid due to the presence of abundant water vapour.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 nueral network and random forest regression) applied to the COMSIC-2 bending angle/refractivity to derive tropospheric profiles of pressure, temperature and water vapour pressure.

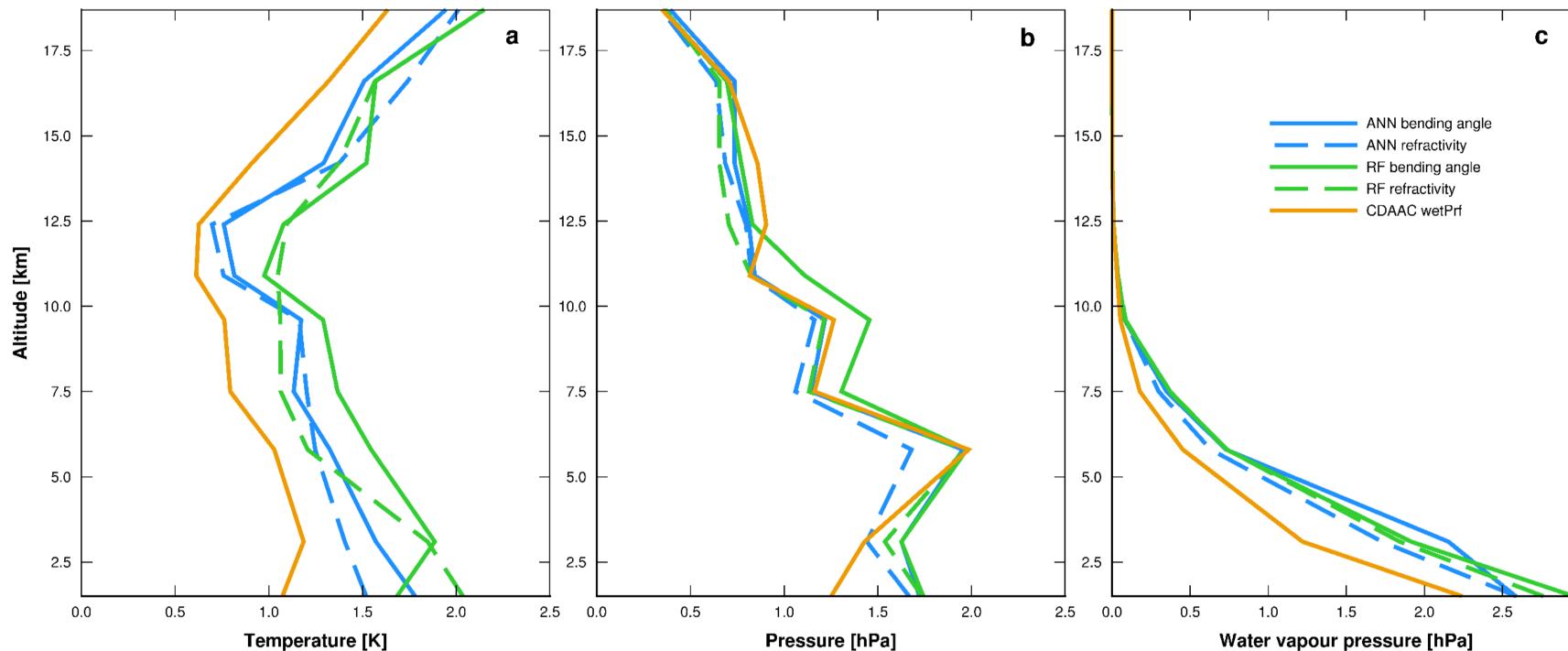
DATA • Study area: western North Pacific in the vicinity of Taiwan (110-130°E; 10-30°N) 6906 ROprofiles from the FORMOSAT-7/COSMIC-2 for a period between 1 October 2019 and 31 May 2020, • ERA5 reanalysis meteorological profiles as the target during training External validation: radiosonde observations from 17 stations, INPUT: RO bending angle/refractivity profiles, latitude, hour and month of the event,

Distribution of RO profiles (black dots) used in the training (a) and testing (b) processes. Red colour denotes RO observations co-located with nearby radiosonde stations (traingles).

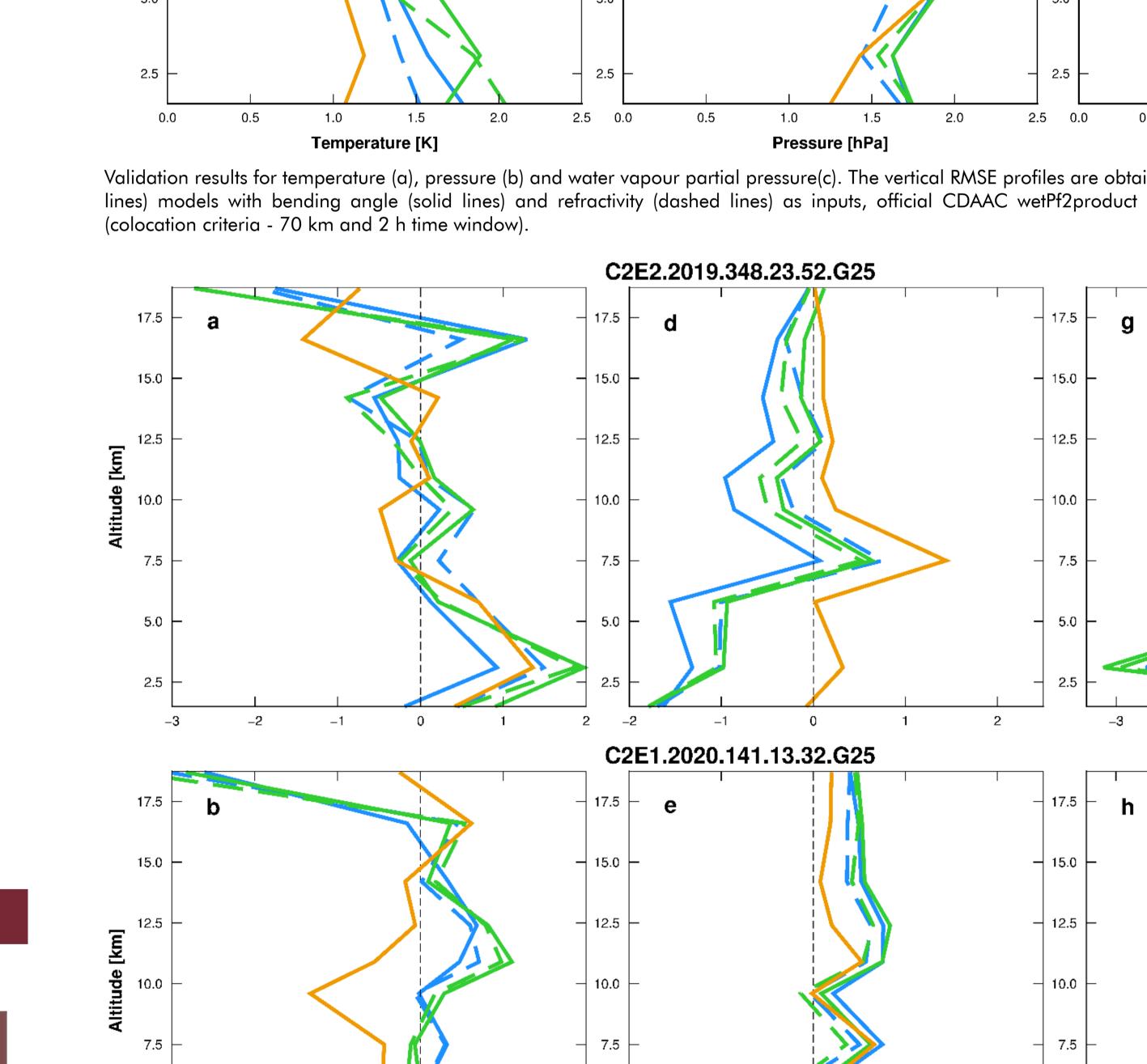
VALIDATION WITH RAOB RESULTS

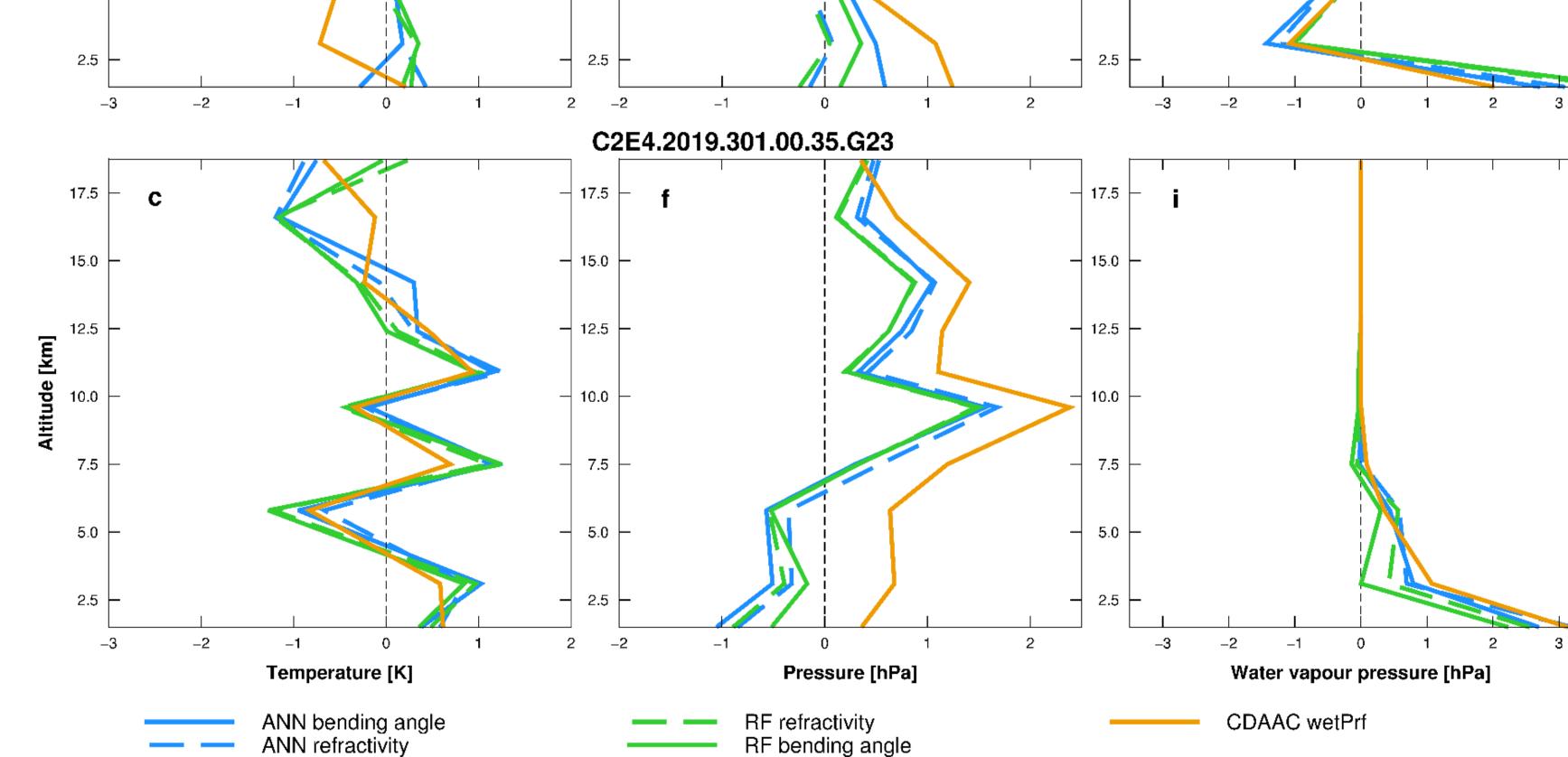
Mean absolute errors (MAE) and vertically averaged root mean square errors (RMSE) between different machine learning approaches, CDAAC wetPrf and 56 colocated RAOB (co-location criteria: 70 km and 2 h window)

			Neural Network		Random Forest	
OUTPUT	INPUT	Bending angle	Refractivity	Bending angle	Refractivity	CDAAC wetPrf
Temperature [K]	MAE	1.00	1.02	1.11	1.06	0.74
	RMSE	1.33	1.31	1.51	1.44	1.00
Pressure [hPa]	MAE	0.88	0.80	0.88	0.84	0.86
	RMSE	1.10	1.01	1.16	1.06	1.04
Water vapour [hPa]	MAE	0.46	0.43	0.48	0.45	0.31
	RMSE	0.60	0.54	0.61	0.58	0.42



Validation results for temperature (a), pressure (b) and water vapour partial pressure(c). The vertical RMSE profiles are obtained using ANN (blue lines) and RF (green lines) models with bending angle (solid lines) and refractivity (dashed lines) as inputs, official CDAAC wetPf2product (orange lines) and 56 colocated RAOBs





Validation results for temperature (a-c), pressure (d-f) and water vapour partial pressure(g-i). The vertical profiles show differences between colocated RAOBs and RO retrievals obtainedusing different machine learning models or 1DVar approach stored in the official wetPf2 CDAACproducts for radiosonde stations in Mactan (top panels), Legazpi (middle panels) and Haikou(bottom panels). Bold titles indicate the CDAAC profile ID, whilst vertical dashed lines representzero difference.

METHODOLOGY

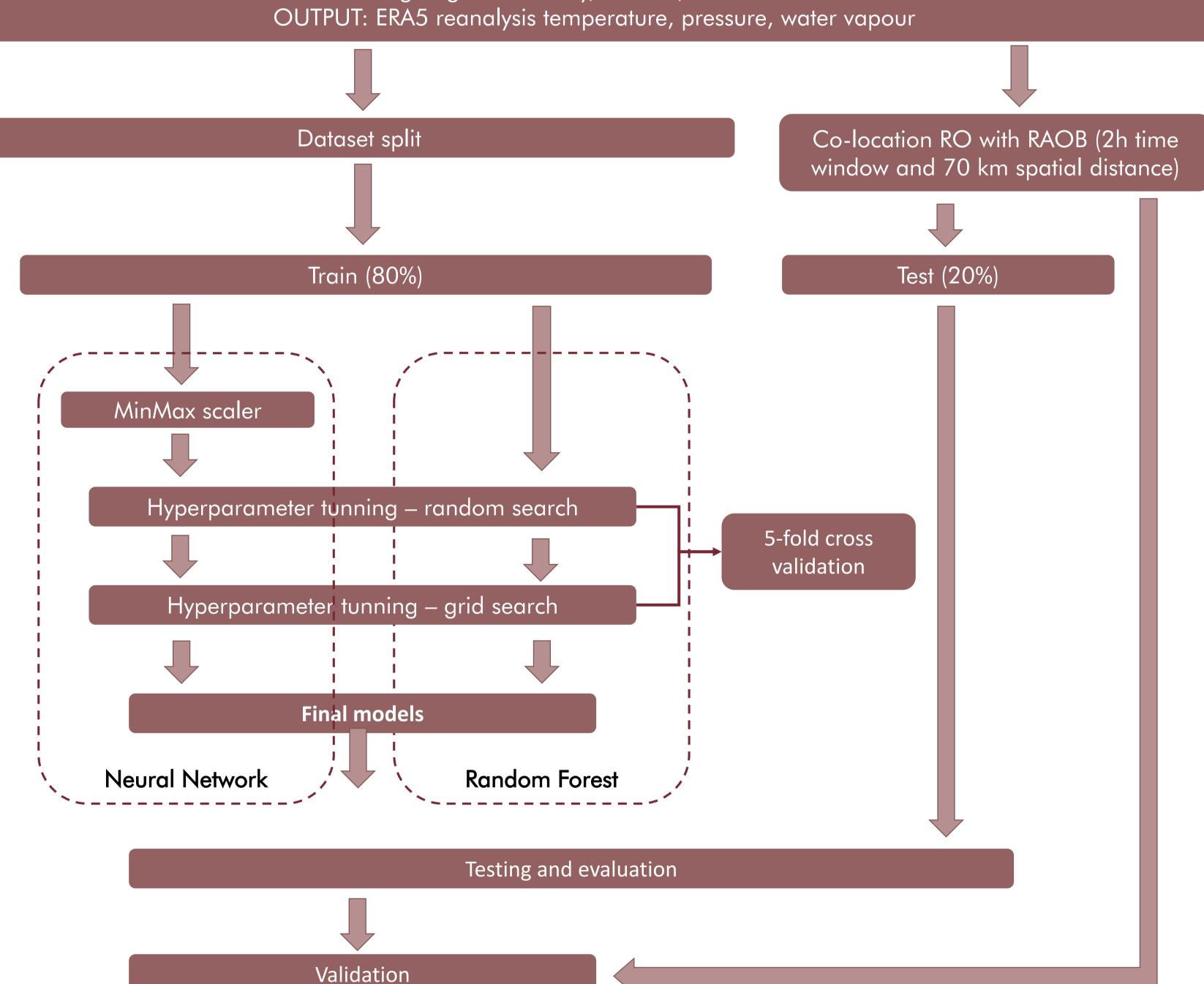
INPUT: RO bending angle/refractivity, latitude, hour and month of the event

• OUPUT: temperature, pressure and water

• All profiles interpolated between 1 and 20

vapour partial pressure

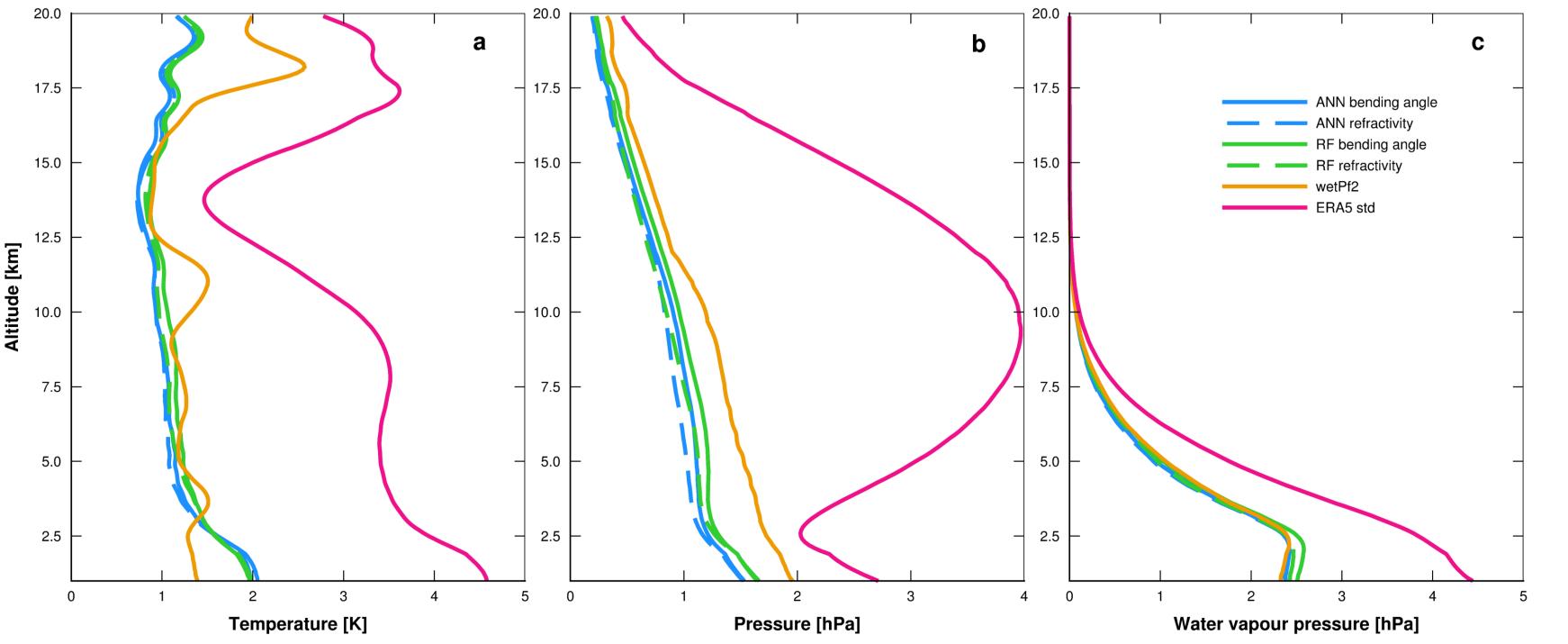
km with 0.1 km spacing



TESTING RESULTS

Mean absolute errors (MAE) and vertically averaged root mean square errors (RMSE) for the temperature, pressure and water vapour partial pressure obtained using different inputs and machine learning approaches on the testing dataset. The right column presents appropriate standard deviations calculated from ERA5 model.

		Neural N	etwork	Random Forest					
INPUT	OUTPUT	Bending angle	Refractivity	Bending angle	Refractivity	CDAAC wetPf2		ERA5	
Temperature [K]	MAE	0.78	0.79	0.84	0.80	0.90		3.04	
	RMSE	1.08	1.07	1.17	1.12	1.36			
Pressure [hPa]	MAE	0.56	0.53	0.59	0.54	0.78		2.64	
	RMSE	0.78	0.72	0.84	0.77	1.04	STD		
Water vapour [hPa]	MAE	0.34	0.33	0.38	0.35	0.33		0.79	
	RMSE	0.46	0.45	0.49	0.46	0.48			



RMSE for the temperature (a), pressure (b) and water vapour partial pressure (c) obtained on the testing dataset using different inputs and machine learning approaches and operational wetPf2 CDAAC product presented together with the ERA5 standard deviation

respectively.

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